Trading Behavior of Institutional Investors: Investment Decisions, Impact and Sustainability Trends

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Declaration of Originality

This thesis is being submitted to Macquarie University and Justus-Liebig University in accordance with the Cotutelle agreement dated 16.01.2018. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person, except where due reference is made in the thesis itself.

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Summary

This dissertation investigates institutional investor trading behavior, profit and losses and associated costs while accounting for market structure complexities. Institutional ownership has seen an increase over the last decades which shows that end-money investors hold larger stakes in companies worldwide. While some institutional investors actively use their influence or select their portfolio based on fundamental research, others remain silent and acquire stock to satisfy a passive investment strategy. Simultaneously, there is a growing awareness of Environmental, Social and Governance (ESG) investments while the marketplace has undergone fundamental changes resulting from technological advances.

The first part of this dissertation examines the dynamic relation between institutional ownership, market liquidity and ESG scores. It addresses the potential endogeneity of the factors and examines their dynamic relationship in a vector autoregressive (VAR) model. Previous research has mainly focused on binary relations between these factors and has highlighted possible implications of reverse causality. Little evidence has been gathered about the dynamic relationship between the full set of factors. The first part presents evidence about the dynamics between liquidity, ESG scores and investment style (which indicates if the investor is either passive or active).

Building on the evidence presented, the second part of this thesis investigates if ESG-oriented investment strategies can achieve excess returns when accounting for liquidity and investment style. Investments in ESG stocks might result from investors actively se-

lecting stocks or from following a passive strategy. In either case, the increase in trading volume interacts with stock liquidity and impacts information asymmetries. First, it is demonstrated that high ESG score stocks display lower information asymmetries compared to low ESG score titles. Additionally, this dissertation provides new insights by showing that ESG investments yield negative returns only for stocks with higher information asymmetries. If information asymmetries are low, ESG strategies show no significant abnormal returns, which is in accordance with the efficient market hypothesis.

The third part investigates venue selection and execution costs of institutional orders. ESG strategies implemented by institutional investors require liquid markets as their investment volume is typically substantial. The execution of these large volumes can cause unfavorable price impacts and be costly in terms of transaction costs when executed as a single order. Hence, institutional investors slice and dice these large orders into smaller ones in an attempt to improve overall transaction prices and market impact. Using a novel proprietary transaction-level dataset from UK equity markets, the third part of this thesis demonstrates that decisions to trade on venues with lower levels of pre-trade transparency are associated with lower transaction costs. Additionally, it is revealed that institutional investors use substitute venues when dark pool trading is prohibited.

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Chapter 1

Introduction

The last decades have seen an unprecedented change in the financial marketplace. Technological advances have evoked an increase in automated trading, opening the gates for the rise and growth of new market participants, structures and products. While trading happens in a faster-paced landscape, assets under management (AUM) experience immense growth. Boston Consulting Group (BCG) reports that by 2019 the value of global assets under management totaled USD 88.7 trillion.[1] PricewaterhouseCoopers (PwC) forecasts that global AUM will increase to USD 145.4 trillion by 2025.[2] Parallel to the inflow of assets, competition among asset managers and among products is growing. Out of asset manager services, passively managed products have outpaced their active counterparts in relative growth, with the global ETF volume increasing over the decades from USD 34 billion in 1999 to USD 4.3 trillion in 2019 in the US alone.[3]

As the volume of invested assets increases, clients become more aware of sustainabil-

[1] https://image-src.bcg.com/Images/BCG-Global-Asset-Management-2020-May-2020-r_tcm9-247209.pdf

[2] https://www.pwc.com/gx/en/asset-management/asset-management-insights/assets/awm-revolution-full-report-final.pdf

[3] Passively managed products aim to closely replicate an index, most prominently with Exchange Traded Funds (ETFs), with the ETF being an index fund that can be traded on exchange and is easily accessible to retail clients. https://www.ici.org/pdf/2020_factbook.pdf

ity and green thinking, which is reflected in their investment decisions. Passive products, especially ETFs, make it easier for clients to access these markets. The Forum of Sustainable and Responsible Investment (US SIF) reports that by the beginning of 2020, 1 out of 3 US Dollars was invested following a sustainable strategy.[4] This growing demand by clients, both retail and institutional, has been met by an increased variety of investment products, suppliers and trading venues. Typically, retail and institutional investors pose as end-investors without direct access to the secondary market. To facilitate trading, they employ brokers who then execute the orders submitted by their clients. Over the same time period, transaction costs have decreased, as markets have moved towards automatic trading initiated by technological advancements. Market wide liquidity and price discovery improved with algorithmic trading (Boehmer et al. (2020); Brogaard et al. (2015)).[5]

This thesis aims to illuminate the increasing complexity of the marketplace. Utilizing the trend towards sustainable investments, it first examines the dynamic relationship between investment style, ESG scores and liquidity. Next, it critically investigates if ESG[6] investments lead to abnormal returns. Finally, the last part of this thesis contributes to the understanding of institutional investors' venue selection and transaction costs.

The first part examines the dynamic effects of investment style, ESG scores and liquidity. Active investors typically engage with management, which can have a direct impact on the company's ESG and profit profile (Brøgger and Kronies (2020)). Passive investors

[4] https://www.ussif.org/files/Trends%20Report%202020%20Executive%20Summary.pdf

[5] However, these technological advancements also created a new trading participant, who generates profits due to their faster speed. These high-frequency traders (HFTs) capitalize on the advantage of being faster than others (Aquilina et al. (2020); Budish et al. (2015); Menkveld (2013)). They are able to detect the presence of institutional orders being executed and can profit by trading against these executions (Battalio et al. (2018)). Van Kervel and Menkveld (2019) note that the presence of fast traders can reduce benefits from analyst research through detection during the execution of large orders. The informational advantage is taken away by the HFTs and hence financial rents are reduced for the long-term informed investors.

[6] The thesis will use the term ESG, corporate social responsibility and social responsibility interchangeably.

do not typically engage with management, but have been criticized for not taking steps to enforce greater sustainability efforts through their large block holdings, resulting in detrimental effects on corporate governance (Bebchuk and Hirst (2019)) and/or sustainability aspects. Generally, the level of institutional ownership conveys signals to the financial market, which can have an impact on liquidity. As highlighted by Cao and Petrasek (2014), the effects depend on the institution type.

Inversely, investors might time their trading activity according to the liquidity level of the financial market (Colling-Dufresne and Fos (2015)). Similarly, high ESG scores might act as a signal and can also improve price informativeness (Egginton and McBrayer (2019)) and consequently liquidity by reducing trading costs. Clearly, multiple impact patterns have been reported and should be accounted for to avoid reverse causality biases. To address the interlinked and autoregressive dependencies, a VAR model is applied. Evidence on the dynamics between investment style (active vs. passive), investment motive (ESG) and liquidity are presented. The results indicate that a shock to active investors' share increases the ESG score, while a positive shock to the ESG score reduces active ownership. This pattern is mirrored for passive investors. Additionally, the study presents evidence that the ESG score increases after a liquidity decreasing shock which is independent of the investment style. However, a positive shock to the ESG score indicates only a significant positive effect on transaction costs when active investors are included. This indicates a difference in the dynamic structures of active and passive investment styles. Considering short-term effects, this analysis uses the realized spread as the measure for liquidity to account for potential price impacts of the transaction. The results indicate that active investors reduce their ownership share after a positive shock to the realized spread, while a positive shock to the active ownership share is followed by an decrease in realized spreads. A shock to the realized spread has no significant effects on passive ownership share, but an increase in passive ownership widens the spread. These findings indicate that signals from active and passive investors are perceived differently by the marketplace.

The second part of this dissertation addresses the question whether ESG-focused strategies can achieve excess returns while accounting for the complex relations presented above. Research has not yet provided a conclusive answer, but the majority posits a positive impact of ESG strategies on financial performance. Indicating that the investment style is important in the dynamic relationship between ESG scores and liquidity, this part of the thesis uses the insights from part one to evaluate if ESG investments yield excess returns. Active investors are thought of as a skilled trader group that performs fundamental research to identify trading possibilities to gain excess returns.[7] Additionally, active, or informed, trading is an important channel that impacts price informativeness (Goldstein and Yang (2015)) and that might be able to detect market trends early on to capitalize on them. One of these market trends is investing with a focus on sustainability, or ESG investing. This part investigates if ESG-related strategies can still achieve abnormal returns when accounting for the liquidity impact. Initial demand for ESG-related products can have an impact on liquidity and the information content of stock prices. This initial motivation of (active) investors to invest in stocks according to an ESG-based strategy could be detected by other market participants who are not necessarily following an ESG-based strategy. Hence, there might be some learning effect, and the increased demand might limit return possibilities.

To understand if ESG drives stock performance, it is critical to account for other confounding factors, such as the investment strategy differences between passive and active investors and the liquidity level of the stocks. To address these, stocks are sorted into portfolios according to their ESG score, liquidity and investment style. Afterwards

[7] On average, this skill seems not to outperform passively followed strategies (Busse et al. (2014)). However, Busse et al. (2014) note that the return distribution is skewed with some active investors achieving large alphas, but note that this can be due to luck as it is difficult to attribute the excess return to the skill level alone.

a Carhart (1997) four-factor model is estimated to extract the portfolio's alpha, which is a measure for excess return accounting for common risk factors. This study shows that ESG investing achieves negative returns only when the portfolio is relatively illiquid, i.e., the spread is relatively wide. The spread measures for liquidity can indicate how ESG-related information is perceived, with information asymmetries being lower for stocks with a smaller spread (Egginton and McBrayer (2019)). For portfolios with a higher level of liquidity (and hence a lower level of information asymmetry), ESG strategies deliver no significant abnormal returns. This part highlights that investing in high ESG stocks delivers negative returns only when information asymmetry is high.

Independent of the return structure of ESG driven strategies, institutional investors that implement and follow such strategies will require liquid markets that are sufficiently deep to achieve the investors' investment target. By executing ESG strategies, investors typically trade large volumes, which may have an impact on transaction costs and create price impacts. Naturally, institutional investors aim to reduce these detrimental effects when executing large quantities. Thereby, the investor splits the large order into smaller ones which then can be routed to different venues. Each venue type offers different levels of transparency and liquidity. The last part of the thesis investigates the execution costs and trading venue choice of institutional investors when being able to choose between these venues. Institutional trading involves the execution of large volumes. An institutional investor typically employs one or more brokers, who in turn use multiple venues to execute their clients' trades. The large institutional order is split and executed over time to reduce the price impact. Still, high-frequency traders (HFTs) can detect and capitalize on them, as presented by Battalio et al. (2018). This increases the incentive of institutions to move towards alternative venues with lower transparency regimes that help avoid detection. Budish et al. (2015), for example, model a market in discrete time where frequently held batch auctions can prevent predatory trading. While previous research mostly focuses on one or two markets, this part of the dissertation contributes by analyzing the venue selection and transaction costs in a multi-venue setting. Among alternative trading venues, prominent examples with no pre-trade transparency include the so-called 'dark pools'. This part demonstrates that transaction costs decrease when institutions route their orders to dark venues. Additionally, the researchers provide evidence that investors route their orders following a pecking-order (Menkveld et al. (2017)) after which venues with lower pre-trade transparency are chosen first. Dark pools are, however, subject to regulatory concerns.[8] The chapter uses the introduction of the so-called 'double volume cap', a rule banning dark pool trading after it exceeds specified thresholds, to show that the ban has no effects on institutional trading costs. Evidence is presented that in the absence of dark pools, investors shift their trading to alternative venues. Specifically, 'periodic auction' venues show similar effects on reducing transaction costs during a period when dark pool trading is banned. After the ban is lifted, volume moves back to dark pools, but with significant volume remaining on periodic auctions.

This dissertation is structured as follows. Chapter 2 reviews the relevant literature. Chapter 3 analyses the dynamic relation between ESG scores, liquidity and investment style. Chapter 4 uses the insights from the previous chapter to investigate the link between ESG investments and stock performance. Chapter 5 presents evidence on institutional investors' execution costs and venue choice, before Chapter 6 concludes this dissertation.

[8]Regulators aim is to increase market transparency, and hence see concerns when trading in venues offers no pre-trade transparency.

Chapter 2

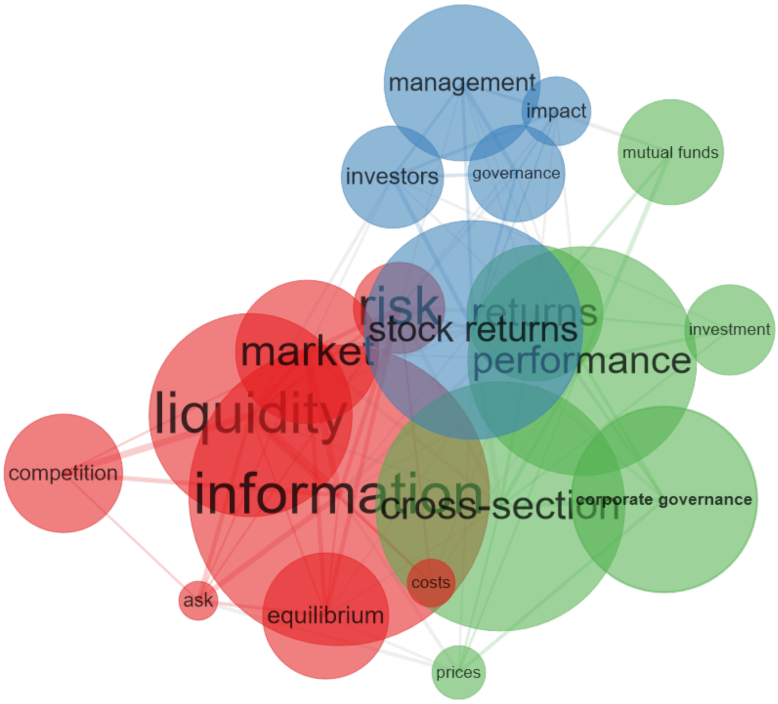
Related Literature

The word cloud in Figure 2.1 uses keywords to visualize the topics covered by the literature presented in this chapter.

Figure 2.1: Word Cloud Literature

Figure 2.2 visually presents the network of thematic categories of the literature used in this thesis and displays connections between subjects. Both figures emphasize the connections between all subjects. Even if these connections are unapparent at first, all subjects share common links.[1]

Figure 2.2: Network Graph Literature



2.1 Market Structure and Participant Types

Limit order books are the most frequently used trading mechanisms in equity markets as of today. Participants can submit limit or market orders to engage in direct trade

[1]Bibliometrix was used to create these figures. The network analysis is based on keywords that are created by natural language processing after collecting metadata from Web of Science. It is worth mentioning that working papers and the most recent publications are not yet available in the database. Many of the excluded papers contain subjects related to the recent trend towards corporate social responsibility and ESG aspects. More information on Bibliometrix can be found here https://www.bibliometrix.org/

with each other. These trades are intermediated by a central clearing counterparty to mitigate default risks. When traders submit a limit order, they define at what price and quantity they are willing to execute, while a market order is executed at any given price for a specified quantity. Market orders are an instrument for filling orders when urgency is of the matter and generally demand liquidity as they sweep the standing orders at the best prices. Their counterpart, i.e., limit orders, can be used when the trader puts more weight on the execution prices. They are seen to be liquidity providing, as these limit orders will be visible in the order book. Foucault et al. (2013) explain how incoming orders follow priority rules when building the book. An incoming order that offers a better price than a standing order will be prioritized. Following the price (and time) priority, the book will always show the best prices at which traders can buy or sell a certain quantity. Both price and volume dimensions can be used to get a general understanding of liquidity, which is generally defined as the ability to buy and sell assets easily.[2] The difference between the bid (price at which investors are willing to buy) and ask (price at which investors are willing to sell) is called the spread. The spread is typically the cost impatient traders pay when using market orders (Harris (2003)). Before limit order books, dealer markets were the most prominent marketplace matching buyers and sellers. However, advances in technology have favored electronic markets. Worldwide adjustments in regulatory requirements have additionally contributed to an increase in the fragmentation of the marketplace.

Seminal research has proposed theories to model trading mechanics which have an influence to this day. Kyle (1985) and Glosten and Milgrom (1985) provide frameworks to explain trading behavior in the presence of an investor group that holds an informational advantage over other groups. Within these models, market makers, or liquidity providers, demand the spread as a compensation for trading against these informed traders. Kyle

[2] Kyle (1985) divides liquidity into multiple dimensions, depending on tightness, depth and resiliency.

(1985) presents a sequential model where informed traders and noise traders engage in a market in which liquidity is provided by a third party, the market maker. In a first step, both informed and uninformed traders set prices unknowingly of each other. In a second phase, the market maker sets prices after observing the order flow without knowing who is informed or uninformed. Trading against an informed trader will result in losses for the market maker, since informed traders generally trade strategically according to their informational advantage. Consequently, the market maker demands compensation for the possibility of trading against informed participants, which is the bid-ask spread. Glosten and Milgrom (1985) present a model in which traders interact directly with the dealer in a quote-driven market. The dealer, or specialist, again does not know if she is trading with an informed or uninformed participant and faces an adverse selection problem. It is assumed that informed traders trade on one side of the market, i.e., buy after good news. The transaction itself contains information; based on the signals conveyed through the trade, the dealer adjusts her expectation regarding the value of the asset. The dealer would accordingly set an ask for buying the asset that is higher than the expected value as well as a bid for selling it which is lower, to account for the presence of the informed trader. This leads to an endogenously derived positive bid-ask spread.

Since the seminal work of Kyle (1985) and Glosten and Milgrom (1985), researchers have investigated the impact of changes in market transparency on transaction costs. Pagano and Roell (1996) provide evidence that in an automated auction market, spreads are narrower than in a dealer market because more information is provided. They conclude that pre-trade transparency improves transaction costs for uninformed traders. The spreads narrow, because liquidity providers can use the provided information about the order flow and better adjust to being exposed to insider trading. Baruch (2005) and Boehmer et al. (2005) support the findings by analysing the introduction of an open limit order book on the New York Stock Exchange (NYSE). After the introduction, overall trading costs decrease and prices contain more informational content. Using NASDAQ data, Simaan et al. (2003) show that liquidity providers post orders more aggressively on less transparent venues, where trading is anonymous (which happens on Electronic Communication Networks, ECNs). This results in wider spreads on the regular market, where the level of pre-trade transparency is greater compared to ECNs. Hendershott and Jones (2005) use a regulatory enforcement in Island to show that transparency decreases after the regulatory change. Transaction costs increase for ETFs traded in Island but decrease on exchanges abroad. After reversing the initial regulatory change, a positive effect on price discovery and transaction costs is observed by the authors. Interestingly, Madhavan et al. (2005) report a negative effect on transaction costs after an increase to pre-trade transparency in the Canadian stock market. After the public dissemination of a limit order book to both automated and floor trading, the authors find increased execution costs and higher volatility.

O'Hara (2015) remarks that with the introduction of high-frequency trading, the market structure has changed, possibly rendering some of the traditional models' predictions obsolete. To account for the shift in market structure, and for the high-frequency environment in particular, several models have introduced a framework in which fast traders (HFTs) compete with slow traders (Hoffmann (2014); Biais et al. (2015); Budish et al. (2015)). Yet, both positive and negative welfare and liquidity effects can result. Faster traders can use their speed advantage to pick off standing limit orders before the order initiator can cancel them (sniping stale orders), which generally has a detrimental effect. In contrast, speed can help adjust inventories and reduce adverse selection exposure more quickly.

On a market-wide level, Hendershott et al. (2011), Brogaard et al. (2015) and Boehmer et al. (2020) demonstrate that overall informational efficiency and liquidity have increased with the level of algorithmic trading. Menkveld (2013) shows that HFTs act as 'new' market makers with a high quota of passive liquidity provision. Focusing on the effects of fast traders, Shkilko and Sokolov (2020), in contrast, investigate the costs and benefits of high-frequency trading in a semi-natural experiment. The authors use episodes of slower connectivity caused by heavy precipitation to show that adverse selection and trading costs decline when fast traders are hindered from engaging in trading activity. Aquilina et al. (2020) use exchange message data to quantify the welfare loss stemming from latency arbitrage. Participants compete for stale quotes, where the standing limit orders are predominantly submitted by slower traders. The authors propose that eliminating latency arbitrage (or arms) races would decrease costs of liquidity by 17%, which translates into approximately USD 5 billion in annual savings.

2.2 Investor Trading Decisions in Fragmented and Automated Markets

Empirical and theoretical evidence highlights that there are costs associated with high-frequency trading. Budish et al. (2015) design a market model to overcome the direct costs of trading against high-frequency traders in the central limit order book. They propose a discrete time model structure in which auctions are held at specified time intervals. Order submission remains unchanged and participants can send, amend and cancel their orders similar to trading in a continuous limit order book. By introducing these batch auctions, the impact of speed advantages and ultimately arms races for stale orders are reduced.

The proposed mechanism has been implemented by market practitioners and has gained more attention in recent years.[3] Market participants who do not wish to be subject to sniping or detection will try to use alternative market structures that help pre-

[3]CBOE is offering a periodic auction which provides auctions throughout the trading day at a random length with a maximum auction duration of 100 milliseconds. The auctions are triggered upon order entry. https://markets.cboe.com/europe/equities/trading/periodic_auctions_book/

vent or limit trading against high-frequency traders. Alongside market regulations and reforms, several alternative market forms have been introduced. This market fragmentation has led to trading volume moving away from the traditional exchanges. Among trading venues, 'dark pools' have become particularly popular. Dark pools are trading mechanisms without pre-trade transparency. Hence, participants are unable to see quotes before the trade and face execution uncertainty as no information about the available liquidity in the dark pool is observable. Dark pools are designed to provide institutional investors with better price conditions while also offering a platform to hide their trading intention from predatory traders. Typically, there is no price formation on dark pools. Therefore, dark pools quote a relevant benchmark price, which is usually taken from the 'primary' continuous lit market.

Research has come to contradictory findings when introducing a dark pool in the decision-making process of trading. While Ye (2011) finds that introducing a dark pool as an alternative trading venue to the regular market lowers price discovery, Zhu (2014) proposes that price discovery can improve. According to Zhu (2014), the increase in price discovery results from a growing ratio of informed to uninformed traders. The author further argues that informed traders tend to trade on one side, and avoid trading in dark pools to obviate execution uncertainty. Uninformed traders anticipate the higher quota of informed traders in lit markets and use dark pools instead. The move towards dark pools reduces liquidity on the exchange, but more price-relevant information remains. Similar impacts on limit order book liquidity are reported by Buti et al. (2017), who additionally report a negative impact on lit market depth. According to the authors, the increase in spread and the reduction in depth is the result of traders using more market orders which are executed in dark pools. While the deterioration of lit market liquidity is accompanied by an increase in overall trading volume, it generally leads to a welfare loss for traders. Menkveld et al. (2017) introduce a pecking order pursuant to which investors rank execution venues according to trading costs and immediacy. Immediacy is the possibility to execute orders quickly and with certainty. According to Menkveld et al. (2017), traders prefer low-cost and low-immediacy venues, like dark pools, over high-cost and high-immediacy venues, like regular lit markets.

Empirical evidence is also mixed. Foley and Putnins (2016) report positive effects on spreads and information efficiency when trading in dark limit order books, while dark pools that cross at the midpoint show no significant effect. The authors use the introduction of price improvement rules in Canada and Australia as a semi-natural experiment. On the other hand, Comerton-Forde and Putnins (2015) show that lit trades are more informed than dark trades and adverse selection is increasing with the level of dark trading. This higher concentration of informed traders in the lit market is in accordance with Zhu (2014). Likewise, Degryse et al. (2015) find a negative impact of dark trading on liquidity in the Dutch equity market. By contrast, Comerton-Forde et al. (2018) show a positive impact on displayed liquidity in the Canadian equity market, after a rule was introduced that requires dark orders to offer price improvement. They show that retail orders move away from a dark pool which was primarily used for the intermediation of these retail orders towards the lit market. However, the authors also provide evidence that another dark pool has increased its market share following the implementation of the same rule because investors were able to engage in trading without intermediation.

Besides dark pools and the already mentioned periodic auctions, other trading venues have gained attention in the EU, especially after the introduction of the second Markets in Financial Instruments Directive (MiFID II) in January 2018. Systematic Internalizers (SIs) already existed but have gained more attention after MiFID II banned 'Broker-Crossing Networks'. They are trading venue-like places with lower pre- and post-trade reporting requirements. As a result, large investment firms (typically large investment banks and electronic liquidity providers[4]) have created their own SIs. The fragmentation of markets also imposes a feature which has not been covered by the initial seminal papers. To account for possible choices between venue types with varying levels of transparency, execution probability and other characteristics, new models have been proposed that aim to explain trading behavior in the presence of venue choice. Gresse (2017) provides evidence that market fragmentation is not harmful to market liquidity. The author uses the implementation of the first Markets in Financial Instruments Directive (MiFID) in 2007 to compare liquidity measures around the event. MiFID supported the fragmentation of the traditional lit trading places and made room for alternative trading platforms. The author finds an overall positive effect on market liquidity, accounting for the effect of algorithmic trading.

2.3 Institutional Investors, Investment Styles and Market Impact

With a co-movement of algorithmic trading and market fragmentation, O'Hara (2015) argues that HFTs should be seen as informed traders, as they are able to gain information from the order flow and can capitalize on short-term information. Battalio et al. (2018) show that electronic liquidity providers (ELPs), a subset of HFTs[5], are able to collect information from the order flow and can capitalize on the information gain. ELPs learn from institutional trades that have been routed to their own venues, which results in increased trading costs for the institutional client, as the ELP can profit by trading against the execution of the institutional order on other venues. Van Kervel and Menkveld (2019) provide additional insights on how the HFTs behave once they detect an institutional

[4]Electronic liquidity providers are usually high-frequency traders who voluntarily make markets by using their speed advantages.

[5]Battalio et al. (2018) name for example Citadel and D.E. Shaw as ELPs.

order. The HFTs initially trade against the wind but sequentially change direction when they learn that an institutional order is present and end up trading in the same direction. This behavior reflects informed trading where strategic investors would trade according to the news (buy on good news, sell on bad news). In their conclusion, Van Kervel and Menkveld (2019) propose that HFTs should be characterized as 'high-tech traders', reflecting their potential to become informed. They also mention the impact on the profitability of longer-term informed traders, as fundamental research might become too costly. HFTs are however not the only informed participants. There are several ways to identify informed traders. Sağlam et al. (2019) define skilled trading based on the probability of correctly forecasting prices in the short-term. A different way to categorize traders is according to investment style, which reflects the trading strategy of investors. Thereby, a common way to categorize investors with a long-term focus is to divide them into active and passive investors. Active investors perform research to beat a benchmark with skill and/or engage with a company's management. Passive investors typically do not engage with management but follow a passive strategy that generally tries to replicate a benchmark.

The presence of large institutional investors and their ownership in equities has increased over the last decades. In an early article, Gabaix et al. (2006) show that stock price movements can be explained by institutional investors activity in illiquid markets. Ben-David et al. (2015) discuss the impact of an increased presence of institutional ownership and its granularity, i.e., the multiple units active within the same organization, on stock price volatility. According to the authors, at the end of 2016, the top ten asset managers held 26.5% of total equity assets. The main concern addressed in their research is the risk stemming from the redemption impact the liquidation of these large positions can have on asset prices. They provide evidence that higher volatility in the underlying stocks can be linked to institutional ownership. Secondly, they show that large institutions exert a stronger market impact than several smaller institutions combined, due to the large institutions' granularity. Granularity, in this sense, describes that the behavior of sub-units within the same organization is alike. Hence, the trading of large volumes by these top institutions shows a larger impact on prices. The increase in volatility, however, results in prices being more efficient, as Ben-David et al. (2015) point to faster price discovery. The authors reason that the large trading volumes impound liquidity shocks into asset prices, which increases the level of noise. Following this reasoning, they show that in periods of market turmoil asset prices experience stronger effects and significantly lower returns when the level of institutional ownership is higher.

Evaluating market liquidity, Cao and Han (2016) show that institutional ownership has a positive impact on financial markets by reducing liquidity risk sensitivity. They, however, remark that different investor types have opposing effects. They show that hedge funds react differently to a liquidity change with respect to their investment strategy. More specifically, hedge funds that use leverage are more sensitive to liquidity risk compared to hedge funds with no leverage usage. Additionally, the authors investigate the relationship between other institutional investor types like mutual funds and banks with liquidity risk. Mutual funds exhibit a weaker link to liquidity risk, while bank ownership is negatively related to liquidity risk. Cao and Han (2016) explain these different links through different trading patterns. According to the authors, the leveraged exposure of hedge funds urges the hedge fund to sell off their assets after a liquidity shock which leads to declining asset prices and increased liquidity risk. This supports a theory by Brunnermeier and Pedersen (2009) according to which market liquidity is linked to a traders' funding liquidity.

Underlining the importance of accommodating for the investment strategy differences, institutional ownership can be divided into active and passive investment orientation. Active investors strategically construct their portfolio to beat their benchmark, e.g., by stock picking (see for example Cremers and Petajisto (2009)). Busse et al. (2014) provide evidence that information-based traders, or active traders, are unable to deliver excess returns over their benchmark. Benchmark returns are synonymous with the return of passively managed funds (not accounting for tracking error costs). While there is no evidence that, on average, active investors outperform passive investors, their impact on liquidity and information provision is still being researched.

Even without a distinguishable performance difference, the presence and type of institutional investors can impact liquidity according to their investment orientation. While traditional models forecast a negative impact between informed investors and liquidity, some new models propose that under certain conditions the impact might be positive. Roşu (2020) proposes a model in which informed traders have a positive impact on liquidity by using limit orders. Colling-Dufresne and Fos (2015) empirically show that liquidity increases on days when insiders trade. Days are actively chosen based on high liquidity levels. Using Securities and Exchange Commission (SEC) reports, the authors classify participants that file these reports as informed. Reports are required to be filed after more than 5% of a company's equity is acquired. They contain information about quantity, trade date and the price of all trades in the target stock. Investigating trades in stocks that are subject to these filings, the authors show that regular measures of adverse selection and stock liquidity fail to detect the presence of informed investors. In fact, the authors show that adverse selection costs are lower on days when informed investors are trading. Colling-Dufresne and Fos (2015) reason that these informed investors with long-lived information select the timing of trades based on the liquidity in the market. Trading in periods of high liquidity would prevent the price from being moved because the level of noise traders is relatively high. Secondly, they demonstrate that long-term orientated informed investors strategically use limit orders, which helps reduce adverse selection costs.

Fundamentally, informed trading should increase the informational level of a stock, as new information entering the market is reflected in the asset price (see Fama (1970)).[6] Goldstein and Yang (2015) model how an increase in informed trading can reduce the general level of uncertainty, which improves price informativeness. They introduce traders that are informed in two distinct dimensions. The authors provide two scenarios on how one group of informed traders reacts when the other group of traders becomes more informed. First, the increase in information in one dimension can reduce uncertainty for the second group, which then trades more aggressively on its own information. Secondly, and controversially, the increased information level in one dimension can lead to a reduction of aggressive trading by the other group if it perceives the new fundamental value as too expensive. Goldstein and Yang (2015) label the first case as strategic complementary, which increases the price informativeness level, and the second as strategic substitutability. They highlight the importance of the interaction between types of investors.

The information dimension can be manifold, but it is generally assumed that informed traders are skilled investors who engage in some form of information acquisition, e.g., by active research. Interestingly, Crane and Crotty (2018) provide empirical evidence that the skill of passive investors is comparable to the skill of active investors. Using index funds, which are passively managed funds that aim to replicate an index, they show that a large fraction can be labeled as skilled. While typical skills, like portfolio selection and market timing, cannot be applied to explain the passive fund managers' skill set, the authors explain their skill with operational management of the fund, e.g., how managers can efficiently operate the index fund upon constituent changes.

The increase of passive investors over the last decades has also impacted other areas of research besides performance evaluations. A surge of assets under management ultimately increased the passive investors' ownership share within a company, which can translate

[6] Famously, the Grossman and Stiglitz (1980) paradox postulates that markets cannot be perfectly efficient as there would be no incentive for costly information gathering. Hence, there must be profit opportunities to motivate information gathering.

into impacts on both company and market level. Previous research has mainly focused on the impact active investors have on a company's governance, because they are the investors that typically engage with management. Admati and Pfleiderer (2009) show that investors can exert pressure through a threat of exit, reducing agency costs. Following this approach, it would not be necessary for investors to actively engage with management to monitor their stock pick, because the threat of exit is enough to signal to the company's management that shareholder expectations should be fulfilled. The exit channel is a threat because active investors can sell their shares. After selling, the stock price will surge and the company's management, which holds shares of the company, faces a financial loss. In a similar manner, Edmans et al. (2013) investigate the impact of liquidity on governance. They argue that liquidity increases the probability of an investor buying a large block. Conditional on the block investment, liquidity then has a decreasing effect on the channel of governance. Thereby, being a more liquid firm makes it easier to afterwards sell the block, hence putting more weight on the 'channel of exit' governance mechanism. The threat of selling the block would lower firm value (by lowering stock prices), which is a more credible threat when stock liquidity is high. They also show that after a passive investor's 13G filing,[7] abnormal returns measured both via operational performance and stock prices are stronger for more liquid firms.[8]

Similarly, Boone and White (2015) show that passive institutional ownership is linked to higher stock liquidity. The authors use the Russell 1000 and Russell 2000 index reconstitution to account for the endogenous relation between institutional ownership and informativeness of the companies. They further employ the index constituency as an exogenous determinant to evaluate the company's informational content after a change in constituency. After a company changes constituency, passive investors, whose primary

[7] A 13G filing is a SEC report that indicates passive ownership by the submitting institutional investors, whereas a 13D filing represents activist desires.

[8] Edmans et al. (2013) argue that the higher share of passive investment is the reason for 'lower' frequency of active funds' activity.

strategy lies in index replication, have a stronger incentive to adapt to these changes than investors who rely more on active trading strategies. The authors show that the informativeness of stocks and liquidity increases with passive ownership. Glosten et al. (2021) argue that passive ownership makes prices more informative in the short-run, using ETF activity. ETFs are exchange-tradable funds that track an underlying index and are passively managed. Stocks in a weak informational environment would especially benefit from ETF activity. The authors argue that individually gathering information for these stocks is costly, whereas trading in ETFs helps to improve the link between short-run fundamentals and the underlying stock prices. Using a similar setting to Boone and White (2015), Appel et al. (2016) investigate the impact of passive institutional ownership on corporate governance. They posit that passive investors have an incentive to increase a company's corporate governance and performance. Firstly, because it increases the value of their assets under management and, secondly, because it is their fiduciary duty. Due to the value-weighting of the Russell indices, passive ownership in stocks that are in the top of the Russell 2000 is higher compared to (similar) stocks that are on the bottom of the Russell 1000. Employing an instrumental variable regression in which the instrument is the Russell 2000 index constituency, the authors find that passive ownership is increasing corporate governance. Governance is proxied with board independence, opposition to anti-takeover provision and opposition to unequal voting rights.

On a more critical note, Ben-David et al. (2018) demonstrate that passive ownership via ETFs increases volatility. Since ETFs are tradable on exchange like regular stocks, high-frequency traders can use information signals gained to enter into arbitrage with the underlying securities. Through this additional impact of signals in the ETF price, the underlying securities' prices inhibit greater volatility. They also demonstrate that stocks with high ETF ownership earn a significant risk premium. DeLisle et al. (2017) present evidence for a negative relationship between passive ownership and earnings predictability, which they use as a proxy for informativeness. Passive investors are not engaging in fundamental-based trading, which increases stock return correlations and decreases price informativeness if their share relative to active investors grows. Kacperczyk et al. (2018) show that, in theory, an increase in the ratio of passive to active ownership has a negative impact on price informativeness via two channels. Firstly, the reduced activity of active investors translates into a smaller amount of information gathering. Secondly, the smaller active investor group is more specialized, which lowers overall price informativeness (but has a positive impact on the subgroup of stock in which the active investor group specializes).

Re-visiting the connection between passive ownership and governance, Schmidt and Fahlenbrach (2017) also employ the index reconstitution setting of the Russel 1000/2000 indices. However, Schmidt and Fahlenbrach (2017) report an overall negative relation between the level of passive ownership and measures for good corporate governance. They reason that the difference between their findings and those of Appel et al. (2016) arises from categorizing the measures into low- and high-cost governance activities. Schmidt and Fahlenbrach (2017) show that passive ownership affects corporate governance and shareholder value negatively when evaluating high-cost activities, such as the monitoring of mergers and acquisitions and the choice of board members. Bebchuk and Hirst (2019) posit that passive investors do not share the same incentives as active managers, resulting in reduced monitoring and increased agency costs. With the increase in passive ownership and assets concentrated under only a few asset managers, they confirm an underinvestment in stewardship for the top three fund managers. More specifically, asset managers spend fewer resources on monitoring, reduce communication, are not focusing on governance principles and vote in favor of the company's management.

The channels through which large shareholders can work are versatile. Institutional ownership not only has an impact on social or financial performance on individual company level based on investment styles, but also through different investment horizons. In the same vein, Oikonomou et al. (2020) stress that long- and short-term investors have different effects on corporate social performance. While long-term orientated investment is positively correlated with corporate social performance, short-term investments hold a negative correlation. Regardless of investment horizon or investment style, sustainability aspects have become an important investment factor for institutional investors.

2.4 Sustainability as a New Investment Trend

The relationship between financial performance and ESG activity has been extensively investigated. Specifically, whether there are return differences between 'greener' and 'browner' stocks. The outcomes however are not conclusive. Riedl and Smeets (2017) provide a theory to explain why investors would invest in socially responsible funds. They combine individual investor holding data with results from surveys and experiments. The authors show that the decision to invest according to social motives overrules investing in sin stocks that potentially yield greater returns. Sin stocks are companies that are part of the alcohol, tobacco and gaming industry. A similar theory is derived by Pástor et al. (2020) in which the authors explain that investors' expected returns for green assets are lower, because they are willing to pay more for them. Instead, investors derive non-financial utility from investing in these assets. Green assets thereby create positive externalities, while brown assets create negative externalities.

In a meta-analysis using over 2,000 research articles, Friede et al. (2015) find an overall positive correlation between ESG and financial performance. However, Derwall et al. (2011) criticize that most studies pool socially responsible investment (SRI) mutual funds together even though they are a heterogeneous group with different investment strategies. Therefore, the values- and profit-orientated strategies could cancel each other out. Derwall et al. (2011) show evidence that, in the period from 1992 to 2008, alpha from investing according to the value-driven strategy in SRI stocks (measured with positive employment screens) declines, whereas a strategy that invests in shunned stocks creates abnormal returns. Shunned stocks, in this context, denote socially controversial stocks. Similar to this, Hong and Kacperczyk (2009) focus on sin stocks. They demonstrate that these sin stocks deliver higher abnormal returns. They reason that socially more constrained investors, e.g., pension plans, decide against investing in these stocks, which gives socially more un-constrained investors a performance edge. Socially unconstrained investors are thereby institutions that are classified as mutual funds and independent investment advisors. Hong and Kacperczyk (2009) show that these institutional investors are more invested in sin stocks and can therefore achieve abnormal returns.

Controversially, when using ESG data from several providers and considering different time horizons, Halbritter and Dorfleitner (2015) cannot identify significant financial out-performance of titles with a relatively high ESG focus. Comparing US and European stocks, Amon et al. (2019) find no evidence that ESG strategies outperform the benchmark, while Bannier et al. (2019) show a negative return when buying high ESG and shorting low ESG stocks. Lins et al. (2017) show that stocks with a focus on corporate social responsibility (CSR) outperform stocks with a lower CSR rating during the 2008-2009 global financial crisis (GFC). However, they deliver no excess return during normal market periods before and after the crisis. They reason that investors grant firms a trust premium during stressed periods. They characterize a company as trustworthy when it inhibits a high level of social capital, approximated by the CSR level. Hence, the more trustworthy a company, the more likely they will outperform untrustworthy companies during times of stress. Also referencing the GFC, Buchanan et al. (2018) show, using a triple Difference-in-Difference approach, that the relation between CSR and firm value is influenced by the influential institutional ownership.[9] Within the same group of high institutional ownership, the negative impact of the financial crisis is significantly lower for high CSR firms. Yet, they categorize a firm as CSR-treated if the firm has reported an ESG score by the end of the year 2006, which might lead to biases, as even 'brown' companies might report their ESG score. Looking at the recent COVID-19 crisis, Broadstock et al. (2021) investigate the role of ESG investing during times of market stress. They show that investors value ESG as an investment-increasing and risk-decreasing factor. Focusing on the Chinese market, the authors demonstrate that high ESG stocks outperform low ESG stocks during periods of stress.

Dimson et al. (2015) provide evidence that institutional investors show interest in ESG aspects. They use proprietary data provided by a large asset manager and present a positive correlation between socially responsible engagements and abnormal returns for the time period between 1999-2009. They also stress that by selecting stocks based on ESG criteria, the asset manager follows a different shareholder style as opposed to a traditional hedge fund, which can be thought of as more confrontational. Hence, attention towards ESG aspects depends on the investor type. This attention towards ESG aspects can in turn have other implications. For example, Pedersen et al. (2020) present evidence that ESG scores play an important role in information provision and in affecting investors' preferences, which has a positive effect on demand.[10] Hartzmark and Sussman (2019) show that investors' demand is positively correlated to the highest sustainability ranking, i.e., they observe a higher demand for the most sustainable funds. The authors use the introduction of fund level sustainability ratings by Morningstar to investigate investors' interests in more sustainable investment possibilities. They also cannot identify performance differences between high and low sustainability-orientated funds.

[9] Buchanan et al. (2018) measure influential ownership as Dedicated Ownership and Quasi-Indexer Ownership, which follows the classification method of (Bushee and Noe, 2000; Bushee, 2001).

[10] Pedersen et al. (2020) derive a portfolio optimization theory where the investor chooses titles along an ESG-efficient frontier.

Egginton and McBrayer (2019) show how improving corporate social responsibility disclosure strategies reduces asymmetric information and consequently increases market liquidity. Similar findings are reported by Siew et al. (2016), who add that a higher level of institutional ownership may attenuate the positive effect on information asymmetry. However, they note that with an increasing level of institutional ownership, the possibility arises that ESG-related insights can be used as insider information, which would contribute negatively to the decrease of information asymmetry.[11] Grewal et al. (2017) investigate the disclosure effect of financially material sustainability information on stock informativeness. By analyzing company filings, they categorize information based on the accounting standards developed by the Sustainability Accounting Standards Board (SASB). Using daily data, the authors show that companies with a higher voluntary disclosure of this as material labeled information exhibit a higher stock informativeness. Cho et al. (2013) investigate the impact of CSR disclosures on information asymmetry. Interestingly, they find evidence that both positive and negative CSR performance reduces information asymmetry, with the latter having a greater effect. Accounting for the level of institutional ownership, the authors show that stocks with a high level of ownership exhibit stronger effects compared to stocks with a lower level of ownership. They reason that more informed investors can exploit this information advantage.[12] Arguing that liquidity is driving ESG aspects, Chang et al. (2018) show that an increase in liquidity has a detrimental effect on CSR ratings. They measure the causal effect stock liquidity has on CSR ratings. Stock liquidity is measured with several alternative variables, but their main focus lies on the effective spread. Finding a negative correlation between CSR ratings and stock liquidity, they argue that short-term investors' interests outweigh long-term activity

[11] Siew et al. (2016) argue that a higher level of institutional ownership translates into a higher degree of informed investors, who this argumentation is based on. This assumption is debatable, as passive investors can be viewed as relatively more uninformed than active investors, which would bias the results.

[12] Cho et al. (2013) treat a high level of institutional ownership as equivalent to a higher level of informed investors.

in CSR investments. Higher stock liquidity thereby translates into short-term pressure for CEOs to perform well, driven by institutional investors who force their exit-strategy upon the management of the company. In return, the company does not engage in CSR investments, which are aimed at longer horizons.

Chapter 3

Dynamics Between ESG Scores, Investment Style and Liquidity

3.1 Introduction

Over the last decades the financial marketplace has undergone significant changes. Electronic trading and automated execution through ever-expanding technological advances have changed the marketplace, with a positive effect on transaction costs and liquidity.[1] Simultaneously, not only has the execution quality changed, but investment targets have evolved from merely monetary motivations towards a greater focus on sustainability and socially responsible aspects.[2] With the progression of investment strategies and trading volumes, the presence of institutional investors has also grown. Their stock ownership has greatly increased over the last decades.[3] With the simultaneous growth of many areas, the complexity of the relationship between these areas increases. Changing one might also impact all others. This becomes even more relevant in times when markets and their

[1] See for example Menkveld (2013); O'Hara (2015)

[2] See for example `https://www.ussif.org/files/Trends%20Report%202020%20Executive%20Summary.pdf`

[3] See Aggarwal et al. (2011)

players get better and more easily connected. This research investigates the connection between the presence of institutional investors, stock liquidity and a stock's sustainability development measured with the ESG score.

The rise of institutional ownership is especially strong for passive investors (Ben-David et al. (2015)).[4] Generally, passive investors refrain from engaging directly with managers and follow index replicating strategies. Yet, the increased and imminent voting power of passive investors creates a new channel through which a company and its management could be impacted. More recently, passive investors have been criticized for a lack of ESG promotion.[5] This highlights that the presence of large institutional investors can have an impact on a company's (ESG) profile. Brøgger and Kronies (2020) confirm that investors use a company's ESG score to make investment decisions. In particular, more skilled investors can correctly forecast the ESG development and can achieve a premium with this forecast. In a similar manner, Drei et al. (2019) document that some investors select companies that are likely to improve their ESG integration. However, they also note that the excess returns for passive investors have diminished.[6]

The increase in institutional ownership might not only affect a company's ESG profile, but it can also have an impact on market liquidity (Boone and White (2015)). Hong and Kacperczyk (2009) report that socially more unconstrained investors, i.e., mutual funds and hedge funds, will act as arbitrageurs in sin stocks. These investors identify under-

[4]Using newly created investment products that also benefited from the changed marketplace, investors also had it easier to invest. Exchange Traded Products have been the most prominent examples of new passive investment products, which saw an immense growth (Ben-David et al. (2017)).

[5]BlackRock, one of the biggest passive investors, has been criticized for not doing enough to promote a better ESG profile, `https://www.cbsnews.com/news/amazon-fires-blackrock-investment-firm-financial-role-cbsn-originals-documentary/`, or more recently, `https://www.ft.com/content/479b9dd2-c738-4310-8b1e-afdfbd3921b0`

[6]Drei et al. (2019) explain the diminishing returns of passive investors with the 'Q4' puzzle. Here, Q4 represents the worst 20-40% of stocks ordered according to their ESG score. They show that stocks in the top and bottom quintiles (Q1 and Q5) remain in their representative groups, while the intermediary quintiles (with a focus on the Q4 quintile, hence the puzzle's name) see an adjustment dynamic. This 'active' adjustment reduces returns of passive investors with a focus on ESG. Also, passive investors are facing a tracking error cost which is independent of the Q4 puzzle.

priced stocks and do not predominantly consider ESG aspects. The arbitrage opportunity arises as investors with social constraints refrain from buying sin stocks. With a higher involvement of mutual and hedge funds, which can also be thought of as more informed investors, the general demand for these stocks and their information content can be impacted. Thereby, the lack of (Hong and Kacperczyk (2009)) or the focus on (Guiso et al. (2008)) ESG aspects can act as a trigger for other market participants to engage in stock trading, even if they do not follow an ESG-based strategy. Traditionally, an increase in informed trading tends to decrease stock liquidity, which is reflected in a widening of the spread (Kyle (1985)). The spread widens because the liquidity provider demands a higher compensation against adverse selection costs, which increase with the probability of informed trading.

Using spread measures, Chang et al. (2018) investigate the link between stock liquidity and CSR.[7] They find a negative correlation between CSR ratings and stock liquidity. They argue that short-term interests outweigh long-term activity in CSR investments. Higher stock liquidity would thereby translate into short-term pressure for CEOs to perform well. The short-term pressure stems from an exit threat, which is more prevalent with greater stock liquidity, as the institutional investor can more easily trade their large block (see Edmans et al. (2013)). As a result, the company does not engage in CSR investments, as these investments are predominantly linked to long-term targets. Chang et al. (2018) emphasize that causality is running from liquidity towards CSR. At the same time, Egginton and McBrayer (2019), for example, present evidence that the informativeness of ESG disclosures conveys information that impacts market liquidity measures, which would indicate a reversed causality relationship.

The above highlights that all factors are interwoven and that isolating the causality stream without accounting for dynamics might not reveal the full picture. This study

[7] Besides CSR rating, Chang et al. (2018) also use ESG ratings and present similar results.

contributes to the literature by analyzing these factors in one system. For this purpose, this study calculates cumulative responses from a vector autoregression (VAR) model, which helps examine the relation between investment style, liquidity and ESG scores. First results show that there are significantly different dynamics when including either active or passive investment style. An increase in active ownership yields positive impacts on ESG scores, whereas an increase in passive ownership tends to have a negative impact on ESG scores. Further evidence is provided that an increase in ESG scores has a negative (positive) impact on active (passive) ownership. This resembles Brøgger and Kronies (2020) findings, which show that skilled investors are able to correctly forecast ESG developments, while relatively more unskilled investors are not.

Next, this study shows that an increase in liquidity has a negative impact on the ESG score, independent of investment style. Greater liquidity increases the threat of a possible exit strategy by institutional investors and puts more pressure on a company's management to focus on profit maximization (Edmans et al. (2013)). However, an increase in the ESG scores shows a positive effect on liquidity only when active investors are included in the model specification. This highlights the complexity of the impact structures in the system. When investigating short-term effects, this study finds again significant differences between models with differing investment styles. Contributing to the understanding of the impact on liquidity, this study provides evidence that an increase in active ownership is linked to a decrease of realized spreads, while an increase in passive ownership is linked to an increase in realized spreads in the short-run. This is in line with Colling-Dufresne and Fos (2015), who show that more informed investors time their trades and can have a positive impact on liquidity.

The rest of this chapter is organized as follows. Section 3.2 provides the hypotheses development and Section 3.3 describes the data and methodology. In Section 3.4, empirical results are presented. Section 3.5 provides robustness checks, before Section 3.6 concludes this chapter.[8]

3.2 Hypotheses Development

Appel et al. (2016) find a positive impact on the long-term performance when passive investors use their large voting blocks to influence a company's governance. Investigating a company's sustainability aspects, Kim et al. (2019) present evidence that long-term active investors have a positive impact on CSR activities, which they achieve through an increase in monitoring, while passive long-term investors have no significant effect. Bebchuk and Hirst (2019) advise that passive managers might not only act according to their clients' interest but also to their own. This highlights that the distinction between active and passive investment style is crucial to understand the institutional investors' impact on a company's long-term targets, such as ESG related goals.

Over the last couple of decades, institutional trading has grown both for active and passive institutional trader types. This increase in trading demand itself, irrespective of whether the motivation originates from active or passive investors, impacts stock liquidity and price informativeness. Rubin (2007) shows that stock liquidity increases with the overall level of ownership but is negatively impacted by large block holders. Additionally, there is some evidence, that some investors actively select and invest in stocks based on their ESG profile (Brøgger and Kronies (2020)).

Colling-Dufresne and Fos (2015) demonstrate that the share of long-term informed investors can also positively relate to stock liquidity. The authors present evidence that, when trading, informed investors strategically select market periods of high liquidity while also improving liquidity by using limit orders. Traditionally, it is assumed that informed investors demand liquidity by using market orders.[9]

[8] The relevant literature is discussed in Section 2.

[9] A market order is an order that executes a specified quantity at the current best bid or ask price.

This highlights that isolating the effects and only considering them bilaterally might bias the results. Hence, this chapter investigates the hypothesis centered around the dynamic relationship between ESG scores, investment style and liquidity.

Hypothesis 3.1: ESG scores, investment style and liquidity show a dynamic relation

3.3 Data and Methodology

This paper combines data from multiple frequencies to end up with quarterly observations for S&P 500 constituents between January 2010 and April 2020[10]. Trade and quote (TAQ) data is gathered from Refinitiv Datascope, which is high-frequency data containing information about each trade and quote for each stock continuously throughout the day. Only regular market hours between 9:30 am and 4:00 pm are considered, crossed spreads are excluded and positive trading volumes are required (Holden and Jacobsen (2014)). High-frequency data is aggregated to quarterly data using a volume-weighted average. The two main spread measures calculated are the *Effective Spread* and the *Realized Spread* according to:

$$\begin{aligned} Effective\ Spread_t &= 2d(price_t - mid_t)/mid_t \\ Realized\ Spread_t &= 2d(price_t - mid_{t+T})/mid_t, \end{aligned} \tag{3.1}$$

where d indicates a buy or sell order signed with the Lee and Ready (1991) algorithm. However, trades are only signed when they do not occur at the midpoint to avoid misclas-

A limit order buys or sells at a specified price and quantity. A sufficiently large market order can 'walk' the book, meaning it can drain liquidity by executing against more than one resting limit orders in the order book. By walking the book, the execution is not only against the best price, it will also increase the investors' execution costs because of less favorable price levels.

[10]The time period starts after the turbulence of the global crisis have calmed down and from when ESG data seems to be adequately available on Refinitiv.

sifications. The *Effective Spread* accounts for trades that execute at prices different from the best bid and ask (outside or inside the spread) and the *Realized Spread* considers a price impact of the trade by comparing the execution price with the mid-quote after T time steps.[11]

Firm fundamental data, including ownership information and ESG scores, is gathered from Refinitiv Eikon. Ownership data is taken only from 13F filings. A company is required to file a 13F report if the company's asset under management exceeds USD 100 million. The firm is then required to provide further information that helps classify the institution.[12] Eikon provides information about the investor type and the investment style, which can be either passive or active. An active investor is more likely to perform research before investing (shows a higher level of skill) and/or engages with management. Passive investors tend to follow index replicating or similar strategies and typically do not engage with management.[13] Information on institutional ownership stemming from 13F filings might lead to an aggregate institutional ownership share of above 100%, which can be the result of errors, unaccounted stock splits or short selling. Cases where the institutional ownership share exceeds 100% are excluded. Instead, the previous report's information is used. Additionally, only the company's initial report is used if data in consecutive reports is stale. This paper follows Brogaard et al. (2017) and fills in missing firm fundamental information with the last available information at the company level. The frequency of accounting and ownership data is quarterly.

The ESG score is taken from Refinitiv Eikon. The ESG score consists of three pillars, also named 'Asset4' pillars. Namely, the ESG score is split between an Environmental, Social and Governance score. The combined score is a weighted average across companies and hence reflects the company's relative ESG position among peers. The score is bound

[11] For this analysis, 10-second realized spreads are calculated unless otherwise indicated.
[12] https://www.sec.gov/divisions/investment/13ffaq.htm
[13] http://banker.thomsonib.com/ta/help/webhelp/Ownership_Glossary.htm

between 0 and 100, where a higher score indicates better ESG performance. Refinitiv is using several sources[14] to compute the ESG score to represent the company's ESG profile. For this research, ESG scores are interpolated from yearly to quarterly observations to include them in the methodology approach, which requires quarterly changes.[15]

An overview of institutional owner types as provided by Eikon is found in Table 3.1. When value-weighting the institutional ownership by market capitalization, Table 3.1 shows that institutional investors (active and passive) hold 73.71% of the companies on average. Within the institutional investors, 'Investment Advisors' and 'Investment Advisors/Hedge Funds' hold the lion's share, with a combined share of 60.13% (30.92% + 29.21%). It is worth noting that the share of active and passive investors differs between the two investor groups 'Investment Advisor/Hedge Fund' and 'Investment Advisor'. While they both account for approximately half of the 'Investment Advisors/Hedge Funds', active investors have a strong majority of 75.92% (22.17%/29.21%) within the 'Investment Advisors' group.

3.3.1 VAR and Impulse Response Functions

Vector autoregressive (VAR) models are used to investigate the dynamic interactions between the variables. A change in institutional ownership might not only impact the ESG score but both liquidity and future ownership share as well. Quarterly data is constructed as a balance between the available frequency of the variables. Therefore, the yearly ESG score is interpolated to create a more granular representation. Afterwards, the observations are volume-weighted by the company's market share to obtain one observation by

[14] `https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/esg-scores-methodology.pdf`

[15] This paper is mostly interested in stock level development and dynamics, i.e., the consistency in ESG score development. This reduces the problems of score differences between ESG score providers, as mentioned in Halbritter and Dorfleitner (2015). Yet, as highlighted by Berg et al. (2019) there is significant disagreement between the ESG rating providers and could potentially impact the results.

Table 3.1: Average Ownership Share by Institution Type and Style
The average ownership share is presented in percentage points across stocks and the observation period based on institutional investor type and style. The ownership share is value-weighted with the company's market capitalization.

Investor Type	All	Active	Passive
Investment Advisor/Hedge Fund	30.92	16.07	14.85
Investment Advisor	29.21	22.17	7.04
Pension Fund	3.69	2.38	1.30
Research Firm	2.44	0.00	2.44
Hedge Fund	2.17	1.89	0.28
Bank and Trust	1.97	1.68	0.29
Insurance Company	1.25	1.20	0.05
Sovereign Wealth Fund	1.00	0.97	0.03
Foundation	0.69	0.08	0.61
Corporation	0.15	0.12	0.03
Holding Company	0.12	0.00	0.12
Private Equity	0.06	0.06	0.00
Endowment Fund	0.03	0.03	0.00
Venture Capital	0.01	0.01	0.00
All	73.71	46.67	27.05

quarter for each of the variables used.[16]

Following Lütkepohl and Krätzig (2009), the reduced form VAR(p) model is defined according to:

$$\boldsymbol{y}_t = \boldsymbol{A}_1 \boldsymbol{y}_{t-1} + ... + \boldsymbol{A}_p \boldsymbol{y}_{t-p} + \boldsymbol{u}_t, \tag{3.2}$$

where the endogenous variables $\boldsymbol{y}$ are *investment style*, *ESG* and *liquidity*, with $\boldsymbol{A}_i$ being the KxK coefficient matrices for $i = 1...p$ and $\boldsymbol{u}$ are $Kx1$ reduced form disturbances. The model can be expressed in its moving average representation as:

$$\boldsymbol{y}_t = \boldsymbol{\Phi}_0 \boldsymbol{u}_t + \boldsymbol{\Phi}_1 \boldsymbol{u}_{t-1} + \boldsymbol{\Phi}_2 \boldsymbol{u}_{t-2} + ..., \tag{3.3}$$

[16] ESG scores are not ESG disclosure, but using scores instead of the actual expectation shows similar qualities according to Cohen et al. (2011).

where $\mathbf{\Phi}_0$ is an identity matrix of dimension K. From the representation in equation 3.3 the orthogonal impulse response function (oirf) can be derived. Orthogonalized impulse responses are obtained by using a Choleski decomposition on the covariance matrix of the error terms:

$$\boldsymbol{y}_t = \mathbf{\Psi}_0 \epsilon_t + \mathbf{\Psi}_1 \epsilon_{t-1} + \mathbf{\Psi}_2 \epsilon_{t-2} + \ldots, \tag{3.4}$$

where the orthogonalized shocks are $\epsilon_t = \boldsymbol{B}^{-1} \boldsymbol{u}_t$, $\Psi_i = \Phi_i(B)$ gives the impulse responses, and $\boldsymbol{B}$ is a lower triangular matrix.

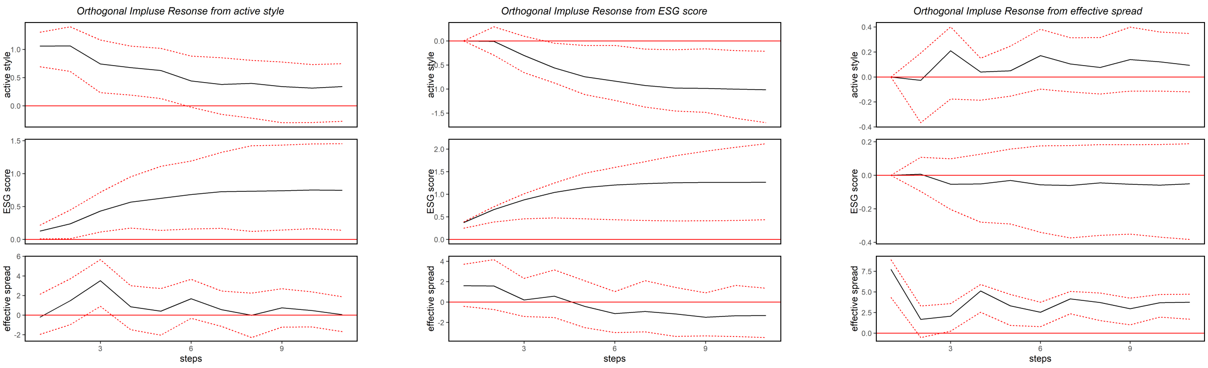
Orthogonalization is sensitive to the ordering of the variables in the VAR system. Thereby, a shock to the first variable has a contemporaneous effect on all variables, whereas a shock to the second variable is not contemporaneously affecting the first variable.

To compute the oirfs the VAR must satisfy stability conditions, more specifically, the time series has to be stationary. Augmented Dickey-Fuller tests reveal unit roots in each of the variables' time series. First differences are calculated, which produces a VAR model that is integrated of order one (I(1)).[17] The optimal lag length selection results in a lag length of two (one) quarters (quarter) when including active (passive) investment style based on the Bayesian/Schwarz Information Criterion (SC, Schwarz (1978)).

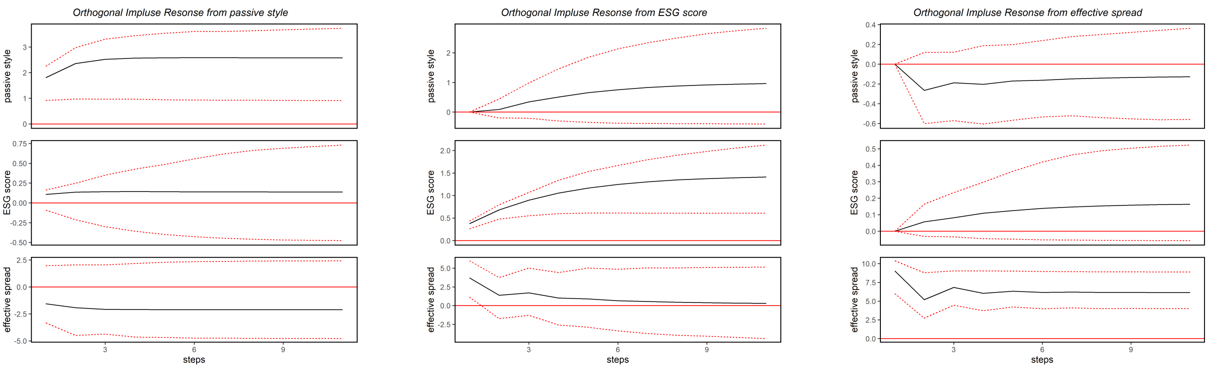
Figure 3.1 displays in Panels (a) to (c) the orthogonal shocks to each variable and their responses in the VAR system for the specification including the active investment style. Panels (d) to (f) show the responses to using passive style instead of active style. The responses in Figure 3.1 are cumulative with bootstrapped confidence intervals.

Panel (a) of Figure 3.1 indicates that a positive shock to 'Active Style' leads to an

[17] Log returns are used for all variables. In order to calculate log returns for the realized spread, a linear transformation is applied. A positive integer is added to the measure before applying the natural logarithm because the realized spread can be negative.



(a) Active Style Shock **(b)** ESG Score Shock **(c)** Effective Spread Shock



(d) Passive Style Shock **(e)** ESG Score Shock **(f)** Effective Spread Shock

Figure 3.1: Orthogonal Impulse Response Functions from Simple VAR model

increase in ESG and the effective spread, hence decreasing liquidity. However, the 95% confidence bands are not indicating a significant response to the impact on effective spread. Panel (d) of Figure 3.1 shows that when the impulse is coming from a shock to 'Passive Style', the effective spread and ESG scores react differently. Shocking the 'ESG score', Panel (b) shows a negative impact on active ownership, while passive ownership shows no clear reaction in Panel (e). Panels (c) and (f) show no significant impact on ESG or investment style when shocking the effective spread.

3.4 Firm Level VAR and Cumulative Responses

The responses shown above are reactions to an averaged sample. They do not consider firm specific responses and can over- or underestimate the response. Drempetic et al. (2020) provide evidence that larger firms might have advantages in providing ESG information. Additionally, Drei et al. (2019) stress the differences between large- and mid-cap companies. Therefore, the next step estimates the I(1) VAR model for each stock and extracts the orthogonalized cumulative responses individually. This enables the researcher to investigate firm-specific responses to shocks in the system. For each stock VAR estimation, the optimal lag length is selected based on the Schwarz information criterion. The cumulative orthogonalized responses are calculated over 8 periods (2 years) to account for the ESG score's sticky characteristics. In a different setting, Hasbrouck (1995) uses the cumulative impulse responses to evaluate the informational content of a trade. Brogaard et al. (2019) extend the approach to analyze the informational content of high-frequency trades by using limit orders. Although not in a high-frequency environment, the method is applied here. A shock to one of the employed variables is likely to accumulate over time.

Table 3.2 shows the results of testing the hypothesis when the cumulative effects are different from zero across stocks. The results help to gain insights about the dynamic relationships of the variables included, which have been used by previous research. Column 'VAR Order' defines the variable order in the estimated VAR. This ultimately indicates which variables have no contemporaneous effects on the other variables. For example, the left side in Panel A shows E $\rightarrow$ A $\rightarrow$ EfS, meaning that the ESG score is the first variable, the second is active investment style and the last is effective spread. Hence, shocking the effective spread has no contemporaneous effects on the other two variables.

Independent of the ordering, Table 3.2 shows that a positive shock to active investment

Table 3.2: Cumulative Responses on Stock Level - Active Investment Style
The table reports t-test statistics to test the hypothesis if the cumulative response is different from zero. Orthogonalized impulse response functions are calculated for each of the 355 stocks. Cumulative responses are calculated over 8 periods after the shock. For ease of presentation the following abbreviations are used: 'E' is short for ESG, 'A' is short for active investment style, 'EfS' is short for effective spread. Column 'VAR Order' shows the ordering of the VAR model, Column 'Impulse' indicates which variable has been shocked. The VAR uses quarterly data between 2010 Q2 and 2019 Q4. Standard errors are presented in parentheses.

VAR Order	Impulse	Response			VAR Order	Response		
		E	A	EfS		E	A	EfS
Panel A. Contemporaneous ESG Impact								
E→ A→ EfS	E	4.84***	-0.16**	-0.40***	E→ EfS→ A	4.84***	-0.16**	-0.40***
		(0.17)	(0.08)	(0.15)		(0.17)	(0.08)	(0.15)
	A	0.26***	4.84***	-0.19		0.26***	4.74***	0.27**
		(0.07)	(0.13)	(0.22)		(0.07)	(0.13)	(0.13)
	EfS	0.31***	-0.04	12.39***		0.32***	-0.24***	12.70***
		(0.05)	(0.05)	(0.22)		(0.05)	(0.08)	(0.24)
Panel B. Contemporaneous Investment Style Impact								
A→ E→ EfS	E	4.72***	-0.12**	-0.32**	A→ EfS→ E	4.59***	-0.15***	-0.45***
		(0.17)	(0.06)	(0.15)		(0.16)	(0.05)	(0.11)
	A	0.19**	4.92***	-0.21		0.19**	4.92***	-0.21
		(0.10)	(0.14)	(0.22)		(0.10)	(0.14)	(0.22)
	EfS	0.31***	-0.04	12.39***		0.39***	-0.01	12.52***
		(0.05)	(0.05)	(0.22)		(0.09)	(0.05)	(0.22)
Panel C. Contemporaneous Liquidity Impact								
EfS→ A→ E	E	4.59***	-0.15***	-0.45***	EfS→ E→ A	4.71***	-0.19***	-0.48***
		(0.16)	(0.05)	(0.11)		(0.17)	(0.07)	(0.12)
	A	0.21**	4.82***	0.19		0.26***	4.74***	0.27**
		(0.09)	(0.13)	(0.14)		(0.07)	(0.13)	(0.13)
	EfS	0.39***	-0.22***	12.81***		0.39***	-0.22***	12.81***
		(0.09)	(0.08)	(0.24)		(0.09)	(0.08)	(0.24)

Note: *p<0.1; **p<0.05; ***p<0.01

style has a positive impact on the ESG score. Kim et al. (2019) argue that with a longer investment horizon, active investors can have a positive impact on the company's CSR activities. Similar to their research, this chapter finds that a greater presence of active investors is connected to an increase in the ESG score. On the contrary, a shock to the ESG score lowers the shares active investors hold. This indicates that an increase in active investors is followed by an increase in a company's ESG score. However, active investors tend to reduce their presence in stocks following a positive ESG development. Brøgger and Kronies (2020) deliver an explanation by which more sophisticated investors are able to forecast a company's ESG development and are able to gain profits via this ESG premium. Active investors try to gain excess returns by detecting, forecasting or maybe even influencing the ESG profile of the company. This strategy requires an exit to realize their advantage. Therefore, active investors should reduce their share after successfully forecasting a positive ESG movement, which is in line with results presented in Table 3.2. The coefficient estimates for the response of the active ownership are consistently negative after the ESG score is shocked (i.e., Panel A row 'E' column 'A' shows a negative value of -0.16).

Table 3.3 shows the opposite effect for passive investors. Passive investors, who typically do not engage with a company's management, tend to increase their share after a positive shock to the ESG score. This is again independent of the variables' order. Many passive investors offer funds that track indices. The trend towards sustainable investments resulted in newly created indices, which in turn requires passive investors to acquire stocks that qualify for these indices. Inversely, a positive shock to passive ownership has a negative impact on the ESG score. This could arise through the absent engagement with a company's ESG-related decisions. With managers relatively more unsupervised, missing supervision can increase agency costs, as described in Ferrell et al. (2016). Generally, the authors show that CSR ratings are moving with firm value, allowing the authors to reject the hypothesis that engaging in CSR postulates an agency cost problem. They report that managers have an incentive to focus on long-term strategies, which include CSR in companies with a relatively high concentration of institutional ownership or a greater presence of block holders. Ferrell et al. (2016), however, do not differentiate between investor types. Focusing on passive investors, Bebchuk et al. (2017) show that index fund managers spend less resources on stewardship, resulting in increased costs related to the agency problem of reduced monitoring. Hence, even an increase in ownership could lead to increased costs when the investors that gain voting rights are not exerting their supervisory powers. The findings presented here are in line with recent criticism towards passive asset managers' lack of sustainability engagement.[18]

Again, independent of the order and the investment style, a shock to the spread has a same-sign impact on ESG scores. With a liquidity increasing shock (i.e., a negative shock to the effective spread), the ESG scores show a negative reaction. Chang et al. (2018) show that with a higher level of short-term oriented investors, the effect on CSR is negative via the liquidity channel. They reason that with higher liquidity the exit channel threat puts pressure on managers to follow mainly profit-orientated motives. This lets managers neglect more long-term focused goals like CSR.

After shocking the ESG score, liquidity shows a positive reaction only when the model includes active investment style. Within the model specification including active investors, a positive shock to active style has a negative effect on stock liquidity (increase in effective spread) only in certain orderings. There, the cumulative response is significantly different from zero only when active ownership does not have a contemporaneous effect on liquidity, namely in the order E→ EfS→ A and EfS→ E→ A. This shows that active and passive investment styles result in very different market dynamics. To illustrate this further, the next steps investigate the impacts in the short-term.

[18] https://www.ft.com/content/7a80f33b-a0ed-4dea-b2d3-ce56381f4084

Table 3.3: Cumulative Responses on Stock Level - Passive Investment Style
The table reports t-test statistics to test the hypothesis if the cumulative response is different from zero. Orthogonalized impulse response functions are calculated for each of the 355 stocks. Cumulative responses are calculated over 8 periods after the shock. For ease of presentation the following abbreviations are used: 'E' is short for ESG, 'P' is short for passive investment style, 'EfS' is short for effective spread. Column 'VAR Order' shows the ordering of the VAR model, Column 'Impulse' indicates which variable has been shocked. The VAR uses quarterly data between 2010 Q2 and 2019 Q4. Standard errors are presented in parentheses.

VAR Order	Impulse	Response			VAR Order	Response		
		E	P	EfS		E	P	EfS
Panel A. Contemporaneous ESG Impact								
E→ P→ EfS	E	5.03***	0.47***	0.06	E→ EfS→ P	5.03***	0.47***	0.06
		(0.16)	(0.09)	(0.40)		(0.16)	(0.09)	(0.40)
	P	-0.40***	5.72***	-0.07		-0.38***	5.60***	-0.19
		(0.09)	(0.18)	(0.56)		(0.08)	(0.18)	(0.12)
	EfS	0.18**	-0.20***	13.21***		0.20***	-0.38***	13.73***
		(0.07)	(0.07)	(0.39)		(0.07)	(0.10)	(0.64)
Panel B. Contemporaneous Investment Style Impact								
P→ E→ EfS	E	4.95***	0.35***	0.01	P→ EfS→ E	4.85***	0.34***	0.07
		(0.16)	(0.08)	(0.36)		(0.16)	(0.08)	(0.49)
	P	-0.27***	5.77***	-0.08		-0.27***	5.77***	-0.08
		(0.10)	(0.18)	(0.58)		(0.10)	(0.18)	(0.58)
	EfS	0.18**	-0.20***	13.21***		0.24**	-0.24***	12.99***
		(0.07)	(0.07)	(0.39)		(0.09)	(0.08)	(0.23)
Panel C. Contemporaneous Liquidity Impact								
EfS→ P→ E	E	4.85***	0.34***	0.07	EfS→ E→ P	4.94***	0.49***	0.25
		(0.16)	(0.08)	(0.49)		(0.16)	(0.10)	(0.65)
	P	-0.22**	5.67***	0.23		-0.38***	5.60***	-0.19
		(0.10)	(0.18)	(0.44)		(0.08)	(0.18)	(0.12)
	EfS	0.26***	-0.42***	13.58***		0.26***	-0.42***	13.58***
		(0.09)	(0.10)	(0.40)		(0.09)	(0.10)	(0.40)

Note: *p<0.1; **p<0.05; ***p<0.01

3.4.1 Long- and Short-Term Effects

Table 3.4 presents results from testing if the cumulative responses are different from zero across stocks after a period of one quarter. This section focuses on contemporaneous effects of liquidity and investment style. Panel A of Table 3.4 shows that when the investment style has no contemporaneous effects on the effective spread, a positive shock to the effective spread lowers both active and passive ownership. A positive shock to the effective spread translates into a decrease in liquidity. If liquidity decreases, a similar reduction for both active and passive investor share can be observed in the short-run (one quarter).

Table 3.4: Short-Term Effects - Effective Spread and Investment Style
The table reports t-test statistics to test the hypothesis if the cumulative response is different from zero. Orthogonalized impulse response functions are calculated for each of the 355 stocks. Short-term cumulative responses are calculated 1 period after the shock. For ease of presentation the following abbreviations are used: 'E' is short for ESG, 'A' is short for active investment style, 'P' is short for passive investment style, 'EfS' is short for effective spread. Column 'VAR Order' shows the ordering of the VAR model, Column 'Impulse' indicates which variable has been shocked. The VAR uses quarterly data between 2010 Q2 and 2019 Q4. Standard errors are presented in parentheses.

VAR Order	Impulse	Response			VAR Order	Response		
		E	A	EfS		E	P	EfS
Panel A. Short-Term Contemporaneous Liquidity Impact (Active vs. Passive)								
EfS→ A→ E	E	3.17***	0.00	0.00	EfS→ P→ E	3.15***	0.00	0.00
		(0.12)	(0.00)	(0.00)		(0.12)	(0.00)	(0.00)
	A/P	-0.04	5.86***	0.00		0.08**	6.74***	0.00
		(0.04)	(0.17)	(0.00)		(0.03)	(0.21)	(0.00)
	EfS	0.04	-0.25***	17.12***		0.04	-0.25***	17.21***
		(0.04)	(0.07)	(0.22)		(0.03)	(0.08)	(0.22)
Panel B. Short-Term Contemporaneous Investment Style Impact (Active vs. Passive)								
A→ EfS→ E	E	3.17***	0.00	0.00	P→ EfS→ E	3.15***	0.00	0.00
		(0.12)	(0.00)	(0.00)		(0.12)	(0.00)	(0.00)
	A/P	-0.03	5.99***	-0.40**		0.07**	6.87***	-0.57***
		(0.03)	(0.17)	(0.20)		(0.03)	(0.21)	(0.17)
	EfS	0.05	0.00	16.73***		0.05	0.00	16.91***
		(0.04)	(0.00)	(0.22)		(0.03)	(0.00)	(0.22)

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B shows that for a contemporaneous effect of investment style, the response of the effective spread is negative after a positive shock to investment style. After investors increase their active or passive ownership, the stock's liquidity tends to increase (lower spreads). The effect of a shock to investment style is bigger in magnitude than a comparable shock to the effective spread (all variables are calculated as log returns).

This dependency shows that it is difficult to disentangle the impact of active investors and their impact on market liquidity (which can be thought of being more informed than passive investors). Colling-Dufresne and Fos (2015) show that informed investors can have a positive impact on liquidity by using limit orders while simultaneously reporting that informed investors time their trades based on the liquidity level. The latter requires stocks to be more liquid before active investors decide to trade and to consequently change their stocks' equity share.

To better identify the dynamics between the presence of informed traders, who might change the informational content of a stock, and market liquidity, the realized spread instead of the effective spread is used. The realized spread captures the transaction costs net of the price impact of the trade. Table 3.5 presents both short- (1 quarter) and long-term (8 quarters) results. Panel A shows that, in the short-run, an increase in realized spread has a negative impact on active investors share (-0.41), but no significant impact on the passive investor share. In Panel B a shock to active investment style has a negative impact on the realized spread (-0.27), but a shock to passive investment style shows a positive relation with the realized spread (0.12). Panels C and D show similar results for active investment style in the long-run. Again, a shock to the realized spread (i.e., an increase in transaction costs) lowers the ownership share of active investors (-0.31), but has no significant effect on the passive share. Panel D however shows that a shock to passive investment style has no significant impact on the realized spread in the long-run, compared to a positive long-term response of the realized spread to a shock to active investment style (-0.24).

This indicates different impacts of investment styles in the short-run. On one hand, an increase in active ownership increases liquidity, while an increase in illiquidity reduces active ownership. On the other hand, an increase in passive ownership decreases liquidity, while a shock to the realized spread has no significant impact on the passive ownership share in the short-run. The former is in accordance with Colling-Dufresne and Fos (2015), who show that informed traders can have a positive impact on liquidity by using more limit orders and prefer to trade when liquidity is high. The latter shows that after a shock to passive investors, or relatively more uninformed participants, realized spreads tend to increase. The realized spread can be used as a profit measure for electronic liquidity providers (or high-frequency traders). Passive investors, which are still large institutions, use their brokers to fill large orders. The liquidity providers are able to identify the presence of the passive investors and earn profits (Battalio et al. (2018); Van Kervel and Menkveld (2019)), which reduce the rents of institutional investors. This profit possibility is only observable in the short-term when passive investors are considered.

Both long- and short-term results provide evidence that there is a dynamic relation between ESG scores, liquidity and investment style and hence support Hypothesis 3.1.

3.4.2 COVID-19 Event as External Liquidity Shock

The model forecasts that active investors and, to some degree, passive investors should reduce their ownership after a shock to liquidity.[19] During crisis times the general uncertainty rises and investors tend to seek safe havens. Equities tend not to be counted as 'safe'. Generally, spreads tend to widen during stress periods as liquidity providers charge a premium to be compensated for the increased level of uncertainty (to cover for potential

[19] With the exception of passive investor share after a shock to realized spreads. However, since it was a market-wide liquidity shock it is not possible to differentiate liquidity impacts for each liquidity measure individually.

Table 3.5: Short- vs. Long-Term Effects - Realized Spread and Investment Style
The table reports t-test statistics to test the hypothesis if the cumulative response is different from zero. Orthogonalized impulse response functions are calculated for each of the 355 stocks. Short-term cumulative responses are calculated 1 period and long-term cumulative responses are calculated 8 periods after the shock. For ease of presentation the following abbreviations are used: 'E' is short for ESG, 'A' is short for active investment style, 'P' is short for passive investment style, 'R' is short for realized spread. Column 'VAR Order' shows the ordering of the VAR model, Column 'Impulse' indicates which variable has been shocked. The VAR uses quarterly data between 2010 Q2 and 2019 Q4. Standard errors are presented in parentheses.

VAR Order	Impulse	Response			VAR Order	Response		
		E	A	R		E	P	R
Panel A. Short-Term Contemporaneous Liquidity Impact (Active vs. Passive)								
R→ A→ E	E	3.17***	0.00	0.00	R→ P→ E	3.18***	0.00	0.00
		(0.12)	(0.00)	(0.00)		(0.12)	(0.00)	(0.00)
	A/P	-0.05	5.96***	0.00		0.04	6.75***	0.00
		(0.04)	(0.23)	(0.00)		(0.03)	(0.21)	(0.00)
	R	-0.06	-0.41***	4.75***		-0.08***	0.05	4.75***
		(0.04)	(0.08)	(0.10)		(0.03)	(0.08)	(0.10)
Panel B. Short-Term Contemporaneous Investment Style Impact (Active vs. Passive)								
A→ R→ E	E	3.17***	0.00	0.00	P→ R→ E	3.18***	0.00	0.00
		(0.12)	(0.00)	(0.00)		(0.12)	(0.00)	(0.00)
	A/P	-0.02	6.11***	-0.27***		0.03	6.88***	0.12**
		(0.04)	(0.23)	(0.07)		(0.03)	(0.22)	(0.05)
	R	-0.07*	0.00	4.61***		-0.09***	0.00	4.66***
		(0.04)	(0.00)	(0.10)		(0.03)	(0.00)	(0.10)
Panel C. Long-Term Contemporaneous Liquidity Impact (Active vs. Passive)								
R→ A→ E	E	4.55***	-0.07	-0.04	R→ P→ E	4.87***	0.31***	-0.11**
		(0.16)	(0.07)	(0.03)		(0.16)	(0.07)	(0.04)
	A/P	0.18*	4.87***	0.07		-0.32***	5.73***	-0.05
		(0.10)	(0.16)	(0.08)		(0.11)	(0.18)	(0.06)
	R	0.08	-0.31***	4.27***		-0.15	-0.17	3.71***
		(0.10)	(0.09)	(0.66)		(0.11)	(0.12)	(0.10)
Panel D. Long-Term Contemporaneous Investment Style Impact (Active vs. Passive)								
A→ R→ E	E	4.55***	-0.07	-0.04	P→ R→ E	4.87***	0.31***	-0.11**
		(0.16)	(0.07)	(0.03)		(0.16)	(0.07)	(0.04)
	A/P	0.19*	4.98***	-0.24***		-0.31***	5.90***	0.03
		(0.10)	(0.17)	(0.07)		(0.11)	(0.19)	(0.09)
	R	0.11	0.03	4.15***		-0.14	-0.19***	3.62***
		(0.10)	(0.06)	(0.66)		(0.10)	(0.07)	(0.09)

Note: *p<0.1; **p<0.05; ***p<0.01

defaults).

First, Table 3.6 shows results from a Difference-in-Difference regression where treated stocks are in the high ESG group and the control group consists of low ESG stocks based on their 2019 score. The stressed time period begins on March 1st (and secondly on March 11th, the date on which the WHO pronounced COVID-19 a global pandemic) with 2019 and the beginning of 2020 as the benchmark period of regular market stress. For treated stocks (high ESG titles) the impact on liquidity measures is significantly lower compared to the control group, given a market wide liquidity shock. COVID-19 was not a shock to the trustworthiness of the financial (banking) sector, but hit the market homogeneously. Table 3.6 uses daily data to show how high ESG scores have a cushioning effect on the general uncertainty shock to the equity market.[20] Lins et al. (2017) utilize the global financial crisis to show that more trustworthy stocks (measured via CSR) have outperformed less trustworthy stocks. In a similar exercise, Broadstock et al. (2021) show that high ESG titles in the Chinese market see smaller stock price impacts than low ESG titles. On top of confirming the results on stock performance in the US market, Albuquerque et al. (2020) also find that investors with a sustainability focus (environmental and social aspects) experience significantly lower volatility during the COVID-19 crisis.

To incorporate the possible impact of the reducing effects of high ESG scores on liquidity, Table 3.7 shows the results of a Difference-in-Difference model with *Investment Style* being either active or passive, where stocks are assigned into treatment and control groups based on their liquidity (measured with the effective spread) first and based on their ESG

[20]Please be referred to Section 4.3 for a more detailed description of used measures additional to those used earlier in this Chapter.

Table 3.6: Impact of COVID-19 on Liquidity in Difference-in-Difference Estimation
This table regresses the Difference-in-Difference model $liquidity = FE + ESG \times Covid + \epsilon$, where $Covid$ is either WHO or $March$. WHO is a time dummy taking 1 for the time period of March 11th to March 31st and 0 for the time period January 3rd to January 24th 2020. $March$ is a time dummy taking 1 for the time period of March 2nd to March 31st and 0 for the time period January 3rd to February 4th 2020. ESG is a dummy variable that equals 1 for stocks that are in the top quintile and 0 if stocks fall into the bottom quintile when ordering by ESG Score. FE are ric and day fixed effects and robust standard errors are shown in brackets. QuoSpr: Time weighted Quoted Spread; ReaSpr(60s): Realized Spread at 60-second grids; ReaSpr(10s): Realized Spread at 10-second grids; PrImp(10s): Price Impact over 10-seconds interval; PrImp(60s): Price Impact over 10-seconds interval; EffSpr: Effective Spread.

	Dependent variable:					
	$QuoSpr$	$ReaSpr(60s)$	$ReaSpr(10s)$	$PrImp(60s)$	$PrImp(10s)$	$EffSpr$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DiD with WHO as COVID-19 Event						
$ESG \times WHO$	-5.465^{***}	-1.340^{***}	-1.745^{***}	-1.748^{***}	-1.259^{***}	-2.996^{***}
	(0.293)	(0.323)	(0.222)	(0.247)	(0.141)	(0.197)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,141	44,141	44,141	44,141	44,141	44,141
R^2	0.771	0.072	0.169	0.412	0.619	0.682
Adjusted R^2	0.769	0.063	0.160	0.406	0.615	0.679
Panel B: DiD using March 2020						
$ESG \times March$	-4.520^{***}	-1.063^{***}	-1.441^{***}	-1.418^{***}	-1.000^{***}	-2.327^{***}
	(0.217)	(0.238)	(0.167)	(0.182)	(0.106)	(0.141)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,141	44,141	44,141	44,141	44,141	44,141
R^2	0.771	0.072	0.168	0.412	0.618	0.681
Adjusted R^2	0.768	0.062	0.160	0.406	0.614	0.677
Note:						*p<0.1; **p<0.05; ***p<0.01

scores second. The model is estimated as follows:

$$Investment\ Style_{j,t} = \alpha + \beta_1 X_j + \beta_2 Covid_t + \beta_3 (X_j \times Covid_t) + \epsilon_{j,t}, \tag{3.5}$$

where $Covid_t$ is a time dummy variable taking the value of 1 for the time period between March 11th and March 31st and 0 for the time period before. X_j is either ESG_j or $Effective_j$. ESG_j is a dummy variable that equals 1 if stock j falls into the top quintile and 0 if it falls into the bottom quintile when ordering by ESG score in the last quarter of 2019. $Effective_j$ is a dummy variable that equals 1 for stocks that are in the bottom quintile and 0 if stocks are in the top quintile when ordering by effective spread in the last quarter of 2019. The lower the effective spread, the more liquid the stock. Hence, the dummy variable $Effective_j$ is 1 for the most liquid stocks.

First, the investment style and the ratio of active to passive investment style on the COVID-19 time dummy variable are investigated. Table 3.7 Columns (1) and (2) show that the shock has a decreasing effect on both active and passive ownership, similar to the forecasts from the cumulative impulses. Column (3) indicates that active investors have reduced their share proportionally more than passive investors, which seems appropriate as a major group of passive investors follow index replicating strategies and hence are not required to adjust their portfolio in a similar way. Column (4) provides evidence that COVID-19 impacts high liquid stocks differently than the low liquid group. The coefficient estimate of $Effective_j \times Covid_t$ is significantly positive in column (4), indicating that active investors have a higher share in more liquid stocks, or, if formulated in the opposite way, have reduced their share in relatively more illiquid stocks. Column (5) presents an insignificant coefficient, showing that the share of passive investors did not change significantly across liquidity groups. In Columns (6) and (7) results are shown for a Difference-in-Difference model when including the ESG_j dummy. This specification is

Table 3.7: Impact of COVID-19 on Investment Style in Difference-in-Difference Estimation

In columns (1) to (3) this table compares investment styles between periods, with stock fixed effects included. In columns (4) to (7) the output of the Difference-in-Difference model according to equation 3.5 is presented. $Covid_t$ is a time dummy taking 1 for the time period between March 11th and March 31st and 0 for the time period before. Quarterly observations from 2019 until 2020 are included. X_j is either ESG_j or $Effective_j$. ESG_j is a dummy variable that equals 1 for stocks that are in the top quintile and 0 if stocks fall into the bottom quintile when ordering by ESG Score in the last quarter of 2019. $Effective_j$ is a dummy variable that equals 1 for stocks that are in the bottom quintile and 0 if stocks fall into the top quintile when ordering by the effective spread in the last quarter of 2019.

	Dependent variable:						
	Active Style	Passive Style	Active to Passive	Active Style	Passive Style	Active Style	Passive Style
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Effective				−8.367***	−4.270***		
				(0.879)	(0.480)		
ESG						−7.828***	−2.887***
						(0.818)	(0.514)
Covid	−9.069***	−6.198***	−0.022**	−11.115***	−6.724***	−9.614***	−6.509***
	(0.353)	(0.237)	(0.010)	(1.139)	(0.719)	(1.055)	(0.702)
Effective × Covid				3.347**	0.905		
				(1.513)	(0.911)		
ESG × Covid						0.871	0.456
						(1.452)	(0.942)
Constant				49.565***	35.500***	51.413***	35.313***
				(0.643)	(0.402)	(0.576)	(0.386)
Stock FE	Yes	Yes	Yes	No	No	No	No
Observations	2,831	2,831	2,826	1,136	1,136	1,136	1,136
R^2	0.578	0.537	0.733	0.174	0.187	0.189	0.156
Adjusted R^2	0.517	0.471	0.695	0.172	0.185	0.187	0.154
Note:							*p<0.1; **p<0.05; ***p<0.01

included based on previous findings indicating a different liquidity impact on high and low ESG titles. However, coefficients for the interaction between ESG and COVID-19 period dummy variable are insignificant.

3.5 Robustness Checks

Investigating Large Companies

To further investigate the size differences between companies, the cumulative responses for a subset of stocks are calculated. Drei et al. (2019) show that size and ESG are correlated and influence performance. Thereby, companies are included if they are ranked among the top 25% by market capitalization. Tables 3.8 and 3.9 highlight how different the reactions are when the largest companies are investigated. Shocks to the system are not distinguishable from zero if they are impacting variables other than themselves, independent of the VAR order when including active investment style. Results again emphasize the different dynamics when including a different set of investor orientation. Table 3.9 shows that depending on the order, a shock to the passive investment style has a decreasing effect on the ESG score. Additionally, a shock to the ESG score shows a negative relationship with passive investment style, but only when the passive investment style is not in the first position of the VAR order. Similar to previous findings, a shock to the effective spread reduces passive investors' share, independent of the order. However, after a shock to the effective spread no significant reaction of the ESG scores for the largest companies is observed.

One possible explanation for the impact differences between active and passive styles could be the higher costs for active investors to acquire enough company shares at larger firms, which ultimately makes it more costly to meaningfully engage with or influence management. Secondly, larger companies tend to be more liquid and a shock to the

Table 3.8: Cumulative Responses on Stock Level - Active Investment Style, Largest 25%

The table reports t-test statistics to test the hypothesis if the cumulative response is different from zero when only including the top 25% of companies measured by average market capitalization. Orthogonalized impulse response functions are calculated for each of the 89 stocks. Cumulative responses are calculated 8 periods after the shock. For ease of presentation the following abbreviations are used: 'E' is short for ESG, 'A' is short for active investment style, 'EfS' is short for effective spread. Column 'VAR Order' shows the ordering of the VAR model, Column 'Impulse' indicates which variable has been shocked. The VAR uses quarterly data between 2010 Q1 and 2019 Q4. Standard errors are presented in parentheses.

VAR Order	Impulse	Response			VAR Order	Response		
		E	A	EfS		E	A	EfS
Panel A. Contemporaneous ESG Impact								
E→ A→ EfS	E	4.24***	-0.15	-0.17	E→ EfS→ A	4.24***	-0.15	-0.17
		(0.36)	(0.18)	(0.37)		(0.36)	(0.18)	(0.37)
	A	0.13	3.51***	-0.18		0.15	3.45***	0.04
		(0.15)	(0.20)	(0.41)		(0.15)	(0.20)	(0.26)
	EfS	0.03	0.06	11.87***		0.02	-0.07	12.20***
		(0.08)	(0.07)	(0.51)		(0.09)	(0.10)	(0.52)
Panel B. Contemporaneous Investment Style Impact								
A→ E→ EfS	E	4.10***	-0.13	-0.13	A→ EfS→ E	4.01***	-0.17	0.02
		(0.35)	(0.13)	(0.35)		(0.33)	(0.13)	(0.27)
	A	0.02	3.61***	-0.07		0.02	3.61***	-0.07
		(0.20)	(0.22)	(0.43)		(0.20)	(0.22)	(0.43)
	EfS	0.03	0.06	11.87***		-0.10	0.05	12.07***
		(0.08)	(0.07)	(0.51)		(0.16)	(0.07)	(0.50)
Panel C. Contemporaneous Liquidity Impact								
EfS→ A→ E	E	4.01***	-0.17	0.02	EfS→ E→ A	4.13***	-0.17	0.10
		(0.33)	(0.13)	(0.27)		(0.34)	(0.17)	(0.28)
	A	0.09	3.56***	0.00		0.15	3.45***	0.04
		(0.19)	(0.21)	(0.27)		(0.15)	(0.20)	(0.26)
	EfS	-0.17	0.02	12.36***		-0.17	0.02	12.36***
		(0.17)	(0.11)	(0.54)		(0.17)	(0.11)	(0.54)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.9: Cumulative Responses on Stock Level - Passive Investment Style, Largest 25%

The table reports t-test statistics to test the hypothesis if the cumulative response is different from zero when only including the top 25% of companies measured by average market capitalization. Orthogonalized impulse response functions are calculated for each of the 89 stocks. Cumulative responses are calculated 8 periods after the shock. For ease of presentation the following abbreviations are used: 'E' is short for ESG, 'P' is short for passive investment style, 'EfS' is short for effective spread. Column 'VAR Order' shows the ordering of the VAR model, Column 'Impulse' indicates which variable has been shocked. The VAR uses quarterly data between 2010 Q1 and 2019 Q4. Standard errors are presented in parentheses.

VAR Order	Impulse	Response			VAR Order	Response		
		E	P	EfS		E	P	EfS
Panel A. Contemporaneous ESG Impact								
E→ P→ EfS	E	4.61***	0.52**	0.03	E→ EfS→ P	4.61***	0.52**	0.03
		(0.34)	(0.20)	(0.31)		(0.34)	(0.20)	(0.31)
	P	-0.35**	4.39***	-0.56*		-0.31**	4.23***	0.13
		(0.16)	(0.36)	(0.31)		(0.16)	(0.34)	(0.17)
	EfS	0.05	-0.27**	12.98***		0.05	-0.46**	13.20***
		(0.09)	(0.12)	(0.44)		(0.10)	(0.20)	(0.45)
Panel B. Contemporaneous Investment Style Impact								
P→ E→ EfS	E	4.48***	0.21	0.00	P→ EfS→ E	4.45***	0.20	0.03
		(0.33)	(0.18)	(0.31)		(0.33)	(0.19)	(0.25)
	P	-0.09	4.39***	-0.50		-0.09	4.39***	-0.50
		(0.23)	(0.37)	(0.31)		(0.23)	(0.37)	(0.31)
	EfS	0.05	-0.27**	12.98***		0.14	-0.21*	13.08***
		(0.09)	(0.12)	(0.44)		(0.11)	(0.12)	(0.45)
Panel C. Contemporaneous Liquidity Impact								
EfS→ P→ E	E	4.45***	0.20	0.03	EfS→ E→ P	4.53***	0.52**	0.03
		(0.33)	(0.19)	(0.25)		(0.34)	(0.20)	(0.25)
	P	-0.02	4.21***	0.22		-0.31**	4.23***	0.13
		(0.21)	(0.36)	(0.17)		(0.16)	(0.34)	(0.17)
	EfS	0.10	-0.46**	13.31***		0.10	-0.46**	13.31***
		(0.13)	(0.20)	(0.45)		(0.13)	(0.20)	(0.45)

Note: *p<0.1; **p<0.05; ***p<0.01

spread might generally be attenuated.

Comparing High- and Low-Response Groups

Previous sections do not consider that a specific variable ordering might be more adequate than the other. This section argues that liquidity and investment style tend to be more likely to have a contemporaneous effect on the other variables, in contrast to the ESG score, which is published once a year. Investment style, or, more generally, ownership share is reported quarterly, while the liquidity measures can be obtained at a higher frequency. Following the availability of data, the following order is chosen: *Liquidity* $\rightarrow$ *Investment Style* $\rightarrow$ *ESG*.[21]

Given the already mentioned heterogeneity among companies and its possible impact on results, this study follows Lins et al. (2017) and adds several firm-fundamental characteristics as described in Table 3.10, which can contain additional information about a company's profile. This robustness check investigates if high- and low- response groups show different characteristics. For example, a company's financial situation might influence the available resources they can spend on ESG aspects and simultaneously might influence the investment decision of active investors. Wong et al. (2020) show how ESG aspects can reduce a firm's cost of capital and increase the firm's value.

The companies are sorted into quintiles according to the magnitude of their reaction. First, companies are ordered by the cumulative response after 8 periods and then assigned to the *'high'* group when they fall in the top 20% and to the *'low'* group when they are part of the bottom 20%. Next, the high and low groups are compared with a logit model and

[21] Arguing with the level of exogeneity, one can argue that ownership share is slower in adapting than liquidity measures. Hence, a change in ownership might impact liquidity quicker in the short-run, meaning intraday. Institutional orders can be picked up by electronic liquidity providers resulting in an adjustment of spreads (Battalio et al. (2018); Van Kervel and Menkveld (2019)). Additionally, Table 3.5 provides some evidence that a change in the realized spread shows an impact on both passive and active investment style, while the opposite is not observed.

Table 3.10: Fundamental Company Variables Description

Excess Return	Stock Return net of the One Month Treasury Bill at the end of the time period (quarter or month).
Size	Number of outstanding shares times close price
Short-Term Debt	Current Liabilities to Total Assets
Long-Term Debt	Long-term debt to Total Assets
Price-to-Book	Market to Book Value of Equity. Refinitiv describes the field as the latest closing price to book value per share. Book value per share is calculated by dividing total equity from the latest fiscal period by current total shares outstanding. It is gathered as a daily time series and afterwards aggregated on quarterly level.
Momentum	Stock Return over past horizon (6 months)
Idiosyncratic Risk	Similar to Mclean and Pontiff (2016), the idiosyncratic risk is calculated as the sum of the residual variance from a daily regression of the Carhart four-factor model and account for auto-correlation by adding the previous day's value to the current over the time interval. At least 500 business days of data points are required and the model is estimated with a fixed window of 500 historic business days.
Profitability	Operating Income to Total Assets
Analysts	Number of analysts that follow the stock

results are given in Table 3.11 (active investment style) and Table 3.12 (passive investment style). Both tables show no clear influence by firm fundamentals. The coefficient estimate for *Profitability*, which is a measure for the return on assets, is larger in both tables, but remains insignificant in most of the specifications. However, the tables show that the active and passive investment style yields different coefficient estimates, which again shows the fundamental difference between the two styles. Yet, comparing high- and low-response groups reveals no fundamental differences between companies that could have driven the results.

Table 3.11: Logit Model High- vs. Low- Response Group with Active Investment Style
Stocks are assigned to a high-responsive group if they are in the top 20% of stocks ordered according to their cumulative responses and assigned 0 if they fall into the bottom 20% of stocks. The impulse response relation is shown as the column header. A (P) describes active (passive) investment style, E the ESG score and EfS the effective spread. $Excess\,return$ is the stocks return net risk free rate, $Short\,debt$ is the short-term debt, $Long\,debt$ is long-term debt, $Size$ is the natural log of market capitalization, P/B is the Market-to-Book ratio, $Momentum$ is the return over the previous 6 months, $Idio\,risk$ is the idiosyncratic risk, $Profitability$ is the ratio of operating income to total assets, $Active$ is the share active investors hold, $Passive$ is the share passive investors hold, ESG is the ESG score, EfS is the effective spread, $Analysts$ is the natural log of the number analysts following the stock.

	Dependent variable:					
	A→E	A→EfS	E→EfS	E→A	EfS→E	EfS→A
	(1)	(2)	(3)	(4)	(5)	(6)
Excess return	0.605	−0.031	0.794	0.335	0.199	−0.941**
	(0.450)	(0.420)	(0.484)	(0.430)	(0.430)	(0.417)
Short debt	0.663	−0.589	−2.469	−1.176	−1.164	−0.873
	(1.568)	(1.480)	(1.738)	(1.372)	(1.516)	(1.342)
Long debt	−0.531	−1.526	−1.225	0.054	0.704	−0.908
	(1.458)	(1.208)	(1.541)	(1.263)	(1.280)	(1.351)
Size	−0.063	0.247	0.682**	0.281	−0.569*	0.134
	(0.324)	(0.308)	(0.315)	(0.299)	(0.329)	(0.288)
P/B	−0.046	0.022	0.053	−0.053	0.131**	−0.025
	(0.064)	(0.041)	(0.053)	(0.052)	(0.062)	(0.054)
Momentum	−0.364	−0.002	−0.381*	−0.140	−0.123	0.537***
	(0.229)	(0.198)	(0.228)	(0.206)	(0.215)	(0.201)
Idio risk	0.895	−15.220	−11.790	1.295	13.810	−0.958
	(5.670)	(9.905)	(8.332)	(4.221)	(10.960)	(5.701)
Profitability	25.010*	20.810	−5.922	−1.948	−34.670**	21.930
	(13.790)	(14.600)	(13.890)	(13.100)	(14.210)	(17.240)
Active	0.086***	0.005	0.005	−0.033*	−0.007	0.022
	(0.024)	(0.021)	(0.020)	(0.019)	(0.021)	(0.020)
Passive	0.012	0.016	−0.025	0.062	0.070	−0.002
	(0.056)	(0.049)	(0.058)	(0.048)	(0.051)	(0.049)
ESG	−0.030**	0.003	0.027**	0.008	−0.025*	0.009
	(0.015)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)
EfS	−0.245	0.425**	0.194	−0.088	−0.017	−0.271*
	(0.176)	(0.190)	(0.160)	(0.146)	(0.171)	(0.162)
Analysts	−0.172	−0.956	−1.577**	−0.398	0.428	0.182
	(0.614)	(0.621)	(0.674)	(0.586)	(0.625)	(0.545)
Constant	−0.564	−5.171	−12.630	−5.218	12.110	−4.567
	(8.429)	(7.611)	(8.006)	(7.415)	(8.148)	(7.569)
Pseudo R^2	0.18	0.08	0.13	0.07	0.17	0.09
Observations	142	141	141	141	141	142
Log Likelihood	−80.340	−89.930	−85.510	−90.470	−80.860	−89.320
Akaike Inf. Crit.	188.700	207.900	199.000	208.900	189.700	206.600
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 3.12: Logit Model High- vs. Low- Response Group with Passive Investment Style
Stocks are assigned to a high-responsive group if they are in the top 20% of stocks ordered according to their cumulative responses and assigned 0 if they fall into the bottom 20% of stocks. The impulse response relation is shown as the column header. A (P) describes active (passive) investment style, E the ESG score and EfS the effective spread. *Excess return* is the stocks return net risk free rate, *Short debt* is the short-term debt, *Long debt* is long-term debt, *Size* is the natural log of market capitalization, P/B is the Market to Book ratio, *Momentum* is the return over the previous 6 months, *Idio risk* is the idiosyncratic risk, *Profitability* is the ratio of operating income to total assets, *Active* is the share active investors hold, *Passive* is the share passive investors hold, *ESG* is the ESG score, *EfS* is the effective spread, *Analysts* is the natural log of the number analysts following the stock.

	Dependent variable:					
	P→E	P→EfS	E→EfS	E→P	EfS→E	EfS→P
	(1)	(2)	(3)	(4)	(5)	(6)
Excess return	0.772*	0.142	0.624	−0.589	−0.030	−0.132
	(0.450)	(0.389)	(0.456)	(0.454)	(0.398)	(0.469)
Short debt	2.117	1.093	−0.670	−0.739	−0.645	2.310
	(1.830)	(1.285)	(1.459)	(1.684)	(1.394)	(1.578)
Long debt	−1.699	0.364	−0.502	−1.219	0.268	0.902
	(1.452)	(1.302)	(1.322)	(1.391)	(1.357)	(1.524)
Size	0.389	0.579*	0.151	−0.446	0.129	0.150
	(0.321)	(0.298)	(0.285)	(0.304)	(0.313)	(0.324)
P/B	−0.153**	−0.050	−0.019	0.152**	0.138**	−0.080
	(0.060)	(0.055)	(0.048)	(0.068)	(0.068)	(0.081)
Momentum	−0.385*	−0.076	−0.287	0.310	−0.019	−0.105
	(0.220)	(0.199)	(0.220)	(0.215)	(0.198)	(0.218)
Idio risk	7.786	−4.004	−2.656	−0.268	−8.436	10.770
	(7.903)	(5.299)	(8.674)	(4.330)	(9.996)	(11.940)
Profitability	6.500	1.579	−10.170	−4.539	−16.160	62.070***
	(14.270)	(13.150)	(13.020)	(16.050)	(13.070)	(17.870)
Active	−0.009	0.007	−0.025	0.007	−0.014	0.009
	(0.020)	(0.020)	(0.019)	(0.020)	(0.022)	(0.022)
Passive	0.058	−0.045	−0.025	−0.048	0.112**	−0.069
	(0.051)	(0.051)	(0.051)	(0.048)	(0.053)	(0.056)
ESG	0.025*	0.003	0.025	−0.017	−0.036**	−0.040**
	(0.015)	(0.013)	(0.016)	(0.015)	(0.015)	(0.017)
EfS	−0.249	−0.129	0.016	0.220	0.492**	−0.017
	(0.176)	(0.134)	(0.152)	(0.168)	(0.231)	(0.189)
Analysts	0.051	−0.313	−0.671	0.520	0.754	0.717
	(0.535)	(0.578)	(0.689)	(0.602)	(0.622)	(0.612)
Constant	−10.640	−11.520	−0.616	9.923	−7.193	−3.616
	(7.915)	(7.148)	(6.610)	(7.467)	(8.065)	(8.134)
Pseudo R^2	0.17	0.07	0.08	0.12	0.14	0.19
Observations	142	142	142	141	141	141
Log Likelihood	−81.490	−91.390	−90.890	−85.790	−83.710	−79.210
Akaike Inf. Crit.	191.000	210.800	209.800	199.600	195.400	186.400
Note:						*p<0.1; **p<0.05; ***p<0.01

3.6 Conclusion

Hoepner et al. (2016) use proprietary data provided from an institutional investor to show that ESG engagement can reduce downside risk. They show that actively influencing a company's management can achieve positive results not only in the interest of the investors by reducing risk, but it can also have a positive impact on non-financial factors, such as environmental aspects. This chapter provides evidence that an increase in active ownership shows a positive correlation with a company's ESG score. Impulse response functions from a VAR model are used to evaluate the cumulative effects of shocks to the system where ESG scores, liquidity and investment style are included. The VAR setting helps to circumvent endogeneity issues, with reverse causality possibly being one of the most obvious issues that could arise. After shocking the ESG score, a decrease in active ownership share is observed, which is in accordance with the reasoning that active investors rather target companies that show a potential ESG growth (Brøgger and Kronies (2020)), instead of companies where the development towards a higher ESG score has already finished.

This research provides empirical evidence that the level of passive ownership and the ESG score are correlated and display a dynamic behavior. A positive shock to passive ownership decreases the ESG score, while a positive shock to the ESG score increases passive ownership. The former finding is consistent with Bebchuk and Hirst (2019), who show that passive investors tend to underinvest in stewardship, which could lead to an under-representation of the client base, who value ESG aspects. The second finding indicates that after an increase in the ESG score, the stock is more likely to be added to an index with sustainability focus. Passive fund managers then replicate this index in accordance to their strategy.

Additionally, evidence is provided that the ESG score increases after a liquidity reducing shock independent of the investment style. A positive shock to the ESG score shows a positive effect on transaction costs only when considering active investors, while no significant effect is observed for passive investors. This indicates that the information content of ESG signals is related to the investment style. To further determine if ESG scores can be a signal through which information is entering the market, short-term effects are investigated. By using the realized spread, which accounts for the price impact of a trade, the study shows that a positive shock to the passive ownership share increases the realized spread in the short-term. Interestingly, this study provides evidence that only passive investors are negatively impacted in the short-run. An increase in active ownership decreases the realized spread. Additionally, after an increase in the realized spread findings indicate that active investors reduce their ownership share. Both findings are in accordance with Colling-Dufresne and Fos (2015), who show that informed traders can have a positive impact on liquidity and trade when liquidity is high.

Chapter 4

ESG Scores and Stock Performance. The Role of Liquidity

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4.1 Introduction

Environmental, social and governance (ESG) aspects have become a major part in the decision-making process of financial markets investors. The US SIF Foundation reports a steady growth in sustainable investing for the US that has reached USD 16.6 trillion by 2020.[1] The Principles for Responsible Investment (PRI) report for 2018[2] states that USD 29.5 trillion invested in equity are following a responsible investment strategy. Undoubtedly, investment decisions are guided by profit prospects, but factors that contain non-financial aspects are increasingly considered in the decision-making process.[3] Simul-

[1] See https://www.ussif.org/files/Trends%20Report%202020%20Executive%20Summary.pdf
[2] https://www.unpri.org/annual-report-2018/how-we-work/the-pri-in-numbers
[3] In a recent newspaper article, the largest fund manager announced a doubling in numbers of ETFs with focus on sustainability. https://www.ft.com/content/57db9dc2-3690-11ea-a6d3-

taneous with the increased interest in ESG investing, markets have also experienced a significant change as a trading place. The last couple of decades have seen a rise in institutional trading volume, with markets and information distribution becoming faster through technological advances.[4] Consequently, market liquidity has increased with technology. Institutional investors acquire stock in accordance with their investment strategy. They can be divided into active and passive investors. Active investors typically try to beat a benchmark by applying fundamental research to identify investment possibilities (Cohen et al. (2005)). They are also more likely to engage with a company's management. New investment opportunities, such as ESG investing, are therefore a possible strategy to generate profit.

The question arises if ESG is still a driving factor in generating returns, or if it is only a spark that has initiated a chain reaction where higher demand of ESG stocks could have created momentum. With an increase in trading volume, e.g. invoked by active investors' interest in ESG aspects, other market participants are also more active and able to learn from the increased order flow.[5] The increased demand typically decreases spreads, which translates into higher liquidity. Additionally, ESG aspects can infuse prices with a new set of information upon which (institutional) investors can trade. Egginton and McBrayer (2019) show that ESG disclosure transparency has a positive impact on equity market liquidity. This in turn impacts the trading demand and can also impact the liquidity and information content of the stock. Stock returns can hence be influenced by ESG directly or indirectly through the channel of liquidity after participants have adapted to the new

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[4] One famous example is the rise of High-frequency trading. High-frequency traders make money by being faster than competitors, and their presence guarantees that new information is incorporated more quickly. For high-frequency related impacts on financial markets see Biais et al. (2015); Menkveld (2013); O'Hara (2015)

[5] More specifically, HFTs are able to detect institutional investor activity. Institutional traders submit large orders to their brokers who execute them in smaller chunks. Van Kervel and Menkveld (2019) show that HFTs are able to detect large institutional orders and can profit by trading against them, lowering the institutional traders profit margins, which might reduce the incentive of performing fundamental research.

ESG related information.

Early studies demonstrate the interest of investors in 'doing' the right thing by picking stocks that adhere to social and corporate standards was already present before the term ESG was embossed (Grossman and Miller (1988)). As early as the motivation to invest in socially responsible companies arose, research tried to identify a relationship between social and financial performance (Bello (2005); Hamilton et al. (1993)). However, investigating the relationship between ESG and financial performance has delivered mixed results. Depending on the period, the financial and the ESG measure, either positive (Edmans (2011)), negative (Krüger (2015)) or inconclusive effects have been documented (Halbritter and Dorfleitner (2015)). It is important to note that the distinction between expected and realized impact on firm performance yields opposite conclusions. Hartzmark and Sussman (2019) show that sustainability positively impacts the expectation of future performance, however with no evidence that high-sustainable funds perform better than low-sustainable funds. These findings are similar to Renneboog et al. (2008), who show no significant difference in risk-adjusted returns between socially responsible investment and regular funds. Chen and Scholtens (2018) show that within the universe of sustainable funds, no outperformance of active compared to passive funds can be found. However, meta-analyses that investigate the results across many studies indicate an overall positive relation (Margolis et al. (2009)) between financial and social performance. In their meta-analysis, Friede et al. (2015) also report an overall positive relationship. The authors show that there is no evidence of a learning effect with regards to ESG investing. One would expect a decreasing alpha over time as the awareness of ESG investment increases. Interestingly, the authors show that the correlation between financial and social performance indeed decreases over time, but remains significantly positive.

Previous research has either studied the impact of ESG on performance, or has investigated the link between liquidity and ESG. However, to the researcher's understanding this is the first attempt that investigates the impact of ESG score differences on performance while incorporating the liquidity channel. Generally, abnormal returns should not be possible when the information content of stock prices is high.[6] To narrow down if ESG aspects provide an edge and can consequently achieve abnormal returns for investors[7], this study seeks to limit the influence of other stock characteristics on stock performance. Therefore, constituents of the S&P 500 index are used to reduce heterogeneity among the companies. This initial selection limits the impact of size and liquidity differences on return characteristics and should support the examination of how prices incorporate ESG related information.[8] To be included in this analysis, companies are required to have sufficient data about ESG scores and liquidity measures. The observation period starts in 2010 and ends in 2019 to exclude periods of financial stress.[9] Further, firm-specific variables, risk factors as well as a set of fixed effects are added to the analysis to further limit heterogeneity.

First, this research shows a positive relation between the ESG score and liquidity. While Egginton and McBrayer (2019) show that stock liquidity is linked to ESG disclosure transparency, this research shows that stocks with a higher ESG score have lower spreads. This supports the idea that, in general, investors have increased their demand for more sustainable assets. The reduction in spreads indicates lower information asymmetry for stocks with higher ESG scores compared to stocks with lower ESG scores. Generally, spreads will increase with information asymmetries. With a higher level of information asymmetry, the probability increases that the trade is against an informed participant, so the market maker demands a higher compensation which is reflected in a widening spread.

[6] See for example Fama (1970) about the efficient market hypothesis, and Grossman and Stiglitz (1980) for the criticism of perfectly efficient markets.

[7] Some investors are able to utilize the informativeness of ESG related information and earn a premium, see Brøgger and Kronies (2020)

[8] E.g. Ben-Rephael et al. (2015) show that small stock companies show a different liquidity premium compared to large-cap companies.

[9] Some regression specifications include lagged variables from 2008 and 2009. However, liquidity measures are only calculated beginning in 2010.

However, liquidity might not only be explained by ESG scores alone. Therefore, to reduce confounding effects, different liquidity buckets are created. ESG related information can be more profound for stocks with higher information asymmetries.[10] This allows the researcher to investigate if ESG strategies achieve alpha accounting for different liquidity levels.

The second finding of this research concludes that portfolio returns for high ESG titles show significantly negative returns only when the level of information asymmetries is high. Pástor et al. (2020) theoretically derive that returns for 'green' assets are negative, while returns for 'brown' assets are positive.[11] The profit possibilities might be detected by other market participants (e.g., arbitrate traders), who in return increase their demand for these stocks. The increased demand can then impact liquidity and hence the informational content of these stocks. With this decrease in information asymmetries, the expected returns will be affected. However, if the general level of liquidity is low (and information asymmetries are high), the ESG effect on expected returns might not be incorporated yet. Therefore, portfolios are constructed by sorting according to ESG score and liquidity to evaluate portfolio returns when the level of information asymmetries is different. After, the Carhart (1997) four-factor model is applied to extract the portfolios alphas and to account for other common risk factors. This helps crystallize the profitability of ESG investments. Results show that portfolios consisting of stocks with higher information asymmetry (low liquidity portfolio) produce negative abnormal returns, which is in line with the predictions of Pástor et al. (2020). However, with greater informativeness (high liquidity portfolio), the portfolio returns are rendered insignificant.

The rest of this chapter is organized as follows. Section 4.2 provides the hypotheses before more details about the data is presented in Section 4.3. Section 4.4 shows empirical

[10] For example, Egginton and McBrayer (2019) highlight that the positive impact of ESG disclosure transparency is increased for companies with a lower level of information environment.

[11] While high ESG score titles should be classified as 'green' assets, it is more difficult to argue that low ESG score stocks can be classified as 'brown' assets.

results on the impact of ESG and ownership on liquidity. Section 4.5 presents results from portfolio return calculations. Section 4.6 performs robustness checks before Section 4.7 concludes this chapter.[12]

4.2 Hypotheses Development

Guiso et al. (2008) find a positive impact of social trust on a company's stock market participation. One might infer that within a similar group of liquid stocks, the titles with a higher ESG score should therefore have an increased demand in trading. The increase of trading in ESG stocks can then attract more traders who do not necessarily apply a socially responsible strategy, but who may follow market trends or are arbitrage traders. A greater coverage and stock attention will result in greater liquidity provision and reduced transaction costs. Another dimension by which stock liquidity can increase initiated by higher ESG scores is by lowering information asymmetries, which can be approximated by the spread measures applied here. Similarly, using the daily bid and ask spread, Egginton and McBrayer (2019) show that CSR disclosures have an information asymmetry-reducing effect. Therefore, the first hypothesis postulates a relationship between higher ESG scores and greater stock liquidity.

Hypothesis 4.1: Stocks with higher ESG scores are more liquid

Active (institutional) investors intend to exploit information asymmetries and general mispricing of stocks or target the companies' management decisions. Brøgger and Kronies (2020) show how some investors can predict ESG development and can use this skill to achieve a premium. Hence, ESG-related strategies can trigger an increase in institutional

[12] The relevant literature is discussed in Section 2.

trading, which can in turn affect the stock's liquidity. For this reason, the effects of active and passive investors are investigated separately, as active investors can be thought of as being more informed than passive investors and hence impact liquidity differently. Traditionally, informed investors activity is related to higher spreads and reduced liquidity. Contrary to this traditional understanding, Colling-Dufresne and Fos (2015) demonstrate how informed investor' timing effects can improve stock liquidity. Consequently, no a priori assumptions about the direction of the effect of different investor styles on liquidity are formulated, as evidence presented in Appel et al. (2016); Ben-David et al. (2015); Boone and White (2015); Gabaix et al. (2006); Oikonomou et al. (2020) highlights uncertainty. Therefore, the hypothesis investigates how the investment style, i.e., active and passive institutional ownership, is related to stock liquidity.

Hypothesis 4.2: Investor style affects the liquidity of stocks

Limiting the stock universe helps account for confounding effects on stock returns. By focusing on S&P 500 constituents as a first step, the analysis can focus more on ESG-driving effects. The next steps require consideration of the effect higher ESG scores have on stock liquidity and the channel through which the ESG-motivated activity of institutional investors conveys additional information content into stock prices. Thereby, investor style may play a role for both ESG and liquidity. Active investors may follow a stock picking approach which can work as a signal to other market participants, or they might be able to predict future ESG score changes, while passive investors target ESG stocks following their passive strategy, e.g., index replication. Investment style and ESG scores can hence both have an impact on liquidity. This makes it necessary to consider stocks with different liquidity levels. If stock-related information is entering the market, which should then be quickly reflected in stock prices, one can argue that no abnormal returns should be possible if the available information is incorporated into prices.[13]

In their theoretical work, Pástor et al. (2020) derive that 'green' assets show negative abnormal returns and 'brown' assets produce positive abnormal returns.[14] The authors name investors' taste for green assets as one source for the negative performance, as investors are willing to pay more for these assets. Another reason is the hedging of climate risks, which reduces the expected profits. This indicates that investing in high ESG titles should yield negative abnormal returns. However, if abnormal return possibilities exist (either positive or negative), other market participants who follow non-ESG strategies might also react, e.g., by arbitrage trading. This increased demand again affects the liquidity and informativeness of stocks. When investigating return differences between high and low ESG stocks, many studies do not account for different liquidity buckets. Egginton and McBrayer (2019) show that ESG disclosures help to reduce information asymmetries. Simultaneously, if the efficient market hypothesis is valid, abnormal returns in an environment of low information asymmetries should not be possible. This poses the question: Will portfolios with different levels of ESG scores be able to deliver abnormal returns in different information environments? News entering the market for stocks with lower spreads and, therefore, a lower level of information asymmetry could be incorporated faster, which leaves less or no room for return potential.

Hypothesis 4.3 posits that ESG strategies should not yield abnormal returns for portfolios that show a high level of liquidity. In an environment with low information asymmetries (high liquidity group), the market might be able to faster incorporate the effect of ESG-related information. On the other hand, if the general level of liquidity is low

[13] An additional impact on the return profile is tied to the direct costs of detection by HFTs. Institutional investors employ brokers to execute their large orders. The execution of these large orders can be detected by HFTs (Battalio et al., 2018; Van Kervel and Menkveld, 2019), which have a direct negative impact on the institutional owner's profit margins. Given the presence of HFTs, new information should be incorporated even faster into stock prices.

[14] Pástor et al. (2020) also provide return expectations for 'brown' assets. However, low ESG score portfolios are not necessarily comparable to 'brown' assets, as 'brown' companies might not report any ESG-related information. Hence, the return expectations for 'brown' assets are not tested here.

and information asymmetries are higher, ESG information might create an edge on which abnormal returns can be achieved. Following Pástor et al. (2020), the abnormal returns should then be negative for high ESG titles. Hence, hypothesis 4.4 posits that buying high ESG portfolios achieve negative abnormal returns when the level of liquidity is low.

Hypothesis 4.3: High ESG portfolios achieve no alpha when liquidity is high

Hypothesis 4.4: High ESG portfolios achieve negative alpha when liquidity is low

The focus of this analysis lies on constituents of the S&P 500 index, which are generally the most liquid stocks available in the (equity) market. By using this sample, differences in size and liquidity are limited, which constitute influencing factors when considering trading strategies. Within the more harmonized group of stocks (in liquidity terms), evaluating the impact of sustainability on liquidity and performance will be more profound. In this more conservative setting, differences in liquidity and ESG are more meaningful, in contrast to comparing high liquid stocks with stocks that are not listed in this index.

4.3 Data

The study uses transaction and quote (TAQ) data from Refinitiv (formerly Thomson Reuters) for S&P 500 constituents[15] between January 2010 and December 2019. S&P 500 constituents are required to be active for the whole period since 2010, which means that some stocks are lost and not repopulated. Following Holden and Jacobsen (2014), this study only takes into consideration TAQ data at normal market hours between 9:30 am and 4:00 pm, excluding crossed spreads, negative-non zero volumes and using the Lee and

[15]The company must be an S&P 500 constituent as of December 2019.

Ready (1991) algorithm to sign trades when they occur away from the midpoint. Trades at the midpoint are not classified, as the application of the tick test can lead to inaccurate signing. Information about firm fundamentals and ESG scores is obtained from Refinitiv Eikon.[16] Institutional ownership information from Eikon is taken only from 13F filings. Eikon's investor orientation categorization into active and passive investors is used. Active investors typically select a portfolio by picking the assets and are more likely to engage with managers, whereas passive investors are not.[17] Subsequent reports are excluded if the filing date does not change. If the combined ownership share exceeds 100%[18], the last quarter's information is used. If no information is available, the observation is excluded. The Carhart four-factor model is using data available from Kenneth R. French's website.[19] Companies are required to have valid ownership, ESG and TAQ data. This results in a total number of 355 companies. The high-frequency tick data, which after applying the quality constraints consists of 83.36 billion quotes and 18.33 billion trades, is aggregated monthly. Stock prices are gathered monthly from Refinitiv Eikon and adjusted for dividend payments. Most of the fundamental information provided by Eikon can be gathered on a quarterly basis, except the ESG score. Individually, each company releases ESG-related information on a yearly basis, but the release date might differ across companies. Refinitiv is re-calculating the ESG score as soon as new information is available. The ESG score reflects the company's ESG profile relative to others.[20] Refinitiv states that, most of the time, the ESG score is updated once a year

[16] Eikon gathers information about ESG scores and investor activity from different reports and sources. More information can be found here https://www.refinitiv.com/en/sustainable-finance/esg-scores.

[17] According to Eikon http://banker.thomsonib.com/ta/help/webhelp/Ownership_Glossary.htm: "Active managers use fundamental research as the basis for investment decisions and typically meet with company management. Passive managers employ indexing and/or quantitative strategies as the sole basis for stock selection. These investors typically do not meet with company management."

[18] This might occur when there is an unaccounted stock split, misreporting or short selling.

[19] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[20] This study is not addressing the absolute level of ESG scores and hence neither the fundamental ESG profile of a company and its potential problems of 'Green Washing'. Different characteristics of companies

after the company publishes their activity in any ESG disclosure.[21]

Table 4.1 lists the used variables, while Table 4.2 shows summary statistics. Panel A of Table 4.2 shows an average time-weighted quoted spread of 3.88 bps, with the effective spread being slightly higher at 3.97 bps. The quoted spread indicates the round-trip costs of an order. It is the difference between the price at which participants are willing to sell and the price at which they are willing to buy in relation to the prevailing mid-price. The higher the quoted spread, the greater the costs of a round-trip. The effective spread incorporates the transaction price, which can differ from the best bid and ask. This helps to account for liquidity-demanding trades. Transaction costs measured with the effective spread, however, do not account for a possible price impact of the trade. Quotes tend to move up after a buyer-initiated trade and move down for a seller-initiated trade. The realized spread accounts for the quote movement by comparing the trade price with the midpoint at a future time. The spreads increase when information asymmetries increase. This is due to the liquidity providers' demand for larger compensation when the probability of trading against informed traders is elevated.[22]

The average 10-sec (1-min) realized spread is 0.74 (0.51) basis points and hence lower than the other two spread measures, as it accounts for the trades' price impact and consequently gives a more realistic approximation of the actual trading costs of a trade. The price impact, which measures the mid-price movement, is 3.23 bps for the 10-second interval and 3.48 for the 1-minute interval.[23] On average, stocks achieve an excess return (stock return minus the risk-free interest rate, here the 1-Month Treasury Bill rate) of

with high and low ESG scores in relative terms are important. The Refinitiv measure considers the general ESG level across companies and is therefore an adequate ESG measure for this analysis.

[21] https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/esg-scores-methodology.pdf

[22] Figure 4.A1 displays the evolution of quoted spreads across all stocks as well as for stocks that are sorted into low (bottom 20%) and high (top 20%) ESG score groups. Upon visual inspection, the difference in spreads appears to remain similar over time.

[23] The simple price impact is the residual of the effective spread and the realized spread, rounding issues occur.

Table 4.1: Measurement and Control Variable Description

Quoted Spread	Transaction price of one round-trip when executing an order that is consuming the first level of depth (available volume at best bid and offer). The spread is calculated as $spread = (ask - bid)/mid$. The quoted spread is the time-weighted average between 9:30 and 4 pm.
Effective Spread	Effective spreads account for trades that execute at prices different from the best bid and ask (outside or inside the spread). It is calculated as $effective\ spread = 2d(price - mid)/mid$, where d indicates a buy or sell order.
Realized Spread	Spread measure net of the price impact of the trade. Comparing the execution price with the mid-quote after t time steps. It is calculated as $realized\ spread = 2d(price - mid_{+t})/mid$, where d indicates a buy or sell order.
Price Impact	Subsequent price impact on mid-quotes, according to $price\ impact = 2d(m_{+t} - mid)/mid$
Amihud Measure	Amihud (2002) illiquidity measure: $10^6 \frac{1}{n} \sum \frac{\lvert r_{i,t} \rvert}{vol_{i,t}}$, where n is the number of days the stock has traded in any given quarter
Excess Return	Stock return net of the 1-Month Treasury Bill rate at the end of the time period (quarter or month).

2.35% with a standard deviation of 12.79% and a median value of 3.43%

Panel B shows that the ESG score averages at 55.22 points with a median value of 57 and a standard deviation of 18.37 points. A look at market capitalization highlights the existence of substantial differences in size between the stocks in the observation group. The average stock has a market capitalization of USD 36.87 billion, while the median firm is sized at USD 16.86 billion, with a standard deviation of USD 53.53 billion. The lowest 5% of firms do not exceed a firm valuation of USD 4.63 billion, while the 95% threshold is at USD 160.05 billion. Daily trading statistics also show a certain level of deviation. The average stock is traded approximately 20,313 times a day with an average daily turnover of USD 182.70 million. Again, the standard deviation as well as the 5% and 95% percentiles highlight how some stocks are traded more heavily than others.

A similar heterogeneity within the index constituents can be observed when looking at the share institutional investors hold. The 'Active Investor Style' is the percentage of shares active investors hold in a company. Similarly, 'Passive Investor Style' is the share of stocks owned by passive investors to total shares outstanding. On average, active

Table 4.2: Descriptive Statistics
Liquidity and performance measures are described in Table 4.1 for the period from 2010 to 2019.

	Unit	Mean	Median	Std	5%	95%
Panel A. Liquidity and Performance Measures						
Realized Spread (1 min)	bps	0.51	0.43	0.85	-0.62	1.88
Realized Spread (10 seconds)	bps	0.74	0.61	0.97	-0.48	2.31
Effective Spread	bps	3.97	3.50	2.06	1.95	7.49
Quoted Spread	bps	3.88	3.12	2.58	1.54	8.79
Amihud Measure		2.67	1.59	3.42	0.25	8.72
Price Impact (1 min)	bps	3.48	3.08	1.86	1.60	6.76
Price Impact (10 seconds)	bps	3.23	2.88	1.62	1.59	6.09
Excess Return	%	2.35	3.43	12.76	-19.95	20.92
Panel B. Other Variables						
ESG score		55.22	57.00	18.37	22.46	82.81
Active Investor Style	%	52.25	53.17	12.05	31.28	70.50
Passive Investor Style	%	26.78	26.01	6.71	17.49	39.16
Average Daily Trades		20,313	13,525	21,551	3,590	61,369
Average Daily Turnover	USD (mn)	182.70	92.61	424.67	21.78	579.69
Average Daily Tradesize	USD	7,976	6,962	4,671	3,231	16,109
Market Capitalization	USD (bn)	36.87	16.86	53.55	4.63	160.05
# Firms	355					

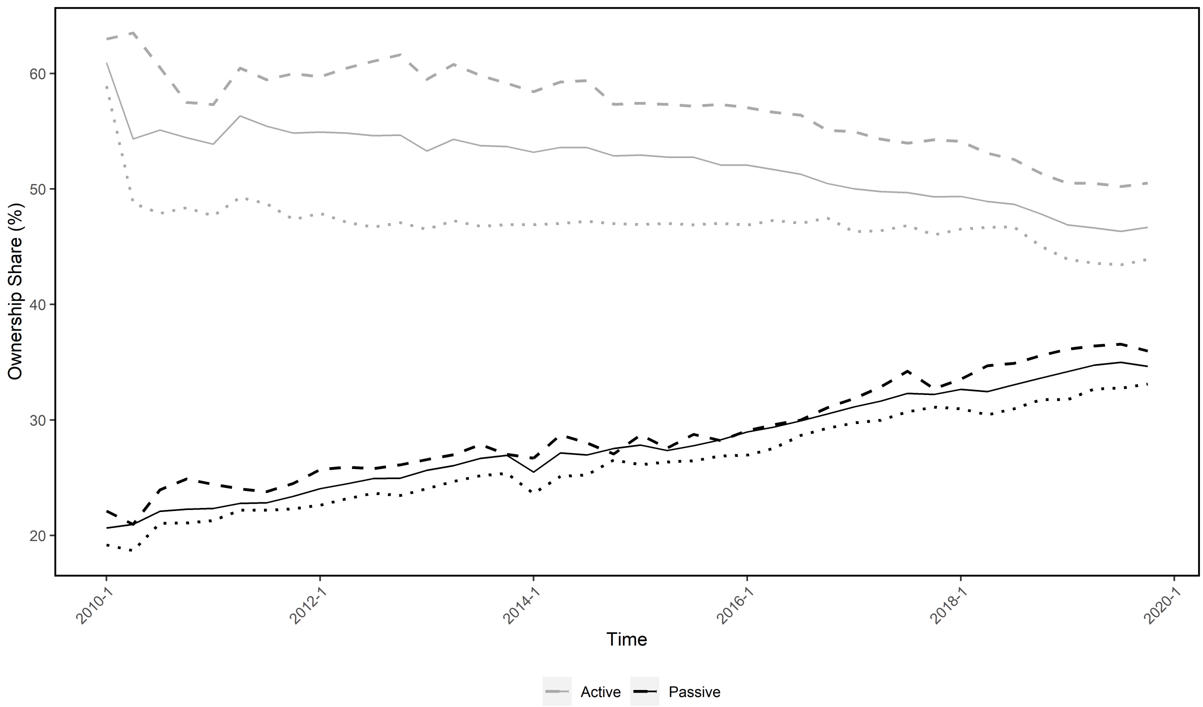
investors own 52.25% of the company, again, with a wide range among the stocks under investigation. While 5% of stocks only show an active (equally-weighted) share of 31.28%, 95% of companies show an active institutional ownership of 70.50%. The average company has 26.78% passive ownership with the median 26.01%. Prominent passive investors are Vanguard, State Street and BlackRock, which are asset managers focusing on passively managed funds. The largest active investors in this sample are Fidelity, T.Rowe Price and Capital World Investors.

Ye (2012) investigates the role of active investors on return co-movement and reports an institutional ownership share of approximately 61% between 1990 and 2000. Borochin and Yang (2017) report an average institutional investor share of 45.5% across 11,116 companies between 1985 and 2013, while Starks et al. (2017) present an average institutional ownership share of 67.98% between 2000 and 2014 with 21,378 firm-years observations.[24] While there is already an observable trend towards a larger share of institutional ownership, the focus lies on a tighter set of stocks with a potentially greater level of (public) awareness. With the companies being constituents of one of the largest global stock indexes, many asset managers include the stocks in their portfolios, especially when providing passively managed funds, i.e., funds that replicate or track an index. Out of the group of passively managed funds, ETFs have experienced significant growth, contributing to the rise of institutional investor share, see Ben-David et al. (2017). A similar development of passive ownership shares can be derived from looking at Figure 4.1.

Figure 4.1 shows the average active and passive investor's share over time. A positive trend of passive investors and a small downwards sloping trend for active investor share can be observed. The difference in active ownership shares between high (dotted line) and low (dashed line) ESG titles is greater than for passive ownership shares. However,

[24]This study investigates 13F institutions, which might explain the low share of mutual funds in this dataset as compared to Starks et al. (2017) and Brøgger and Kronies (2020), who report a much larger share of mutual funds. Eikon offers information about fund-level holdings, but this research is interested in the ultimate owner of an individual fund.

Figure 4.1: Active and Passive Ownership Share Over Time
Ownership by active and passive investor style. The respective ownership share is equally-weighted at the end of each quarter. The solid black lines represent all stocks under investigation, the dashed lines represent the bottom 20% of stocks ordered according to the ESG score, dotted lines represent the top 20%. The quartiles are generated each year to represent updates to ESG scores.



as time passes, the gap between high and low ESG titles narrows for active ownership.

4.4 Impact of ESG Scores and Investment Style on Liquidity

ESG Scores and Liquidity

This section investigates if the ESG score is associated with higher stock liquidity. First, a set of liquidity metrics liq is regressed on the ESG score and control variables according to:

$$liq_{i,t} = \alpha_s + \delta_t + \beta_1 ESG_{i,t-T} + \beta_2 C_{i,t} + \epsilon_{i,t}, \tag{4.1}$$

where $ESG_{i,t-T}$ is a dummy variable that equals 1 if the stock i is in the top ESG quintile and 0 if it is in the bottom quintile at time $t-T$, α_s and δ_t are sector and time fixed effects, $C_{i,t}$ are stock i specific control variables following Comerton-Forde and Putnins (2015); Degryse et al. (2015); O'Hara and Ye (2011). The control variables are the natural logarithm of market capitalization, the log of daily trading turnover, a measure of volatility (natural logarithm of the standard deviation of daily returns of stock i) and the natural logarithm of the close price. The set of liquidity measures liq includes high-frequency measures that capture the transaction costs (quoted, effective and realized spread), price impact and the Amihud ratio. The Amihud ratio is a low-frequency measure based on daily data. The difference is that high-frequency measures are costs of liquidity and also have a direct impact on the realized return of the stock, see Hagströmer et al. (2013). The data is aggregated on monthly levels, the ESG score however is only updated on a yearly basis. Data is reordered every quarter to adjust for possible ESG score changes.

The effect of revealing new information, e.g., arising from annual reports, will be quickly incorporated in stock prices and quotes, if not already anticipated by informed investors. Hence, aggregating the data on a monthly frequency should prevent overweighting surprise events while simultaneously not removing too much volatility in the measures themselves. Fu (2009), for example, uses monthly data to investigate the impact of idiosyncratic risk on expected returns using a Fama-French-3-factor model. Cao and Han (2016) use weekly return series to investigate the costly arbitrage theory where arbitrageurs would exploit miss-pricing. Aslan et al. (2011) describe the long-term linkage between high-frequency data and firm-fundamental data by comparing a measure for the probability of informed trading to firm fundamental values on a yearly basis. Monthly data is used as a compromise between data availability and keeping as much information as possible.

Table 4.3 shows in Panel A that the ESG score is associated with lower transaction costs as indicated by a lower quoted, effective and realized spread, significant to the 1% level High ESG titles also show significantly lower price impacts and a lower Amihud ratio. Panel A shows that the quoted spread for more socially responsible companies is on average nearly 0.95 bps lower. The realized spread at the 60-second (10-second) interval are 0.25 (0.34) bps lower in the high ESG group. The Amihud measure is also indicating greater liquidity in the high ESG group. To allow for adjustments over time, 4.A1 and 4.A2 use values for ESG score and investment style that are lagged by one and two years, respectively. They show similar results when comparing high to low ESG titles. This also shows that the ESG score is rather sticky. Results from Table 4.3 confirm Hypothesis 4.1, as both the high- and low-frequency liquidity measures indicate greater liquidity for high ESG titles. Similar to Egginton and McBrayer (2019), evidence is presented that a higher level of ESG can reduce information asymmetry (price impact and spreads are smaller).

Table 4.3: Impact of ESG Score and Ownership on Liquidity
High-frequency liquidity measures are calculated daily and aggregated monthly. Columns (1) to (7) investigate the impact of the ESG score or investment style on the liquidity where a dummy variable is included that equals 1 if the stock is in the top quintile of ESG score or investment style and 0 if the stock is in the first quintile. Investment style is either the active investor share or the passive investor share per company. ESG score and investment style are lagged by one month. The used variables are QuoSpr: Quoted spread; ReaSpr(60s): Realized spread at 60-second grids; ReaSpr(10s): Realized spread at 10-second grids; PrImp(10s): Price impact over 10-second interval; PrImp(60s): Price impact over 60-second interval; EffSpr: Effective spread; Amihud: Amihud (2002) illiquidity measure. Control variables: sd.close: Volatility measured with standard deviation of close price returns, market.cap: Market capitalization, turnover is the average daily turnover and price.close is the stock's closing price. All control variables are averaged across days within each month and afterwards the natural logarithm is taken. Control variables are not displayed in the table below. The dataset consists of 355 stocks between 2010 and 2019. Sector and time fixed effects are included. Standard errors are clustered on stock level and shown in parentheses.

	QuoSpr	ReaSpr(60s)	ReaSpr(10s)	PrImp(60s)	PrImp(10s)	EffSpr	Amihud
Panel A: ESG Score Previous Month							
$\text{ESG.dummy}_{\text{t-1}}$	-0.95^{***}	-0.25^{***}	-0.34^{***}	-0.44^{***}	-0.33^{***}	-0.66^{***}	-0.31^{**}
	(0.25)	(0.06)	(0.07)	(0.15)	(0.12)	(0.17)	(0.15)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,998	16,998	16,998	16,998	16,998	16,998	16,998
Adjusted R^2	0.27	0.25	0.30	0.37	0.43	0.35	0.53
Panel B: Active Investor Share Previous Month							
$\text{Active.dummy}_{\text{t-1}}$	0.28	0.11^{**}	0.13^{**}	0.12	0.10	0.23	0.15
	(0.26)	(0.05)	(0.07)	(0.17)	(0.14)	(0.18)	(0.17)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,997	16,997	16,997	16,997	16,997	16,997	16,997
Adjusted R^2	0.24	0.24	0.30	0.35	0.41	0.33	0.54
Panel C: Passive Investor Share Previous Month							
$\text{Passive.dummy}_{\text{t-1}}$	-0.41^{*}	-0.22^{***}	-0.28^{***}	-0.13	-0.08	-0.35^{**}	-0.53^{***}
	(0.24)	(0.05)	(0.06)	(0.17)	(0.14)	(0.17)	(0.18)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,998	16,998	16,998	16,998	16,998	16,998	16,998
Adjusted R^2	0.20	0.26	0.32	0.35	0.42	0.33	0.55

Note: *p<0.1; **p<0.05; ***p<0.01

Investor Style Effect on Liquidity

Liquidity might not only be affected by ESG Scores, but also by signals sent through the level and type of ownership. Next, the following model is estimated:

$$liq_{i,t} = \alpha_s + \delta_t + \beta_1 Investor\ Style_{i,t-T} + \beta_2 C_{i,t} + \epsilon_{i,t}, \tag{4.2}$$

where $Investor\ Style_{i,t-T}$ is a dummy variable that equals 1 if the stock is in the top quintile and 0 if the stock is in the bottom quintile. $Investor\ Style$ can either be the 'active' or 'passive' ownership share of stock i at time $t-T$. The remaining variables are similar to Equation 4.1.

Panel B of Table 4.3 shows the results of comparing high to low groups created by sorting 'Investor Style'. Comparing stocks with a high active ownership to stocks with low active ownership shows a significant difference in realized spreads only. Stocks with a high concentration of active owners have significantly larger realized spreads, while all other liquidity coefficients estimates remain insignificant. The realized spread can be used as an indicator for high-frequency trader's profits (Brogaard and Garriott (2019); Foley and Putnins (2016)). It measures the trading costs net of the price impact. High-frequency traders are able to capitalize on the presence of higher active ownership shares. This is in line with the understanding that market makers demand a higher premium when trading with informed participants (Glosten and Milgrom (1985)). Generally, an increase in institutional ownership irrespective of investment style is related to an increased liquidity (Boone and White (2015); Cao and Han (2016)). However, new evidence shows that when large institutional block holders engage in trading, they might have a significant effect on price impact (Ben-Rephael et al. (2015). No significant difference in price impact between the high and low active ownership groups are observed. This effect is strongest in the short-term where the 60-second (10-second) realized spread in the top quintile is 0.11

(0.13) bps higher compared to the lowest quintile. Allowing for a stickier adjustment, Tables 4.A1 and 4.A2 indicate that the differences between high and low active ownership groups are losing statistical and economic power, but remain significant as reported in Panel B in the respective tables.

When comparing stocks with a high level of passive investors to low level stocks, Panel C shows that a higher level of passive investor share is associated with higher liquidity. Quoted, effective and realized spreads are significantly lower for stocks in the high passive investor style group. The realized spreads at the 60-second (10-second) intervals are 0.22 (0.28) basis points lower, effective spreads decrease by 0.35 basis points and quoted spreads decrease by 0.41 basis points. Price impact shows no significant differences, with the Amihud measure showing a significantly lower measure in the top group.[25] Generally, the results indicate a higher liquidity in stocks with a higher share of passive investors.[26] However, this also indicates that realized spreads are significantly higher in shares with a small level of passive ownership.[27]

Table 4.4 interacts ESG score and investor style and finds no comprehensive correlation between ESG and active ownership presented in Panels A and B. However, the interaction between ESG scores and passive ownership shows a significant positive coefficient for realized spreads in Panel D with some significant coefficients for price impact and the Amihud measure.

The above shows that both ESG and investor style are related to liquidity measures. A higher level of ESG scores is linked to smaller price impacts and spreads. Lower spreads and price impacts indicate lower information asymmetries. These findings are consistent

[25] See Goyenko et al. (2009) for a comparison between low- and high-frequency measures of price impact.

[26] Appendix 4.A presents similar results when using alternative lag lengths for the variables under interest, see Tables 4.A1 and 4.A2.

[27] It is worth mentioning that a small level of passive ownership does not necessarily translate into a high level of active ownership, as investors are only required to file a 13F report if their AUM are greater than USD 100 million. Additionally, a company can be owned by individuals, who do not fall under any investor style used in this research.

Table 4.4: Cross Products Ownership and ESG on Liquidity
High-frequency liquidity measures are calculated daily and aggregated monthly. Columns (1) to (7) investigate the interaction between past investment style and past ESG scores on liquidity measures. The used variables are QuoSpr: Quoted spread; ReaSpr(60s): Realized spread at 60-second grids; ReaSpr(10s): Realized spread at 10-second grids; PrImp(10s): Price impact over 10-second interval; PrImp(60s): Price impact over 60-second interval; EffSpr: Effective spread; Amihud: Amihud (2002) illiquidity measure. Control variables: sd.close: Volatility measured with standard deviation of close price returns, market.cap: Market capitalization, turnover is the average daily turnover and price.close is the stock's closing price. All control variables are averaged across days within each month and afterwards the natural logarithm is taken. Control variables are not displayed in the table below. The dataset consists of 355 stocks between 2010 and 2019. Sector and time fixed effects are included. Standard errors are clustered on stock level and shown in parentheses.

	Dependent variable:						
	QuoSpr	ReaSpr(60s)	ReaSpr(10s)	PrImp(60s)	PrImp(10s)	EffSpr	Amihud
Panel A: Active Investor Share and ESG Score Previous Month							
L1.active.share	-0.05^{**}	0.002	0.001	-0.03^{**}	-0.03^{***}	-0.03^{*}	0.03^{*}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
L1.ESG	−0.02	0.003	0.004	−0.01	−0.01	−0.01	0.03^{*}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
L1.active.share:L1.ESG	0.0004	−0.0001	−0.0001	0.0003	0.0003	0.0002	-0.001^{*}
	(0.0004)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,462	42,462	42,462	42,462	42,462	42,462	42,462
Adjusted R^2	0.67	0.34	0.45	0.69	0.72	0.66	0.63
Panel B: Active Investor Share and ESG Score Previous Year							
L4.active.share	-0.05^{***}	0.002	−0.0001	-0.03^{***}	-0.03^{***}	-0.03^{**}	0.02
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
L4.ESG	−0.02	0.01	0.01	−0.01	−0.01	−0.01	0.02
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
L4.active.share:L4.ESG	0.0004	−0.0001	−0.0001	0.0002	0.0002	0.0001	−0.0003
	(0.0004)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,405	42,405	42,405	42,405	42,405	42,405	42,405
Adjusted R^2	0.67	0.33	0.45	0.69	0.72	0.66	0.63
Panel C: Passive Investor Share and ESG Score Previous Month							
L1.passive.share	0.03	−0.02	−0.02	0.04^{*}	0.03^{**}	0.005	-0.11^{***}
	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)
L1.ESG	0.02	−0.005	−0.01	0.02^{**}	0.02^{**}	0.01	-0.03^{**}
	(0.01)	(0.004)	(0.004)	(0.01)	(0.01)	(0.01)	(0.01)
L1.passive.share:L1.ESG	−0.001	0.0001	0.0002	-0.001^{**}	-0.001^{**}	−0.0003	0.001^{***}
	(0.0004)	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0005)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,462	42,462	42,462	42,462	42,462	42,462	42,462
Adjusted R^2	0.67	0.34	0.45	0.69	0.72	0.66	0.63
Panel D: Passive Investor Share and ESG Score Previous Year							
L4.passive.share	0.01	-0.03^{***}	-0.04^{***}	0.02	0.02	−0.02	-0.15^{***}
	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
L4.ESG	0.01	-0.01^{***}	-0.01^{***}	0.01^{*}	0.01^{**}	0.0004	-0.04^{***}
	(0.01)	(0.003)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)
L4.passive.share:L4.ESG	−0.0003	0.0004^{***}	0.0005^{***}	−0.0005	-0.0004^{*}	0.0000	0.002^{***}
	(0.0004)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0004)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,405	42,405	42,405	42,405	42,405	42,405	42,405
Adjusted R^2	0.67	0.34	0.45	0.69	0.72	0.66	0.63
Note:							*p<0.1; **p<0.05; ***p<0.01

with Egginton and McBrayer (2019), who show that ESG disclosures work as a channel providing information to the market.

A higher level of passive ownership is linked to a decrease in spread measures and the Amihud ratio, indicating greater liquidity for stocks that have a greater presence of passive investors. On the other hand, a high level of active investors is linked with a higher realized spread, indicating that liquidity providers earn a greater compensation when trading against more informed participants (Korajczyk and Murphy (2019)). These findings indicate that Hypothesis 4.2 cannot be rejected.

4.5 Portfolio Return Analysis

The liquidity premium is the extra return more illiquid stocks need to offer to compensate for being more costly to sell or buy. Liquidity constraints are thereby more pronounced when fewer participants trade rather unknown stocks. Ben-Rephael et al. (2015) show a general decline in possible excess returns through liquidity risk premium, as general liquidity has increased over time. Independent of ESG-related impact, it is helpful to differentiate low- and high-liquidity stocks to account for this potential return impact.

To investigate a strategy that buys high ESG stocks and sells low ESG stocks, in a first step, four portfolios are created that are rebalanced quarterly according to their (previous year's) ESG score. Carhart (1997)'s four factor model is applied and takes the form of:

$$R_{i,t} - r_f = \alpha_i + \beta_1(R_{m,t} - r_f) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \epsilon_{i,t}, \tag{4.3}$$

where $R_{i,t}$ is the return of portfolio i, r_f is the risk free rate (1-month Treasury Bill rate), SMB and HML are risk factors capturing small vs. big and value vs. growth stocks respectively, according to Fama and French (1993). *MOM* captures the momentum of stock returns following Carhart (1997). The inclusion of the momentum factor captures market trends, and should additionally help to determine if ESG-focused investments can achieve alpha. Portfolio returns are equally weighted.

In columns (1) to (4), Table 4.5 shows the results of a regression per ESG quartile portfolio and indicates a negative abnormal return for the highest two quartiles. The regression constant indicates a negative abnormal return of -18 bps for the third quartile and -41 bps for the fourth quartile. In other words, last year's top ESG titles yield negative portfolio returns. As shown in column 'Q4 - Q1' a long-short strategy which buys high ESG stocks and sells low ESG stocks delivers negative excess returns of -29 bps, .

Table 4.5: Carhart Four-Factor Model on Double Sorted Portfolios
Stocks ordered by ESG score and assigned to quartiles. The ESG score is lagged by one year. Portfolio returns are created using equal weights between 2010 and 2019. Newey and West (1987) robust standard errors with a lag length of 12 months are used.

	return				
	Q1	Q2	Q3	Q4	Q4 - Q1
MKT	0.98***	0.97***	1.01***	0.95***	−0.03
	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)
SMB	0.15***	0.12***	0.09***	−0.08***	−0.23***
	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)
HML	0.02	0.04	0.09	0.11***	0.10*
	(0.05)	(0.04)	(0.06)	(0.03)	(0.05)
MOM	−0.001	−0.05*	0.01	−0.05**	−0.05
	(0.04)	(0.03)	(0.05)	(0.02)	(0.05)
Constant	−0.12	−0.10	−0.18**	−0.41***	−0.29***
	(0.09)	(0.08)	(0.08)	(0.06)	(0.08)
Observations	120	120	120	120	120
R^2	0.93	0.96	0.96	0.97	0.22
Adjusted R^2	0.93	0.96	0.96	0.97	0.19
Note:					*p<0.1; **p<0.05; ***p<0.01

4.5.1 Double Sorted Portfolios

ESG and Liquidity

Incorporating the insights from the previous section, the next step creates double sorted portfolios. First, stocks are sorted according to their ESG score and then conditionally by liquidity, measured with the quoted spread. This approach creates portfolios that account for liquidity differences in similar ESG score environments. Section 4.4 reports that high ESG stocks have lower information asymmetries. Hence, first creating ESG groups further accounts for confounding information asymmetry impacts within ESG peers. For example, if significant differences between the top and bottom liquidity groups exist within the top ESG group, these may indicate that stocks with a high information asymmetry have not yet incorporated the ESG-related information and might impact returns through this channel.

Following Brøgger and Kronies (2020), the ESG score is lagged by one year to allow for adjustments. Secondly, stocks are sorted according to the ESG score and then investment style. Stocks are assigned to quartiles based on their ESG score, before quartiles are conditionally created according to either liquidity or investment style. The bottom 25% of stocks are labeled as 'low', except for the quoted spread, where the 'high' label is assigned to the bottom 25% because a lower value for the quoted spread represents higher liquidity. This approach produces a total of 16 portfolios which are re-sampled every month. Next, long-short portfolios are created. For each constructed group, a long-short portfolio is simulated that buys stocks that are in the high group and sells stocks that are in the low group. For example, one possible long-short strategy would buy the high ESG stocks and would sell the low ESG stocks when the liquidity level is high. For each created portfolio and long-short strategy the constant, or alpha, from regression model 4.3 is extracted, which indicates the abnormal return of the portfolio.

Panel C in Table 4.6 double sorts ESG score and conditionally on quoted spread. Column 'LS_{ESG}' and row 'Liquidity Low' shows the return of a strategy that buys high ESG titles and sells low ESG titles where liquidity is low for both ESG groups. This strategy achieves a negative abnormal return of -72 basis points, which is significant to the 1% level. Similar results are reported when stocks are part of the second least liquid group 'Liquidity Q2'. This long-short strategy yields a negative return of -37 bps, significant to the 5% level. Hence, within levels of (low) liquidity, ESG scores impact the performance negatively. ESG long-short returns are indistinguishable from zero when the stocks are part of the higher liquidity groups (row 'Liquidity Q3' and 'Liquidity High'). Interestingly, a long-short strategy that buys the high liquid stock and sells the low liquid stocks achieves a significantly positive abnormal return for the Q2 and Q4 ESG group. For high ESG titles, buying liquid stocks and selling illiquid stocks makes a profit of 73 bps. Negative performance increases with the level of ESG scores in liquidity groups Low and Q2. In row 'Liquidity Low', the Q2 ESG portfolio shows a negative return of -38 bps, which increases to a negative return of -82 bps. The Q3 and high ESG portfolio of the second lowest liquidity group (Q2) also show negative returns of -39 bps and -67 bps respectively.

Including Active and Passive Investor Style

Previous results showed that there is a relationship between ESG scores and liquidity which has an impact on portfolio returns. However, institutional investors invested in ESG stocks follow different strategies. Investment might be the result of an active decision to target companies depending on their ESG aspects, described in Brøgger and Kronies (2020). Another possibility could be the need of passive institutional investors to include ESG titles in their ETFs or mutual funds when tracking a sustainability index. Consequently, the next step differentiates between active and passive investment style.

Table 4.6: Double Sorted Portfolio Returns
Alphas from Carhart four-factor model presented in Equation 4.3. Double sorted portfolios are created by first ordering according to the previous year's ESG score and then conditionally on a. investment style and b. liquidity. The quoted spread is used as the liquidity measure in this table. The investment style is either the active investor share or the passive investor share per company. This results in a total of 16 portfolios. Panel A thereby presents results when ordering by the passive investment style and Panel B by the active investment style. Column 'LS_{ESG}' shows alphas from a long-short when buying high ESG titles and selling low ESG titles in the respective investment style group. Row 'LS_{Style}' ('$LS_{Liquidity}$') shows alphas from a long-short strategy when buying stocks with a high level of active or passive share (liquidity) and selling stocks with a low level in the respective ESG group. Portfolios are created monthly and the observation period is between 2010 and 2019. Newey and West (1987) robust standard errors with a lag length of 12 months are used and presented in parentheses.

	ESG Low	ESG Q2	ESG Q3	ESG High	LS_{ESG}
Panel A: Passive Investors					
Style Low	-0.14	-0.21*	-0.06	-0.32**	-0.18*
	(0.16)	(0.13)	(0.18)	(0.14)	(0.09)
Style Q2	-0.20	-0.12	-0.33**	-0.50***	-0.30*
	(0.14)	(0.13)	(0.13)	(0.12)	(0.17)
Style Q3	-0.13	-0.11	-0.05	-0.54***	-0.41***
	(0.10)	(0.11)	(0.09)	(0.11)	(0.15)
Style High	0.00	0.04	-0.28	-0.27**	-0.27
	(0.16)	(0.12)	(0.19)	(0.12)	(0.18)
LS_{Style}	0.14	0.25	-0.22	0.05	
	(0.20)	(0.17)	(0.28)	(0.19)	
Panel B: Active Investors					
Style Low	-0.19*	-0.06	0.04	-0.51***	-0.32**
	(0.10)	(0.09)	(0.11)	(0.09)	(0.14)
Style Q2	-0.06	-0.26***	-0.29**	-0.17	-0.11
	(0.13)	(0.10)	(0.14)	(0.11)	(0.13)
Style Q3	0.14	-0.15	-0.27**	-0.53***	-0.67***
	(0.16)	(0.15)	(0.13)	(0.09)	(0.20)
Style High	-0.37**	0.04	-0.20	-0.41***	-0.04
	(0.16)	(0.17)	(0.16)	(0.15)	(0.21)
LS_{Style}	-0.18	0.09	-0.24	0.10	
	(0.20)	(0.19)	(0.15)	(0.17)	
Panel C: Liquidity					
Liquidity Low	-0.10	-0.38***	-0.21	-0.82***	-0.72***
	(0.17)	(0.12)	(0.17)	(0.15)	(0.24)
Liquidity Q2	-0.31*	-0.04	-0.39**	-0.67***	-0.37**
	(0.17)	(0.11)	(0.15)	(0.08)	(0.14)
Liquidity Q3	-0.10	-0.21	-0.14	-0.06	0.05
	(0.14)	(0.15)	(0.11)	(0.10)	(0.18)
Liquidity High	0.03	0.20	0.03	-0.09	-0.12
	(0.09)	(0.17)	(0.08)	(0.13)	(0.14)
$LS_{Liquidity}$	0.13	0.57**	0.24	0.73***	
	(0.19)	(0.23)	(0.15)	(0.22)	

Note: *p<0.1; **p<0.05; ***p<0.01

The classification provided by Refinitiv Eikon is used, which splits ownership into 'active' and 'passive' investors collected from 13F reports. Active (Passive) investment style is the percentage active (passive) investors hold as shares in a listed company.

Sixteen double sorted portfolios based on ESG score and investment style are constructed. Panels A and B in Table 4.6 show the alphas of Carhart-4-factor regressions using the double sorted portfolios. Panel A gives the results when ordering by passive investment style, Panel B shows the abnormal returns when active investment style is used instead. The table reports abnormal returns when applying a long-short strategy that buys high ESG stocks and sells low ESG stocks within groups of similar levels of investment styles in column 'LS_{ESG}'. For example, the abnormal return of a long-short strategy that buys high ESG and sells low ESG in the Q3 group of passive investment style achieves a negative abnormal return of -41 bps. Panel B reports a negative return of -68 bps when buying high ESG titles and shorting low ESG titles only for stocks that are in the third quartile of active investment style.

However, the main driver across portfolios appears to be the significantly negative performance of high ESG titles. This result rejects the argument that low ESG stocks show abnormal returns (Derwall et al. (2011)) as there are no (positive) abnormal returns observable in the low ESG portfolios. This view is consistent for all levels and types of investment styles. Overall, Table 4.6 reports negative abnormal returns for higher ESG score portfolios when the level of liquidity is low and information asymmetries are greater. For portfolios with a reduced level of information asymmetry (i.e., high liquid groups), no abnormal returns are reported.

4.5.2 Triple Sorted Portfolios

Next, portfolios are triple sorted based on ESG score, investment style and liquidity. As shown in Section 4.4 this approach additionally controls for potential confounding effects between investment style and liquidity. Creating portfolios based on the investment style allows for possible implications on the ESG score development based on varying levels of ownership. This approach also allows for institutional investor trade timings based on the general level of liquidity, as shown by Colling-Dufresne and Fos (2015). The authors show that informed investors strategically select market times with periods of high liquidity when trading. These additional controls help to further narrow down the ESG effect. First, stocks are ordered into terciles according to their ESG score, then conditionally on investment style and lastly on liquidity measured with the quoted spread. This results in a total of 27 portfolios. Table 4.7 shows alphas for portfolios when liquidity is either low or high. Thereby, Panel A (B) shows the results for the low (high) liquidity group when sorted by ESG score and passive investment style.

Portfolios with significant abnormal returns include stocks that are in the medium or high level ESG group. This is only true for more illiquid stocks. Panel A reports significantly negative returns for high ESG stocks independent of the level of passive investor share. However, the lower the share held by passive investors within the companies, the higher the absolute negative return. In row 'Style Low' and column 'ESG High', the portfolio return for low liquid stocks is -72 bps, which changes to -65 bps and -40 bps when passive investor share is medium (Q2) and high, respectively. There are no return-generating long-short strategies for buying high and selling low ESG titles when using passive investment style. Panel B shows no significant returns, except in the high ESG group. For high levels of passive investors, high ESG titles show a positive return of 29 bps and again no significant long-short strategies.

Panels C and D show portfolio returns when active investment style is used in the ordering exercise. Similar returns are presented for illiquid stocks, with a strong indication that high ESG titles show a significantly negative performance. Buying high ESG titles and selling low ESG titles with a medium level of active investor share delivers -95 bps,

Table 4.7: Triple Sorted Portfolio Returns - ESG, Investment Style, Liquidity with Quoted Spread

Alphas from Carhart four-factor model presented in Equation 4.3. Triple sorted portfolios are created each month by sorting according to the previous year's ESG score, the investment style and liquidity. Panel A and B present results when the investment style is passive. Panel C and D present results when the investment style is active. Only results for low and high liquidity groups are presented. Column 'LS_{ESG}' shows alphas from a long-short when buying high ESG titles and selling low ESG titles in the respective investment style group. Row 'LS_{Style}' shows alphas from a long-short strategy that buys stocks with a high level of investment style and sells stocks with a low level in the respective ESG group. Portfolios are created monthly and the observation period is between 2010 and 2019. The used liquidity measure is the quoted spread. Newey and West (1987) robust standard errors with a lag length of 12 months are used and presented in parentheses.

	ESG Low	ESG Q2	ESG High	LS_{ESG}	ESG Low	ESG Q2	ESG High	LS_{ESG}
Passive Investment Style								
	Panel A: Low Liquidity Portfolio				Panel B: High Liquidity Portfolio			
Style Low	-0.28	-0.48***	-0.72***	-0.44*	0.09	-0.03	0.09	0.00
	(0.20)	(0.16)	(0.22)	(0.24)	(0.14)	(0.16)	(0.16)	(0.17)
Style Q2	-0.28	-0.04	-0.65***	-0.37	-0.26	-0.03	-0.21	0.05
	(0.17)	(0.17)	(0.22)	(0.25)	(0.25)	(0.14)	(0.14)	(0.33)
Style High	-0.06	-0.61***	-0.40***	-0.34*	0.08	0.07	0.29**	0.20
	(0.17)	(0.18)	(0.14)	(0.20)	(0.18)	(0.12)	(0.13)	(0.18)
LS_{Style}	0.22	-0.13	0.31		-0.01	0.10	0.20	
	(0.24)	(0.27)	(0.25)		(0.19)	(0.14)	(0.14)	
Active Investment Style								
	Panel C: Low Liquidity Portfolio				Panel D: High Liquidity Portfolio			
Style Low	-0.49***	-0.31*	-0.47***	0.02	0.03	0.06	-0.08	-0.11
	(0.16)	(0.16)	(0.18)	(0.27)	(0.15)	(0.23)	(0.16)	(0.25)
Style Q2	0.24	-0.27	-0.71***	-0.95***	0.11	-0.06	-0.11	-0.22
	(0.23)	(0.17)	(0.14)	(0.23)	(0.15)	(0.11)	(0.16)	(0.14)
Style High	-0.31	-0.30*	-0.66***	-0.35	-0.20	-0.17	0.09	0.30
	(0.22)	(0.17)	(0.23)	(0.36)	(0.24)	(0.19)	(0.15)	(0.27)
LS_{Style}	0.18	0.02	-0.20		-0.23	-0.23	0.17	
	(0.33)	(0.23)	(0.34)		(0.26)	(0.33)	(0.23)	

Note: *p<0.1; **p<0.05; ***p<0.01

which is the highest absolute return in the presented table. High liquid stocks do not show any significant returns. The evidence suggests shorting high ESG titles with relatively low liquidity levels gains profits.

By accounting for performance-driving factors like liquidity and investment style, this portfolio-creating approach narrows down the effect of ESG investing and finds evidence that high ESG titles achieve abnormal negative returns only when the stocks are relatively more illiquid. High ESG titles do not show significant abnormal returns when the level of liquidity is high or, in other words, information asymmetries are low.

Portfolio returns are significantly negative when information asymmetries are low and the ESG scores are medium or high. The results indicate that buying stocks with high or moderate ESG scores yields negative returns when accounting for similar levels of low liquidity. For similar levels of liquidity, significant differences in returns are observable that can be linked to different ESG scores. This is in line with Pástor et al. (2020), who derive that abnormal returns for green(er) assets are negative. However, the significant negative returns vanish with decreasing information asymmetries. Additionally, the results indicate that portfolio returns are not impacted by different investment styles. Both low and high levels for active or passive ownership show significantly negative returns for high ESG titles.[28]

In summary, Hypothesis 4.3 cannot be rejected, as no significant abnormal returns are observed for portfolios with high liquidity. Hypothesis 4.4 is also not rejected, as high ESG titles show a significant negative return in the low liquidity environment. Results

[28]For the portfolio return calculations, stock returns are used. Evidence is provided that portfolio returns are negative for low liquid stocks, i.e., for stocks with a higher spread. The argumentation here uses the channel of price informativeness. However, the dimension of increased costs through higher spreads on portfolio returns also exists, but this is not further investigated here. It is worth mentioning that a higher spread has a negative impact on the realization of portfolio returns. This implies that buying high ESG titles in a low liquidity group, i.e., where spreads are high, has another impact channel on the profitability of the portfolio besides the stock price evolution. However, the 'real' transaction cost impact can also be influenced by other factors, such as broker or management fees, or the implementation shortfall.

remain qualitatively similar for different investment styles.

4.6 Robustness

Selecting stocks that are part of the S&P 500 index by December 2019 helps to reduce heterogeneity, rendering size and liquidity levels more similar. Constituency, however, changes over time and stocks may not have been as liquid at the beginning of the observation period. A first robustness check only focuses on stocks that have been a constituent of the index in both January 2010 and December 2019. This approach improves validity by imposing further restrictions on the homogeneity of the stock group with respect to liquidity. Table 4.8 shows that a large number of stocks in the sample (280 out of 355) were an index constituent in January 2010. Qualitatively, Panel A in Table 4.8 provides similar results, except for the low-frequency measure in column 'Amihud', which is no longer significant. Panel B displays that the significance of the coefficient estimates for the realized spread measures is rendered insignificant when comparing high and low active investor groups. Panel C still highlights that stocks in the high group of passive ownership show significantly lower transaction costs measured with the realized spread, but the other coefficient estimates lose significance. ESG impact on liquidity measures is more robust than ownership impact on liquidity.

Different Liquidity Measures and Alternative Ordering

Similar results as reported in Section 4.5 are observed when using alternative measures for liquidity. Again, every ownership tercile shows significantly negative abnormal returns for high ESG titles in the low liquidity group when using the effective or realized spread shown in Tables 4.9 and 4.10 instead of the quoted spread.

The use of effective and realized spread as alternative measures accounts for execution

Table 4.8: Impact of ESG Score and Ownership on Liquidity for Continuous Constituents
This specification only includes stocks that have been a constituent in the S&P 500 at the beginning of the sample in 2010 and at the end in 2019. High-frequency liquidity measures are calculated daily and aggregated monthly. Columns (1) to (7) investigate the impact of the ESG score or investment style on the liquidity where a dummy variable is included that equals 1 if the stock is in the top quintile of ESG score or investment style and 0 if the stock is in the first quintile. Investment style is either the share of active investor share or the share of passive investor share per company. ESG score and investment style are lagged by one month. The used variables are QuoSpr: Quoted spread; ReaSpr(60s): Realized spread at 60-second grids; ReaSpr(10s): Realized spread at 10-second grids; PrImp(10s): Price impact over 10-second interval; PrImp(60s): Price impact over 60-second interval; EffSpr: Effective spread; Amihud: Amihud (2002) illiquidity measure. Control variables: sd.close: Volatility measured with standard deviation of close price returns, market.cap: Market capitalization, turnover is the average daily turnover and price.close is the stock's closing price. All control variables are averaged across days within each month and afterwards the natural logarithm is taken. Control variables are not displayed in the table below. The dataset consists of 280 stocks between 2010 and 2019. Sector and time fixed effects are included. Standard errors are clustered on stock level and shown in parentheses.

	QuoSpr	ReaSpr(60s)	ReaSpr(10s)	PrImp(60s)	PrImp(10s)	EffSpr	Amihud
Panel A: ESG Score Previous Month							
$ESG.dummy_{t-1}$	-0.64^{**}	-0.19^{***}	-0.23^{***}	-0.28^{*}	-0.22^{*}	-0.44^{**}	-0.11
	(0.26)	(0.05)	(0.07)	(0.16)	(0.13)	(0.18)	(0.17)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,411	13,411	13,411	13,411	13,411	13,411	13,411
Adjusted R^2	0.23	0.24	0.29	0.43	0.49	0.38	0.54
Panel B: Active Investor Share Previous Month							
$Active.dummy_{t-1}$	-0.03	0.02	0.01	0.01	0.03	0.03	0.16
	(0.29)	(0.06)	(0.07)	(0.19)	(0.16)	(0.22)	(0.20)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,407	13,407	13,407	13,407	13,407	13,407	13,407
Adjusted R^2	0.20	0.24	0.27	0.40	0.46	0.36	0.50
Panel C: Passive Investor Share Previous Month							
$Passive.dummy_{t-1}$	-0.16	-0.12^{**}	-0.14^{**}	-0.05	-0.04	-0.18	-0.06
	(0.23)	(0.05)	(0.06)	(0.16)	(0.14)	(0.18)	(0.16)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,411	13,411	13,411	13,411	13,411	13,411	13,411
Adjusted R^2	0.21	0.24	0.28	0.44	0.49	0.39	0.52

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.9: Triple Sorted Portfolio Returns - ESG, Investment Style, Liquidity with Effective Spread

Alphas from Carhart four-factor model presented in Equation 4.3. Triple sorted portfolios are created each month by sorting according to the previous year's ESG score, the investment style and liquidity. Panel A and B present results when the investment style is passive. Panel C and D present results when the investment style is active. Only results for low and high liquidity groups are presented. Column 'LS_{ESG}' shows alphas from a long-short when buying high ESG titles and selling low ESG titles in the respective investment style group. Row 'LS_{Style}' shows alphas from a long-short strategy that buys stocks with a high level of investment style and sells stocks with a low level in the respective ESG group. Portfolios are created monthly and the observation period is between 2010 and 2019. The used liquidity measure is the effective spread. Newey and West (1987) robust standard errors with a lag length of 12 months are used and presented in parentheses.

	ESG Low	ESG Q2	ESG High	LS_{ESG}	ESG Low	ESG Q2	ESG High	LS_{ESG}
Passive Investment Style								
	Panel A: Low Liquidity Portfolio				Panel B: High Liquidity Portfolio			
Style Low	-0.48**	-0.43***	-0.88***	-0.40	0.20	0.20	0.19**	0.00
	(0.19)	(0.16)	(0.23)	(0.25)	(0.14)	(0.17)	(0.09)	(0.14)
Style Q2	-0.30	-0.15	-0.81***	-0.51*	0.05	0.13	0.02	-0.03
	(0.19)	(0.19)	(0.20)	(0.27)	(0.23)	(0.13)	(0.17)	(0.35)
Style High	-0.23	-0.72***	-0.45**	-0.22	0.31	0.28*	0.16	-0.15
	(0.20)	(0.22)	(0.19)	(0.28)	(0.19)	(0.16)	(0.15)	(0.11)
LS_{Style}	0.25	-0.29	0.43*		0.11	0.07	-0.03	
	(0.30)	(0.27)	(0.25)		(0.21)	(0.16)	(0.11)	
Active Investment Style								
	Panel C: Low Liquidity Portfolio				Panel D: High Liquidity Portfolio			
Style Low	-0.55***	-0.45***	-0.63***	-0.08	0.04	0.10	0.05	0.01
	(0.17)	(0.15)	(0.17)	(0.22)	(0.12)	(0.21)	(0.15)	(0.15)
Style Q2	0.01	-0.66***	-0.66***	-0.67**	0.35***	0.23	0.08	-0.28*
	(0.27)	(0.18)	(0.17)	(0.32)	(0.13)	(0.15)	(0.18)	(0.14)
Style High	-0.40	-0.46*	-0.63***	-0.23	-0.02	0.21	0.26***	0.27
	(0.24)	(0.25)	(0.22)	(0.37)	(0.21)	(0.16)	(0.09)	(0.21)
LS_{Style}	0.15	-0.01	0.00		-0.06	0.11	0.20	
	(0.37)	(0.21)	(0.28)		(0.21)	(0.30)	(0.18)	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.10: Triple Sorted Portfolio Returns - ESG, Investment Style, Liquidity with Realized Spread (10s)

Alphas from Carhart four-factor model presented in Equation 4.3. Triple sorted portfolios are created each month by sorting according to the previous year's ESG score, the investment style and liquidity. Panel A and B present results when the investment style is passive. Panel C and D present results when the investment style is active. Only results for low and high liquidity groups are presented. Column 'LS_{ESG}' shows alphas from a long-short when buying high ESG titles and selling low ESG titles in the respective investment style group. Row 'LS_{Style}' shows alphas from a long-short strategy that buys stocks with a high level of investment style and sells stocks with a low level in the respective ESG group. Portfolios are created monthly and the observation period is between 2010 and 2019. The used liquidity measure is the realized spread (10s). Newey and West (1987) robust standard errors with a lag length of 12 months are used and presented in parentheses.

	ESG Low	ESG Q2	ESG High	LS_{ESG}	ESG Low	ESG Q2	ESG High	LS_{ESG}
Passive Investment Style								
	Panel A: Low Liquidity Portfolio				Panel B: High Liquidity Portfolio			
Style Low	-0.17	-0.31	-0.60**	-0.43	-0.16	-0.15	0.06	0.21
	(0.22)	(0.19)	(0.27)	(0.27)	(0.11)	(0.18)	(0.16)	(0.22)
Style Q2	-0.24	-0.19	-0.54***	-0.30	-0.03	-0.17	-0.27	-0.23
	(0.22)	(0.20)	(0.16)	(0.21)	(0.19)	(0.11)	(0.19)	(0.23)
Style High	0.07	-0.27*	-0.32*	-0.39*	-0.15	-0.36**	-0.15	0.00
	(0.18)	(0.14)	(0.17)	(0.23)	(0.17)	(0.18)	(0.19)	(0.21)
LS_{Style}	0.24	0.05	0.28*		0.01	-0.21	-0.20	
	(0.23)	(0.23)	(0.16)		(0.23)	(0.17)	(0.21)	
Active Investment Style								
	Panel C: Low Liquidity Portfolio				Panel D: High Liquidity Portfolio			
Style Low	-0.41**	-0.15	-0.56**	-0.15	-0.06	-0.26	0.05	0.10
	(0.16)	(0.13)	(0.22)	(0.20)	(0.13)	(0.22)	(0.17)	(0.16)
Style Q2	0.24	-0.18	-0.33	-0.56*	0.07	-0.19	-0.48**	-0.56***
	(0.24)	(0.16)	(0.20)	(0.30)	(0.14)	(0.14)	(0.21)	(0.19)
Style High	0.04	-0.37	-0.61***	-0.66**	-0.16	-0.20	0.01	0.17
	(0.20)	(0.23)	(0.19)	(0.28)	(0.18)	(0.21)	(0.13)	(0.21)
LS_{Style}	0.45*	-0.23	-0.05		-0.10	0.06	-0.03	
	(0.26)	(0.26)	(0.17)		(0.17)	(0.35)	(0.18)	

Note: *p<0.1; **p<0.05; ***p<0.01

prices that differ from the best bid or ask prices and the price impact of the trade, respectively. The realized spread can be used as an approximation for HFT profits and can help to additionally approximate for the potential return-reducing effects of the presence of these market participants. Thereby, HFTs earn a larger profit with higher spreads. Results in Table 4.10 confirm that the portfolio returns are not significantly varying with the level of institutional ownership, but are significantly negative only for portfolios consisting of high ESG and low liquid (higher spread) stocks.

In a next robustness check, the order by which the portfolios are constructed is changed. Table 4.11 creates double sorted portfolios by first ordering according to investment style or the quoted spread as the liquidity measure, before ordering conditionally according to the ESG score. The table reports similar results, indicating that stocks with higher ESG scores show a negative abnormal return when ordering according to investment style. It however shows that changing the order has an impact on the results. In Panel C high ESG titles show negative returns for low and high liquid groups, however the significance in the high liquid group is reduced. Again, positive returns can be achieved by following a long-short strategy based on buying highly liquid and selling illiquid stocks, only this time in the lowest ESG group (60 bps) and in the group 'ESG Q3' (50 bps). Table 4.12 presents portfolio returns that have been created by first ordering according to the investment style, secondly by ESG scores and lastly according to liquidity. When accounting for both liquidity and investment style, portfolios show negative abnormal returns when the liquidity level is low and the ESG score level is high or moderate. For liquid stocks, most portfolios show no significant returns. Similarly, Table 4.13 shows negative portfolio returns for low liquid and moderate/high ESG portfolios when ordering first according to ESG scores, then liquidity and lastly according to investment style. Again, most returns are insignificant for high liquid portfolios.[29]

[29]There are some exceptions (Panel B and Panel D), however no pattern is observable.

Table 4.11: Double Sorted Portfolio Returns - Alternative Order
Alphas from Carhart four-factor model presented in Equation 4.3. Double sorted portfolios are created by first ordering according to a. investment style and b. liquidity and then conditionally on the previous year's ESG score. The quoted spread is used as the liquidity measure in this table. The investment style is either the active investor share or the passive investor share per company. This results in a total of 16 portfolios. Panel A thereby presents results when ordering by passive investment style and Panel B by active investment style. Column 'LS_{ESG}' shows alphas from a long-short when buying high ESG titles and selling low ESG titles in the respective investment style group. Row 'LS_{Style}' ('$LS_{Liquidity}$') shows alphas from a long-short strategy when buying stocks with a high level of active or passive share (liquidity) and selling stocks with a low level in the respective ESG group. Portfolios are created monthly and the observation period is between 2010 and 2019. Newey and West (1987) robust standard errors with a lag length of 12 months are used and presented in parentheses.

	ESG Low	ESG Q2	ESG Q3	ESG High	LS_{ESG}
Panel A: Passive Investors					
Style Low	-0.16	-0.14	-0.13	-0.25	-0.10
	(0.14)	(0.13)	(0.17)	(0.19)	(0.13)
Style Q2	-0.36***	-0.15	-0.29***	-0.53***	-0.18
	(0.12)	(0.15)	(0.10)	(0.12)	(0.15)
Style Q3	-0.02	-0.13	-0.15	-0.30**	-0.29
	(0.12)	(0.10)	(0.10)	(0.13)	(0.19)
Style High	0.03	-0.04	-0.23	-0.37***	-0.40***
	(0.15)	(0.11)	(0.15)	(0.11)	(0.13)
LS_{Style}	0.19	0.10	-0.10	-0.11	
	(0.19)	(0.18)	(0.19)	(0.21)	
Panel B: Active Investors					
Style Low	-0.24***	-0.11	-0.09	-0.40***	-0.16
	(0.09)	(0.12)	(0.08)	(0.15)	(0.19)
Style Q2	-0.16*	-0.22***	-0.45***	-0.40***	-0.24**
	(0.09)	(0.08)	(0.13)	(0.06)	(0.12)
Style Q3	-0.02	0.09	-0.33**	-0.35***	-0.33*
	(0.13)	(0.09)	(0.13)	(0.11)	(0.18)
Style High	-0.16	-0.08	-0.08	-0.23**	-0.08
	(0.22)	(0.20)	(0.15)	(0.09)	(0.22)
LS_{Style}	0.09	0.03	0.00	0.17	
	(0.27)	(0.18)	(0.14)	(0.19)	
Panel C: Liquidity					
Liquidity Low	-0.35*	-0.02	-0.38***	-0.51**	-0.16
	(0.18)	(0.12)	(0.11)	(0.21)	(0.25)
Liquidity Q2	-0.09	0.02	-0.45***	-0.54***	-0.45***
	(0.10)	(0.13)	(0.15)	(0.14)	(0.16)
Liquidity Q3	-0.13	-0.19	-0.32**	-0.57***	-0.44***
	(0.12)	(0.12)	(0.12)	(0.10)	(0.16)
Liquidity High	0.26*	0.09	0.12	-0.20**	-0.45**
	(0.15)	(0.08)	(0.13)	(0.08)	(0.19)
$LS_{Liquidity}$	0.60***	0.11	0.50***	0.31	
	(0.22)	(0.11)	(0.16)	(0.26)	
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 4.12: Triple Sorted Portfolio Returns Alternative Order - Investment Style, ESG, Liquidity with Quoted Spread

Alphas from Carhart four-factor model presented in Equation 4.3. Triple sorted portfolios are created each month by sorting according to investment style, previous year's ESG score and liquidity. Panel A and B present results when the investment style is passive. Panel C and D present results when the investment style is active. Only results for low and high liquidity groups are presented. Column 'LS_{ESG}' shows alphas from a long-short when buying high ESG titles and selling low ESG titles in the respective investment style group. Row 'LS_{Style}' shows alphas from a long-short strategy that buys stocks with a high level of investment style and sells stocks with a low level in the respective ESG group. Portfolios are created monthly and the observation period is between 2010 and 2019. The used liquidity measure is the quoted spread. Newey and West (1987) robust standard errors with a lag length of 12 months are used and presented in parentheses.

	ESG Low	ESG Q2	ESG High	LS_{ESG}	ESG Low	ESG Q2	ESG High	LS_{ESG}
Passive Investment Style								
	Panel A: Low Liquidity Portfolio				Panel B: High Liquidity Portfolio			
Style Low	-0.43**	-0.58***	-0.59***	-0.16	0.03	-0.02	0.09	0.06
	(0.18)	(0.17)	(0.22)	(0.21)	(0.15)	(0.14)	(0.13)	(0.17)
Style Q2	-0.18	0.01	-0.65***	-0.47**	-0.35	-0.04	-0.07	0.03**
	(0.17)	(0.18)	(0.19)	(0.22)	(0.22)	(0.16)	(0.14)	(0.22)
Style High	-0.10	-0.51**	-0.46***	-0.37*	0.28	0.01	0.25*	-0.04
	(0.19)	(0.20)	(0.15)	(0.22)	(0.19)	(0.14)	(0.14)	(0.18)
LS_{Style}	0.34	0.07	0.13		0.25	0.03	0.15	
	(0.27)	(0.30)	(0.29)		(0.22)	(0.13)	(0.13)	
Active Investment Style								
	Panel C: Low Liquidity Portfolio				Panel D: High Liquidity Portfolio			
Style Low	-0.51***	-0.13	-0.73***	-0.21	0.09	0.34***	-0.11	-0.19
	(0.11)	(0.12)	(0.15)	(0.17)	(0.14)	(0.12)	(0.14)	(0.18)
Style Q2	0.08	-0.38***	-0.64***	-0.72***	-0.11	-0.05	-0.25*	-0.27***
	(0.10)	(0.14)	(0.13)	(0.16)	(0.12)	(0.12)	(0.14)	(0.16)
Style High	-0.28	-0.19	-0.47**	-0.19	0.05	0.07	0.02	-0.03
	(0.22)	(0.16)	(0.21)	(0.23)	(0.20)	(0.19)	(0.10)	(0.20)
LS_{Style}	0.23	-0.06	0.26		-0.04	-0.27	0.13	
	(0.26)	(0.18)	(0.22)		(0.29)	(0.24)	(0.17)	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.13: Triple Sorted Portfolio Returns Alternative Order - ESG, Liquidity with Quoted Spread and Investment Style
Alphas from Carhart four-factor model presented in Equation 4.3. Triple sorted portfolios are created each month by sorting according to previous year's ESG score, liquidity and investment style. Panel A and B present results when the investment style is passive. Panel C and D present results when the investment style is active. Only results for low and high liquidity groups are presented. Column 'LS_{ESG}' shows alphas from a long-short when buying high ESG titles and selling low ESG titles in the respective investment style group. Row 'LS_{Style}' shows alphas from a long-short strategy that buys stocks with a high level of investment style and sells stocks with a low level in the respective ESG group. Portfolios are created monthly and the observation period is between 2010 and 2019. The used liquidity measure is the quoted spread. Newey and West (1987) robust standard errors with a lag length of 12 months are used and presented in parentheses.

	ESG Low	ESG Q2	ESG High	LS_{ESG}	ESG Low	ESG Q2	ESG High	LS_{ESG}
Passive Investment Style								
	Panel A: Low Liquidity Portfolio				Panel B: High Liquidity Portfolio			
Style Low	-0.39**	-0.36**	-0.65***	-0.26	0.11	-0.02	-0.01	-0.12
	(0.17)	(0.16)	(0.19)	(0.22)	(0.13)	(0.16)	(0.14)	(0.16)
Style Q2	-0.31	-0.07	-0.65***	-0.35	-0.23	-0.16	-0.10	0.13
	(0.19)	(0.18)	(0.18)	(0.26)	(0.22)	(0.11)	(0.13)	(0.31)
Style High	0.08	-0.63***	-0.46**	-0.54**	0.14	0.24*	-0.06	-0.20
	(0.18)	(0.21)	(0.23)	(0.24)	(0.18)	(0.13)	(0.13)	(0.19)
LS_{Style}	0.47*	-0.27	0.18		0.03	0.26*	-0.05	
	(0.24)	(0.29)	(0.27)		(0.18)	(0.15)	(0.19)	
Active Investment Style								
	Panel C: Low Liquidity Portfolio				Panel D: High Liquidity Portfolio			
Style Low	-0.37***	-0.39**	-0.46***	-0.09	-0.09	0.05	-0.17	-0.08
	(0.13)	(0.16)	(0.14)	(0.19)	(0.13)	(0.21)	(0.16)	(0.21)
Style Q2	0.08	-0.34**	-0.61***	-0.70***	0.12	-0.09	0.17*	0.05
	(0.24)	(0.17)	(0.12)	(0.23)	(0.15)	(0.14)	(0.10)	(0.17)
Style High	-0.31	-0.36*	-0.68***	-0.37	-0.01	0.11	-0.17	-0.16
	(0.20)	(0.20)	(0.23)	(0.29)	(0.20)	(0.16)	(0.16)	(0.23)
LS_{Style}	0.07	0.03	-0.21		0.08	0.05	-0.01	
	(0.25)	(0.23)	(0.27)		(0.18)	(0.27)	(0.22)	

Note: *p<0.1; **p<0.05; ***p<0.01

4.7 Conclusion

Both market liquidity and interest in ESG characteristics have increased over the last couple of decades. Simultaneously, institutional investors have increased their ownership in equities, which might also impact both liquidity and ESG scores. Thereby, institutional investors can be divided into active and passive investors. Active investors select portfolios based on research and/or engage with management directly, while passive investors dominantly follow passive strategies, like index replication. The distinction between these institutional investor styles is crucial when reflecting on their impact on liquidity and their relation to ESG aspects. For example, Brøgger and Kronies (2020) show that certain institutional investors can predict ESG developments and can profit from this skill.

While researchers have mainly focused on investigating the link between ESG and stock performance, few have investigated the impact of ESG on market liquidity and the role institutional ownership plays in this relation. Similar to Egginton and McBrayer (2019), this study finds a positive correlation between higher ESG scores and market liquidity, indicating that higher ESG scores improve price informativeness. This study also provides evidence that the investor style affects stock liquidity. Realized spreads of stocks with a high level of active ownership are higher compared to stocks with a lower level of active ownership. On the other hand, stocks with a high level of passive ownership show significantly higher liquidity (lower spreads).

To identify the subtle effects of ESG investing, this paper acknowledges the liquidity channel, which can have an impact on stock performance through information asymmetry effects. To limit the influence of confounding factors, the universe of stocks in this sample is restricted to constituents of the S&P 500 index. Next, portfolios are created by sorting stocks based on ESG score, liquidity and investment style. This reveals that higher ESG score stocks have a significantly negative return only when the stocks are more illiquid. This finding is independent of the investment style and the liquidity measures used. Evidence is provided that there are no abnormal returns for high ESG titles when the information environment of the portfolio is high, which is in line with the efficient market hypothesis. However, for stocks with a high level of information asymmetries, high ESG titles achieve significantly negative abnormal returns, which is according to Pástor et al. (2020).

4.A Appendix 4.A

Figure 4.A1: Quoted Spread Over Time
This figure shows equally-weighted quoted spreads over time. The solid black lines represent all stocks under investigation, the dashed lines represent the bottom 20% of stocks ordered according to the ESG score, dotted lines represent the top 20%. The quartiles are generated each year to represent updates to ESG scores.

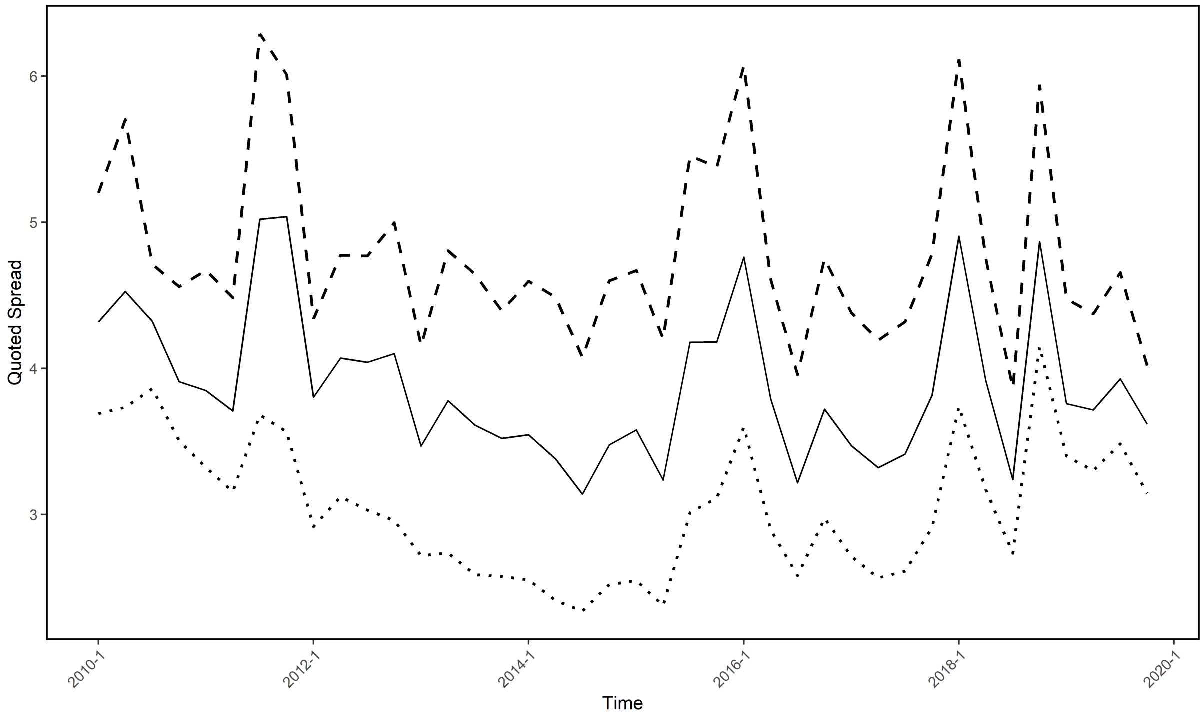


Table 4.A1: Impact of ESG Score and Ownership on Liquidity - Previous Year
High-frequency liquidity measures are calculated daily and aggregated monthly. Columns (1) to (7) investigate the impact of the ESG score or investment style on the liquidity where a dummy variable is included that equals 1 if the stock is in the top quintile of ESG score or investment style and 0 if the stock is in the first quintile. Investment style is either the active investor share or the passive investor share per company. ESG score and investment style are lagged by one year. The used variables are QuoSpr: Quoted spread; ReaSpr(60s): Realized spread at 60-second grids; ReaSpr(10s): Realized spread at 10-second grids; PrImp(10s): Price impact over 10-second interval; PrImp(60s): Price impact over 60-second interval; EffSpr: Effective spread; Amihud: Amihud (2002) illiquidity measure. Control variables: sd.close: Volatility measured with standard deviation of close price returns, market.cap: Market capitalization, turnover is the average daily turnover and price.close is the stock's closing price. All control variables are averaged across days within each month and afterwards the natural logarithm is taken. Control variables are not displayed in the table below. The dataset consists of 355 stocks between 2010 and 2019. Sector and time fixed effects are included. Standard errors are clustered on stock level and shown in parentheses.

	QuoSpr	ReaSpr(60s)	ReaSpr(10s)	PrImp(60s)	PrImp(10s)	EffSpr	Amihud
Panel A: ESG Score Previous Year							
$\text{ESG.dummy}_{\text{y-1}}$	-0.94^{***}	-0.25^{***}	-0.34^{***}	-0.43^{***}	-0.32^{***}	-0.66^{***}	-0.33^{**}
	(0.25)	(0.05)	(0.07)	(0.15)	(0.12)	(0.17)	(0.15)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,981	16,981	16,981	16,981	16,981	16,981	16,981
Adjusted R^2	0.27	0.25	0.31	0.36	0.43	0.34	0.54
Panel B: Active Investor Share Previous Year							
$\text{Active.dummy}_{\text{y-1}}$	0.28	0.08	0.11^{*}	0.14	0.11	0.22	0.24
	(0.26)	(0.05)	(0.07)	(0.17)	(0.14)	(0.18)	(0.18)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,994	16,994	16,994	16,994	16,994	16,994	16,994
Adjusted R^2	0.24	0.25	0.31	0.34	0.40	0.33	0.54
Panel C: Passive Investor Share Previous Year							
$\text{Passive.dummy}_{\text{y-1}}$	-0.40^{*}	-0.22^{***}	-0.28^{***}	-0.14	-0.08	-0.35^{**}	-0.58^{***}
	(0.24)	(0.05)	(0.06)	(0.16)	(0.13)	(0.16)	(0.17)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,992	16,992	16,992	16,992	16,992	16,992	16,992
Adjusted R^2	0.20	0.26	0.32	0.34	0.41	0.32	0.56
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 4.A2: Impact of ESG Score and Ownership on Liquidity - Two Years Ago
High-frequency liquidity measures are calculated daily and aggregated monthly. Columns (1) to (7) investigate the impact of the ESG score or investment style on the liquidity where a dummy variable is included that equals 1 if the stock is in the top quintile of ESG score or investment style and 0 if the stock is in the first quintile. Investment style is either the active investor share or the passive investor share per company. ESG score and investment style are lagged by one year. The used variables are QuoSpr: Quoted spread; ReaSpr(60s): Realized spread at 60-second grids; ReaSpr(10s): Realized spread at 10-second grids; PrImp(10s): Price impact over 10-second interval; PrImp(60s): Price impact over 60-second interval; EffSpr: Effective spread; Amihud: Amihud (2002) illiquidity measure. Control variables: sd.close: Volatility measured with standard deviation of close price returns, market.cap: Market capitalization, turnover is the average daily turnover and price.close is the stock's closing price. All control variables are averaged across days within each month and afterwards the natural logarithm is taken. Control variables are not displayed in the table below. The dataset consists of 355 stocks between 2010 and 2019. Sector and time fixed effects are included. Standard errors are clustered on stock level and shown in parentheses.

	QuoSpr	ReaSpr(60s)	ReaSpr(10s)	PrImp(60s)	PrImp(10s)	EffSpr	Amihud
Panel A: ESG Score Two Years Ago							
$ESG.dummy_{y\text{-}2}$	-0.91^{***}	-0.21^{***}	-0.31^{***}	-0.42^{***}	-0.31^{**}	-0.61^{***}	-0.26^{*}
	(0.25)	(0.05)	(0.06)	(0.15)	(0.13)	(0.17)	(0.15)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,244	16,244	16,244	16,244	16,244	16,244	16,244
Adjusted R^2	0.27	0.24	0.30	0.36	0.42	0.34	0.54
Panel B: Active Investor Share Two Years Ago							
$Active.dummy_{y\text{-}2}$	0.32	0.09	0.11^{*}	0.17	0.14	0.25	0.24
	(0.26)	(0.05)	(0.07)	(0.17)	(0.14)	(0.18)	(0.18)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,914	16,914	16,914	16,914	16,914	16,914	16,914
Adjusted R^2	0.25	0.24	0.30	0.33	0.39	0.33	0.54
Panel C: Passive Investor Share Two Years Ago							
$Passive.dummy_{y\text{-}2}$	-0.38	-0.18^{***}	-0.24^{***}	-0.15	-0.09	-0.34^{**}	-0.45^{***}
	(0.23)	(0.05)	(0.06)	(0.15)	(0.13)	(0.16)	(0.16)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,919	16,919	16,919	16,919	16,919	16,919	16,919
Adjusted R^2	0.22	0.27	0.34	0.34	0.40	0.33	0.56

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.A3: Cross Products Ownership and ESG on Liquidity, Increased Lag Length
High-frequency liquidity measures are calculated daily and aggregated monthly. Columns (1) to (7) investigate the interaction between past investment style and past ESG scores on liquidity measures. The used variables are QuoSpr: Quoted spread; ReaSpr(60s): Realized spread at 60-second grids; ReaSpr(10s): Realized spread at 10-second grids; PrImp(10s): Price impact over 10-second interval; PrImp(60s): Price impact over 60-second interval; EffSpr: Effective spread; Amihud: Amihud (2002) illiquidity measure. Control variables: sd.close: Volatility measured with standard deviation of close price returns, market.cap: Market capitalization, turnover is the average daily turnover and price.close is the stock's closing price. All control variables are averaged across days within each month and afterwards the natural logarithm is taken. Control variables are not displayed in the table below. The dataset consists of 355 stocks between 2010 and 2019. Sector and time fixed effects are included. Standard errors are clustered on stock level and shown in parentheses.

	Dependent variable:						
	QuoSpr	ReaSpr(60s)	ReaSpr(10s)	PrImp(60s)	PrImp(10s)	EffSpr	Amihud
Panel A: Active Investor Share and ESG Score Two Years Ago							
L8.active.share	-0.04^{***}	0.002	-0.0001	-0.02^{**}	-0.02^{***}	-0.02^{**}	0.003
	(0.01)	(0.004)	(0.005)	(0.01)	(0.01)	(0.01)	(0.01)
L8.ESG	-0.03^{*}	0.0005	-0.0001	-0.01	-0.01	-0.01	-0.005
	(0.02)	(0.004)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L8.active.share:L8.ESG	0.001^{*}	-0.0000	-0.0000	0.0003	0.0003^{*}	0.0003	0.0001
	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,496	40,496	40,496	40,496	40,496	40,496	40,496
Adjusted R^2	0.69	0.33	0.44	0.70	0.73	0.66	0.63
Panel B: Active Investor Share Two years Ago and ESG Score Previous Year							
L8.active.share	-0.04^{***}	0.0002	-0.002	-0.02^{**}	-0.02^{***}	-0.02^{**}	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L4.ESG	-0.03^{*}	-0.0003	-0.001	-0.01	-0.01	-0.01	0.01
	(0.02)	(0.004)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
L8.active.share:L4.ESG	0.001^{*}	-0.0000	0.0000	0.0003	0.0003^{*}	0.0003	-0.0001
	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,225	42,225	42,225	42,225	42,225	42,225	42,225
Adjusted R^2	0.67	0.33	0.45	0.69	0.72	0.66	0.63
Panel C: Passive Investor Share and ESG Score Two Years Ago							
L8.passive.share	0.001	-0.02^{***}	-0.03^{***}	0.01	0.02	-0.02	-0.12^{***}
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)
L8.ESG	0.01	-0.01^{***}	-0.01^{***}	0.01^{*}	0.01^{**}	0.002	-0.04^{***}
	(0.01)	(0.003)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)
L8.passive.share:L8.ESG	-0.0003	0.0004^{***}	0.0004^{***}	-0.0004	-0.0004^{*}	0.0001	0.002^{***}
	(0.0004)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0004)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,496	40,496	40,496	40,496	40,496	40,496	40,496
Adjusted R^2	0.69	0.33	0.44	0.69	0.73	0.66	0.64
Panel D: Passive Investor Share Two years Ago and ESG Score Previous Year							
L8.passive.share	0.01	-0.02^{***}	-0.03^{***}	0.02	0.02^{*}	-0.01	-0.11^{***}
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
L4.ESG	0.02	-0.01^{***}	-0.01^{***}	0.02^{**}	0.02^{**}	0.005	-0.03^{***}
	(0.01)	(0.003)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)
L8.passive.share:L4.ESG	-0.0005	0.0004^{***}	0.0004^{***}	-0.001^{**}	-0.001^{**}	-0.0001	0.001^{***}
	(0.0004)	(0.0001)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0004)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,225	42,225	42,225	42,225	42,225	42,225	42,225
Adjusted R^2	0.67	0.33	0.45	0.69	0.72	0.66	0.63
Note:					*p<0.1; **p<0.05; ***p<0.01		

Chapter 5

Banning Dark Pools: Venue Selection and Investor Trading Costs

This work was co-authored with Arie Gozluklu, Peter Hoffmann, Peter O'Neill and Felix Suntheim.

The paper was presented at the European Financial Management Association 2021 Annual Meeting, online, June/July 2021

The paper was presented at the 28th Finance Forum, the Annual Meeting of the Spanish Finance Association, online, June/July 2021

The paper was presented at the 48th European Finance Association Annual Meeting, online, August 2021

The paper was presented at the 2021 FMA Annual Meeting, online, October 2021

5.1 Introduction

Investors transacting in modern equity markets must select from a long menu of venues to execute their trades with varying degrees of market transparency. On the one extreme, the 'lit' markets of public exchanges offer high degrees of pre- and post-trade transparency, while 'dark' trading venues (such as dark pools) offer the least. Aside from these extremes, choices also include venues and trading mechanisms that cannot be classified as either dark or lit, such as periodic (batch) auctions or systematic internalizers (SIs). Given this complex net of routing choices, order exposure decisions have become increasingly more important for investors.

While the proliferation of different trading venues has received considerable attention in the academic literature, empirical evidence on the effects of routing decisions on trading costs remains scant at best (e.g., Anand et al. (2021); Battalio et al. (2018); Gomber et al. (2016)). This gap in the literature is largely due to the lack of detailed data, which means it is not possible to assess trade execution performance in a setting with a large set of available venue types.

The effects of transparency on market participants are also an important regulatory issue since price discovery and fair access to financial markets are of major concern to regulators.[1] In response to the increasing market share of dark trading venues and their effects on market quality, European regulators introduced the so-called 'double-volume cap' (DVC) on 12 March 2018. This policy has banned trading on a set of trading venues with no pre-trade transparency (referred to as dark pools).

Against this backdrop, this chapter sheds light on two important questions: First, what role does dark trading play in increasing or decreasing investors' trading costs? Second, what was the effect of the DVC?

[1] See, e.g. the SEC's officially stated goals, available here or European Securities and Markets Authority's (ESMA's) MiFID II/MiFIR Review Report, available here.

First, this research shows that the use of trading venues with lower pre-trade transparency is associated with lower execution costs. Importantly, results are obtained after controlling for a wide set of fixed effects at the investor, broker, and stock-day level. Interestingly, the effects of dark and periodic auction (PA) trading are *very similar*, suggesting that these trading mechanisms are close substitutes in terms of their effect on execution costs. Dark pools offer less transparency than PA venues as they do not disclose any volume information, while PAs reveal indicative auction uncrossing volumes. However, similar to dark pools but unlike central limit order books, PAs do not disclose buying and selling interest at individual price levels. See Section 5.2 for a more detailed discussion of venue characteristics.

Previous research has focused on the impact of dark trading on standard measures of market quality (e.g., spreads and depth), with mixed evidence. Some papers (Conrad et al. (2003); Buti et al. (2016); Garvey et al. (2016); Gresse (2017)) find that dark trading improves market quality through increased liquidity from lower transaction costs for individual trades. Others show that the effect is either not significant (Comerton-Forde et al. (2018); Farley et al. (2018)) or even detrimental to the lit markets (Degryse et al. (2015)). Comerton-Forde and Putnins (2015) show that the effect on price discovery is non-linear, with adverse consequences of high levels of dark trading activity. An experimental study by Bloomfield et al. (2015) finds that changes to market opacity affect trading strategies of both informed and uninformed participants, but do not significantly affect liquidity. Because dark pools are designed to reduce the 'market impact' of large block executions, studies that only examine the bid-ask spreads of individual trade executions are incomplete.

Because dark pools are designed to reduce the 'market impact' of large orders, studies that only examine the bid-ask spreads of individual trade executions are, by construction, incomplete. Using regulatory data from the UK, this chapter computes the implementation shortfall Perold (1988) of large institutional trade executions across multiple trading venues. The institutional setting allows the researchers to exploit variation in pre-trade transparency across a variety of trading mechanisms. To the researchers knowledge, this is the first paper to examine the effects of dark trading on execution costs in a multi-venue setting.

Similar to Menkveld et al. (2017), this study finds evidence for dark pools to rank first in the venue selection 'pecking order' within the parent order life cycle. Trade executions in dark pools are more likely to occur earlier in the trading day when there is a lower demand for immediacy.[2]

Second, the causal impact of the DVC trading restriction in a Difference-in-Difference setting is examined, both when it was introduced and when it was subsequently lifted. This research finds that the DVC did not have any significant impact on investors' execution costs. Investors that relied heavily on dark pool trading before the ban did not experience a change in their implementation shortfall relative to a control group of investors that did not rely much on dark trading. The same is true for the subsequent removal of the DVC.

Evidence is provided consistent with investors shifting their activity to alternative venues that were not affected by the policy. These venues, such as periodic auctions, offer trading with limited pre-trade transparency. In other words, it is likely that the DVC policy did not affect transaction costs, because substitutes like periodic auction-based venues are available. Importantly, after the ban was lifted, participant volume returned to dark pools, suggesting that participants prefer dark pools to periodic auctions when both options are available. However, this preference is not universal and significant volumes

[2] There is a growing literature highlighting the importance of examining investor venue routing decisions, especially in the context of high-frequency trading (Battalio et al. (2018); Chakrabarty et al. (2020); Hendershott et al. (2013); Sağlam et al. (2019); Van Kervel and Menkveld (2019)). However, these studies do not examine the trade-off between pre-trade transparency and execution quality in fragmented markets.

remain on PA venues.

Finally, no evidence is found that different investors reacted differently to the DVC. To this end, investors are distinguished based on their informedness and size. Neither of these characteristics affected the estimated treatment effects.

The presented findings on the effects of the DVC complement those of Johann et al. (2019), who show that the DVC did not affect lit market quality, leading trading to move from dark venues to close substitutes. A recent study by Guagliano et al. (2020) extends the analysis by including the lifting of the ban, finding that market liquidity improves during ban periods. The authors also highlight the increased use of periodic auctions. The researchers are also able to examine the spectrum of venue choices, demonstrating that trading in periodic auctions, in addition to large-in-scale dark and regular dark trading, reduces investor transaction costs.

The rest of the chapter is organized as follows. Section 5.2 describes the regulatory environment and is followed by the hypotheses development in Section 5.3. Section 5.4 provides the details of the dataset and descriptive statistics. Section 5.5 contains empirical results and Section 5.6 applies some robustness checks. Section 5.7 concludes this chapter.[3]

5.2 Regulatory Environment

The second iteration of the Markets in Financial Instruments Directive (MiFID II), a suite of new regulations for EU capital markets, came into force on January 3, 2018. As part of this set of rules, the so-called 'double volume cap' (DVC) restriction on 'dark pool trading' came into effect a few months later, on March 12, 2018.

Under MiFID II, trades on regulated markets or multilateral trading facilities that are not pre-trade transparent must trade under at least one of four conditional 'waivers': i)

[3]The relevant literature is discussed in Section 2.

the 'Large In Scale' (LIS) waiver, for trades that are sufficiently large (often termed 'block trades'); ii) the 'reference price waiver', for trades referencing a 'widely regarded reference price' - typically dark pool MTFs (for example UBS MTF) referencing the primary market mid-quote; iii) the 'negotiated trade waiver', for trades that are negotiated off-market but formalized on-market; or iv) the 'order management facility' waiver, for trades that are held within the exchange, pending disclosure - in practice, 'iceberg' orders.

Under the DVC, all trading under reference price or the negotiated trade waivers in the respective instrument is banned for a duration of six months if it exceeds any of two predefined thresholds. The two thresholds are: i) a market-wide cap triggered if the total volume across EU dark pools exceeds 8% of the total traded volume in the preceding 12 months, and ii) a venue-specific cap that is triggered by a specific dark pool exceeding a share of 4% of the volume in the preceding 12 months.

Under MiFID I, dark trading could also occur on so-called 'Broker Crossing Networks' (BCNs), such as Credit Suisse's 'Crossfinder' venue. As these venues were unregulated, they did not require a pre-trade transparency waiver. They were banned under MiFID II - effective from 3 Jan 2018.

There are several trading mechanisms not subject to the DVC, which are potential substitutes to dark pools:

- Similar to dark pools, 'Systematic Internalizers' (SIs) publish quotes based on primary or market-wide best-bid or offer prices. They were touted as alternatives to dark pools ahead of the ban, and several were created in anticipation of it, such as those operated by proprietary trading firms Virtu, Citadel and Hudson River.

- BATS Chi-X Europe (Now CBOE) was the first to develop a 'periodic batch auction'[4] mechanism where participants can submit orders with the option of pegging

[4] Also referred to as 'frequent batch auction'

to the midpoint of the European Best Bid or Offer price (EBBO). As the EU allows trading to occur across different countries, the EBBO is analogous to a 'National Best Bid or Offer'(NBBO). These auctions are triggered on order entry, occur throughout the day and can be as frequent as several times a second. Periodic batch auctions provide some pre-trade transparency by disclosing an indicative uncrossing price and volume for the auction. But they do not disclose the buying and selling interest at each price level as in a conventional lit market auction. Orders in the periodic auction can specify the price to reference the EBBO mid-price at the time of the auction, equivalent to dark pool MTF and BCN reference of the primary midpoint under the reference price waiver. So, batch auctions provide slightly more pre-trade transparency than dark pools while retaining the functionality of hiding a given participant's order and allowing reference pricing.

- Trades that are designated Off-book, or Over-the-Counter (OTC), are the outcome of bilateral negotiations with brokers or other participants - usually brokers source liquidity on behalf of clients via internalization or through their dealer networks.[5]

- Finally, dark trades that use the LIS waiver could potentially be considered a substitute for smaller reference price waiver dark trades if traders are able to modify their execution strategies to aggregate child orders.

5.3 Hypotheses Development

Research has found both positive and negative effects on market quality, execution costs and trading volume when integrating dark pools in their theoretical work or when examining them empirically. Foley and Putnins (2016) present evidence that spreads decrease

[5]These trades use the OTC, or the Negotiated Trade waiver, or are executed on the London Stock Exchange (LSE) without a Central Clearing Counterparty. See Appendix 5.B

in the presence of a dark limit order book. Similar effects on spreads are reported by Buti et al. (2016), who analyze the US market. Focusing on the Dutch market, Degryse et al. (2015) report an increase in spreads after trading in a dark pool. For the most part, research has focused on analyzing the effects of dark trading in a two-venue setting. The data used in this chapter allows the researchers to obtain information from multiple venue types. Hence, the first hypothesis in this chapter investigates the impact of dark pool usage in a multi-venue setting on institutional investors' trading costs.

Hypothesis 5.1: Dark trading is associated with lower transaction costs of large institutional trades

The introduction of the DVC is an ideal setting to test whether such regulatory constraint would increase the execution costs of institutional investors who rely on dark venues to improve execution quality. A potential concern behind the regulatory intervention is the concentration of trading on dark venues which might limit price discovery and reduce the liquidity on lit markets (Buti et al. (2017); Ye (2011)). The availability of alternative trading platforms which substitute dark trading can attenuate such policy intervention.

Hypothesis 5.2: Introduction of DVC has no effect on transaction costs for institutional investors

If both Hypothesis 5.1 and 5.2 are supported, one possible hypothesis would be that institutional investors substitute dark pools with similar venues. However, participants not only decide based on execution costs but also on execution certainty. Menkveld et al. (2017) show that participants decide to route their orders first to low-cost and low-immediacy venues like dark pools. Johann et al. (2019) document an increase in trading volume in 'quasi-dark venues', which makes them a potential substitute in this pecking order hypothesis. Hence, the next hypothesis is centered around institutional investors' order routing decisions.

Hypothesis 5.3: Institutional investors use alternative venues to execute their trades when dark trading is prohibited

5.4 Data and Descriptive Statistics

Transaction-level trade data is sourced from the Financial Conduct Authority's (FCA) Market Data Processor (MDP) database. Importantly, this data allows for the identification of individual market participants.[6] All stocks that were a constituent of the FTSE 100 and FTSE 250 share index during the period January 2018 to October 2018 are selected. The sample is restricted to the 327 stocks classified as 'liquid' by the European Securities and Markets Authority (ESMA).[7] The sample period comprises 80 days in the period from February 12 to October 11, 2018. More specifically, it covers the 40-day event windows around both events: the introduction of the DVC on March 12 and its lift on September 12, respectively. This dataset is complemented with quote data from Refinitiv (Thomson Reuters) Datascope Select. Data to classify counterparties is taken from Orbis and internal FCA sources.

[6]The dataset has been anonymized by the Financial Conduct Authority before being handed over to the authors, so that identification of individuals is not possible. The lowest level of identification is the Legal Entity Identifier (LEI).

[7]In order to label a stock liquid/illiquid, ESMA calculates the Standard Market Size at the stock level, which is based on the average value of a transaction (see Article 11 and Annex II of COMMISSION DELEGATED REGULATION (EU) 2017/587).

DVC effects on UK equity markets

ESMA publishes a monthly list of suspended and non-suspended stocks together with their share of dark trading volume.[8] With the implementation of the DVC on March 12th, dark trading was banned for 257 of the sample stocks.

Table 5.1 reports descriptive statistics. The period around the implementation of the DVC is labeled as BAN (from February 12 to April 10), and the period around its lift as LIFT (from August 14 until October 11).[9] Stocks affected by the suspension have lower spreads, a higher number of transactions, and a large percentage of dark trading (Panel A). Panel B shows the variables for the 225 stocks after the ban was lifted and for the 67 stocks that were never subject to the ban. Naturally, the waiver percentage correlates with the stock's share of dark trading, but the ban has elicited a decrease after it is lifted. Interestingly, even unaffected stocks show lower activity in dark trading and smaller waiver usage during the second event observation period compared to the pre-ban period.

Table 5.2 shows how the breakdown of trading activity across venue types changed during the BAN and LIFT periods, both for suspended and non-suspended stocks. Venues/trading mechanisms are classified as follows: i) Auctions (traditional opening, midday and closing auctions on LSE); ii) Dark (trading venues that are exempt from pre-trade transparency under the reference price waiver); iii) Dark (LIS) (trades that use the large-in-scale waiver); iv) Lit (fully pre- and post-trade transparent trading venues, i.e., regular exchanges and multilateral trading facilities); v) Off-book (bilateral trades or trades using the OTC waiver); vi) Periodic Auctions (Frequent Batch Auctions) and vii) Systematic

[8] ESMA is applying a 12-months rolling window to calculate the share traded under the use of the reference price and the negotiated transaction waiver. The data can be found at `https://www.esma.europa.eu/double-volume-cap-mechanism`.

[9] The days of the ban and the lift (March 12 and September 12), as well as the quadruple witching dates (the third Friday of every March, June, September and December) are excluded. On these days, the expiry of listed derivatives causes abnormal trading volume.

Table 5.1: Descriptive Statistics
This table contains statistics for banned and lifted stocks during the first observation period (February 12th - April 12th) and second observation period (August 14th - October 11th). Stocks that are a constituent of the FTSE100 or FTSE250 index at any given month over the complete observation period and are classified as liquid based on ESMA classification are included. Liquidity Measures and 'Dark trading %' for the respective groups are calculated in the pre-BAN period and the post-LIFT period, respectively. Thereby, the event days on which the ban commences and the lift occurs for the first time (March 12th and September 12th), as well as the quadruple witching dates (March 16th and September 21st) are excluded. Waiver % (Dark trading %) gives the average reference price waiver usage (average dark pool share of trading) across stocks in the period on which dark trading is allowed, i.e., before the ban commenced and after the suspension was lifted. The effective spread is calculated as $effective\ spread = 2d(price - mid)/mid$, where d indicates a buy or sell order. Data for liquidity metrics is taken from Refinitiv and covers the LSE order book and has been winsorized at the 1% level. Trades have been signed with the Lee and Ready (1991) algorithm, and if the trade executes at the mid, and an institutional investor is either buyer or seller (not both), this trade is classified as either buyer or seller initiated, depending on the side the institutional investors trades. 'Banned' indicates stocks that have been suspended from dark trading; 'Lifted' indicates stocks for which the suspension has been lifted again. Stocks that are labeled 're-suspended' by ESMA are not considered.

Panel A: First Event (BAN)		
	Not Banned	Banned
# Stocks	72	257
Average Daily Turnover (GBP mil)	32.96	46.68
Average Daily Trades	4,051	6,680
Waiver %	5.41	11.28
Dark trading %	3.71	6.51
Effective Spread	16.83	9.21
Panel B: Second Event (LIFT)		
	Not Lifted	Lifted
# Stocks	67	225
Average Daily Turnover (GBP mil)	34.13	47.71
Average Daily Trades	3,971	6,345
Waiver %	4.63	5.03
Dark trading %	2.48	4.62
Effective Spread	15.17	8.31

Internalizers.

Dark trading for suspended stocks ceased after the ban, with a small decrease in non-banned stocks.[10] Lit trading decreased significantly, but less in suspended stocks than in non-suspended stocks, with trading volume migrating towards periodic auctions, off-book, as well as to systematic internalizers. Panel C formally tests for these changes in venue share by using an unbalanced Difference-in-Difference regression, where suspended stocks are the treated and non-suspended stocks are the control group. Suspended stocks show a significant and positive coefficient for auction, lit and periodic auction trading, and a significant negative difference for dark trading.

With the end of the first suspension period on September 12th, dark trading volumes increased again. However, the increase was not of the same magnitude as the previous decrease that followed the introduction of the ban. Similarly, lit trading showed a significant decrease of about 5 %. Within the affected stocks, the increased trading volume went to all other trading venues, with off-book trading taking the lion's share (Panel A). The coefficient for un-suspended stocks shows the opposite sign for off-book trading but the same direction for 'Periodic', 'SI' and 'Dark (LIS)'. Notably, trading in periodic auction venues did not return to the pre-BAN level, but remained instead at a significantly higher level for both affected and unaffected stocks (column '(%) post' of Table 5.2). Hence, market participants continued to trade on alternative trading venues even after trading on traditional dark pools became available again.

Trader Types on UK Trading Venues

To investigate how venue choice and the DVC affect execution costs, this section focuses on the trading activity of institutional investors. These are real-money investors that

[10] On September 24th and 25th trading activity in SKY was excluded, after Comcast announced they would acquire the company. Inclusion causes very large SI activity, most likely OTC trades.

Table 5.2: Changes in Share of Trading by Venue Type - Around Ban and Lift Events
This table contains the change of trading of a stock on a particular venue around BAN and LIFT events. This table includes stocks that are a constituent of the FTSE100 or FTSE250 index at any given month over the complete observation period and are classified as liquid based on ESMA classification. This table reports differences between the pre-BAN (12 February to 9 March) and post-BAN (13 March to 12 April) periods and pre-LIFT (14 August to 9 September) to post-LIFT (13 September to 11 October). Trading on a venue is calculated as the ratio of turnover in the respective venue to total turnover on stock level per period. This table shows the results of a t-test, with clustered standard errors on stock level. Panel A (B) reports the results for stocks (not) affected by trading suspension due to BAN and LIFT events. Levels and differences are shown in percentage points. Standard errors in brackets. The sample in Panel A includes 257 stocks that were banned in the first three columns, 225 stocks that were lifted, and in the next three columns 216 that were subject to both (the overlapping sample). The sample in Panel A includes 72 stocks that were not banned in the first three columns, 67 stocks that were not lifted in the next three columns and 53 that were subject to both (the overlapping sample). Panel C reports estimates for a Difference-in-Difference model where affected stocks are the treatment group and unaffected stocks are the control group. The following model is estimated: $venue\ share_{j,t} = \alpha_j + \gamma_t + \delta(treated_j \times post_t) + \epsilon_{j,t}$.

	(%) pre	(%) post	post-BAN to pre-BAN	(%) pre	(%) post	post-LIFT to pre-LIFT
Panel A: Stocks that were banned, and stocks that were lifted						
# stocks			257			225
Auction	10.41	10.50	0.09	11.43	11.22	-0.22*
			(0.15)			(0.12)
Dark	6.00	0.00	-6.00***	0.00	4.46	4.46***
			(0.17)			(0.12)
Dark (LIS)	2.22	2.44	0.21	2.51	2.63	0.12
			(0.16)			(0.17)
Lit	36.74	36.24	-0.49**	33.88	32.34	-1.53***
			(0.25)			(0.23)
Off-book	20.12	24.16	4.04***	24.01	22.73	-1.28***
			(0.33)			(0.31)
Periodic Auction	0.53	2.05	1.52***	3.38	1.56	-1.82***
			(0.06)			(0.09)
SI	23.98	24.61	0.63**	24.78	25.05	0.27
			(0.27)			(0.27)
Panel B: Stocks that were not banned and not lifted						
# stocks			72			67
Auction	8.19	7.27	-0.92***	7.94	8.61	0.67***
			(0.26)			(0.25)
Dark	4.40	3.85	-0.55*	2.68	3.05	0.38
			(0.32)			(0.28)
Dark (LIS)	1.21	1.07	-0.14	0.82	1.09	0.27*
			(0.27)			(0.16)
Lit	25.38	23.39	-1.99***	24.81	25.88	1.06*
			(0.56)			(0.56)
Off-book	45.59	48.38	2.79***	45.31	42.69	-2.62***
			(0.77)			(0.63)
Periodic Auction	0.28	0.60	0.32**	1.42	1.39	-0.03
			(0.15)			(0.24)
SI	14.94	15.43	0.49	17.03	17.29	0.26
			(0.51)			(0.63)
Panel C: Unbalanced Difference-in-Difference with affected and un-affected stocks						
# stocks			329			292
Auction			1.09***			-0.85***
			(0.33)			(0.28)
Dark			-5.43***			4.09***
			(0.37)			(0.30)
Dark (LIS)			0.35			-0.16
			(0.32)			(0.24)
Lit			1.29**			-2.45***
			(0.64)			(0.61)
Off-book			1.38			1.14*
			(0.84)			(0.68)
Periodic Auction			1.19***			-1.78***
			(0.16)			(0.26)
SI			0.12			0.01
			(0.58)			(0.71)

typically trade directionally and execute large blocks of shares over time in an effort to minimize transaction costs. In the 20 days leading up to the introduction of the DVC, these investors account for 10.15 % of the total trading activity.[11]

To assess the execution costs of institutional investors, *parent orders* are constructed as the sum of all individual trade executions (henceforth referred to as 'child orders') on each side of a stock-day-participant-broker combination.[12] The sample includes 58,437 parent orders, which are required to be of at least GBP 100,000 in total size, to consist of at least five child orders, and whose execution takes at least 10 minutes.[13] Moreover, parent orders must have a directionality of at least 90%.

Transaction costs are measured using the implementation shortfall (IS) developed by Perold (1988). It is defined as:

$$IS = D \times \frac{p - p_0}{p_0},$$

where p_0 is the mid-quote at the time the trade starts (execution of first child order), p is the value-weighted execution price of the entire parent order, and D is a trade direction indicator ($D = 1$ for buy orders and $D = -1$ for sell orders). Implementation shortfall is winsorized at the 1%.

Panel A of Table 5.3 provides summary statistics on parent orders executed in periods when dark trading is not affected by the DVC. The average parent order has a value of

[11] While this appears a rather modest percentage, it is important to know that many institutional investors (especially hedge funds) trade in UK equities through derivatives such as Total Return Swaps, Contracts for Differences, and Spread-Bets. Accordingly, some of their trading is reflected by the hedging activity of broker-dealers in the cash market but cannot be allocated to individual institutional investors. While some information about derivatives trading is available in the MDP database, it is subject to data quality issues and can thus only be interpreted in aggregate.

[12] The terms child trade and child order are used interchangeably. The 1% child transactions with the largest price deviations relative to the current mid-quote are excluded. More information about mapping parent and children orders can be found in Appendix 5.B.

[13] Additionally, the Volume Weighted Average Price (VWAP) of parent orders is required to deviate no more than 1bps from the 'true' parent order VWAP. The 'true' VWAP is the price reported in the MDP report. More details in Appendix 5.B

Table 5.3: Descriptive Statistics of Investor Parent Orders
This table contains descriptive statistics of parent orders that have a value of at least GBP 100,000 , last 10 minutes or longer, and consist of five or more children. Parent orders have been winsorized at the 1% level with respect to implementation shortfall. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP and parent orders must have a directionality of at least 90%. Average value (GBP millions) is the average parent order size in GBP, average number of children is the average number of child trades per parent order, average duration is the average time difference of first trade to last trade in parent order per stock-day-participant in hours, average IS is the average volume weighted implementation shortfall per parent order in bps, Number of parent orders and number of children gives the total number of each. Additionally, this table shows the share of venue type usage across parent orders. Panel A shows parent order statistics during dark-trading periods (pre-BAN and post-LIFT). Panel B shows parent order statistics across periods. Trades from stocks that are liquid and subject to suspension and lifting are included. Standard deviation for the respective measure is shown in brackets.

	All	Above 1 mln	100k to 1 mln
Panel A: Parent Order Characteristics during dark-trading periods			
Average value (GBP, millions)	0.99	3.12	0.35
	(2.15)	(3.73)	(0.23)
Average number of children	165.63	417.37	90.23
	(276.83)	(475.65)	(84.63)
Average duration	4.36	5.04	4.15
	(3.05)	(2.92)	(3.05)
Average IS (bps)	12.13	13.87	7.47
Number of parent orders	29,404	6,777	22,627
Number of children	4,870,239	2,828,539	2,041,700
Number of participants	840	499	789
Auction (%)	15.33	15.99	13.55
Dark (%)	16.19	16.34	15.78
Dark (LIS) (%)	11.10	14.73	1.41
Lit (%)	46.83	42.89	57.35
Periodic Auction (%)	2.92	2.62	3.72
SI (%)	2.41	2.16	3.07
Off-book (%)	5.23	5.26	5.13
Panel B: Parent Order Characteristics over full sample (dark and no-dark periods)			
Average value (GBP, millions)	0.95	3.07	0.35
	(2.18)	(3.95)	(0.23)
Average number of children	167.21	427.31	93.32
	(272.40)	(467.88)	(91.74)
Average duration	4.37	5.13	4.16
	(3.06)	(2.94)	(3.06)
Average IS (bps)	12.42	14.41	7.43
Number of parent orders	58,437	12,928	45,509
Number of children	9,771,014	5,524,247	4,246,767
Number of participants	989	632	931
Auction (%)	15.55	16.19	13.94
Dark (%)	8.53	8.76	7.97
Dark (LIS) (%)	11.72	15.67	1.81
Lit (%)	49.83	45.72	60.13
Periodic Auction (%)	5.69	5.13	7.10
SI (%)	2.42	2.18	3.05
Off-book (%)	6.25	6.35	6.00

GBP 989,000, consists of 166 child executions and needs almost 4.5 hours to be executed fully. The average implementation shortfall is 12.13 basis points and increases in order size. For orders above GBP 1 million, the implementation shortfall is 13.87 bps, compared to 7.47 bps for parent orders below GBP 1 million. Similarly, the average execution time increases from 4.15 hours to 5.04 hours.[14] Panel A of Table 5.3 also provides a breakdown of parent orders across trading venues/mechanisms. On average, 46.83 % of the total value is traded in lit venues, 16.19 % in dark, 15.22 % during auctions, 11.10 % in large-in-scale dark, 5.23 % off-book, 2.92 % in periodic auctions, and 2.41 % on systematic internalizers. Large orders display a significantly lower share of lit trading and, naturally, a significantly larger use of large-in-scale dark trading. Panel B shows the parent order statistics when combining dark and no-dark period observations. The data covers a total of 989 unique investors, among which only 632 are engaged in the execution of orders larger than GBP 1 million.

Menkveld et al. (2017) develop a venue pecking order theory according to which market participants first attempt to trade in dark venues and over time resort to more transparent trading mechanisms as order execution becomes more important. Figure 5.1 provides some visual evidence that is consistent with this view. The top Panel shows the breakdown of parent buy orders across venues/mechanisms over the order life-cycle. The life-cycle is constructed by splitting the parent order chronologically into quintiles. Hence, the first bar shows the venue distribution in the first 20% of the parent order life-cycle and the second bar shows the venue usage for 20% to 40%, and so on.

Importantly, Figure 5.1 only includes parent orders from pre-BAN and post-LIFT periods, i.e., when dark trading is not subject to the DVC. The researchers find that the share of dark and large-in-scale dark during the first 20% of the parent order is larger than during the remaining parent order. In the first quintile shown in Figure 5.1, dark and

[14] By the researchers' definition, parent orders cannot span more than one business day.

large-in-scale dark venues account for 41.9% of trade executions. During the lifetime of a parent order, the share of dark and large-in-scale dark trading decreases and eventually drops to 18.6%, yet during the last (20%) part of the parent order life-cycle a large portion is executed in the closing auction, as the last bar in the upper panel indicates. The lower panel of Figure 5.1 shows a similar pattern over trading hours. However, the preference for dark venues during the early trading hours is not as salient as in the beginning of the parent orders' life-cycle.

This is confirmed by the results from a simple linear probability model in Table 5.4 where dummy variables indicating the use of dark trading venues are regressed on a set of order life-cycle dummy variables and fixed effects. The probability of choosing dark venues (and large-in-scale dark venues) decreases with the duration of the parent order. Interestingly, a similar pattern is observable for periodic auctions during times when dark trading is banned.[15]

5.5 The Impact of Venue Choice on Investor Trading Costs

This section tests how the choice of trading venues affects execution costs as measured by the implementation shortfall. Using data from the pre-BAN and post-LIFT periods where dark trading is allowed, the following regression is estimated:

$$IS_\tau = \alpha + \sum_{n=1}^{N-1} \beta_n \, PctVenue_{n,\tau} + \gamma_1 Size_\tau + \gamma_2 Execution\, time_\tau + FE + \epsilon_\tau, \tag{5.1}$$

where $PctVenue_{n,\tau}$ is the share of parent order τ executed in venue n. The idea is to compare the implementation shortfall across trades with different levels of dark trading

[15](Tables 5.14 and 5.13) show results from a multinomial logit regression and provide additional insights on venue choice.

Figure 5.1: Parent Order Venue Choice - by % Depleted and by Trading Hour
The figure below shows the parent order life-cycle. Parent orders and their corresponding child executions are included when dark trading is possible, i.e., in the pre-BAN and post-LIFT period. Venue choice is reported for each quintile of original parent order value. Quintiles are calculated on parent order level (Parent orders are all child orders summed up by day, stock, broker, participant). Hence, the below life-cycle is an equally weighted average display of the depletion within parent orders. Parent orders must have a value of at least GBP 100,000, last 10 minutes or longer, and consist of five or more children.

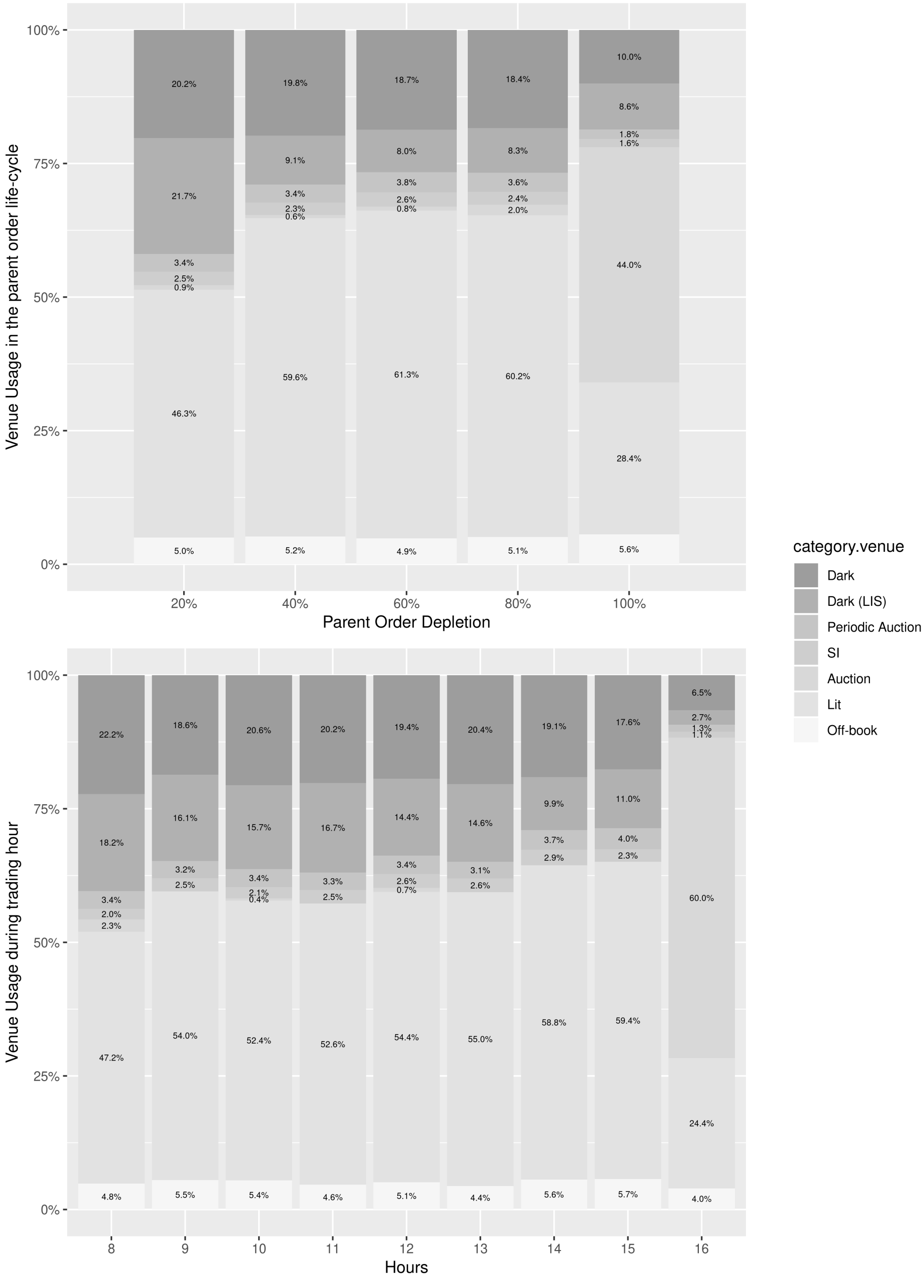


Table 5.4: Parent Order Venue Choice - Linear Probability Model
The table below shows the results from a linear probability model that shows the probability of a child being executed at a certain time in the life of the parent order on specific venue choices. A binary variable for each of the columns presented below is created that equals 1 if the child order has been executed in a) Dark venues, b) Dark venues including Dark (LIS), c) Periodic Auction, d) Periodic Auction including Dark (LIS). The binary variable equals 0 if the child is not executed in the venues of interest. Columns (1) and (2) thereby consider periods when dark trading is allowed (pre-BAN and post-LIFT), whereas columns (3) and (4) consider periods when dark trading is prohibited (post-BAN and pre-LIFT). 'Depletion Bucket' indicates the time in the parent orders life in quintiles, e.g., 'Depletion Bucket 2' indicates child orders that are executed between 20% and 40% of the parent order's life-cycle. The reference level below is the first bucket, i.e., the first 20% of the parent order. Stock-day, participant and broker fixed effects are included. Standard errors are clustered by participant level.

	Dependent variable:			
	Dark	Dark and Dark (LIS)	Periodic Auction	Periodic Auction and Dark (LIS)
	(1)	(2)	(3)	(4)
Depletion Bucket 2	-0.005^{***}	-0.005^{***}	-0.003^{**}	-0.003^{***}
	(0.002)	(0.002)	(0.001)	(0.001)
Depletion Bucket 3	-0.007^{***}	-0.007^{***}	-0.002^{**}	-0.003^{**}
	(0.002)	(0.002)	(0.001)	(0.001)
Depletion Bucket 4	-0.010^{***}	-0.011^{***}	-0.002	-0.003^{*}
	(0.002)	(0.002)	(0.002)	(0.002)
Depletion Bucket 5	-0.016^{***}	-0.016^{***}	-0.004^{***}	-0.004^{***}
	(0.002)	(0.002)	(0.001)	(0.001)
Stock-Day FE	Yes	Yes	Yes	Yes
Participant FE	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes
Period	pre-BAN and post-LIFT	pre-BAN and post-LIFT	post-BAN and pre-LIFT	post-BAN and pre-LIFT
Observations	4,851,067	4,851,067	4,885,124	4,885,124
R^2	0.315	0.318	0.170	0.174
Adjusted R^2	0.314	0.317	0.168	0.173
Note:				*p<0.1; **p<0.05; ***p<0.01

that are otherwise similar. To do so, a rich set of fixed effects (FE) is included, such that the study can compare trade executions that take place in the same stock on the same day. The inclusion additionally controls for observed and unobserved heterogeneity at the investor and broker level, which all may affect execution quality. The model additionally controls for the trade size ($Size_\tau$) in GBP and the time of execution ($Execution\,time_\tau$) measured in hours. For the latter two, the variable is transformed using the natural logarithm.

The results in Table 5.5 focus on the period where dark trading is not subject to any ban, showing that dark trading is associated with significantly reduced execution costs. For example, a 10 % increase in the proportion of a parent order executed on a dark venue reduces implementation shortfall by 0.97 bps. This is in line with Hypothesis 5.1.

Interestingly, the effects of dark and large-in-scale dark trading are qualitatively similar, and the null hypothesis that they are equal cannot be rejected. In contrast, lit trading and off-book trading are associated with significantly higher execution costs. As expected, larger trades incur a higher implementation shortfall, while execution time has no effect.

Table 5.6 focuses on periods with constrained dark trading, the post-BAN and pre-LIFT periods, meaning that it does not contain 'Dark (%)'.[16] Results are similar to the unconstrained period, with lit trading showing a positive impact on transaction costs and large-in-scale dark trading showing a negative impact. Interestingly, during periods with no dark trading, the reduction of transaction costs associated with trading in periodic auction venues is similar in extent to the effect of dark pools in the unconstrained period at 1.17 basis points for a 10 % increase in proportion traded. The researchers find that regular auction participation also reduces transaction costs in the constrained period.

The similar effects that are observed from periodic auction and dark trading mechanisms imply that they might be close substitutes. The researchers cannot say whether

[16] A small number of trades are excluded, that are reported to have occurred in dark venues for these periods, as they are likely erroneous transaction reports. They account for less than 0.01% of total trades.

Table 5.5: Effect of Venue Trading Share on Implementation Shortfall - Non-Ban Period

The table below shows the impact of dark trading on implementation shortfall (IS) for each venue type individually and combined according to regression specification 5.1. Parent orders from both the pre-BAN and post-LIFT period are included. In the combined specification (last column) the lit venue is excluded to prevent perfect multicollinearity. Parent orders that have a value of at least GBP 100,000, last 10 minutes or longer, and consist of five or more children are included. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP and parent orders must have a directionality of at least 90%. Parent orders are constructed from trades in the 257 stocks that were subject to a suspension in the BAN period and 225 of those stocks which had their suspension lifted in the LIFT period. The variables of interest are the trading percentages of each parent order on a particular venue. Additional control variables are the (natural logarithm of the) parent order size, *Size*, and execution time in hours (also log), *Execution time*. The specifications include stock-day, participant and broker fixed effects. Standard errors are clustered by participant level. After-hours trading is excluded.

	Dependent variable:							
	Total IS (bps)							
Lit (%)	0.057***							
	(0.020)							
Dark (%)		−0.073***						−0.097***
		(0.022)						(0.024)
Dark (LIS) (%)			−0.161***					−0.203***
			(0.036)					(0.042)
Periodic Auction (%)				−0.012				−0.037
				(0.041)				(0.041)
Auction (%)					0.015			−0.022
					(0.031)			(0.031)
SI (%)						0.023		0.007
						(0.063)		(0.065)
Off-book (%)							0.066**	0.026
							(0.029)	(0.034)
Size	3.876***	3.566***	4.169***	3.586***	3.557***	3.599***	3.582***	4.317***
	(0.646)	(0.631)	(0.635)	(0.617)	(0.641)	(0.619)	(0.619)	(0.673)
Execution time	−0.368	−0.342	−0.395	−0.238	−0.244	−0.234	−0.235	−0.561
	(0.615)	(0.602)	(0.589)	(0.597)	(0.592)	(0.595)	(0.597)	(0.598)
Stock-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Participant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,616	28,616	28,616	28,616	28,616	28,616	28,616	28,616
R^2	0.370	0.371	0.371	0.370	0.370	0.370	0.370	0.371
Adjusted R^2	0.106	0.106	0.106	0.105	0.105	0.105	0.105	0.107
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 5.6: Effect of Venue Trading Share on Implementation Shortfall - Ban Period The table below shows the impact of dark trading on implementation shortfall (IS) for each venue type individually and combined according to Equation 5.1. Parent orders from both the post-BAN and pre-LIFT period are included. In the combined specification (last column) the lit venue is excluded to prevent perfect multicollinearity. Parent orders that have a value of at least GBP 100,000, last 10 minutes or longer, and consist of five or more children are included. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP and parent orders must have a directionality of at least 90%. Parent orders are constructed from trades in the 257 stocks that were subject to a suspension in the BAN period and 225 of those stocks which had their suspension lifted in the LIFT period. The variables of interest are the trading percentages of each parent order on a particular venue. Additional control variables are the (natural logarithm of the) parent order size, *Size*, and execution time in hours (also log), *Execution time*. The specifications include stock-day, participant and broker fixed effects. Standard errors are clustered by participant level. After-hours trading is excluded.

	Dependent variable:						
	Total IS (bps)						
Lit (%)	0.091***						
	(0.019)						
Dark (LIS) (%)		−0.122***					−0.164***
		(0.036)					(0.038)
Periodic Auction (%)			−0.084***				−0.117***
			(0.018)				(0.017)
Auction (%)				−0.036			−0.069**
				(0.029)			(0.030)
SI (%)					0.042		−0.003
					(0.047)		(0.045)
Off-book (%)						0.003	−0.041
						(0.030)	(0.033)
Size	4.401***	4.455***	3.862***	4.009***	3.953***	3.933***	4.681***
	(0.556)	(0.606)	(0.568)	(0.558)	(0.562)	(0.565)	(0.599)
Execution time	−0.103	−0.147	−0.033	0.083	0.057	0.052	−0.269
	(0.624)	(0.611)	(0.610)	(0.598)	(0.609)	(0.610)	(0.607)
Stock-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Participant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,335	28,335	28,335	28,335	28,335	28,335	28,335
R^2	0.376	0.375	0.375	0.375	0.375	0.375	0.376
Adjusted R^2	0.109	0.108	0.108	0.108	0.108	0.108	0.110
Note:							*p<0.1; **p<0.05; ***p<0.01

the transaction cost benefits originate from the characteristics of the venue itself, or the trading flows directed to it, or both. The fact that an improvement for periodic auction trading is only observed after dark trading is constrained implies that flow is important, but, of course, flow is a function of investor choices in response to venue characteristics. There is evidence for a migration of flow in Table 5.2.

Next, the effects of the DVC on execution costs are examined in a Difference-in-Difference setting. The approach is based on the idea that the policy change will have a larger effect on institutional investors that tend to trade more in dark pools. Specifically, the following Difference-in-Difference regression at the market participant level is estimated:

$$IS_{j,t} = \alpha_j + \gamma_t + \beta(Dark\,participant_j \times Post_t) + \epsilon_{j,t}. \tag{5.2}$$

In this specification, α_j and γ_t are participant and day fixed effects; $IS_{j,t}$ denotes the volume-weighted implementation shortfall for participant j on date t; $Dark\,participant_j$ is a dummy variable equaling 1 for active dark pool users and zero otherwise; $Post_t$ equals 1 during the time period after the event, taking the value of 1 for the post-BAN and post-LIFT period and zero otherwise. Active dark pool users are defined as institutional investors above the cross-sectional median of dark pool usage prior to March 12, 2018. Figure 5.2 plots the distribution of volume-weighted dark pool usage by participants during the pre-BAN and shows that the median dark usage is 9.8%.

Regression 5.2 is estimated for both BAN and LIFT periods separately to assess both the effects of the DVC's inception and the lifting of the restriction.

Table 5.7 presents the estimated treatment effects, where standard errors are clustered at the participant level. It is observed that neither the introduction of the DVC nor its suspension had a statistically significant effect and execution costs remained the same.

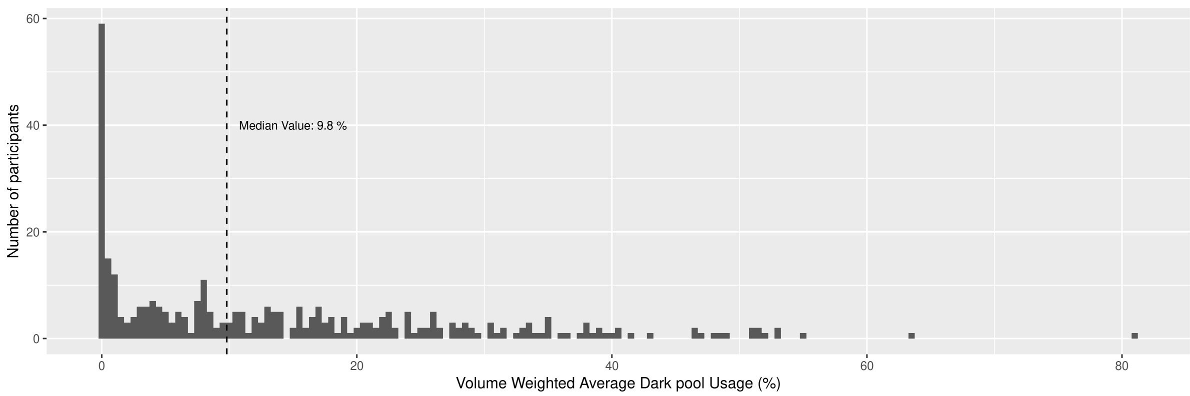
Table 5.7: Effect of Dark Pool Ban and Lift on Implementation Shortfall
The table below shows the baseline Difference-in-Difference estimates for two separate periods: pre-BAN (20 business days, 12 February to 9 March) to post-BAN (20 business days, 13 March to 12 April), and pre-LIFT (20 business days, 14 August to 9 September) to post-LIFT (20 business days, 13 September to 11 October) periods according to Equation 5.2. Observations are participant mean IS constructed from at least 10 parent orders that have a value of at least GBP 100,000, last 10 minutes or longer, and consist of five or more children. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP and parent orders must have a directionality of at least 90%. Parent orders are constructed from trades in the 257 stocks that were subject to a suspension in the BAN period and 225 of those stocks which had their suspension lifted in the LIFT period. Participants are considered treated if they trade at or above the median value of dark trading across participants (are heavy users of dark venues and are thus impacted by the ban/lift), time post equals 1 for the post-BAN and post-LIFT period. Standard errors are clustered by participant level.

	Dependent variable:	
	Total IS (bps)	
	BAN	LIFT
	(1)	(2)
Dark participant×Post	0.519	3.649
	(2.780)	(2.830)
Day FE	Yes	Yes
Participant FE	Yes	Yes
Observations	6,199	5,546
R^2	0.106	0.112
Adjusted R^2	0.048	0.055
Note:	*p<0.1; **p<0.05; ***p<0.01	

This is in support of Hypothesis 5.2. These results show that alternative venues to dark pools provide similar execution cost benefits. A possible explanation is that banned trading flows migrated to these alternatives, which would mitigate the impact of the ban on investor trading costs.

To examine the causes of the insignificant transaction cost effect in more detail, the researchers investigate how dark participants' venue choices changed after the event using a Difference-in-Difference regression. Panel A of Table 5.8 shows that dark users increase their share in Periodic Auctions compared to the non-dark users. They also increase their share in lit venues by an even larger amount. When combined with evidence from Table 5.6, it could be argued that the increase in lit markets has a negative impact on

Figure 5.2: Distribution of Participant Dark Pool Utilization - Pre-Ban Period
Distribution of participants according to average dark pool usage in the pre-BAN period (12 February to 9 March). The average dark pool usage is calculated as a volume-weighted mean across all parent orders on participant level. Parent orders that have at least GBP 100,000 in size, consist of at least five child transactions, and last at least ten minutes are included. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP. Parent orders must have a directionality of at least 90% and must originate from stocks which are liquid and subject to the suspension or lifting. Bin size is 0.5%.



transaction costs, which offsets the positive impact of Periodic Auctions. These findings support Hypothesis 5.3.[17]

5.5.1 Trader Heterogeneity and Venue Choice

Results in the previous section are aggregated across all parent orders and do not capture unobserved behavior of (groups of) participants that execute their parent orders differently based on their level of trading informedness and size. Sağlam et al. (2019) show that trader ability to forecast future returns (informedness) impacts their order size and venue choices. Therefore, the DVC may impact participants of different sizes or forecasting abilities differently.

[17]Additionally, Table 5.11 interacts the venue choice with the event (both Ban and Lift). This helps to identify if the venue choice's impact on transaction cost is changing between periods. In column (1) the interaction between Periodic Auction (%) and Post is significantly negative, while the coefficient in column (2), which compares pre- and post-Lift, remains insignificant. This indicates that initially the switch to Periodic Auctions has a positive impact on transaction costs. Table 5.11 also shows that only the most liquid stocks (FTSE100) are affected, while less liquid stocks (FTSE250) do not show the same transaction cost benefit.

Table 5.8: Effect of Dark Pool Ban and Lift on Participant Venue Choice
The table below shows estimates of Difference-in-Difference for two separate periods: pre-BAN (20 business days, 12 February to 9 March) to post-BAN (20 business days, 13 March to 12 April), and pre-LIFT (20 business days, 14 August to 9 September) to post-LIFT (20 business days, 13 September to 11 October) periods according to the equation $PctVenue_{j,t} = \alpha_j + \gamma_t + \beta(Dark\ Participant_j \times \delta Post_t) + \epsilon_{j,t}$, where $PctVenue_{j,t}$ is the share of participant j trading on each venue on day t, $Dark\ participant_j$ indicates active and non-active dark users, $Post_t$ equals 1 during the time period after the event (post-BAN and post-LIFT). Observations are participant mean venue shares constructed from at least 10 parent orders that have a value of at least GBP 100,000, last 10 minutes or longer, and consist of five or more children. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP and parent orders must have a directionality of at least 90%. Parent orders are constructed from trades in 254 stocks that were subject to a ban in the BAN period, 227 of those stocks which had their bans lifted in the LIFT period. Participants are considered treated if they trade at or above the median value of dark trading across participants (are heavy users of dark venues and are thus impacted by the ban/lift). After-hours are excluded. Standard errors are clustered by participant level.

	Dependent variable:					
Panel A: Ban Event						
	Periodic Auction	Lit	Dark (LIS)	Auction	SI	Off-book
	(1)	(2)	(3)	(4)	(5)	(6)
Dark participant×Post	0.068***	0.123***	0.011	0.019**	0.009**	0.001
	(0.009)	(0.018)	(0.007)	(0.009)	(0.004)	(0.013)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Participant FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,199	6,199	6,199	6,199	6,199	6,199
R^2	0.250	0.438	0.217	0.250	0.562	0.455
Adjusted R^2	0.201	0.402	0.166	0.202	0.533	0.420
Panel B: Lift Event						
Dark participant×Post	−0.075***	−0.095***	0.005	−0.014	−0.015**	0.009
	(0.014)	(0.020)	(0.011)	(0.010)	(0.007)	(0.009)
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Participant FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,546	5,546	5,546	5,546	5,546	5,546
R^2	0.337	0.403	0.208	0.256	0.442	0.470
Adjusted R^2	0.295	0.364	0.157	0.208	0.406	0.436
Note:						*p<0.1; **p<0.05; ***p<0.01

To address this participant heterogeneity, participant types are grouped based on their forecasting precision, which the researchers call informedness, and based on their relative size.

The informedness measure is calculated as the ability to predict a stock i's price movement between the closing price of day t and day $t+1$ ($return(t+1,t)_i$). Afterwards, the following regression is estimated at the participant level:

$$\begin{aligned} return(t+1,t)_i = \beta_0 + \beta_1 Trade\ Side_{i,\tau,p} + \beta_2 Size_\tau \\ +\beta_3 vola_i + \sum_{d=0}^{-4} \gamma_d\, Trade\ Side_{i,\tau,p} \times return(d,d-1)_i + \epsilon_\tau, \end{aligned} \tag{5.3}$$

where $Trade\ Side_{i,\tau,p}$ is 1 for a buying parent order τ in stock i of participant p and -1 for a selling parent order, $Size_\tau$ is the natural logarithm of the trade size (measured in GBP) and $vola_i$ is the stock's intraday transaction price volatility. Additionally, five lagged one-day returns are included. The researchers then follow Sağlam et al. (2019) and define participants as informed when they show a positive and significant sign (estimate of β_1) at the 10 % level.[18]

Additionally, participants are categorized based on their (trade) size. This is done by taking the first and fifth quintile by total parent order size, where a higher quintile means larger size.

Next, Table 5.9 investigates the difference between the informed and matched control group in terms of venue choice. Propensity Score Matching is used to identify the matched control group.[19] The 30 informed participants use lit venues significantly more than the control group, both in times when dark trading is allowed and when dark trading is

[18] There are too few observations with significant and negative coefficients to form the uninformed group.

[19] For the Propensity Score Matching a matching sample out of the residual participants is drawn where the binary dependent variable $informed$ equals 1 if the participant shows a positive and significant coefficient and 0 otherwise. The specification includes the total parent order size, the average parent order size and the number of brokers used as explanatory variables.

prohibited, which is similar to the findings of Sağlam et al. (2019). During periods with no restrictions on dark trading, informed participants route fewer orders to dark venues and auctions (both regular and periodic) which is displayed in columns 'Difference' and 'Difference (Fixed Effects)'. During periods with restricted dark trading, large-in-scale dark shows a significant negative sign. Additionally, the size of the coefficient for periodic auction increases in absolute terms.

The basic Difference-in-Difference approach is augmented by including an indicator if the participant is informed or large according to:

$$\begin{aligned} IS_{j,t} = \alpha_j + \gamma_t + \beta(Characteristic_j \times Dark\,participant_j) + \theta(Post_t \times Dark\,participant_j) \\ + \delta(Dark\,participant_j \times Characteristic_j \times Post_t) + \epsilon_{j,t}, \end{aligned} \tag{5.4}$$

where α_j and γ_t are participant and time fixed effects, $Dark\,participant_j$ indicates active and non-active dark users, $Post_t$ equals 1 during the time period after the event (post-BAN and post-LIFT), $Characteristic_j$ indicates either large vs small or informed vs uninformed (matched) investors. Within each quintile, the median value for dark trading is calculated and participants are assigned to the treatment group, i.e., active dark traders, if they trade above the median value within each quintile.[20] The assignment of participants to their $Characteristic_j$ variable is carried out during the pre-BAN period when comparing the first event and the comparison between pre-BAN and post-LIFT. When examining the second event only, the assignment is based on post-LIFT observations.

Table 5.10 shows the outcome of the estimation results of the modified Difference-in-Difference Equation 5.4 and finds no evidence that informed participants exhibit a

[20] $Dark\,participant_j \times Characteristic_j$ equals 0 if the participant is not an active dark pool user and a member of the lowest quintile, i.e., uninformed or small.

Table 5.9: Venue Shares of Informed Participants - Around Ban and Lift Events
Average usage of venues between the informed group and matched group during periods of dark trading and periods of prohibited dark trading. A comparison is provided between informed investors and a matched control group. Investors are informed if the β_1 coefficient estimate from Equation 5.3 is positive and significant at the 10% level during the pre-BAN and post-LIFT period. Afterwards, informed participants are matched to a control sample based on trade size with a propensity score matching using a nearest neighbor algorithm (logit). Column 'Difference' shows the results of a regular t-test between the two groups. Column 'Difference (Fixed Effects)' shows the results of a regression of the form $venue(\%) = FE_{stock-day} + informed.dummy + \epsilon$. Standard errors are clustered by stock-day. The same sample of 30 treated participants is used for both comparisons. Two participants from the control group are not active during the post-BAN and pre-LIFT period and two new participants are matched based on a Propensity Score Matching (PSM) performed during the post-BAN and pre-LIFT period. The PSM is using 'Total Parent Order Size', 'Average Parent Order Size' and 'Average Number of Brokers'. Standard errors are presented in brackets.

	Informed Share (%)	Matched Share (%)	Difference	Difference (Fixed Effects)
Panel A: Period when dark trading is allowed (pre-BAN and post-LIFT)				
Number of Participants	30	30		
Total Parent Order Size (mln GBP)	5,879	4,212		
Average Parent Order Size (mln GBP)	0.96	1.33		
Average Number of Brokers	11.54	13.32		
Auction	12.80	17.97	-5.17***	-6.21***
			(0.53)	(1.30)
Dark	15.46	24.93	-9.47***	-8.12***
			(0.65)	(1.47)
Dark (LIS)	2.71	3.75	-1.05***	-1.07
			(0.31)	(0.66)
Lit	60.26	42.48	17.78***	16.86***
			(0.76)	(1.72)
Off-book	2.40	3.22	-0.82***	-0.49
			(0.30)	(0.69)
Periodic Auction	3.70	5.23	-1.54***	-1.13*
			(0.28)	(0.60)
SI	2.58	1.97	0.61***	0.45
			(0.21)	(0.46)
Panel B: Period when dark trading is prohibited (post-BAN and pre-LIFT)				
Number of Participants	30	30		
Total Parent Order Size (mln GBP)	4,442	3,356		
Average Parent Order Size (mln GBP)	0.84	1.05		
Average Number of Brokers	12.20	12.12		
Auction	15.51	18.54	-3.03***	-4.31***
			(0.60)	(1.36)
Dark (LIS)	3.30	4.57	-1.28***	-2.08**
			(0.37)	(0.88)
Lit	63.92	53.43	10.49***	14.46***
			(0.81)	(1.79)
Off-book	2.85	4.77	-1.93***	-0.96
			(0.38)	(1.06)
Periodic Auction	11.43	15.98	-4.55***	-7.21***
			(0.59)	(1.37)
SI	2.88	2.46	0.42*	0.31
			(0.24)	(0.49)

significantly different transaction cost impact compared to their matched control group. Table 5.A2 conducts a similar exercise where the specification differentiates participants based on their size (total trading activity), finding no significant differences. In sum, the researchers cannot find evidence for a heterogeneous impact of the DVC across different participants.

5.6 Robustness

A first robustness check investigates how implementation shortfall has changed between periods. Therefore, the implementation shortfall is regressed on a time variable dummy that allows the researchers to compare time periods according to:

$$\begin{aligned} IS_\tau = \alpha + (\beta_n \sum_{n=1}^{N-1} PctVenue_{n,\tau}) \times \delta Post_t \\ + \gamma_1 Size_\tau + \gamma_2 Execution\, time_\tau + FE + \epsilon_\tau, \end{aligned} \tag{5.5}$$

where the time variable $Post_t$ equals to 1 for the post event in each period, i.e., post-BAN or post-LIFT. This supports the substitution theory of periodic auctions. Table 5.11 shows that the ban led to a statistically significant decline in the execution costs associated with periodic auction trading for FTSE100 constituent stocks. Results are insignificant when comparing the pre to post-LIFT period and FTSE250 constituents.

Table 5.12 applies a propensity score matching with different explanatory variables. Informed participants are matched to the control group using the total parent order size, the average parent order size, the number of parent orders and the average number of traded stocks. Results show that informed participants prefer lit venues in the pre-BAN and post-LIFT period. However, the coefficient estimate loses significance in the post-BAN and pre-LIFT period when fixed effects are included. Additionally, the difference

Table 5.10: Effect of Ban and Lift on Informed Dark Participant Implementation Shortfall

The table below displays the Difference-in-Difference estimates including informed and matched participants estimates for two separate periods: pre-BAN (20 business days, 12 February to 9 March) to post-BAN (20 business days, 13 March to 12 April), and pre-LIFT (20 business days, 14 August to 9 September) to post-LIFT (20 business days, 13 September to 11 October) periods according to Equation 5.4. Observations are averaged implementation shortfall measures on participant level from at least 10 parent orders that have a value of at least GBP 100,000, last 10 minutes or longer, and consist of five or more children. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP and parent orders must have a directionality of at least 90%. Parent orders are constructed from trades in 254 stocks that were subject to a Ban in the BAN period, 227 of those stocks which had their bans lifted in the LIFT period. Investors are informed if the β_1 coefficient from Equation 5.3 is positive and significant at the 10% level. Afterwards, informed participants are matched to a control sample based on trade size with a propensity score matching using a nearest neighbor algorithm (logit). Standard errors are clustered by participant level. The specification uses the observation period pre-BAN and post-LIFT to create the treated group. Thereby, 30 matches to the treatment group are identified (i.e., 30 informed investors). Three participants from the control group are not active during the post-BAN and pre-LIFT period and are replaced with three new participants based on a PSM performed during the post-BAN and pre-LIFT period.

	Dependent variable:	
	Total IS (bps)	
	BAN	LIFT
	(1)	(2)
Informed × Post × Dark participant	−2.770	4.812
	(8.206)	(10.401)
Informed × Post	−4.914	−4.559
	(5.988)	(9.137)
Post × Dark participant	−0.957	−6.189
	(6.245)	(7.372)
Day FE	Yes	Yes
Participant FE	Yes	Yes
Observations	1,196	1,122
R^2	0.096	0.137
Adjusted R^2	0.011	0.054
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 5.11: Impact of Event on Implementation Shortfall

The table below shows the impact of the event on implementation shortfall (IS) according to Equation 5.5. In the combined specification the lit venue is excluded to prevent perfect multicollinearity. Parent orders that have a value of at least GBP 100,000, last 10 minutes or longer, and consist of five or more children are included. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP and parent orders must have at least a directionality of 90%. Parent orders are constructed from trades in the 257 stocks that were subject to a suspension in the BAN period and 225 of those stocks which have their suspension lifted in the LIFT period. The variables of interest are the trading percentages of each parent order on a particular venue. Additional control variables are the parent order size, *Size*, and execution time in hours, *Execution time*. The explanatory variables are standardized. The specifications include stock-day, participant and broker fixed effects. Standard errors are clustered by participant level. After-hours trading is excluded. The specification only includes stocks if they are traded on periodic auction venues (at least 1% turnover on periodic auction venues) and exclude trades from participants who trade less than 10 days in each period.

	Dependent variable:			
	IS_total_bps			
	Pre vs Post-BAN	Pre vs Post-LIFT	Pre vs Post-BAN	Pre vs Post-LIFT
Dark (%)	−0.069**	−0.055	−0.094	−0.151**
	(0.032)	(0.034)	(0.074)	(0.069)
Dark (LIS) (%)	−0.127**	−0.122**	−0.367***	−0.294***
	(0.063)	(0.052)	(0.109)	(0.103)
Periodic Auction (%)	0.105	−0.088***	−0.245	−0.135*
	(0.094)	(0.029)	(0.180)	(0.082)
Auction (%)	−0.056	−0.059	0.001	0.028
	(0.036)	(0.067)	(0.091)	(0.098)
SI (%)	0.106	0.058	−0.304	−0.108
	(0.090)	(0.053)	(0.186)	(0.150)
Off-book (%)	0.062	0.008	0.051	0.040
	(0.052)	(0.060)	(0.123)	(0.143)
Size	4.098***	3.916***	5.834***	8.394***
	(0.580)	(0.682)	(1.799)	(2.107)
Execution time	−0.381	−1.065*	1.040	−2.113
	(0.548)	(0.598)	(1.546)	(2.026)
Dark (LIS) (%)×Post	−0.016	−0.049	0.130	0.064
	(0.076)	(0.060)	(0.121)	(0.170)
Periodic Auction (%)×Post	−0.214**	0.086	0.029	−0.078
	(0.098)	(0.059)	(0.196)	(0.128)
Auction (%)×Post	0.010	0.030	−0.072	−0.073
	(0.038)	(0.071)	(0.117)	(0.132)
SI (%)×Post	−0.109	−0.031	0.332	−0.136
	(0.077)	(0.070)	(0.241)	(0.342)
Off-book (%)×Post	−0.049	−0.024	−0.025	−0.001
	(0.044)	(0.060)	(0.149)	(0.193)
Index	FTSE100	FTSE100	FTSE250	FTSE250
Stock-Day FE	Yes	Yes	Yes	Yes
Participant FE	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes
Observations	17,287	16,190	10,126	7,876
R^2	0.252	0.262	0.506	0.524
Adjusted R^2	0.055	0.052	0.047	0.017
Note:				*p<0.1; **p<0.05; ***p<0.01

in dark pool usage is indistinguishable from zero in the pre-BAN and post-LIFT period between the informed and matched group.

The pecking order theory is so far tested with a linear probability model, that only distinguishes between the selected venue (e.g. dark pools) and compares it to all other venues. To incorporate the multi-venue choice a next robustness test uses a multinomial logit model to investigate the pecking order assumption. The model includes all venue alternatives, i.e. auction, dark, dark (LIS), off-book, periodic auction and systemic internalizer venues. Table 5.13 shows the estimation of the multinomial logit model and marginal effects are reported in Table 5.14. They present similar results to the linear probability model. Participants are more likely to first employ dark venues early on in the parent order life-cycle. During periods of dark pool bans, Table 5.13 shows in column (2) a significantly negative coefficient estimate for periodic auctions, which indicates that the probability decreases to select periodic auction venues as the parent order is being worked on.

Table 5.12: Venue Shares of Informed Participants with Alternative Propensity Score Matching - Around Ban and Lift Events
Average usage of venues between the informed group and the matched group during periods of dark trading and periods of prohibited dark trading. A comparison is provided between informed investors and a matched control group. Investors are informed if the β_1 coefficient estimate from Equation 5.3 is positive and significant at the 10% level during the pre-BAN and post-LIFT period. Afterwards, informed participants are matched to a control sample based on trade size with a propensity score matching using a nearest neighbor algorithm (logit). Column 'Difference' shows the results of a regular t-test between the two groups. Column 'Difference (Fixed Effects)' shows the results of a regression of the form $venue(\%) = FE_{stock-day} + informed.dummy + \epsilon$. Standard errors are clustered by stock-day. The same sample of 29 treated participants is used for both comparisons. Four participants from the control group are not active during the post-BAN and pre-LIFT period and new participants are matched based on a PSM performed during the post-BAN and pre-LIFT period. The PSM is using 'Total Parent Order Size', 'Average Parent Order Size', 'Number of Parent Orders' and 'Average Number of Traded Stocks'. Standard errors are presented in brackets.

	Informed Share (%)	Matched Share (%)	Difference	Difference (Fixed Effects)
Panel A: Period when dark trading is allowed (pre-BAN and post-LIFT)				
Number of Participants	29	29		
Total Parent Order Size (mln GBP)	4,853	3,729		
Average Parent Order Size (mln GBP)	1.12	1.26		
Number of Parent Orders	412.11	440.84		
Average Number of Traded Stocks	100.70	124.63		
Auction	10.88	15.50	-4.62***	-4.27***
			(0.51)	(1.40)
Dark	16.84	17.17	-0.33	0.14
			(0.63)	(1.61)
Dark (LIS)	4.22	2.88	1.34***	2.35**
			(0.37)	(0.92)
Lit	57.03	47.89	9.15***	8.77***
			(0.84)	(2.20)
Off-book	5.09	9.79	-4.70***	-6.44***
			(0.54)	(1.48)
Periodic Auction	3.31	4.36	-1.05***	0.25
			(0.26)	(0.67)
SI	2.49	2.40	0.09	-0.82
			(0.24)	(0.53)
Panel B: Period when dark trading is prohibited (post-BAN and pre-LIFT)				
Number of Participants	29	29		
Total Parent Order Size (mln GBP)	3,727	4,019		
Average Parent Order Size (mln GBP)	1.02	1.10		
Number of Parent Orders	406.74	604.95		
Average Number of Traded Stocks	92.29	145.87		
Auction	14.46	17.30	-2.84***	-1.84
			(0.59)	(1.61)
Dark (LIS)	5.46	3.16	2.30***	1.97*
			(0.41)	(1.03)
Lit	59.94	53.60	6.35***	3.23
			(0.88)	(2.30)
Off-book	7.02	11.26	-4.24***	-3.24**
			(0.62)	(1.58)
Periodic Auction	10.74	11.70	-0.96*	0.45
			(0.55)	(1.28)
SI	2.25	2.71	-0.46*	-0.38
			(0.27)	(0.61)

Table 5.13: Parent Order Venue Choice - Multinomial Logit Model
The table below shows the results from a multinomial logit model that shows the probability of a child being executed at a certain time in the life of the parent order on a specific venue. The dependent variable, or discrete choice, thereby indicates on which venue the child order is executed. Column (1) considers periods when dark trading is allowed (pre-BAN and post-LIFT), whereas column (2) considers periods when dark trading is prohibited (post-BAN and pre-LIFT). 'Depletion Bucket' indicates the time in the parent orders life in quintiles, e.g., the first bucket indicates child orders that are executed between 20% and 40% of the parent orders life cycle. The reference level for the model is the lit market.

	Dependent variable:	
	Choice	
	(1)	(2)
Auction (intercept)	−6.094***	−5.919***
	(0.012)	(0.011)
Dark (intercept)	−2.052***	
	(0.004)	
Dark (LIS) (intercept)	−7.003***	−6.942***
	(0.042)	(0.041)
Off-book (intercept)	−2.874***	−2.585***
	(0.005)	(0.004)
Periodic Auction (intercept)	−3.567***	−2.936***
	(0.007)	(0.005)
SI (intercept)	−4.064***	−4.120***
	(0.009)	(0.009)
Auction×Depletion Bucket	0.696***	0.651***
	(0.003)	(0.003)
Dark×Depletion Bucket	−0.028***	
	(0.001)	
Dark (LIS)×Depletion Bucket	−0.079***	−0.122***
	(0.013)	(0.013)
Off-book×Depletion Bucket	0.014***	0.005***
	(0.002)	(0.001)
Periodic Auction×Depletion Bucket	0.008***	−0.005***
	(0.002)	(0.002)
SI×Depletion Bucket	−0.003	−0.027***
	(0.003)	(0.003)
Period	pre-BAN and post-LIFT	post-BAN and pre-LIFT
Observations	4,851,067	4,883,551
R^2	0.011	0.013
Log Likelihood	−3,747,356	−2,897,123
LR Test	79,991*** (df = 12)	75,833*** (df = 10)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5.14: Parent Order Venue Choice - Marginal Effects
Marginal Effects of multinomial regressions presented in Table 5.13.

Lit	Auction	Dark	Dark (LIS)	Off-book	Periodic Auction	SI
Panel A: Periods of dark trading (pre-BAN and post-LIFT)						
-0.025	2.061	-0.109	-0.261	0.019	-0.002	-0.035
Panel B: Periods of no dark trading (post-BAN and pre-LIFT)						
-0.031	1.921		-0.398	-0.015	-0.045	-0.112

5.7 Conclusion

This chapter provides evidence that investors can reduce their execution costs by selecting venues with less pre-trade transparency, such as dark pools or venues with similar characteristics. The researchers find that venue selection decisions matter. By analyzing 58,437 parent orders from 989 distinct market participants, this study observes that the higher the proportion of dark or large-in-scale dark executions in the parent order, the lower its implementation shortfall. It also finds that periodic batch auctions reduce implementation shortfall when dark pools are banned.

Banning one venue type (dark pools) does not affect investor trading costs when similar alternatives exist. Evidence is provided that investors reallocate trading flows in response to a ban on dark pool trading; and these reallocations do not fully reverse after the ban is lifted. The researchers do this by examining the MiFID II DVC mechanism, introduced on 12 March 2018 with the aim of increasing pre-trade transparency by banning dark pool trading in individual stocks. Most UK stocks were subject to the ban. The lifting of the ban is also examined and no impact on investor trading costs for either event is found. Yet, the researchers do observe a substantial reversal towards dark pools after the lift, indicating that investors exhibit a preference for dark pools over periodic auctions. The researchers also find that the dark pool ban or lift does not affect investors of varying sizes or informedness differently.

While previous research has examined the impact of dark pools and low transparency venues on measures of liquidity and measures of trading costs at the individual trade level (such as effective spreads), the researchers investigate their impact on a more complete measure of investor execution costs – implementation shortfall. Individual trade executions within a parent order are not independent; earlier executions can impact subsequent executions. It follows that the venue composition of the parent order matters for determining its overall cost. Consistent with this, this study shows that investors choose venues in a sequence of increasing transparency over the life of the parent order.

5.A Appendix 5.A: Changes in Participant Venue Choices

Table 5.A1 shows that the two events related to DVC have affected venue choices of different market participants.

Panel A shows that Broker-Dealers significantly increase trading in PA venues and off-book during the BAN period. A similar pattern can be seen for HFTs, however their economic increase is smaller compared to Broker-Dealers. Institutional investors increase their share in lit venues and off-book. However, informed institutional investors show a significant reduction in lit venues. Although Panel B shows a decrease for both Broker-Dealers and HFTs in PA venues, Panel C demonstrates that there is an overall trend towards these venues, as the positive coefficient when comparing post-LIFT to pre-BAN is strongly significant. Institutional investors significantly reduce their trading activity from pre-BAN to post-LIFT in both dark and lit venues, but show a significant increase in both PA and off-book transactions.

5.B Appendix 5.B: Duplicate Transaction Reports

For a single trade MDP will typically contain at least two transaction reports, one from each leg of the transaction. The researchers remove redundant transaction reports as follows: For transactions taking place at the same venue, the trading venue's transaction identification code is used to link buy and sell transaction reports. For transactions not sharing the same trading venue transaction identification code, the researchers combine the transaction legs chronologically. Typically, transactions involve several intermediaries, such as central counterparties (CCPs) and brokers providing direct market access. To find the ultimate buyer and seller connected to a transaction, the researchers first eliminate all central counterparties and link both legs of the transaction. Second, direct market access brokers may report transactions with other (direct market access) brokers. In this

Table 5.A1: Changes in Share of Trading by Venue Type and Trader Type - Around Ban and Lift Events

The table below shows the change in trader type participation on each trading venue between event windows. Participation is measured by the ratio of trader type turnover to total turnover per day. This table shows the results of a t-test to compare trader type participation between event windows with clustered standard errors on day level, and report standard errors in parentheses. Event windows are pre-BAN (February 12th to March 9th), post-BAN (March 13th to April 12th); pre-LIFT (August 14th to September 9th) and post-LIFT (September 13th to October 11th). Values are shown in percentage points.

Metric	Auction	Dark	Dark (LIS)	Lit	Off-book	Periodic Auction	SI
Panel A: BAN (pre- vs. post-event)							
Banks	0.06*		0.01**	-0.08***	-0.13	0.02***	-0.06
	(0.03)		(0.01)	(0.02)	(0.38)	(0.00)	(0.11)
Broker-Dealer	0.43		0.05	0.30	2.71***	0.90***	-0.17
	(0.45)		(0.04)	(0.51)	(0.55)	(0.04)	(1.34)
Prop Trader - HFT	0.04		-0.03***	-0.89*	0.13***	0.08***	0.12*
	(0.05)		(0.01)	(0.48)	(0.04)	(0.01)	(0.07)
Institutional	-0.03		-0.03	0.17**	0.58***	0.16***	0.25
	(0.09)		(0.10)	(0.06)	(0.13)	(0.01)	(0.31)
Other	0.01		0.06	-0.03	0.47***	0.03***	0.06
	(0.03)		(0.06)	(0.02)	(0.15)	(0.01)	(0.13)
Panel B: LIFT (pre- vs. post-event)							
Banks	-0.01		-0.00	-0.03*	-0.21	-0.02***	-0.50**
	(0.01)		(0.00)	(0.02)	(0.14)	(0.00)	(0.24)
Broker-Dealer	-0.44		-0.08	-1.30***	-0.29	-0.96***	0.54
	(0.40)		(0.09)	(0.46)	(0.51)	(0.05)	(0.79)
Prop Trader - HFT	-0.05		0.01	-0.04	-0.31*	-0.09***	0.16*
	(0.06)		(0.02)	(0.46)	(0.16)	(0.01)	(0.08)
Institutional	-0.15		0.06	-0.13	0.07	-0.20***	0.21
	(0.13)		(0.11)	(0.10)	(0.09)	(0.02)	(0.27)
Other	0.02		0.11***	0.06**	-0.11	-0.04***	-0.23*
	(0.02)		(0.03)	(0.03)	(0.08)	(0.01)	(0.13)
Panel C: Pre-BAN vs. post-LIFT							
Banks	-0.01	-0.02**	0.00	-0.17***	-0.99***	0.01***	-0.08
	(0.01)	(0.01)	(0.00)	(0.02)	(0.29)	(0.00)	(0.13)
Broker-Dealer	0.80*	-0.61***	0.14*	-2.46***	1.74***	0.63***	0.23
	(0.42)	(0.12)	(0.08)	(0.40)	(0.44)	(0.03)	(0.70)
Prop Trader - HFT	0.03	-0.40***	0.00	0.40	0.05	0.17***	0.79***
	(0.04)	(0.03)	(0.01)	(0.31)	(0.05)	(0.01)	(0.07)
Institutional	-0.14	-0.17***	0.14	-0.78***	0.21***	0.07***	0.09
	(0.09)	(0.03)	(0.10)	(0.09)	(0.06)	(0.01)	(0.30)
	(0.04)	(0.02)	(0.04)	(0.06)	(0.03)	(0.01)	(0.06)
Other	0.02	-0.06***	0.08***	0.13***	0.02	0.02***	0.11
	(0.02)	(0.01)	(0.03)	(0.02)	(0.06)	(0.00)	(0.13)

Table 5.A2: Effect of Ban and Lift on Large Dark Participants Implementation Shortfall

The table below shows the Difference-in-Difference estimates including large and small participants estimates for three separate periods: pre-BAN (20 business days, 12 February to 9 March) to post-BAN (20 business days, 13 March to 12 April), and pre-LIFT (20 business days, 14 August to 9 September) to post-LIFT (20 business days, 13 September to 11 October) periods according to equation 5.4. Size is measured with the participants trading volume. Observations are participant mean IS constructed from at least 10 parent orders that have a value of at least GBP 100,000, last ten minutes or longer, and consist of five or more children. The VWAP of parent orders is not to deviate more than 1bps from 'true' parent order VWAP and parent orders must have at least a directionality of 90%. Parent orders are constructed from trades in the 257 stocks that were subject to a suspension in the BAN period and 225 of those stocks which have their suspension lifted in the LIFT period. Size equals 0 for lowest quintile and 1 for the highest quintile, the middle quintiles are disregarded. Within each quintile, participants are considered treated if they trade at or above the median value of dark trading across participants (are heavy users of dark venues and are thus impacted by the ban/lift), time post is one for the post-BAN and post-LIFT period. Standard errors are clustered by participant level.

	Dependent variable:	
	Total IS (bps)	
	BAN	LIFT
	(1)	(2)
Size × Post	1.278	3.730
	(6.467)	(6.454)
Post × Dark participant	−4.407	4.067
	(9.813)	(10.336)
Size × Post × Dark participant	10.189	1.372
	(10.453)	(10.974)
Day FE	Yes	Yes
Participant FE	Yes	Yes
Observations	2,764	2,578
R^2	0.135	0.153
Adjusted R^2	0.076	0.097
Note:	*p<0.1; **p<0.05; ***p<0.01	

scenario, instead of the CCP, the broker is the intermediary between the client and the other broker. Additionally, trades where no CCP is involved may also be a double report by the involved brokers. In these cases, the researchers identify the ultimate client by eliminating either double reports or removing the intermediary broker. Differentiating between on-market, off-market and OFF-book trades is used to mark possible parent orders. The researchers distinguish OFF-BOOK, OTC and off-market trades. OFF-BOOK trades are bilateral agreements between two parties. If a trade is not specifically flagged (identified with a corresponding waiver as laid out in the Annex of RTS 22) as Over-The-Counter (OTC) or if a trade is executed according to the rules of the venue, the researchers label it OFF-BOOK.[21] Thereby, 'according to the rules of the venue' means that an OFF-BOOK trade will be identified when there is a single transaction report, without any other reported leg and no CCP involved, but reported with the venue market identifier code (MIC) of the trading venue that is not XOFF.[22] Off-market trades are disregarded and not added to off-book trades; they are reports occurring in the XOFF venue that cannot be classified in any category mentioned above.

Mapping parent and child orders

A broker can execute a trade on behalf of a client either as an agency trade or as a principal trade. In MDP agency trades, i.e., when a broker directly executes a client order on-market, the reported trading capacity is 'MTCH' (Matched Principal Trading Capacity) or 'AOTC' (Any Other Trading Capacity). The researchers label both cases as direct agency trading (DAT). A principal trade occurs if a broker performs a transaction against its own books and the trading capacity 'DEAL' is reported. Yet, it is not necessary that the 'DEAL' capacity reflects a proprietary trade. A parent order may occur in the

[21]See Guidelines 5.16.1.3. The researchers combine OFF-BOOK and OTC to off-book trading.
[22]The venue MIC is a code used to identify trading venues.

'DEAL' capacity in two cases:

i) principal trading: it is the sum of executed child orders of the same executing entity (i.e., either a dealer or prop HFT). In principal trading, the researchers can identify the child orders as those coming from the same dealer over a specified trading horizon (e.g., the regular trading hours) and get the (synthetic) parent order by aggregating the child orders using the trade direction. Thus, by construction the coverage ratio equals 100%.

ii) indirect agency trading (IAT): it is the sum of executed child orders of the same executing entity (i.e., dealer) trading on behalf of a client (any institutional investor). In this case, the researchers identify the parent order as any order that is recorded in the XOFF venue where the dealer acts in deal capacity with an institutional investor. However, in this case, it is not certain that the recorded transaction in the XOFF venue is a parent order, because it can in principle be also a prop trade or misreporting.

In a principal or agency trade a parent order is the sum of all executed child orders (at least two) of the same client via an intermediary (i.e., a broker) in the same direction over a regular trading day. The client order can originate from any market participant classified as an institutional investor. In such cases the on-market child transactions are ultimately followed by the parent order between the ultimate client and the broker. The researchers identify such parent orders as orders that are recorded off-venue and where the dealer acts in the deal capacity with an institutional investor. To map child orders to parent orders, the researchers create a rolling sum of one-directional broker transactions, beginning with the Opening Auction, until the corresponding off-venue parent order is filled. The rolling sum is reset once a parent order is filled. In the case of multiple clients per broker it is not clear whether the mapping of child to parent orders is not necessarily unique, e.g., if the broker mixes market execution to fill orders simultaneously. The researchers use information about the investment decision person, i.e., the trader, the desk trader or the ultimate beneficiary to overcome this problem. This approach will still have an issue if there are several client orders per broker-trader ID combination, but will reduce the noise in the initial case where only the broker information is used. Generally, the reporting of the client order execution in the XOFF venue contains the volume-weighted average price (VWAP) the client is paying or receiving for their parent order. Comparing this 'true' order price to the VWAP of the constructed parent is a first quality constraint. The researchers impose that the difference between the two VWAPs must not exceed 1 basis points (bps). However, when applying this narrow comparison criteria, the researchers lose a significant number of potential transactions from the *DAT*. Further analysis is loosening the assumption about the difference in basis points. Next, the researchers combine the *IAT* and *DAT* trades to a synthetic parent order with a maximum execution period of one day. The researchers exclude any parent order with only one child trade and impose a trade directionality of 90%. Directionality is calculated by dividing the absolute difference between buying and selling volume by the sum of both sides. Identification of market participant categories is done via the mapping of the MDP Legal Entity Identifier information to ORBIS and then using the fields 'Peer Group Description' and 'Specialization' from ORBIS to group market participants into aggregate categories.

Chapter 6

Conclusion

In equities markets, institutional investors continue to grow in size and influence. Along with technological advances and the trend towards more sustainable investments, the marketplace is becoming more complex. The traditional picture of institutional investors as active traders who pick their stock and engage with management is still persistent, but their passive counterpart is claiming more market share. This thesis investigates the impact of institutional investors on execution costs, sheds light onto their venue selection and evaluates their relationship with sustainable investment and liquidity.

The first part addresses the complexity under which institutional investors operate. By categorizing the investors into active and passive investment styles, the first part shows that the ownership share of each type influences and impacts liquidity as well as the company's ESG score. Using S&P 500 constituents to limit heterogeneity among companies, the analysis reveals in a Vector Autoregressive environment the inter-temporal relation between the variables. A shock to the system not only impacts variables in a one-way fashion, but highlights the dynamic responses. The study shows that a positive shock to active (passive) ownership increases (decreases) the ESG score, while a positive shock to the ESG score has a negative (positive) effect on the active (passive) ownership share.

The same shock to the ESG score only shows a significantly positive impact on liquidity when active investors are considered. Similarly, different relations between liquidity and investment type can be observed. Additionally, analyzing short-term effects reveals that a positive shock to liquidity only impacts active investors who reduce their share. Similarly, an increase in active (passive) ownership increases (decreases) liquidity in the short-run.

Accounting for the channels through which institutional investors can impact and be impacted by liquidity and ESG scores, part two analyses if ESG investments are profitable by evaluating portfolio returns. ESG-motivated investments might have created a spark upon which other participants who follow different investment strategies, e.g., arbitrage traders, react. The increased demand in ESG titles has an impact on their liquidity and informativeness. Investors are willing to expect negative returns for 'green', or high ESG, assets according to Pástor et al. (2020). However, once the informativeness levels of ESG titles are high, no abnormal returns should be obtained if the efficient market hypothesis is valid. To examine if ESG strategies achieve abnormal returns, portfolios are constructed by ordering stocks according to liquidity, investment style and ESG score. First, this research shows that spreads and hence information asymmetries are lower for high ESG titles compared to low ESG titles. Second, abnormal returns are negative only in the low liquidity portfolio for high ESG scores. The high liquidity portfolios show no significant abnormal returns for any level of ESG score.

In the final part, this dissertation investigates institutional investor trading costs and venue selection decisions. ESG motivated trading strategies require institutional investors to execute large orders which demand liquidity. Institutional investors split these large orders into smaller ones and use a set of available venues to satisfy their liquidity needs. Using a transaction level dataset, results show that investors can reduce their execution costs when using trading venues with no or low pre-trade transparency. The study calculates the implementation shortfall of institutional order executions and demonstrates that using dark pools has a beneficial effect on transaction costs. Using a policy implementation that bans dark trading, the so-called 'double-volume cap', evidence is provided that investor trading costs are not affected. Investors substitute dark pools with alternative trading venues. Specifically, periodic auctions are shown to decrease transaction costs when dark pool trading is not possible. After the ban was lifted, participants moved volume back to dark pools, but significant trading volume has remained on periodic auction venues. Employing a linear probability model evidence for the pecking order introduced by Menkveld et al. (2017) is confirmed. According to the pecking order participants prefer dark pools. Similar preferences are presented for periodic auctions when dark trading is prohibited.

This dissertation uses constituents of the S&P 500 index for some analysis, which can be regarded as large-cap companies. Future research could investigate if ESG as an investment factor behaves differently for small- or mid-cap companies. These companies tend to be not as liquid and hence prices should not have the same level of informativeness as prices for large-cap companies. Additionally, Serafeim and Yoon (2021) examine the reaction of stock prices following different types of ESG news. This indicates that there is a movement from the general to the more detailed selection of ESG-related information that could be investigated further with respect to the impact on stock liquidity and portfolio selection. Moreover, the third part of this dissertation demonstrates the importance of pre-trade transparency in venue selection decisions. The examination of other important factors that determine trading costs, such as the use of passive versus aggressive limit orders, execution algorithm design and broker skill are important avenues for future research.

Appendix: Authorship Statement

Table A1: Author Contribution Share

Author	Concept/ Idea	Methodology and Design	Data Collection and Cleaning	Analysis	Writing
Panel A: Chapter 3 - Dynamics Between ESG Scores, Investment Style and Liquidity					
Christian Neumeier	100	100	100	100	100
Panel B: Chapter 4 - ESG Scores and Stock Performance. The Role of Liquidity					
Christian Neumeier	100	100	100	100	100
Panel C: Chapter 5 - Banning Dark Pools: Venue Selection and Investor Trading Costs					
Arie Gozluklu	15	10	0	15	15
Peter Hoffmann	15	40	0	5	15
Christian Neumeier	10	40	100	60	45
Peter O'Neill	15	10	0	15	15
Felix Suntheim	45	0	0	5	10

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