Two Shades of Opacity: Hidden Orders versus Dark Trading[*]

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Abstract

This paper investigates two distinct ways in which traders can hide their trading intentions and thus manage their exposure risk: (1) hidden orders on otherwise lit trading venues and (2) completely dark trading venues (dark pools, OTC, ...). First, we examine how several market conditions affect both types of opaque trading. Also, we deal with hidden order trading across lit venues. Second, we address the relation between hidden order and dark trading and assess whether they are complements or substitutes for traders. Using a detailed high-frequency dataset, we find that a number of market condition differently affect hidden orders and dark trading. In particular, hidden order trading is preferred over dark trading on high volume days, when visible depth is smaller, the quoted spread is more narrow and fewer traders employ smart order routers. Algorithmic trading is negatively related to both types of opaque trading. Furthermore, hidden order traders substitute lit venues with deeper visible order books for lit venues with shallower order books. Second, we find that dark trading and hidden order trading are substitutes. However, dark trading appears to be a better substitute for hidden order trading than the other way around. These findings have implications for regulation: regulatory restriction on dark trading might harm some classes of investors that now use dark trading venues, since hidden orders do not offer a perfect substitute.

Keywords: Dark Trading, Hidden Orders, Dark Pools, OTC Trading, Opacity, Transparency

JEL Codes: G10, G15

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1 Introduction

Technology has allowed financial markets to become ever more transparent. Trading venues are now disseminating a greater amount of pre- and post-trade information in real-time. This is especially the case for equities, where the electronic limit order book has become the dominant mechanism by which shares are traded.[1] Typically, traders observe not just the best quotes but also prices and depths further down the book. Moreover, past trades are also disseminated. Such a great amount of displayed order book information has proved to be valuable for arriving traders as they adjust their trading strategies depending on the state of the limit order book (Ranaldo, 2004). Large limit orders, for instance, provide incentives for future traders on the same side of the market to undercut these orders (Buti and Rindi, 2013). To the extreme, parasitic traders may engage in predatory strategies aimed at exploiting other traders' orders (Brunnermeier and Pedersen, 2005). Moreover, limit orders can contain fundamental information and therefore impact prices (see, e.g., Kaniel and Liu, 2006; Cao, Hansch, and Wang, 2009). Transparency therefore goes hand in hand with increased exposure costs for traders.

To allow traders to mitigate their exposure costs several tools have been developed that offer traders more possibilities to hide their trading intentions. These tools, which provide traders with the possibility to submit committed orders without these being displayed to the market, can be divided into two categories. The first is that of hidden orders on lit venues, i.e. orders that are submitted to visible order books, but for which traders do not have to fully display the quantity they are willing to transact. These orders hide among the visible liquidity that is offered in the lit market. We refer to transactions that execute against the hidden part of the book as *hidden order trading* activity. The second tool is trading in completely dark venues. This form of dark trading does not only encompass trading in traditional dark pools (i.e. trading venues that match third-party orders without any pre-trade transparency), but also bilateral transactions executed away from the lit market. The latter includes orders that are internalized (i.e. client orders that are matched by brokers in-house) and transactions that are executed in the over-the-counter (OTC) market. We denominate these transactions away

[1] Jain (2005) provides evidence that between 1977 and 2001 the leading exchanges in 101 of 120 countries investigated switched from floor-based trading to electronic trading systems, an evolution that has continued after the end of the sample period. Furthermore, the proliferation of new trading venues that have been competing with the incumbent exchanges in the U.S. and Europe has been driven by advances in information and communication technologies. Indeed, these new market places are virtual rather than physical.

from the lit market as *dark trading* activity.[2] We use the term *opaque trading* as the general classification for all forms of trading against non-displayed orders.

Both types of opaque trading are used extensively by traders. De Winne and D'Hondt (2007) and Bessembinder, Panayides, and Venkataraman (2009) show that around 45% of the order volume submitted on Euronext in a sample of CAC40 stocks is hidden. Rosenblatt Securities argues there are more than 40 dark pools active in the U.S. with a market share of around 14% (Rosenblatt Securities, 2012) and at least 19 dark pools in Europe with an estimated market share of about 11% (Rosenblatt Securities, 2013) An even larger part of European dark volume is taking place away from regulated venues, in the OTC market, with estimates of up to 40% of volume (Gomber and Pierron, 2010). While traders have two tools to hide their trading intentions, the academic literature focuses either on hidden orders or dark venues in isolation of one another. Nevertheless, although it is often suggested that hidden orders and dark venues may compete with each other, to the best of our knowledge no prior research exists (theoretical nor empirical) to evaluate these claims.[3] We aim to bridge this gap in the literature by exploring the interplay between hidden order trading and dark trading. Furthermore, we are the first to investigate hidden order trading explicitly in a setting where multiple venues compete for order flow. We are also the first to examine the determinants of dark trading while making a distinction between regular-sized and block-sized transaction.

Our key goal and contribution is twofold. First, we examine how several market conditions affect both types of opaque trading. This allows us to observe which market conditions impact hidden order and dark trading similarly (and thus segment the market into visible volume and opaque volume), and which conditions have a different impact (and thus segment into hidden order volume and dark volume). Hidden order trading and dark trading can be impacted differently when certain market conditions impact venue selection rather than the order exposure decision itself. Venue selection entails the choice between a lit trading venue or a dark trading venue, and within lit venues the choice between the main listing exchange or an alternative venue. Potential determinants are selected on the basis of theoretical predictions and previous empirical research.

Second, we investigate the relation between hidden order trading and dark trading directly

[2]Sometimes the use of completely hidden orders on lit venues, such as hidden midpoint-pegged orders, are also referred to as a form of dark trading. In a U.S. context trading away from lit venues would be also referred to as off-exchange trading, as opposed to trades executed on the exchanges.

[3]See claims in e.g., Buti, Rindi, and Werner (2011); Hautsch and Huang (2012); Boulatov and George (2013); Buti and Rindi (2013); Foley, Malinova, and Park (2013).

using a simultaneous equations framework. This allows us to asses whether hidden order trading and dark trading are complements or substitutes for traders. If they are complements, this means that traders wanting to hide their trading intentions always use both opaque trading mechanisms alongside each other. If, however, hidden order trading and dark trading are substitutes, traders who wish to hide would select one type over the other at one point in time, but the other way around on other moments, depending on certain market conditions. It is easy to see intuitively why hidden order trading and dark trading could be substitutes when traders decide to which venue to route their orders. Indeed, given that a trader wants to trade opaquely, if the submission of a hidden order is expected to be less profitable (e.g., due to low execution probabilities), he is likely to choose a dark order as an alternative, and vice versa. However, both types of opaque trading can be (strategic) complements due to liquidity externalities. If a trader expects that more traders will trade opaque, he will be more willing to trade dark as well. Empirically, this will result in a positive relation between hidden order volume and dark volume, which can be interpreted as both being complements.

Understanding the interplay between both types of opaque trading is highly relevant considering the ongoing debate among regulators, practitioners and academics on the role of market fragmentation and transparency. The current proliferation of dark trading venues is a consequence of regulation aimed at fostering competition between trading venues. However, regulators are increasingly worried about their growing market share and their impact on order execution quality, price discovery, market liquidity, fair access and market quality in general (see, e.g., Securities and Exchange Commission, 2010; European Commission, 2011, 2014). In a recent speech, SEC Chair Mary Jo White raises further concerns on the lack of transparency of dark venues and states that "*we must continue to examine whether dark trading volume is approaching a level that risks seriously undermining the quality of price discovery provided by lit venues*" (White, 2014). Most empirical researchers find that high levels of dark trading indeed harm market liquidity (Degryse, de Jong, and van Kervel, 2014; Weaver, 2014; Nimalendran and Ray, 2014), price discovery (Comerton-Forde and Putniņš, 2015) or both (Hatheway, Kwan, and Zheng, 2014). A notable exception is Buti, Rindi, and Werner (2011), who find that dark trading increases liquidity, while the effect on price efficiency is mixed. One reason for the deterioration in market quality of lit venues is the cream-skimming of uninformed order flow by dark venues (Zhu, 2014). By contrast, the use of hidden orders on lit venues is generally not associated with reduced market quality (Bloomfield, O'Hara, and Saar, 2014), and may even enhance liquidity under some circumstances (Aitken, Berkman, and Mak, 2001; Moinas, 2010; Boulatov and George, 2013; Buti and Rindi, 2013; Gozluklu, 2014). If hidden order trading on lit venues is indeed a substitute for dark trading, then curtailing dark trading, such as currently proposed by the European Commission with a double cap (4% for single dark venues, 8% at the stock level, see European Commission, 2014), could bring opaque trading back to lit venues, improving market quality. If substitution from dark venues to hidden orders is less likely, then a regulatory restriction on dark trading might harm some classes of investors that now use dark trading venues.

For our analysis we use a high-frequency dataset (timestamped to the millisecond) spanning nearly four years, and covering all Dutch large cap index stocks. For each stock, we have information on trading volume on the main venue where the stock is listed (Euronext) and on all alternative lit trading venues where the stock is trading (Chi-X, Turquoise and BATS Europe). Moreover, for each of these venues, we also have limit order book data. These data allow us to infer hidden order trading: we compute hidden order executions on lit venues by matching transaction and order book data in each venue. In addition, we have trades that are executed away from the lit market, so-called MiFID reported trades. These represent a collection of dark pool trades, internalized orders and OTC transactions. We distinguish these transactions into regular dark transactions and block transactions. Because we cannot explicitly distinguish between dark and block trades as in Comerton-Forde and Putniņš (2015) we use a size-based criterion, similar to Hatheway, Kwan, and Zheng (2014) and Degryse, de Jong, and van Kervel (2014). We classify all trades reported by dark venues that are larger than 1 percent of the 30-day average consolidated lit venue turnover as block trades.

Our main findings can be summarized as follows. First, we identify the effect of several market and order book conditions on hidden order trading, dark trading and block trading. We show that the fraction of volume executed against hidden orders is higher on high volume days, while the opposite is true for the fraction of volume executed in dark venues. When volume is interpreted as a proxy for trading desire, the execution probability of hidden orders increases with trading volume because more traders demand immediacy and thus start trading more aggressively. Dark venues become less attractive compared to lit venues because they provide less immediacy. Furthermore, when traders on at least one side of the market are tempted to go to immediacy providing lit venues, dark venue execution probabilities are harmed. Volume positively affects block trading though. When we include the very large trades in the analysis it appears that these form a large part of the trading desire that are quite difficult to execute on automated lit or dark venues. Surprisingly, volatility, as another market condition that affects the desire for immediacy and hence execution probabilities of both hidden orders and dark orders, does not impact hidden order or dark trading. It does, however, significantly negatively affect block trading.

Visible depth and the quoted spread are two variables that measure lit market liquidity and may affect opaque trading behavior. We find that hidden order trading is decreasing in visible depth, while dark trading is unaffected. A larger visible depth queue decreases the execution probability of hidden orders because visible depth has execution priority over hidden depth. The effect of visible depth on dark trading can be twofold, depending on whether liquidity demanders or liquidity providers are affected. A larger hidden depth on lit venues means liquidity demanders have fewer reasons to submit orders to dark venues, while liquidity suppliers can be tempted to substitute (hidden) limit orders on lit venues for dark orders because the lit venue is too competitive. The insignificant coefficient indicates that ultimately both effects might balance each other out. Block trading, however, is slightly negatively affected by visible depth. A wider quoted spread diminishes hidden order trading, most likely through the execution probability channel. A wider spread makes aggressive market orders (that are more likely to trade against hidden depth) more costly. The quoted spread has no significant effect on dark trading or block trading.

Furthermore, we find that competition for liquidity provision affects hidden order trading *across* different lit venues. When more visible depth is quoted on one lit venue (which decreases hidden order execution probabilities), hidden order trading on competing venues increases. Hidden order traders thus substitute lit venues with deeper order books for lit venues with shallower order books to increase their execution probability. However, we only find an effect of substitution away from the alternative lit venues to the main listing exchange.

Two variables are used to capture the characteristics of the population of traders: a proxy for algorithmic trading and an estimate of the fraction of traders using smart order routers. Algorithmic trading activity negatively affects hidden order trading and dark trading, but positively impacts block trading. One explanation could be that the use of algorithms substitutes for opaque orders. When algorithms are associated with predatory trading practices, large patient traders that are likely to use opaque orders may retract from both lit and dark trading venues and resort to (negotiated) block trades. Moreover, the use of algorithms also increases competition for liquidity provision on lit venues, reducing the execution probability of hidden orders. A special case of algorithms are smart order routers, which are used to tap into the liquidity of different venues at the same time. When a larger fraction of traders use smart order routers, hidden order trading diminishes, but dark trading increases. The use of smart order routers reduces the execution probability of hidden orders, while at the same time connecting more traders to dark venues. Block trading decreases in the use of smart order routers because this technology effectively serves as a substitute for block trading.

We now turn to our second research question which deals with the interplay between the different types of opaque trading. We find that dark trading and hidden order trading are substitutes to each other: hidden order trading and dark trading negatively impact each other. We conjecture that the order submission decision is a two-stage decision. In a first-stage decision traders choose their optimal level of *exposure* in the market: how much of their order should be hidden from other market participants? In the second stage traders decide on *how* or *where* they want to hide by submitting an opaque order to a facility that provides this opportunity. This can be a dark venue, but also a hidden order on an otherwise lit venue. However, dark trading appears to be a better substitute for hidden order trading than the other way around. We find that the negative coefficient of hidden order trading is significant in the dark trading equation, but the effect of hidden order trading on dark trading is insignificant. A potential explanation lies in the observation that orders placed on dark venues are relatively more opaque than hidden orders on lit venues. Because the latter are more easily detectable their use may not be a good substitute for trading on dark venues. This finding warrants caution for regulators who want to impose restrictions on the use of dark venues. The curtailing of dark trading could be harmful for classes of traders who now make heavy use of these venues, as the lit market does not offer an adequate alternative.

Our research is related to empirical studies that examine the use of hidden orders in limit order markets. Harris (1996), Aitken, Berkman, and Mak (2001), De Winne and D'Hondt (2007) and Bessembinder, Panayides, and Venkataraman (2009) show that hidden orders are used to reduce the cost associated with order exposure. These studies use order-level data and focus on the submission of hidden orders to the limit order book. By contrast, we match order book level and transaction data to infer the part of hidden orders that was actually executed while it was opaque to other market participants. A similar measure of hidden order executions is used by Yao (2012) to study the information content of hidden orders. Our focus on executed volumes is more in line with the volume measures typically used to measure trading activity on dark venues. Furthermore, contrary to previous studies, we measure hidden order trading on multiple lit trading venues.

Our findings also relate to the empirical literature on dark trading activity. Menkveld, Yueshen, and Zhu (2014) show that the degree to which traders desire immediacy is an important determinant of venue selection. They argue that dark and lit trading venues can be ranked according to a pecking order. Midpoint matching dark venues, which have lower trading costs but offer also lower immediacy, are at the top of the pecking order, while costly immediacy providing lit trading venues are at the bottom. They show that exogenous increases in the desire for immediacy reduce the market share of dark trading venues at the bottom of the pecking order relatively more, while the market share of the lit market increases. However, they do not explicitly account for the option to submit hidden orders to lit exchanges. On the one hand, hidden orders are characterized by even lower trading costs than a midpoint matching dark venue, but also face a large risk of non-execution due to competition with other liquidity suppliers. On the other hand, hidden orders are submitted to lit venues and face a better execution probability when more impatient traders trade more aggressively on these venues. Buti, Rindi, and Werner (2011) and Ready (2014) both study the market share of a selection of dark venues and find evidence in line with the prediction that more lit market competition for liquidity supply drives traders to dark venues (Buti, Rindi, and Werner, 2014).

The remainder of this paper is organized as follows. Section 2 discusses the related literature on opaque trading. Section 3 discusses the institutional background and presents the dataset employed in our analysis, while Section 4 describes the key variables. Section 5 investigates the drivers of hidden order trading, while Section 6 does the same for dark trading. The main analysis that relates hidden order trading to dark trading is in Section 7. Finally, Section 8 concludes.

2 Related Literature

2.1 Motives for Opaque Trading

The order exposure decision is crucial for most traders, especially so when they trade large sizes. The exposure decision pertains to how, where, when and to who trading intentions should be revealed to other market participants.[4] Order exposure has both benefits and costs associated with it (Harris, 1997). The primary benefit is that exposed orders can attract natural counterparties. If no traders wanted to expose their trading intentions, then also no trades would occur. Formalized trading structures, designed to facilitate the search for counterparties, cannot work without at least some traders present who are willing to expose their trading intentions. Besides, in most trading venues non-displayed or opaque orders loose execution priority over displayed or visible orders.Visible orders are thus more likely to fully execute. Furthermore, execution probabilities in completely opaque or dark venues are generally also quite low. The increased execution probability is therefore the major benefit of order display. However, there are also costs associated with order display because other traders (which do not represent a natural counterparty) can react to the exposed trading intention. This is consistent with the finding of Bessembinder, Panayides, and Venkataraman (2009) that fully displayed orders have higher execution costs compared to only partially displayed orders.

There are several reasons why the reaction of other traders can make trading more costly. First, traders that have trading intentions on the same side of the market could engage into more aggressive trading strategies as a reaction to the visible order. Buti and Rindi (2013) show that reserve orders, which reduce the visible part of a limit order, can help to avoid undercutting by aggressive traders. Although hiding a part of the trading intention reduces the execution probability of a limit order, reduced competition also decreases overall execution costs for large traders. In an experimental design without asymmetric information Gozluklu (2014) shows that large traders indeed shift to using opaque orders to limit their trading losses.

Second, exposure of trading intentions may lead other traders to engage into parasitic or predatory trading strategies that increase trading costs for the original trader (Harris, 1997; Brunnermeier and Pedersen, 2005). When predatory traders can easily detect large unfilled orders they can front-run these orders by taking liquidity from the market ahead of the original trader. In doing so, they drive the market prices in an unfavorable direction and can make a

[4] In a broker-oriented trading structure where floor-based trading and electronic trading systems operate next to an upstairs market in which brokers arrange block trades, the question for buy-side traders is related to that of broker selection. Traders can either solicit brokers to work large orders through the upstairs market (Keim and Madhavan, 1996), use their discretion to trade these on the floor (Blume and Goldstein, 1997), split the order over time (Chan and Lakonishok, 1995) or submit non-displayed committed orders to the market (Harris, 1996). With the increased automation of financial market infrastructure, the relative importance of non-displayed or opaque orders submitted to electronic trading systems has grown. In fact, in automated venues opaque orders are substitutes for some services previously provided by floor brokers. As multiple automated venues are now competing for order flow, the order exposure decision today entails order selection as well as venue selection.

profit later on by trading against the original trader at these worse prices.[5]

The third motive relates to the option value that is embedded into limit orders (Copeland and Galai, 1983). When visible orders provide committed trading options to other market participants, as is the case with limit orders, these can be picked off by better informed traders that are able to trade faster when new information is released (Foucault, 1999). The risk of being picked off exists because monitoring the market and adjusting order submissions is costly. Aitken, Berkman, and Mak (2001) argue that reducing exposure complicates strategies aimed at exploiting the free option value of limit orders because there is more uncertainty about the total order size.

Finally, exposing trading intentions in a market where traders are asymmetrically informed about the fundamental value of securities may cause prices to move in an unfavorable direction because traders assign an informational value to other traders' intentions (Harris, 1997). Moinas (2010) finds in a theory model that in the presence of informed liquidity suppliers, both informed and uninformed traders hide part of their limit orders to soften their informational impact. Boulatov and George (2013) show that informed traders compete more intensely as liquidity suppliers when they can hide their orders, causing an overall increase in market quality. In experimental market designs informed traders submit opaque orders in an effort to maintain their informational advantage for a longer period (see, e.g., Bloomfield, O'Hara, and Saar, 2014; Gozluklu, 2014). Esser and Mönch (2007) examine optimal liquidation strategies in the presence of reserve orders. The rational for hiding the true order size in their model is reducing the direct and indirect price impact of a large limit order.

In a multi-venue setting, where lit and dark venues compete for order flow, the exposure decision is typically not explicitly modeled in the literature. Order choice in these models is between a costly market order on a traditional exchange, or a cheaper dark venue order. The former is more costly because it provides certainty of execution, whereas execution in a dark venue is more uncertain. Hendershott and Mendelson (2000), Degryse, Van Achter, and Wuyts (2009) and Daniëls, Dönges, and Heinemann (2013) model the lit venue (or traditional exchange) as a dealer market in which traders pay the half-spread for a guaranteed execution of their order. In the models by Ye (2012) and Zhu (2014) buy and sell orders (including

[5]A front-running strategy that is specifically applicable to visible limit orders is quote-matching (Harris, 1996). Quote-matchers try to trade in front of large limit orders. Similar to other speculative strategies, they earn a profit when prices move in a favorable direction, while they remain protected from incurring heavy losses by the free options embedded in the limit order. Limit order traders are harmed because quote-matchers reduce their execution probabilities and at the same time try to extract the option value from their limit order.

those of informed traders) are balanced and the heavier side incurs a market impact cost. On the lit venue, market impact translates into a price impact, while on the dark venue market impact results in non-execution (consistent with empirical evidence by Gresse (2006) and Naes and Odegaard (2006)). Although not explicitly modeled, the impact of exposure is implicit in the greater market impact of visible orders on lit venues. A similar reasoning is followed by Menkveld, Yueshen, and Zhu (2014) who put forward a pecking order theory of trading venues. They argue that investors trade off trading costs with their desire for immediacy, for different types of dark and lit trading venues. The most patient traders transact as much as possible in the cheapest (midquote matching) dark venues, while the most impatient traders choose for the immediacy offered by lit trading venues.

2.2 Hidden Orders or Dark Trading?

Hidden order trading and dark trading have in common that they can be used to reduce exposure. Furthermore, for both opaque order types reduced exposure also comes at the cost of lower execution probabilities. Both hidden order and dark trading are passive strategies, i.e. they do not react to liquidity offered by other traders. Instead, hidden orders and dark orders both provide opaque liquidity to other market participants, which makes their execution uncertain. Uncertainty is further raised because their opaque nature makes it more difficult to attract counterparties.

Besides similarities there are also important differences between both types of opaque orders. The main difference is that hidden orders interact with marketable orders on lit venues, while dark orders can only interact with other dark orders. As such, hidden orders interact with more aggressive active orders. These are submitted by traders willing to pay for certainty of execution. Because hidden orders interact with marketable orders on lit venues they are also more easily detectable, and upon detection their presence is revealed to all traders monitoring the market (De Winne and D'Hondt, 2007; Frey and Sandas, 2009; Pardo and Pascual, 2012). Dark orders, by contrast, interact with similar passive orders, i.e. orders submitted by traders that have a similar desire to reduce their exposure and are willing to face lower execution probabilities. Dark orders are therefore more opaque than hidden orders because they can be detected less easily. To detect a dark order traders need to *ping* for dark liquidity on each of the dark venues separately to see whether there is a counterparty. When execution is not continuous detecting dark orders is even more challenging. Furthermore, dark trading is restricted to traders that have actual access to dark trading venues, while all traders can use some form of hidden orders, either on the main listing exchange, or an alternative venue if they have access to it.

Buti, Rindi, and Werner (2014) and Brolley (2014) provide the only models of competition between a lit venue and a dark venue in which traders can also choose to submit passive orders to the lit venue. Although both models do not incorporate hidden orders on the lit venue, they are the most closely related to our work. Buti, Rindi, and Werner (2014) show that patient traders are more likely to substitute limit orders on the lit venue for dark orders when competition for liquidity provision in the limit order book is intense, i.e. when spreads are narrow and the order book is deep. A deeper order book reduces the execution probability for newly submitted limit orders, while a narrow spread makes midquote execution of a dark venue relatively more attractive. They thus predict more active dark venues when liquidity on the lit venue is higher. Buti, Rindi, and Werner (2011) show empirically that indeed dark venue market share is higher for stocks with narrower spreads and higher depth. The model's results are driven by a trade-off in execution probabilities on the lit and the dark venue. Considering the priority of visible size on lit venues, the order migration to dark venues should be even stronger for hidden limit orders compared to visible limit orders.

Brolley (2014) incorporates liquidity providers in his model which are active in both the lit and the dark venue. Investors who submit orders to dark venues interact with the liquidity providers instead of directly trading with each other. The model also incorporates asymmetric information (picking-off risk) and non-midquote pricing (a trade-at rule) for dark venues. When the dark venue offers substantial price improvement, but with a low execution probability, consolidated volume increases because both limit order traders and investors that would otherwise abstain from trading submit orders to the dark venue. When the dark venue offers only small price improvements, but the execution probability is high, also market order traders submit dark orders and as a consequence volume migrates to the dark venue.

3 Sample Description

3.1 Institutional Background

Technological innovation and regulatory changes have allowed the structure of financial markets to change from a largely consolidated system into a market where order flow is fragmented over different trading venues. In the U.S. the structure of today's equity market is determined by Regulation National Market System (Reg NMS) that was phased in over the course of 2007. It has accomplished that the U.S. equity market now comprises of several automated trading venues that are all connected to each other. The European counterpart of Reg NMS is the Markets for Financial Instruments Directive (MiFID), which came into force in November 2007 in the European Economic Area. It has expanded the set of regulated trading venues from the Regulated Markets (RMs), which encompass the traditional national stock exchanges, to also include Multilateral Trading Facilities (MTFs) and Systematic Internalizers (SIs). Both RMs and MTFs are multilateral trading venues that match third-party order flow. Most of these trading venues are also 'lit' as they are subject to pre-trade transparency requirements. They operate public limit order books that display a large amount of the orders that are submitted to their books, which makes them similar to Electronic Communication Networks (ECNs) in the U.S. However, trading venues can also be granted waivers from pre-trade transparency provided that they meet certain conditions. This allows for the existence of dark venues and hidden orders on lit trading venues in Europe.

SIs are investment firms that internalize client orders on a frequent basis and thus offer an alternative to executions on multilateral trading venues. Also SIs are subject to the pre-trade transparency requirements and must publish firm quotes in the stocks in which they are dealing. But because the orders from their books are not exposed to the market directly, transactions on SIs can also be considered opaque in nature. Next to the regulated trading venues, MiFID also allows transactions in the dark over-the-counter (OTC) market. As reported by Gomber and Pierron (2010) around 40% of volume is in the OTC market, particularly in broker/dealer crossing networks, which operate in a similar way as some dark venues.

Traders can submit hidden orders on all lit venues from our sample. The main trading venue (the listing exchange) is Euronext, which allows hidden liquidity only in the form of reserve orders with fixed peak size replenishments. The most important alternative trading venues, Chi-X, BATS and Turquoise, allow reserve orders as well as completely hidden limit orders and pegged hidden orders. As such, they provide traders with a broader range of options to trade dark in their order books.

3.2 Data

Data are taken from Thomson Reuters Tick History. Our sample consists of 27 Dutch large cap stocks, listed on Euronext Amsterdam. For these stocks we have a time series of 738 trading days available, which ranges from November 2007 until end September 2010. This long time window allows us to capture a variety of market and economic conditions. Moreover, the available data are very detailed since they comprise data not only of the regulated market where the stocks are listed (Euronext), but also include the other European lit and dark venues where these stocks are traded. The alternative lit trading venues cover the most relevant transparent limit order books for our stock sample: Chi-X, Turquoise ans BATS.[6] Chi-X is the only MTF that was operational during the full sample period. Turquoise starts trading most of the stocks on September 1, 2008; BATS on November 14, 2008.

The dataset has three parts. The first part of the dataset contains trade by trade data, timestamped to the millisecond, of trades on all lit venues. The second part concerns order book data. These are available for each lit trading venue, also timestamped to the millisecond, identifying prices and visible depth for the ten best quotes available at each point in time. This part of the dataset is used to compute our measures for hidden order trading, as well as identify a number of market variables, such as spreads, visible order book depth, volatility, algorithmic trading and the fraction of traders using SORT. We do not have information on hidden orders directly but detect volume executed against the hidden part of the order book upon execution.

The final part of our dataset further includes transaction data for trades that are executed away from lit markets, these are so-called MiFID reported trades. Most of these trades are reported through Markit BOAT, but they can be reported through facilities provided by lit venues such as Euronext, Deutsche Börse or Chi-X as well. This part of the dataset allows us to compute our measure of dark trading. Do note that, in contrast to the lit venues of the dataset, we only have reported executed volume available, not the order books of these dark venues.

The fact that we use such long time series of data at a granular level uniquely distinguishes our research from other recent empirical studies into the determinants of dark trading activity,

[6] We exclude Nasdaq OMX Europe, Euro TLX, Virt-X, Xetra and a number of local German exchanges from our sample. Although these venues may provide depth throughout our sample period, trading is usually not on a daily basis and in any case trading volume is quite low (less than 0.5% of the sample). Moreover, not all these venues operate as a fully automated limit order markets with visible and hidden liquidity, and are therefore less relevant for our research.

which focus on broader cross-sections of stocks (Buti, Rindi, and Werner, 2011; Ready, 2014), or a time series analysis at a more granular level (Menkveld, Yueshen, and Zhu, 2014). The most closely related to our study is Buti, Rindi, and Werner (2011), which employ one year of data from 4,482 stocks, but their sample of dark trading activity consists only of eleven dark venues who report the data voluntarily. Their sample thus excludes other types of dark trading and does not account for hidden order trading on lit venues.

We filter our data by removing all trades outside the trading hours of the continuous market session, and in addition all trades that are within a minute after opening, or a minute before closing of the market. We also winsorize all variables at the 99% level to remove any effects of potential outliers, i.e. extreme volume days.

4 Variable Definitions

4.1 Trading Volume

The focus of our research is on trading volume, and more specifically, on opaque trading volume. Investigating executed volume instead of submitted volume is useful since it are executions that finally matter for market participants. Furthermore, the number of limit orders that is now unexecuted because of cancellations has grown tremendously over the last years (Hasbrouck and Saar, 2009).

Total *executed* trading volume contains four components: visible trading volume $VisV_{i,t}$, hidden order trading volume $HidV_{i,t}$, dark trading volume $DarkV_{i,t}$, and block trading volume $BlockV_{i,t}$. Subscript i refers to the stock and t refers to days (we aggregate our data at a daily frequency). These measures are the key variables in our analysis.

To develop a proxy for hidden order trading, we compute executed hidden order volume for stock i on lit venue l during day t, denoted $HidV_{l,i,t}$. We do this by matching data on executed trades with limit order book updates. When a market order executes against a limit order on lit venue l, this affects depth outstanding in the limit order book on l. If it is executed against a visible order, visible depth at that price is reduced by the same amount as the volume of the order. In contrast, if the market order executes against a (partially) hidden order, visible depth is not reduced by that same amount. In fact, visible depth may not be reduced at all due to a new peak replenishment of a reserve order. The excess of the order volume that was not executed against visible depth, is executed against (part of) a hidden order. This volume is categorized as hidden order volume on lit venue l: $HidV_{l,i,t}$.[7] Hidden order trading volume consolidated over all lit venues is then defined as $HidV_{i,t} = \sum_l HidV_{l,i,t}$.[9]. By analogy, the visible trading volume $VisV_{l,i,t}$ for stock i on day t that is executed on venue l is calculated as the trading volume that is not executed against hidden depth, and which thus can be matched to a limit order book update. Visible trading volume consolidated over all trading venues l is denoted by $VisV_{i,t}$.

Because we find a large dispersion in size for MiFID reported transactions we segment this volume (which stems from completely dark venues) into two categories: dark trading, denoted $DarkV_{i,t}$, and block trading, denoted $BlockV_{i,t}$. The first category comprises of transactions of 'regular size', more or less in line with the transaction size on lit venues (see Panel A of Table 1), while a second category consists of very large trades that are unlikely to find execution as a whole on lit venues.[10] We include in the first category all transactions that are smaller than 1% of the average daily euro volume on lit venues over the last 30 trading days. All other dark trades we consider to be 'block trades'. Although we cannot identify with certainty which trades are executed in dark pools, SIs or the OTC market (i.e., outside of regulated trading venues), we believe that a classification based on size can make a meaningful distinction here. Regular sized dark transactions are more likely to be executed through automated trading venues such as dark pools, while big blocks of shares are likely executed through designated block trading mechanisms. Typically these block trades are negotiated bilaterally (over the phone or electronic networks) or matched in special block crossing networks, such as provided by Liquidnet. For a large part of the analysis we exclude block trading volume because it tends to be volatile and dominated by extreme observations.

Figure 1 presents the daily cross-sectional average and median levels of the four volume components over our sample period (in euro), while Figure 2 shows the same volume compo-

[7]Do note the difference between our measure of *executed* hidden order volume on lit venues and the volume of hidden orders *submitted* on lit venues. While the submitted hidden order volume on the lit venues can be substantial[8], volume that is executed against the hidden part of the order book is in the range of 4% to 6% of trading volume executed on lit venues, according to Panel C of Table 1. The difference stems from the fact that not all submitted hidden orders find execution, but also not all orders that were *submitted* hidden are *executed* when they are hidden. As the visible part of a reserve order is executed the peak size is replenished. Orders which were originally hidden may find themselves visibly executed if traders each time only trade against the visible part of the order book.

[9]Yao (2012) uses a similar measure of hidden order trading and shows that on average 19% of shares is executed against hidden depth on NASDAQ. Other studies also use a combination of order book data and transaction data to infer hidden order executions. Their focus, however, is on the detection of hidden orders by other market participants (see, e.g., De Winne and D'Hondt, 2007; Frey and Sandas, 2009; Pardo and Pascual, 2012)

[10]Depending on the size of the transaction relative to the Normal Market Size of stocks, large trades can also be eligible for delayed reporting.

nents, measured relative to the total trading volume. Table 1 Panel B presents statistics on the daily euro volume, average trade size and number of trades for the four different components of trading volume. We compute each variable on a stock-day basis and then take the daily mean and median over all stocks. Total daily transaction volume is 129 million euro on average, but only 60 million euro for the median stock-day observation. The large standard deviations for volume measures (183 million euro for total volume), and the considerable difference between the 95th and 5th percentile (483 million euro for total volume) imply that there is considerable variation in volume across stocks and over time. We control for unobserved heterogeneity driving these differences by employing a standardization procedure to the data later on that takes into account stock-quarter fixed effects. Furthermore, because of the large scale differences in volume observations across stocks the standardization re-expresses volume and other variables in terms of standard deviations.

Please insert Table 1 around here.

From the Figures 1 and 2 it can be seen that volume does not exhibit a particular trend during our sample period. We do observe a considerable decline in the second half of 2008 during the outbreak of the financial crisis. Also, during the holiday season the last few days of the year trading volume declines compared to the rest of the year.

Please insert Figure 1 around here.

The division of volume in the four components remains relatively stable over the sample period. Visible volume accounts for about 62% of volume on average (with 72% the median), while average daily block volume is 27% of total average volume (a median of 12%). Hidden order trading diminishes over the sample period, with an average and median volume share of 4% over the entire sample sample. Dark trading by contrast increases somewhat, but to a lesser extent. Measured relative to total volume, the share of dark trading becomes larger than that of hidden order trading in the second half of 2008. The average volume share is about 6.7%, with a median of 4.6%. Overall, it is clear that both types of dark trading do not necessarily move together over time. This observation is at the core of our research questions on how both types of dark trading relate, and under which conditions market participants favor the use of one type over another, and under which conditions they are reinforcing each other.

Please insert Figure 2 around here.

Upon comparing trade size and the number of trades for block volume with the other volume components in Table 1 Panel B it becomes clear why it is distinctly different from other types of transactions. Block trades are limited to a mean (median) of 7 (5) transactions per day, while their average size is 78 times larger than that of other dark trades and much larger even than that of visible or hidden transactions. This provides us with a rational for removing these large blocks from the dark trading component.[11]

4.2 Market and Order Book Variables

Most of the market and order book variables we consider have a consolidated total market version (i.e., grouped over all trading venues, lit and dark), denoted by the subscript Tot, a consolidated lit market version (i.e., grouped over all lit trading venues), denoted by the subscript *Lit*, and a lit venue-specific version which is denoted by the subscript l. There are four lit trading venues in our data sample. Euronext is the listing exchange and main trading venue by volume. Chi-X, Turquoise and BATS are three alternative venues (MTFs) of which Chi-X is the largest by volume (see Table 1 Panel C) and the only venue that trades stocks during the entire sample period. Because of these distinct differences we distinguish between the main trading venue ($Main$) to which all traders generally have access on the one hand, and the consolidated alternative trading venues (*Alt*) on the other hand. Only a fraction of traders has access to the latter trading venues. We further distinguish these alternative venues into the largest competitor (*Alt_L*, i.e., Chi-X) and other trading venues (*Alt_S*, i.e. Turquoise and BATS), the smaller competitors which are not present during the full sample period, but only start trading during the last quarter of 2008. Table 1 Panel D provides descriptive statistics on a selection of the market and order book variables.

Volume. We include volume as a market variable and potential determinant of dark and hidden order trading behavior because it is a proxy for trading interest. Hidden orders are more likely to be executed when there is a heavier trading interest. When the market is active and trading interest is higher, impatient traders are more likely to trade beyond visible depth in the limit order book to execute their marketable orders. More trading volume thus increases the execution probability of hidden orders. Similarly, dark orders have also a higher execution probability when trading interest in dark venues is higher. However, when the larger trading

[11] Do note, however, that for visible and hidden order trading we are not comparing trade sizes of submitted limit orders. Large limit orders may be executed against several market orders. When part of a limit order is submitted as hidden, the limit order can be executed as hidden or visible. The trade sizes displayed here are that of marketable orders executing against the depth in the limit order book, either visible or hidden.

interest is driven by an increased demand for immediacy, traders may favor lit venues over dark venues, reducing the market share of dark venues.

Volume can be either measured as total volume $Volume_{Tot,i,t}$, lit market volume $Volume_{Lit,i,t}$ or venue-specific volume $Volume_{l,i,t}$

Volatility. Volatility increases the option value of limit orders, which provides incentives to hide the full order size. But limit orders also tend to be less aggressively priced when volatility is larger because picking-off risk is greater (Foucault, 1999). This increases trading costs for marketable orders, which in turn could reduce executed hidden order volume at the cost of visible order volume. For dark venues, when volatility proxies for adverse selection, Zhu (2014) predicts that dark pool market share decreases when volatility increases. Volatility also increases the demand for immediacy and decreases execution probabilities in dark venues.

Volatility $Volat_{i,t}$ is measured only on the market level as the standard deviation of five-minute midquote returns using the midquote of the consolidated limit order book. Table 1 Panel D shows that our stock-specific daily volatility estimate $Volat_{i,t}$ is 23.45 basis points on average, with 9.01 basis points on low-volatility days in the 5th percentile and 50.42 basis points on high-volatility days in the 95th percentile.

Spread. Using hidden orders as tools to protect against predatory or competitive behavior of other traders is only useful when the bid-ask spread is sufficiently large. Therefore, hidden order submissions are expected to be more likely when the spread is larger. However, with regard to execution of hidden orders, a larger bid-ask spread also increases trading costs for marketable orders. In turn this reduces the execution probability of hidden depth more than that of visible depth. For dark venues, Buti, Rindi, and Werner (2014) predict that due to competition between liquidity providers a narrower spread induces traders to migrate away from lit venues. A narrower spread makes the midquote execution (which is typical in many dark venues) relatively more attractive for patient traders. Alternatively, when primarily traders who would otherwise demand liquidity on lit venues substitute the latter for dark venues, dark trading should be increasing in the size of the spread (Hendershott and Mendelson, 2000; Degryse, Van Achter, and Wuyts, 2009).

$QSpread_{i,t,l}$ denotes the quoted spread between the best bid and ask quote for venue l; $QSpread_{i,t,Lit}$ is the consolidated lit market quoted bid-ask spread. The bid-ask spread is measured relative to the midquote. We record from the order book based on one-minute snapshots and then time-weight these observations to have a daily measure. The consolidated quoted spread $QSpread_{i,t,Lit}$ is on average (median) 7.76 (6.66) basis points of the midquote, as can be judged from Panel D in Table 1. $QSpread_{i,t,l}$ is the tightest on the main trading venue (10.38 basis points on average) and the widest on the smaller alternative trading venues (17.65 basis points on average).

Visible Depth. Because of the lower execution priority of hidden depth over visible depth, hidden depth is only executed insofar visible depth is depleted. Hence, when visible depth is larger, the volume share that is executed against hidden orders is expected to be lower. The lower execution probability further reduces incentives to submit hidden orders. Both De Winne and D'Hondt (2007) and Bessembinder, Panayides, and Venkataraman (2009) find that visible depth on the same side of the market reduces the probability of submitting a hidden orders. In a market where multiple trading venues are competing and offering options to hide the full order size, more visible depth on one venue induces large patient traders to submit their hidden orders on another venue. These traders are effectively crowded out on the most liquid venue and substitute it for a venue where less visible depth is offered. For dark venues the prediction from Buti, Rindi, and Werner (2014) with regard to the effect of depth is similar to that for the quoted spread : as more liquidity providers compete for execution in the lit market it becomes deeper, and some traders are crowded out to dark venues.

We use the Depth(X) measure from Degryse, de Jong, and van Kervel (2014) as an empirical proxy for visible depth. It is constructed as follows:

$$\begin{aligned} DepthAsk(X) &= P_j^{Ask} Q_j^{Ask} \mathbb{1}\{P_j^{Ask} < M(1+X)\} \\ DepthBid(X) &= P_j^{Bid} Q_j^{Bid} \mathbb{1}\{P_j^{Bid} > M(1-X)\} \\ Depth(X) &= DepthAsk(X) + DepthBid(X) \end{aligned}$$

Where j denotes a level on the pricing grid of a venue and M the midquote of the consolidated order book across all lit venues. By measuring depth relative to the consolidated midquote M we take into account that only visible depth that is relatively close to the best prices of the consolidated market is relevant and competitive. We choose $X = 50$ basis points. For each venue l we denote *own* venue visible depth as $VisDepth_{i,t,l}$ and aggregated visible depth across the *other* lit venues $l' \neq l$ as $VisDepth_{i,t,l' \neq l}$. $VisDepth_{i,t,Lit}$ is the consolidated lit market visible depth. Similar to the quoted spread, visible depth is calculated from the limit order book based on one-minute snapshots and then time-weighted throughout the day to have a daily measure of depth.

In Table 1 Panel D we find that $VisDepth_{i,t,Lit}$ is on average 409,022 euro, with a median of 273,526 euro. The large range between the 5th and 95th percentile that was found for volume measures in Panel B, is also found for depth, with a 1,240,000 euro difference. On average a little bit over half of that visible depth is quoted by the main trading venue, the remainder by alternative trading venues. For the alternative trading venues more than half of the depth is quoted by Chi-X, the largest competitor.

Algorithmic Trading. An important feature of today's markets is the use of algorithms by several classes of traders. For instance, brokers and buy-side traders use algorithms to optimally split and time their trades. An important class of algorithmic trading (AT) is high-frequency trading (HFT).[12] The presence algorithmic traders (and the strategies they employ) could impact the use and execution probability of opaque orders. Since ATs are highly competitive when they provide liquidity hidden orders are not suitable order types because of their relatively low execution probability. Because ATs compete fiercly with each other and other liquidity providers for order execution, hidden order executions are likely to suffer from the presence of ATs. Furthermore, some AT strategies may be designed to front-run large traders or exploit their orders in some other way. If large traders fear the presence of ATs they may refrain from trading opaquely and seek execution of their orders elsewhere (i.e., using block trading mechanisms). This behavior reduces opaque trading. In addition, algorithms can also be used as a substitute to opaque trading by large traders to split up their order, which further reduces opaque trading.

Algorithmic Trading AT is derived from the message-to-volume ratio (i.e., the number if messages that needs to be transmitted to transact one euro of volume). We use the measure from Hendershott, Jones, and Menkveld (2011) to proxy for AT on each lit venue l:

$$AT_{i,t,l} = -\frac{\frac{LitV_{i,t,l}}{100}}{Messages_{i,t,l}}$$

Where $LitV_{i,t,l}$ is the euro volume executed on the lit venue and $Messages_{i,t,l}$ is the number of electronic messages in the limit order book (which consists of order submissions, cancellations

[12] High-frequency traders are proprietary traders who rely on algorithms to make their trading decisions and compete primarily on speed. They use their speed advantage for a diversity of trading strategies. Market making is one of the strategies for which HFT technology seems to be advantageous, as high-frequency traders are now responsible for a large part of liquidity provision (see, e.g., Menkveld, 2013; Hagströmer and Nordén, 2013; Brogaard, Hendershott, and Riordan, 2014).

and modifications). AT is increasing in algorithmic trading. $AT_{i,t,Lit}$ is the same measure applied to the consolidated market.

On an average day, for the average stock, 378,313 messages are sent to lit trading venues, but this goes up to 1,188,858 messages for the 95th percentile of stock-days, as shown in Table 1 Panel D. Less than a third is disseminated to the main exchange on average days, but again there is considerable variation with a P5-P95 range from 12.54 percent to 48.48 percent. A similar amount of messages is sent to the largest alternative venue (Chi-X) each day, with up to 38 percent of the messages sent to the smaller alternative venues. Because volumes are much lower on alternative trading venues, while the amount of messages sent is similar or even higher, our algorithmic trading proxy indicates that there is more algorithmic trading on these trading venues. The mean (median) of $AT_{i,t,l}$ is -8.95 (-4.45) for the main venue and -0.96 (-0.69) for the alternative trading venues.

Smart Order Routers. A fragmented market is characterized by how well its different trading venues are interconnected. In a European context where there is no National Market System or trade-through prohibition this depends on the use of Smart Order Routing Technology (SORT) by traders. The more traders use SORT, the more trading venues are competing with each other. The use of SORT can turn a fragmented market into a virtually consolidated market. A trader using SORT that wants to trade a given size will first deplete depth at the trading venue that provides the best price, and then continue to the trading venue that offers a similar price, until his order is filled or all depth at the best price is depleted. If the order is not entirely filled it is send to the venue quoting the second best price and so. Non-SORT traders are constrained to trade on a single venue (typically the listing exchange) and therefore often trade at worse prices. The presence of SORT traders increases competition between liquidity providers among trading venues since it increases the visible depth available to traders. This reduces the execution probability of limit orders on a single trading venue, and the execution probability of the lower-priority hidden orders relatively more compared to visible orders. The presence of more SORT traders therefore reduces the volume share executed against hidden orders.

For dark venues the opposite is true: there can only be volume in dark venues insofar traders have access to these venues. The more traders have access to dark venues, the larger the execution probability of dark orders and thus the more dark trading takes place. If the fraction of SORT traders on lit venues bears any relation to the fraction of SORT traders in total (i.e., the fraction of traders connected to multiple lit venues *and* dark venues) it should be positively related to dark trading.

The fraction of traders that used SORT, $SORT_{i,t}$ is measured only on the market level.[13] We use the measure from van Kervel (2014), which is based on the fraction of trades that occurs simultaneously across markets. A trade is set to occur simultaneously with a previous trade on another venue when the best quotes of the executing venue have not changed, they are of the same sign and occur within 100 milliseconds. This leads to a dummy variable $S_{i,t,k}$ equal to one when a trade occurs simultaneously. To account for the fact that a trade only occurs simultaneously when depth on one executing venue is not sufficient to fill the trade, the following linear regression is estimated for each stock i and day t on a trade-by-trade basis:

$$S_{i,t,k} = SORT_{i,t}P(x > T)_{i,t,k} + \epsilon_{i,t,k}$$

Where $P(x > T)$ denotes the probability that an order of size x exceeds the threshold T. Following van Kervel (2014) we set the threshold $T_{i,t,k}$ as the depth of the most liquid venue at time k and assume that order size is distributed exponentially with mean $\phi_{i,t}$, and thus $P(x > T)_{i,t,k} = exp(\frac{-T_{i,t,k}}{\phi_{i,t}})$. We estimate $\phi_{i,t}$ as the average trade size for stock i during day t.[14]

Table 1 Panel D shows that $SORT_{i,t}$ has a value of 7.43 percent on average, with a median of 7.03. These estimates are relatively low compared to the mean of 40 percent reported by van Kervel (2014), but his sample is characterized by a relatively larger fragmentation of trading across venues (39 percent is not traded on the listing exchange, compared to 22 percent on average in our sample, see Panel C of Table 1).

5 Hidden Order Trading

5.1 Methodology

We now turn to the question which market conditions affect the share of hidden order trading, *relative* to total trading activity. By investigating the determinants of the volume shares of hidden order trading $\%HidV_{i,t}$ we gain insight in which circumstances (1) patient traders

[13] Although in practice the connectivity of traders to alternative trading venues may differ across venues.

[14] We also use two alternatives to proxy for the fraction of SORT traders: (1) The daily average of the dummy $S_{i,t,k}$, and (2) The fraction of non-trade-throughs, similar to Foucault and Menkveld (2008). All measures are correlated and lead to qualitatively similar results.

choose to submit a hidden order on a lit venue, and (2) impatient traders are more likely to trade against hidden depth. Volume shares or relative volume measures are more suited for this analysis than absolute levels of trading as their scaling makes them independent of total trading activity. This makes relative hidden order volume a proxy for hidden order trading that relates more to the submission (or routing) decision and execution probability than to trading desire. We estimate the following model to asses how market and order book conditions impact hidden order trading.

$$\%HidV_{i,t,l} \quad = \quad \boldsymbol{\gamma}'\mathbf{X}_{i,t,l} + \boldsymbol{\lambda}'\mathbf{Z}_{i,t,l} + \eta_{i,t,l} \tag{1}$$

An intercept is not included because all variables in the model are standardized by stock and quarter: we subtract the stock-specific mean of the given quarter of which day t is a part, and divide by the standard deviation. De-meaning the variables allows to control for unobserved heterogeneity in volume components across stocks by quarter. Because we are measuring our variables as deviations from their stock-quarter specific means, our estimation procedure in effect exploits the time series variation in volume components within each quarter. By dividing the variables by their standard deviation we normalize their units to standard deviations. This allows for an easy economic interpretation of results and more comparability across firms. A similar procedure is used by Buti, Rindi, and Werner (2011) and Hasbrouck and Saar (2013).

Market and order book characteristics as defined in subsections 4.1 and 4.2 are contained in the vector $\mathbf{X}_{i,t,l}$ for the variables we assume to be endogenous ($Volume_{i,t,l}$, $VisDepth_{i,t,l}$, $QSpread_{i,t,l}$, $Volat_{i,t}$), and in the vector $\mathbf{Z}_{i,t,l}$ for the variables we believe are exogenous ($AT_{i,t,l}$ and $SORT_{i,t}$). Because of their potential endogeneity we instrument the variables $x_{i,t,l}$ by using their *market* version $x_{i'\neq i,t}$, i.e. for each stock i and each day t we calculate the cross-sectional average of $x_{j,t,l}$ over all stocks $j \in 1, ..., N$ excluding stock i. This approach is justified by the observation that, on the one hand, the variables included in our models are known to have a common market component to them. For instance, Chordia, Roll, and Subrahmanyam (2000) show there is a common market-wide component to liquidity while Hasbrouck and Seppi (2001) document commonality in liquidity, order imbalances, prices and volatility. On the other hand, it is hard to see how hidden order trading activity in one stock could impact these market variables at the market level. A similar approach is used by Buti, Rindi, and Werner (2011) to instrument dark trading, by Degryse, de Jong, and van Kervel (2014) to instrument dark trading and visible fragmentation, and by Hasbrouck and Saar (2013) to instrument low-latency trading. Following Hasbrouck and Saar (2013) we further exclude stocks that are in the same industry to reduce the potential of reversed causality even more.

We calculate these variables somewhat differently depending on the venue subsample that we investigate. For the consolidated lit venue sample the full specifications are:

$$
\begin{aligned}
\%HidV_{i,t,Tot} &= \gamma_1 Volume^*_{i,t,Tot} + \gamma_2 VisDepth^*_{i,t,Lit} + \gamma_3 QSpread^*_{i,t,Lit} + \gamma_4 Volat^*_{i,t} \\
&\quad + \lambda_1 AT_{i,t,Lit} + \lambda_2 SORT_{i,t} + \eta_{i,t} \qquad (2)\\
\%HidV_{i,t,Lit} &= \gamma_1 Volume^*_{i,t,Lit} + \gamma_2 VisDepth^*_{i,t,Lit} + \gamma_3 QSpread^*_{i,t,Lit} + \gamma_4 Volat^*_{i,t} \\
&\quad + \lambda_1 AT_{i,t,Lit} + \lambda_2 SORT_{i,t} + \eta_{i,t} \qquad (3)
\end{aligned}
$$

The difference between equation 3 and equation 2 is that in the former the dependent variable hidden order volume is scaled by consolidated lit venue volume, while in the latter it is scaled by total volume. We add an * to denote that the endogenous variables that are instrumented. For the venue subsamples we distinguish between own venue depth and other venue depth to recognize that both may have an opposite impact on hidden order volume due to competition between trading venues. This leads to the following full specification of the model.

$$
\begin{aligned}
\%HidV_{i,t,l} &= \gamma_1 Volume^*_{i,t,l} + \gamma_2 VisDepth^*_{i,t,l} + \gamma_{2'} VisDepth^*_{i,t,l' \neq l} + \gamma_3 QSpread^*_{i,t,l} \\
&\quad + \gamma_4 Volat^*_{i,t} + \lambda_1 AT_{i,t,l} + \lambda_2 SORT_{i,t} + \eta_{i,t,l} \qquad (4)
\end{aligned}
$$

5.2 Results

Table 2 presents estimation results for different specifications of Equation 1 on different subsamples. Panel A shows the results of Equation 3 in columns (1-4) and Equation 2 in columns (5-8), which have hidden order trading on the consolidated level as the dependent variable. Total volume or consolidated lit venue volume have a significant and strong positive effect in all specifications. From column (1), if total volume increases with one standard deviation, the fraction of volume executed against hidden orders increases with 0.271 standard deviations. We interpret this as a positive effect from trading interest in a stock on hidden order trading volume. When the trading desire in a stock increases, and traders become more anxious to fill their trades, they are more likely to trade deeper in the limit order book and the execution probability of hidden orders increases.

Volatility does not have a clear effect on hidden order trading. Only when volume is excluded from the specification does volatility become significantly positive due to the high correlation between volatility and volume measures. Indeed, increased volatility may reflect new information and induce investors to trade. The positive effect of volatility on hidden order activity is thus mainly indirect through volume. We find no evidence that an increase in volatility directly impacts hidden order trading activity through an increase in hidden order submissions as predicted by Harris (1996) and Aitken, Berkman, and Mak (2001).

As expected, consolidated visible depth has a significant negative effect on hidden order trading, consistent over all specifications. If visible depth increases by one standard deviation, ceteris paribus, the fraction of volume executed against hidden orders decreases by 0.118 standard deviations (from column (1)). When more visible depth is quoted on lit venues this reduces the execution probability of hidden orders, thereby also reducing incentives to submit hidden orders.

Our other measure of market quality, the consolidated quoted spread, has an opposite effect. Hidden order trading is decreasing in the size of the spread (i.e., increasing in liquidity), controlling for visible depth. When the spread increases with one standard deviation the fraction of trades executed against hidden order reduces by 0.144 standard deviations. This is somewhat surprising, as theory predicts that patient large traders should be more likely to submit hidden orders when the spread is wider when hidden orders are used as a tool to limit competition from other liquidity suppliers (Buti and Rindi, 2013). However, the relation between the spread and hidden order usage may be more complex, as De Winne and D'Hondt (2007) also find a negative relation between spread size and the submission of hidden orders. Furthermore, the execution probability of hidden orders may also be hampered when the spread is wider, leading to more executed hidden orders when the spread is narrow.

Algorithmic trading consistently has a negative effect of around -0.130 on hidden order trading (when not controlled for volume the effect even becomes more negative). There are three potential explanations. First, algorithms used by traders can substitute for hidden orders, reducing the amount of hidden orders that is submitted to lit trading venues. This is similar to the finding by De Winne and D'Hondt (2007) that 'principal' orders (which are submitted by brokers for their own account) are less likely to make use of hidden orders compared to 'client' orders (which are submitted by brokers on behalf of clients). The former are more sophisticated traders who tend to substitute hidden order usage by a better monitoring of the market. Similarly, algorithms may contain a fair amount of sophistication, but more importantly, they are designed to constantly monitor the market and trade whenever opportunities present themselves. Second, the presence of algorithmic traders increases competition for order flow among liquidity suppliers, especially when they also have a speed advantage, such as the case of HFTs. The increased competition then decreases the execution probability of those orders that have the lowest execution priority, i.e. hidden orders. Third, algorithmic trading is sometimes associated with concerns of front-running or order flow toxicity. If large patient traders (who would consider hidden orders) observe that the lit venues are more crowded with algorithms, they may refrain from trading here.

The fraction of trades that is executed against hidden orders is also negatively affected by the usage of SORT by traders. When more liquidity takers use SORT to trade (simultaneously) on multiple lit venues hidden order trading declines. A one standard deviation in the fraction of SORT traders decreases the relative hidden order volume by 0.078 standard deviations. As with algorithmic trading there are two explanations, depending on *who* uses SORT. First, SORT can be used as a substitute by traders to execute their large orders through order splitting over multiple venues to find cheaper execution. Second, when more traders use SORT to tap into the liquidity offered at different trading venues the amount of visible depth with which hidden order traders are competing increases, reducing their execution probability. In turn this also reduces incentives to submit hidden orders.

Please insert Table 2 around here.

Panels B, C, D and E of Table 2 present estimation results of Equation 4 for four subsamples based on the executing venue. For the main trading venue (Panel B) results are highly similar to those with consolidated hidden order trading as the independent variable (Panel A) since hidden order volume on the main venue is on average 82 percent of total hidden order volume. The additional variable $VisDepth_{l' \neq l}$ has a positive and significant sign as expected. When visible depth on alternative venues increases with one standard deviation, the fraction of volume executed against hidden order on the main venue increases by 0.079 standard deviations. This is in line with the explanation that as it becomes more difficult to obtain execution for hidden orders on the alternative venues, traders who wish to trade with hidden orders substitute those venues for the main venue.

Panels C, D and E show that volume is not a significant determinant of hidden order trading on alternative venues. Only on the largest alternative venue is volume significant in 3 out of 4 specifications where it is included, but not the full specification. An increase in trading intentions on alternative venues does not increase hidden order trading. Own venue depth remains to have a significantly negative impact on hidden order trading, but other venue depth is generally insignificant. When visible depth is building up on competing lit venues hidden order traders do not substitute their venue for any of the alternative venues. A potential explanation is that hidden depth on competing lit venues constitutes of main venue depth for a large part, and that the connectivity of traders to alternative venues is too limited to have a significant impact. The quoted spread, algorithmic trading and SORT have the same sign as before, and remain significant.

6 Dark Trading

6.1 Methodology

Similar to hidden order trading we investigate which market conditions affect the share of dark trading, *relative* to total trading activity. As with hidden orders, dark volume shares depend both on the routing decision and the execution probability of dark orders. In addition to our primary definition of dark trading, the bulk of volume that is transacted in completely dark venues consists of block trades. Therefore we also examine the market conditions driving this volume component. The following models are estimated to examine the impact of market conditions on dark and block trading activity.

$$\%DarkV_{i,t} = \boldsymbol{\gamma}'\mathbf{X}_{i,t} + \boldsymbol{\lambda}'\mathbf{Z}_{i,t} + \nu_{i,t} \tag{5}$$

$$\%BlockV_{i,t} = \boldsymbol{\gamma}'\mathbf{X}_{i,t} + \boldsymbol{\lambda}'\mathbf{Z}_{i,t} + \xi_{i,t} \tag{6}$$

Similar to Equation 1 an intercept is not included because variables are standardized by stock and quarter. We also use the same market and order book characteristics as in equation 2, which leads to the following full specifications.

$$\begin{aligned}
\%DarkV_{i,t} &= \gamma_1 Volume^*_{i,t,Tot} + \gamma_2 VisDepth^*_{i,t,Lit} + \gamma_3 QSpread^*_{i,t,Lit} + \gamma_4 Volat^*_{i,t} \\
&\quad + \lambda_1 AT_{i,t,Lit} + \lambda_2 SORT_{i,t} + \nu_{i,t} \qquad (7) \\
\%BlockV_{i,t} &= \gamma_1 Volume^*_{i,t,Tot+Block} + \gamma_2 VisDepth^*_{i,t,Lit} + \gamma_3 QSpread^*_{i,t,Lit} + \gamma_4 Volat^*_{i,t} \\
&\quad + \lambda_5 AT_{i,t,Lit} + \lambda_6 SORT_{i,t} + \xi_{i,t} \qquad (8)
\end{aligned}$$

In Equation 8 we measure the dependent variable relative to the total volume including the block volume. Similarly, on the right hand side we have the total volume with block volume included as a determinant. Because block volume is an outlier-sensitive variable we have excluded it so far in the analyses. But by estimating the model from 8 we are trying to increase our understanding of the market conditions affecting block volume.

6.2 Results

Table 3 presents results for different specifications of Equations 5 and 6. Columns (1-4) present results with $\%DarkV$ as the dependent variable, while columns (5-8) show results for $\%BlockV$. In contrast to hidden order trading, dark trading is negatively affected by trading intentions, as proxied by total volume. When total volume increases by a one standard deviation, the fraction of volume executed dark decreases by 0.196 standard deviations. When the trading interest increases, so does the desire to trade immediately. Dark trading venues do not perform well in providing immediacy (Menkveld, Yueshen, and Zhu, 2014). As a result, traders are more likely to switch to lit venues to execute their trades. Similar to the results for hidden order trading, volatility only has a significant negative impact when we do not control for volume.

Contrary to our expectations, lit market quality as measured by visible depth and the quoted spread does not affect dark trading. Possibly because market quality affects the venue submission choice for patient and impatient traders differently. A liquid market attracts order flow from impatient traders, but the increased competition for (hidden) order execution can crowd out patient traders such that they switch to another (dark) venue to submit their orders. When both effects offset each other the combined effect may be zero.

The presence of algorithmic traders negatively affects dark trading when we control for volume, similar to hidden orders. Two potential explanations also hold for dark trading. First, algorithms on lit venues may substitute for dark trading if they monitor the market closely and slice and dice large orders to the market. Second, insofar as algorithmic trading is perceived as toxic *and* when dark venues are perceived to be crowded with toxic algorithms, large traders may reduce their dark order submissions.

The fraction of traders using SORT is positively related to dark trading. When traders that are using SORT do not only connect to lit venues, but also engage in searches for liquidity in dark venues, an increase in the fraction of traders using the technology results in an increase in dark trading.

Please insert Table 3 around here.

For block trading in columns (5-8) we find somewhat different results. First, total volume is strongly positively related to block trading activity. Ceteris paribus, when there are bigger trading needs in the market, a larger portion of that tends to go through block trading. A one standard deviation increase in total volume leads to a 0.359 standard deviation increase in block volume. Given that block volume is about 27 percent of average daily market volume which represent only 7 trades of about 4.4 million euro on average this is hardly surprising. There are few alternatives to work trades of this size through the market other than through designated block trading mechanisms. Second, volatility has a strong and significant negative effect on block trading with a coefficient of -0.307. Traders tend to avoid block trades in volatile markets, either because the execution uncertainty is too large, or because the price uncertainty is larger. Third, in contrast to the model for dark trading, the coefficient for visible depth is negative and mildly significant in columns (5) and (6). Block trading is thus decreasing in lit venue liquidity, which suggests that order splitting in lit venues can be a substitute for block trading when lit venues are liquid. It is remarkable then that coefficient for visible depth is insignificant in the model for dark trading because non-block dark venues are more similar to lit venues than block venues. Fourth, controlling for volume and volatility, algorithmic trading is positively related to block trading. This is consistent with the notion that algorithmic trading is partly toxic. When large traders fear order flow toxicity they may refrain from trading in any venue to which algorithms have access to, and instead resort to the designated block trading markets where information leakage is minimal. Finally, SORT is negatively related to block trading because smart order routers that split orders over multiple lit venues can substitute for block trading mechanisms.

7 Hidden Order versus Dark Trading: Complements or Substitutes?

7.1 Methodology

This section analyzes hidden order and dark trading activity on a consolidated market level by stock. For each stock we examine the aggregated volume of trading on dark venues and the aggregate volume of hidden order trading that takes place on the various lit venues that trade in these stocks. We investigate how hidden order trading impacts dark trading and vice versa, while controlling for market conditions. In particular, we ask the question whether hidden order trading and dark trading behave as complements or substitutes. In addition, we discuss in further detail how market conditions impact both types of dark trading activity.

To quantify the contemporaneous impact of two variables that are determined simultaneously one needs to employ a simultaneous equation model. The two endogenous variables of interest, dark trading activity and hidden order trading activity, are modeled as a function of each other and variables that are designed to capture prevailing order book and market conditions that potentially impact the volume measures. As these control variables themselves are potentially endogenous these are also instrumented.

Dark trading and hidden order trading volume can positively affect each other as both are driven by an underlying desire to trade opaquely (e.g. to diminish the informational impact of orders, or to protect large orders from predatory traders). When traders with an opaque trading interest have access to both opaque trading tools they may decide to split their opaque orders over these alternatives. When hidden order trading and dark trading are highly similar, we expect order submissions and executions using these opaque trading tools to be as well. As a result, both components of opaque trading volume would move together and we expect a positive coefficient. However, this does not necessarily imply a causal relation in the sense that e.g., traders are more inclined to trade in a dark venue when hidden volume on lit venues is increasing. The underlying driver of opaque trading volume is the latent interest in opaque trading, which is in turn fueled by the general trading interest and the desire to reduce order exposure costs.

Contrary to the complementary behavior of the opaque trading components is the assertion that dark trading and hidden order trading are natural substitutes. Even though both types of opaque trading share similarities, under certain circumstances traders may favor the one over the other and therefore do not evenly split orders over opaque trading alternatives. In addition, when a dark order is executed in, say, a dark venue, traders could cancel their hidden orders on lit venues. Or they may re-submit their unexecuted orders from the dark venue to a lit venue as hidden orders. Under such circumstances, both types of opaque trading could indeed serve as substitutes for each other. When sufficient controls that could proxy for the latent opaque or general trading interest are added to the model, executed dark trading can negatively affect executed hidden order trading and vice versa.

To test whether dark trading and hidden order trading behave as complements or substitutes we estimate the following panel system of simultaneous equations:

$$\begin{aligned}
DarkV_{i,t} &= \beta_{1,1} HidV^*_{i,t} + \beta_{1,2} VisV^*_{i,t} + \alpha_1 DarkV_{i' \neq i,t} + \boldsymbol{\gamma}'_1 \mathbf{X}_{i,t} + \boldsymbol{\lambda}'_1 \mathbf{Z}_{i,t} + \upsilon_{i,t} \\
HidV_{i,t} &= \beta_{2,1} DarkV^*_{i,t} + \beta_{2,2} VisV^*_{i,t} + \alpha_2 HidV_{i' \neq i,t} + \boldsymbol{\gamma}'_2 \mathbf{X}_{i,t} + \boldsymbol{\lambda}'_2 \mathbf{Z}_{i,t} + \eta_{i,t} \qquad (9) \\
VisV_{i,t} &= \beta_{3,1} DarkV^*_{i,t} + \beta_{3,2} HidV^*_{i,t} + \alpha_3 VisV_{i' \neq i,t} + \boldsymbol{\gamma}'_3 \mathbf{X}_{i,t} + \boldsymbol{\lambda}'_3 \mathbf{Z}_{i,t} + \omega_{i,t}
\end{aligned}$$

An intercept is not included because all variables are standardized by stock and quarter. Our empirical proxies for the different components of trading volume are defined in subsection 4.1. We use the levels of volumes as opposed to volumes relative to the total executed volume because we are interested in the interplay between trading categories, which is quantified by the β coefficients. As mentioned before, a positive β indicates complementary or spill-over behavior, while a negative β is an indication of substitution between the types of trading. If relative volumes are used a mechanical negative correlation is built in into the analysis because volume not executed through one of these trading alternatives is executed through one of the two other mechanisms.

As the components of trading volume are simultaneously determined we need to instrument them. We use as instruments, excluded from the other regressions in the system, the daily cross-sectional mean of $DarkV_{i' \neq i,t}$, $HidV_{i' \neq i,t}$ and $VisV_{i' \neq i,t}$ i.e. the mean of the volume components across all other stocks in the sample. The positive correlation in different volume measures between stock i and the other stocks in the sample ('the market') on day t reflects a commonality in opaque and visible trading volumes. Intuitively, e.g., a correlated desire to trade in dark venues might be capturing a latent demand for the services that dark venues provide. In turn, this might be driven by institutional investors who make trading decisions for portfolios of stocks at the same time. Their routing and execution strategies are likely to be correlated across stocks. The vector $\mathbf{X}_{i,t}$ contains as the same market and order book conditions as before.

As a robustness test we include block trading volume. Large blocks are transacted through designated mechanisms for which hidden order trading is probably a poor substitute. We modify Equation 9 to include $BlockV_{i,t}$, which is defined as the euro volume of block trades that is executed in dark venues for stock i on day t. Block trades are defined to have a minimum trade size of 1% of the daily average turnover on lit trading venues of a stock. These transactions comprise of the truly big blocks of shares that are usually negotiated or executed by a block crossing network.

$$\begin{aligned}
DarkV_{i,t} &= \beta_{1,1}HidV^*_{i,t} + \beta_{1,2}VisV^*_{i,t} + \beta_{2,3}BlockV^*_{i,t} + \alpha_1 DarkV_{i'\neq i,t} + \boldsymbol{\gamma}'_1\mathbf{X}_{i,t} + \boldsymbol{\lambda}'_1\mathbf{Z}_{i,t} + \upsilon_{i,t} \\
HidV_{i,t} &= \beta_{2,1}DarkV^*_{i,t} + \beta_{2,2}VisV^*_{i,t} + \beta_{3,3}BlockV^*_{i,t} + \alpha_2 HidV_{i'\neq i,t} + \boldsymbol{\gamma}'_2\mathbf{X}_{i,t} + \boldsymbol{\lambda}'_2\mathbf{Z}_{i,t} + \eta_{i,t} \\
VisV_{i,t} &= \beta_{3,1}DarkV^*_{i,t} + \beta_{3,2}HidV^*_{i,t} + \beta_{3,3}BlockV^*_{i,t} + \alpha_3 VisV_{i'\neq i,t} + \boldsymbol{\gamma}'_3\mathbf{X}_{i,t} + \boldsymbol{\lambda}'_3\mathbf{Z}_{i,t} + \omega_{i,t} \\
BlockV_{i,t} &= \beta_{4,1}DarkV^*_{i,t} + \beta_{4,2}HidV^*_{i,t} + \beta_{4,3}VisV^*_{i,t} + \alpha_4 BlockV_{i'\neq i,t} + \boldsymbol{\gamma}'_4\mathbf{X}_{i,t} + \boldsymbol{\lambda}'_4\mathbf{Z}_{i,t} + \vartheta_{i,t}
\end{aligned} \tag{10}$$

7.2 Results

Table 4 presents the estimation results of Equation 9. We estimate six specifications: a full specification under header (1), and five specifications that exclude one or several control variables. We follow this approach because the instrumentation procedure may decrease the power of our statistical tests. However, results are fairly robust across subsamples. We find that hidden order trading and dark trading are negatively related to each other, despite both being driven by an unobservable opaque trading desire in the stock. Hidden order volume is significantly negatively affected by executed dark volume, while dark volume is also negatively affected by hidden order trading activity, but not significantly. This suggests that both types of opaque trading activity substitute for each other, rather than that they behave as complements. To understand this relation, recall that executed volume (or any subdivision or category of volume) has three determinants: trading desire, submission rate and execution rate. The inherent trading desire in a stock is likely to be determined by the same (exogenous) factors for both opaque and visible order trading volume (e.g. speculation, fundamentals or liquidity reasons). Next, the decision to reduce exposure to the market and thus to submit an opaque order type is driven by the same considerations, irrespective of the chosen type of opaque order (see Section 2). Because both types of opaque trading are strongly determined by the trading desire in general and the opaque trading desire in particular both volume measures tend to be correlated positively. However, we control for these trading interests by including the visible volume for the stock and the market levels of dark or hidden order volume (our instruments). Because the different types of opaque orders share the important similarity that they reduce exposure, but may further differ on other characteristics, hidden orders and dark orders are natural substitutes in a second stage decision, *after* deciding to trade opaquely. For instance, traders may choose one type of opaque trading over another based on perceived market conditions on the lit venues versus dark venues. The effect of execution reinforces any substitution effect in the submission phase between hidden order and dark trading. For instance, when traders observe worse than expected execution rates in a dark venue, they may re-route any unexecuted orders to a lit venue as a hidden order.

The effect of dark volume on hidden order volume is economically smaller than the effect of hidden order volume on dark volume (-0.043 compared to -0.127 in the full specification), and insignificant. Dark volume can thus be a good substitute to hidden order volume, while substitution effects from hidden order to dark venues are less likely. A potential explanation is that there remain to be important differences between both types of opaque trading that make substitution from dark venues to hidden orders less likely. The most important difference is that hidden orders are far less opaque than orders on dark venues, because the former are more easily detectable. When a marketable order trades against a hidden order on a lit venue it is immediately revealed to all traders that monitor the market that there is hidden liquidity available. As such, other traders often adjust their trading strategies by trading more aggressively against these orders (see, e.g., De Winne and D'Hondt, 2007; Frey and Sandas, 2009; Pardo and Pascual, 2012). Because dark venues do not have publicly displayed order books (by definition) traders that have an interest in detecting dark liquidity need to *ping* each individual dark venue, a strategy that is even more challenging when execution on dark venues is only periodic.

Hidden volume also negatively affects visible volume, as hidden and visible orders substitute for each other within the order books of lit venues. Visible volume is increasing in visible depth, while hidden order volume is not significantly affected. Dark volume is also positively affected by visible depth, but to a lesser extent. Volatility is strongly related to all measures of volume, but the strongest to visible volume (0.282) and somewhat lesser to hidden volume (0.176) and dark volume (0.129). This consistent with the findings of Menkveld, Yueshen, and Zhu (2014) that traders opt relatively less for dark venues when volatility is higher. The effect of algorithmic trading is significantly negative for all volume measures. The fraction of SORT traders is positively related to dark volume and visible volume, but negatively to hidden order volume.

Please insert Table 4 around here.

We estimate equation 10 using the same procedures as before. The main results are presented in Table 5 and appear to be robust to including block volume as a fourth category of volume in the specification: our coefficients remain of a similar sign, economic magnitude and statistical significance. Visible volume can be a substitute for block volume as visible volume is negatively affected by block volume. Dark trading and block trading are complementary because there is some overlap in trading venues between non-block dark trades and block trades.

Please insert Table 5 around here.

8 Conclusion

Financial markets offer different opportunities to trade opaquely. This paper studies two forms of opaque trading – hidden order trading that can take place on several lit trading venues and dark trading, away from lit trading venues. Using a detailed high-frequency dataset our research provides insight in the segmentation of opaque trading into these two shades of opacity.

Our main results can be summarized as follows. First, we establish the determinants of hidden order trading and dark trading separately. We show that hidden order trading is increasing in total volume, while the opposite is true for dark trading. A larger trading desire tends to increase executions of hidden order lit venues, in particular on the listing exchange, while decreasing executions on dark venues. This is consistent with the conjecture that traders choose to trade on venues that offer more liquidity and immediacy when they have a stronger trading desire. Hidden order trading is decreasing in the size of visible depth offered, and in increasing as the spread narrows. Both measures of liquidity directly impact the execution probability of hidden orders. Contrary to the predictions of Buti, Rindi, and Werner

(2014) dark trading is largely unaffected by market quality measures on lit venues, possibly because too few traders have access to dark venues. Smart order routers reduce the execution probability of hidden orders because they increase the competition from other trading venues. At the same time SORT may provide a substitute to large patient traders to execute their trades. Overall, hidden order trading is decreasing in the use of SORT, while dark trading is increasing, as more traders tap into dark liquidity. Algorithmic trading activity negatively affects both types of opaque trading, either because algorithms substitute for opaque orders, or because they increase order flow toxicity too much for large traders. The latter is consistent with the finding that block trading increases with algorithmic trading. For hidden orders the presence of algorithmic trading may also hamper execution due to increased competition between liquidity suppliers.

Second, using a simultaneous equations framework we show that dark trading and hidden order trading negatively affect each other. This supports the idea that dark trading and hidden order trading, both forms of opaque trading, are substitutes. After deciding that a trader wants to reduce the visibility of his order in the market he decides whether he wants to trade in a dark venue, or whether he wants to trade with a hidden order in the lit market. This decision is likely to be based on personal preferences, order characteristics and the prevailing market conditions. However, we also find that the substitution is more likely from hidden orders to dark orders than the other way around. The effect from dark trading on hidden order trading is relatively small and insignificant. One explanation is that the relative difference in opacity between hidden orders and orders on dark venues makes the use of hidden orders a more inadequate substitute to dark trading than the other way around.

The high amount of hidden orders on lit venues and the growing market share of dark venues makes insight into opaque trading activity in all its appearances relevant for traders, market operators, brokers and regulators. From the regulatory perspective, the growing amount of dark trading has caused regulators to be concerned abouts its consequences for market quality and welfare. This can be judged from several regulatory initiatives, such as the concerns expressed in the SEC's Concept Release on Equity Market Structure (Securities and Exchange Commission, 2010) and the European Commission's proposals on MiFID II that aim to curb dark trading activity in two ways (European Commission, 2014). First, the Commission aims to bring OTC volume to regulated trading venues by forcing brokers that match client orders to register as an MTF or either as a SI when trades are internalized. Second, on the regulated trading venues the Commission proposes to limit the use of the reference price waiver and negotiated trade waiver by imposing market share caps at 4 percent for an individual trading venues and 8 percent for the global market. Furthermore, the scope of the reference price waiver will be narrowed to midpoint matching only. The large in scale waiver remains unaltered in order to continue to allow the trading of very large blocks of shares without alerting the market. In addition, the order management facility waiver which allows for hidden order trading also remains in place without restrictions. If the proposed legislation comes into force without any further adjustments we expect that some classes of traders who now make heavy use of dark trading as a tool in their trading strategy, could be harmed. Although dark trading can be a substitute for hidden order trading, hidden orders appear to be a less adequate substitute for orders on dark venues. It is therefore questionable whether dark volumes can currently be attracted to lit venues.

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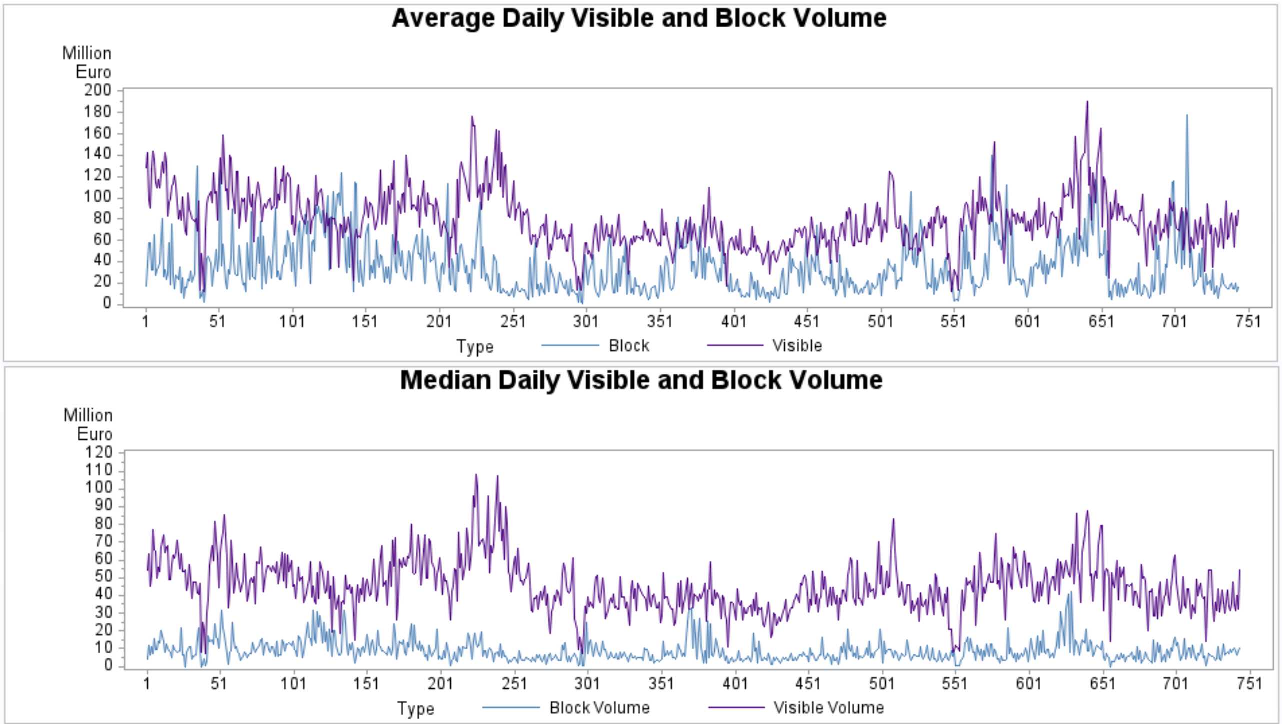
Figure 1: Daily Levels of Trading Volume

Note: This figure presents the daily cross-sectional average and median values for the levels of the four components of trading volume that we define. Panel A shows the visible volume (the volume of trades executed against displayed depth on lit trading venues) and block volume (volume of block trades executed on completely dark trading venues). Panel B shows the hidden order volume (the volume of trades executed against hidden depth on lit trading venues) and dark trading volume (volume of trades executed on completely dark trading venues, excluding large blocks).

Panel A: Visible and Block Volume



Panel B: Hidden Order and Dark Volume

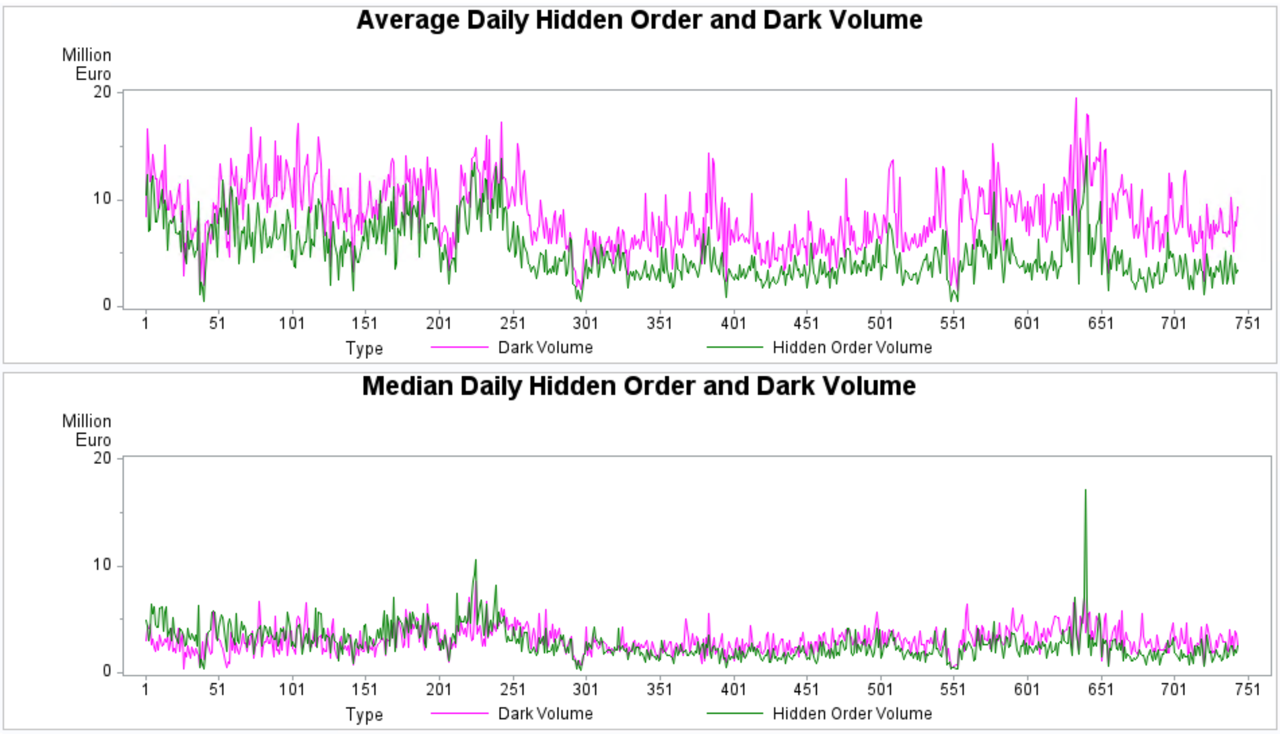
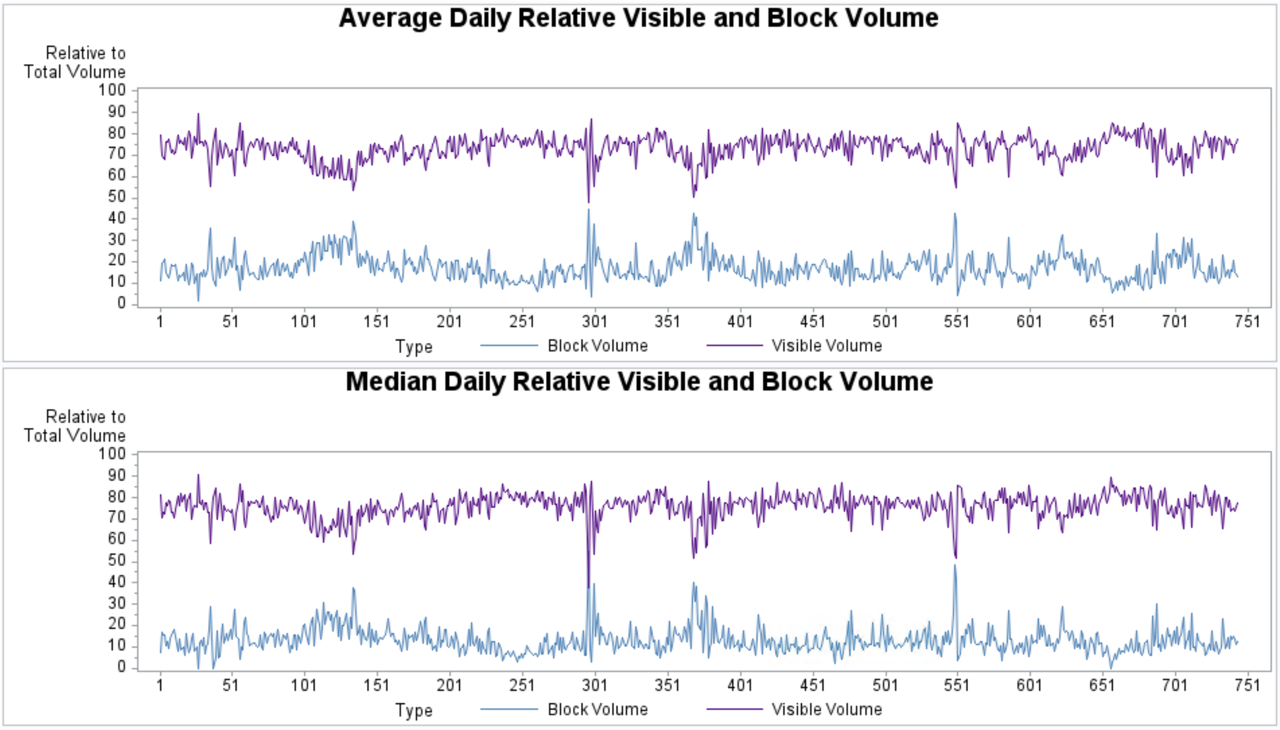


Figure 2: Daily Trading Volume Relative to Total Volume

Note: This figure presents the daily cross-sectional average and median values for the relative four components of trading volume that we define. Panel A shows the visible volume (the volume of trades executed against displayed depth on lit trading venues) and block volume (volume of block trades executed on completely dark trading venues). Panel B shows the hidden order volume (the volume of trades executed against hidden depth on lit trading venues) and dark trading volume (volume of trades executed on completely dark trading venues, excluding large blocks).

Panel A: Visible and Block Volume



Panel B: Hidden Order and Dark Volume

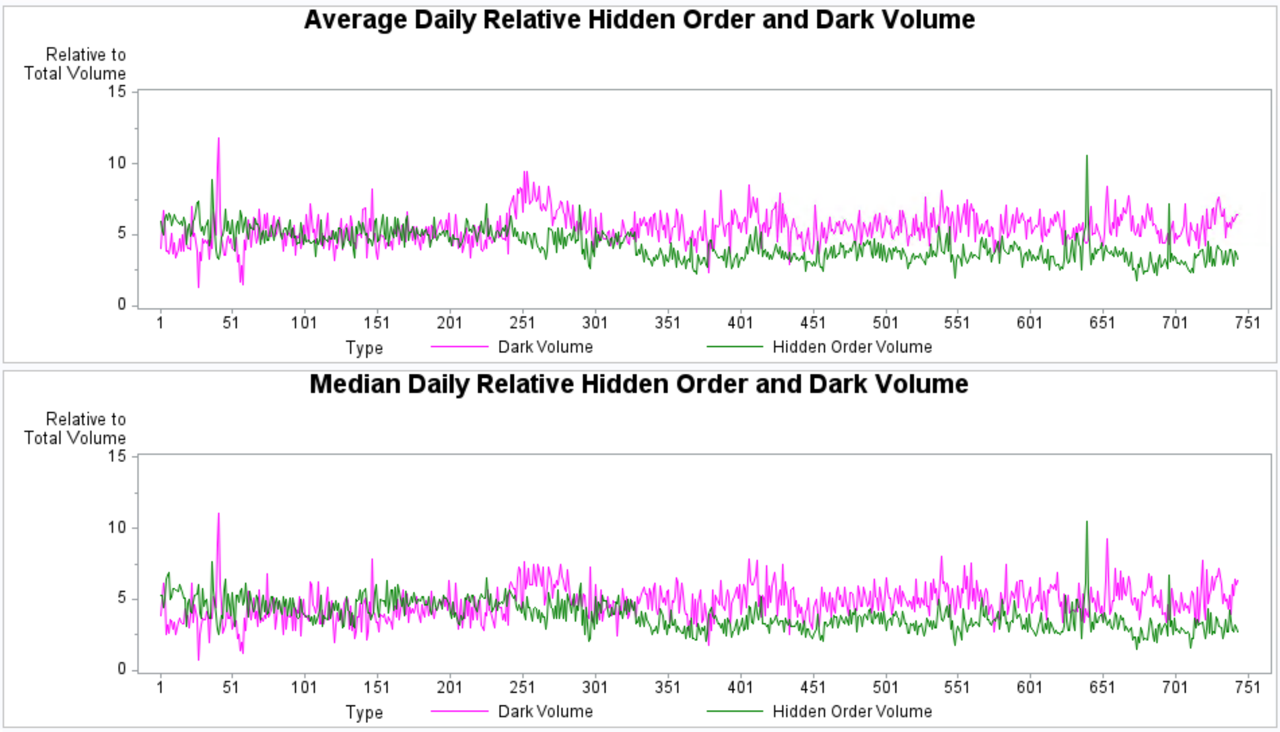


Table 1: Descriptive Statistics

Note: This table presents summary statistics based on daily observations for a number of variables. Panel A shows the number of stock-days for which there are observations in total, as well as for the subsamples. MTF is the subsample for which at least one MTF is trading the stock; CHI is the subsample for which Chi-X is trading; TUR and BAT are similar subsamples for Turquoise and BATS respectively. Panel B shows statistics concerning the transactions at the consolidated market level: euro volume (in thousands), euro size, and number of trades. Panel C shows volume statistics across the different trading venues: lit venue euro volume, hidden order euro volume and the fraction of lit volume executed against hidden orders (in percentage points). In the first two blocks subsample volumes are expressed as a fraction of consolidated lit market volume (%, in percentage points). Subsamples are defined as follows: Main refers to the main trading venue, Alt refers to the consolidated alternative trading venues, CHI refers to Chi-X, TUR refers to Turquoise and BAT refers to BATS. Summary statistics in Panel C are based on observations for which at least one alternative venue trades the stock; for relative measures: when at least two alternative trading venues trade the stock, such that the total sums to 1.

Panel A: Number of Observations across Lit Venues

	Total	MTF	CHI	TUR	BATS
N	17,416	15,564	15,556	10,898	10,318

Panel B: Transactions at the Consolidated Level

	Mean	St. Dev.	P5	Med	P95
$Volume$					
Total	128,617	183,637	7,521	60,657	490,387
Lit	84,827	104,895	6,480	46,011	304,551
Visible	79,734	98,162	6,149	43,396	286,260
Hidden	5,093	7,749	182	2,410	19,009
Dark	8,614	15,105	102	2,783	38,795
Block	35,176	101,827	0	7,142	149,518
$Size$					
Lit	9,517	6,189	3,772	7,770	22,867
Visible	9,154	5,791	3,695	7,515	21,709
Hidden	12,300	10,155	3,678	9,332	32,233
Dark	57,833	86,934	5,067	25,920	225,038
Block	4,422,763	9,212,945	196,301	1,621,873	18,800,000
$NrTrades$					
Lit	8,076	7,845	1,137	5,878	22,971
Visible	7,853	7,578	1,108	5,733	22,285
Hidden	358	453	36	243	1,029
Dark	175	228	7	98	606
Block	7	9	0	5	19

Panel C: Lit Volume across Venue Subsamples

	Mean	St. Dev.	P5	Med	P95
$LitVolume$	89,458	104,754	7,257	50,501	309,267
%Main	77.64	12.59	58.29	76.93	98.00
%Alt	22.36	12.59	2.00	23.07	41.71
%CHI	15.82	8.77	1.81	15.79	29.18
%TUR	4.04	4.10	-	3.48	11.77
%BAT	2.51	2.93	-	1.75	8.21
$HiddenVolume$	5,271	7,702	198	2,602	19,386
%Main	81.91	17.63	43.30	87.77	99.27
%Alt	18.09	17.63	0.73	12.23	56.70
%CHI	10.22	10.55	0.46	7.16	30.47
%TUR	5.52	10.05	-	1.00	26.74
%BAT	2.35	4.06	-	0.71	9.86
$\%HiddenVolume$	5.35	2.84	1.85	4.79	10.76
Main	5.67	3.18	1.66	5.12	11.48
Alt	4.43	5.74	0.56	2.82	13.05
CHI	3.87	5.74	0.28	2.35	11.98
TUR	6.84	11.33	-	2.93	26.25
BAT	5.92	12.95	-	2.49	20.76

Table 1 continued

Note: Panel D presents statistics on market and order book variables. The first block shows visible depth $VisDepth$ measured in euro and the fraction of visible depth (%, in percentage points) that is quoted on selected subsamples of lit venues. Visible depth is defined as the consolidated lit market visible depth offered in an interval of 50 basis points around the midquote, based on Degryse, de Jong, and van Kervel (2014). The second block shows the consolidated quoted spread $QSpread$, relative to the midquote (expressed in basis points) across all trading venues, and that of selected subsamples of lit venues. Both visible depth and quoted spread are based on daily time-weighted averages derived from minute-by-minute order book snapshots. The third block shows the number of $Messages$ transmitted to the consolidated market, and the fraction of those messages that (%, in percentage points) is transmitted to selected subsamples of lit venues. The fourth block shows statistics for algorithmic trading AT at the consolidated lit market level, and AT on selected subsamples of lit venues. The AT measure is based on Hendershott, Jones, and Menkveld (2011). The next-to-last row presents statistics on the fraction of $SORT$ traders based on the γ_2 proxy of van Kervel (2014), while the last row presents statistics on volatility at the consolidated lit market level (expressed in basis points). Subsamples are defined as follows: Main refers to the main trading venue, Alt refers to the consolidated alternative venues, Alt_L refers to the largest alternative trading venue, Alt_S refers to the other alternative trading venues. Summary statistics in Panel D are based on observations for which at least one alternative venue trades the stock; for relative measures: when at least two alternative venues trade the stock, such that the total sums to 1.

Panel D: Market and Order Book Variables

	Mean	St. Dev.	P5	Med	P95
$VisibleDepth$	409,022	439,459	31,311	273,526	1,270,413
%Main	51.46	8.78	36.83	51.94	65.69
%Alt	48.54	8.78	34.31	48.06	63.17
%Alt_L	26.35	6.41	14.95	26.91	35.47
%Alt_S	22.20	8.67	11.08	20.43	38.96
$QuotedSpread$	7.72	5.15	2.97	6.66	16.70
Main	10.38	6.13	4.11	8.95	21.89
Alt	12.96	18.94	3.88	9.03	34.16
Alt_L	16.34	24.67	4.34	10.29	47.63
Alt_S	17.65	17.69	6.70	12.88	41.45
$Messages$	378,313	422,321	31,268	236,088	1,188,858
%Main	31.67	10.97	12.54	32.82	48.48
%Alt	68.33	10.97	51.52	67.18	87.46
%Alt_L	30.32	9.35	16.60	30.00	46.22
%Alt_S	38.01	12.76	21.46	35.85	62.81
$Algo$	-4.52	6.61	-19.37	-1.83	-0.41
Main	-8.95	11.14	-34.22	-4.45	-1.01
Alt	-0.96	0.93	-2.81	-0.69	-0.10
Alt_L	-1.21	0.98	-3.11	-0.94	-0.18
Alt_S	-0.44	0.48	-1.29	-0.30	-0.03
$SORT$	7.43	4.88	0.85	7.03	15.69
$Volatility$	23.45	15.57	9.01	19.60	50.42

Table 2: Determinants of Hidden Volume

Note: This Table presents estimation results of Equation 1. Panel A shows results of Equations 3 and 3 for different specifications. The dependent variable is $\%HidV$ the volume of hidden orders executed across all lit venues relative to the total consolidated volume (columns 1-4) or relative to the consolidated volume across all lit venues (columns 5-8). Panel B presents estimation results of equation 4 for different specifications for the Euronext subsample, Panel C for the MTF subsample, Panel D for the Chi-Xsubsample and Panel E for the Other MTF (Turquoise and BATS) subsample. In Panels B-E the dependent variable is $\%HidV$ the volume of hidden orders executed across the lit venue(s) in the subsample relative to the total lit venue volume from the subsample. Independent variables in the models are: $Volume_{Tot}$, the consolidated volume across all lit venues; $Volume_{Lit}$, the consolidated volume across all lit venues; $Volume_l$, the lit venue volume; $Volat$, the daily standard deviation of five-minute midquote returns; $VisDepth_{Lit}$, the time-averaged consolidated lit market depth quoted within 50 basis points of the midquote; $VisDepth_l$, the time-averaged lit venue depth quoted within 50 basis points of the consolidated midquote, based on Degryse, de Jong, and van Kervel (2014); $Qspread_{Lit}$, the time-averaged consolidated market quoted bid-ask spread (relative to the midquote); AT_{Lit}, a proxy for algorithmic trading based on Hendershott, Jones, and Menkveld (2011), and $SORT$, an estimate of the fraction of traders employing smart order routers, based on van Kervel (2014).

All equations are estimated by 2SLS on a panel of daily observations for 27 Dutch large cap stocks which spans 738 trading days, from November 2007 until September 2010. Variables are standardized by stock-quarter by subtracting the mean and dividing by the standard deviation. Endogenous independent variables $Volume_x$, $Volat$, $VisDepth_x$ and $Qspread_x$ are instrumented by using their 'market version', i.e. for each stock i and day t we take the cross-sectional mean of the variable excluding stock i. AT_x and $SORT$ are assumed to be exogenous. Standard errors are Newey-West for panel data, t-statistics are shown in parentheses, and ***, ***, * indicates significance at the 1%, 5% and 10% level respectively.

Panel A: Consolidated Hidden Order Trading								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to $TotV$				Relative to $LitV$			
$Volume_{Tot}$	0.271***	0.302***		0.288***				
	(10.59)	(13.78)		(14.99)				
$Volume_{Lit}$					0.252***	0.285***		0.271***
					(9.99)	(13.14)		(14.20)
$Volat$	0.029	-0.032	0.244***		0.032	-0.031	0.233***	
	(1.18)	(-1.38)	(12.73)		(1.36)	(-1.36)	(12.25)	
$VisDepth_{Lit}$	-0.118***	-0.140***	-0.065***	-0.124***	-0.119***	-0.142***	-0.070***	-0.125***
	(-5.17)	(-6.24)	(-2.78)	(-5.48)	(-5.20)	(-6.29)	(-2.99)	(-5.56)
$Qspread_{Lit}$	-0.144***	-0.151***	-0.188***	-0.132***	-0.142***	-0.150***	-0.184***	-0.129***
	(-5.97)	(-6.25)	(-7.54)	(-6.06)	(-5.96)	(-6.28)	(-7.43)	(-5.93)
AT_{Lit}	-0.131***		-0.246***	-0.126***	-0.138***		-0.245***	-0.133***
	(-8.80)		(-25.24)	(-9.05)	(-9.34)		(-25.25)	(-9.57)
$SORT$	-0.078***		-0.066***	-0.078***	-0.076***		-0.065***	-0.076***
	(-9.32)		(-7.73)	(-9.32)	(-9.09)		(-7.66)	(-9.08)
N	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416
R^2	0.123	0.102	0.076	0.125	0.119	0.097	0.075	0.121

Table 2 continued

Panel B: Main Venue Hidden Order Trading					
	(1)	(2)	(3)	(4)	(5)
$Volume_l$	0.275***	0.351***		0.285***	0.280***
	(8.71)	(15.04)		(11.09)	(8.72)
$Volat$	0.018	-0.045*	0.207***		-0.018
	(0.74)	(-1.92)	(9.79)		(-0.77)
$VisDepth_l$	-0.219***	-0.207***	-0.203***	-0.223***	-0.202***
	(-9.86)	(-9.29)	(-8.94)	(-10.17)	(-9.39)
$VisDepth_{l' \neq l}$	0.079***	0.021	0.136***	0.081***	0.102***
	(3.31)	(1.02)	(5.98)	(3.35)	(4.72)
$Qspread_l$	-0.068***	-0.102***	-0.064***	-0.060***	
	(-3.01)	(-4.87)	(-2.79)	(-2.75)	
AT_l	-0.180***		-0.333***	-0.178***	-0.194***
	(-7.80)		(-27.13)	(-7.99)	(-9.03)
$SORT$	-0.054***		-0.060***	-0.054***	-0.054***
	(-6.47)		(-6.96)	(-6.45)	(-6.38)
N	15,564	15,564	15,564	15,564	15,564
R^2	0.139	0.116	0.101	0.139	0.141

Panel C: Alternative Venue Hidden Order Trading					
	(1)	(2)	(3)	(4)	(5)
$Volume_l$	0.000	0.028		0.003	0.035
	(0.00)	(1.23)		(0.15)	(1.32)
$Volat$	0.004	-0.047**	0.004		-0.050**
	(0.18)	(-2.12)	(0.25)		(-2.33)
$VisDepth_l$	-0.070**	-0.154***	-0.070***	-0.070**	-0.013
	(-2.43)	(-5.94)	(-2.67)	(-2.45)	(-0.49)
$VisDepth_{l' \neq l}$	-0.031	0.070***	-0.031	-0.032	-0.009
	(-1.19)	(3.11)	(-1.26)	(-1.21)	(-0.33)
$Qspread_l$	-0.120***	-0.109***	-0.120***	-0.118***	
	(-5.25)	(-4.79)	(-5.29)	(-5.60)	
AT_l	-0.212***		-0.212***	-0.211***	-0.208***
	(-11.44)		(-16.66)	(-12.15)	(-11.30)
$SORT$	-0.107***		-0.107***	-0.107***	-0.100***
	(-10.19)		(-10.27)	(-10.31)	(-9.69)
N	15,564	15,564	15,564	15,564	15,564
R^2	0.050	0.012	0.050	0.050	0.050

Panel D: Largest Alternative Venue Hidden Order Trading					
	(1)	(2)	(3)	(4)	(5)
$Volume_l$	0.024	0.057***		0.034*	0.044*
	(0.98)	(2.67)		(1.77)	(1.80)
$Volat$	0.017	-0.044**	0.033*		0.001
	(0.73)	(-1.97)	(1.83)		(0.04)
$VisDepth_l$	-0.154*	-0.040	-0.156*	-0.175**	0.021
	(-1.88)	(-0.49)	(-1.91)	(-2.17)	(0.31)
$VisDepth_{l' \neq l}$	-0.093	0.036	-0.101	-0.110	0.050
	(-1.17)	(0.48)	(-1.29)	(-1.40)	(0.72)
$Qspread_l$	-0.080***	-0.070***	-0.084***	-0.078***	
	(-3.21)	(-2.84)	(-3.40)	(-3.18)	
AT_l	-0.199***		-0.210***	-0.196***	-0.187***
	(-11.21)		(-17.40)	(-11.63)	(-10.57)
$SORT$	-0.071***		-0.068***	-0.071***	-0.066***
	(-7.37)		(-7.15)	(-7.45)	(-6.94)
N	15,556	15,556	15,556	15,556	15,556
R^2	0.040	0.005	0.041	0.040	0.042

Panel E: Other Alternative Venue Hidden Order Trading					
	(1)	(2)	(3)	(4)	(5)
$Volume_l$	0.038	0.031		0.030	0.063*
	(1.10)	(1.20)		(1.06)	(1.86)
$Volat$	-0.014	-0.018	0.005		-0.049*
	(-0.46)	(-0.62)	(0.18)		(-1.73)
$VisDepth_l$	-0.202***	-0.193**	-0.203***	-0.192***	0.007
	(-2.67)	(-2.53)	(-2.68)	(-2.58)	(0.12)
$VisDepth_{l' \neq l}$	-0.080	-0.066	-0.093	-0.070	0.116*
	(-1.03)	(-0.86)	(-1.21)	(-0.92)	(1.80)
$Qspread_l$	-0.131***	-0.140***	-0.135***	-0.135***	
	(-4.17)	(-4.36)	(-4.39)	(-4.58)	
AT_l	-0.150***		-0.170***	-0.152***	-0.145***
	(-6.22)		(-11.97)	(-6.51)	(-5.96)
$SORT$	-0.144***		-0.139***	-0.143***	-0.149***
	(-11.93)		(-11.78)	(-12.12)	(-12.63)
N	11,465	11,472	11,465	11,465	11,465
R^2	0.051	0.020	0.050	0.050	0.050

Table 3: Determinants of Dark and Block Volume

Note: This Table presents estimation results of equations 5 and 6 for different specifications. The dependent variable is $\%DarkV$ the volume of non-block trades executed across all dark venues relative to the total consolidated volume (columns 1-4) or $\%BlockV$ the volume of block trades executed across all dark venues relative to the consolidated total volume (columns 5-8). Independent variables in the models are: $Volume_{Tot}$, the consolidated volume across all lit venues; $Volat$, the daily standard deviation of five-minute midquote returns; $VisDepth_{Lit}$, the time-averaged consolidated lit market depth quoted within 50 basis points of the midquote, based on Degryse, de Jong, and van Kervel (2014); $Qspread_{Lit}$, the time-averaged consolidated market quoted bid-ask spread (relative to the midquote); AT_{Lit}, a proxy for algorithmic trading based on Hendershott, Jones, and Menkveld (2011), and $SORT$, an estimate of the fraction of traders employing smart order routers, based on van Kervel (2014).

All equations are estimated by 2SLS on a panel of daily observations for 27 Dutch large cap stocks which spans 738 trading days, from November 2007 until September 2010. Variables are standardized by stock-quarter by subtracting the mean and dividing by the standard deviation. Endogenous independent variables $Volume_{Tot}$, $Volat$, $VisDepth_{Lit}$ and $Qspread_{Lit}$ are instrumented by using their 'market version', i.e. for each stock i and day t we take the cross-sectional mean of the variable excluding stock i. AT_{Lit} and $SORT$ are assumed to be exogenous. Standard errors are Newey-West for panel data, t-statistics are shown in parentheses, and ***, ***, * indicates significance at the 1%, 5% and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dark Volume				Block Volume			
$Volume_{Tot}$	-0.196***	-0.167***		-0.178***				
	(-7.48)	(-7.42)		(-9.28)				
$Volume_{Tot+Block}$					0.359***	0.328***		0.148***
					(12.39)	(13.05)		(6.32)
$Volat$	0.030	-0.003	-0.126***		-0.307***	-0.277***	-0.088***	
	(1.23)	(-0.13)	(-6.84)		(-11.94)	(-11.26)	(-4.33)	
$VisDepth_{Lit}$	0.015	0.008	-0.023	0.009	-0.050**	-0.041*	0.022	0.019
	(0.72)	(0.39)	(-1.11)	(0.46)	(-2.28)	(-1.91)	(0.94)	(0.88)
$Qspread_{Lit}$	0.021	0.013	0.053**	0.033	0.025	0.031	-0.031	-0.116***
	(0.92)	(0.59)	(2.34)	(1.63)	(1.02)	(1.31)	(-1.24)	(-5.45)
AT_{Lit}	-0.075***		0.009	-0.069***	0.073***		-0.058***	0.023
	(-5.20)		(0.94)	(-5.29)	(5.11)		(-5.77)	(1.54)
$SORT$	0.030***		0.022**	0.031***	-0.020**		-0.008	-0.023***
	(3.37)		(2.47)	(3.39)	(-2.52)		(-0.83)	(-2.66)
N	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416
R^2	-0.017	-0.016	0.000	-0.014	0.227	0.214	0.002	0.107

Table 4: Hidden Order versus Dark Trading: Simultaneous Equation System

Note: This Table presents estimation results of the system of equations 9 for different specifications. The endogenous dependent variables are $DarkV$ the euro volume of non-block trades executed across all dark venues relative to the total consolidated volume; $HidV$, the euro volume of hidden orders executed across all lit venues; and $VisV$, the euro volume of visible orders executed across all lit venues. Independent variables in the models are: $Qspread_{Lit}$, the time-averaged consolidated market quoted bid-ask spread (relative to the midquote); $VisDepth_{Lit}$, the time-averaged consolidated lit market depth quoted within 50 basis points of the midquote, based on Degryse, de Jong, and van Kervel (2014); $Volat$, the daily standard deviation of five-minute midquote returns; AT_{Lit}, a proxy for algorithmic trading based on Hendershott, Jones, and Menkveld (2011), and $SORT$, an estimate of the fraction of traders employing smart order routers, based on van Kervel (2014). $V_{i' \neq i}$ is the instrument for the different volume measures, either $DarkV_{i' \neq i,t}$, $HidkV_{i' \neq i,t}$ or $VisV_{i' \neq i,t}$.

All equations are estimated by 2SLS on a panel of daily observations for 27 Dutch large cap stocks which spans 738 trading days, from November 2007 until September 2010. Variables are standardized by stock-quarter by subtracting the mean and dividing by the standard deviation. Endogenous independent variables $Qspread_{Lit}$, $VisDepth_{Lit}$ and $Volat$ are instrumented by using their 'market version', i.e. for each stock i and day t we take the cross-sectional mean of the variable excluding stock i. AT_{Lit} and $SORT$ are assumed to be exogenous. Standard errors are Newey-West for panel data, t-statistics are shown in parentheses, and ***, ***, * indicates significance at the 1%, 5% and 10% level respectively.

	(1)			(2)			(3)		
	$DarkV$	$HidV$	$VisV$	$DarkV$	$HidV$	$VisV$	$DarkV$	$HidV$	$VisV$
$DarkV$		-0.043	-0.041		-0.037	-0.017		-0.043	-0.039
		(-1.23)	(-1.04)		(-0.97)	(-0.41)		(-1.24)	(-1.00)
$HidV$	-0.127**		-0.212***	-0.048		-0.032	-0.140***		-0.246***
	(-2.37)		(-3.29)	(-0.96)		(-0.62)	(-2.70)		(-3.83)
$VisV$	0.150***	0.175***		0.177***	0.229***		0.154***	0.174***	
	(3.58)	(4.88)		(4.29)	(6.61)		(3.73)	(4.89)	
$Qspread_{Lit}$	0.022	-0.004	0.053**	0.007	-0.025	0.022			
	(1.10)	(-0.22)	(2.57)	(0.34)	(-1.43)	(1.11)			
$VisDepth_{Lit}$	0.038*	0.018	0.068***	0.016	-0.023	0.017	0.029*	0.019	0.047***
	(1.91)	(0.99)	(3.38)	(0.82)	(-1.25)	(0.81)	(1.69)	(1.22)	(2.59)
$Volat$	0.129***	0.176***	0.282***	0.016	0.010	0.026	0.140***	0.175***	0.313***
	(5.77)	(8.70)	(11.82)	(0.82)	(0.55)	(1.31)	(6.62)	(8.76)	(14.33)
AT_{Lit}	-0.256***	-0.377***	-0.583***				-0.257***	-0.378***	-0.589***
	(-14.41)	(-20.25)	(-17.07)				(-14.40)	(-21.05)	(-17.07)
$SORT$	0.031***	-0.033***	0.037***				0.030***	-0.033***	0.035***
	(3.65)	(-4.92)	(4.59)				(3.55)	(-4.91)	(4.32)
$V_{i' \neq i}$	0.596***	0.542***	0.870***	0.604***	0.615***	0.919***	0.597***	0.543***	0.878***
	(23.04)	(14.99)	(22.51)	(23.47)	(16.40)	(22.67)	(23.01)	(15.32)	(22.71)
N	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416
R^2	0.185	0.465	0.404	0.172	0.347	0.238	0.183	0.465	0.395

Table 4 continued

	(4)			(5)			(6)		
	$DarkV$	$HidV$	$VisV$	$DarkV$	$HidV$	$VisV$	$DarkV$	$HidV$	$VisV$
$DarkV$		-0.040	-0.033		-0.030	-0.024		-0.031	-0.022
		(-1.17)	(-0.82)		(-0.88)	(-0.54)		(-0.91)	(-0.47)
$HidV$	-0.151***		-0.263***	-0.125**		-0.243***	-0.166***		-0.381***
	(-2.92)		(-3.97)	(-2.34)		(-3.07)	(-3.18)		(-4.12)
$VisV$	0.171***	0.182***		0.222***	0.272***		0.262***	0.296***	
	(4.36)	(5.35)		(5.53)	(8.92)		(6.89)	(10.43)	
$Qspread_{Lit}$	0.005	-0.011	0.025	0.075***	0.069***	0.200***			
	(0.29)	(-0.76)	(1.28)	(4.02)	(3.98)	(8.92)			
$VisDepth_{Lit}$				0.012	-0.018	0.012			
				(0.61)	(-1.10)	(0.54)			
$Volat$	0.120***	0.170***	0.276***						
	(5.46)	(8.94)	(11.22)						
AT_{Lit}	-0.258***	-0.373***	-0.605***	-0.236***	-0.348***	-0.631***	-0.223***	-0.322***	-0.658***
	(-14.43)	(-21.15)	(-17.18)	(-14.40)	(-20.07)	(-14.66)	(-14.43)	(-22.35)	(-13.63)
$SORT$	0.031***	-0.033***	0.039***	0.031***	-0.033***	0.044***	0.024***	-0.040***	0.028***
	(3.67)	(-4.89)	(4.63)	(3.70)	(-4.93)	(4.73)	(2.94)	(-6.23)	(2.90)
$V_{i' \neq i}$	0.600***	0.536***	0.903***	0.602***	0.544***	1.028***	0.604***	0.530***	1.143***
	(23.17)	(15.43)	(22.70)	(23.27)	(14.59)	(19.00)	(23.40)	(14.83)	(18.29)
N	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416
R^2	0.183	0.471	0.368	0.189	0.480	0.238	0.190	0.495	0.152

Table 5: Hidden Order versus Dark Trading: Simultaneous Equation System (with Block Volume)

Note: This Table presents estimation results of the system of equations 10 for different specifications. The endogenous dependent variables are $DarkV$ the euro volume of non-block trades executed across all dark venues relative to the total consolidated volume; $HidV$, the euro volume of hidden orders executed across all lit venues; $VisV$, the euro volume of visible orders executed across all lit venues; and $BlockV$, the euro volume of block trades executed across all dark venues. Independent variables in the models are: $Qspread_{Lit}$, the time-averaged consolidated market quoted bid-ask spread (relative to the midquote); $VisDepth_{Lit}$, the time-averaged consolidated lit market depth quoted within 50 basis points of the midquote, based on Degryse, de Jong, and van Kervel (2014); $Volat$, the daily standard deviation of five-minute midquote returns; AT_{Lit}, a proxy for algorithmic trading based on Hendershott, Jones, and Menkveld (2011), and $SORT$, an estimate of the fraction of traders employing smart order routers, based on van Kervel (2014). $V_{i'\neq i}$ is the instrument for the different volume measures, either $DarkV_{i'\neq i,t}$, $HidkV_{i'\neq i,t}$, $VisV_{i'\neq i,t}$ or $BlockV_{i'\neq i,t}$.

All equations are estimated by 2SLS on a panel of daily observations for 27 Dutch large cap stocks which spans 738 trading days, from November 2007 until September 2010. Variables are standardized by stock-quarter by subtracting the mean and dividing by the standard deviation. Endogenous independent variables $Qspread_{Lit}$, $VisDepth_{Lit}$ and $Volat$ are instrumented by using their 'market version', i.e. for each stock i and day t we take the cross-sectional mean of the variable excluding stock i. AT_{Lit} and $SORT$ are assumed to be exogenous. Standard errors are Newey-West for panel data, t-statistics are shown in parentheses, and ***, ***, * indicates significance at the 1%, 5% and 10% level respectively.

	(1)				(2)				(3)			
	$DarkV$	$HidV$	$VisV$	$BlockV$	$DarkV$	$HidV$	$VisV$	$BlockV$	$DarkV$	$HidV$	$VisV$	$BlockV$
$DarkV$		-0.031	-0.016	0.088*		-0.036	-0.011	0.090*		-0.031	-0.012	0.088*
		(-0.83)	(-0.38)	(1.88)		(-0.90)	(-0.25)	(1.91)		(-0.84)	(-0.30)	(1.88)
$HidV$	-0.131**		-0.204***	-0.049	-0.057		-0.030	0.004	-0.144***		-0.235***	-0.047
	(-2.45)		(-3.18)	(-0.74)	(-1.13)		(-0.57)	(0.07)	(-2.79)		(-3.70)	(-0.73)
$VisV$	0.147***	0.176***		0.025	0.171***	0.229***		0.039	0.151***	0.176***		0.024
	(3.51)	(4.93)		(0.50)	(4.16)	(6.62)		(0.79)	(3.66)	(4.93)		(0.49)
$BlockV$	0.051	-0.038	-0.077**		0.076*	-0.001	-0.019		0.049	-0.038	-0.083**	
	(1.21)	(-1.11)	(-1.97)		(1.84)	(-0.03)	(-0.43)		(1.16)	(-1.10)	(-2.11)	
$Qspread_{Lit}$	0.023	-0.005	0.051**	-0.003	0.009	-0.025	0.021	-0.012				
	(1.16)	(-0.28)	(2.46)	(-0.14)	(0.46)	(-1.43)	(1.08)	(-0.57)				
$VisDepth_{Lit}$	0.033*	0.021	0.074***	0.049**	0.010	-0.022	0.018	0.032	0.024	0.022	0.054***	0.051***
	(1.66)	(1.14)	(3.63)	(2.25)	(0.52)	(-1.24)	(0.87)	(1.44)	(1.39)	(1.40)	(2.94)	(2.62)
$Volat$	0.129***	0.175***	0.279***	0.053**	0.021	0.010	0.025	-0.024	0.141***	0.173***	0.308***	0.052**
	(5.80)	(8.64)	(11.71)	(2.25)	(1.05)	(0.54)	(1.23)	(-1.15)	(6.70)	(8.68)	(14.12)	(2.29)
AT_{Lit}	-0.249***	-0.381***	-0.587***	-0.177***					-0.250***	-0.382***	-0.594***	-0.177***
	(-13.06)	(-19.74)	(-17.11)	(-9.11)					(-13.05)	(-20.43)	(-17.14)	(-9.11)
$SORT$	0.031***	-0.034***	0.036***	-0.005					0.030***	-0.034***	0.034***	-0.005
	(3.67)	(-5.00)	(4.47)	(-0.56)					(3.57)	(-4.99)	(4.21)	(-0.55)
$V_{i'\neq i}$	0.587***	0.544***	0.871***	0.578***	0.589***	0.615***	0.919***	0.588***	0.587***	0.546***	0.879***	0.578***
	(21.57)	(14.88)	(22.50)	(18.63)	(21.98)	(16.28)	(22.65)	(18.71)	(21.53)	(15.18)	(22.72)	(18.62)
N	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416
R^2	0.192	0.461	0.400	0.103	0.184	0.347	0.236	0.089	0.191	0.460	0.390	0.103

Table 5 continued

	(4)				(5)				(6)			
	$DarkV$	$HidV$	$VisV$	$BlockV$	$DarkV$	$HidV$	$VisV$	$BlockV$	$DarkV$	$HidV$	$VisV$	$BlockV$
$DarkV$		-0.029	-0.012	0.092**		-0.009	0.022	0.094**		0.005	0.066	0.096**
		(-0.79)	(-0.28)	(1.97)		(-0.26)	(0.47)	(2.03)		(0.14)	(1.34)	(2.09)
$HidV$	-0.152***		-0.260***	-0.081	-0.128**		-0.227***	-0.046	-0.166***		-0.352***	-0.072
	(-2.94)		(-3.94)	(-1.24)	(-2.39)		(-2.89)	(-0.70)	(-3.18)		(-3.88)	(-1.11)
$VisV$	0.165***	0.185***		0.052	0.221***	0.273***		0.053	0.262***	0.297***		0.070
	(4.16)	(5.45)		(1.08)	(5.48)	(8.93)		(1.07)	(6.86)	(10.33)		(1.42)
$BlockV$	0.058	-0.033	-0.063		0.032	-0.065*	-0.141***		-0.007	-0.109***	-0.264***	
	(1.43)	(-0.98)	(-1.57)		(0.75)	(-1.88)	(-3.08)		(-0.18)	(-3.22)	(-5.33)	
$Qspread_{Lit}$	0.009	-0.013	0.021	-0.024	0.076***	0.066***	0.193***	0.019				
	(0.50)	(-0.90)	(1.07)	(-1.37)	(4.09)	(3.82)	(8.56)	(0.95)				
$VisDepth_{Lit}$					0.009	-0.013	0.025	0.039*				
					(0.45)	(-0.74)	(1.04)	(1.83)				
$Volat$	0.122***	0.168***	0.273***	0.043*								
	(5.56)	(8.84)	(11.11)	(1.85)								
AT_{Lit}	-0.250***	-0.376***	-0.611***	-0.179***	-0.232***	-0.354***	-0.638***	-0.167***	-0.224***	-0.335***	-0.675***	-0.171***
	(-13.04)	(-20.78)	(-17.18)	(-9.16)	(-12.92)	(-19.40)	(-14.70)	(-9.45)	(-12.68)	(-21.17)	(-13.68)	(-10.21)
$SORT$	0.031***	-0.034***	0.038***	-0.005	0.031***	-0.034***	0.043***	-0.005	0.024***	-0.041***	0.027***	-0.005
	(3.70)	(-4.96)	(4.55)	(-0.54)	(3.72)	(-5.06)	(4.53)	(-0.55)	(2.95)	(-6.24)	(2.76)	(-0.52)
$V_{i' \neq i}$	0.588***	0.537***	0.906***	0.585***	0.596***	0.548***	1.027***	0.573***	0.605***	0.536***	1.136***	0.580***
	(21.58)	(15.37)	(22.69)	(18.90)	(21.76)	(14.43)	(18.95)	(18.70)	(21.70)	(14.70)	(18.14)	(19.46)
N	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416	17,416
R^2	0.192	0.469	0.363	0.103	0.194	0.471	0.223	0.105	0.189	0.476	0.091	0.105