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Out of the Dark - Shedding Light on the Effects of Fragmentation and Dark Trading on Liquidity

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Abstract

Vor 2007 dominierten nationalen Börsen den Orderflow auf europäischen Aktienmärkten. Mit der Implementierung von MiFID nahm die Fragmentierung der Finanzmärkte erheblich zu und nationale Börsen verloren aufgrund dessen einen hohen Marktanteil an pan-europäische Handelsplattformen. Der Übergang von einer konsolidierten hin zu einer fragmentierten Marktstruktur führte zu mehr Wettbewerb und Innovation in Bezug auf Transaktionen, Gebühren und Transparenz. MiFID begünstigte auch das Entstehen von Dark Pools, d. h. von Handelsplätzen, an denen Transaktionen ohne öffentliche Bekanntgabe von Auftragsdetails durchgeführt werden können. In der EU unterliegen Dark Pools dem Double Volume Cap Mechanism, der den Handel in Dark Pools aussetzt, sobald der Marktanteil von Dark Pool einen bestimmten Schwellenwert überschreitet. Anhand von Paneldaten zu 357 Aktien über einen Zeitraum von mehr als sieben Jahren untersuche ich, ob die Marktfragmentierung und der Handel in Dark Pools positive oder negative Auswirkungen auf die Liquidität haben. Die Ergebnisse zeigen, dass sich die Fragmentierung negativ auf die Liquidität der nationalen Börse auswirkt, indem sie die Kursspannen vergrößert und die Preisauswirkungen erhöht. Die Fragmentierung wirkt sich allerdings auch positiv auf die Liquidität aus, indem sie zu einer geringeren Preisvolatilität führt. Im Gegensatz zu früheren Studien finde ich keine Belege dafür, dass Dark Pools besonders schädlich für die Liquidität von Aktien ist. Im Gegenteil, ich stelle fest, dass Dark Trading die Preisvolatilität von mittelgroßen Unternehmen verringert. Die Ergebnisse machen deutlich, dass angesichts der begrenzten Literatur zu diesem Thema weitere Untersuchungen zu Dark Trading und Liquidität erforderlich sind.

Abstract

Prior to 2007, national exchanges dominated order flow in European equity markets. The implementation of MiFID has fragmented the financial landscape and shifted significant market share to pan-European trading platforms. The transition from a consolidated market structure to fragmented trading venues has led to increased competition and innovation in execution speed, fees, and transparency. MiFID has also facilitated the emergence of dark pools—trading venues that allow transactions without public disclosure of order details. In the EU, dark pool trading is subject to the Double Volume Cap Mechanism, which suspends dark trading if its market share exceeds specified thresholds. Using panel data consisting of 357 stocks over seven years, I assess whether fragmentation of visible markets and dark pool trading exhibit a positive or negative impact on liquidity. The results show that visible fragmentation negatively affects liquidity at the venue level by widening the quoted spreads of the national exchange and by increasing the price impact. However, stocks also experience reduced price volatility, as indicated by narrower intra-day price ranges. In contrast to previous studies, I find no evidence that dark trading is particularly harmful for liquidity. On the contrary, I find that dark trading reduces price volatility, particularly for mid caps. The findings highlight the need for further research on dark trading and liquidity, given the limited existing literature on this topic.

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Nomenclature

AMEX American Stock Exchange

DVCM Double Volume Cap Mechanism

ECN Electronic Communication Network

EoD End-of-Day

EoM End-of-Month

ESMA European Securities and Markets Authority

EU European Union

HHI Herfindahl-Hirschman Index

IV Instrumental Variables

MiFID Markets in Financial Instruments Directive

MiFIR Markets in Financial Instruments Regulation

MPIR Minimum Price Improvement Rule

MTF Multilateral Trading Facility

Nasdaq National Association of Securities Dealers Automated Quotations

NYSE New York Stock Exchange

OTC Over-the-Counter

Reg NMS Regulation National Market System

RM Regulated Market

SI Systematic Internaliser

TRF Trade Reporting Facility

Chapter 1

Introduction

Financial markets have undergone significant transformations over the past few decades, particularly in the structure and nature of trading venues. The rise of electronic trading in the 2000s and the introduction of new regulatory frameworks, such as the Markets in Financial Instruments Directive (MiFID) in the European Economic Area and Regulation National Market Systems (Reg NMS) in the US, have dramatically altered the financial landscape. In the past, secondary market trading used to be consolidated on national exchanges ((Gomber and Pierron, 2010); (Gomber et al., 2023)). National exchanges executed most on-exchange orders, while over-the-counter (OTC) markets processed most off-exchange orders. This was largely because prior to MiFID, most EU countries applied the concentration rule, i.e. on-exchange orders were only allowed to be executed on national exchanges. The introduction of MiFID reshaped the market by eliminating the concentration rule, resulting in a significant growth in alternative trading venues. This has led to the fragmentation of financial markets, where the same stock can now be traded across multiple venues rather than being consolidated on a single national exchange. These new venues compete with each other and also with national exchanges by differentiating their trading attributes such as execution speed, tick size, fees and commissions, and the ability to execute block trades (Bernales et al., 2018). After MiFID came into effect in January 2008, the share of the European equity market held by national exchanges fell from 64% to 45% in just three years (Gentile and Fioravanti, 2011). Meanwhile, the competing trading venues—in the European regulatory framework known as Multilateral Trading Facilities (MTFs)—increased their market share in equities from 0% to 18% over the same period (ibid.). Recent statistics from official EU market authorities indicate that this trend towards increasingly fragmented markets has continued, albeit at a slower pace: In 2022, national exchanges held around 40% market share in equities trading, while MTFs held around 32% (ESMA, 2023).

While competing for order flow, these alternatives offer different innovative features to cater to various types of investors. For instance, some venues utilise a continuous limit order book, which publicly displays order details such as price and quantity, ensuring pre-trade transparency. However, other venues operate without this transparency characteristic, known as dark pools. Dark pools attract investors by offering protection against predatory high-frequency traders, as the lack of pre-trade transparency prevents frontrunning (Petrescu and Wedow, 2017). In these venues, buyers and sellers are usually matched at the midpoint of the best bid and ask of the national exchange. This makes dark pools particularly appealing to traders with large orders, as orders in dark pools don't interact with the market depth of lit[1] exchanges. In contrast, large market orders in lit markets can have a significant price impact because such trades consume liquidity at levels of market depth. The matching algorithm in midpoint dark pools naturally ensures that there is no risk of market impact (ibid.). Additionally, dark pools provide a cost advantage as investors typically do not pay the full spread as they would on lit exchanges. This often results in price improvements, especially in stocks with wider spreads, where the benefit of trading at the midpoint is more pronounced. Petrescu and Wedow (2017) provide evidence that most trades conducted in dark pools resulted in price improvements over similar trades that would have been placed as market orders on lit exchanges. Similar to the increase in fragmentation of trading volume on national exchanges and MTFs, dark trading[2] in Europe has increased since MiFID came into effect. The market share of dark pools in European equity markets has grown significantly, from 1% in 2009 to over 8% in 2016 (Petrescu and Wedow, 2017). Dark trading has become a subject of debate among researchers and regulators, largely due to its uncertain effects on market dynamics and its opacity, which creates an uneven playing field vis-à-vis lit markets (Johann et al., 2019). Additionally, there are concerns that the opacity of trades may hinder the natural price discovery process, as large trades are executed away from visible markets (ibid.). Originally designed to facilitate large block trades without significantly affecting market prices, empirical evidence suggests that dark pools are being used for much smaller trades than expected. A study by Fidessa (2013) reveals that the average trade size in European dark pools fell by more than 66% between 2009 and 2013, while the overall volume of dark trading increased over the same period. Petrescu and Wedow (2017) reveal that only two out of twelve dark pools in Europe have voluntarily implemented a minimum trade size requirement. Notably, the other ten dark pools that did not set a minimum trade size requirement accounted for 94% of the total dark trading volume, with the median trade size within these ten dark pools below EUR 5,000.

The rising market share of dark pools in equities and the surrounding controversies have led EU authorities to take action. In 2018 MiFID II and MiFIR (Markets in Financial Instruments Regulation) were implemented in the European Economic Area, aiming to curb the expansion of dark pools by capping their market share in equity trading.

[1] I refer to markets that provide pre- and post-trade transparency as lit or visible markets, e.g. continuous auction markets.

[2] I refer to dark trading and trades executed in dark pools interchangeably.

Before the regulation took effect, dark pools had reached a peak market share of 12%, following the implementation of MiFID II and MiFIR, their market share fell to 7–8%[3] in 2021 (BigXYT, 2021). These events and developments in financial markets raise the question of whether dark trading and fragmentation are actually detrimental to market microstructure. The existing literature does not provide a clear consensus on the impact of market fragmentation and dark trading on aspects such as spreads, market depth, price discovery or volatility. While some studies suggest that dark pools may improve liquidity by executing large trades away from lit markets, thereby eliminating the market impact, other studies point to increasing spreads and reduced market depth as liquidity migrates from lit to dark markets. Studies on market fragmentation suggest that more competition is beneficial overall, but it also decreases liquidity at the exchange level (Degryse et al., 2015) or harms smaller sized firms ((Gresse, 2017); (Lausen et al., 2022)). Moreover, traders who are unable to route their orders to several exchanges at the same time may be worse off.

I utilise the Double Volume Cap (DVC) files published by the European Securities and Markets Authority (ESMA), which contain data on European dark pools, to estimate monthly dark trading volumes over a time horizon of more than seven years. To my knowledge, no academic paper has been published post-MiFID II that examines the impact of dark pools on liquidity in European equity markets in a time series analysis setting. The dark trading data in this thesis captures, on average, smaller sized dark trades subject to pre-trade waivers set by the EU, which excludes OTC trades, dark trades exceeding a certain volume threshold and trades executed in systematic internalisers. Using a sample of 357 stocks from five of the largest eurozone economies, further divided into subsamples by market size, I test whether lit fragmentation and dark trading impose a positive or negative externality on liquidity. I find that lit fragmentation harms liquidity at the venue level of stocks across all market sizes, as found by Degryse et al. (2015), Gresse (2017) and Lausen et al. (2022). In addition, greater fragmentation leads to higher price impact and lower intra-day price range for large and mid caps. The underlying reason may be because fragmentation disperses liquidity across venues, leading to higher spreads and a higher price impact due to less available liquidity on individual venues. At the same time, intra-day price volatility is reduced due to more efficient cross-exchange arbitrage. The direction of dark trading is less clear: dark trading activity reduces the intra-day price range of mid caps, but the effect on large and small caps remains uncertain. This result may imply that informed traders trade in dark pools, contrary to the findings of previous literature ((Zhu, 2014); (Degryse et al., 2015)).

This thesis contributes to the ongoing debate by examining the impact of both lit fragmentation and dark pool trading on liquidity in the context of post-MiFID II Eu-

[3] This figure excludes block trades waived from pre-trade transparency requirements, OTC trading, trades conducted in systematic internalisers and periodic auctions, iceberg orders, and hidden orders.

ropean financial markets. Furthermore, by using a similar methodological approach to Degryse et al. (2015), I provide an evaluation of their framework and findings within the MiFID II environment. Additionally, I estimate dark trading using the DVC files. I have not come across any paper taking on this approach. The estimation result also serves as an indication of the data quality of the DVC files. The remainder of this thesis is organised as follows: Chapter two presents an overview of the theoretical framework, including a discussion of the relevant literature, a description of the adverse selection problem of dark pools, and a summary of the main regulatory aspects of MiFID I/II. Chapter three examines the data, discusses the control variables and liquidity measures, and provides an overview of the fragmentation and dark trading metrics. Chapter four explains the methodology used in this thesis. This chapter covers the hypotheses, model specifications and strategies to address issues arising from endogeneity. Chapter five presents the empirical results on the impact of lit fragmentation and dark trading on liquidity measures, followed by a discussion of these results. Finally, in chapter six, I provide a conclusion to the thesis and suggest recommendations for future research.

Chapter 2

Theoretical Background

2.1 Literature Review

The literature dating back to the early 2000s has mainly focused on the impact of exchange switching on various aspects of market quality in the US financial market. These studies have examined the movement of listings from Nasdaq, a fragmented dealer market, to the New York Stock Exchange (NYSE) or the American Stock Exchange (AMEX), both of which represent consolidated auction markets. Barclay (1997) provides research on the impact of exchange switches on market quality by analysing securities, which moved from Nasdaq to the NYSE or the AMEX between 1983 and 1992. The study finds that this move resulted in significantly narrower bid-ask spreads. This is attributable to the fact that market maker coordination was less frequent on consolidated markets. Nasdaq market makers had artificially inflated the bid-ask spread of certain stocks by avoiding the odd-eighth tick size.[1] Switching to consolidated markets also leads to a lower probability of informed trading, lower execution costs and reduced price volatility ((Heidle and Huang, 2002); (Bennett and Wei, 2006)). Collectively, these studies suggest an improvement in market quality following a move from Nasdaq to the more consolidated NYSE or AMEX. However, these studies were conducted before significant regulatory changes, such as MiFID in Europe and Reg NMS in the US, which have since dramatically altered market structure. Thus, the fragmentation and market dynamics observed in these studies may not fully represent the post-regulation environment.

Shifting to more recent literature, the focus expands to the impact of fragmentation on liquidity following the introduction of competitors alongside incumbent stock exchanges—a change enabled by the previously mentioned regulations. In contrast to the findings of the previous papers, the introduction of a competing exchange (i.e. increasing fragmentation) leads to an improvement in market quality. Foucault and Menkveld (2008) find that the entry of the London Stock Exchange into the Dutch stock market, led to an increase

[1] Christie and Schultz (1994) provide evidence on this malpractice by Nasdaq market makers.

in consolidated market depth. Chlistalla and Lutat (2011) analyse the post-MiFID entry of Chi-X into the European market and find that spreads of the most actively traded French stocks on Euronext Paris decreased. Similarly, Aitken et al. (2017) find that the entry of Chi-X into the Australian market improved quoted and effective spreads and increased market depth.

Turning to studies that examine fragmentation as a prevailing market condition, O'Hara and Ye (2011) examine US markets and find that more fragmented stocks exhibit lower effective spreads and faster execution times. However, there are some limitations to their results: During their sample period, Electronic Communication Networks (ECNs)—the American equivalent of MTFs in Europe—were required by US regulation to report their trading volume to Trade Reporting Facilities (TRFs), which then report to the US Consolidated Tape, a system that collects and consolidates financial data. The possibility of multiple ECNs reporting to the same TRF complicates the ability to distinguish trading volumes across individual venues, making their fragmentation metric, which is based purely on off-exchange volume, a less reliable measure of fragmentation. Degryse et al. (2015) are able to examine trading volumes by exchange and also differentiate by lit and dark trading, overcoming the issues of O'Hara and Ye (2011). They find that global consolidated depth and best-market depth benefit from lit fragmentation, while liquidity on the main listing exchange deteriorates. They attribute this to the migration of limit orders on the main exchange to competing venues, which reduces liquidity on the main exchange. Further, their findings on the effects of dark trading on liquidity show that it negatively impacts spreads. The authors also show that this is mainly due to large sized dark trades, which contrasts with the results of Hatheway et al. (2017), who find that dark block trades can have a positive effect on liquidity. Contrary to the findings of Degryse et al. (2015), Gresse (2017) finds that both lit and dark fragmentation generally improve market quality of large caps. However, she also highlights the drawbacks of lit fragmentation: The market depth of mid caps decreases with higher fragmentation. Adding to this inconclusive discussion, Buti et al. (2022) explore the effect of dark trading on market quality in US equity markets, dividing their analysis into two time periods: 2009 and 2020. They find that in 2009, a higher dark pool market share and increased OTC trading led to narrower spreads. However, for the 2020 sample, dark trading consistently harms the market quality of large caps.

In conclusion, the effect of fragmentation on market quality is not straightforward. Sample selection, methodology, and the market environment play an important role in shaping the results of these studies. The contradictory results could stem from endogeneity issues associated with dark trading, market quality, and market fragmentation (Johann et al., 2019). It is worth noting that the body of literature on this topic remains relatively limited, especially for the literature on dark trading. For a comprehensive literature review on fragmentation and dark trading, see Gomber et al. (2017).

2.2 The Adverse Selection Problem of Dark Pools

There is an ongoing debate whether dark pools affect price discovery or not. While many studies have centered their research around crossing networks and their interaction with dealer or auction markets, both in theoretical[2] and empirical[3] contexts, the impact of other types of dark pools on market quality remains relatively unexplored (Gomber et al., 2017). Zhu (2014) provides a theoretical basis for the effect of dark trading on price discovery. Building on the famous Kyle model (Kyle, 1985), Zhu (2014) models the competition between a crossing network (dark pool) and a dealer market (exchange). In a manner similar to Kyle's model, there are two types of traders: informed traders, who know the true value of the asset, and uninformed traders, who have intrinsic motivations to trade (e.g. hedging, liquidating assets, or rebalancing portfolios). Market makers on the exchange form expectations about the proportion of informed traders and quote prices accordingly. A higher expected share of informed traders leads to higher spreads due to the adverse selection problem, where market makers protect themselves from potential losses caused by trading with informed traders. Both informed and uninformed traders can choose where to trade. Since informed traders know the true value of the asset, they tend to cluster on the buy or sell side, depending on the true value of the asset. This clustering leads to the self-selection of participants: The dark pool matches buyers and sellers at the midpoint of the exchange. However, because informed traders cluster on one side, there is not enough liquidity on the opposite side from uninformed traders, who are independently and identically distributed and therefore do not cluster. This execution risk leads informed traders to route their orders to the exchange, where they are guaranteed execution but pay higher spreads. Uninformed traders, on the other hand, prefer to trade in dark pools due to more favourable pricing compared to the exchange. According to Zhu (2014), dark pools "cream-skim" noise traders, which can improve price discovery because the exchange retains more information-rich trades. However, this higher level of price discovery comes at a cost, as the adverse selection problem leads to higher spreads and lower liquidity. Market makers anticipate the higher share of informed traders in lit markets an adjust their spreads accordingly.

Supporting Zhu's prediction, Comerton-Forde and Putniņš (2015) find empirical evidence that low levels of dark trading can be beneficial by reducing market impact on lit exchanges and increasing information efficiency, while higher levels of dark trading harm price discovery by increasing adverse selection risks and widening bid-ask spreads. Additionally, Menkveld et al. (2017) provide further evidence on the cream-skimming effect. They theorize that uninformed traders switch back from dark pools to lit markets as the urgency to trade increases. Their empirical analysis shows that midpoint dark pools lose

[2]See e.g. Hendershott and Mendelson (2000), Degryse et al. (2009), Mao and Zhu (2020), Zhu (2014) and Buti et al. (2017).

[3]See e.g. Gresse (2006), Naes and Ødegaard (2006) and Nimalendran and Ray (2014).

4.6% in market share following a 0.01% upward shock in the Volatility Index.

2.3 Regulatory Background in the European Union

2.3.1 MiFID II Definitions

In order to understand the scope of this thesis, I provide a brief overview of the key aspects of MiFID I/II and MiFIR. The time series data analysed in this study covers the period following the implementation of MiFID II and MiFIR, which have had a significant impact on the European financial landscape. Certain aspects of MiFID II and MiFIR, such as the double volume cap are central to this thesis.

Being implemented in 2007, MiFID was a game changer for the European financial market. The key objective of MiFID was to increase market efficiency by changing competition, implementing stricter transparency requirements, and facilitating market entrance. Before MiFID, most secondary market trading took place on national exchanges (Gomber and Pierron, 2010). The abolition of the concentration rule,[4] which required securities transactions to be executed on national exchanges, led to a sharp increase in competition between trading venues (Petrescu and Wedow, 2017). MiFID defines three different types of trading venues, consisting of Regulated Markets (RM), Multilateral Trading Facilities (MTF), and Systematic Internalisers (SI). Dark pools are not defined as a separate type of trading venues, rather they are trading venues that rely on specific pre-trade transparency waivers.

A *Regulated Market* is defined as a "multilateral system managed by a market operator which brings together or facilitates the bringing together of multiple third-party buying and selling interests in financial instruments" (EU Directive 2014/65, Article 4). National stock exchanges usually qualify as regulated markets.

Multilateral Trading Facilities are "operated by investment firms or market operators, which brings together multiple third-party buying and selling interests in financial instruments" (EU Directive 2014/65, Article 4). In broader terms, MTFs are pan-European trading platforms, offering a variety of securities across multiple countries and compete for market share through trading fees, financial innovation and the number of securities traded (Degryse et al., 2015). The definitions of MTFs and RMs are similar, but what distinguishes them in essence is that RMs are subject to stricter regulation, as a significant part of their business involves initial public offerings. MTFs with notable market share in Europe include Turquoise, Bats and Chi-X (both now owned by CBOE Europe), Aquis and Equiduct.

Systematic Internalisers are investment firms that execute client trading orders on

[4]The concentration rule was implemented by some EU member states (France, Italy, Spain, Belgium, to name a few) and was then abolished at supranational level through MiFID.

their own account outside a RM or MTF (EU Directive 2014/65 Article 4), meaning that the counterparty for each buyer or seller would be the investment firm itself. The EU Commission has set quantitative thresholds regarding trading frequency and volume that the investment firm must meet to qualify as a SI (EU Regulation 2017/565, Article 12). SI trading does not involve limit order book trading, however, SIs are required to publish pre-trade transparent bids and asks on a continuous basis and to publish post-trade information through a data reporting facility (Approved Publication Arrangement) "as close to real-time as is technically possible" (EU Directive 2014/65 Article 14 & 15). To give some examples of Systematic Internalisers, HSBC, Goldman Sachs, UBS and many other investment firms offer order internalisation services for equity trading.

2.3.2 Double Volume Cap Mechanism

Regarding markets without pre-trade transparency, EU authorities established a regulatory framework, which entered into force in 2018 called the "volume cap mechanism", also known as the "Double Volume Cap Mechanism" (DVCM). The DVCM aims to control the market share of dark trading, through two caps on trading volume in venues without pre-trade transparency: One that applies to individual dark pools and another that applies to the entire European dark pool market. The first limit states that no single dark pool may account for more than 4% of the total volume in a particular stock over a period of 12 months. A dark pool breaching this limit will have to suspend trading in that stock for a period of six months. The second limit stipulates that dark trading in a single stock must not exceed 8% of total trading volume in the EU over a 12-month period. If this limit is breached, trading without pre-trade transparency is suspended across the EU for a period of six months (EU Regulation 2014/600, Article 5).

The Markets in Financial Instruments Regulation (MiFIR) states that trading in venues without pre-trade transparency is only allowed under four specific price waivers. Price waivers are mechanisms that permit trading in dark markets without the usual requirements of pre-trade information disclosure. MiFIR defines four different price mechanisms for pre-trade transparency waivers namely (i) the reference price waiver, (ii) the negotiated price waiver, (iii) the large-in-scale waiver and (iv) the order management facility waiver (EU Regulation 2014/600, Article 4).

The *reference price waiver* applies to trading systems where the transaction price is determined by referencing a reliable price from another system, e.g. the stock exchange where the specific stock is listed. This is commonly used in dark pools where trades are executed at the midpoint of the best bid and offer prices from a primary exchange.

The *negotiated price waiver* permits transactions within the current volume-weighted bid-ask spread or transactions subject to conditions other than the current market price (e.g. volume weighted average price transaction).

Transactions that are *large in scale* compared to normal market sizes can be exempt from certain transparency requirements. The *large-in-scale waiver* applies to block trades that exceed predefined size thresholds set by MiFIR.

The last waiver applies to orders held in an *order management facility* pending their disclosure to the market. This includes mechanisms such as iceberg orders. Iceberg orders are limit orders that display only a small portion of the total order size, concealing the full quantity. They are generally seen as a substitute for dark pools.

The DVCM applies only to trading venues using the *reference price waiver* and the *negotiated price waiver* on equity instruments that possess a liquid market (EU Regulation 2014/600 Article 5). The intention of this is to allow dark pools to continue their original idea of executing block trades by implementing no limit on this type of trading activity and to implement caps on the amount of smaller but more frequent trades in dark pools.

Whilst the DVCM has achieved its goal of reducing the dark pool market share, it has caused a migration of order flow from dark pools to "quasi-dark[5] markets". Johann et al. (2019) investigate the impact of banning dark pools in equity markets using the double volume cap mechanism as a quasi-natural experiment. The authors find that banning dark pools results in a shift of trading volume to quasi-dark trading systems such as periodic auctions and order internalisation systems, rather than a return to transparent public markets. In terms of market liquidity and price efficiency on lit exchanges, Johann et al. (2019) show that the ban had a negligible impact. Similar results were also found by Anagnostidis et al. (2019), who examined the impact of dark trading on market quality following the implementation of MiFID II in Europe. The study finds that the DVC implementation has led to a 53% increase in iceberg orders in the lit order book. Furthermore, the reduction in dark trading volume resulting from the DVC mechanism led to increased volatility in lit markets contrary to the expectations of the regulators. Ran (2021) finds that before the COVID-19 pandemic, dark pool suspensions improved market liquidity and reduced price discovery. However, in the post-COVID-19 period, these effects were reversed, with suspensions harming liquidity and increasing return volatility.

In the Canadian and Australian financial markets, local regulators have adopted a different approach compared to the EU. Specifically, the Minimum Price Improvement Rule (MPIR) requires dark pools to offer a small price improvement over the national best bid and offer. Comerton-Forde et al. (2018) study the effects of the MPIR in Canadian markets. Similar to the DVCM, the MPIR is an attempt to reduce smaller sized trades in dark pools, as the MPIR applies to orders below 50 standard trading units or 100,000 CAD. Following the implementation of this rule, dark trading decreased by 42%. The

[5]This term was coined by Johann et al. (2019) and refers to trading venues that neither possess full pre-trade transparency, nor exhibit complete pre-trade transparency such as continuous auction markets. Quasi-dark markets include SIs, OTC trading and periodic auctions.

authors find that the reduction in dark pool trading led to no highly significant changes in volatility or effective spreads. Foley and Putniņš (2016) further explore the impact of MPIR in both Canada and Australia, noting that while the regulation reduced dark trading by about a third, it also led to wider spreads and larger price impacts. They also observed a decline in broker internalisation of client orders, as the practice became less profitable post regulation.

In conclusion, the researchers find that the DVCM has had a somewhat underwhelming impact on the European financial landscape,[6] in that the double volume cap partially achieved its intended goal of reducing the dark market share, but also resulted in unintended side effects: For instance, the volume of dark trading fell to 0.15%[7] after the implementation of MiFIR. However, recent reports indicate that dark pool trading has returned to around 9%[8] by April 2019, almost back to pre-MiFIR levels. In addition, while regulators had hoped to see a shift of dark trading volume to lit venues, the market instead saw an increase in the market share of quasi-dark markets and iceberg orders. In the post-Brexit UK, regulators were quick to abolish the DVC regulation, taking a more laissez-faire approach to venues without pre-trade transparency than the EU.[9] The responsible authorities are likely to be aware of the shortcomings associated with the DVCM, as existing research clearly points to its weaknesses. The EU's response to these issues is embedded in the MiFID II/MiFIR review which came into effect in March 2024. Alongside other changes to MiFID II and MiFIR, it abolishes the 4% venue cap and further reduces cap on the EU-level dark pool market share from 8% to 7%.

[6]See Johann et al. (2019), Anagnostidis et al. (2019) and Ran (2021).
[7]European Securities and Markets Authority (2018).
[8]McDowell (2019).
[9]Gregory (2022).

Chapter 3

Data Description, Variables and Descriptive Statistics

3.1 Data Description

Between January 2017 and March 2024, I collect end-of-day (EoD) market data using Refinitiv Datastream. My data collection focuses on all stocks listed on Xetra, Euronext Paris & Amsterdam and Borsa Italiana. I target stocks that are native to their respective stock exchange, i.e. I only collect Dutch stocks listed on Euronext Amsterdam, German stocks listed on Xetra, and so forth. For each stock I collect the EoD market capitalisation, the close, high, and low price as well as the bid and ask price from the main exchange. Additionally, I collect the Euro trading volume from the main exchange and various other trading venues available through Refinitiv Datastream. These venues include both regulated markets and MTFs, such as Turquoise, Aquis Exchange, Equiduct, CBOE (formerly Chi-X and Bats Trading Europe).

Due to the highly restrictive accessibility of dark trading data, I have to rely on estimating dark trading volume using the DVCM files published monthly by ESMA. For each stock, these files contain data on consolidated total trading volume across the EU and dark trading volume under the reference price and negotiated price waiver (also across the EU and broken down by trading venue). Each file corresponds to a twelve-month period during which trading volumes were recorded. In order to accurately estimate end-of-month (EoM) dark trading volumes, I address the limitations of the DVCM files, which only provide data in twelve-month aggregates. To do this, I take several steps to disaggregate dark trading volumes on a monthly basis: First, an assumption is needed in order to calculate the first twelve months of dark trading. I assume that the distribution of dark trading volume in 2017 is correlated with the distribution of lit trading volume in 2017. To implement this approach, I calculate the percentage distribution of lit trading volume for each month in 2017 using market data from Datastream. I multiply these percentages by the total dark trading volume recorded in the first published DVCM file, which contains data from 1 January 2017 to 31 December 2017. This approach allows me to estimate the dark trading volume for each month of 2017, which serves as the basis for completing the EoM dark trading volume data to March 2024. To extend this estimation method beyond 2017, I calculate the delta between consecutive dark trading volumes as reported in each DVCM file. For each delta, I add back the EoM dark trading volume from the first month of the subtrahend file. This method works in theory because each successive DVCM file reflects a twelve-month period that is shifted forward by one month each time a new file is published. For example, to estimate the dark trading volume for January 2020, I calculate the delta between two DVCM files, one from 1 January 2019 to 31 December 2019 and the other from 1 February 2019 to 31 January 2020. I then add the EoM dark trading volume for January 2019 to the delta. By applying this method consistently, I am able to construct a continuous series of estimated monthly dark trading volumes for the entire time horizon. A further refinement is made for stocks that are suspended for breaching the 8% cap, which is explained in the Appendix. In my dataset, 195 out of 357 stocks were suspended at least once throughout the time series, which highlights the importance of controlling for suspensions.

My unfiltered sample consists of 2004 stocks. I remove stocks that don't have order flow data for the first 30 days of the time series. After filtering for trading volume, my sample is reduced to 1205 stocks. I also remove stocks for which no continuous chain of DVCM files could be calculated, as this is a prerequisite for calculating the delta between DVCM files. Some stocks did not appear in every DVCM file, so they were eventually dropped from the sample.[1] 767 stocks are removed from the sample after this filtering measure. To limit the impact of stocks containing data errors, I remove stocks with an average quoted spread above 300bps, a mean Amihud ratio above 1bps and a fragmentation level below 0.01 from the dataset. There is a risk that trading volume by venue is not reported correctly, e.g. trading volume on each venue is close to zero but price movements are high, which would lead to large outliers in the Amihud ratio and the fragmentation proxy. I also noticed that some EoD bid and ask prices were reported incorrectly. For example, in some cases the bid or ask price was not available, which would lead to negative or extremely high quoted spreads. Table 3.1 shows the breakdown of my sample selection pre- and post-filtering measures. After applying all the filtering measures, I divide the sample into three sub-samples: large, mid, and small caps based on their market capitalization. Large caps are stocks with a market value above EUR 10,000m, mid caps are stocks with a market value below EUR 10,000m and above EUR 1,000m and small caps are stocks with a market cap below EUR 1,000m.

[1]The reason for this is unknown to me. I suspect it is due to data reporting and consolidation issues.

Table 3.1: *Sample size and filtering process.*

Initial sample of stocks	**2004**
Filter description	**No. of Stocks removed**
January 2017 trading volume = 0	799
Incomplete data on DVC reporting	767
Mean quoted spread above 300 bps or below 0 bps	14
Fragmentation level below 0.01	33
Mean Amihud ratio above 1bps	34
Total stocks left	357

3.2 Variables

3.2.1 Control Variables

In this section of my analysis, I perform various calculations and transformations on the collected EoD market data for each stock that will end up in the regression. I transform the daily price, market value and total trading volume into monthly averages, to match the time frame of the estimated dark trading volume. For each stock in the dataset, I calculate the daily arithmetic return and subsequently the monthly geometric return of daily arithmetic returns, which is used as a control variable in the regression. I calculate volatility as the monthly standard deviation of daily arithmetic returns. Finally, my control variables consist of the closing price, market capitalisation, trading volume in lit markets, geometric return, and standard deviation. Table 3.2 shows the descriptive statistics of the control variables for each sub-sample from January 2017 to March 2024. The descriptive statistics are in line with general market expectations: Price and trading volume are lower for smaller sized stocks, while return and volatility are higher for smaller sized stocks. Table 3.2 shows that there is positive skewness in several control variables in each sub-sample. The majority of stocks in the sample fall into the mid cap category, outnumbering both large and small cap stocks combined. Large caps and small caps are represented in roughly equal numbers.

Table 3.2: *Descriptive statistics of control variables by firm size.* This table shows the mean, standard deviation (SD), the 25th, 50th (median), 75th quantile, and number of stocks of each control variable for each sub-sample in the dataset. Geometric return and volatility are expressed as percentages; market value and volume are expressed in millions.

	Large Caps					
	Mean	SD	25%	Median	75%	No. of Stocks
Market Value	31,361	27,150	13,733	23,303	40,335	77
Price	71	94	17	42	90	77
Geometric Return	0.44	8.30	-4.14	0.43	4.91	77
Volatility	1.62	0.95	1.04	1.38	1.90	77
Volume	3,511	2,996	1,422	2,695	4,846	77
	Mid Caps					
	Mean	SD	25%	Median	75%	No. of Stocks
Market Value	4,613	4,367	1,827	3,321	5,978	197
Price	60	235	13	27	58	197
Geometric Return	0.52	9.93	-4.94	0.40	5.78	197
Volatility	1.91	1.06	1.24	1.66	2.27	197
Volume	512	680	102	282	658	197
	Small Caps					
	Mean	SD	25%	Median	75%	No. of Stocks
Market Value	892	694	451	707	1,095	83
Price	38	93	6	16	34	83
Geometric Return	1.02	11.53	-5.30	0.43	6.68	83
Volatility	2.16	1.18	1.47	1.92	2.59	83
Volume	68	132	12	25	60	83

3.2.2 Liquidity proxies

Local Quoted Spreads

Liquidity in financial markets can be referred to as the ease with which an asset can be bought or sold in the market without affecting its price. To put it as Y. Amihud wrote: "Liquidity is an elusive concept" (Amihud, 2002, p. 33), it has no definitive metric. When measuring the impact of dark trading on liquidity in a high-frequency environment, relevant literature commonly uses time-weighted or trade-weighted spread measures, such as average quoted spread, effective spread, or price impact and depth measures.[2] Degryse et al. (2015) use, next to the national exchange spread, the best available spread and a global spread measure, which is the spread of the consolidated order book of all lit trading venues in their dataset. This allows for a broader investigation on market quality. Due to limitations in data availability, I can only calculate the EoD quoted spread of the main exchange, which I will refer to as the local quoted spread (LQS). Formally, I calculate the local quoted spread as:

$$\mathrm{LQS} = \frac{P^{\mathrm{ask}} - P^{\mathrm{bid}}}{\frac{P^{\mathrm{ask}} + P^{\mathrm{bid}}}{2}} * 10000, \tag{3.1}$$

where P^{ask} and P^{bid} represent the EoD ask and bid price on the main exchange. The denominator of the fraction is also known as the midpoint or midprice. The equation is multiplied by 10,000 to express the spread in basis points. The daily measure LQS is further transformed into a monthly average.

Amihud Illiquidity Ratio

Amihud (2002) suggests a stock illiquidity ratio when studying the effects of liquidity and asset prices (henceforth referred to as the "Amihud ratio"). The Amihud ratio serves as a measure of illiquidity, indicating the price impact per unit of trading volume (Amihud, 2002). This measure has been widely adopted due to its simplicity and the availability of the necessary data. I compute the Amihud ratio on a daily basis and consequently form the monthly average. As Marshall et al. (2012) show in their study of various liquidity measures, the Amihud ratio has proven to be the most reliable liquidity proxy among other low-frequency measures. It can also be used as a proxy for the price impact, since it reflects the return in relation to its volume (Goyenko et al., 2009), or as a measure of price informativeness (Coën and de La Bruslerie, 2019). Next to the standard Amihud ratio, I also calculate a local Amihud ratio by replacing the total trading volume in lit markets with the trading volume on the national exchange. For a given stock, the Amihud ratio is calculated as follows:

[2] See e.g. Degryse et al. (2015), Gresse (2017) or Buti et al. (2022).

$$\text{Amihud}_t = \frac{|r_t|}{\text{Euro-Volume}_t} * 10,000, \tag{3.2}$$

where the nominator is the absolute arithmetic return of the day-on-day closing price change and the denominator is the euro turnover on lit markets on day t for a given stock measured in thousands of euros. The measure is multiplied by 10,000 to express the ratio in basis points.

Intra-Day Price Range

The price range, which measures the difference between the highest and lowest prices of a stock over a given period, adjusted by the closing price, is particularly useful in medium- to low-frequency trading environments because it captures the intra-day price fluctuations and volatility. Formally, the price range is defined as:

$$\text{Price Range} = \frac{P_{\text{high}} - P_{\text{low}}}{P_{\text{close}}} * 10000. \tag{3.3}$$

Again, this measure is multiplied by 10,000 to express it in basis points.

3.2.3 Fragmentation and Dark Trading

In this section I define the independent variables of interest. There are also issues of endogeneity regarding these variables. An approach to address these concerns is laid out in the subsequent chapter.

Fragmentation

Following the approach of Degryse et al. (2015), I compute the daily Herfindahl-Hirschman Index (HHI) as a proxy for lit fragmentation for each stock in my sample, using the previously mentioned trading volumes by venue. The HHI is calculated as the sum of squared market shares of visible trading venues in my dataset, formally calculated as:

$$\text{HHI}_{it} = \sum_{v=1}^{N} s_{v,it}^2, \tag{3.4}$$

where $s_{v,it}$ is the percentage market share of trading venue v on day t for stock i. The HHI ranges from 0 to 1, with markets dominated by a few trading being characterised by values closer to 1, and highly fragmented markets by values closer to 0. Since the interpretation of the HHI is inverse to its scale, research usually resorts to a linear transformation, so that higher values of this transformation are associated with greater fragmentation and vice versa. The final proxy for lit fragmentation is

$$\text{LitFrag}_{it} = 1 - HHI_{it}, \tag{3.5}$$

such that an equal distribution of visible fragmentation goes to $1 - \frac{1}{N}$ (Degryse et al., 2015). Figure 3.1 shows the median fragmentation level over time for stocks originating from one of the five countries in my sample. Evident from the chart, fragmentation is increasing in each country over time, the exception being Italian stocks. This could be explained by the lower market size and trading volume of Italian stocks, which are strong predictors of fragmentation. Figure 3.2 shows that there is a positive relationship between market capitalization and fragmentation. These results are in line with previous research which often highlights the positive correlation between market capitalization and fragmentation (Degryse et al. (2015) and Lausen et al. (2022)).

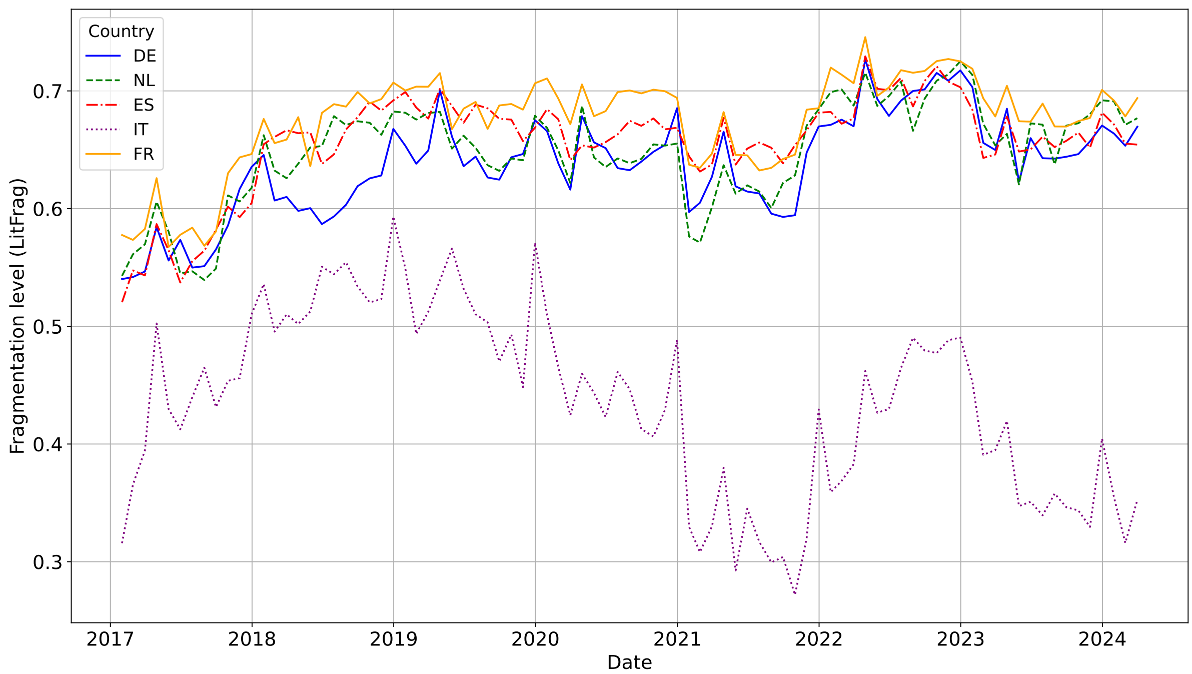

Figure 3.1: *Fragmentation by country over time.* This figure shows the monthly median of lit fragmentation (calculated as *LitFrag*) for each country, beginning from January 2017 till March 2024.

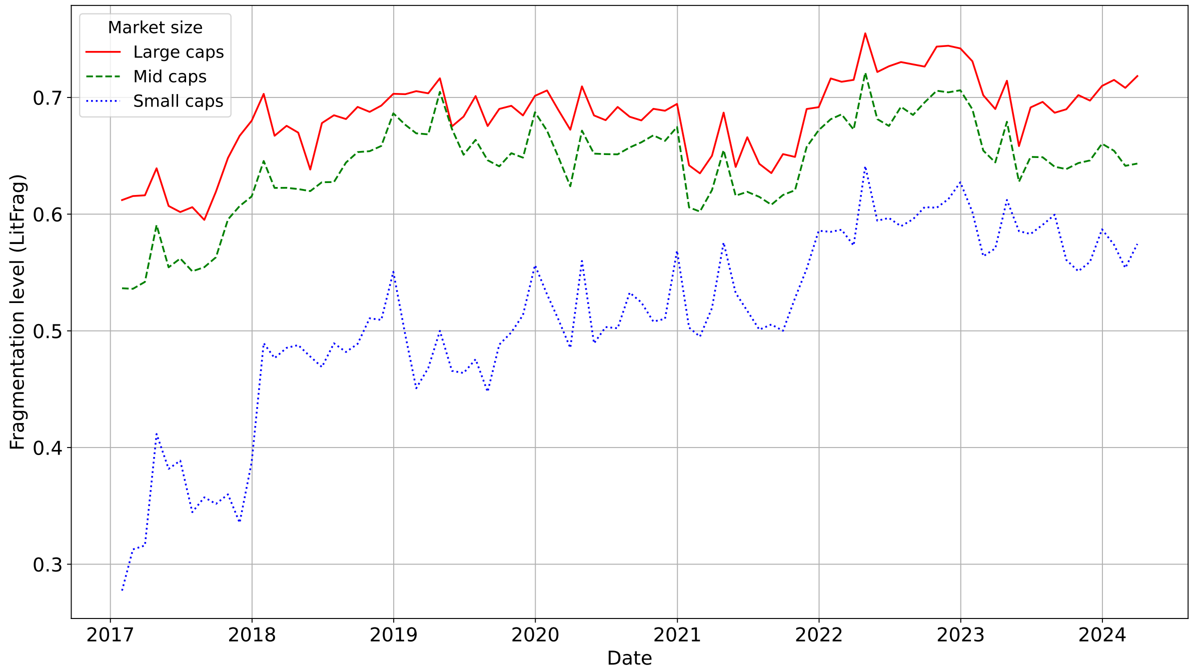

Figure 3.2: *Fragmentation by market size over time.* This figure shows the monthly median of lit fragmentation level (calculated as *LitFrag*) for large, mid and small caps, beginning from January 2017 till March 2024.

Dark Trading

In my thesis, the measure of dark trading is the monthly percentage market share of dark trading volume estimated from the DVCM files, referred to as *Dark*. The market share of dark trading is commonly used as a proxy for dark trading in previous literature. Degryse et al. (2015) and Gresse (2017) use the same proxy with the exception that they include trading volume from OTC markets and SIs, in addition to trading under pre-trade transparency waivers, which is only captured in my proxy. I compute *Dark* as the euro trading volume under pre-trade waivers divided by the total euro trading volume. Using euro turnover provides an advantage over pure share turnover, as it includes the price dimension in the measure (Hatheway et al., 2017). Similar to Degryse et al. (2015) and Gresse (2017), I do not further divide the measure of dark trading into each source of dark pool, as the question of interest is the impact of total dark trading on liquidity and not the fragmentation of dark trading. For research on this specific topic, I would refer to Buti et al. (2022), who use a measure of dark pool fragmentation in their study. Figure 3.3 shows the estimated median dark market share of the whole sample over time. The near constant dark market share in 2017 is explained by my assumption in estimating the dark market share. I assume that dark trading follows a similar distribution as the lit trading in 2017. The sudden drop in dark trading in 2018 is explained by the large number of suspended stocks when the DVC mechanism came into effect. Johann et al. (2019) studying the effect of the DVCM, report a similar sudden decrease in dark trading after the DVCM was enforced. My estimation result is also in line with recent reports stating that the dark market share recovered to pre MiFID II levels.[3] My stock sample does not include British stocks,[4] which are prone to be most frequently traded in dark pools of all European stocks.[5] Excluding British stocks may explain the fact that my estimation of dark market share is on average a few percentage points lower than the reported figures in the articles cited.

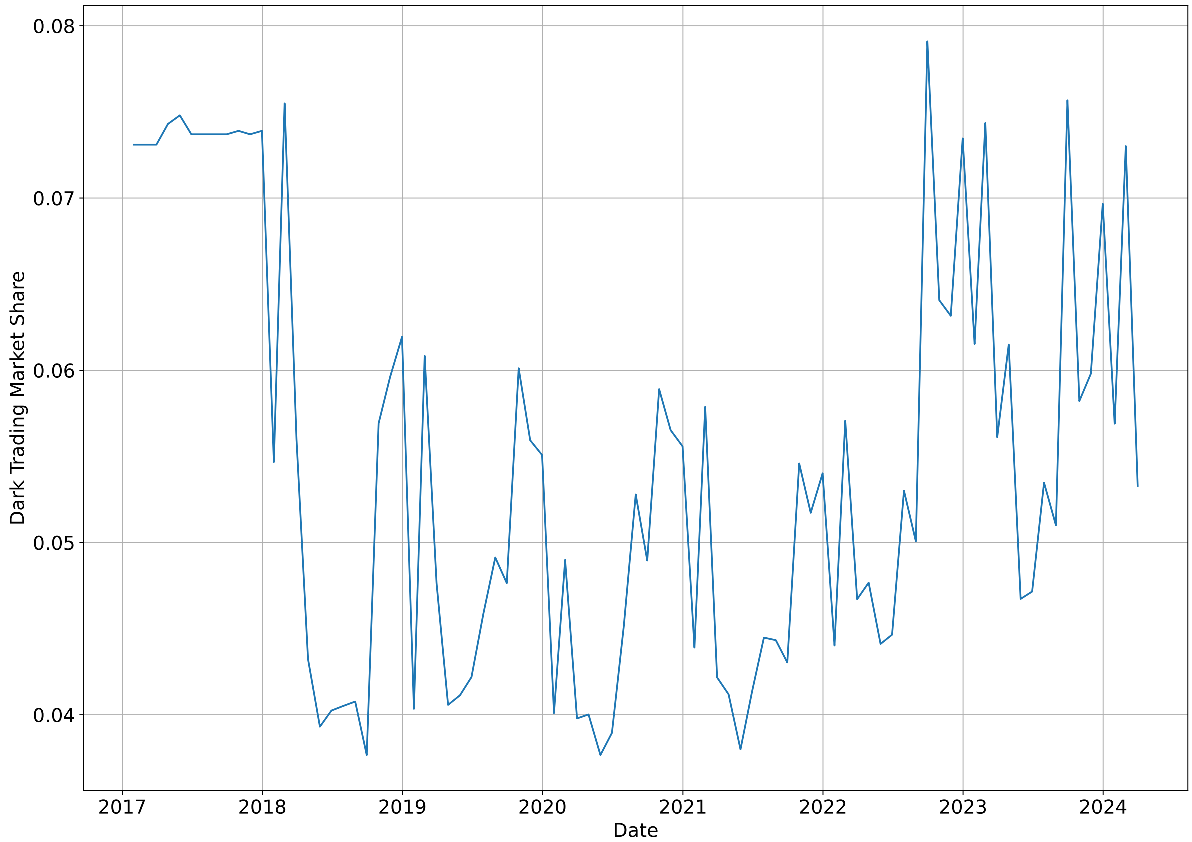

Figure 3.3: *Estimated Market share of dark trading.* This figure shows the monthly median market share of dark venues for the full sample, beginning from January 2017 to March 2024. The market share of dark trading consists of trading under the reference price and negotiated price waivers.

[3]See e.g. McDowell (2019).

[4]The reason being that British stocks are not subject to the DVC mechanism since they left the EU.

[5]Petrescu and Wedow (2017) report that stocks listed on the London Stock Exchange had a dark market share of 12% compared to 8% and 7% of stocks listed in Paris and Frankfurt respectively.

Table 3.3 shows the descriptive statistics of the endogenous and dependent variables. The standard deviation of *Dark* is higher in the mid and small cap sample, indicating greater variability in dark trading for these stock categories. However, it could also indicate a less precise estimation of *Dark* for these stocks. Large caps are on average more liquid than mid and small caps, which is consistent with market expectations. Consistent with Figure 3.2, fragmentation is on average higher and less volatile for large caps in the cross-section.

Table 3.3: *Descriptive statistics of endogenous and liquidity variables by firm size.* This table shows the mean, standard deviation (SD), the 25th, 50th (median), 75th quantile, and number of stocks of each endogenous and liquidity variable for each sample in the dataset. Liquidity variables are expressed in basis points.

	Large Caps					
	Mean	SD	25%	Median	75%	No. of Stocks
LitFrag	0.66	0.08	0.63	0.68	0.71	77
Dark	0.06	0.08	0.03	0.05	0.07	77
Local Quoted Spread	20.66	27.16	5.91	9.59	27.30	77
Amihud Ratio	0.0033	0.0114	0.0005	0.0009	0.0018	77
Price Range	212.40	106.62	147.56	185.33	243.50	77
	Mid Caps					
	Mean	SD	25%	Median	75%	No. of Stocks
LitFrag	0.61	0.12	0.55	0.64	0.69	197
Dark	0.07	0.25	0.02	0.05	0.08	197
Local Quoted Spread	41.57	54.99	13.66	22.37	51.58	197
Amihud Ratio	0.0393	0.1954	0.0044	0.0108	0.0325	197
Price Range	242.51	114.46	170.53	218.40	283.98	197
	Small Caps					
	Mean	SD	25%	Median	75%	No. of Stocks
LitFrag	0.47	0.17	0.35	0.51	0.60	83
Dark	0.06	0.38	0.01	0.03	0.06	83
Local Quoted Spread	78.70	69.22	37.06	60.36	96.44	83
Amihud Ratio	0.29	0.54	0.06	0.14	0.31	83
Price Range	282.44	119.13	205.32	260.15	333.45	83

Chapter 4

Methodology

4.1 Hypotheses

Considering the broader empirical literature, which often identifies a positive relationship between lit fragmentation and various measures of liquidity, I expect—generally speaking—that the liquidity proxies in my thesis will behave similarly to the findings of the previous literature in the context of lit fragmentation. Studies such as O'Hara and Ye (2011) and Foucault and Menkveld (2008) suggest that increased competition between trading venues can improve liquidity by narrowing spreads and increasing market depth. Studies on fragmentation generally find a positive impact on liquidity across different national financial markets. For example, O'Hara and Ye (2011) find positive externalities in the US market, Degryse et al. (2015) demonstrate similar findings in the Dutch market, and Gresse (2017) observe comparable results in the French and British markets. Only when differentiating by the liquidity level or market size, studies tend to find a deteriorating effect of fragmentation . I predict diverging effects: Fragmentation harms liquidity on the venue level but improves it on the global level. This means that the spread measure—which consists of EoD quoted spreads of the national exchange and is therefore a suitable proxy of venue-level liquidity—increases with higher fragmentation. The Amihud ratio and price range, both proxies for liquidity at the global level, decrease with higher fragmentation.

> **H1a:** *Fragmentation decreases liquidity at the venue-level (local quoted spreads increase).*
> **H1b:** *Fragmentation increases liquidity at the global level (Amihud ratio and/or Price Range decrease).*

This prediction is based on the specific findings of Foucault and Menkveld (2008) and Degryse et al. (2015). The rationale is that liquidity disperses across multiple venues due to fragmentation. Market makers route orders to multiple venues, which increases competition for consolidated spreads and increases overall supply but reduces liquidity at the venue level. Following this logic, the dilution of liquidity at the venue level could lead to a higher price impact (also evident from the results of Degryse et al. (2015)). I measure the price impact using the Amihud ratio, which is commonly used as a proxy in the market microstructure literature.[1]

> **H1c:** *The price impact increases with higher fragmentation (Amihud ratio increases).*

The hypotheses *H1b* and *H1c* highlight the complexity of measuring liquidity across fragmented markets. While the Amihud ratio serves as a useful proxy for global liquidity by capturing the general price impact across multiple venues, it also indicates price sensitivity at the venue level. I will also consider the local Amihud ratio based on the trading volume of the national exchange to identify any notable differences between the two measures.

When differentiating by market size, studies find varying results when analysing the effect of fragmentation on liquidity. Degryse et al. (2015) empirically find an optimal level of fragmentation where liquidity is maximised. However, for small and mid cap, increasing fragmentation appears to have a detrimental effect on liquidity, as observed by Lausen et al. (2022) and Gresse (2017). These findings suggest that smaller stocks may lack the order flow necessary to maintain liquidity across multiple venues, resulting in thinner liquidity and a greater price impact in fragmented markets.

> **H1d:** *The liquidity of large caps benefit from higher fragmentation (local quoted spreads, Amihud ratio, and/or intra-day price range decrease).*
> **H1e:** *The liquidity of small and mid caps deteriorates with higher fragmentation (local quoted spreads, Amihud ratio, and/or intra-day price range increase).*

Based on the theoretical framework of Zhu (2014) and the empirical findings from Degryse et al. (2015), I hypothesize to find a cream-skimming effect of dark markets. Theory predicts that due to the trade urgency of informed traders—who choose to trade in lit markets and cluster on one side—liquidity decreases (Zhu, 2014). Degryse et al. (2015) provide evidence for this phenomenon. On the contrary, Gresse (2017) finds mostly no significant or at best a positive effect of dark trading on liquidity. Furthermore, Foley and Putniņš (2016) find that limit order trading in dark pools can have a positive effect on liquidity, while midpoint crossing networks have no consistently significant effect on liquidity. Similarly, Buti et al. (2022) find mixed results in their two time series analyses

[1] E.g. Næs et al. (2011).

conducted in 2009 and 2020. Following the conclusions of these papers, I formulate the null and alternative hypotheses:

H0f: *Dark trading does not cream-skim lit markets (local quoted spreads, Amihud ratio, and/or price range are unaffected or decrease).*
H1f: *Dark trading cream-skims lit markets reducing the liquidity on lit market (local quoted spreads, Amihud ratio, and/or price range increase).*

Based on the theoretical framework from Buti et al. (2017) and the interaction analysis between dark trading and stock liquidity from Degryse et al. (2015), I expect to observe differential liquidity effects based on firm size. Theory suggests that smaller, less liquid stocks may experience a greater negative impact from dark trading due to the migration of limit orders to dark pools. Investors face higher adverse selection risks and seek greater price improvement (Buti et al., 2017). This migration drains liquidity from lit venues, where liquidity is already scarce for smaller stocks. In contrast, the effect may be different for larger, more liquid stocks. Buti et al. (2017) predict that the reduced market impact in dark pools provides incentives for investors to migrate their market orders from lit markets to dark pools. This migration eases the pressure of market orders on liquidity and reduces the competition for spreads between market orders, thereby lowering transaction costs for traders without significantly diminishing market depth (ibid.). This is consistent with the findings of Degryse et al. (2015) and Gresse (2017) regarding the behaviour of limit and market orders in dark pools based on firm size.

H0g: *The interaction between dark trading and firm size does not lead to different effects in liquidity. There is no significant difference in liquidity between large, mid, and small caps due to dark trading.*
H1g: *The interaction between dark trading and firm size leads to different effects in liquidity. There is a significant difference in liquidity between large, mid, and small caps as a result of dark trading.*

I expect to find statistically significant differences in the coefficients of large and mid, or large and small, or mid and small caps to confirm the prediction. I predict that large caps, with their deeper liquidity pools, are less likely to experience severe adverse effects from dark trading, while mid and small caps, with thinner order books, are more likely to experience wider spreads, greater intra-day price ranges and a higher price impact.

4.2 Addressing Endogeneity

Endogeneity poses a significant challenge in assessing the relationship between market fragmentation, dark trading, and liquidity due to potential reverse causality. As highlighted by Johann et al. (2019), the level of liquidity in a stock may influence market fragmentation or dark trading. For example, higher levels of liquidity could attract more trading across different venues, leading to increased fragmentation or increased dark trading. This directional causality complicates the task of determining whether fragmentation and dark trading influence liquidity, or vice versa. As Gresse (2017) notes, endogeneity may arise at several levels when studying the impact of fragmentation on liquidity:

- **Firm Level:** If trading in larger stocks is more fragmented, greater liquidity in more fragmented stocks could merely reflect the fact that larger stocks tend to be more liquid.

- **Order Level:** The decision to route an order to a specific venue or to split it between platforms is endogenous to the relative liquidity levels at each trading venue.

- **Market Level:** Liquidity and fragmentation can be co-determined, with fragmentation affecting liquidity and vice versa. For example, insufficient liquidity in the primary market may drive traders to other markets, while greater liquidity may be necessary to increase fragmentation in newly established trading systems.

4.3 The Model

To address the mentioned endogeneity concerns, I apply an instrumental variables (IV) regression, which is effective in isolating the exogenous variation in the endogenous variables. I follow an approach similar to Degryse et al. (2015), where visible fragmentation, visible fragmentation squared, and dark trading are treated as endogenous variables. I include the squared measure of fragmentation, similar to Degryse et al. (2015), due to the potential existence of a U-shaped relationship between fragmentation and liquidity, which should capture the drawbacks of extreme levels of fragmentation. I use the average levels of visible fragmentation and dark trading for stocks within the same size group, excluding stock i, as instruments. The instruments for $LitFrag$, $LitFrag^2$, and $Dark$ are $AvgLitFrag_{-i,t}$, $AvgLitFrag^2_{-i,t}$, and $AvgDark_{-i,t}$ respectively. The choice of instruments is based on the behaviour of institutional investors, who often trade several stocks within the same size group across different venues on the same day. This trading behaviour creates a positive correlation between the instruments and the endogenous variables. These instruments address the concern of reverse causality, as it is unlikely that changes in the liquidity of a particular stock would directly affect the fragmentation or dark trading levels of other stocks in the same size group, thus ensuring the exogeneity of the instruments (Degryse et al., 2015). In the two-stage regression model, the first stage involves regressing the endogenous variables—fragmentation ($\mathit{LitFrag}_{i,t}$), its squared term ($\mathit{LitFrag}^2_{i,t}$), and dark trading ($\mathit{Dark}_{i,t}$)—on the instruments and control variables (see Table 3.2). To ensure that the isolated variation in fragmentation and dark trading is independent of common liquidity patterns affecting multiple stocks within the same size group, I include the average degree of the dependent liquidity variable for stocks within the same size group, excluding stock i as a control variable, referred to as $\mathit{AvgDV}_{-i,t}$.

The first-stage regression equations are specified as follows:

$$\mathit{LitFrag}_{i,t} = \delta_1 \mathit{AvgLitFrag}_{-i,t} + \delta_2 \mathit{AvgLitFrag}^2_{-i,t} + \delta_3 \mathit{AvgDark}_{-i,t} + \lambda_1 X_{i,t} + u_{i,t}, \quad (4.1)$$

$$\mathit{LitFrag}^2_{i,t} = \delta_4 \mathit{AvgLitFrag}_{-i,t} + \delta_5 \mathit{AvgLitFrag}^2_{-i,t} + \delta_6 \mathit{AvgDark}_{-i,t} + \lambda_2 X_{i,t} + v_{i,t}, \quad (4.2)$$

$$\mathit{Dark}_{i,t} = \delta_7 \mathit{AvgLitFrag}_{-i,t} + \delta_8 \mathit{AvgLitFrag}^2_{-i,t} + \delta_9 \mathit{AvgDark}_{-i,t} + \lambda_3 X_{i,t} + w_{i,t}. \quad (4.3)$$

In these equations, $\mathit{LitFrag}_{i,t}$, $\mathit{LitFrag}^2_{i,t}$, and $\mathit{Dark}_{i,t}$ are treated as endogenous variables. $\mathit{AvgLitFrag}_{-i,t}$, $\mathit{AvgLitFrag}^2_{-i,t}$, and $\mathit{AvgDark}_{-i,t}$ serve as the instruments. $X_{i,t}$ represents a set of control variables that account for other factors influencing the endogenous variables, including the control variables described in Section 3.2 and $\mathit{AvgDV}_{-i,t}$. δ and λ are regression coefficients. Finally $u_{i,t}$, $v_{i,t}$, and $w_{i,t}$ represent the error terms.

The second stage uses the fitted values from the three auxiliary regressions (equations 4.1), (4.2), and (4.3)) in the main model, which is specified as follows:

$$DV_{i,t} = \beta_1 \widehat{\mathit{LitFrag}}_{i,t} + \beta_2 \widehat{\mathit{LitFrag}}^2_{i,t} + \beta_3 \widehat{\mathit{Dark}}_{i,t} + \lambda X_{i,t} + \epsilon_{i,t}, \quad (4.4)$$

where $DV_{i,t}$ is the dependent liquidity variable, being either local quoted spread $\mathit{LQS}_{i,t}$, the Amihud ratio $\mathit{Amihud}_{i,t}$, or the intra-day price range $\mathit{Price\ Range}_{i,t}$ as described in Section 3.2. $\widehat{\mathit{LitFrag}}_{i,t}$, $\widehat{\mathit{LitFrag}}^2_{i,t}$, and $\widehat{\mathit{Dark}}_{i,t}$ are the predicted values from the first stage. $X_{i,t}$ is the same set of control variables used in the first stage. β and λ are regression coefficients. Lastly, $\epsilon_{i,t}$ represents the error term.

To control for firm fixed effects, I perform a within-transformation by subtracting the mean of variable X for firm i (calculated across all time periods) from each observation X_t of that firm. I run a Generalised Method of Moments (GMM) regression, which, unlike Ordinary Least Squares regression, is robust to heteroskedasticity and autocorrelation in the error terms. The GMM estimator minimises the weighted sum of squares of the moment conditions to produce consistent parameter estimates. Further, I apply heteroskedasticity and autocorrelation (HAC) robust standard errors based on five lags.

Chapter 5

The Impact of Lit Fragmentation and Dark Trading

In this section I will provide an overview of the results of equation 4.4, including a review of the hypotheses and a careful interpretation. The coefficients and standard errors of the endogenous variables of the second stage regression are presented in Table 5.1. The full regression tables including the coefficients of the control variables and the results of the first stage are presented in the Appendix.

5.1 Results

The analysis of the impact of lit fragmentation on liquidity for large caps yields a surprising result. In the regression on *Amihud*, the coefficient for *LitFrag* is positive and significant at the 1% level. A one standard deviation increase in visible fragmentation increases the Amihud ratio by 0.0069 bps, which is substantial given that the mean Amihud ratio is 0.0033 bps. In addition, the squared term for $LitFrag^2$ is also significant, indicating a U-shaped relationship with the Amihud ratio. In contrast, for every one standard deviation increase in fragmentation, the price range decreases by 20 bps. In the sample of mid caps, visible fragmentation has a significant negative impact on liquidity. Specifically, a one standard deviation increase in fragmentation is associated with a 29 bps increase in local quoted spreads and a 0.1587 bps increase in the Amihud ratio, both of which represent significant changes in liquidity. The price range decreases significantly with higher fragmentation, falling by 49 bps for every one standard deviation increase. For small caps, the coefficient of *LitFrag* in the regression on local quoted spreads is positive and significant at the 1% level, consistent with the findings of Lausen et al. (2022). A one standard deviation increase in fragmentation leads to a 61 bps increase in local exchange spreads. The effects on other liquidity variables are insignificant in the sample of small caps.

Table 5.1: *The effect of fragmentation and dark trading on liquidity: Second stage regression results of main variables.* The table shows the results from the second-stage IV-GMM regression for large, mid, and small stocks as defined in Section 3.1. Variables of interest are *LitFrag*, *LitFrag²*, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. Dependent variables are local quoted spreads *LQS*, *Amihud ratio*, and *Price Range*. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LQS	Amihud	Price Range
Panel A: Large caps			
LitFrag	77.036	0.0866***	-249.36**
	(74.665)	(0.0277)	(122.24)
LitFrag^2	-22.040	-0.0422**	207.90**
	(53.189)	(0.0189)	(88.472)
Dark	8.4850	-0.0095	10.618
	(26.028)	(0.0088)	(38.855)
Observations	6699	6699	6699
R^2	0.0217	0.1793	0.8919
Panel B: Mid caps			
LitFrag	239.46**	1.3221***	-404.70***
	(98.100)	(0.4151)	(103.32)
LitFrag^2	-158.64**	-0.9500***	319.93***
	(76.063)	(0.3250)	(78.952)
Dark	-26.230	-0.1771	-91.369***
	(30.426)	(0.1511)	(32.691)
Observations	17139	17139	17139
R^2	0.0741	0.0272	0.7771
Panel C: Small caps			
LitFrag	359.13***	-0.0387	-70.453
	(100.02)	(1.1329)	(128.07)
LitFrag^2	-242.79**	-0.0280	22.469
	(95.572)	(1.0448)	(119.35)
Dark	62.199	-0.5438	213.72
	(199.34)	(0.8716)	(151.61)
Observations	7221	7221	7221
R^2	-0.0325	0.1368	0.0307

Pooling mid and large caps together yields similar results regarding fragmentation, evident from Table 5.2. There is weak evidence that fragmentation increases spreads on the main stock exchange, as the coefficient is only significant at the 10% level. However, fragmentation leads to a higher price impact, as shown by the positive coefficient in the regression on *Amihud*. The price range decreases with fragmentation, in line with the regression results for large and mid caps.

Table 5.3 shows the results of the second stage of the linear regression, which excludes the squared fragmentation term from the regression. Otherwise it follows the same methodology described in Section 4.3. Removing $LitFrag^2$ does not lead to substantially different results. The coefficients of *LitFrag* in the regression on *Price Range* are no longer statistically significant, but the effect on local quoted spreads is now more pronounced in the regression on large and mid caps. Overall, the linear regression yields less severe liquidity effects, indicated by the coefficients.

Table 5.2: *The effect of fragmentation and dark trading on liquidity: Second stage regression results of the pooled sample.* The table shows the results of the second-stage IV-GMM regression for stocks above EUR 1,000m. Endogenous variables are *LitFrag*, $LitFrag^2$, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. $AvgDV_{-i}$ is the average dependent variable excluding stock *i*. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LQS	Amihud	Price Range
Pooled Sample			
Log Market Value	33.923**	0.1763**	1.5642
	(13.565)	(0.0862)	(10.062)
Log Price	-41.474**	-0.2353*	-22.624**
	(19.270)	(0.1206)	(9.9479)
Geometric Return	-4.3669	-0.0224	-37.164***
	(4.4627)	(0.0178)	(5.7846)
Volatility	285.84***	1.1264***	6760.3***
	(49.641)	(0.1742)	(166.80)
Log Volume	-9.6955***	-0.0573***	5.1151***
	(1.5116)	(0.0096)	(1.4605)
DV_{-i}	0.6757***		0.3926***
	(0.0578)		(0.0163)
LitFrag	150.17*	0.6745***	-333.39***
	(78.435)	(0.2754)	(85.995)
$LitFrag^2$	-88.959	-0.4512**	267.47***
	(59.996)	(0.2111)	(64.649)
Dark	-18.506	-0.1198	-79.522***
	(24.712)	(0.1105)	(26.661)
Observations	23838	23838	23838
R^2	0.0940	0.0549	0.8155

Table 5.3: *The effect of fragmentation and dark trading on liquidity: Second stage results of the linear regression of main variables.* The table shows the second stage regression results of the linear regression (exluding *LitFrag*^{2}). Variables of interest are *LitFrag* and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. Dependent variables are local quoted spreads *LQS*, *Amihud ratio*, and *Price Range*. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LQS	Amihud	Price Range
Panel A: Large caps			
LitFrag	48.455***	0.0322***	18.977
	(13.791)	(0.0061)	(19.096)
Dark	9.166	-0.0080	2.608
	(26.051)	(0.0088)	(38.345)
Observations	6699	6699	6699
R^2	0.0285	0.2006	0.8926
Panel B: Mid caps			
LitFrag	47.692***	0.1736***	-17.260
	(11.114)	(0.0360)	(14.030)
Dark	-30.767	-0.2121	-81.175***
	(29.228)	(0.1549)	(30.698)
Observations	17139	17139	17139
R^2	0.1003	0.0222	0.7926
Panel C: Small caps			
LitFrag	144.73***	-0.0633	-50.487
	(33.303)	(0.2825)	(38.470)
Dark	20.164	-0.5476	216.02
	(187.77)	(0.8397)	(149.68)
Observations	7221	7221	7221
R^2	0.1227	0.1346	0.0163
Panel D: Pooled sample			
LitFrag	41.122***	0.1210***	-4.7587
	(8.9576)	(0.0259)	(11.840)
Dark	-20.497	-0.1334	-72.650***
	(24.073)	(0.1106)	(25.499)
Observations	23838	23838	23838
R^2	0.1107	0.0560	0.8232

Based on these results, I find strong support for hypothesis *H1a*, stating that fragmentation is detrimental to liquidity at the venue level. The local quoted spreads of mid and small stocks and the pooled sample increase with fragmentation, which is consistent with the findings of Degryse et al. (2015). The results of the linear regression provide further evidence for this hypothesis. I find mixed support for hypothesis *H1b*, stating that global liquidity increases with greater fragmentation. In the large and mid cap sample, the coefficients of the Amihud ratio and the price range do not point in the same direction, leading to an uncertain direction of liquidity. The positive fragmentation coefficient in the *Amihud* regression indicates an increased price impact in lit markets, supporting hypothesis *H1c*. The regression on the local Amihud ratio shows that the price impact of large and mid caps on the national stock exchange has the same relationship with respect to fragmentation as the standard Amihud ratio regression. There is no clear evidence that large caps benefit from higher fragmentation, but I find some support for the hypothesis *H1e*, the liquidity of small and mid caps deteriorates with higher fragmentation. This prediction is more pronounced in the linear regression. These results support the findings of Gresse (2017) and Lausen et al. (2022), who find that fragmentation is detrimental to the liquidity of small and mid caps.

Regarding dark trading, my results mostly show no significant effect on any liquidity parameter across firm size. The exception is the regression on the price range of mid caps and the pooled sample. The price range of mid caps decreases by 23 bps with one SD increase in dark market share. The lack of evidence of a cream-skimming effect of dark pools leads me to fail to reject hypothesis *H0f*. On the contrary, similar to the findings of Gresse (2017), I find that dark trading has at worst no effect on liquidity and at best a positive effect on liquidity. Regarding the interaction between dark trading and firm size, I cannot reject *H0g*. While dark trading has a positive effect on the liquidity of mid caps, the effects on large and small caps are statistically insignificant. The evidence is rather scarce, therefore, I cannot conclude that dark trading leads to significant differential effects across all firm sizes. These results are partially consistent with Buti et al.'s (2017) framework, which predicts that more liquid stocks are better off than less liquid stocks when a dark pool exists next to a lit venue. Nevertheless, the framework needs further testing.

5.2 Discussion

My findings reveal that fragmentation imposes both positive and negative externalities on liquidity, which highlights the complexity of fragmentation. For large and mid caps, greater fragmentation may lead to inefficiencies. While earlier research such as Degryse et al. (2015) and Gresse (2017) indicate certain benefits of fragmentation in large caps, such as tighter global spreads and increased market depth, greater fragmentation leads to higher spreads on the national exchange and higher price impact as measured by the Amihud ratio in my dataset. Traders using smart order routing (SOR) may benefit from the dispersion of liquidity across venues as they can access the global liquidity (Degryse et al., 2015). Degryse et al. (2015) argue, that the greater price impact of fragmentation may stem from informed SOR traders consuming liquidity across venues. However, the consistency between the global and local Amihud ratios suggests that fragmentation reduces market depth around the midpoint both globally and at the local level. Spreads on the national exchange increases with fragmentation in my dataset across different market sizes, in line with the previous findings of Degryse et al. (2015). This may be explained by a migration of limit orders from the local venue to close competitors. On the other hand, there are also benefits of fragmentation as the *price range* of large and mid caps decreases. This could be explained by an improved price discovery process, where the distribution of trading activity across multiple venues leads to more stable prices. Fragmentation enables cross-exchange arbitrage, which can smooth out extreme price movements resulting in a narrower price range (Chen and Duffie, 2021). For small caps, fragmentation seems to worsen liquidity, indicated by larger spreads. Lausen et al. (2022) show that the negative effect of fragmentation on liquidity is more pronounced for smaller stocks, as the already dispersed market depth deteriorates further under increased fragmentation. SOR mitigates the negative effect of dispersing liquidity between trading venues, though according to Lausen et al. (2022), SOR is used less often trading smaller sized stocks than large caps.

Fragmentation has continued to increase since the implementation of MiFID.[1] Chen and Duffie (2021) theorize that too much fragmentation leads to trading inefficiencies in the form of reduced market depth. They argue that while fragmentation initially encourages competition and reduces transaction costs, beyond a certain point, the cross-exchange price impact becomes significant. This leads to overly aggressive trading behaviour and higher volatility, which may counteract the earlier benefits of fragmentation. This theory is in line with the findings of Degryse et al. (2015), who empirically find an optimal level of fragmentation at which market depth is maximized. In Figure 5.1 the implied effect of fragmentation on each liquidity measure is plotted. In mid caps, quoted spreads reach their maximum at $\mathit{LitFrag} = 0.76$. The price range of large and mid caps decreases by 75 bps and 128 bps at $\mathit{LitFrag} = 0.60$ and 0.64, respectively, which is close to the mean fragmentation of the cross-section. Increasing fragmentation beyond this level would diminish the positive effect of fragmentation on the price range

[1]For example, the median fragmentation of Degryse et al. (2015) was 0.30 in 2009 versus 0.68 in my cross-section of large stocks, while applying the same proxy.

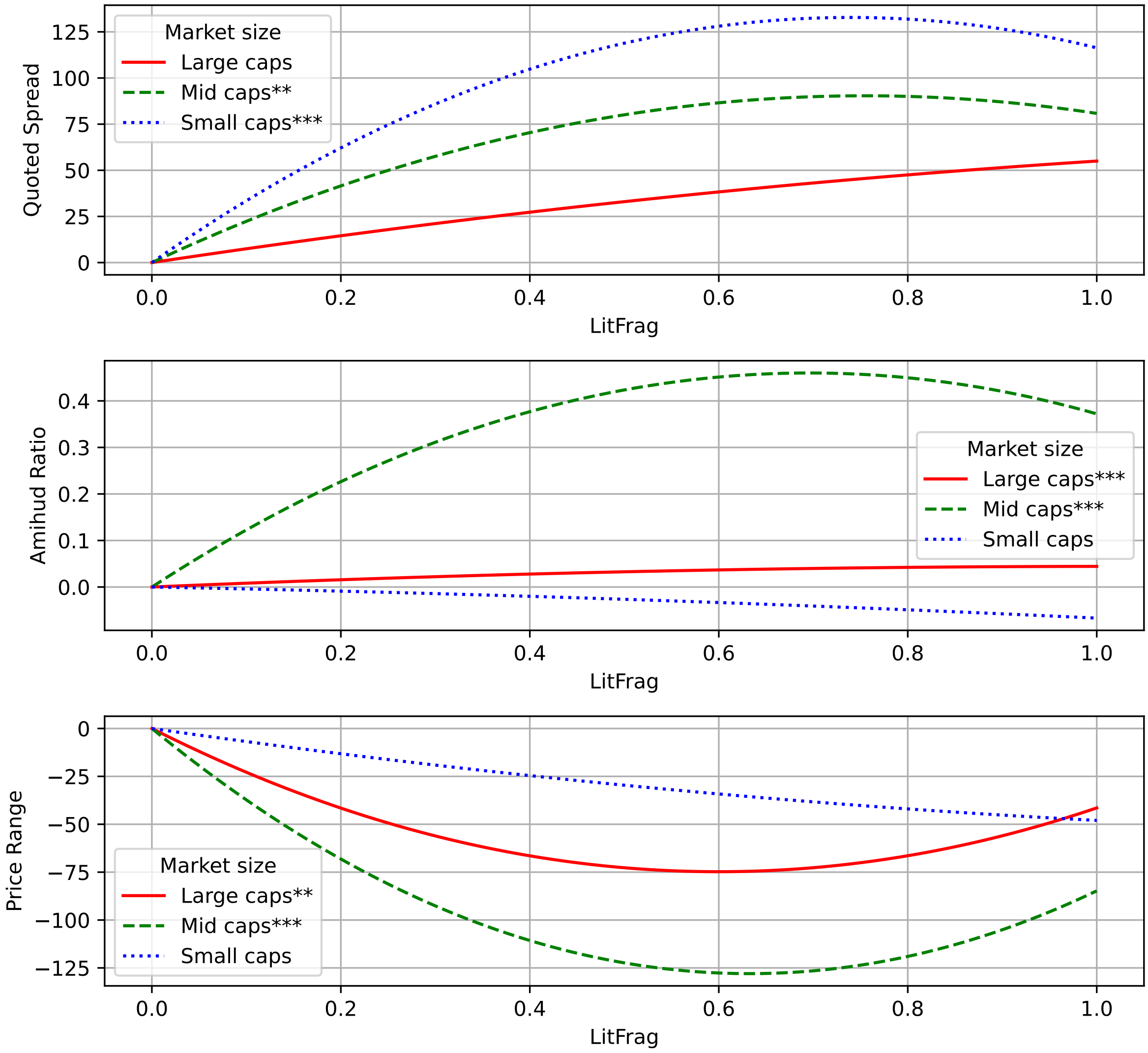

Figure 5.1: *Implied effect of fragmentation on liquidity.* This figure shows the implied effect of *LitFrag* on each liquidity variable. It is a plot of the coefficients of *LitFrag* and *LitFrag²* from Table 5.1 against their implied effects on each liquidity variable. *LitFrag* is calculated as *1-HHI*. *Quoted spread*, *Amihud ratio*, and *Price range* are scaled in basis points. Taken from Table 5.1, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The negative effect of dark trading is not in line with the findings of Degryse et al. (2015), who find that dark trading is particularly detrimental to the liquidity of mid caps. It is worth noting that my proxy for dark trading captures smaller trades on average, as they are subject to the reference and negotiated price waivers, whereas the proxy of Degryse et al. (2015) also includes block trades. When controlling for order size, Degryse et al. (2015) find that the cream-skimming effect of dark trading is attributed to block trades, while smaller trades have no significant effect on liquidity. It is likely that institutional investors (pension funds, insurance companies, mutual funds) use dark pools to execute block trades for reasons other than insider trading, i.e. rebalancing portfolio weights, de-risking, allocating capital to new segments, while informed traders use dark pools relying on the reference and negotiated price waivers because they may not meet the trade size requirements for block trades, hence the cream-skimming effect is not observable in my dataset. Another explanation is offered by the theoretical framework of Mao and Zhu (2020), which in contrast to the model of Zhu (2014) allows for manipulative trading strategies by informed traders, i.e. trading in the dark pool to hide the trading intent, while trading in the opposite direction of the asset's true value in the lit market. Mao and Zhu (2020) argue that dark pools reduce price discovery and volatility by attracting informed traders due to the opacity and reduced price impact. Another issue of the results of dark trading is the efficiency of the instruments. Table A.1 in the Appendix, shows that the endogenous variables are positively correlated with their respective instruments, although much less so for *Dark*. The relatively low F-statistic of 3.19–21.75 indicates rather weak instruments for *Dark*. For *LitFrag* and $LitFrag^2$ the instruments are strong, with F-statistics ranging from 544–1542.[2]

[2]For the F-statistics, see the first stage regression tables in the Appendix.

Chapter 6

Conclusion

Financial markets are complex systems, the transition into a fragmented market has increased rather than reduced complexity. The same is true for recent regulations, such as the double volume cap mechanism. Finding causal relationships between these structural changes is often complicated by issues of endogeneity, the search for reliable instruments, and the accessibility of dark trading data and order flow data. Previous studies have highlighted positive effects of fragmentation on liquidity. However, most of these studies were conducted during periods when markets had already begun to fragment. The empirical data that I provide in Figure 3.2 shows that fragmentation has increased dramatically, thus I raise the question, whether the benefits of further fragmentation still outweigh the drawbacks. Arguably, the early phases of fragmentation in 2007–2009 brought many benefits and opportunities for traders and competing exchanges. However, this might not be the case any more. The results of this analysis reveal nuanced and firm-size-specific effects of lit fragmentation and dark trading on liquidity. Lit fragmentation consistently imposes negative externalities on venue-level liquidity across mid and small caps. Mid caps experience significant increases in quoted spreads and the Amihud ratio, while the price range narrows, suggesting that fragmentation raises costs for traders while slightly improving price stability. For small caps, fragmentation leads to sizeable increases in local quoted spreads, confirming their vulnerability to market dispersion, while other liquidity effects remain insignificant. In large caps, fragmentation exhibits mixed effects on global liquidity. A positive and significant relationship with the Amihud ratio indicates a greater price impact, but the reduction in the price range suggests reduced price volatility.

On the other hand, dark trading does not seem to have a significant detrimental effect on liquidity across firm sizes. For mid caps, dark trading is associated with a narrower price range, implying that informed traders use dark pools that rely on the reference and negotiated price waivers. There is no evidence to support the cream-skimming hypothesis that dark pools disproportionately extract uninformed liquidity from lit markets. In addition, dark trading does not show significant differential effects across firm size, with its impact on large and small caps being statistically insignificant.

My findings on fragmentation are largely consistent with those of Degryse et al. (2015), Gresse (2017), and Lausen et al. (2022), which highlight both the benefits and drawbacks of fragmentation. However, the findings on dark trading are mostly in line with those of Gresse (2017).

The reliance on DVC files for estimating dark trading data presents a vulnerability of this study. However, focusing on trades subject to the reference and negotiated price waivers still captures a meaningful proportion of the market share, around 6-7% of the cross-section. Future research with access to more granular data could provide a more comprehensive understanding of the impact of total dark trading on market liquidity. While the IV approach helps to mitigate endogeneity concerns, the weaker instruments for dark trading indicate that the results for this variable should be interpreted with caution. The relatively low F-statistic suggest that the instruments may not fully capture the causal effects of dark trading. Strengthening the instruments or exploring alternative methods could provide more robust findings in future studies. Moreover, the explanatory power of this model would greatly benefit from high-frequency proxies of global liquidity, like consolidated spreads or market depth, as these provide a broader perspective on fragmentation and dark trading. Due to the unavailability of such data, this was not feasible in this thesis.

Finally, this thesis focuses exclusively on European equity markets under MiFID II, which may limit the applicability of the findings to markets operating under different regulatory environments or with lower levels of fragmentation. This thesis does not offer welfare or policy implications directly but aims to contribute to the literature by providing insights into the complex interplay between market fragmentation, dark trading, and liquidity. The relatively scarce literature on this topic highlights the need for further research in this area. This thesis should aim to motivate further research that can guide policymakers with concise, evidence-based recommendations.

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Appendix A

Appendix

A.1 Additional Information

Table A.1: *Correlation matrix of endogenous variables and instruments.* This table shows the correlation between *LitFrag*, *LitFrag*^{2}, and *Dark* and their respective instruments for large, mid, and small cap stocks.

	Large caps			**Mid caps**			**Small caps**		
	LitFrag	LitFrag^2	Dark	LitFrag	LitFrag^2	Dark	LitFrag	LitFrag^2	Dark
Adj LitFrag (-i)	0.6011	0.6553	-0.0346	0.5481	0.6075	-0.0289	0.5726	0.5824	0.0147
Adj LitFrag (-i)^2	0.6094	0.6737	-0.0364	0.5527	0.6240	-0.0262	0.5736	0.6078	0.0165
Adj Dark Share (-i)	-0.0775	-0.0891	0.1555	-0.0909	-0.0906	0.0620	0.0241	0.0315	0.0141

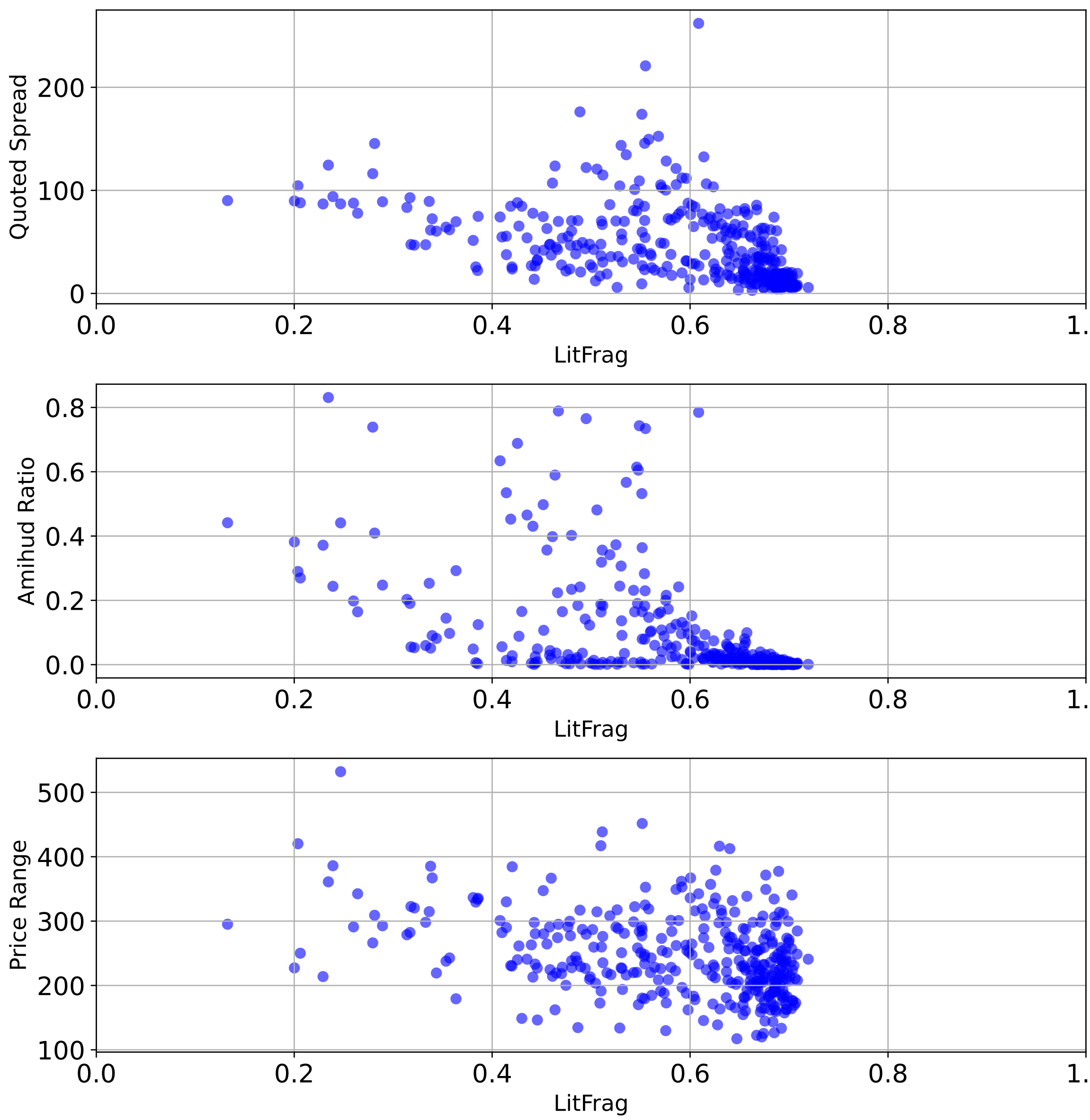

Figure A.1: *Scatter Plot: Liquidity and fragmentation.* This figure shows the mean of each liquidity variable plotted against the mean market capitalisation of each company in the dataset.

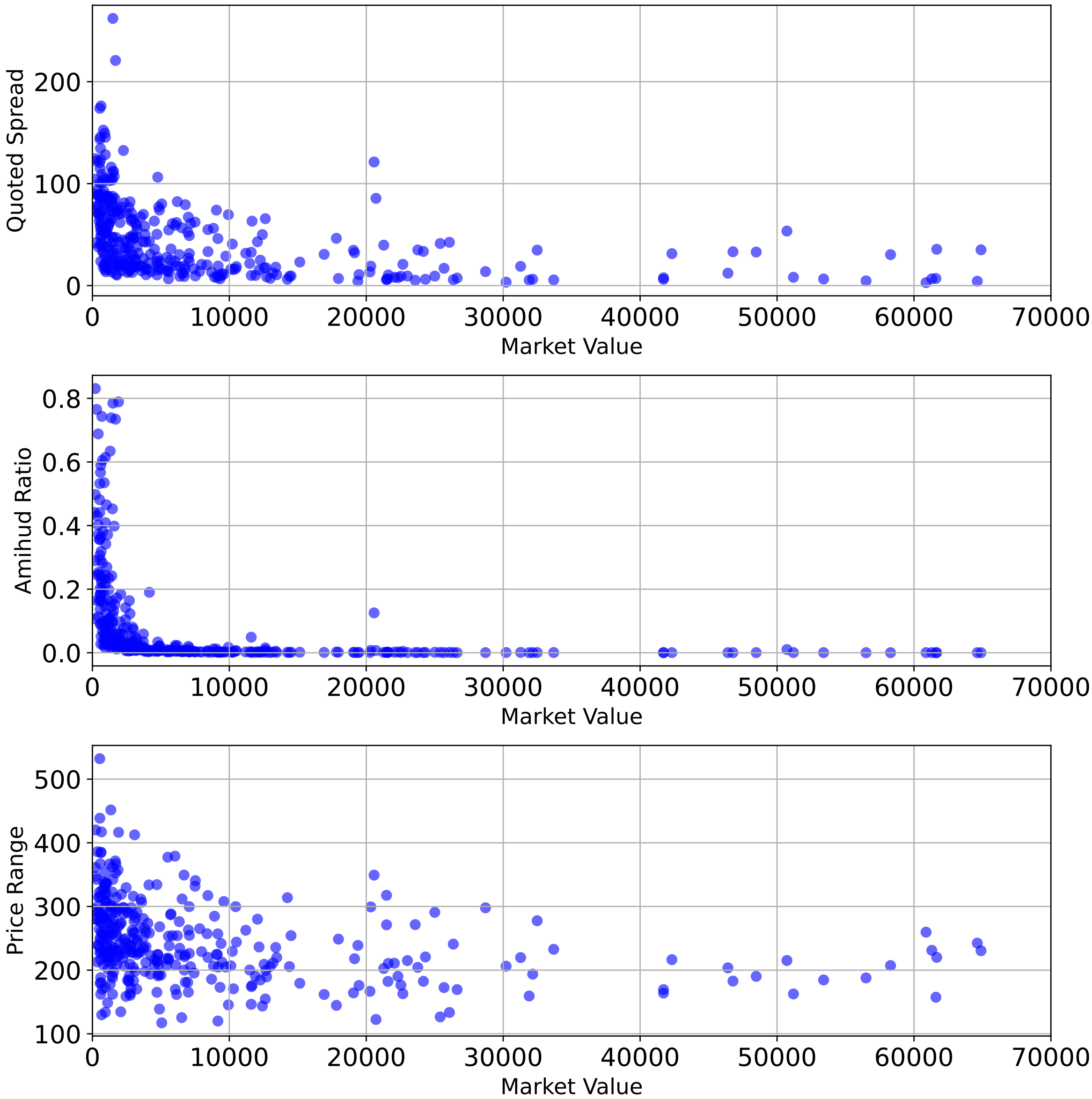

Figure A.2: *Scatter Plot: Liquidity and market capitalisation.* This figure shows the mean of each liquidity variable plotted against the mean market capitalisation of each company in the dataset.

Table A.2: *Descriptive statistics of the pooled sample.* This table shows the mean, standard deviation (SD), the 25th, 50th (median), and 75th quantile of each control, endogenous, and liquidity variable of the pooled sample. *Market Value* and *Volume* are expressed in EUR millions. *Geometric Return* and *Volatility* are expressed in percentages. *Local Quoted Spread*, *Amihud Ratio* and *Price Range* are expressed in basis points. All variables are defined in Section 3.2

	Descriptive Statistics					No. of Stocks
	Mean	SD	25%	Median	75%	
Market Value	12,130	19,115	2,383	5,072	12,753	274
Price	63	205	14	30	67	274
Geometric Return (%)	0.50	9.50	-4.69	0.41	5.51	274
Volatility (%)	1.83	1.04	1.17	1.58	2.18	274
Volume	1,355	2,162	154	485	1,535	274
LitFrag	0.62	0.11	0.57	0.65	0.70	274
Dark	0.07	0.22	0.03	0.05	0.08	274
Local Quoted Spread	35.69	49.70	10.60	19.14	43.60	274
Amihud Ratio	0.0291	0.1658	0.0017	0.0059	0.0213	274
Price Range	234.05	113.12	162.18	208.65	273.56	274

Table A.3: *The effect of fragmentation and dark trading on liquidity: First stage regression results of large caps.* The table shows the results of the first stage IV-GMM regression for stocks with a market cap above EUR 10,000m. Endogenous variables are *LitFrag*, *LitFrag²*, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. $AvgLQS_{-i}$ is the average local quoted spread excluding stock *i*. $AvgLQS_{-i}$ was chosen as an example, the regression is also run using $AvgPriceRange_{-i}$ instead. The impact of this variable on other coefficients is negligible. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LitFrag	LitFrag^2	Dark
Panel A: Large caps			
Log Market Value	-0.0041	-0.0109***	0.0051
	(0.0036)	(0.0037)	(0.0037)
Log Price	0.0018	-0.0102	0.0027
	(0.0064)	(0.0064)	(0.0082)
Geometric Return	-0.2015*	-0.2155***	-0.0603
	(0.1143)	(0.0707)	(0.1338)
Volatility	0.0184***	0.0236***	-0.0039
	(0.0025)	(0.0026)	(0.0035)
Log Total Volume	0.0006***	0.0001	0.0002
	(0.0002)	(0.0001)	(0.0002)
AvgLQS_{-i}	0.0006***	0.0004***	0.0002
	(0.0002)	(7.697e-05)	(0.0002)
AvgLitFrag_{-i}	-0.3039	-1.0782***	0.0784
	(0.2268)	(0.1220)	(0.1504)
AvgLitFrag^2_{-i}	0.8792***	1.7523***	-0.0909
	(0.1694)	(0.0947)	(0.1162)
AvgDark_{-i}	-0.0017	0.0080	0.4683***
	(0.0272)	(0.0138)	(0.0966)
Observations	6699	6699	6699
R^2	0.3941	0.4849	0.0253
F-Statistic	543.96	787.40	21.75

Table A.4: *The effect of fragmentation and dark trading on liquidity: Second stage regression results of large caps.* The table shows the results of the second-stage IV-GMM regression for stocks with a market cap above EUR 10,000m. Endogenous variables are *LitFrag*, *LitFrag²*, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. $AvgDV_{-i}$ is average dependent variable excluding stock *i*. $AvgDV_{-i}$ is excluded from the regression of *Amihud* because of issues arising from multicollinearity. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LQS	Amihud	Price Range
Panel A: Large caps			
Log Market Value	2.1756	0.0121**	-4.7518
	(10.434)	(0.0059)	(8.2616)
Log Price	-4.2261	-0.0115*	-24.957***
	(10.266)	(0.0059)	(7.8752)
Geometric Return	-2.1307	-0.0020	-38.501***
	(2.9324)	(0.0013)	(8.8831)
Volatility	258.83***	0.1964***	7150.8***
	(54.788)	(0.0246)	(200.50)
Log Total Volume	-4.7984***	-0.0088***	6.2765***
	(1.5762)	(0.0014)	(2.2653)
$AvgDV_{-i}$	0.2722***		0.3459***
	(0.0690)		(0.0222)
LitFrag	77.036	0.0866***	-249.36**
	(74.665)	(0.0277)	(122.24)
$LitFrag^2$	-22.040	-0.0422**	207.90**
	(53.189)	(0.0189)	(88.472)
Dark	8.4850	-0.0095	10.618
	(26.028)	(0.0088)	(38.855)
Observations	6699	6699	6699
R^2	0.0217	0.1793	0.8919

Table A.5: *The effect of fragmentation and dark trading on liquidity: First stage regression results of mid caps.* The table shows the results of the first stage IV-GMM regression for stocks with a market cap between EUR 1,000m and EUR 10,000m. Endogenous variables are *LitFrag*, *LitFrag²*, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. $AvgLQS_{-i}$ is the average local quoted spread excluding stock *i*. $AvgLQS_{-i}$ was chosen as an example, the regression is also run using $AvgPriceRange_{-i}$ instead. The impact of this variable on other coefficients is negligible. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LitFrag	LitFrag^2	Dark
Panel B: Mid caps			
Log Market Value	-0.0082*	-0.0109***	0.0097
	(0.0041)	(0.0037)	(0.0077)
Log Price	-0.0123*	-0.0102	-0.0058
	(0.0065)	(0.0064)	(0.0198)
Geometric Return	-0.1414	-0.2155***	-0.3768*
	(0.0865)	(0.0707)	(0.1955)
Volatility	0.0202***	0.0236***	-0.0181***
	(0.0029)	(0.0026)	(0.0049)
Log Total Volume	8.801e-05	9.598e-05	0.0002
	(6.594e-05)	(6.023e-05)	(0.0001)
AvgLQS$_{-i}$	-0.1584	-1.0782***	-0.1618
	(0.1256)	(0.1220)	(0.3397)
AvgLitFrag$_{-i}$	-0.1584	-1.0782***	-0.1618
	(0.1256)	(0.1220)	(0.3397)
AvgLitFrag$^2_{-i}$	0.8268***	1.7523***	0.0974
	(0.0961)	(0.0947)	(0.2644)
AvgDark$_{-i}$	0.0025	0.0080	0.2792**
	(0.0132)	(0.0138)	(0.1031)
Observations	17139	17139	17139
R^2	0.3273	0.4187	0.0064
F-Statistic	1042.00	1542.20	13.76

Table A.6: *The effect of fragmentation and dark trading on liquidity: Second stage regression results of mid caps.* The table shows the results of the second-stage IV-GMM regression for stocks with a market cap between EUR 1,000m - EUR 10,000m. Endogenous variables are *LitFrag*, *LitFrag²*, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. $AvgDV_{-i}$ is average dependent variable excluding stock *i*. $AvgDV_{-i}$ is excluded from the regression of *Amihud* because of issues arising from multicollinearity. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LQS	Amihud	Price Range
Panel B: Mid caps			
Log Market Value	40.284**	0.2141**	4.8092
	(16.421)	(0.1051)	(12.640)
Log Price	-49.562**	-0.2872*	-23.285
	(23.530)	(0.1468)	(12.396)
Geometric Return	-4.7089	-0.0203	-37.426***
	(5.4688)	(0.0214)	(6.9602)
Volatility	305.93***	1.4022***	6659.8***
	(64.489)	(0.2437)	(202.74)
Log Total Volume	-11.095***	-0.0702***	4.8189***
	(1.9104)	(0.0121)	(1.8367)
$AvgDV_{-i}$	0.6792***		0.4071***
	(0.0665)		(0.0201)
LitFrag	239.46**	1.3221***	-404.70***
	(98.100)	(0.4151)	(103.32)
$LitFrag^2$	-158.64**	-0.9500***	319.93***
	(76.063)	(0.3250)	(78.952)
Dark	-26.230	-0.1771	-91.369***
	(30.426)	(0.1511)	(32.691)
Observations	17139	17139	17139
R^2	0.0741	0.0272	0.7771

Table A.7: *The effect of fragmentation and dark trading on liquidity: First stage regression results of small caps.* The table shows the results of the first stage IV-GMM regression for stocks with a market cap below EUR 1,000m. Endogenous variables are *LitFrag*, *LitFrag²*, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. $AvgLQS_{-i}$ is the average local quoted spread excluding stock *i*. $AvgLQS_{-i}$ was chosen as an example, the regression is also run using $AvgPriceRange_{-i}$ instead. The impact of this variable on other coefficients is negligible. All variables are demeaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LitFrag	LitFrag^2	Dark
Panel C: Small caps			
Log Market Value	0.0130	0.0047	0.0505
	(0.0109)	(0.0081)	(0.0329)
Log Price	0.0130	0.0047	0.0505
	(0.0109)	(0.0081)	(0.0329)
Geometric Return	-0.0642***	-0.0506***	0.0050
	(0.0129)	(0.0094)	(0.0159)
Volatility	-0.2286	-0.2558	-0.3038*
	(0.2486)	(0.2053)	(0.2423)
Log Total Volume	0.0287***	0.0233***	-0.0287*
	(0.0045)	(0.0042)	(0.0163)
AvgLQS$_{-i}$	0.0004***	0.0004***	0.0003***
	(0.0001)	(7.697e-05)	(7.942e-05)
AvgLitFrag$_{-i}$	0.0637	-0.5987***	-0.0429
	(0.0983)	(0.0778)	(0.1799)
AvgLitFrag$^2_{-i}$	0.6958***	1.3843***	0.1480
	(0.0930)	(0.0714)	(0.1652)
AvgDark$_{-i}$	-0.0115	-0.0058	0.0349**
	(0.0126)	(0.0093)	(0.0165)
Observations	7221	7221	7221
R^2	0.3899	0.4218	0.0035
F-Statistic	576.27	657.64	3.19

Table A.8: *The effect of fragmentation and dark trading on liquidity: Second stage regression results of small caps.* The table shows the results of the second-stage IV-GMM regression for stocks with a market cap below EUR 1,000m. Endogenous variables are *LitFrag*, *LitFrag²*, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. $AvgDV_{-i}$ is average dependent variable excluding stock *i*. $AvgDV_{-i}$ is excluded from the regression of *Amihud* because of issues arising from multicollinearity. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	LQS	Amihud	Price Range
Panel C: Small caps			
Log Market Value	-25.484	0.1098	-5.7952
	(22.353)	(0.1595)	(17.586)
Log Price	10.222	-0.0579	-37.750**
	(21.648)	(0.1269)	(13.547)
Geometric Return	8.7525	-0.0892	-51.163**
	(8.0782)	(0.0597)	(22.952)
Volatility	544.71***	7.5168***	5263.7***
	(186.22)	(1.6249)	(951.29)
Log Total Volume	-19.259***	-0.3500***	31.400***
	(7.0620)	(0.0447)	(8.2909)
AvgDV_{-i}	0.5989***		0.4424***
	(0.0981)		(0.0571)
LitFrag	359.13***	-0.0387	-70.453
	(100.02)	(1.1329)	(128.07)
LitFrag^2	-242.79**	-0.0280	22.469
	(95.572)	(1.0448)	(119.35)
Dark	62.199	-0.5438	213.72
	(199.34)	(0.8716)	(151.61)
Observations	7221	7221	7221
R^2	-0.0325	0.1368	0.0307

Table A.9: *The effect of fragmentation and dark trading on liquidity: Second stage regression on local Amihud ratio.* The table shows the results of the second-stage IV-GMM regression on the local Amihud ratio (only taking trading venue of the national exchange into account) for large, mid and small caps. Endogenous variables are *LitFrag*, *LitFrag²*, and *Dark*. *LitFrag* is calculated as *1-HHI* and *Dark* as the market share of trading under the reference and negotiated price waivers. All variables are de-meaned by their in-sample average. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors based on 5-lags are given in parentheses below coefficients. Coefficients are measured in bps.

	Large caps	Mid caps	Small caps
Local Amihud ratio			
Log Market Value	32.306*	39.052*	44.431
	(19.539)	(20.481)	(59.219)
Log Price	-35.734*	-62.631**	-61.007
	(19.721)	(27.756)	(54.252)
Geometric Return	-7.0212	3.8493	-33.384
	(7.7897)	(6.3109)	(46.898)
Volatility	81.498	223.58***	-99.505
	(55.274)	(72.567)	(251.09)
Log Total Volume	-15.608***	-4.1005*	-15.532
	(4.3842)	(2.4306)	(13.490)
LitFrag	214.66**	359.23***	284.26
	(106.81)	(120.29)	(337.73)
LitFrag^2	-104.64	-225.19**	-141.74
	(73.627)	(92.157)	(340.09)
Dark	-54.108	26.171	-282.21
	(35.764)	(33.187)	(283.94)
Observations	6699	17139	7221
R^2	0.8919	0.0140	-0.0621

A.2 Methodology for Dark Trading Suspensions and Review of the Estimation Method

My estimation method accounts for trading suspension arising from breaching the volume caps. I use data published by ESMA on trading suspensions, which provides both start and end dates and specifies whether the suspension applies at the venue level (4% cap) or the EU level (8% cap). I only consider EU level suspensions, as I assume that traders can easily access other dark pools, effectively bypassing the 4% cap. When a suspension is detected for a given stock, I set the dark trading volume to zero for the duration of the stated suspension. Furthermore, for each suspended period, I redistribute the monthly trading volume that was initially estimated for the suspended months[1] to the previous 12 months. To clarify this approach an example is provided: Consider a stock where a suspension was detected in December 2020 for exceeding the 8% cap. First, I redistribute the initially estimated dark trading volume for the suspended period to the previous 12 months. Following this redistribution, I set the dark trading volume for the suspension period (e.g., from December 2020 to May 2021) to zero. In this case, the volume for December 2020 is equally distributed across the last 12 months, i.e., from December 2019 to November 2020, excluding any suspended months in this period. For January 2021, the trading volume in this month is redistributed to the period from January 2020 to November 2020, with December 2020 excluded, as it is a suspended month. Afterwards, the suspended months are set to zero. This iteration is applied to each suspended month. This approach reduces the error margin between the actual observable 12-month trading volume and the estimated 12-month volume. Detecting a stock's suspension results in a complete ban on dark trading for six months. However, only setting the trading volume for suspended months to zero is insufficient. As specified in Section 3.1, my estimation of dark trading splits the observable 12-month trading volume across each month using the cyclicality of 2017's trading volume, regardless of whether a stock was suspended or not. If the estimated trading volume could not have occurred in the suspended months due to the trading ban, I assume that the trading occurred in the months preceding the stock's suspension. This adjustment increases the trading volume before the ban and retrospectively explains the stock's suspension. In my dataset, 195 out of 357 stocks were suspended at least once throughout the time series.

[1] As described in Section 3.1

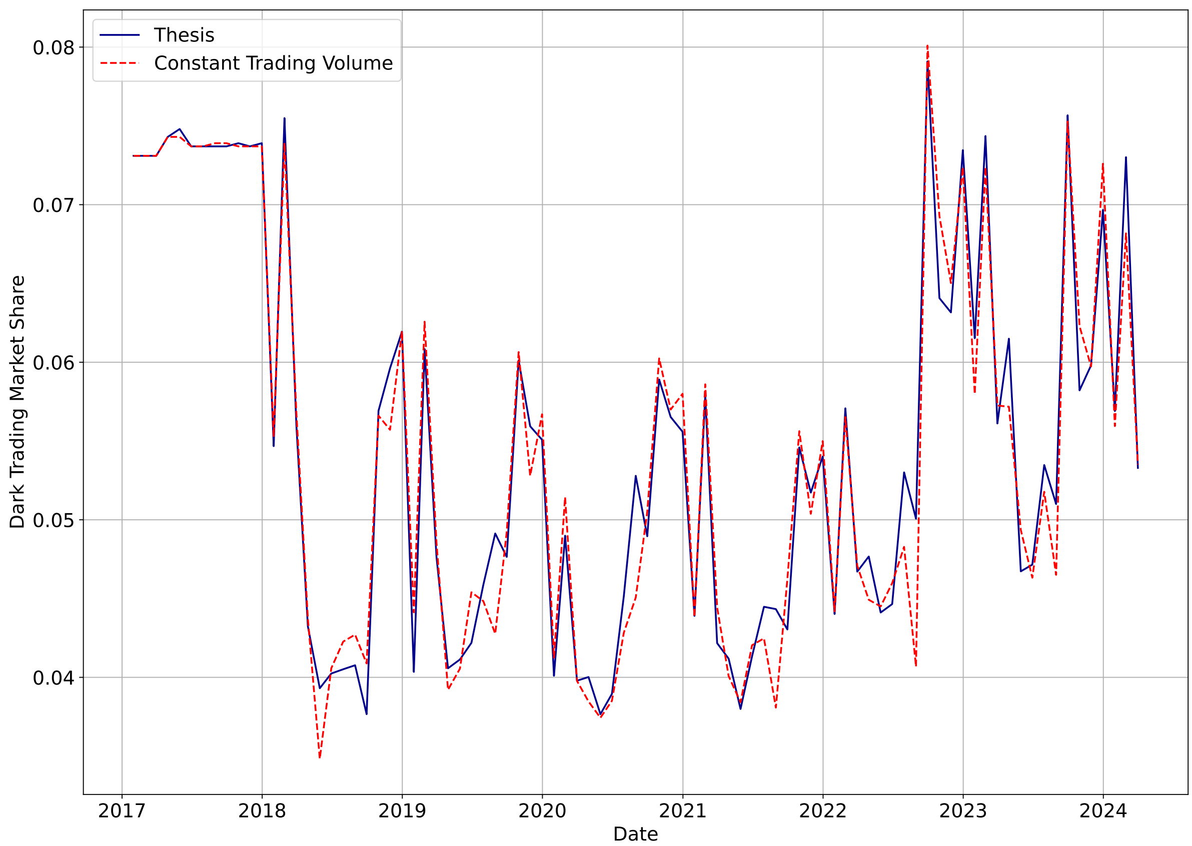

Figure A.3: *Comparison of dark trading estimation methods: constant trading volume.* This figure shows the monthly median of *Dark* of the estimation method used in the thesis (solid line) and the constant estimation method (dotted line). The dotted line assumes that the trading volume in 2017 is constant in each month, i.e. 1/12 of the total trading volume in 2017 in each month. Whereas the solid line assumes that the monthly dark trading in 2017 mimics the monthly lit trading volume in 2017. The result of the constant estimation method is close to the estimation method used in the thesis.

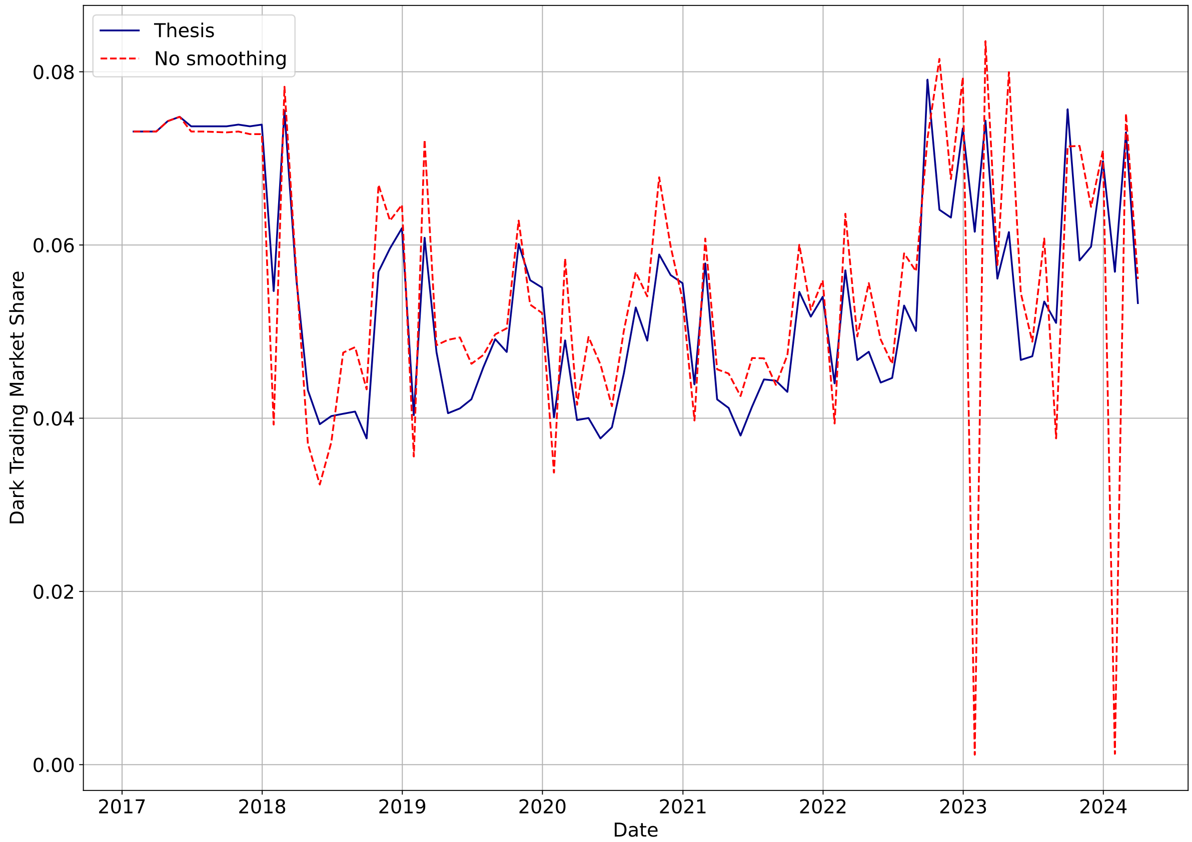

Figure A.4: *Comparison of dark trading estimation methods: no smoothing.* This figure shows the monthly median of *Dark* of the variable estimation method used in the thesis (solid line) and a method that does not apply any smoothing to dark trading (dotted line). The solid line applies a simple moving average, weighting the current value by 60% and the last four values by 10% each. This diminishes the variation in dark trading, but as it is visible from the dotted line, for a necessary reason. I assume that there were some technical difficulties in the data reporting in the DVC files. For it is hard to believe that, in a large cross-section, most stocks experience a sudden drop to near zero followed by a consequent rise to the previous level in *Dark* around January 2023 and January 2024. Looking further at the data, the large drop results from the delta in 12-month total trading volume between the DVC files and not from the estimation method itself. For the 12-month trading volume in the DVC files published on January 2023 and 2024, the average of the 12-month trading volume in the DVC files published one month before and after the respective files are taken instead, to control for this high variation.