UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Do dark pools affect asset price volatility?

A Study of the US Equity Market

Josefin Johansson and Sara Andersson

Gothenburg, Sweden Spring 2019

Abstract

Recent years there has been an increased usage of dark pools followed by a rise in interest to study the field. During 2018, 14% of the US equity trading was made in dark pools. It is therefore highly relevant to consider dark pools effect on market qualities such as asset price volatility. This thesis investigates if there is a relation between dark pool trading and asset price volatility on the US equity market during the time period of 2015-2019. A quantitative method has been applied by running two regressions with time fixed effects on historical data. With statistical significance, the thesis suggests that there is a relation. Further, the results imply that there is an increasing effect on asset price volatility when dark trading percentage is high. The thesis is based on historical data for 100 stocks in the national market system tier 1 listed as alternative trading systems who report to the Financial Industry Regulatory Authority.

Acknowledgement

Table of content

1. Introduction

Dark pools or dark markets are private exchanges for security trading where trading is performed in the absence of order books (Mizuta et al., 2015). Dark trading, as the terms implies, is characterized by lack of transparency (ibid). Even though the term "dark pool" is relatively new, the concept has been used for a long time and was initially called upstairs trading (Foley and Putniņš, 2016). Historically dark pools were used by large institutions buying large asset volumes (Zhu, 2013). As stated by Mizuta et al. (2015), large orders can send strong buy or sell signals to the market, which might consequently affect the market price. It is further explained that some investors choose to trade in dark pools to avoid this problem. This since intentions of buying or selling requires publication in the public market. The risk of such an action is sudden and abnormal fluctuations in the market price. Since transactions in dark pools are not published until after it is executed, the risk of price fluctuations is reduced (Mizuta et al., 2015).

How large percentage part of the total trading done in dark pools is not all clear. Bain, (2018) reports that dark pools represent 14% of US equity trading in 2018. Furthermore, over 60% of the participants were investment banks and the other 40% was represented by market makers, independent investors and broker consortiums. Petrescu and Wedow (2017) report that the market share of dark pools in Europe has grown from less than 1% in 2009 to be slightly below 10% in 2017. Further, they state that banks and brokers account for over 50% of the volume traded and that other operators on the dark market are principally entities ran by public exchanges.

Zhu, (2013) describes the participation in dark pools as a trade-off between a possible price improvement and a risk of no execution. Further, he states that the probability of no execution is more extensive in a dark pool than in the public market, since order execution requires matching orders i.e. a counterparty placing a matching order on the opposite side of the market. If no matching order is placed there will be no execution and the order will be delayed (for example, see appendix 3). Ye, (2009) claims that in dark pools, executions have no immediate price impact since the action is not public. Thus, the probability of execution will decrease when the order size is increased. He explains that as the prices in a dark pool are indirectly dependent on the execution prices in the public exchange and orders are matched using these

prices as a benchmark. Hence, profits made in dark pools indirectly depend on the trading made in the public exchange.

In order to create more liquidity, dark pools are not restricted to large institutions trading large volumes anymore (Zhu, 2013). Dark pools are becoming more attractive to smaller and individual investors, mainly because of the reduction of execution costs (Petrescu and Wedow, 2017). The large institutional investors are still the main trader in dark pools though (Mizuta et al. 2015). Both banks and brokers are large dark pool actors, by using their own dark pools they can avoid paying fees in order to participate in the public market (Petrescu and Wedow, 2017). As Petrescu and Wedow (2017) explain, it is in fact up to the ones managing the dark pools to decide on restrictions about volumes and participants as well as other rules to apply. They also claim that, as the high-frequency trading is increasing, the prevalence of dark pools is also increasing because of the protection from this action. National authorities are monitoring these operations and interests and requirements of control and managing are growing when the market share of dark pools increases (Securities and Exchange Commission, 2010).

The rising attention and usage of dark pools have brought light to the topic and an increased interest to further study the subject. In particular the urge to analyze the impact of dark pools on public markets. Studies are inconsistent in the advantages and disadvantages of dark pool usage as well as the impact on public markets. Petrescu and Wedow (2017) present a few implications on why dark pool activity, on one hand, may lead to increased volatility and an overall reduction in market stability, but on the other hand, it might lead to the complete opposite. Hence, reduced volatility and an overall improvement of market stability. The first implication is consistent with the studies of O'Hara and Ye (2011) as well as Garvey, Huang, and Wu (2016). The effect is explained as when orders are relocated from public exchanges into dark pools, the information in the public order books are reduced. Since prices are formed in order books, less information in the price formation might lead to increased price volatility.

The second implication is consistent with Ye (2009), Buti, Rindi, and Werner (2011), Foley, Malinova, and Park (2013). Petrescu and Wedow (2017) expand the previous assumption by accounting for how different type of traders, informed and uninformed, will behave when choosing a trading venue. The implication is that informed traders will concentrate on the public exchange and uninformed traders will relocate to dark markets in order to make a profit. A

larger concentration of informed traders on the public exchange will improve price formation and reduce price volatility.

The central focus of this study is to examine the relation between price volatility and dark pool activity. Since the main reason for dark pool usage is to reduce market impact and abnormal fluctuations in asset prices, the intuition might be that price volatility in public markets should be reduced with increasing usage of dark pools. Thus, this does not always seem to be the case.

1.2. Problem definition

As already mentioned, previous studies on the effect of dark pool trading activity on public markets are inconclusive. Since extensive empirical research has to be made in order to account for all aspects to predict the causal effect of dark trading on the market, researchers usually focus on one or a few measures. The market can be affected in many ways, related literature mainly focuses on market factors such as price discovery, market efficiency, market stability, liquidity, volatility, and informational efficiency. Since dark pools are facing growing demand and gaining market shares, further studies would be interesting. The lack of transparency and detailed data available have limited the range of studies made on the subject.

A question that caught our interest was how dark pool trading affects volatility in stock prices. Since the main reason for using dark pools is to prevent abnormal volatility, is it plausible to predict the volatility to decrease when dark pool activity in the stock is increased? The focus of this thesis is to examine the volatility of market prices for stocks traded on the US equity market and how it is affected by the proportion of dark pools in relation to total volume traded. In order to do so, two null hypotheses are constructed as follows:

Null hypothesis I: *The proportion of dark pool trading relative to total volume of shares traded **does not** affect the volatility of asset prices.*

Alternative hypothesis I: *The proportion of dark pool trading relative to total volume of shares traded **does** affect the volatility of asset prices.*

Null hypothesis II: *The relative effect of dark pool trading on asset price volatility **will not** change regardless of the proportion dark pool trading relative to total volume of shares traded.*

Alternative hypothesis II: *The relative effect of dark pool trading on asset price volatility **will change** when the proportion of dark pool trading relative to total volume of shares traded is changed.*

We believe that our thesis will contribute to the research on the topic since it will broaden the perspective by looking at the effect on price volatility. The increasing usage of dark markets has led to a situation where new regulations are needed. It is therefore of interest to further study how the public stock market is affected, as a foundation for policymakers when developing new regulations. Even though some studies include price volatility as one possible explanatory variable for dark pool trading it is rarely the main focus. While many studies focus on how the price volatility is affecting the dark pool trading activity this study will examine the opposite relation.

1.3. Purpose

The purpose of this thesis is to examine the association between the market share of dark pool trading and asset price volatility. The aim is to conclude whether dark pools are desirable or not in the perspective of market stability. Furthermore, if the effect of dark pool trading changes with the level of usage.

1.4. Thesis structure

The study is organized as followed. In the second section, theoretical implications that constitute a foundation for the study are described as well as previous research made on the subject. In the third section, the process of data collection is described. In the fourth section, the methodology and the actual performance of the study are presented. The fifth section states the empirical results reached in previous sections. In the sixth section, the result is discussed. In the seventh, and last section the study is concluded.

2. Theoretical framework and literature review

This section will present previous studies on the topic and the theoretical framework related to this study will be described. Since this subject is relatively unexplored means that previous research is limited. Moreover, the lack of transparency and detailed data available limits the range of studies made on dark pools.

As already pointed out, the studies about dark pools and the effect on public markets are inconclusive. Different market factors are used in different studies to describe the effect of dark pools on the public market. When searching the literature, we have found a few studies that include dark pool trading as one possible explanatory variable for price volatility, rarely it is the main focus though. Many studies focus on the opposite relation, that is, how price volatility affects the usage of dark pools.

Ye (2009), Buti, Rindi, and Werner (2011), Foley, Malinova and Park (2013) and Petrescu, Wedow and Lari (2016) consistently claim that an increased market share of dark pool trading will reduce volatility. However, all of them perform different explanations of why such a relationship appears. Foley, Malinova, and Park (2013) find that increased dark pool trading leads to a reduction of intraday price impact and volatility. The other way around, Buti, Rindi, and Werner (2011) rather finds the reversed relation, that is, low intraday volatility is one reason for increased dark pool activity.

A common theoretical implication about why increased dark pool activity is associated with lower volatility is based on the behavior of different types of traders. Foley and Putniņš, (2016) as well as Zhu (2013) explains the concept and describes the importance of accounting for these when describing the behavior of investors in the market. Since traders have different goals, they will act in different ways. The types of traders are often divided into informed, uninformed and liquidity traders (Foley and Putniņš, 2016). Informed traders can predict the direction of the price and therefore beat the market. Uninformed traders, as the term imply, trades without having access to information about the market. Liquidity traders are not investing to get the best possible future payoff, they invest to fulfill their liquidity needs i.e. selling when they need liquidity, buying when they have liquidity (Zhu, 2013). Their trades are triggered by exogenous factors and do not relate to available market information. Liquidity traders are often big institutions or hedge funds (Ibid).

Zhu (2013), Foley, Malinova and Park (2013), Comerton-Forde and Putniņš (2015) and Petrescu, Wedow and Lari (2016) all states that increased dark pool activity is associated with lower volatility. The interpretation of that is the behavior of informed and uninformed investors when meeting fluctuating volatility in asset prices. Informed traders tend to concentrate on the public market. This will increase the information in the public market and therefore make order books and prices more informative, the increased information will improve the process of price formation. Also, uninformed traders will relocate from the public markets into dark pools because of the difficulties to make a profit among the informed investors. They all conclude that the increased concentration of informed investors in the public market as well as more information in the prices will decrease price volatility. On the other hand, this division between investors will increase the adverse selection risk (Zhu, 2013 and Comerton-Forde and Putniņš 2015).

In contrast, O'Hara and Ye (2011), Huang and Wu (2016), as well as Petrescu and Wedow (2017), presents a different theory on the association between dark pool activity and price volatility. That is, increased dark pool activity may lead to increased price volatility and an overall reduction of market stability and price volatility. Petrescu and Wedow (2017) explanation are that market participants are more likely to relocate to the dark markets when market conditions in the public market are less profitable. High volatility indicates such an environment and will further increase the intention to invest in dark trading (ibid). Further, they state, when orders are relocated from public exchanges into dark pools, the information in the public order books are reduced. Prices are formed in order books and when prices on the public market contain less information, prices are more uncertain leading to increased volatility and reduced market stability (Petrescu and Wedow, 2017). Less information in price formation might lead to increased price volatility (ibid).

Buti, Rindi, and Werner (2011) on the other hand imply that traders are more likely to trade on the public exchange when volatility is high. They explain the finding as the market participants want to avoid the additional risk of no execution related to dark pools when market conditions are already bad. Petrescu, Wedow and Lari (2016) find similar results as O'Hara and Ye (2011), Garvey, Huang and Wu (2016) as well as Petrescu and Wedow (2017) but only for smaller dark pool trading venues where daily average trading volume is low. The relation might occur because these types of venues attract informed traders rather than uninformed because of the high volatility (Petrescu, Wedow and Lari, 2016).

Why these completely opposite results appear is hard to predict. Theory about the impact of dark pool trading on asset price volatility seems to correspond to the vitality of information available in prices and the process of forming those. In which way it is fulfilled is, on the other hand, not as certain and different explanations will impact on the results. Thus, the studies are all performed in different ways using different methods, time spans, markets, assumptions as well as they all have different objectives to focus on. Probably these disparities will affect the performance as well as the results of the studies. For example, Buti, Rindi, and Werner (2011) have selected 11 dark pool in the US, while Petrescu, Wedow, and Lari (2016) are looking at specific dark pool trading venues in Europe, Comerton-Forde and Putniņš (2015) using data from multiple markets including the USA, Canada, and Australia. Also, Foley, Malinova, and Park (2013) study the Canadian market.

Zhu (2013), Preece and Rosov (2014), Foley and Putniņš (2016) point out the importance of considering different types of dark pool trading systems when looking at the effect of dark pool trading on the market. Theory suggests two types of dark trading, the first trading system means trading at one single price (one-sided) (Foley and Putniņš, 2016). Such as a midpoint crossing system similar to the midpoint of national best bid and offer (NBBO). The midpoint system executes orders in the middle of the bid and ask spread (ibid). Since neither of the traders has to pay the full spread the system is associated with lower execution costs (Petrescu and Wedow, 2017). Further, the liquidity will only exist on one side of the buy-sell side and the system implies a zero spread, meaning orders will be concentrated on one side, either buy or sell side. The second trading system corresponds to a limit order market, similar to public markets where it is possible to place an order at the preferred price (Zhu, 2013). Liquidity can be available on both sides of the spread, indicating a spread separate from zero (Petrescu and Wedow, 2017). Foley and Putniņš (2016) and Preece and Rosov (2014) intend that the different trading systems will change the probability of execution, trading strategies and the information available which will all impact on the public market. Foley and Putniņš (2016) find evidence that a one-sided system will reduce price volatility and that the two-sided system will have an overall positive impact on the market. For an example of the two different systems, see appendix 3.

Whether it is the volatility itself that affects the market share of dark pools or if it is the other way around is not very clear when looking at the literature. Though, the majority of the above research stresses the importance of accounting for disparities among investors when looking for relations between dark pool activity and market factors. When analyzing the literature, price

volatility seem to be dependent on the actions of informed and uninformed investors. One important implication of the discussion is that market participants seem to respond to the price volatility and relocate their orders when price volatility is changed. Another important implication in a few of the mentioned studies is the relevance of different kinds of dark pool trading systems and how these have a different effect on the public markets which might have an impact on the results. To account for different types of traders as well as different kinds of dark pool trading systems are not in the scope of our study. Our study will rather examine the overall impact of dark pool trading and whether it is desirable or not in the aspect of price volatility in the public market. Although, the mentioned aspects will be discussed as possible explanatory reasons for our result, which will be based on the related literature introduced.

3. Data Collection

In this section, the process of data collection will be described. Specifically, where the data used in the study is extracted as well as which databases used in the purpose of doing so.

3.1. Financial Industry Regulatory Authority (FINRA)

The transaction data related to dark pools are all collected from the Financial Industry Regulatory Authority (FINRA) in their database for alternative trading systems (ATS) transparency data. ATSs are non-regulated exchanges that do not publicly disclose pre-trade information to the public. Dark pools are one type of an alternative trading system but the terms are, in studies, often applied as synonyms. In our study, the transaction data derived from FINRA will be used as a proxy for dark pool transactions.

In 2014 SEC (Securities and Exchange Commission) approved a rule, Regulatory Notice 14-07, of reporting requirements of ATS data (FINRA, 2014). The new rule means that ATS facilities are required to report weekly transactions to FINRA. Furthermore, equity volume, as well as the number of securities, needs to be reported. As the requirements were implemented, FINRA is making the reports publicly available, though with some time of delay.

We have selected the 1,662 assets in the national market system (NMS) tier 1 listed as ATSs on FINRA. The assets in NMS tier 1 are derived from the S&P 500, Russel 1000 as well as selected exchange-traded products. Out of the 1,662 assets, 100 company stocks were randomly selected. Since the regulations regarding publishing post-trade data for ATSs is fairly new, FINRA reports from 2015 and onwards. Hence, we will use data from 2015-01-01 to 2019-04-12 which implies 223 weeks. With more than four years of data compounded into weekly observations in combination with a sample size of 100 different shares, the data result in 22,300 observations and is considered as a satisfying amount of observations for this study.

The data collected from FINRA is the total volume of shares traded in different dark pools for each stock. All data collected is on a weekly basis and for all shares, the weekly trade sizes in the different dark pool venues are summarized to a total amount for each share. Resulting in a weekly trading size for each share and week.

3.2. Bloomberg terminal

From the Bloomberg terminal, we extracted data on the trading volumes on all available markets for each stock and week. We also collected the market capitalizations for each stock and week. We use this data to calculate the percentage volume of trading in dark pools as will be presented in the following section. Further, we collected daily closing prices from Bloomberg in order to calculate the daily return, which is also explained in the following section.

3.3. Descriptive Statistics

Table 1. Descriptive statistics

Variable	Mean	Median	Max	Min	Std. dev.	Nr. Obs.
Realized volatility (%)	1.473	1.188	24.728	0	1.1300	22,200
Dark percentage (%)	12.634	12.733	65.111	0	5.947	22,200
Total volume (M)	13.840	7.904	647.620	0.178	17.600	22,200
Market cap. (MUSD)	26,906	10,569	544,570	700.330	54,817	22,200
Avg. trade size	147.870	149.920	912.680	0	61.385	22,200

Note to table 1: Dark percentage is the percentage of dark pool trading relative to total trading, Avg. trade size is the average trade size in the dark market measured in units of shares and Lag RV is the lagged value of the realized volatility for one time period, in this case one week. Total volume is measured in millions units. Number of observations is measured in units.

Table 1 provides descriptive statistics for the data used in this thesis. The data represents the entire sample period from 2015-01-01 to 2019-04-12. As stated in the table, the average percentage of dark pool trading per week is at 12.6 % which is in line with the average for the US equity market at 14% (Baines, 2018). The highest percentage in this sample is 65.1%. Regarding the realized volatility, the average for the period is 1.47% while the highest value is 24.73%.

4. Method

In this section, we describe the way of processing the data mentioned in the previous section. Further, a description of the method used for the empirical findings as well as the process to compute the econometric models follows.

4.1. Dark pool calculations

The data collected in the previous section is used to calculate the percentage of dark pool trading volume (equation 1). By dividing the Total number of shares traded in dark pools with the total number of trades in dark pools the average trade size for each stock in the dark market is calculated (equation 2).

$$Dark\ percentage = \frac{Dark\ volume}{Total\ volume + Dark\ volume} \ x\ 100 \qquad (1)$$

$$Averagae\ dark\ trade\ size = \frac{Dark\ volume}{Dark\ trades} \qquad (2)$$

Total volume = total number of shares traded
Dark volume = total number of shares traded in dark pools
Dark trades = total number of trades in dark pools

4.2. Realized Volatility

We use realized volatility as a measure for asset price volatility. Realized volatility will be the dependent variable in the regression model. Since realized volatility is the historical volatility of asset returns, it is more appropriate in our study than implied volatility. Unlike implied volatility, which reflects the future volatility, realized volatility measures what have already happened (Nasdaq, 2019). Regularly, realized volatility is calculated by summarizing the squared intraday returns giving the realized volatility for a specific day, which can be processed into weekly, monthly or annual volatility. Using the same method as for daily realized volatility using intraday returns, it is possible to use a longer time frame, although it will not have the same accuracy (Andersen et al., 2001). The method of calculating the volatility from daily rather than intraday data were often used before the technic made accessibility to such as easy as today (Liu and Tse, 2013). When calculating weekly volatility from daily data, only five

return observation will be used to calculate each weekly estimate (ibid). That is why the method might lead to estimation errors (ibid). Anyhow, to fit the characteristics of the dark pool data provided, weekly realized volatility will be used and calculated from daily closing prices.

The first step in calculating the weekly realized volatility is to calculate the daily return of an asset. This is done using the logarithmic forms of the closing prices as shown in the formula below:

$$r_d = \log(P_d) - \log(P_{d-1}) \hspace{4cm} (3)$$

d = day
r_d = return of day d
P_d = Closing price of day d
P_{d-1} = Closing price of the previous day to day d (d-1)

Liu and Tse (2013) states that in order to calculate volatility for a month or a shorter time frame, in our case weekly, the daily returns (r_t) for the period are squared and summarized. The sum of the squared returns represents the realized variance for this study, which catches the price variations over the week.

$$RVar_{t,i}^{(w)} = \sum_{i=1}^{N} r_{d,i}^2 \hspace{4cm} (4)$$

d = day
t = the aggregation period, time interval of one week
i = the equity instrument
$r_{d,i}$ = daily return for one equity instrument
$RVar_{t,I}$ = Realized variance for one week and equity instrument
N = total number of days in the week (N=5)
w = indicates the weekly time span

By taking the square root of the realized variance, the realized volatility is received.

$$RV_{t,i}^{(w)} = \sqrt{RVar_{t,i}^{(w)}} \hspace{4cm} (5)$$

t = the aggregation period, time interval of one week
i = the equity instrument

RV_{t,i}= Realized volatility for one week

$RV_{t,i}$= *Realized volatility for one week*

$RVar_{t,i}$= *Realized variance for one week*

w = indicates the weekly time span

4.3. The regression models

We evaluate the relationship between the stock price volatility of the stocks trading on the US equity market and the proportion of dark trading for these stocks. We use a classical linear regression model (CLR). When using the CLR model, there are five basic assumptions that need to be accounted for (Kennedy, 2009). For this data set heteroskedasticity and autocorrelation are present, which violates one of the assumptions of the CLR model. In order to account for this, the option cluster is used. The result of the tests made can be found in Appendix 1.

The data used is of panel type. The main advantage of using panel data is the correction for heterogeneity, as well as the exploiting of information, giving better analysis of dynamic adjustment (Kennedy, 2009). Further, it gives more efficient estimations from combining cross-sectional variation with time-dependent variation.

The model used to test the null hypothesis is a fixed effects model. This type of model assumes the same slopes and a constant variance for the cross-sections while examining the individual differences in intercepts (Park, 2011). One of the biggest drawbacks with this model is that degrees of freedom are being lost, leading to less efficient estimates of the common slope (Kennedy, 2009).

As explained by Kennedy (2009) the fixed effects model estimates short-run effects since the estimator is based on the time series component of the data. When the difference between short- and long-run reactions is expected, it is further explained that these dynamics need to be built into the model. Thus, a lagged value of the realized volatility is included in our model.

When using a lagged value of the dependent variable in a fixed effects model, the estimators are biased. However, when the number of time periods is greater than 30 this can be off seen by the greater precision, which is underlined by Attansio, Picci, and Scorcu (2000).

4.3.1. Regression I

The regression model is inspired by the one used by Baskin (1989) as well as other relevant studies on stock price volatility (Ilaboya and Aggreh (2013), Shah and Noreen (2016), Seng and Yang (2017) and Zainudin et al. (2018)). They all use volatility as a dependent variable in a regression model to test their explanatory variables effect on stock price volatility. In accordance with Ilaboya and Aggreh (2013), a fixed effect model with panel data is used to test this relationship. As for the variable of interest, we use the percentage of trading in dark pools. Since the volatility is affected by multiple variables, we decided to control for some of these. Following the mentioned studies (Baskin (1989), Ilaboya and Aggreh (2013), Shah and Noreen (2016), Seng and Yang (2017) and Zainudin et al. (2018)), market capitalization is included as a control variable. In addition to this, the total trading volume for the stocks, average dark trading size and a time lag of one week for the realized volatility are included.

$$Realized\ volatility_{i,t} = \alpha + \beta_1 Dark\ percentage_{i,t} + \beta_2 Total\ volume_{i,t} +$$
$$\beta_3 Market\ capitalization_{i,t} + \beta_4 Average\ trade\ size_{i,t} +$$
$$\beta_5 Lagged\ realized\ volatility_{i,t} + \varepsilon_{i,t} \quad\quad\quad\quad (6)$$

i = the equity instrument
t = the aggregation period, time interval of one week
α = intercept
β_{1-5}= the slope coefficient for the variables
Dark percentage = the percentage of trading in dark pools
Total volume = the total trading volume
Market capitalization = the current market capitalization
Average trade size = average dark trade size
Lagged realized volatility = realized volatility for t-1
ε = error term

We expect the variable of dark percentage to have a decreasing effect on the dependent variable. This because it is plausible to believe that the lower market impact due to dark pool trading would decrease the volatility, which coincides with the results of Ye (2009), Buti, Rindi, and Werner (2011), and Foley, Malinova and Park (2013). For the variable total volume, we expect a positive sign implying that a more traded stock would have higher volatility. Regarding the variable market capitalization, we expect a negative sign. This in accordance with Christie

(1982) who imply that bigger firms tend to be less volatile. For average trade size, we expect a negative sign, since large trades on the public exchange tend to have a high market impact, thus trading the same amount in a dark pool instead would plausibly mitigate the effect on price volatility (Mizuta et al., 2015).

4.3.2. Regression II

To further test the relation between dark pool trading activity and asset price volatility we expand the data set by including dummy variables. The dummy variables are constructed to represent whether dark pool trading activity is high or low. High and low values are defined by calculating the mean of the percentage of dark pool trading in relation to total trades (Dark percentage). Thus, because of some shares absence of dark pool trading during certain time spans, these periods will be excluded from the mean. It is done in order to keep the mean from being deceptive i.e. long time periods of non-dark pool trading will decrease the mean, sometimes severe. After the mean is calculated, the 20 shares with the highest as well as the 20 shares with the lowest mean are selected for the dummies. The 20 shares with the highest mean go from 15.55%. The 20 shares with the lowest mean go up to 11.9%.

Whether dark pool trading affects the price volatility is tested using the first regression. The purpose of the other regression model is to test whether low percentages of dark pool trading relative to total trades significantly differs from high ones and if it is a change in the marginal effect of dark pool trading. To test this, we will create interaction terms of the dummy variables and the percentage of dark pool trading. Testing this will tell us if dark pool trading is preferred at a high or low level in the aspect of asset price volatility. This regression is compounded to estimate the effect of low and high proportion of dark pool trading in relation to total trades (Dark percentage). The dependent variable is once again realized volatility.

Fixed effect is not possible to apply when using dummy variables. The effect will be differentiated away because of the time dummies created by the demand. It is only possible to use time-varying variables and since the dummy in our case is constant for entities over the whole time span it will be omitted by Stata. Instead, we will use an OLS model and adjust it to keep the fixed effect for both time and entities.

$$Realized\ volatility_{i,t} = \alpha + \beta_1 Dark\ percentage_{i,t} + \gamma_1 Low\ dark\ percentage +$$

$$\gamma_2 High\ dark\ percentage + \gamma_3(Low\ dark\ percentage \times Dark\ percentage_{i,t}) +$$

$$\gamma_4(High\ dark\ percentage \times Dark\ percentage_{i,t}) + \beta_2 Total\ volume_{i,t} +$$

$$\beta_3 Market\ capitalization_{i,t} + \beta_4 Average\ trade\ size_{i,t} +$$

$$\beta_5 Lagged\ realized\ volatilty_{i,t} + \varepsilon_{i,t} \qquad\qquad (7)$$

i = the equity instrument

t = the aggregation period, time interval of one week

α = intercept

β_{1-5} = the slope coefficient for the variables

Dark percentage = the percentage of trading in dark pools

γ_{1-2} = the slope coefficient for the dummy variables

γ_{3-4} = the slope coefficient for the interaction terms

Low dark percentage = dummy variable, (1 if mean < 11.90, 0 if mean >11.90)

High dark percentage = dummy variable, (1 if mean > 15.55, 0 if mean < 15.55)

Total volume = the total trading volume

Market capitalization = the current market capitalization

Average trade size = average dark trade size

Lagged realized volatility = realized volatility for t-1

ε = error term

We expect the variables included in the first regression to have the same sign for this regression as well. The dummy variables are expected to have values different from each other, where high values will be greater than for low percentage of dark pool trading. For the interaction terms, we expect the slope coefficients to be different from each other. Whereas the one for low dark percentage would be negative and the one for high dark percent to be positive. This would indicate that a low dark percentage have a smaller impact on price volatility than a high dark percentage in relation to the benchmark group of medium dark percentage.

5. Empirical Results

In this section, we present the output of the regression models constructed in previous sections followed by the results of the hypotheses tests.

5.1. Hypothesis I

Table 2. Results from regression I

Number of observations		**22,200**
Number of groups		100
F(226, 21872)		35.36
Prob > F		0.0000
Within R-squared		0.2676
Between R-squared		0.1618
Overall R-squared		0.2301

Realized volatility	Coefficient	P-value
Constant	1.229284**	0.000
Dark percentage	0.0120112**	0.000
Total volume	0.000000026**	0.000
Market cap.	0.000000931	0.140
Avg. trade size	-0.0011695**	0.000
Lag RV	0.0744556**	0.000

The regression is provided in order to analyze the relationship between realized volatility and dark pool trading activity. As the Null hypothesis is formulated: The percentage of dark pools relative to the total volume of shares traded does not affect the volatility of asset prices. The null and alternative hypotheses are therefore established as below:

$H_0: \beta_1 = 0$

$H_A: \beta_1 \neq 0$

As the results from the regression imply the variable of interest, dark pool trading as a percentage of the total trading (dark percentage), is positively correlated to volatility. The coefficient received is 0.012 which means that the effect of a 1% increase in dark pool trading relative to total trading indicates a 0.012% increase in volatility, all else equal.

As the p-value (0.000) implies the null hypothesis can be rejected at a 1% significance level. The results indicate that the null hypothesis can be rejected. Hence, the proportion of dark pools relative to the total volume of shares traded does affect the volatility of asset prices. Further, the model produced in Stata automatically provides an F-test. Prob > F 0.000 means that the estimated coefficient are statistically significant, with a certainty above 99.999%.

In fixed effect regressions, the within R^2 rather than another measure of R^2 is of interest. This regression model provides a within R^2 of 0.2676, which means that the variance within the panel units in this model accounts for 26.76%.

5.2. Hypothesis II

Table 3. Results from regression II

Number of observations	**22,200**
Number of groups	100

F(228, 21969)		48.65
Prob > F		0.0000
R-squared		0.3375
Realized volatility	**Coefficient**	**P-value**
Constant	1.213376**	0.000
Dark percentage	0.0093887**	0.000
Low dark percentage	-0.0216083	0.678
High dark percentage	-0.1142061**	0.002
Low*Dark percentage	-0.0105619*	0.016
High*Dark percentage	0.0137982**	0.000
Total volume	0.0000000218**	0.000
Market cap.	-0.00000348**	0.000
Avg. trade size	-0.0023315**	0.000
Lag RV	0.2645634**	0.000

Note to table 3: Dark percentage is the percentage of dark pool trading relative to total trading. Low*Dark percentage is the interaction term between the dummy variable, Low dark percentage (1 if mean < 11.9, 0 if mean >11.9) and the percentage of dark pool trading, High*Dark percentage is the interaction term between the dummy variable High dark percentage (1 if mean > 15.5, 0 if mean < 15.5) and the percentage of dark pool trading. Avg. trade size is the average trade size in the dark market and Lag RV is the lagged value of the realized volatility for one time period, in this case a week. In addition to this, the related p-values are reported.

*significant at a 5% level

**significant at a 1% level

The regression is provided in order to further analyze the relationship between realized volatility and dark pool trading activity. As the second null hypothesis is formulated: The relative effect of dark pool trading on asset price volatility will not change regardless of the proportion dark pool trading relative to the total volume of shares traded, the null and alternative hypotheses is established as below:

$H_0 \; \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$

$H_A: \gamma_\mu \neq 0$ for at least one $\mu \in \{1, 2, 3, 4\}$

By including dummy variables, as well as interaction terms to the regression model, will allow for groups of high and low values of the mean to affect both the intercept and the marginal effect of dark pool trading on asset price volatility. For equity instruments with high dark pool trading, the marginal effect is 0.023 (0.009 + 0.014) relative medium. In the same time, the intercept is reduced in relation to medium with an estimate for the intercept of high dark pool trading of 1.099 (1.213 - 0.114). All of this with a significance at a 1% level.

There is no significant difference in the intercept between low levels of dark pool trading and medium ones. Though, the marginal effect differs at a 5% significance level. Indicating a slope coefficient for low levels of dark pool trading of -0.001 (0.009-0.011). Hence, a reduced impact in comparison to medium levels of dark pool trading.

To test the hypothesis stated above the joint significance of the variables are tested. The F-test of the variables provides an F-statistics of 33.49 which indicates that we can reject the null hypothesis at a 1% significance level.

This regression model provides an R^2 value of 0.3375 meaning that 33.75% of the model is explained by the variables included.

6. Discussion

In this section, we discuss the result provided in the previous section. We construct a critical discussion in order to describe the shortcomings of the study. After that, we discuss the hypotheses and the empirical results reached.

6.1. Critical discussion

As already pointed out the data collected from FINRA is data reported from ATSs. Dark pools are only one type of an alternative trading system. However, in studies, the concepts of ATS and dark pools are often referred to as a proxy because of the lack of transparency which will be consistent even for this thesis.

Realized volatility is often calculated using intraday data. This is done in order to catch all movements of the asset price which will provide an accurate measure of the intraday or daily return. By using the daily return to calculate the realized volatility over the week might not provide the same accuracy. However, since all accessible dark pool data was provided weekly the choice of weekly realized volatility was definite.

There are some limitations in the data set regarding dark pools. In the sample of stocks provided a few stocks have periods of no dark pool activity. By basing the random sample on stocks where dark pool activity is consistent through the whole time span may have an impact on the result. Same goes for the calculation of the mean values. Because of some shares absence of dark pool trading during certain time spans, we exclude these periods from the mean values. It is done to keep the mean from being deceptive i.e. long time periods of non-dark pool trading will decrease the means, sometimes severe.

Further, the only accessible data found was presented weekly. The results might be different if using a shorter time span. A dataset with daily or even intraday data would be preferred in order to account for the volatility in a more reliable way. Also, the accessible time period of the data was four years, to extend the sample using a longer time period would probably increase the accuracy of the test. When using time series, a long period is needed to find repeated reactions. However, this could be offset by the fact that the data set is of panel type. When using panel

data, these repeated reactions are found by looking at the reactions of the different cross-sectional units, in this case, 100 different stocks.

6.2. Hypothesis I and hypothesis II

As stated earlier, the first null hypothesis can be rejected, meaning that dark trading has an impact on asset price volatility. The results indicate an increase of 0.012% in asset price volatility for a 1% increase of dark pool trading. It doesn't seem like a large influence, though, in a very stable share this could anyway have an impact.

Further, the second null hypothesis is also rejected, stating that the extent of dark pool trading has a different impact on asset price volatility. In contrast to the first regression model, the second regression shows an association between dark pool trading and asset price volatility dependent on the quantity of trading. The second regression model shows that low percentage of dark pool trading relative medium percentages will reduce the volatility. For high percentages of dark pool trading, the slope is higher than for medium percentages, however, with a lower intercept. Anyway, the differences in the intercept will soon be outweighed by the marginal effect and high percentages will have a larger impact on the price volatility than medium ones.

The results for the first regression model as well as for medium and high percentages of dark pool trading concur with the results of Garvey, Huang, and Wu (2016) as well as O'Hara and Ye (2011). Both of these studies suggest a positive correlation between volatility and dark pool trading. Furthermore, they give no further explanation of the reason for this correlation. Though, Petrescu and Wedow (2017) explain the relation as, when orders are relocated from public exchanges into dark pools, the information in the public order books are reduced. Since prices are formed in order books, less information in the price formation might lead to increased price volatility.

The result of the second regression model corroborate with those of Ye (2009), Buti, Rindi, and Werner (2011), and Foley, Malinova and Park (2013) but only up to a certain point. They all imply that the volatility decreases when dark trading increase, which corresponds with the result of the interaction term for low percentage of dark trading in relation to medium percentage. Such relation is explained by the theory of different type of traders. The implication is that

informed traders will concentrate on the public exchange and uninformed traders will relocate to dark markets in order to make a profit. A larger concentration of informed traders on the public exchange will improve price formation and reduce price volatility (Zhu, 2013). Further, Foley and Putniņš (2016) find evidence that a one-sided system will reduce price volatility. Since the one-sided dark pool markets seem to be the most common on the US equity market this might be another explanatory factor for the result, in line with theory implications.

Our results regarding the decreasing asset price volatility for low percentage of dark trading relative medium percentage could be explained by the behavior of different types of investors as well as different kinds of markets, as mentioned earlier. In addition to this, we speculate that the lack of transparency in dark pools used to reduce market impact and volatility in asset prices also could be an explanation. On the other hand, when dark trading is increased a negative effect of reduced information in market prices could follow. When traders relocate to the dark markets, available information will decrease. Since asset prices on the public market are based on this information, the volatility will be affected and increased. As dark pool trading goes up, this effect will plausibly increase and thereby offset the positive effect of reduced market impact.

The reason for these different results could be explained by a number of reasons. First, the studies are performed on different markets where different regulations, as well as requirements, has to be met which may affect the usage of dark pool trading activity. Foley, Malinova, and Park (2013) for example look at the Canadian market while Petrescu, Wedow and Lari (2016) are looking into the European market. Low percentages in our model denote a mean up to 11.9%. For some markets, this infers a relatively high value already. For example, the overall market share of dark trading on the European market is below 10% (Petrescu and Wedow, 2017). Therefore, some low, as well as medium values in our model, could already be classified as high values in the European market. This might be an explanation to why our results may differ from studies made on other markets. Second, the major variations in samples and sample sizes will probably affect the results. Where some studies using just a few stocks or only looking into one dark pool, as Ye (2009). Third, the different kinds of data set and the usage of different types of variables. For example, volatility is a measure that can imply a range of differences. Foley, Malinova, and Park (2013) uses implied volatility, rather than realized. Fourth, the time span of the studies differs at large. Since volatility tends to differ depending on the overall

economic situations, periods of examination may impact on the results. Fifth, the disparities in the choice of methods used for the performance of the study.

By using the regression models provided we can only see linear relations between the variables. The results showed in the second regression model though might be an indication of a non-linear relation between dark pool trading and asset price volatility. For further studies, an examination of a non-linear relation between dark pool trading and asset price volatility would, therefore, be of value. An exponential relation could also provide a preferred amount of dark pool trading in the aspect of price volatility. To consider the disparities when it comes to different types of dark pools as well as a different type of traders would also be valuable in future research. Since these differences may affect the market and stock price volatility in different ways. Treating all dark pools as a homogeneous group may be deceptive and to take different type of traders into consideration would further broaden the perspective of the study, in the aspect of explaining for different behavior patterns. It could also be valuable to conduct studies with a longer time span, other aspects of market quality than volatility as the dependent variable or the usage of other control variables that affects the volatility.

7. Conclusion

By focusing on the effect of dark pool trading on asset price volatility, this thesis contributes to the unexplored field of dark pool trading and the effect on public markets. The results have led to a broader perspective of the field but would require further studies to find the real causal relation of dark pool trading on asset price volatility.

When looking at the result, the first null hypothesis stating that there is no relationship between dark pool trading and realized volatility could be rejected at 1% significance level. This in combination with the regression output suggests that there is a positive relationship between the dependent and the independent variable. These findings imply that the realized volatility increases with 0.012% when the ratio of dark pool trading increase with 1%.

The second null hypothesis can also be rejected at 1% significance level, implying that the effect of dark pool trading on asset price volatility will change with the extent of dark pool trading. The regression estimate that low percentages of dark pool trading compared to medium percentage decreases the volatility of asset prices. In contrast, when the percentage of dark pool trading is high compared to medium percentage the volatility will be enhanced. These results suggest that there seems to be a threshold where the reduced asset price volatility due to dark pool trading will be canceled out by the effect of reduced information on market prices.

These findings are interesting and supported by some of the prior research made on the subject. Our hope is that this will increase the interest for further studies related to dark pools, despite the limited access of data.

References

Andersen, T., Bollerslev, T., Diebold, F. and Labys, P. (2001). The Distribution of Realized Stock Return Volatility. *SSRN Electronic Journal*.

Attanasio, O., Picci, L. and Scorcu, A. (2000). Saving, Growth, and Investment: A Macroeconomic Analysis Using a Panel of Countries. *Review of Economics and Statistics*, 82(2), pp.182-211.

Bain, B. (2018). *Wall Street Dark Pools to Come Out of Shadows Thanks to SEC*. [online] Bloomberg.com. Available at: https://www.bloomberg.com/news/articles/2018-07-18/wall-street-dark-pools-set-to-come-out-of-shadows-thanks-to-sec [Accessed 4 Apr. 2019].

Baskin, J. (1989). Dividend policy and the volatility of common stocks. *The Journal of Portfolio Management*, 15(3), pp.19-25.

Buti, S., Rindi, B. and Werner, I. (2011). Diving into Dark Pools. *SSRN Electronic Journal*.

Christie, A. (1982). The stochastic behavior of common stock variances Value, leverage and interest rate effects. *Journal of Financial Economics*, 10(4), pp.407-432.

Comerton-Forde, C. and Putniņš, T. (2015). Dark trading and price discovery. *Journal of Financial Economics*, 118(1), pp.70-92.

Financial Industry Regulatory Authority (2014). *Regulatory notice 14-07*.

Foley, S. and Putniņš, T. (2016). Should we be afraid of the dark? Dark trading and market quality. *Journal of Financial Economics*, 122(3), pp.456-481.

Foley, S., Malinova, K. and Park, A. (2012). Dark Trading on Public Exchanges. *SSRN Electronic Journal*.

Garvey, R., Huang, T. and Wu, F. (2014). Why Do Traders Choose Dark Markets?. *SSRN Electronic Journal*.

Ilaboya, O. and Aggreh, M. (2013). Dividend Policy and Share Price Volatility. *Journal of Asian Development Studies*, 2(2), pp.109-122.

Kennedy, P. (2009). *A guide to econometrics*. Malden, Mass. [u.a.]: Blackwell.

Liu, S. and Tse, Y. (2012). Estimation of Monthly Volatility: An Empirical Comparison of Realized Volatility, GARCH and ACD-ICV Methods. *Research Collection School Of Economics*.

Mizuta, T., Kosugi, S., Kusumoto, T., Matsumoto, W. and Izumi, K. (2015). Effects of dark pools on financial markets' efficiency and price discovery function: an investigation by multi-agent simulations. *Evolutionary and Institutional Economics Review*, 12(2), pp.375-394.

NASDAQ. (2019). *Realized volatility Definition*. [online] Available at: https://www.nasdaq.com/investing/glossary/r/realized-volatility [Accessed 27 May 2019].

Noreen, U. and Shah, S. (2016). Stock Price Volatility and Role of Dividend Policy: Empirical Evidence from Pakistan. *International Journal of Economics and Financial*, 6(2), pp.461-472.

O'Hara, M. and Ye, M. (2009). Is Market Fragmentation Harming Market Quality?. *SSRN Electronic Journal*.

Park, H. (2011). *Practical Guides To Panel Data Modeling: A Step by Step Analysis Using Stata*. International University of Japan.

Petrescu, M. and Wedow, M. (2017). *Occasional Paper Series Dark pools in European equity markets: emergence, competition and implications*. European Central Bank

Petrescu, M., Wedow, M. and Lari, N. (2016). Do dark pools amplify volatility in times of stress?. *Applied Economics Letters*, 24(1), pp.25-29.

Securities and Exchange Commission (2010). *Concept Release on Equity Market Structure. Release No. 34-61358. 14 January*.

Seng, J. and Yang, H. (2017). The association between stock price volatility and financial news – a sentiment analysis approach. *Kybernetes*, 46(8), pp.1341-1365.

Ye, M. (2011). A Glimpse into the Dark: Price Formation, Transaction Cost and Market Share of the Crossing Network. *SSRN Electronic Journal*.

Zainudin, R., Mahdzan, N. and Yet, C. (2018). Dividend policy and stock price volatility of industrial products firms in Malaysia. *International Journal of Emerging Markets*, 13(1), pp.203-217.

Zhu, H. (2013). Do Dark Pools Harm Price Discovery?. *Review of Financial Studies*, 27(3), pp.747-789.

Databases

Bloomberg.com. (2019). Bloomberg [online] Available at: https://www.bloomberg.com/ [Accessed 27 May 2019].

Financial Industry Regulatory Authority. (2019). *OTC Transparency Data*. [online] Available at: https://otctransparency.finra.org/otctransparency/AtsIssueData [Accessed 27 May 2019].

Appendices

Appendix 1A. Breusch and Pagan Lagrangian multiplier test for random effects

Estimated results	Var	sd=sqrt(Var)
rv	1.276549	1.129844
e	0.8207176	0.9059347
u	0	0

Test: Var(u) = 0

Chibar2(01) = 0.00

Prob > chibar2 = 1.0000

Note to Appendix 1A: The high test result leads to no rejection of the test, hence a random effect is not better than a pooled OLS. The random effects model should therefore not be used.

Appendix 1B. F-test for fixed effects

F test that all u_i=0:

$F(99, 22095) = 36.80$

Prob > F = 0.0000

Note to Appendix 1B: The low f-value leads to rejection of the null, hence a fixed effect is favored over pooled OLS. The fixed effects model should therefore be used.

Appendix 1C. Hausman test for fixed or random effects

Test: Ho: difference in coefficients not systematic

$Chi2(3) = (b-B)'[(V\_b-V\_B)^{(-1)}](b-B)$

= 12050.62

Prob > chi2 = 0.0000

Note to Appendix 1C: The low test result leads to rejection of the null, hence the difference in coefficients is systematic. The fixed effects model should therefore be used.

Appendix 1D. Testing for time-fixed effects

F(221, 21874) =	**16.02**
Prob > F =	0.0000

Note to Appendix 1D: The low f-value leads to rejection of the null that the coefficients for all time periods are jointly equal to zero, a timed-fixed effect should therefore be used.

Appendix 1E. Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i	
Chi2(100) =	14858.29
Prob > chi2 =	0.0000

Note to Appendix 1E: The low test result leads to rejection of the null, meaning that heteroskedasticity is present and needs to be accounted for in the model.

Appendix 1F. Bias-corrected Born and Breitung (2016) Q(p)-test as postestimation

Variable	Q(p)-stat	p-value	N	maxT
Post	21.03	0.000	100	222
Estimation				
Under H0, Q(p) ~ chi2(p)				
H0: No serial correlation up to order 2				
Ha: Some serial correlation up to order 2				

Note to Appendix 1F: The low p-value leads to rejection of the null, hence there is some serial correlation present.

Appendix 1G. Test for multicollinearity

Correlation	Realized volatility	Dark percentage	Total volume	Market cap.	Avg. trade size	Lag RV
Realized volatility	1.0000					
Dark percentage	0.0539	1.0000				
Total volume	0.3242	0.0315	1.0000			
Market cap.	-0.1327	-0.1998	0.2580	1.0000		
Avg. trade size	0.0692	0.7155	0.3400	-0.1149	1.0000	
Lag RV	0.3973	0.0223	0.2166	-0.1325	0.0361	1.0000

Variable	VIF	1/VIF
Dark percentage	2.31	0.433548
Total volume	1.49	0.672586
Market cap.	1.19	0.843065
Avg. trade size	2.63	0.379694
Lag RV	1.11	0.904879
Mean VIF	1.74	

Note to Appendix 1G: The values reported in the top part measures how the independent variables correlate with each other. Since all values are below 0.8 there is no sign of correlation. The values reported in the second part measures the amount by which the variance if the ith coefficient estimate is increased due to its linear association with the other explanatory variables A high VIF indicates an R^2 near unity and hence suggest collinearity. Since all values are below 10 there is no sign of collinearity. Hence, the no-multicollinearity assumption holds. (Kennedy, 2009)

Appendix 1H. Pesaran's test of cross sectional independence

Pesaran's test of cross sectional independence =	**-1.614, Pr = 0.1066**
Average absolute value of the off-diagonal elements =	0.088

Note to Appendix 1H: The null for this test is saying that there is cross sectional independence. The high p-value leads to no rejection of the null.

Appendix 2. List of stocks included in the study

TICKER			
ABMD US Equity	EPR US Equity	MHK US Equity	SLGN US Equity
ADI US Equity	EQIX US Equity	MKC US Equity	SON US Equity
ADSK US Equity	FDS US Equity	MLM US Equity	SPR US Equity
AEE US Equity	FHN US Equity	MNST US Equity	SRE US Equity
AIV US Equity	FLIR US Equity	MRO US Equity	STAY US Equity
ALLE US Equity	FMC US Equity	MSM US Equity	STI US Equity
AMGN US Equity	GD US Equity	NATI US Equity	TCF US Equity
AXP US Equity	GDDY US Equity	NBL US Equity	TCO US Equity
BBY US Equity	GRA US Equity	NBR US Equity	TEL US Equity
BDX US Equity	GT US Equity	NEM US Equity	TER US Equity
BK US Equity	HON US Equity	NKE US Equity	TKR US Equity
BKNG US Equity	HPP US Equity	OI US Equity	TSS US Equity
BOKF US Equity	INCY US Equity	OKE US Equity	URBN US Equity
BRK/B US Equity	INFO US Equity	PFG US Equity	USG US Equity
CLGX US Equity	IONS US Equity	PG US Equity	USM US Equity
CNA US Equity	IP US Equity	PPL US Equity	UTX US Equity
CTAS US Equity	KRC US Equity	PRGO US Equity	WAL US Equity
CY US Equity	KSS US Equity	PSA US Equity	WLL US Equity
CZR US Equity	LBRDK US Equity	RCL US Equity	WMT US Equity
DCI US Equity	LNG US Equity	REG US Equity	WRB US Equity

DEI US Equity	LOGM US Equity	SAGE US Equity	XEC US Equity
DOV US Equity	LULU US Equity	SCCO US Equity	XRX US Equity
DVN US Equity	LUV US Equity	SCHW US Equity	XYL US Equity
EA US Equity	LVS US Equity	SFM US Equity	ZBH US Equity
EFX US Equity	MAC US Equity	SKX US Equity	ZTS US Equity

Appendix 3. Example of dark pool markets

Consider a fund manager, Investor A, who wants to sell 2 million ABC shares. If doing this in a public exchange, other investors may consider the large transactions as a signal to sell ABC. The consequence of such action might make it harder for investor A to receive the desired profit and the market price of ABC would suffer from abnormal volatility. To not cause a movement of the price in the public market, investor A would have to split the sell order into smaller pieces, the risk of such action is that the pattern is captured by companies using algorithms and the price of ABS is regardless starting to decrease. Investor A will therefore make less profit than intended.

Imagine that investor A instead places the sell order of 2 million ABC shares into a dark pool. The dark pool computer system will match investor A with other investors placing buy orders into the dark pool to fill the order. In a dark pool with a limit-order system (two-sided) investor A will have to wait for a matching order at the same price to be placed or change the sell price himself and pay the spread. The buy orders do not necessarily have to be placed with the same number of shares. If 20 other investors each places order with 100.000 shares at the same price as the sell order of investor A, the orders can be executed, and Investor A will receive the preferred amount. If only 10 other investors have placed orders of 100.000 ABC share each, one million of Investor A's shares will be executed, the other million shares will be delayed in the dark pool, waiting for new buy orders to be placed.

In a dark pool with a midpoint system the orders will be matched in the middle of the offered buy and sell price and investor A will have to pay half the spread.