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Abstract

In this thesis, I present the theory behind transaction costs, trade execution and algorithmic trading and empirically examine the transaction costs of SilentSeas Group's long-short equity hedge fund business. Concerning the theory, we comprehensively report the types of transaction costs, measures and determinants, the way that market participants create and consume liquidity, the orders and the limit order book, the buy-sell asymmetry as well as a well known approach, the implementation shortfall approach, of measuring total execution costs. Furthermore, I analyze popular algorithmic trading strategies, how orders interact in the limit order book, the way that pre- and post-trade equilibrium is established and the rationale behind optimal execution. I also summarize important studies on transaction costs and present the empirical findings. At first, the results suggest that commissions, which are equal to an average 5.1551 bps, and implicit transaction costs, which are equal to an average 39.1533 bps (VWAP cost), do present buy-sell asymmetry, hence sell orders have higher costs than buy orders. For instance, the average of VWAP cost is equal to -72.3893 bps for buys and 147.2049 bps for sells. The results by dividing the sample into high and low stock specific returns are similar concerning the buy-sell asymmetry. What is intriguing is that high movement stocks have lower explicit transaction costs on average, while low movement stocks have lower implicit transaction costs. Additionally, more principal has been traded on low movement stocks. The decomposition of implicit transaction costs into a VWAP cost component and a market movement cost component suggest that, based on separate panel regressions with fixed effects, transaction costs depend largely on VWAP cost and thus these costs can be approximated by VWAP cost. In addition, according to the panel regression analysis of implicit transaction costs, I find that transaction costs are affected by market capitalization, relative volume, inverse prior close, price momentum, VWAP, tap, perimeter and IS strategies, buy indicator and duration. From these factors only the buy indicator and duration are negatively related to transaction costs, while VWAP algorithmic trading strategy presents the highest costs. Also, transaction costs are not driven by return volatility and market index return, whereas the region dummies are omitted because of collinearity. From a forecasting perspective, I test out-of-sample the three models by running stepwise regressions and also include three naïve models which assume that transaction costs are always equal to the mean value of the realized costs. The findings suggest that, based on mean squared errors, the naïve models better predict costs, with the naïve VWAP cost model presenting the lowest respective value and thus predicting with better accuracy. However, these estimates should be interpreted with caution, as the mean values of the realized costs and the respective forecasted costs substantially differ and the standard deviations of the absolute forecast errors are large in magnitude in comparison with the mean values.

Keywords: Algorithmic trading, transaction costs, measures, determinants and decomposition of implicit transaction costs, panel regression with fixed effects, stepwise regression, out-of-sample forecasting.

JEL classification: C30, C33, G10, G12.

Introduction

By definition, trading constitutes an indispensable part of the investment process, as it reduces or even eliminates portfolio returns, due to the fact that financial markets are not frictionless and costs incur when buying or selling securities. As Domowitz (2001) states, investment performance is affected by two factors. First, from the underlying investment strategy of the portfolio manager and second from the transaction costs that arise from their implementation. Thus, due to the importance and the high levels of transaction costs, efficient and careful management of the incurred costs is imperative for every portfolio manager. If reducing trading costs can result in a slight increase of portfolio returns, it can be translated into a substantial amount of money, especially during years where the performance of equities is very low or even flat. In the process of monitoring the trading costs, all the data that are associated with the transaction process and are available must be captured and analyzed in order to identify the sources of trading costs and to estimate the impact on investment performance. According to Torre and Ferrari (1999), superior investment performance is the result of expecting reasonable return, controlling risk, controlling costs and controlling and monitoring the investment process to assure that is consistent with the initial investment program.

Previous studies analyze the magnitude and the determinants of transaction costs, for instance market capitalization inverse prior close price, relative volume, return volatility, buy indicator, price momentum etc., examine the buy-sell asymmetry according to which buy orders have higher transaction costs than sell orders, often driven by market conditions, the behavior of institutional traders by analyzing the order type, the determinants of trade duration and the motivations for trade, and highlight the importance of predicting transaction costs. They also study the interaction between cost, liquidity and volatility, the effect of stock trading on prices and present the differences between different cost measures and the use of alternative trading systems.

The objective of this dissertation is to present an overview of the theory behind transaction costs and trade execution as well as algorithmic trading and empirically examine the transaction costs of SilentSeas Group's long-short equity hedge fund business. Specifically, I measure implicit trading costs using different types of measures (e.g. prior close cost, VWAP cost, close cost), provide summary statistics of important measures such as explicit and implicit costs, principal traded, shares traded, market index movement and also divide the sample by side (buy and sell) and by specific return during the trading horizon, examine the existence or non existence of buy-sell asymmetry. Also, I run decomposition regressions of implicit trading costs on all transactions and separately on high as well as on low stock specific return during the trading horizon and implement a regression analysis of implicit trading costs by analyzing how various factors can affect costs. Lastly, I test out-of-sample the predictive power of the previous regression models.

This dissertation is organized as follows. Section 1 provides an introduction to transaction costs. Section 2 defines transaction costs and their components, their measures and determinants, as well as their relation with liquidity and the implementation shortfall approach of Perold (1998). In section 3 I discuss issues related to algorithmic trading and investment management, including popular strategies, market impact and the limit order book and optimal execution. Section 4 provides a brief review of the literature on transaction costs. Section 5 describes the data and section 6 presents the empirical results and a discussion on them. Finally section 7 summarizes and concludes.

Chapter 1: Transaction Costs

1.1 Introduction to Transaction Costs

As Kissell (2014) states, transaction costs are the fees paid by buyers or sellers. Another definition is that they represent the premium (discount) above (below) the market price in order to attract additional sellers (buyers) into the market. Generally, transaction costs incur each time securities are bought or sold.

According to Bodie et al. (2014), commissions is one of the components of trading costs that is explicit and obvious and must be paid to brokers. In addition to that, there is another component that is implicit such as dealer's bid-ask spread.

So, transaction costs are divided into two categories: explicit costs that are fixed and observable, and implicit costs that vary and are not so obvious, so there are several techniques in order to estimate them. Explicit costs include commissions, fees, taxes and bid-ask spreads, while implicit costs include investment delay, market impact costs, opportunity costs and market timing costs.

We can define two main categories of brokers: full-service brokers and discount brokers. The former category includes brokers that analyze and forecast economic, industry and company data and conditions and make recommendations to buy or sell. On the other hand, the latter category includes brokers that provide price quotations, buy or sell securities, offer margin loans, hold securities for safekeeping or short sale them.

1.2 Explicit Transaction Costs

Commissions are charged by brokers to execute trades and are commonly expressed per share or as a percentage of the total transaction value. They are negotiable and vary by broker, fund, trading type or trading difficulty.

Fees are categorized into custodial fees that investors pay to institutions to hold the securities in safekeeping, and transfer fees, which arise when the ownership over a stock is transferred. They also include clearing and settlement costs, exchange fees, ticket charges and SEC transaction fees.

According to tax law there are two types of taxes. Taxes on short-term and long-term capital gains and taxes on dividends. Generally, tax rates vary by investment and type of earnings. Apparently, tax planning is a significantly important component that must be included in investment strategies.

Bid-ask spread is defined as the difference between the quoted sell and buy price and is a direct transaction cost that compensates market makers for the risks that they take and are related to buying and holding an inventory, adverse selection and transactions with more informed investors. According to empirical results, high levels of liquidity are associated with small bid-ask spreads.

1.3 Implicit Transaction Costs

The time between the decision of a portfolio manager to buy or sell a security and when the actual trade is executed by the trader is referred to as investment delay. Investment delay cost is the price change that occurs if the price of the underlying security changes during this time and depends on the investment strategy and the trading system that have been used. For instance, traditional trading systems, according to which there must be an approval before the trade, are related to high delay costs, whereas quantitative trading systems, where the order is submitted automatically, exhibit low delay costs.

The difference between the transaction price and the market (mid) price that would have prevailed unless the trade had been executed, represents the market impact cost, while the price movement is the cost for liquidity. If a trader buys at a price below the market (mid) price, the market impact can be negative, so liquidity providers face negative market impact costs, whereas liquidity demanders face positive market impact costs. There are two types of market impact costs, temporary and permanent. Temporary market impact cost occurs due to liquidity demand by the side of the investor in his effort to buy or sell and at the same time the market has insufficient counterparties to completely execute the order. So, it is the premium that investors pay or the price discount that sellers provide in order to attract additional counterparties. Permanent market impact cost is caused by the information content of the trade and results in a persistent price change due to market adjustments. For instance, a buy order reveals to the market participants that the underlying security is undervalued, so the security price changes in order to reflect investors' perceptions and all the available information. As

Torre and Ferrari (1999) highlight, a simple and easy way to measure market impact is to look at the quoted prices prior to the trade, which market participants are prepared to buy (bid) or to sell (ask). It is defined that these quotes are offered for a limited and specified quantity of shares called quote depth. The difference between ask and bid prices represents the bid-ask spread, while the average of bid and ask prices is the midquote. Halfspread is the difference between quote price and the midquote. Assuming that midquote represents the price that would have prevailed in the absence of the transaction, the halfspread is an estimate of the market impact. The transaction will occur at the bid or ask price only if the size of the transaction is less than the quote depth. Otherwise, the transaction will occur at a less favorable price. The difference between this less favorable execution price and the halfspread represents the incremental market impact. A trader who is not demanding immediate liquidity can decrease the temporary market impact by breaking a parent order into small portions during a longer trading horizon, executing each time a small percentage of the average volume but with increased opportunity costs, delay costs and price movement risk. According to previous studies (e.g. Chan and Lakonishok 1993; Keim and Madhavan, 1996; Hu, 2009), there is an asymmetric behavior between market impact costs of buy and sell orders, proposing that buy (sell) orders have higher (lower) implicit trading costs, especially in bullish (bearish) markets. So, this asymmetry is mainly driven by the underlying market conditions rather than market microstructure effects.

It is a fact that stocks trend up or down, as the stock market drifts positively or negatively. Price movement risk is the situation where the stock price change during the trade is due to the general trend of the security, while the remaining part is market impact costs. For example, if a trader buys (sells) at rising (falling) market, he might pay (receive) more (less) than he expected. So, trading in the same direction as the market gives rise to price risk.

Market timing costs occur when the price of the security changes at the time of the transaction and can be attributed to other market participants or market volatility. It is empirically estimated that market timing costs are higher for larger trades when they are broken into small portions and traded over a long period of time. Also, they are proportional to the standard deviation of the security returns multiplied by the square root of the time until the completion of the trade.

The cost that arises from not transacting, that is in the case that a trade fails to execute and thus the portfolio manager misses an opportunity, is referred to as opportunity cost. It can be estimated as the deviation of the desired investment from the actual investment after transaction costs and is driven by price risk and market volatility. Consequently, the longer the trading horizon, the greater the chance to face high opportunity costs.

1.4 Liquidity

Participants who transact in the financial markets by buying or selling securities create liquidity, while brokers or dealers just intermediate and execute the orders that have been delegated to them. Highly liquid market means immediately executed large transactions and low transaction costs. In the ideal form of an indefinitely liquid market, a trader can execute a large trade at the quoted bid-ask prices. However, in practice the prevailing prices deviate from the quoted in a less favorable manner. Also, transaction size significantly influences market impact costs, which vary during the day as traders change their limit orders that are resting in the limit order book. Thus, liquidity, transaction size and transaction costs are interrelated.

Concerning the types of orders, a limit order is conditional and is executed only at the specified or a better price, while a market order is unconditional and is executed at the best possible price. Limit orders are used to improve the quality of the trade by obtaining a better execution price with the drawbacks of uncertainty and not immediacy of the execution. A limit order book represents the prevailing demand (limit buy orders) and supply (limit sell orders) in the market, as the resting orders constitute the existing liquidity. If there is a perfect match between bid and ask side, a trade could incur. Generally, the gap, that is the difference between bid and ask side, gauges liquidity. The smaller the gap, the more liquid the market and the willingness of participants to trade.

1.5 Measures of Implicit Transaction Costs

To measure the true implicit transaction costs, we need to estimate the difference between the price of the security in the absence of the trade, which is not observable, and the execution price. It is worth noting that the execution price depends on supply and demand conditions at the margin, that is on the structure of the market mechanism, and on being sensitive to the behavior of traders who demand immediate liquidity and to traders with similar motives.

There are many different measures of transaction costs. Generally, they are estimated as the difference between the execution price and a fair market benchmark. The difference between these measures lies on the benchmark that is used.

$$\text{Implicit Trading Cost} = \text{Side} * \frac{\text{Execution Price} - \text{Benchmark Price}}{\text{Execution Price}} \tag{1}$$

where, side is equal to 1 for buys and -1 for sells and benchmark price is equal to the closing price on the day prior to the trade (Perold, 1988) / opening price on the same day (pre-trade measure) or to the volume-weighted average price of all market transactions during the trading horizon (VWAP) (Berkowitz et al., 1988) or to the closing price of the trading horizon or opening / closing price on the next day (Beebower and Priest, 1980) (post-trade measure).

It is also common to control for market-wide during trade market movement by subtracting the market index return over the trading horizon.

$$\text{Implicit Trading Cost} = \text{Side} * \frac{\text{Execution Price} - \text{Benchmark Price}}{\text{Execution Price}} - \text{Market Index Movement} \tag{2}$$

Apparently, different benchmarks can result in different results. The selection of the appropriate benchmark can be based on the particular application.

1.6 Implementation Shortfall Approach

According to implementation shortfall approach (Perold, 1998), in the process of analyzing portfolio's returns in order to attribute the performance to investment profits/losses and trading profits/losses, it is useful to decompose investment decisions from order execution. Practically, the portfolio manager initially decides which securities to buy or sell and afterwards the trader implements these decisions. We can estimate the implementation shortfall, which represents the total cost of execution, as the deviation of the actual portfolio profit/loss from the desired (paper) portfolio. Paper return is defined as the difference between the ending portfolio value and its starting value. Actual return is calculated as the difference between the actual ending portfolio value and the initial value of all securities acquired, minus all fees of the transaction.

1.7 Determinants of Implicit Transaction Costs

An analysis of the factors that affect implicit trading costs is very useful in forecasting trading costs and in constructing optimal trading approaches. Although explicit transaction costs are observable and easy to estimate and forecast, implicit transaction costs and especially market impact cost, which is one of the main and more costly transaction components and results in adverse price changes, are the costs that are more difficult to estimate and forecast and the ones that I am going to focus. As discussed in a previous section, market impact is the change in price caused by a specific trade. The methodology of estimating and forecasting market impact costs is based on a linear factor model, where market impact (implicit costs) is the dependent variable, and trade- and asset-based factors are the independent variables.

According to previous studies, a few examples of trade-based factors are trade size, relative trade size, price of market liquidity, type of trade, efficiency and trading style of the investor, characteristics of the market, time of trade submissions, trade execution and order type. Trade size is defined as the number of shares traded or the dollar value of trade, while relative trade size equals trade size divided by average daily trading volume (usually over the 5 prior trading days) to measure temporary market impact, or divided by the total number of shares outstanding for permanent market impact. Obviously, since a large trade requires more liquidity, we expect that high magnitude of relative trade size increases temporary market impact. Traders can be categorized according to their investment style into technical, value and index. Thus, each investment style requires different levels of liquidity immediacy. Technical traders seek to capture short-term price movements. An index trader who mimics a benchmark portfolio with minimum tracking error, faces low opportunity costs and high price impact and commission costs, while a value trader who identifies opportunities based on fundamental values incurs large opportunity costs and low price impact and commission costs.

1.8 Buy-sell Asymmetry

According to many previous studies (e.g. Chan and Lakonishok, 1993; Chiyachantana et al., 2004; Hu, 2009), buy orders have higher implicit trading costs than sell orders. Actually, a trader would expect that there is no buy-sell asymmetry if implicit trading costs are a true measure of execution quality. It is empirically defined that this asymmetry is driven by many factors, with market conditions being the dominant. Buy orders incur higher implicit trading costs in rising markets, while the opposite exists in falling markets. It can be also explained by the fact that liquidity available for buys is higher than for sells. So, when the market conditions are bullish, sells consume liquidity and buys provide liquidity. In addition, this buy-sell asymmetry also depends on firm-specific factors, order characteristics and cross-country differences. Chiyachantana et al. (2004) suggest that this asymmetry is not caused by the fact that buys contain more information than sells. They found that large size trades are affected by market movements and pay a higher premium for liquidity when they trade on the same side of the market. Thus, liquidity available to buy is higher in falling market conditions. Hu (2009) argued that the differences and the magnitude of the costs are dependent on the mechanical characteristics of the measures, that is on the benchmark that has been used, and on market movement. When a trader uses pre-trade measures, buys have higher implicit trading costs during rising markets. On the other hand, post-trade measures result quite the opposite, that is sells have higher implicit trading costs during rising markets. Obviously, both types of measures are highly influenced by market movements, whereas during-trade measures, i.e. VWAP, are neutral to market movements.

Chapter 2: Algorithmic Trading

2.1 Introduction to Algorithmic Trading

In this section I display some of the most important algorithmic trading strategies. In our era, technology has a significant impact on the way that securities are traded. A large fraction of all the trading volume can be attributed to algorithmic trading, that is automated trading based on a set of rules. These algorithms determine the time, the price and the size of trades that minimize the risk-adjusted costs.

There are a few execution strategies that are typically offered by banks and institutional brokers/dealers. Mainly, an algorithmic trading strategy is driven by a style of trading or a theme and its objective is to minimize either absolute or risk-adjusted costs relative to a benchmark. Often, an optimization is executed for some strategies, in order to find how to best use the strategy to maximize a trader's utility. According to Fabozzi, Focardi and Kolm (2010), "a trade schedule- or trajectory- is planned for strategies with a target quantity of shares to execute. The order placement engine –sometimes called the microtrader- translates from a strategy's broad objectives to individual orders. User defined input parameters control the trade schedule and order placement strategy".

2.2 Algorithmic Trading Strategies

Volume-Weighted Average Price

Volume-weighted average price (VWAP) execution strategy is the second most popular strategy after arrival price, and it is attractive due to the easy to compute benchmark. The input parameters of a VWAP execution strategy are the start time, the end time, the number of shares to execute and optionally, the risk aversion.

According to the VWAP strategy, a trade schedule is estimated to match a fraction of the daily trading volume pattern over the execution period. For instance, if 15% of a day's volume is expected to be transacted in the first hour and the execution period is one day, then the trader would trade 15% of his target quantity in the first hour of the day. It is evident that the daily volume pattern is U-shaped, so there is more trading in the first and the last hours of the day and less in the middle. Thus, a VWAP strategy would have the same shape and follow the same pattern of trading throughout the day.

If a trader has little or no alpha, is benchmarked against the VWAP, states that market impact is minimized when his rate of trading constitutes the smallest possible fraction of the whole trading activity and has determined a target quantity to trade, then VWAP is the appropriate strategy to use.

A VWAP model typically uses a simple historical average of the fractional volume to forecast the daily trading volume. Obviously, this prediction is noisy and the actual volume pattern of the day substantially differs from it, making the achievement of the strategy's objective more difficult and complicated. In an attempt to minimize this deviation, some VWAP models base their predictions on observed results during the day and make dynamic adjustments. Also, a trader who uses this strategy can lower his expected costs by increasing his exposure to risk, for example by placing limit orders during the trading day and a market order at the end of the day in order to fill the remaining quantity of shares to be traded.

Time-Weighted Average Price

The objective of the time-weighted average price (TWAP) strategy is to minimize market impact costs preserving a constant rate of trading over the execution period. The input parameters are the same as VWAP's strategy i.e. start time, end time, target quantity and optionally, risk aversion. Actually, it is the simplest strategy to implement and in its basic form breaks a large parent order into small orders and executes them at a constant rate throughout the execution period. It is observed that in an effort to improve execution quality, except for market orders, the strategy may place some limit orders to obtain more favorable prices. It is the appropriate strategy for traders with the same characteristics as VWAP's traders, except for the fact that they must believe that the lowest trading rate incurs the lowest market impact costs.

Participation

The participation strategy is based on maintaining a trading rate as a fraction of the market's total trading rate that is constant during the execution period. However, this strategy can not guarantee a target fill quantity if the trading rate is maintained exactly the same. In contrast to other trading strategies, participation strategy does not use trading schedule, as its objective is just to participate in volume. In practice, this strategy waits for trading volume to arise and follows this volume using market orders.

The parameters of this strategy are the start time, end time, fraction of market volume and the maximum number of shares to execute. Also, VWAP and arrival price benchmarks are used to measure the quality of participation strategy, with VWAP being the most appropriate as the volume pattern of a perfectly executed participation strategy is the market's volume pattern throughout the execution period. An ideal user of this strategy has the same characteristics as VWAP's, except that he is disposed to pass over particular execution to maintain the lowest possible fractional participation rate. The main advantage of this strategy is that it can closely track and follow the actual trading volume pattern, unlike a VWAP strategy which incurs large deviations, but with the drawback of large expected market impact costs that are caused by placing fewer and larger market orders.

Market-on-Close

Market-on-close strategy attracts traders or portfolio managers whose objective is either to minimize risk-adjusted costs relative to the closing price of the day or to manipulate (game) the close price to make the execution seem good, by executing rapidly near the close of the day and making the closing price to equal the trade print[1]. The input parameters are the start time, end time, the number of shares to execute and optionally, risk aversion for optimization. It is addressed to traders who are benchmarked against the close price of the day and has low or even negative alpha. As in a market-on-close strategy, a back-weighted trading schedule incurs less risk than a front-weighted, thus a risk averse trader would execute all the target quantity at the closing of the day. Fortunately, as the use of VWAP and arrival price strategies have increased, the use of market-on-close strategy to manipulate the close price has become less frequent.

Arrival Price

The arrival price (implementation shortfall) strategy minimizes risk-adjusted costs based on the arrival price as a benchmark. In order for a trader to use this strategy, they must be benchmarked against the arrival price, be risk averse, have high positive or negative alpha and believe that by maintaining a constant rate of trading over the maximum execution period and keeping small trade size, market impact is minimized. According to arrival price strategy, a risk averse trader executes all the target quantity

[1] Trade print is defined as the price at which the trade takes place.

at the opening of the day. It assesses a number of trade schedules and chooses the one which minimizes risk-adjusted costs relative to the benchmark. The parameters are start and end time, alpha, shares to execute and risk aversion. It is evident that for buyers, positive alpha demands faster trading. In addition, market impact costs encourage slower trading, whereas for both buyers and sellers risk encourages faster trading. According to this strategy, the feasible region of solutions that takes into account both positive and negative alpha incorporate both front-weighted and back-weighted trade schedules.

Another form of arrival price strategy is adaptive arrival price, according to which, a favorable execution may induce a large number of shares to take place at a price below the arrival and should be used by risk averse traders in their effort to reduce risk.

Crossing

Crossing networks are based on the limitation of information leakage of the open books of electronic exchanges which display limit orders, by making them opaque to anyone concerned (antigaming logic). The underlying concept of crossing networks is that limit orders are not sufficiently protected in a public exchange, so the information that leaks is used by participants to trade more passively, expecting that as time passes the traders will be forced to replace limit orders with market orders. Except for opaqueness, other forms of antigaming include the minimum size of an order, the minimum time that an order remains in the network, crossing only similar size orders, prevention of crossing during times of unusual market activity, limiting the activity of active traders and monitoring clients' activities.

A variant of crossing networks is continuous crossing network strategy, which constantly scans the limit order book in order to match buy with sell orders. Another form is discrete crossing network, according to which the matching takes place at specified points in time. Automated crossing networks match resting orders according to a set of rules, without the cooperation among the counterparties. In negotiated crossing networks, the traders first indicate their interests and then negotiate the price and size. Private dark pools, one more form of crossing networks, constitute of orders that are not available to the public. Also, there are some exchanges that allow the use of invisible orders, that is orders that are not visible to other participants. A crossing aggregator manages a single large order across a few crossing networks in return for a fee. This constitutes a relatively complex task as every network differs in order placement and antigaming rules. In addition, they might use information such as historical and real-time fills in order to direct orders. Liquidity seeking strategy attempts to exploit available liquidity, thus trading speeding up or slowing down accordingly. The objective of financed trading is hedging by financing the purchase of a buy order.

2.3 Market Impact

The limit order book consists of resting limit orders that provide liquidity and awaits other orders which represent the demand for liquidity, to arise and to be matched. It is divided into two sides: buy and sell. The buy side includes bid orders to buy a number of shares at a specified price and the offer side includes offer orders to sell a number of shares at a specified price. A market order demands immediate execution of a target quantity at the best possible price. Another form of order is marketable limit order that can be executed at a specified or a better price.

Based on Fabozzi, Focardi and Kolm (2010), I present an example of how market orders to buy interact with limit orders to sell in the limit order book. At first, the state of the book establishes a pre-trade equilibrium. As the buy order arrives, the algorithm scans and at the same time depletes the offer side of the book by matching with resting limit orders to sell. By depleting the offer side, the orders obtain increasingly higher (less favorable) price and result in the trade print. It is defined that trade print is the price at which the trade takes place. If there is no other activity, liquidity providers replenish the offer book and a post-trade equilibrium is established. The difference between post-trade and pre-trade equilibrium is called permanent market impact, which is actually the market's response to information. The difference between post-trade equilibrium and trade print represents the temporary market impact and is caused by the trader who is willing to obtain a less favorable price in his effort to fill his order. As a result, impact models have been created in order to predict changes in price that are caused by trading activity.

2.4 Optimal Execution

Price risk, that is the risk of obtaining a less favorable price because of the random movement of prices, arises as a trader waits between two trades. A risk averse trader demands immediacy and is willing to pay a premium to reduce risk. The premium that incurs is actually a higher temporary market impact. Thus, high risk aversion encourages fast trading, while high expected temporary market impact induces slower trading. Shortfall is defined as the difference between the effective execution price and the arrival price and the variance of this measure can be used as a proxy for risk. For instance, if a trader executes all the quantity to be traded via only one transaction, he may pay higher costs to reduce risk, while if he divides for example the target quantity into two transactions, he may incur high variance of shortfalls in return for lower costs. Additionally, expectation of price change influences the timing of the trade. For instance, positive alpha represents the profits that are expected from the execution of a trade, so faster trade captures more of the profits that are related to this expectation of price change.

The rationale of optimal execution is to determine the best trade-off between market impact, alpha and the effect of risk by minimizing the risk-adjusted costs relative to a benchmark, such as VWAP and arrival price.

Chapter 3: Literature Review

In this section, I present a summary of some of the studies of the large and growing literature that especially documents methods of measuring implicit trading costs and factors that affect and predict market impact costs.

The early work of Collins and Fabozzi (1991) reviewed the definition of trading costs and their components and proposed a methodology for analyzing the transaction process in order to provide insights into its evaluation. Specifically, they defined execution, opportunity, implementation, market timing and implied execution costs, market impact as well as informationless and rebalancing trades. They analyzed the methodologies for measuring transaction costs, including pre-trade, post-trade and during-day measures, using the appropriate price benchmarks. Then, they provided a portfolio profit and loss statement, a transaction cost analysis report which includes details of the transaction process such as execution costs (using both pre- and post-trade measures for market impact) and market timing costs, comparing the VWAP with the trade-weighted average price, and liquidity conditions (including the fraction of the portfolio that can be executed). Following, they presented comparisons of the executed portfolio with the benchmark portfolio as well as a pre-trade analysis table which provides information about the portfolio such as dollar value based on the last sale, the bid and the ask prices and the spread impact of buying or selling the portfolio. They also stated that the current size of the market quoted on the bid or the ask may not be a perfect indicator of the liquidity actually available in the market. Concluding, they presented a total cost comparison between the actual portfolio and an investor's desired portfolio and a stock summary report that can help a portfolio manager identify stocks that are difficult to trade.

Chan and Lakonishok (1993) in their paper examined the effect of stock trading on prices and showed that the magnitude of this effect is small on average and that trades are related to price impact asymmetry between buy and sell orders. In particular, they related this to the demand for stocks, the transaction costs and the determinants of market impact. Despite all the other determinants of price impact, they stated that the dominant one that influences it the most is the identity of the money manager and hence the investment style and the trading strategies that they use. It is also evident that institutional trading is related to some price pressure, and particularly a principalweighted average price increase of 0.22% for buy orders and a respective decrease of 0.14% for sell orders in relation to the opening price on the date of trade that is caused by prior release of information, short-run liquidity or even positive-feedback trading. In their analysis of the post-trade behavior of prices, they concluded that sell orders reflect short-run liquidity, whereas buy orders reflect either information effects or inelastic excess demand curves. Their empirical results also showed that sells used to involve intermediary brokers and its price impact reflect a temporary discount, while buys are motivated by information signals.

Keim and Madhavan (1995) examined the behavior of institutional traders by analyzing the motivations for trade, the determinants of trade duration and the choice of order type and provided insights into the anatomy of the trading process. In particular, they found that in some cases there is relationship between buy or sell decision and past excess returns, although there might be no effect due to the strategies of the traders which contradict. They presented that as order size and market liquidity increase, trade duration increases too. They also confirmed the buy-sell asymmetry and proved that buy orders have higher duration than sell ones. Concluding, they stated that institutions with different investment strategies tend to choose different order types. For instance, index traders whose objective is to mimic an index may use market orders in order to maximize the correlation with the benchmark they use.

Keim and Madhavan (1997) analyzed the determinants and the magnitude of transaction costs. They used data that include different investment styles (technical, index, value) and found that costs vary with trader-specific factors, reflecting differences in trading ability, and are substantially related to trade difficulty (positively) and market liquidity. In their sample, value traders mainly use limit orders and have negative implicit costs when they sell exchange-listed stocks, while technical traders have the greatest demand for liquidity and rely on market orders. They also asserted that market impact is low in liquid stocks with large market capitalization and that in small quantiles of market capitalization, total costs tend to rise with trade size. In addition, total transaction costs are inversely related to market capitalization in small quantiles of trade size. Finally, they concluded that trade initiation and exchange listing affect trading costs and emphasized the importance of analyzing trading costs and accounting for investment style.

Keim and Madhavan (1998) provided an overview of the size and the determinants of transaction costs. More specifically, they presented and described the components of transaction costs in parallel with respective previous studies and issues in measuring implicit trading costs. The importance of measuring and predicting trading costs, determining their effect on actual portfolio performance, examining the behavior of traders is undeniable. They stated that in order to measure trading costs with accuracy, both implicit and explicit costs must be taken into consideration and the measurement should be at the level of the entire order as in Perold's (1988) approach. They found that commissions average from $0.4 to $0.05 per share and increased to $0.15 in 1991-1993 and proposed as other authors did that effective bid-ask spread, which is based on transaction prices, is a better measure of the actual spread than the quoted one. Another important issue is that, in order to measure total costs you can not just add up the components of transaction costs as it is misleading. The measurement must be at order or transaction level data. Also, large packages of trades is a more accurate unit of observation than individual trades which are used in numerous studies. Additionally, they related transaction costs to some factors. For instance, they stated that liquid stocks have lower total costs than small market capitalization stocks and that large trades incur large costs. They indicated the buy-sell asymmetry, with sells appearing to be more costly than buys. They also found that investment style affects costs as aggressive traders who demand immediate liquidity have higher costs than less-aggressive ones. Other factors are the trading skills and reputation of the trader. Finally, they presented implications for public policy and for portfolio managers.

Conrad et al. (2001) divided trades into two categories, according to the brokers that they are directed to. The first category regards trades that are directed to soft dollar brokers, that is brokers that execute trades and provide other non-execution services, and the second considers trades for pure execution. They demonstrated that institutions are more likely to choose brokers depending on trade difficulty and investment style. They also estimated a shadow price for soft dollar payments by performing cross-sectional regressions and found that these trades increase costs by approximately 23 basis points although these costs vary across traders. As expected, the magnitude and the variation in soft dollar services cause problems to regulators, practitioners and academics such as conflicts of interest, incentive problems, excessive commissions, overtrade, inferior execution or even manipulation of fund expenses. They also showed that, due to the fact that soft dollar rebates appear in NYSE-Amex securities, comparisons of costs with Nasdaq may be biased.

Domowitz et al. (2001) in their study about the interaction between cost, liquidity and volatility, following and extending another previous study (Domowitz et al., 1999), analyzed panel data from 47 countries and found significant variations across countries. Especially, emerging markets tend to have the higher implicit costs, but in general terms, costs show a decline, except in East Europe. Despite the fact that high volatility reduces returns, it also reduces turnover, which is inversely related to costs, and mitigates the impact. They also pointed out the importance of predicting trading costs and the factors that affect its accuracy. First, it is the nature of cost components, where some of them are very easy to predict (commissions, taxes), while others e.g. opportunity and timing costs depend on market movements and investment style and thus display high variance. Except for the above, there are other factors that can not be observed and approximated with accuracy which explain this variation. In cases of risk averse traders, they highlighted that there is a tendency to change their trading strategy toward others such as crossing networks, automated limit order book systems and guaranteed principal bids, in which prediction is better. Finally, they constructed global efficient portfolios which seem to change substantially when cost and turnover are included in the analysis.

Conrad et al. (2003) examined the use of alternative trading systems. They classified orders according to the trading system that have been used into crossing systems, electronic communication networks and traditional brokers. They found evidence that after controlling for endogeneity in the choice of trading system, using an endogenous switching regression, and for variation in security characteristics, transaction costs are higher when orders are executed by traditional brokers. In their sample, crossing systems have the lowest fill rate, but have presented lower costs than broker-filled orders, after ECNs. They also indicated that cost differences across trading systems reflect a component of costs that is not included or a benefit of broker trading that is not measured or is a temporary situation as markets change equilibrium. Finally, they pointed out that the 1997 order handling rules and the change in tick sizes played a crucial role in the reduction of the advantage of trading on ECNs and subsequently, in the reduction of ECN use and cost differences.

Keim (2003), in his paper extended other previous studies that examine the relation between stock returns and other ex ante variables by distinguishing realizable returns from returns to simulated strategies, which are most commonly used. He incorporated transaction costs into the actual implementation of momentum strategies as there is no empirical evidence that these strategies can be successfully executed the way size and value strategies can. In particular, he analyzed the costs of three different investment styles and found evidence that momentum traders' trades are conditional on prior price movements and their costs are greater than the respective unconditional costs. He also highlighted that the returns of simulated strategies that most studies report are not sufficient to cover the costs of their implementation.

In their paper, Chiyachantana et al. (2004) used international data for the periods of January 1997 to March 1998 and January to September 2001, with the first period being bullish and the second bearish. As in previous studies, they found that price impact is mainly driven by market conditions. In rising markets, buys have higher market impact than sells, while in falling markets the opposite exists. This can be explained by the fact that liquidity available for buys is higher than for sells. So, when the market conditions are bullish, sells consume liquidity and buys provide liquidity. In addition, they stated that this buy-sell asymmetry also depends on order characteristics, firm-specific factors and cross-country differences. In contrast with previous papers, they suggest that this asymmetry is not caused by the fact that buys contain more information than sells. They found that large size trades are affected by market movements and pay a higher premium for liquidity when they trade on the same side of the market. Thus, liquidity available to buy is higher in falling market conditions. Also, their findings suggest that price impact is negatively correlated with prices and market capitalization and is higher when the order is large and when the order is split over multiple brokers and days. Trading costs are also higher for emerging and non-liberalized markets or for markets with poor shareholder rights.

Bikker et al. (2007) analyzed market impact costs of one of the largest pension funds in the world and found that they are low but significant as their magnitude affects its profitability. Their work is consistent with the paper of Chiyachantana et al. (2004) as for the buy-sell asymmetry, with buy orders having lower market impact costs than sell orders in falling markets. They found evidence that market impact costs depend on momentum, volatility, trade type (agency/single or principal), trading strategy, trading venue, sector and timing. Although longer duration trades have lower market impact costs, they have higher volatility. Also, trades that demand immediate liquidity have higher costs, but less uncertainty.

As previous studies showed (e.g. Chan and Lakonishok, 1993; Keim and Madhavan, 1996), there is a buy-sell asymmetry in implicit trading costs. Hu (2009) also mainly studied this asymmetry and confirmed the previous results. He found that the differences and the magnitude of the costs is dependent on the mechanical characteristics of the measures, that is on the benchmark that has been used, and on market movement. When a trader uses pre-trade measures, he finds that buys have higher implicit trading costs during rising markets. On the other hand, post-trade measures result quite the opposite, that is sells have higher implicit trading costs during rising markets. Thus, it is obvious that both types of measures are highly influenced by market movements, whereas during-trade measures, i.e. VWAP, are neutral to market movements. Also, he decomposed prior close cost and close cost into two components. The first component is the VWAP cost and the other one is the market movement cost. He concluded that both measures depend mainly on the market movement component, so each cost can be approximated with high accuracy without even knowing the execution price. Finally, he estimated multivariate regressions to analyze implicit trading costs and demonstrated that prior close cost, VWAP cost and close cost are affected by factors such as market capitalization, relative volume, inverse prior close price, a buy indicator, a listed indicator and return volatility.

Chapter 4: Data

The data sample used in this study contains information on the equity transactions of SilentSeas for the period 05/02/2014 – 28/07/2016. It includes data of 162,940 orders such as order identifiers, security name, sector, trade date, duration, strategy, region, order quantity, arrival and execution price, excluding limit orders and OTC trades. Also, additional data about prices, market capitalization, volume, shares outstanding, exchange rates and market indices etc. for the respective period have been obtained from Capital IQ and Bloomberg. The sample expands across 16 countries including USA, UK, Greece, Switzerland, Australia, Japan, Singapore, Hong Kong, France etc.. I follow SilentSeas' practice and divide the sample into 6 regions, that is Europe, Australia, Japan, the United Kingdom, the United States and Asia excluding Japan (i.e. Hong Kong and Singapore) and I use the respective market indices[2]. The prime broker employed until 31/03/2015 was J.P. Morgan and then changed to UBS.

[2] S&P 500 for USA, Topix 100 for Japan, ASX 300 for Australia, Hang Seng for AEXJP, FTSE 100 for UK, STOXX 600 for Europe.

Chapter 5: Empirical Results and Discussion

It is defined that MATLAB and Stata are used in order to conduct all the calculations and estimate the empirical results that I present below.

5.1 Measurement of Implicit Transaction Costs and Summary Statistics

As I presented in section 1.5 there are different measures of implicit trading costs. I proceed by estimating prior close cost, VWAP cost, close cost as well as average cost that is defined as the average of high, low, open and close price of each security, which is an intraday measure that captures volatility.

Following previous studies (e.g. Hu, 2009), in Table 1, I present the percentiles as well as the mean value and the standard deviation of implicit trading cost measures and their components as well as of the market index movement of the trade date, all measured in basis points. It is observed that all measures are symmetric around their medians and can be both positive and negative. Especially, in all measures, the 10^{th} and the 25^{th} percentiles are negative, whereas from the 50^{th} percentile they become positive. As expected, prior close cost is much higher in magnitude than VWAP cost as, VWAP cost constitutes one of the former's components together with market movement cost prior close to VWAP. For instance, the median (mean) of prior close cost is equal to 15.08 bps (44.82 bps), while the median (mean) of VWAP cost equals 6.73 bps (39.15 bps). In addition, close cost measure provides the lowest cost, that is median (mean) equal to 0 bps (32.19 bps). Also, the median (mean) of the market index movement is equal to -4.0453 bps (-3.7394 bps).

[Insert Table 1 about here]

The fund used 6 different algorithmic trading strategies with dominant the VWAP (used in 147,517 orders) and less popular the Tap Now (used in 258 orders). The other strategies that have been used include At Open (5,875 orders), IS (4,990 orders), Perimeter (3,796 orders) and Tap (504 orders).

As presented in section 2.2, VWAP strategy targets liquidity demand with a stock's expected volume pattern over a specified period, while the objective of At Open strategy is to achieve the opening price. Tap strategy has the intelligence to seek optimal execution in both displayed and non-displayed venues simultaneously, whereas Tap Now strategy is the most aggressive variant of Tap and strives to opportunistically seize liquidity from all possible sources, while optimizing and adjusting the rate of execution, based on price and market impact. This strategy targets completion over minimizing price impact and has no volume limit. It posts in all accessible non-displayed venues and always requires a price limit. The objective of implementation shortfall (IS) strategy is to minimize the risk-adjusted transaction costs by adjusting its aggression based on real-time market movements, that is increase or decrease the rate of execution according to the movements of the stock price, while perimeter strategy enables trading outside of regular US market hours by controlling the urgency of the order.

In Table 2, I present a few summary statistics of transaction orders such as the number of transactions, the principal and the shares traded as well as the average magnitude of explicit (i.e. commissions) and implicit trading cost measures and their components. As I will discuss in a following section, prior close cost and close cost can be decomposed into two components: a VWAP cost component and a market movement cost component. These statistics consider all the transactions of our sample and also are decomposed into buy and sell orders. The sample includes 162,940 orders (81,479 buys and 81,461 sells), 279.99806 million shares traded (141.33201 million shares bought and 138.66605 million shares sold) that correspond to $1,119.85619 million traded ($558.289406 million in buys and $564.566787 million is sells) and 7,831 different equities. We observe that commissions do appear buy-sell asymmetry, in contrast to Hu (2009), and on average are equal to 5.15 bps (5.06 bps for buys and 5.21 bps for sells). Also, my findings are consistent with previous studies (e.g. Hu, 2009) as implicit trading costs for sell orders are higher than for buy orders in all cases. For example, implicit costs range from 32.19 bps (-83.05 bps for buys and 147.24 bps for sells) for close cost to 44.82 bps (-86.49 bps for buys and 175.85 bps for sells) for prior close cost, on average, while VWAP cost ranges in between, with an average of 39.15 bps (-72.38 bps for buys and 147.20 bps for sells).In addition, the prior close cost that is net of market index movement has an average of 44.89 bps (-82.40 bps or buys and 171.89 bps for sells).

[Insert Table 2 about here]

In Table 3, I segment Table 2 by stock specific market movement during the trading horizon dividing the sample into two segments. I follow Hu (2009) and assume that the cutoffs are -2% and 2%. So, the first segment includes high return stocks (Ri ≤ -2% or Ri > 2%) and the second includes low return stocks (Ri > -2% or Ri ≤ 2%). It is defined that the trading horizon is always one day. Thus, all orders are completely executed in the same day that they were released to the broker. We observe almost the same pattern as in the case of using all the sample. Commissions do exhibit buy-sell asymmetry in either case and sell orders have higher implicit trading costs than buy orders in all cases. What is intriguing is the fact that commissions of high movement stocks are lower by about 0.77 bps on average, whereas implicit trading costs are lower in low movement stocks. VWAP cost for instance is equal to 47.67 bps for low movement stocks and 15.93 bps for high movement stocks. It is obvious that there are more investments (about $379.8 million more) in low movement stocks.

[Insert Table 3 about here]

5.2 Panel Decomposition Regressions of Implicit Transaction Costs with Fixed Effects

According to Hu (2009), we can decompose prior close cost and close cost into two components in order to learn more about their characteristics. Each measure can be decomposed into a VWAP cost component and a market movement cost component.

$$\text{Prior Close Cost} = \text{VWAP Cost} + \text{Market Movement Cost Prior Close to VWAP} <=> \left(\text{Side} * \frac{P_E - \text{Prior Close}}{P_E}\right) = \left(\text{Side} * \frac{P_E - \text{VWAP}}{P_E}\right) + \left(\text{Side} * \frac{\text{VWAP} - \text{Prior Close}}{P_E}\right) \quad (3)$$

$$\text{Close Cost} = \text{VWAP Cost} - \text{Market Movement Cost VWAP to Close} <=> \left(\text{Side} * \frac{P_E - \text{Close}}{P_E}\right) = \left(\text{Side} * \frac{P_E - \text{VWAP}}{P_E}\right) - \left(\text{Side} * \frac{\text{Close} - \text{VWAP}}{P_E}\right) \quad (4)$$

As equations (3) and (4) show, prior close cost is equal to VWAP cost plus market movement cost prior close to VWAP and close cost is equal to VWAP cost minus market movement cost VWAP to close.

In Table 4, I perform decomposition regressions of implicit trading costs, where each cost measure is regressed separately on each of its components, as equations 5-8 show.

$$\text{Prior Close Cost}_i = \alpha + \beta * \text{VWAP Cost}_i \tag{5}$$

$$\text{Prior Close Cost}_i = \alpha + \beta * \text{Market Movement Cost Prior Close to VWAP}_i \tag{6}$$

$$\text{Close Cost}_i = \alpha + \beta * \text{VWAP Cost}_i \tag{7}$$

$$\text{Close Cost}_i = \alpha + \beta * \text{Market Movement Cost VWAP to Close}_i \tag{8}$$

At first, I run unbalanced panel regressions using all the sample and then divide the sample into two segments: the first segment, like in the previous section, includes stocks with high movement and the second one includes stocks with low movement. I use the different equities as cross-section identifiers and allow each equity to have its own intercept (fixed effects). Also, all standard errors are clustered by equity in order to have more robust results and avoid problems such as heteroskedasticity and autocorrelation. I focus only in the R-squares in order to capture the importance of each component. In contrast to Hu (2009), who showed that the dominant is the market movement cost component and thus prior close cost can be approximated without knowing the execution price, in our sample I observe that dominant is the VWAP cost component. Specifically, I show that prior close cost and close cost depend mostly on VWAP cost (R^2 = 98.88% and R^2 = 99.87% respectively) with the slope coefficient being close to one. In addition, the findings, when I divide the sample into high and low movement, reinforce the previous results. Thus, we conclude that prior close and close cost can be approximated with high accuracy by VWAP cost.

[Insert Table 4 about here]

5.3 Panel Regression Analysis of Implicit Transaction Costs with Fixed Effects

In this section, I analyze how various factors can affect trading costs. Specifically, I run multiple unbalanced panel regressions using prior close cost, VWAP cost and close cost as dependent variables and, as independent variables, factors that have been identified affecting trading costs, as shown in equations 9-11. I use, as cross-section identifier, the different equities and allow each equity to have its own intercept (fixed effects).

Also, all standard errors are clustered by equity in order to have more robust results and avoid problems such as heteroskedasticity and autocorrelation.

$$\text{Prior Close Cost}_i = \alpha + \beta_1 * \text{Buy}_i + \beta_2 * \log(\text{market cap})_i + \beta_3 * \log(\text{relative volume})_i + \beta_4 * \text{Inverse prior close}_i + \beta_5 * \text{Return volatility}_i + \beta_6 * \text{Price momentum}_i + \beta_7 * \text{Europe}_i + \beta_8 * \text{USA}_i + \beta_9 * \text{UK}_i + \beta_{10} * \text{Australia}_i + \beta_{11} * \text{Japan}_i + \beta_{12} * \text{VWAP}_i + \beta_{13} * \text{Tap}_i + \beta_{14} * \text{At open}_i + \beta_{15} * \text{Perimeter}_i + \beta_{16} * \text{IS}_i + \beta_{17} * \text{Sided market index return}_i + \beta_{18} * \text{Duration}_i \qquad (9)$$

$$\text{VWAP Cost}_i = \alpha + \beta_1 * \text{Buy}_i + \beta_2 * \log(\text{market cap})_i + \beta_3 * \log(\text{relative volume})_i + \beta_4 * \text{Inverse prior close}_i + \beta_5 * \text{Return volatility}_i + \beta_6 * \text{Price momentum}_i + \beta_7 * \text{Europe}_i + \beta_8 * \text{USA}_i + \beta_9 * \text{UK}_i + \beta_{10} * \text{Australia}_i + \beta_{11} * \text{Japan}_i + \beta_{12} * \text{VWAP}_i + \beta_{13} * \text{Tap}_i + \beta_{14} * \text{At open}_i + \beta_{15} * \text{Perimeter}_i + \beta_{16} * \text{IS}_i + \beta_{17} * \text{Sided market index return}_i + \beta_{18} * \text{Duration}_i \qquad (10)$$

$$\text{Close Cost}_i = \alpha + \beta_1 * \text{Buy}_i + \beta_2 * \log(\text{market cap})_i + \beta_3 * \log(\text{relative volume})_i + \beta_4 * \text{Inverse prior close}_i + \beta_5 * \text{Return volatility}_i + \beta_6 * \text{Price momentum}_i + \beta_7 * \text{Europe}_i + \beta_8 * \text{USA}_i + \beta_9 * \text{UK}_i + \beta_{10} * \text{Australia}_i + \beta_{11} * \text{Japan}_i + \beta_{12} * \text{VWAP}_i + \beta_{13} * \text{Tap}_i + \beta_{14} * \text{At open}_i + \beta_{15} * \text{Perimeter}_i + \beta_{16} * \text{IS}_i + \beta_{17} * \text{Sided market index return}_i + \beta_{18} * \text{Duration}_i \qquad (11)$$

I follow previous studies (e.g. Keim and Madhavan, 1995, 1997, 1998, 2003; Domowitz et al., 1999, 2001; Conrad et al., 2001, 2003; Bikker et al., 2007; Chiyachantana et al., 2007; Hu, 2009) and use the following factors: buy indicator (1 for buy orders and 0 for sell orders), log(market capitalization), log(relative volume) measured as the natural logarithm of the executed quantity divided by the average trading volume over the 5 previous trading days, inverse prior close price, return volatility of stock returns over the 10 previous trading days (bps), price momentum measured as the volume-weighted average daily stock return over the last 5 trading days prior to the trade (%) to examine if there is a buying or selling trend for a specific equity and sided market index return, that is market index return during the trading horizon multiplied by -1 for sell orders in order to take into account the market movement during the trade. In addition, I include a dummy variable for each region (Europe, USA, UK, Australia and Japan, excluding

AEXJP because intercept is included), a dummy variable for each algorithmic trading strategy (VWAP, Tap, At open, Perimeter, IS, excluding Tap Now) and the duration from the start time of each trade until the end time, measured in seconds. In table 5, I perform the above mentioned regressions.

[Insert Table 5 about here]

As shown in the above table, the common factors that are statistically significant are the following: buy indicator, market capitalization, relative volume, inverse prior close, VWAP and duration. In addition, Tap, Perimeter and IS strategies are statistically significant in VWAP cost and close cost regressions, while price momentum is only in prior close cost regression. As expected, the signs of the variables are the same among the 3 regressions, while only the buy indicator and the duration are negatively related to transaction costs. Thus, an increase in market capitalization, relative volume and inverse prior close increases transaction costs, whereas an increase in duration decreases costs. The buy indicator shows that sell orders present higher transaction costs, that is buy orders indicate lower mean transaction costs than sell orders by 250.8437 bps, 227.4625 bps and 226.3138 bps respectively for each of the 3 regressions. Also, by examining the algorithmic trading strategies used, we observe that the use of VWAP, Tap, Perimeter and IS strategies increase transaction costs with VWAP presenting the biggest increment (for instance 184.5677 bps more than the other strategies in VWAP cost regression). What is unexpected is the fact that return volatility and market index return do not affect transaction costs, while the region dummies are omitted because of collinearity.

It is important that most of the findings are consistent with previous research. For instance, considering the common variables with our research, Keim and Madhavan (1997) showed positive relation of transaction costs with trade size and inverse price and negative relation with market capitalization. Conrad et al. (2001) reported positive slope coefficients of trade size and inverse price in contrast to market capitalization and buy indicator which had negative coefficients. Domowitz et al. (2001) found negative relation of costs with market capitalization and positive with volatility. Chiyachantana et al. (2004) found negative relation of transaction costs with market capitalization and with the buy indicator when market was bearish and positive relation with the buy indicator when market was bullish, inverse stock price, complexity of decision and volatility. Hu (2009) found that costs are negatively related to buy and to sided market index return and sided stock return, while they are positively related to market capitalization, relative volume, inverse prior close and return volatility. So, to conclude the main difference is in the market capitalization where my results are inconsistent with the previous mentioned studies, except for Hu’s (2009).

5.4 Out-of-sample Forecast of Implicit Transaction Costs

In the last section of the empirical results, I analyze the regression results from the previous section from a forecasting perspective. To illustrate the methodology applied, I test out-of-sample the predictive power of the 3 models, without including duration and market index movement which are known after the trade has taken place, running stepwise regressions using the forward entry method on the 4/5 of the sample, that is until 09/05/2016, as shown in Table 6 and then use all the slope coefficients, which are statistically significant at the 1% level, obtained in order to forecast the costs of the remaining 1/5 of the sample, that is from 09/05/2016 to 28/07/2016. In addition, I use three naïve models, one for each type of cost measure (prior cost, VWAP cost, close cost), which assume that transaction costs are always equal to the mean value. Afterwards, I calculate the mean squared errors (MSE) in order to measure the average of the squares of the deviations by comparing the realized with the forecasted values.

$$\text{Prior Close Cost}_\text{i} = 182.7831 - 263.7388 * \text{Buy}_\text{i} + 1.00157 * \log(\text{relative volume})_\text{i} \quad (12)$$

$$\text{VWAP Cost}_\text{i} = 162.3385 - 234.7504 * \text{Buy}_\text{i} + 1.001298 * \log(\text{relative volume})_\text{i} \quad (13)$$

$$\text{Close Cost}_\text{i} = 154.0085 - 231.4123 * \text{Buy}_\text{i} + 1.001007 * \log(\text{relative volume})_\text{i} \quad (14)$$

As shown in Table 6, the common factors in the 3 models that are statistically significant are the following: buy and relative volume The findings show that from these factors only the buy is negatively correlated with transaction costs. To evaluate the predictive power of the six models, at first, I observe the mean squared errors. Among the three initially performed regressions, VWAP cost has the lowest MSE (437,119.6) and thus better accuracy, while among the three naïve models, the respective model is the VWAP cost (421,103.5). Obviously, if we consider all the six prediction models, all the naïve models have lower mean value of the squared errors than the respective regression models, with the naïve VWAP cost model being the best.

[Insert Table 6 about here]

To provide insight into the magnitude and the variance of the errors, I report the descriptive statistics of their absolute values in Table 7. Based on the mean values, the empirical findings reinforce the previous results and conclude that all the naïve models have substantially better prediction ability than the respective regression models and as previously mentioned, the naïve model of VWAP cost provides the lowest errors (77.18641 bps). If we take into account the magnitude of the standard deviation of absolute forecast errors, for instance 644.3279 bps for the naïve VWAP cost model, which is extremely high, we should interpret the forecast results with caution.

[Insert Table 7 about here]

In addition, in Table 8, I present the descriptive statistics of the forecasted and of the realized transaction costs, where we notice that all the statistics present substantial differences. For example, the mean value of the forecasted VWAP cost is equal to 40.2460 bps, while the respective value of the realized VWAP cost equals 17.9350 bps. Furthermore, in comparison with the previous table (6), we notice that the magnitude of the mean value of the absolute forecast errors is larger than the respective mean values of the realized costs. For instance, the absolute forecast errors of the naïve close cost model have mean value equal to 100.8713 bps and the mean value of the realized close cost equals 15.005 bps, verifying the large differences that exist between forecasted and realized costs.

[Insert Table 8 about here]

Conclusion

In this study, at first, I presented an overview of the theory of transaction costs, algorithmic trading and trade execution and then I empirically examined the transaction costs of SilentSeas Group's long-short equity hedge fund business.

More specifically, I reported the different types of costs (explicit and implicit), the way that market participants create or consume liquidity along with details about the orders and limit order books, measures of implicit transaction costs (prior close cost, VWAP cost, close cost) and Perold's (1998) implementation shortfall approach according to which, total cost of execution is equal to the difference between actual portfolio profit/loss and desired portfolio. Then, I presented the determinants that previous studies have identified that affect transaction costs e.g. trade size, market capitalization, return volatility, investment style etc. and facts about buy-sell asymmetry, that is evidence that buy orders have higher implicit trading costs than sell orders, and possible factors that may cause it. Also, I described popular algorithmic trading strategies including VWAP, TWAP, participation, market-on-close, arrival price and crossing and reported an example on how orders interact in limit order books and the way that temporary and permanent market impact, that is pre- and post-trade equilibrium, is established. In addition, I briefly described the rationale behind optimal execution. In the third section, I summarized some of the most important studies on transaction costs that generally examine the magnitude and the determinants of transaction costs.

To empirically examine transaction costs, firstly, I measured implicit transaction costs using different measures and presented summary statistics of many important variables. For instance, commissions on average are equal to 5.1551 bps and average implicit transaction costs range from 0.6829 bps (average costs) to 44.8249 bps (prior close costs) according to the measure used. It is important that explicit and implicit transaction costs do appear buy-sell asymmetry and we conclude that sell orders have higher transaction costs than buy orders, as Hu (2008) and other previous studies also documented concerning the latter. We also draw almost the same conclusions by dividing the sample according to the stock return during the trading horizon. Next, I ran decomposition regressions to analyze the components of prior close and close cost. I found that both costs mostly depend on VWAP cost rather on market movement cost. The results from the same regressions on high and low movement stocks are similar.

Thus, prior close and close cost can be approximated by VWAP cost. In the regression analysis of implicit transaction costs, I initially used factors that previous studies had identified e.g. market capitalization, relative volume, return volatility, inverse prior close and also included duration and a dummy variable for each algorithmic trading strategy used. The results showed that the factors that are statistically significant are buy indicator, market capitalization, relative volume, inverse prior close, price momentum, VWAP, tap, perimeter, IS and duration. From these factors only the buy indicator and duration are negatively related to costs, suggesting that sell orders and orders that have high duration have higher transaction costs. As expected, market capitalization, relative volume and inverse prior close increase transaction costs and VWAP is the most expensive algorithmic trading strategy. Return volatility and market index return do not seem to affect transaction costs, while regions are omitted because of collinearity. Last but not least, I tested out-of-sample the predictive power of regression models used previously by running stepwise regressions on the 4/5 of the sample and forecast the remaining 1/5. Additionally, I included three more models that are naïve and assume that transaction costs are always equal to the mean value. The empirical findings suggest that, based on mean squared errors, all the naïve models outperform the respective regression models and provide better predictions. However, due to its large standard deviation we should interpret these forecasts with caution. To further illustrate this point, consider that the mean value of the absolute forecast errors of the naïve VWAP cost model is equal to 77.18641 bps with 644.3279 bps standard deviation.

The contribution of this research and thus the differentiation from other previous studies is that, apart from the theory that I presented in detail, I empirically examined the transaction costs of a fund that substantially differs from the respective funds that are often used. What I mean is that, in contrast to other studies which use data from many institutions with billions or even trillions of dollars, I employed data from a single fund that is smaller in size and yet found many similar results. Thus, the sample is respresentative. Furthermore, the data sample spans a more recent time period, that is until 28/07/2016. In addition, I used a few more factors, duration and a dummy variable for each algorithmic trading strategy that are statistically significant and explain transaction costs and are not usually included in respective studies. One more contribution is that I tested out-of-sample the predictive power of the regression models, whereas most previous studies do not.

Future research should further investigate the possible explanation why in the decomposition regressions, the VWAP cost component is dominant rather than the market movement component, find additional factors that explain transaction costs maybe using nonlinear models, examine other prediction models that may forecast transaction costs with better accuracy and continue with an optimal execution to find the best combination of algorithmic trading strategies that minimize transaction costs.

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Appendix A: Tables

Table 1: Descriptive Statistics of Measures of Implicit Transaction Costs and Market Index Movement

This table presents the percentiles as well as the mean and the standard deviation of implicit trading cost measures and their components, all measured in basis points. It is defined that prior close cost is equal to VWAP cost plus market movement cost prior close to VWAP and close cost is equal to VWAP cost minus market movement cost VWAP to close. All trading costs are measure in basis points.

Percentile	Prior Close Cost (bps)	VWAP Cost (bps)	Close cost (bps)	Average Cost (bps)	Prior close cost net of market index movement (bps)	Market Movement Cost Prior close to VWAP (bps)	Market Movement Cost VWAP to Close (bps)	Market Index Movement (bps)
Mean	44.82491545	39.1533787	32.1933208	0.68294707	44.89259217	7.409019785	6.33448603	-4.04534823
Standard Deviation	6,295.950608	6,273.72993	6,079.457173	7,434.90519	6,296.674558	729.2190456	332.102045	124.767945
10th	-222.78	-60.1813	-95.6076	-4,666.17	-226.65	-95.2024	-206.23	-147.539
25th	-79.4553	-17.0736	-31.0107	-199.479	-92.2181	-38.3774	-80.7657	-65.195
Median	15.0877	6.734993	0	8.192671	5.789382	1.980198	17.084	-3.73945
75th	122.0753	37.85496	42.10386	218.2837	109.6539	46.59215	120.69	50.27974
90th	277.9049	92.96482	116.4986	4,511.393	249.8777	109.6676	261.9575	142.9234

Table 2: Descriptive Statistics

This table presents a few summary statistics of transaction orders as well as of trading costs and their components. The principal traded is expressed in millions of US dollars and the shares traded in millions. The transaction costs are measured in basis points.

Side	N	$ Principal Traded (M)	Shares Traded (M)	Commissions (bps)	Prior Close Cost (bps)	VWAP Cost (bps)	Close cost (bps)	Average Cost (bps)	Prior close cost net of market index movement (bps)	Market Movement Cost Prior close to VWAP (bps)	Market Movement Cost VWAP to Close (bps)	Market Index Movement (bps)
All	162,940	1,119.85619	279.99806	5.15518494	44.82491545	39.1533787	32.1933208	0.68294707	44.89259217	7.409019785	6.33448603	-4.04534823
Buys	81,479	558.289406	141.33201	5.06092367	-86.4912264	-72.389396	-83.0586759	1296.74107	-82.4052868	-13.9185261	11.1932047	-4.11681715
Sells	81,461	561.566787	138.66605	5.21364825	175.8586251	147.204922	147.2471014	-1295.66634	171.89621	28.07596633	0.90587234	-3.97386352

Table 3: Descriptive Statistics with Stocks' Return Segmentation

This table presents a few summary statistics of transaction orders as well as of trading costs and their components, like in the previous table (2), but each measure is divided into two categories: a high movement category which includes stocks with return Ri ≤ -2% or Ri > 2% and a low movement category which includes stocks with return R_i > -2% or Ri ≤ 2% during the trading horizon. It is defined that the trading horizon is always one day. The principal traded is expressed in millions of US dollars and the shares traded in millions. The transaction costs are measured in basis points.

Specific Return During the Trading Horizon	Side	N	$ Principal Traded (M)	Shares Traded (M)	Commissions (bps)	Prior Close Cost (bps)	VWAP Cost (bps)	Close cost (bps)	Average Cost (bps)	Prior close cost net of market index movement (bps)	Market Movement Cost Prior close to VWAP (bps)	Market Movement Cost VWAP to Close (bps)	Market Index Movement (bps)
High Movement	All	52,763	370.0249193	109.812832	4.616322044	32.70690095	15.93239476	3.24987282	-25.3834658	29.23379673	17.01468229	12.53784262	6.31585415
Ri ≤ -2%	Buys	26,229	184.3471846	55.607062	4.599450989	-254.6731781	-225.563024	-242.3428319	1332.97624	-253.9622826	-26.49948191	17.16964657	4.43062795
or Ri > 2%	Sells	26,534	185.6777347	54.20577	4.632999171	316.7836362	254.6518998	246.0195665	-1368.12925	309.174626	60.02866484	7.9592798	2.58918481
Low Movement	All	110,177	749.8312732	170.185223	5.386759487	50.3978744	47.67422972	45.88875384	13.16243792	52.15311712	2.317026442	2.943175063	1.06727365
R_i > -2%	Buys	55,250	373.9422212	85.724945	5.28	-6.64969865	0.327184917	-7.441225661	1279.539041	-0.961514019	-7.945930821	8.355990271	0.41498009
or Ri ≤ 2%	Sells	54,927	375.889052	84.460278	5.494146777	107.7809175	95.29970035	99.53234202	-1260.66113	105.5800906	12.64033536	-2.50147038	0.79019637

Table 4: Panel Decomposition Regressions of Implicit Transaction Costs with Fixed Effects

This table presents panel decomposition regressions of implicit trading costs with fixed effects, where each cost measure is regressed separately on each of its components. At first, I run regressions using all the sample and then divide the sample into two segments: the first segment, includes stocks with high movement and the second one includes stocks with low movement during the trading horizon. The dependent variables are prior close cost and close cost and the independent variable is either VWAP cost or one of the two market movement costs. Trading costs are expressed in basis points and standard errors are clustered by equity and are presented in parentheses below each coefficient. Also, I allow each equity to have its own intercept (fixed effects). R-squares are also presented for each regression. Statistical significance is indicated by *** for the 1% level, ** for the 5% level and * for the 10% level.

	Dependent Variables	Intercept	Market Movement Cost Prior close to VWAP (bps)	Market Movement Cost VWAP to Close (bps)	VWAP Cost (bps)	R^2 (%)
All	Prior Close Cost (bps)	5.815971***	-	-	1.019177***	0.9888
		(0.1941031)			(0.0049575)	
		25.69292***	2.703091**	-	-	0.0715
		(8.912621)	(1.202942)			
	Close Cost (bps)	-5.039078***			0.9884252***	0.9987
		(0.1300505)			(0.0033216)	
		18.26109		-3.311794		0.0292
		(17.95843)		(3.861984)		
High Movement	Prior Close Cost (bps)	15.93336***	-	-	1.026947***	0.9828
		(0.1670312)			(0.0100955)	
$R_i \leq -2\%$ or $R_i > 2\%$		2.007605	1.749769***			0.1573
		(7.661468)	(0.43361)			
	Close Cost (bps)	-11.66391***	-	-	0.9959939***	0.9989
		(0.0485789)			(0.0029361)	
		6.882643	-	0.19805	-	0.0369
		(10.5187)		(1.007503)		
Low Movement	Prior Close Cost (bps)	2.190669***			0.9924096***	0.9982
		(0.1404632)			(0.002803)	

$R_i > -2\%$ or $R_i \leq 2\%$		50.75957***	0.4776507			0.0057
		(0.7699526)	(0.3161329)			
	Close Cost (bps)	-2.163959***			0.9939235***	0.9984
		(0.1235829)			(0.0024661)	
		48.65009***		0.5457504**		0.0223
		(0.4580537)		(0.2485057)		

Table 5: Panel Regression Analysis of Implicit Transaction Costs with Fixed Effects

This table presents an analysis of how various factors affect transaction costs by estimating multiple unbalanced panel regressions with fixed effects. The dependent variables are prior close cost, VWAP cost and close cost, all expressed in basis points. As independent variables we use the following: buy indicator, log(market capitalization), log(relative volume), inverse prior close, return volatility expressed in basis points, price momentum, Europe dummy, USA dummy, UK dummy, Australia dummy, Japan dummy, VWAP strategy dummy, tap strategy dummy, at open strategy dummy, perimeter strategy dummy, IS strategy dummy, sided market index return during the trading horizon expressed in basis points (multiplied by -1 for sell orders) and duration in seconds. Standard errors are clustered by equity and are presented in parentheses below each coefficient. Also, I allow each equity to have its own intercept (fixed effects). Overall R-squares, the number of observations and the number of clusters are also presented for each regression. Statistical significance is indicated by *** for the 1% level, ** for the 5% level and * for the 10% level. The exact definition of each variable is presented in section 5.3.

	Prior Close Cost (bps)	VWAP Cost (bps)	Close Cost (bps)
Intercept	-4,236.276*	-4,077.937*	-4,077.937*
	(2,263.454)	(2,203.004)	(2,203.004)
Buy indicator	-250.8437***	-227.4625**	-226.3138**
	(93.39076)	(95.5233)	(95.5233)
Log (market capitalization)	612.6943*	581.0963*	549.3346*
	(321.05)	(312.0435)	(312.0435)
Log (relative volume)	0.9979983***	0.9979836***	0.9986185***
	(0.0010593)	(0.0012307)	(0.0012307)
Inverse Prior Close	296.7369*	267.2273*	267.2273*
	(156.1356)	(149.5068)	(149.5068)
Return Volatility (bps)	0.0870546	0.0620568	0.0620568
	(0.0951396)	(0.085128)	(0.085128)
Price momentum	1,202.137*	1,164.874	1,164.874
	(719.3389)	(736.5107)	(736.5107)
Europe dummy	0 (omitted)	0 (omitted)	0 (omitted)
USA dummy	0 (omitted)	0 (omitted)	0 (omitted)
UK dummy	0 (omitted)	0 (omitted)	0 (omitted)
Australia dummy	0 (omitted)	0 (omitted)	0 (omitted)
Japan dummy	0 (omitted)	0 (omitted)	0 (omitted)
VWAP Strategy Dummy	132.1979**	184.5677***	184.5677***

	(66.08033)	(70.33946)	(70.33946)
Tap Strategy Dummy	79.14073	121.0858**	121.0858**
	(54.07762)	(58.13171)	(58.13171)
At Open Strategy Dummy	39.41356	66.16655	66.16655
	(41.47243)	(46.71542)	(46.71542)
Perimeter Strategy Dummy	90.52536	134.2815**	134.2815**
	(55.14218)	(59.21678)	(59.21678)
IS Strategy Dummy	68.41237	110.0127**	110.0127**
	(50.38634)	(55.07192)	(55.07192)
Sided Market Index Return	3,320.224	-3,569.124	-3,569.124
	(2,866.415)	(3,012.617)	(3,012.617)
Duration (seconds)	-0.0046008**	-0.0050028**	-0.0050028**
	(0.001946)	(0.0019552)	(0.0019552)
R^2 (overall)	0.0000	0.0001	0.0001
Number of Observations	160,715	153,983	153,983
Number of Clusters	7,673	7,324	7,324

Table 6: Out-of-sample Forecast of Implicit Transaction Costs

This table presents an analysis of how various factors affect transaction costs by estimating stepwise regressions using the forward entry method on the 4/5 of the sample in order to forecast the remaining 1/5. The dependent variables are prior close cost, VWAP cost and close cost, all expressed in basis points. As independent variables we use the following: buy indicator, log(market capitalization), log(relative volume), inverse prior close, return volatility expressed in basis points, price momentum, Europe dummy, USA dummy, UK dummy, Australia dummy, Japan dummy, VWAP strategy dummy, tap strategy dummy, at open strategy dummy, perimeter strategy dummy and IS strategy dummy. Following, we use the coefficients that are all statistically significant in the 1% level in order to predict the transaction costs of the remaining 1/5 of the sample. Then, we estimate the mean squared errors of each prediction to gauge its quality. Along with the results we present the forecasts of the three naïve models and the respective mean squared errors. Standard errors are presented in parentheses below each coefficient. R-squares and the number of observations are also presented for each regression. Statistical significance is indicated by *** for the 1% level, ** for the 5% level and * for the 10% level. The exact definition of each variable is presented in section 5.3.

	Prior Close Cost (bps)	VWAP Cost (bps)	Close Cost (bps)
Intercept	182.7831***	162.3385***	154.0085***
	(22.27503)	(22.65951)	(21.50828)
Buy indicator	-263.7388***	-234.7504 ***	-231.4123***
	(31.50057)	(32.06592)	(30.41626)
Log (market capitalization)	-	-	-
Log (relative volume)	1.00157***	1.001298***	1.001007***
	(0.0681171)	(0.067872)	(0.0657724)
Inverse Prior Close	-	-	-
Return Volatility (bps)	-	-	-
Price momentum	-	-	-
Europe dummy	-	-	-
USA dummy	-	-	-
UK dummy	-	-	-
Australia dummy	-	-	-
Japan dummy	-	-	-
VWAP Strategy Dummy	-	-	-
Tap Strategy Dummy	-	-	-
At Open Strategy Dummy	-	-	-

Perimeter Strategy Dummy	-	-	-
IS Strategy Dummy	-	-	-
Sided Market Index Return	-	-	-
Duration (seconds)	-	-	-
R^2 (overall)	0.0018	0.0018	0.0018
Number of Observations	160,715	153,983	160,715
Mean Squared Errors (MSE)	472,664.4	437,119.6	446,056.7
Forecast of the Respective Naïve Models (Mean of Transaction Costs)	48.82215	44.4252	36.50285
Mean Squared Errors (MSE) of the Respective Naïve Models	457,219.8	421,103.5	429,934.4

Table 7: Descriptive Statistics of Absolute Forecast Errors

This table presents the mean, the standard deviation and 5 percentiles of the absolute forecast errors of the 6 previously mentioned prediction models.

	Absolute Forecast Errors of Prior Close Cost (bps)	Absolute Forecast Errors of VWAP Cost (bps)	Absolute Forecast Errors of Close Cost (bps)	Absolute Forecast Errors of Prior Close Cost (bps) (naïve model)	Absolute Forecast Errors of VWAP Cost (bps) (naïve model)	Absolute Forecast Errors of Close Cost (bps) (naïve model)
Mean	204.2194	149.5018	159.9334	160.6629	77.18641	100.8713
Standard Deviation	656.4846	644.0354	648.4527	656.8261	644.3279	647.8983
10^{th} Percentile	35.67959	62.03816	39.91067	16.5904	12.96211	11.76461
25^{th} Percentile	80.83136	82.70015	79.33481	42.10501	27.82077	28.8841
Median	148.5758	124.223	124.2258	89.38195	44.40811	49.4884
75^{th} Percentile	235.6747	158.4741	171.0465	178.7934	61.22014	97.71698
90^{th} Percentile	361.1884	188.91	244.4674	316.8108	102.5655	176.6506

Table 8: Descriptive Statistics of Forecasted and Realized Implicit Transaction Costs

This table presents the mean, the standard deviation and 5 percentiles of the forecasted and the realized transaction costs, except for the three naïve models according to which transaction costs are always equal to the mean value of the realized transaction costs, for the period 09/05/2016 - 28/07/2016.

	Forecasted Prior Close Cost (bps)	Forecasted VWAP Cost (bps)	Forecasted Close Cost (bps)	Prior Close Cost (bps)	VWAP Cost (bps)	Close Cost (bps)
Mean	46.38666	40.24602	33.56479	28.88216	17.93502	15.005
Standard Deviation	131.903	117.4129	115.7443	676.2893	665.0555	655.733
10^{th} Percentile	-89.4921	-80.946	-85.9354	-180.176	-42.5597	-99.9177
25^{th} Percentile	-87.2753	-78.7298	-83.7198	-64.1817	-11.2885	-34.5843
Median	171.0208	150.5794	142.2528	13.50745	6.290622	0
75^{th} Percentile	176.5106	156.0677	147.7395	103.697	29.49166	48.03036
90^{th} Percentile	178.8791	158.4355	150.1067	233.0391	72.00312	117.8396