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Why do traders choose dark markets?

Ryan Garvey [a,*], Tao Huang [b,c,1], Fei Wu [c,2]

[a] Duquesne University, 600 Forbes Avenue, Pittsburgh, PA 15282, United States
[b] International Business School Suzhou, Xi'an Jiangtong-Liverpool University, Suzhou, China
[c] Shanghai Advanced Institute of Finance, Shanghai Jiao Tong University, Shanghai, China

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We examine U.S. equity trader use of dark and lit markets. Marketable orders executed in the dark have lower information content and smaller fill rates. Dark orders take longer to execute, but they execute at more favorable prices. Traders are more likely to go dark when the bid-ask spread is wider and those with higher dark participation are more sophisticated. Although market regulators have expressed concern over the rise in dark trading, our results indicate that dark markets provide important benefits to traders that lit markets do not.

1. Introduction

An increasingly large portion of U.S. equity trading volume is moving away from traditional stock exchanges. For example, in 2013, approximately 37% of stock trading occurred away from U.S. exchanges, an increase above the average of 29% in 2008.[3] Traders are bypassing public (i.e., lit) markets at an increasing rate in favor of private (i.e., dark) markets. In lit markets, buyers' and sellers' orders are displayed to the rest of the marketplace. In dark markets, the trading interests of market participants are not displayed prior to execution. The declining market share of U.S. stock exchanges is causing many in the securities industry, including market regulators, to question the value of dark markets openly. While recent studies on dark trading have attempted to address the issue of whether the existence of dark venues operating alongside lit venues improves overall market quality, in our study, we take a different approach and examine dark trading from the perspective of an individual trader. We seek to provide some insight for answering a fundamental question related to dark trading: *Why do traders choose dark markets?* Answering this question is important for understanding not only the issues involved in dark trading, but also the (dis)advantages that continually confront traders when choosing dark versus lit order execution in U.S. equities.

To conduct the study, we obtained proprietary data from a U.S. direct market access (DMA) broker. DMA data are advantageous because their brokers allow clients to choose where and how orders are executed. The brokerage-level data enable us to analyze trading from the order submission decision and measure various dimensions of execution quality that are not observable in transaction-level data, including time to execution and percentage of an order filled. We are also able to analyze characteristics of traders who use dark markets more often. These factors are not examined in recent studies on dark trading that use data sources at the market center-level (e.g., Degryse et al., 2014; Comerton-Forde and Putnins, 2015). We study more than two and one-half million dark/lit marketable order execution decisions, and more than six million trading decisions overall. The results are based on more than three thousand equity traders who are geographically dispersed throughout the U.S.

Why might traders choose dark over lit markets? First, content regarding trader information is likely an important factor. For example, Zhu (2014) argues that informed traders have low execution probabilities in dark venues because they all tend to trade in the same direction at the same time. In contrast, uninformed traders are equally likely to buy or sell and this increases the probability of finding a match in the dark. Consequently, dark (lit) markets will be more attractive on average to uninformed (informed) traders. We find that significant differences exist in the information content behind dark and lit marketable order executions. Lit trades are

* Corresponding author. Tel.: +1 (412) 396 4003; fax: +1 (412) 396 4764.
E-mail addresses: Garvey@duq.edu (R. Garvey), thuang@saif.sjtu.edu.cn (T. Huang), fwu@saif.sjtu.edu.cn (F. Wu).
1 Tel./fax: +86 216 293 4063.
2 Tel.: +86 791 381 6750; fax: +86 791 381 6792.
3 "SEC Chairman Targets Dark Pools, High-Speed Trading" by Scott Patterson, *Wall Street Journal*, June 6, 2014, C1.

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informative about future price direction while dark trades are not. Furthermore, we find that the average fill rate for a dark marketable order execution is lower than that of a lit marketable order execution. This is also in line with Zhu's (2014) prediction that finding a match in the dark is more difficult for the informed.

Traders may also choose dark venues because they offer better prices. For example, in our setting, the dark venue is operated by a large wholesale market maker. The firm seeks to profit by matching incoming retail/institutional order flow in the dark either at or within the lit market spread. Price improvement may occur on trades because market makers are particularly good at "cream-skimming" uninformed order flow and pay for it by offering slightly better prices (see, for example, Easley et al., 1996; Barclay et al., 2003). We find that dark marketable order executions have significantly lower effective spreads than lit orders and that price improvement occurs on more than 80% of the dark orders executed, thus saving traders more than $6.3 million (on average, $18.66 per order). This cost-saving estimate assumes traders could have obtained the NBBO quote displayed in the lit markets at the time of their order submission to the dark market.

If, on average, dark orders execute at better prices, then presumably the cost-saving benefit must be traded off with slower execution. The financial literature has long noted the price-time tradeoff with trader decision to use a market order versus a limit order (see Cohen et al., 1981). For example, market orders execute quickly but pay the bid-ask spread. Limit orders are slower to execute (and may not execute), but they avoid the bid-ask spread.[4] Overall, we find that the average time-to-execution for a dark order execution is much longer than for a lit order execution, and the average effective spread for a dark order execution is much smaller than for a lit order execution. The price-time tradeoff a trader faces with the use of a dark venue versus a lit venue is similar to the one they face with the use of a market order versus a limit order. Our results suggest dark trades result from patient traders who are motivated to trade for liquidity reasons and are willing to trade waiting costs for better prices.

Order size may also influence a trader's decision to go dark. In general, dark markets are good for locating large counterparties. Trading in the dark enables a trader to hide his or her interest, which prevents front running practices. A trader does not want to display a large limit order in a lit market because it offers free options to other market participants. Executing a large marketable order in a lit market results in a cost as well, because market makers need to be compensated for inventory risk and the risk of adverse selection. Academic researchers have studied differences in trading between "upstairs" and "downstairs" markets. An upstairs market is one where brokers work privately to negotiate terms and find counterparties for large block transactions. In such non-anonymous settings, Seppi (1990) and Madhavan and Cheng (1997) argue that reputation mechanisms exist that enable uninformed traders to credibly signal their block trades are motivated by liquidity and, in return, execute with smaller price impact. The wholesale market-making firm that operates the dark venue in our setting is not able to identify individual market participants, but is able to identify where order flow originates and the information content that is typically behind it. We find that orders sent to the dark market are significantly larger in size. The average submitted size of a dark order execution is more than twice the size of the average trade size in the overall marketplace. In addition, dark block orders (10,000 + shares) have a shorter time-to-execution and smaller price impact than lit orders.

Finally, market conditions and trader characteristics likely influence trader decision to execute in the dark. For example, consistent with Zhu (2014) and others, we find that a wider bid-ask spread in the lit market (and other factors) increases the likelihood of a dark order execution. Trader characteristics are also correlated with dark trading. Overall, we find that the more experienced and skillful one is at trading, the higher their dark market participation. For example, traders who more often execute in the dark execute significantly more orders overall. They are more patient with executing orders, use more trading venues and order types, trade over a longer period of time, and pay a lower overall cost to trade. It is important to note that traders who execute in the dark more often also appear to be better at forecasting future price direction. For example, when traders with higher (lower) dark market participation buy, market prices are more likely to rise (fall); and, when they sell, market prices are more likely to fall (rise). Ex-post performance is measured by using three time intervals (e.g., five minutes, one hour, and to the end of the trading day).

Most of the recent empirical and theoretical studies on dark trading have attempted to address the issue of whether the existence of dark venues operating alongside lit venues improves overall market quality. The findings are mixed.[5] For example, one way to proxy for dark trading activity in the overall market is by means of data from a trade reporting facility (TRF).[6] Trades reported to a TRF often originate from dark venues (dark pools and broker-dealer internalization), although they can also originate from lit venues such as electronic communication networks (ECNs). O'Hara and Ye (2011) find that stocks with higher TRF reporting exhibit better market quality. Weaver (2014) examines a more recent sample period when TRF reporting is driven by broker-dealer internalization and finds a negative relationship between market quality and higher TRF reporting. Both Buti et al. (2011), as well as Nimalendran and Ray (2012), study trading data that are provided by dark pool operators. In particular, Buti et al. (2011) find that increased dark pool activity improves market quality measures such as spreads, depth, and daily (intradaily) volatility, whereas Nimalendran and Ray (2012) find that, in less liquid stocks, trading in the dark market leads to increased spreads and higher price impacts in the lit market. Theoretical studies on the impact of dark trading also seem to indicate varying results. For example, Zhu (2014) conjectures that the existence of dark trading alongside lit trading improves market quality; yet, Ye (2012) predicts an opposite result.

The impact of dark trading on market quality is not well understood. In addition, whether or not the proliferation of dark venues operating alongside lit venues in the fragmented U.S. equity market is beneficial remains a highly controversial topic.[7] In our study, we examine dark trading from a different perspective, namely that of an individual trader. Unlike the aforementioned prior studies, we use U.S. brokerage-level data and examine trading over a different sample period that spans eight calendar years ending in May 2006. Our motivation is to provide some insight into why traders choose dark markets. Answering this question is important for understanding not only the issues involved in dark trading but, also, the (dis)advantages with which traders are continually confronted when choosing

[4] Boehmer (2005) and Hodrick and Moulton (2009) also emphasize a trade-off between the various dimensions of order execution quality such as price and time (e.g., Boehmer, 2005) and price, time and size (e.g., Hodrick and Moulton, 2009).

[5] Researchers have examined the relationship between dark trading and market quality in settings outside the U.S. As in the case of U.S. equities, the results appear mixed. For example, Comerton-Forde and Putnins (2015) find that increases in dark trading adversely impact market quality in Australia, whereas Degryse et al. (2014) find that increases in dark trading lessen market quality in Dutch stocks. Brugler (2015) finds that increases in dark trading improve market quality in the U.K., whereas both Brandes and Domowitz (2011) as well as Buchanan et al. (2011) find that increases in dark trading improve market quality in Europe.

[6] Public exchanges (also) allow traders to post orders that are hidden from the rest of the market. These trade executions are not identified as such when exchanges report their trades to the consolidated tape. Hautsch and Huang (2012) study hidden order placement strategies on the NASDAQ (lit) stock market.

[7] Market regulators have recently requested information from dark pool operators in an attempt to gain a better understanding of trading in their markets. "Dark Pools Face Scrutiny" by Scott Patterson, *Wall Street Journal*, June 5, 2013, C1.

between dark and lit order executions in U.S. equities. From a policy implication standpoint, an important shortcoming of many studies, including O'Hara and Ye (2011), Weaver (2014), and others, is that they examine the impact of dark trading on lit liquidity, but ignore liquidity in the dark market. Our study incorporates dark liquidity. For example, effective dark spreads are analyzed.

In the next section, we describe the market setting under analysis, and in Section 3, we describe the data used in the study. In Section 4, we examine trader use of dark and lit markets. This includes an examination of quality differences in order execution between dark and lit markets because this can influence the decision of trading venue. We also examine who is more likely to use dark markets by analyzing differences between those with higher (lower) dark market participation. Section 5 of the paper provides concluding remarks.

2. Description of the market

2.1. The overall market environment

Our focus is on the trading of NASDAQ-listed stocks, and the data sample spans eight calendar years beginning in October 1999 and ending in May 2006. Naturally there are changes in the trading environment over this extended time period. In general, though, trading in NASDAQ-listed stocks is characterized over the sample period as an electronically-driven marketplace between competing NASDAQ market makers and ECNs (see, for example, Barclay et al., 2003; Goldstein et al., 2008). ECNs are electronic order books that automatically match buy and sell orders at specified prices. While any market participant (e.g., retail and institutional investors, broker-dealers, etc.) can subscribe to an ECN and access its order book, many ECNs display their order books free over the Internet. ECNs display their top of book prices through either the exchanges or alternative display facility. In the NASDAQ stock market, registered market makers are required to maintain two-sided quotes throughout market opening hours. Traders can view and access market maker quotes automatically using NASDAQ trading systems or by trading with market-making firms outside of NASDAQ in dark pools and internalization markets.

For much of our sample period, there are important differences between trading on an ECN and the NASDAQ stock market. For one, most ECNs operate as open limit order books without designated liquidity providers. In contrast, on the NASDAQ stock market, competing market makers ensure a guaranteed source of liquidity by standing ready to buy and sell throughout the day. Trading on ECNs tends to be faster than trading on NASDAQ, and ECNs provide full (pre- and post-trade) anonymity whereas NASDAQ does not. Speed, anonymity, and a guaranteed source of liquidity are all important factors that many traders consider when choosing a trading venue.

As time progresses over our sample period, ECNs become increasingly popular and their market share rises significantly relative to NASDAQ. There is also consolidation among ECNs, which enables several of the venues to become more formidable competitors to NASDAQ on a direct basis (rather than in the aggregate). In response to declining market share in its own listed companies, NASDAQ acquires some of the major ECNs (e.g., BRUT and INET) and begins to transition its trading platform to more closely resemble the ECN open limit order book model. For example, in the latter part of our sample, NASDAQ provides fully anonymous trading and allows non-market maker traders to submit limit orders to its system, thereby competing with market makers directly for order flow. In addition, NASDAQ engages in a series of major upgrades to its trading system, which, among other things, results in increased trading speed that rivals many of the ECNs.

Toward the end of our sample period, the Securities and Exchange Commission (SEC) passed an important regulation, Regulation National Market System (NMS), and implemented its new set of rules in 2007. Regulation NMS, among other things, resulted in greater linkages between U.S. trading centers because it required exchanges and brokers to immediately route orders to the electronic market center displaying the best price, thereby removing the possibility of having orders traded through. Prior to the implementation of Regulation NMS, on NASDAQ-listed stocks, brokers (including our sample firm) and exchanges were already scanning numerous market centers for the best price and routing orders accordingly. However, Regulation NMS increased the amount of scanning and sped up trading in the overall marketplace. The new rules spurred other changes as well. For example, Regulation NMS created greater incentives for trading venues to become registered stock exchanges in order to link to the major market centers and qualify for order protection. Some major ECNs (e.g., BATS and Direct Edge) converted to full-fledged exchanges shortly after Regulation NMS was adopted. Regulation NMS is also thought to have moved more trading away from lit markets to dark markets. For example, the access fees that exchanges charge provided brokers with a greater incentive to send orders to (new) dark venues which typically have lower trading costs (e.g., no access fees) and offer price improvement opportunity.

The market environment that we observe in our setting is not the same one that exists today or the one that will exist tomorrow. The U.S. equity market is highly dynamic and constantly evolving. In the current market environment, trading is faster and more technologically advanced, there are more trading venues (both lit and dark), and different types of market participants (e.g., high frequency traders are more present in the current market than in our setting). However, in a general sense, the market setting that we observe is very similar to the one that exists today. For example, both in our sample setting and in the current market environment, NASDAQ is an electronically-driven marketplace, order flow is highly fragmented across numerous (lit and dark) venues, and electronic order books are the common form of market design.

2.2. The dark market

During our sample period, traders had the ability to transact in both lit and dark venues. Exchanges and ECNs publicly display prices, and they are commonly classified (aggregated) as lit venues. Dark pools and broker-dealer internalization markets do not publicly display prices, and they are commonly classified (aggregated) as dark venues. The DMA broker provided their clients with direct access to all of the U.S. equity markets (e.g., exchanges/ECNs) that publicly displayed their buy and sell orders. In addition, the DMA traders could submit marketable orders (market orders and marketable limit orders) only through a direct connection to a large U.S. wholesale market-maker. The market making firm operates a single dark pool, where they match incoming retail/institutional order flow from numerous clients. The securities firm that operates the dark pool is one of the largest equity market makers in the U.S. and it is well known among market professionals, both during our sample period and in the current market environment, for providing "deep pools of liquidity" other than those available on lit markets.

When a trader submits a marketable order to the dark venue, the order may match against the wholesale market maker (i.e., internalization), a client of the wholesale market maker, or another NASDAQ dealer. We are unable to determine the contra party on dark order executions, and we do not know to what extent (if any) the wholesaler is actually using its own capital to fill the dark marketable order executions that we observe.[8] There is no

[8] In the late 1990s/early 2000s, many NASDAQ market makers changed their business models and began acting more as agents rather than principals. The change was brought on by the proliferation of alternative trading systems (e.g., electronic limit order books) and switch to decimal pricing (see GAO, 2005).

order size limit on orders sent to the dark venue, and the dark market operator is unable to identify individual traders who submit orders to the pool. Trader orders are routed anonymously under the DMA broker identification.

The wholesaler facilitates order matching in the dark the following way. First, the firm seeks to make markets and bridge the liquidity by quickly matching incoming order flow using its own capital. For example, buying from those who want to sell, and moments later, selling to those who want to buy (often within the NBBO). However, market makers set designated limits on the amount of capital they are willing to commit (risk) for trading each stock. If an order imbalance begins to develop and the wholesaler accumulates a long (short) position during the day that triggers an internal risk limit, it will then seek to match incoming marketable order flow against other clients of the firm. The wholesaler contracts with numerous clients (e.g., large buy-side institutions) to execute orders on their behalf. If the market maker cannot match an order itself or against another client resting order in house, the firm will then match an order against another NASDAQ dealer. Firms registered to make markets in NASDAQ-listed stocks are required to maintain two-sided quotes throughout market opening hours, and they often maintain direct trading links with each other. Market makers who do not wish to trade will post non-competitive prices relative to the NBBO. If the wholesaler fills an order against another client resting order or NASDAQ dealer, the firm is generally not at risk (or acting as a riskless principal) because execution of the order is contingent upon the market maker finding a match with another trader.

As the order matching process shifts from one method to the next, this inevitably increases time to execution and the chances that a trader will cancel an order prior to execution. The wholesaler risks its own capital and provides liquidity throughout the day. Thus, the firm is exposed to adverse selection risk and they inevitably lose money on certain trades (e.g., when their position risk limit is hit). Overall, the firm appears highly profitable though as evident by their financial reports, size, and longevity as a leading market maker in U.S. equities. The wholesaler guarantees execution of market orders, but their adverse selection risk is still limited under the program because they will only accumulate a long (short) position intraday for a set number of shares. The wholesaler can guarantee execution of market orders, but simultaneously stop committing its own capital when they reach their position limit, because the market maker can act in either a principal or agent capacity and there is always a continuous two-sided market available in the NASDAQ marketplace which the firm can access to help fill its incoming client order flow. When the wholesaler acts as an agent and fills an order against another NASDAQ dealer, the firm is essentially performing a function that the DMA traders could do themselves. For example, the DMA traders can access market maker quotes in the NASDAQ stock market directly and NASDAQ guarantees execution of market orders.

When the DMA traders send market orders to the lit markets they may or may not fill. For example, market orders sent to NASDAQ will eventually fill against two-sided market maker quotes, but market orders (if allowed) sent to ECNs operating without a designated liquidity provider may not fill if the order book is not two-sided. Marketable limit orders (i.e., a limit buy order priced at or above the NBO at order submission time and a limit sell order priced at or below the NBB at order submission time) sent to dark or lit markets may not always fill either. For example, assume that the national best offer is $10.10 and a trader submits a marketable limit buy order priced at $10.15. If the national best offer rises to $10.20 before the trader's order reaches the market, the order will not fill.

While the dark venue that we observe is primarily organized to match marketable order flow, the wholesale market maker accepts both marketable orders and non-marketable limit orders from its base of numerous clients. And, as mentioned, marketable order flow routed to the dark venue can interact with limit orders that the wholesale market maker is seeking to execute on behalf of its clients. However, when the wholesale market maker receives a client limit order, it will typically first display it in the lit markets for a potential match unless it is for a large size or the client instructs otherwise.

DMA traders manage all aspects of the trading process, including how and where orders are routed for execution. However, order routing is not completely open-ended, and the broker does impose some restrictions. For example, it is not advantageous for our sample traders to submit a non-marketable limit order to the wholesale market maker for execution, and the DMA firm's trading software restricts traders from doing so. There are various reasons for this. First, the traders sign up with the DMA broker so that they can directly access markets and execute their own orders. Sending a limit order to the wholesale market maker to execute on their behalf would be counterintuitive to their underlying objective, and it would slow down the trading process. Second, the wholesaler does not offer favorable pricing to our sample DMA broker for trader non-marketable limit order execution. For example, liquidity rebates are not paid for non-marketable limit order execution. In contrast, many lit U.S. equity market centers use a pricing model that charges an access fee for orders that take liquidity (i.e., marketable orders) and pays a rebate for orders that provide liquidity (i.e., non-marketable limit orders). Liquidity rebates may be paid in lit markets for both hidden and displayed limit order execution. The DMA broker offers varying commission plans to its clients over our sample period. Some DMA traders pay fixed commissions while others are on a commission plan where market access fees and liquidity rebates are passed through to the trader. We do not have complete commission data for each trader over our sample period. However, irrespective of whether access fees and liquidity rebates are passed through to the trader, from a trading and pricing perspective, it is not advantageous to route a non-marketable limit order to the wholesale market maker for execution. The firm's trading software does not provide traders with this option. For other types of market participants who have different trading objectives, pricing arrangements and/or access to the market, submitting limit orders to the market maker may be desirable.

One potential concern with the sample setting is that we are unable to observe orders that go 100% unfilled. A disproportionate number of fully cancelled orders in the dark venue, when the market is less liquid, would result in a selection bias. In subsequent analysis, we attempt to address this issue by estimating a two-stage selection model. Our focus on marketable orders (i.e., orders that are sent for immediate execution) may also help to mitigate selection bias. For example, marketable orders are far more likely to execute than non-marketable limit orders. Both the dark and lit markets provide deep pools of liquidity and high fill probabilities for marketable orders. The firm operating the dark pool is a leading market maker and has a strong incentive to facilitate quality order executions in order to attract subsequent order flow.

The dark environment that we observe more closely resembles dark pools today that operate as "liquidity-provider platforms" (see Zhu, 2013). There are, of course, many different types of dark pools operated by many different entities. As is the case with the overall market environment, there are differences and similarities in the dark setting that we observe with what exists today. Advances in trading technology have made trading in the dark (as well as lit markets) faster and routing algorithms have become increasingly sophisticated with moving in and out of dark (lit) markets in search of liquidity. For example, in the current market environment, if a trader wants to execute a marketable order it is common for an algorithm to first sweep a dark pool in order to seek price improvement. If no execution occurs, the marketable order may route to a lit market displaying the best price and execute accordingly (some dark venues today provide onward routing while others do not). In our setting, routing algorithms are not used to send orders between dark and lit markets. For example, the only way an order could route to the dark venue is if a discretionary trader sends their order to the dark market directly. And within the dark venue itself, the market maker that facilitates order matching does not use algorithms to onward route orders to lit venues for execution.

There are similarities with our setting to the current market environment. For one, the wholesale market maker that operates the dark market in our setting is still one of the largest equity market makers in the U.S. today. It also continues to facilitate a robust liquidity matching pool, away from lit exchanges, where it operates in both a principal and agent capacity in much the same general way described above (albeit much faster and more technologically advanced). Market pricing schemes also remain similar. Consequently, order routing fragmentation between the two main order types remains common practice in U.S. equities trading, both during our sample period and in the current market environment. For example, many U.S. discount brokers who execute orders on behalf of retail clients are known to direct their non-marketable limit order flow to lit venues to capture liquidity rebates and marketable order flow to dark pools operated by wholesale market makers to avoid access fees and obtain potential price improvement (individual traders who execute their own orders and are confronted with similar market pricing models will be incentivized to do the same). The occurrence is known to account for much of the marketable order flow going first into dark markets. While such order routing practices enable brokers to profit from their clients' order flow, they have become increasingly controversial in recent years (see Battalio et al., 2014).

In conclusion, we analyze individual trader decisions to use lit versus dark markets in U.S. equity markets. Traders must choose directly between using lit versus dark markets. The focus is on marketable order execution in an electronically-driven market where trading is fragmented across numerous trading venues (both lit and dark). Our underlying motivation is to provide some insight into why an individual trader might choose a dark market over a lit market and vice versa. To the best of our knowledge, our study is the first to study dark trading in this manner.

3. Data description

The main data source used in this study originates from a U.S. broker-dealer.[9] The firm has several trading operations. For example, they are a registered market maker on NASDAQ, and they own and operate alternative trading systems. Our focus is on the brokerage operation, which specializes in providing direct market access (DMA) capabilities for trading in U.S. equities. The data are advantageous for conducting this study because DMA traders manage all aspects of the trading process, including how and where orders are routed for execution. Thus, we are able to analyze millions of trader decisions between dark and lit markets (ex-ante) and order execution quality dimensions (ex-post) between the two markets.[10] DMA firms attract a wide variety of users with different trading objectives and strategies. In general, however, clients of these firms tend to be fairly active and possess larger capital amounts because of the sophisticated trading tools and services that are provided. The clients pay for these sophisticated trading tools and services in the form of higher commissions.[11] Consequently, order flow through DMA brokers accounts for a significant portion of U.S. equity trading volume.[12]

All of the trading analyzed is automated. The discretionary (human) traders enter order instructions into the firm's electronic trading platform, and algorithms execute orders according to trader pre-programmed instructions, which may include factors relating to price, timing, venue, quantity, etc. All of the sample traders that we observe use broker-supplied algorithms. The firm did allow certain clients to use their own customized algorithms in another operation that provided designated technical support, but we do not have trading data from this operation. During our sample period (and similar to the current market environment), NASDAQ trading was highly fragmented across numerous venues, and a frequently used algorithm (according to the firm) would scan and route a trader marketable order to the lit market(s) posting the best price. The algorithm did not scan dark markets because prices are not displayed.[13]

The only way an order could route to the dark venue that we observe in our setting is if a discretionary trader sends an order to the dark market directly. Orders sent to the dark market in the sample data could not initiate from a broker-supplied routing algorithm for scanning multiple markets. Traders use the same electronic trading system to access dark and lit markets, and, while the way in which dark orders are sent to the market can differ from the way in which lit orders are sent, the two orders can also be sent in a similar manner. For example, a trader may send an order to a lit market directly without using a routing algorithm to scan multiple markets (similar to how a dark order is sent) or use a routing algorithm to scan and send an order across multiple lit markets (not possible with the single dark market trading option). Nevertheless, traders in our setting must first make a conscious choice between using dark and lit markets, and our analysis begins before an order is even sent to the market. For example, we not only examine dark and lit trade execution sizes but, also, the original size of a dark or lit order before it is sent to market. Examining both order submission and subsequent trade execution data can provide useful insights for understanding why traders choose dark markets.

Overall, the proprietary data comprise 3014 U.S. equity traders who execute 6.2 million orders (9.3 million trades) and 12.1 billion shares (dollar value of $104 billion) through the firm. In Appendix A, we provide information on the representativeness

[9] Time was spent observing dark/lit execution on the broker's electronic trading platform and talking with traders and employees of the firm.

[10] We examine order (submissions) executions through a single broker and do not know if an order is part of a larger overall order being worked through multiple brokers. While traders certainly have the ability to split an order across brokers, this is less likely to occur in our setting. Large buy side traders often split their orders across brokers, in large part, to hide their trading intentions. However, DMA traders execute their own orders and they have access to an array of sophisticated trading tools and services for hiding their trading intentions within the single broker.

[11] For example, around the middle of our sample period, the DMA traders had the option of paying a fixed commission schedule that was around $25 per trade (source: firm pricing information). In contrast, popular online brokers (e.g., Ameritrade, E-Trade, etc.) were charging around $15 for non-DMA online trades during the same time period (see, for example, Angel et al., 2011). Broker-assisted or high-touch trading services would be more expensive than the low-touch trading setting that we observe.

[12] Several research analyst reports (available upon request) estimated that order flow through DMA brokers accounted for approximately 40% of U.S. equity trading volume around the middle of our sample period.

[13] Algorithms used for lit order routing could make decisions based on factors other than price. For example, rather than scan lit markets for price, an algorithm could scan lit markets for size and route an order to the venue(s) displaying the largest size at a competitive price. Algorithms supplied by the broker could also make lit routing decisions based on venue type or factors related to execution time. Each client who joined the broker received detailed information on how to use the electronic trading platform and how various algorithms worked. The firm also provided on-site training at its headquarters and branch offices. The trading technology is highly sophisticated and we do not know to what extent, say, clients understood how trading algorithms worked and/or to what extent they tested and assessed the effectiveness of broker algorithms.

of the sample data. The proprietary data list various information for each order execution, including the venue where an order is executed, which is the focus of our study. The firm also provided proprietary trading manuals and other supplementary information that allows for identification of each market center as lit or dark. In addition to the proprietary order-level data obtained from the U.S. securities firm, three public data sources are used in order to enhance the analysis. First, the Thomson Reuters tick history database is used to examine market conditions when traders place their orders. The tick data are also useful for measuring the quality of order execution. For example, trading cost measures, such as the effective spread, are based on the NBBO quote midpoint at the time an executed order is submitted and this can be obtained from the tick database. The matching analysis entails sifting through billions of intraday market pricing observations on thousands of stocks over eight calendar years in order to match millions of order executions from the proprietary data. Order execution records in the proprietary data are time stamped to the second and matched with the corresponding (last) NBBO stock quote in the same second from Thomson Reuters. Slight discrepancies in time may exist between the two datasets, potentially resulting in measurement error. However, time is critical to the DMA broker (traders), and representatives from the firm noted that their computer clocks were closely aligned with market center computer clocks and the official U.S. time. The second data source used in conjunction with the proprietary data is the Center for Research and Security Price (CRSP). CRSP is useful because it allows us to examine various characteristics of the stocks traded which can also influence the decision on trading venue. The third data source used is Rule 605 reports. The SEC requires market centers to make available to the public monthly reports containing uniform statistical measures of execution quality. This allows us to compare execution quality between sample traders and others in the marketplace.

Before conducting the analysis, we filtered the original data by means of various techniques. First, we eliminated trading on stocks for which we were unable to retrieve matching market data from Thomson Reuters and CRSP. Without the matching market data, we were unable to fully examine differences in trader use of dark and lit markets. Trading which occurs outside the normal market opening hours was also eliminated because trading before the open or after the close occurs in a very different manner. Consequently, including these observations could bias the analysis. Lastly, we focus on NASDAQ-listed stock trading only because during our sample period different trading protocols existed between NYSE- and NASDAQ-listed stocks. Trading on NASDAQ stocks occurs over multiple electronic markets, both dark and lit. The primary benefit of using a DMA broker is the ability to access liquidity quickly and directly across the multiple electronic markets. By contrast, NYSE-listed trading is mainly confined to a single physical trading floor location during the sample period, whereas dark or lit trading away from the NYSE is much less common than on NASDAQ stocks.[14] Consequently, most order executions through DMA brokers (including the firm under analysis) during the sample period occur on NASDAQ-listed stocks. These three filters do not significantly limit the overall data. For example, on the whole, we analyze more than 90% of the trading activity originating from the firm's brokerage operation.

[14] Furthermore, trading is much slower (often manual) on the NYSE trading floor than on NASDAQ trading venues, and automated trading is heavily restricted. This is no longer the case in the existing market environment. The NYSE launched its Hybrid Market model at the end of 2006 which dramatically increased automated trading and execution speed (see Hendershott and Moulton, 2011).

4. Empirical results

4.1. Execution quality characteristics of dark and lit orders

The traders executed a total of 337,000 dark orders (13% of the total number of marketable orders executed) and 726 million dark order shares (17% of the total number of marketable order shares executed) in the sample data. The main question we seek to answer is: *Why do traders choose dark markets?* To provide some insight for answering this question, we examine differences in execution quality between dark and lit markets because market venue execution quality can influence where a trader sends an order for execution (e.g., Boehmer et al., 2007). Because order size is an important consideration when assessing execution quality, we begin by computing order size differences between dark and lit markets. On an overall basis, the average size of a dark order is more than double that of a lit order. The average submitted size of a dark (lit) order execution is approximately 3500 (1600) shares. For approximately 23% (31%) of dark (lit) orders, the size of the submitted order is greater than the NBBO displayed depth available in lit markets. Perhaps the size difference between dark and lit markets exists because traders using the dark venue are trading stocks with a larger average (market) trade size and/or traders using the dark venue are, in general, larger size traders. Thus, we examine order size relative to average trade size in the market and average trader trade size. Fig. 1A shows the average of order submission size divided by average daily trade size of the stock in the overall market for orders executed in dark and lit markets. Fig. 1B shows the average of order submission size divided by the trader average trade size for orders executed in dark and lit markets. Both results continue to indicate that dark orders are significantly larger than lit orders.

The size difference may also arise because of differences in the way dark and lit orders can be sent to the market. For example, when using lit markets, traders had the ability to use routing algorithms to send their orders across multiple markets. However, what we are able to determine from our brokerage-level (order submission) data is that the size of a dark order is significantly larger than a lit order before the orders are even sent to the market. The subsequent execution size of a dark order at the market center level is also significantly larger than a lit order. While dark markets are more likely to facilitate larger order size transactions during our sample period, this has changed in recent years with advances in electronic trading. For example, Tuttle (2013) examines FINRA's OATS data over a five-day period in May 2012 and finds that dark and lit trade sizes are very similar. Zhu (2013) notes that there are many different types of dark pools and that transaction sizes can vary substantially across the different venues. The sharp contrast in sizes can be attributed to the use of algorithms that slice larger orders into smaller parts.

We compute various dimensions of order execution quality for dark and lit orders and the results are displayed in Fig. 2. First, execution time is measured in seconds from order submission time to order execution time (share-weighted for multiple trade orders). On average, dark orders take more than twice as long to execute than lit orders. The average execution time for dark (lit) marketable orders is 77 (33) seconds. The fill rate is computed for each order as the number of shares executed divided by the original order size. Lit orders have a higher fill rate than dark orders. The average fill rate for dark (lit) orders is 84% (90%).

For many traders, price is the most important dimension of order execution quality. We compute the percentage effective spread for dark and lit orders. The percentage effective spread measure for buy (sell) orders is twice the difference between the share-weighted order execution price (NBBO quote midpoint)

Fig. 1. Order size. (A) Depicts the average of order execution submission size divided by stock average (daily) trade size in the overall marketplace for marketable orders executed in dark and lit markets. (B) Depicts the average of order execution submission size divided by trader average trade size for marketable orders executed in dark and lit markets. Data from two sources are used to construct figure results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker. The sample begins in October 1999 and ends in May 2006; and (2) Thomson Reuters tick data are used to obtain stock average daily trade sizes.

and the NBBO quote midpoint (share-weighted order execution price) at the time of order submission divided by the share-weighted order execution price. The average percentage effective spread for dark (lit) marketable orders is 0.03% (0.58%). An effective spread of zero would indicate that an order executes at the NBBO midpoint price.

We compute the percentage of time dark (lit) marketable orders achieve price improvement by matching the more than 2.5 million marketable orders over the eight calendar year sample period with the Thomson Reuters tick data. For buy (sell) orders, price improvement occurs when the share-weighted execution price of the order is below (above) the national best offer (bid) quote at the time of order submission. Price improvement occurs on dark (lit) marketable orders approximately 82% (6%) of the time. For buy (sell) orders, the actual (dollar) price improvement is computed as the difference between the national best offer quote (share-weighted execution price) at order submission and the share-weighted execution price (national best bid at order submission). The average price improvement for dark orders is \$0.0057.[15] The average cost savings per order (i.e., the price improvement multiplied by the number of shares) is \$18.66, and the total cost savings across all orders in our sample is \$6.3 million (see Table 1). The dollar cost-saving estimate assumes traders could have obtained the NBBO quote displayed in the lit markets at the time of their order submission decision and it does not include costs that may result from unfilled orders. For robustness, we calculate results assuming that unfilled shares are executed at future lit market prices. For buy (sell) orders, the remaining unfilled shares are assumed to execute at the national best offer (bid) quote five minutes after the last trade execution of an order. The partial fill adjustment results in lower (although still significant) price improvement. For example, the total cost savings across all orders is reduced to \$5.1 million.

The price impact of an order is another important measure of execution quality. We compute price impact differences between dark and lit orders, and the results are summarized in Fig. 3A. Price impact is measured as the change in the NBBO quote midpoint from order submission to after order execution by using three different time horizons (a five-minute interval is the most common in the financial literature). For buy orders, price impact is computed as the NBBO quote midpoint five minutes after the last trade execution of an order, one hour after the last trade execution of an order, and at the end of the trading day, minus the NBBO quote midpoint at the time of order submission. For sell orders, price impact is the NBBO quote midpoint at the time of order submission minus the subsequent five-minute, one-hour, and end-of-day NBBO midpoint. For each time horizon, the results indicate that dark orders incur very little price impact, whereas the price impact for lit orders is much larger. Dark markets can facilitate larger order execution at more favorable prices and with little price impact.

In Fig. 3B, we report price changes before the order submission decision. For buy orders, price change is the NBBO quote midpoint at the time of order submission minus the prior five-minute, one-hour, and beginning-of-trading-day NBBO quote midpoint. For sell orders, price change is the NBBO quote midpoint five minutes before order submission, one hour before order submission, and at the beginning of the trading day, minus the NBBO quote midpoint at the time of order submission. Traders select lit markets when prices start to move (e.g., five-minute interval). The result is likely driven by the execution time differences between markets. When price trends begin to develop, lit markets become more attractive to informed traders because of their fast execution.[16]

The decision to use dark or lit markets appears, in part, to be one of trade-offs for the individual trader. For example, if, on average, a market venue is able to facilitate execution at better prices, then this cost-saving benefit must be traded off with slower execution. This is analogous to the price-time tradeoff with trader decision to use a market order versus a limit order (see Cohen et al., 1981). That is, a market order executes quickly but pays the bid-ask spread. On the other hand, a limit order is slower to execute (if execution occurs) but captures the bid-ask spread. The initial summary results indicate that effective spreads are smaller and price improvement is greater for dark order executions, but also, execution times are higher. Time versus price tradeoffs can also be observed by comparing dark NBBO midpoint executions with dark buy (sell) orders that execute at the NBB (NBO). For example, Buti et al. (2014) distinguish between dark midpoint executions and non-dark midpoint executions. Dark orders that execute at the NBBO midpoint (worse price) at the time of order submission, on average, execute in 8 s. Dark buy (sell) orders that execute at the NBB (NBO) at the time of order submission (better price), on average, execute in 41 s. The mean difference is statistically significant at the 1% level.

[15] Price improvement will vary based on a number of factors including stock, timing, venue, etc. Using SEC Rule 605 data, we examine current levels of price improvement for all eligible marketable orders (100–9999 shares), across all reporting market centers (70), in January 2015. The percentage of shares executed with price improvement is 28.3% and the average price improvement on these shares is \$0.0072.

[16] The price impact results are also conducted by averaging across traders. The results are similar to those reported and are available upon request.

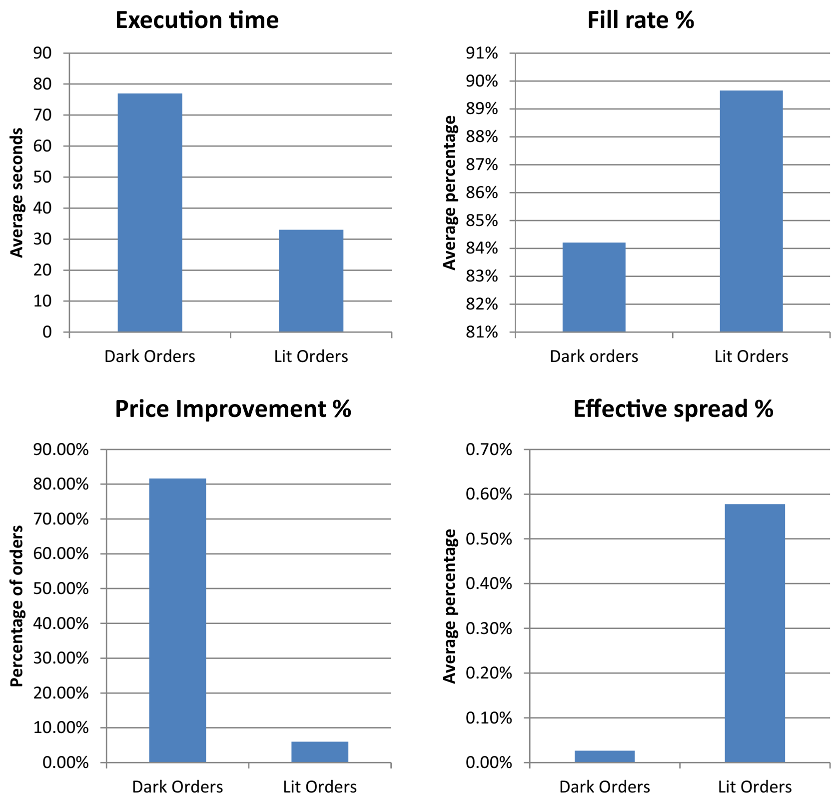

Fig. 2. Order execution quality. The figures depict average execution quality differences between dark and lit marketable orders. Data from two sources are used to construct the figure results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker and (2) Thomson Reuters tick data are used to obtain the NBBO for computing trader effective spread and price improvement measures. Execution time is the time difference (seconds) between the order execution time and the order submission time (share-weighted for multiple trade orders). Fill rate is the executed order size divided by the original order size. Price improvement for buy (sell) orders is the percentage of time the share-weighted execution price is below (above) the national best offer (bid) at the time of order submission. Effective spread for buy (sell) orders is twice the difference between the share-weighted order execution price (NBBO quote midpoint) and the NBBO quote midpoint (share-weighted order execution price) at the time of order submission, divided by the share-weighted execution price.

A longer wait time is critical to the informed. For example, Zhu (2014) argues that informed traders are less likely to use dark venues because they tend to trade in the same direction around the same time and this reduces the likelihood of finding a matching order on the opposite side of the market. The initial summary results seem consistent with this prediction. For example, lit marketable order executions are more informed (i.e., higher price impact) and have higher fill rates than dark order executions.

Order size is another important factor with dark trading. In general, dark markets are favorable for executing larger sized orders. While dark orders are clearly larger in size than lit orders in our setting, we examine execution quality differences between block orders (10,000 + shares) separately. There are 2344 (6241) dark (lit) block order executions in the sample data. Dark block orders execute quicker and with lower costs than lit orders. For example, the average execution time and price impact for block dark (lit) orders is 96 (150) seconds and $0.0017 ($0.0121), respectively. Block order effective spreads are 86% higher in the lit market than in the dark market. These results suggest trading blocks in the dark can be advantageous for liquidity motivated traders.

4.2. A two-stage selection model of venue choice and execution quality

We are interested in examining if execution quality differences between dark and lit markets are statistically significant when controlling for various factors. For example, do dark orders have lower effective spreads or take longer to execute when order characteristics (e.g., order size, etc.), market conditions (e.g., bid-ask spread, etc.), stock characteristics (e.g., turnover, etc.), etc. are simultaneously considered? One way to answer this question is to estimate a simple ordinary least squares (OLS) regression model where execution quality is used as a dependent variable, a dark (or lit) dummy variable is used as the main independent variable, and controls representing various factors cited above are included as additional independent variables. However, selection bias issues may arise with the simple OLS approach.[17] For example, prior results indicate that dark and lit executions exhibit different characteristics. In addition, dark order execution may be more (less) likely to occur when the dark market is liquid (illiquid) with many (fewer) traders on both sides of the market. If observed dark executions are more likely to be associated with favorable market conditions, and dark orders that go unexecuted in illiquid markets are not analyzed, then a selection bias results in the quality dimensions of dark order execution being overstated.

4.2.1. Model description

To address these issues, we estimate a two-stage selection model proposed by Heckman (1979). A similar approach is used by Degryse et al. (2014) to study the impact of dark trading on Dutch stock market quality. And the two-stage model has been commonly used in other multi-market trading studies in the financial literature to control for trader endogenous venue selection. For example, Madhavan and Cheng (1997) and Bessembinder and Venkataraman (2004) use the two-stage model to examine trading between upstairs and downstairs market and Conrad et al. (2003)

[17] The main findings are similar if a single regression approach is used. The results may be obtained by contacting the authors.

Table 1
Cost-savings of going dark.

	No adjustment	Partial fill adjustment
All dark orders		
Average price improvement	\$0.0057***	\$0.0035***
Average order cost-saving	\$18.66	\$15.29
Total cost-saving	\$6,281,497	\$5,146,246
Number of observations	336,649	336,649
Buy dark orders		
Average price improvement	\$0.0051***	\$0.0032***
Average order cost-saving	\$17.60	\$14.49
Total cost-saving	\$3,767,875	\$3,101,681
Number of observations	214,031	214,031
Sell dark orders		
Average price improvement	\$0.0069***	\$0.0041***
Average order cost-saving	\$20.50	\$16.67
Total cost-saving	\$2,513,622	\$2,044,566
Number of observations	122,618	122,618

The table results provide a hypothetical estimate of how much traders are able to save by executing their marketable orders in dark rather than lit markets. Data from two sources are used to construct table results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker and (2) Thomson Reuters tick data are used to obtain the NBBO for computing trader price improvement and partial fill adjustment measures. For buy (sell) orders, price improvement is computed as the difference between the national best offer quote (share-weighted execution price) at order submission time and the share-weighted execution price (national best bid quote at order submission). Order cost-saving is the price improvement multiplied by the number of shares per order. The average price improvement and order cost-saving are reported in the table. Total cost-saving is the sum of the order cost-saving observations. Partial fill adjustment assumes any unfilled shares with orders are executed at future lit market prices. For buy (sell) orders, the remaining unfilled shares are assumed to execute at the national best offer (bid) quote five minutes after the last trade execution. ***Indicate the mean price improvement is significantly different from zero at the 1% level.

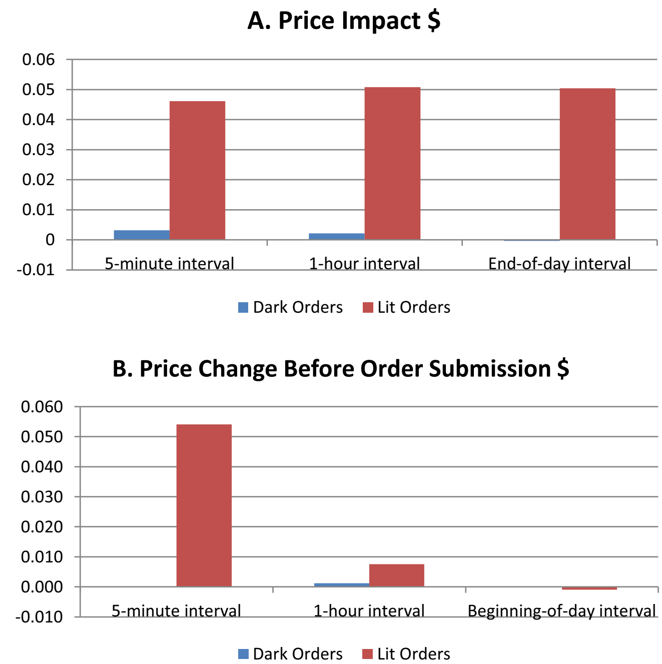

Fig. 3. Price impact. The figures depict average NBBO quote midpoint changes before/after dark and lit marketable order submissions/executions. Data from two sources are used to construct the figure results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker and (2) Thomson Reuters tick data are used to obtain the NBBO for computing trader price impact and price change measures. (A) Depicts the average price impact for marketable orders executed in dark and lit markets. Price impact measures the change in the NBBO quote midpoint from order submission to after order execution by using three different time horizons. For buy orders (the reverse calculation is done for sell orders), price impact is the NBBO quote midpoint five minutes after the last trade execution of an order, one hour after the last trade execution of an order, and at the end of the trading day, minus the NBBO quote midpoint at the time of order submission. (B) Depicts price change before order submission. For buy orders (the reverse calculation is done for sell orders), price change is the NBBO quote midpoint at the time of order submission minus the prior five-minute, one-hour, and beginning of trading day NBBO quote midpoint.

use the approach to examine institutional trader use of traditional versus alternative trading systems.

The first-stage regression predicts whether an order execution occurs in the dark or lit markets by means of a Probit model, which is then incorporated within an OLS (Tobit) second-stage regression with the focus on a dark dummy variable that distinguishes effective spread, price impact, execution time, and fill rate differences between dark and lit markets. The two-stage regression model has the format:

$$D_i^{\text{Dark market}} = \delta + \vartheta V_i + \theta I_i + u_i \tag{1}$$

$$y_i = \alpha + \beta D_i^{\text{Dark market}} + \lambda V_i + \gamma IMR_i + \varepsilon_i \tag{2}$$

In the first stage Probit model, the dependent variable is set equal to one (zero) if a trader executes an order in a dark (lit) market.[18] V_i is a vector of control variables which includes the submitted size of an order execution divided by the average daily trade size for the stock (number of shares); a dummy variable that takes the value of one for a buy order and zero for a sell order; the NBBO percentage spread at the time of order submission (100 * [ask price – bid price]/midpoint price); the quoted (displayed) depth at the NBBO at the time of order submission (ask depth for buy orders and bid depth for sell orders); a dummy variable that takes the value of one, or zero otherwise, if an order is executed after the change to decimal pricing; the prior year average daily turnover for the stock (volume/shares outstanding) from when an order is executed; the prior year-end log market capitalization for the stock from when an order is executed and the prior year end inverse price for the stock from when an order is executed.

The vector I_i represents instruments which are excluded from the second stage equation. We use trader prior tendency to go dark which is calculated as the daily average percentage of dark market order execution over the sum of marketable order execution (share volume) prior to the day order ***i*** is executed by the trader, the time (in minutes) since the trader's most recent execution, the number of trader executions in the past ten minutes, and realized volatility over the past ten minutes which is the standard deviation of NBBO midpoint returns.[19] The instrument selection is motivated for the following reasons. First, traders with higher dark market participation in the past may be more likely to execute a subsequent order in the dark. Second, a tradeoff exists between execution time and execution price. Thus, a longer time since a prior order execution (worse time dimension) may lead to a higher likelihood of a dark order execution (better price dimension). Third, during active periods traders may be more likely to execute quickly using lit markets (better time dimension) and pay for this with higher effective spreads (worse price dimension). Finally, if dark executions are more likely in calmer periods it suggests that dark traders are more patient and indeed time the market waiting for liquid periods. It is important to recognize that the instruments may not be exogenous, which

[18] Prior studies have modeled trader use of different lit markets such as NASDAQ market makers and ECNs (e.g., Barclay et al., 2003; Garvey and Wu, 2011).

[19] We also compute first (second) stage results using an alternative volatility measure that is the difference between the high and low NBBO midpoint in the prior ten minutes divided by the average NBBO midpoint (as in Foucault and Menkveld, 2008). The results are qualitatively similar to those reported and are omitted for brevity.

Table 2
When dark order execution occurs.

First stage probit	Coefficient	z-Stat	Marginal effects	z-Stat
Intercept	−5.066***	(−28.19)		
Order size	0.155***	(7.36)	0.0034***	(4.37)
Buy dummy	0.382***	(6.78)	0.0083***	(4.49)
Bid-ask spread	0.056***	(9.13)	0.0012***	(5.01)
Quoted depth	0.188***	(14.06)	0.0041***	(5.25)
Decimal dummy	2.061***	(11.53)	0.0448***	(8.07)
Turnover	6.152***	(11.78)	0.1338***	(5.31)
Market capitalization	−0.002	(−1.33)	−0.0000	(−1.28)
Inverse price	0.100***	(6.27)	0.0022***	(4.04)
Dark execution tendency	2.840***	(26.02)	0.0618***	(5.60)
Time since prior execution	0.077***	(7.42)	0.0017***	(4.55)
Number of trades	0.051**	(2.29)	0.0011**	(2.03)
Volatility	0.004***	(3.39)	0.0001***	(2.96)
Obs. (000,000 s)	2.5			
Pseudo R^2	50.36%			

The table provides first stage results of a Heckman model that is estimated to highlight trader dark versus lit marketable order execution quality differences while controlling for endogenous selection. Data from three sources are used to construct table results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker; (2) Thomson Reuters tick data are used to compute intraday market condition measures when order executions are submitted; (3) CRSP data are used to compute stock characteristic measures on the stocks traded. The first-stage regression in the Heckman model is a Probit model, which is subsequently fed into a second-stage OLS regression (see Tables 3 and 4), with a dependent variable equal to one for a dark order and zero for a lit order. Independent variables include the submitted size of an order execution divided by the average daily trade size for the stock (number of shares); a dummy variable that takes the value of one for a buy order and zero for a sell order; the NBBO percentage spread at the time of order submission (100*[ask price – bid price]/midpoint price); the quoted (displayed) depth at the NBBO at the time of order submission (ask depth for buy orders and bid depth for sell orders); a dummy variable that takes the value of one, or zero otherwise, if an order is executed after the change to decimal pricing; the prior year average daily turnover for the stock (volume/shares outstanding) from when an order is executed; the prior year-end log market capitalization for the stock from when an order is executed and the prior year end inverse price for the stock from when an order is executed. The instruments are trader dark execution tendency, which is the daily average percentage of dark order execution over all marketable order execution (share volume) prior to the day the trader order is executed; the time (in minutes) since the most recent trader execution; the number of trader executions in the past ten minutes; and realized volatility over the past ten minutes which is the standard deviation of NBBO midpoint returns. In addition to the Probit model results, the table reports the first stage marginal effects dP/dx (x is an independent variable) evaluated at the means of all variables and corresponding z-statistics. ***,**Indicate significance at the 1%, and 5% level, respectively.

could bias results. For example, (in upcoming analysis) we find that traders with higher dark market participation appear to be more skillful at trading, and trader skill would presumably be correlated with different dimensions of execution quality.

In the second stage model, y_i is the effective spread, price improvement, price impact, execution time, or fill rate for order i; $D_i^{\text{Dark market}}$ is a dummy variable that takes the value of 1, or 0 otherwise, if order i is executed in the dark market; V_i is a vector of controls (see discussion of controls above); IMR_i is the Inverse Mills Ratio of the Heckman model and is intended to correct for self-selection bias. The t-statistics associated with the coefficients are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level.

4.2.2. First stage results: choice of venue

The first stage results are reported in Table 2. In addition to the Probit model results, the table reports the first stage marginal effects dP/dx (x is an independent variable) evaluated at the means of all variables and corresponding z-statistics. Many coefficients are statistically significant and indicate that order characteristics, market conditions, stock characteristics, etc., are correlated with trader dark (lit) market order execution. For example, the standardized order size coefficient is positive (0.155) and statistically significant at the 1% level. Thus, the submission size of an order executed in the dark is more likely to exceed the average trade size in the overall marketplace. When buy and sell orders are not displayed in the market, this creates a natural setting that is more conducive to larger size trading. In part, this is likely because the lack of order transparency mitigates front running risk for those transacting in larger sizes. The results also indicate that traders are more likely to execute buy orders in the dark. Approximately 65% of dark order executions are buys, and the buy coefficient is positive and highly significant (buy and sell orders are identified as such in the proprietary data). While there could be various reasons for this result in our setting, prior studies (e.g., Keim and Madhavan, 1995; Harris and Hasbrouck, 1996) do find execution performance and trader behavior differences with buy and sell orders.

Market conditions are another important determinant of dark execution. The results indicate that, when the bid-ask spread is wider, there is a greater chance that a trader will execute in the dark. The result is in line with Zhu's (2014) theoretical prediction and is consistent with several empirical papers, including Degryse et al. (2014), Comerton-Forde and Putnins (2015), and Weaver (2014). The decimal trading dummy variable is positive and highly significant, indicating that traders are more likely to go dark in the post decimal trading environment. The change to a smaller tick size is known to have made the market environment more challenging, and it is well documented that more trading began to move off-exchange in the years after decimalization.

The instrument variable signs are all positive and statistically significant. As expected, we find that dark order execution is more likely to occur if a trader has a higher dark market participation rate and a longer time has elapsed in between trader executions. Volatility is positively correlated with dark trading. More difficult trading conditions in lit markets may drive traders to the dark. For example, Weaver (2014) finds that trading away from U.S. stock exchanges is greater when volatility is higher. The results also indicate that dark order execution is more likely to occur when trading activity is greater over the past ten minutes. When trader activity rises, dark market usage may increase because of reduced liquidity in the lit markets. In Fig. 4, we graph times when dark and lit order executions are submitted throughout the day. Dark (lit) order submission is highest during the opening hours of trading when trading activity in the overall marketplace is known to be highest (e.g., Admati and Pfleiderer, 1988). The main market opening hours are 9:30 a.m.–4:00 p.m.

4.2.3. Second stage results: dark trading and execution quality

The second stage results are reported in Tables 3 and 4. Both the effective spread and price impact are lower when an order executes in the dark. For example, the dark dummy coefficient is negative and statistically significant at the 1% level in both regressions.

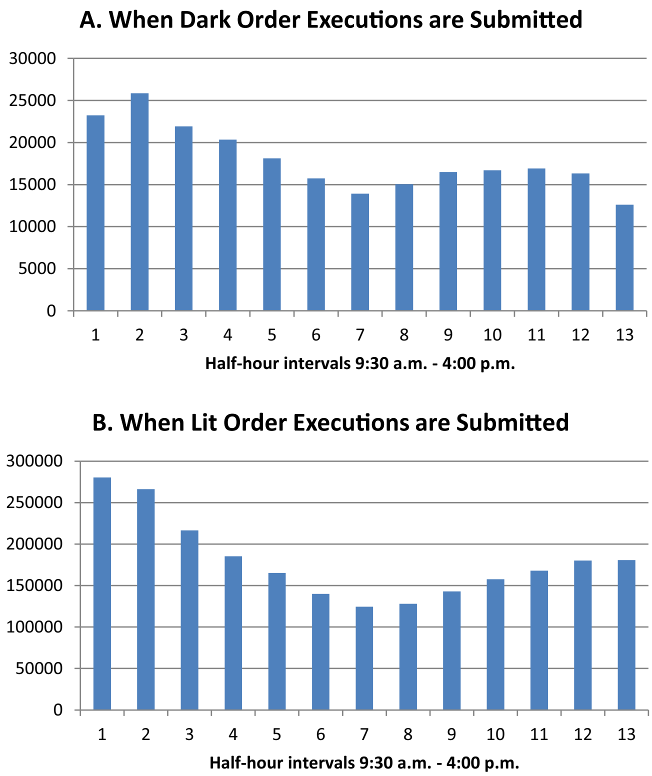

Fig. 4. Time of day. The figures depict when dark (lit) marketable order executions are submitted during the day. The orders are aggregated into thirteen half-hour periods across market opening hours (9:30 a.m.–4:00 p.m.). The order execution data on individual stock traders are from a U.S. direct market access broker.

The price improvement dummy is positive and highly significant, indicating that dark orders exhibit greater price improvement, all else being equal. There are other factors correlated with larger (smaller) effective spread, price improvement, and price impact. For example, in all regressions, the bid-ask spread coefficient is positive and statistically significant at the 1% level. The result indicates that, when the spread in the lit market is wider, traders are more likely to pay higher effective spreads (price impacts) and achieve price improvement.

In Table 4, we report regressions with execution time and fill rate as dependent variables. A tobit model is estimated with execution time (seconds). A tobit model is advantageous for modeling execution time because it corrects for censoring the data. For example, the dependent variable (execution time) is never negative, and there are many zero observations because marketable orders can execute within a second. For the fill rate, we continue to use OLS. The key independent variable of interest is the dummy variable that takes the value of one, or zero otherwise, if the order is executed in the dark market. The other independent variables are the same as those used in prior regressions.

The dark dummy coefficient is positive (negative) in the execution time (fill rate) regression and statistically significant. Thus, when holding other variables constant such as order characteristics, market conditions, etc., dark orders take longer to execute, and have a lower fill rate. As with the execution cost regression results, other variables are correlated with these two dimensions of order execution quality. For example, the buy dummy variable is negative (positive) and highly significant in the execution time (fill rate) regression. Thus, buy orders execute quicker and have a higher fill rate.

Significant market rule changes were implemented just before (e.g., the implementation of the Order Handling Rules in 1997) and after (e.g., the implementation of Regulation NMS in 2007) our sample period. Perhaps the most notable market structure rule change that occurred during our sample period was the implementation of decimal pricing in 2001. The reduction in the minimum price increment from 6.25 cents to one cent, among other things, resulted in a sharp reduction in the quoted bid-ask spread. While we include a dummy variable in our main regression results to control for this significant event, we also conduct baseline regression results separately before and after the conversion to decimal pricing. The second stage regression results are reported in Table 5 (for brevity, only the dark dummy variable coefficient results are reported). Overall, we do not find a significant change in the main

Table 3
Order execution quality differences.

Second stage OLS	Effective spread		Price improvement		Price impact	
	Coefficient	*t*-Stat	Coefficient	*t*-Stat	Coefficient	*t*-Stat
Intercept	0.331***	(9.96)	−0.168***	(−11.70)	0.221***	(14.47)
Dark dummy	−1.066***	(−12.60)	0.527***	(12.71)	−0.093***	(−3.95)
Order size	0.020**	(2.41)	−0.010	(−2.44)	0.026***	(7.06)
Buy dummy	0.000	(0.01)	−0.016**	(−1.98)	0.061***	(8.04)
Bid-ask spread	0.632***	(13.99)	0.198***	(10.30)	0.207***	(12.84)
Quoted depth	−0.035***	(−5.86)	0.017***	(5.74)	−0.033***	(−14.70)
Decimal dummy	0.088***	(4.45)	−0.041***	(−4.09)	−0.018**	(−2.03)
Turnover	1.364***	(4.34)	−0.663***	(−4.38)	0.676***	(7.46)
Market capitalization	−0.004***	(−3.63)	0.002***	(5.08)	−0.003***	(−7.47)
Inverse price	−0.088***	(−3.19)	0.041***	(3.05)	0.019*	(1.88)
Inverse Mill's Ratio	0.191**	(2.21)	−0.096**	(2.24)	−0.030	(−0.91)
Obs. (000,000 s)	2.5		2.5		2.5	
Adjusted R^2	13.69%		12.87%		3.23%	

The table provides second stage results of a Heckman model that is estimated to highlight trader dark versus lit marketable order execution quality differences controlling for endogenous selection. Effective spread, price improvement, and price impact are used as dependent variables in three separate OLS regressions. Effective spread for buy (sell) orders is twice the difference between the share-weighted order execution price (NBBO quote midpoint) and the NBBO quote midpoint (share-weighted order execution price) at the time of order submission. Price improvement for buy (sell) orders is the difference between the national best offer quote (share-weighted execution price) at order submission and the share-weighted execution price (national best bid at order submission). Price impact for buy (sell) orders is the NBBO quote midpoint five minutes after the last trade execution of an order (NBBO quote midpoint at the time of order submission) minus the NBBO midpoint at the time of order submission (NBBO quote midpoint five minutes after the last trade execution of an order). The dollar effective spread, price improvement, and price impact are divided by the share-weighted execution price and multiplied by 100. The key independent variable is a dummy variable that takes the value of one (zero) if a trader executes an order in the dark (lit) market. See Table 2 for a description of the other independent variables. The Inverse Mill's Ratio of the Heckman model is intended to control for selection bias. The *t*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level. ***,**,*Indicate significance at the 1%, 5%, and 10% level, respectively.

Table 4
Order execution quality differences (continued).

Second stage tobit/OLS	Execution time		Fill rate	
	Coefficient	*t*-Stat	Coefficient	*t*-Stat
Intercept	−16.996	(−2.44)	0.891***	(147.73)
Dark dummy	53.810***	(5.53)	−0.108***	(−8.27)
Order size	4.896**	(2.27)	−0.046***	(−18.28)
Buy dummy	−7.891***	(−3.44)	0.010***	(4.52)
Bid-ask spread	5.308***	(3.69)	−0.006***	(−3.59)
Quoted depth	4.310**	(2.39)	0.022***	(13.37)
Decimal dummy	−18.736***	(−3.17)	0.014***	(3.49)
Turnover	−395.412*	(−1.75)	−0.410***	(−4.89)
Market capitalization	−1.309***	(−5.33)	−0.000	(−0.11)
Inverse price	53.917***	(5.29)	0.002	(1.12)
Inverse Mill's ratio	44.617***	(2.84)	0.033	(1.53)
Obs. (000,000 s)	2.5		2.5	
Pseudo/adjusted R^2	0.12%		6.50%	

The table provides second stage results of a Heckman model that is estimated to highlight trader dark versus lit marketable order execution quality differences controlling for endogenous selection. A tobit model is estimated in the first regression. The dependent variable is the execution time or the time difference (seconds) between the order execution time and the order submission time (share-weighted for multiple trade orders). An OLS model is estimated in the second regression. The dependent variable is the fill rate or the executed order size divided by the original order size. See Table 2 for a description of the independent variables. The *t*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level. ***,**,*Indicate significance at the 1%, 5%, and 10% level, respectively.

Table 5
Market structure change and dark trading.

	Before decimalization		After decimalization	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
Effective spread	−0.200***	(−3.07)	−1.064***	(−12.61)
Price improvement	0.107***	(3.24)	0.527***	(12.73)
Price impact	0.249*	(1.77)	−0.093***	(−3.93)
Execution time	4.021***	(3.64)	65.066*	(1.70)
Fill rate	−0.258***	(−3.28)	−0.108***	(−8.25)

The table provides second stage results of the two-stage Heckman model (see Tables 3 and 4) before and after the implementation of decimal pricing in 2001. For brevity, the key independent dummy variable that takes the value of one (zero) if a trader executes an order in the dark (lit) market is reported only. The *t*-statistics (in parentheses) are calculated using clustered standard errors (as in Petersen, 2009), where the cluster is defined at the trader and day level. ***,**,*Indicate significance at the 1%, 5%, and 10% level, respectively.

results. For example, nine out of ten dark dummy variable coefficients are of the same sign as in the overall regression and statistically significant.

Our use of trader-level data to measure order execution quality dimensions across dark and lit venues has a number of advantages over studies that use transaction-level data sources. However, it is important to recognize that our analysis does not include the cost incurred with orders that go completely unfilled. A complete measurement of the true cost of transacting across venues requires analysis of all order submissions. Thus, our analysis is susceptible to a shortcoming present in all studies of observed trading costs.

4.3. Non-marketable limit order execution quality

Our focus is on trader use of dark and lit markets for marketable orders. The traders are not able to submit a non-marketable limit order to the dark market (e.g., a buy order with a limit price set below the national best offer or a sell order with a limit price set above the national best bid). Nevertheless, we examine non-marketable limit order execution quality for comparison purposes. Two important factors need to be considered with these results. First, non-marketable limit orders are far more likely than marketable orders to go completely unfilled and our focus is on (partially) executed orders only. Second, lit markets allow traders to post limit orders that are hidden from the rest of the market, and we are not able to determine whether non-marketable limit orders are displayed or are not displayed in the lit venue prior to execution.

Table 6
Non-marketable limit order execution quality.

Execution quality measure	
Execution time	213
Submitted order size	2114
Fill rate	93%
Limit order placement	
Better than NBBO	21.6%
Equal to NBBO	58.7%
Away from NBBO	19.7%
Ex post cost (5 min interval)	
Overall average	\$0.0203***
Better than NBBO	\$0.0247***
Equal to NBBO	\$0.0173***
Away from NBBO	\$0.0242***

The table results highlight trader execution quality measures for non-marketable limit orders executed in lit markets. Data from two sources are used to construct table results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker and (2) Thomson Reuters tick data are used to obtain the NBBO for computing limit order placement and ex post cost measures. Execution time is the time difference (seconds) between the order execution time and the order submission time (share-weighted for multiple trade orders). Original order size is the submitted order size (shares). Fill rate is the executed order size divided by the original order size. Limit buy (sell) orders submitted with a price above (below) the national best bid (offer) quote at order submission time are classified as better than the NBBO. Limit buy (sell) orders submitted with a price equal to the national best bid (offer) quote at order submission time are classified as equal to the NBBO. Limit buy (sell) orders submitted with a price below (above) the national best bid (offer) quote at order submission time are classified as away from the NBBO. For buy (sell) orders, ex post cost is the execution price (national best offer quote) minus the national best bid quote five minutes after execution (execution price). ***Indicate the mean is statistically different from zero at the 1% level.

Table 6 highlights price improvement for executed buy and sell limit orders. We segregate non-marketable limit order executions based on if they are submitted with a price better than the NBBO, equal to the NBBO, or away from the NBBO at the time of order submission. Limit buy (sell) orders submitted with a price above (below) the national best bid (offer) quote at order submission time are classified as better than the NBBO. Limit buy (sell) orders submitted with a price equal to the national best bid (offer) quote at order submission time are classified as equal to the NBBO. Limit buy (sell) orders submitted with a price below (above) the national best bid (offer) quote at order submission time are classified as away from the NBBO. More than 80% of limit order executions are better than or equal to the NBBO at the time of order submission.

Table 6 results also highlight execution quality measures for non-marketable limit orders. Execution time is the time difference (seconds) between the limit order execution time and the order submission time (share-weighted for multiple trade orders). Original order size is the submitted limit order size (shares). Fill rate is the executed limit order size divided by the original order size. We provide an estimate of adverse selection costs using a similar approach to Peterson and Sirri (2003), Harris and Hasbrouck (1996), and others. For buy (sell) orders, ex post cost is the execution price (national best offer quote) minus the national best bid quote five minutes after execution (execution price).

The results indicate that limit orders achieve price improvement but they also take longer to execute and are susceptible to adverse selection costs. For example, the average execution time for executed limit orders is 213 s. From prior results, recall that the average execution time for a dark marketable order is 77 s. Adverse selection costs exist with limit order execution. When

Table 7
Trader characteristic differences.

	Lowest	2	3	4	Highest	Diff. (5–1)	*t*-Stat
Marketable orders							
Order size	1.0032	1.5338	1.4309	1.2073	1.5506	0.5474***	(5.64)
Price impact	0.0421	0.0226	0.0036	0.0041	0.0025	−0.0396***	(−12.31)
Fill rate	0.9159	0.8927	0.9186	0.9218	0.8815	−0.0344***	(−3.83)
Effective spread	0.0079	0.0071	0.0083	0.0067	0.0023	−0.0056***	(−4.08)
Price improvement	−0.0018	−0.0003	−0.0028	0.0010	0.0034	0.0052***	(8.89)
Execution time	14	30	84	52	78	64***	(5.31)
All orders							
Percentage of limit orders	51%	58%	67%	67%	57%	6%***	(4.33)
Number of shares (000 s)	991	42,877	55,815	33,875	24,720	23,729***	(6.43)
Number of trades	1525	28,684	32,454	19,465	14,420	12,895***	(7.00)
Number of orders	999	19,034	21,499	13,838	10,082	9082***	(7.16)
Number of trading days	75	260	328	258	186	111***	(5.03)
Market venue concentration	0.5245	0.4740	0.4194	0.4098	0.3254	−0.1990***	(−15.25)
Trading time concentration	0.1479	0.0920	0.0858	0.0843	0.0907	−0.0572***	(−10.08)
Order type concentration	0.3496	0.3486	0.3021	0.2984	0.2618	−0.0877***	(−11.30)
Performance (5 min)	−0.0006	0.0049	−0.0004	0.0001	0.0004	0.0010***	(3.36)
Performance (1 h)	−0.0006	0.0052	−0.0002	0.0001	0.0005	0.0011***	(4.55)
Performance (End-of-day)	−0.0012	0.0049	−0.0002	0.0000	0.0005	0.0017***	(5.65)

Traders are sorted into quintiles based on their percentage of dark trading (number of dark shares executed divided by shares executed). Trader characteristic measures are computed for each individual trader and then averaged across traders in each group. Data from two sources are used to construct the table results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker and (2) Thomson Reuters tick data are used to compute intraday market condition measures. Order size is the marketable order submission size on executions divided by average (daily) trade size of the stock in the overall marketplace. Price impact for marketable buy (sell) orders is the NBBO quote midpoint five minutes after the last trade execution of an order (NBBO quote midpoint at the time of order submission) minus the NBBO midpoint at the time of order submission (NBBO quote midpoint five minutes after the last trade execution of an order). Fill rate for marketable orders is the executed order size divided by the original order size. Effective spread for marketable buy (sell) orders is twice the difference between the share-weighted order execution price (NBBO quote midpoint) and the NBBO quote midpoint (share-weighted order execution price) at the time of order submission, divided by the share-weighted order execution price. Price improvement for marketable buy (sell) orders is the national best offer quote (share-weighted execution price) at order submission minus the share-weighted execution price (national best bid at order submission), divided by the share-weighted execution price. Execution time for marketable orders is the time difference (seconds) between the order execution time and the order submission time (share-weighted for multiple trade orders). Percentage of limit orders is the number of non-marketable limit orders divided by all orders (marketable orders and non-marketable limit orders) for each trader. Trading activity measures include total number of shares traded, number of trades and number of orders for each trader. Market venue concentration is the sum of the squared percentage of trading activity occurring in each trading venue for each trader. Trading time concentration is the sum of the squared percentage of trading activity in each half-hour interval of the trading day for each trader. Order type concentration is the sum of the squared percentage of trading activity occurring in each order type for each trader. Trading days is the total number of days a trader is active. For each trader buy order (the reverse calculation is done for sell orders), performance is computed as the NBBO midpoint 5 min after execution, 1 h after execution, and at the end of the trading day minus the share-weighted order execution price, divided by the share-weighted order execution price. The *t*-statistics indicate whether or not the highest and lowest mean differences are statistically different from zero. ***Indicates significance at the 1% level.

using a 5-min interval and the relevant bid or ask price as a reference the overall average is $0.0203. The average submitted size (fill rate) for non-marketable orders is smaller (higher) than dark orders. For example, the average submitted size of a limit order is for 2113 shares and the average fill rate is 93%.

4.4. Who executes in the dark?

An advantage of using brokerage-level data is that we are able to match executed orders to individual traders. This is not possible in many datasets because the data originate at the market center level and trader identity is anonymous. In this section, we use the unique features of our data to study the trader characteristics of those who are more (less) likely to execute in dark markets. Traders are sorted into quintiles based on their percentage of dark trading (i.e., the number of dark shares executed divided by the total number of shares executed).[20] We compute a number of trader characteristic measures for each individual trader and then average the measures across traders in each group. The 15 measures selected are:

- The average of order submission size (marketable orders) divided by average daily trade size of the stock per trader.
- The average price impact (marketable orders) per trader.
- The average fill rate (marketable orders) per trader.
- The average percentage effective spread (marketable orders) per trader.
- The average percentage price improvement (marketable orders) per trader.
- The average execution time (marketable orders) per trader.
- Percentage of limit orders which, for each trader, is the total number of non-marketable limit order executions divided by all order executions.
- Total number of shares executed per trader.
- Total number of trades executed per trader.
- Total number of orders executed per trader.
- Market venue concentration which, for each trader, is the sum of the squared percentage of trading activity occurring in each trading venue.
- Time concentration which, for each trader, is the sum of the squared percentage of trading activity in each half-hour interval of the trading day.
- Order type concentration which, for each trader, is the sum of the squared percentage of trading activity occurring in each order type.
- Total number of days a trader is active.
- The average performance per trader which, for each buy order (the reverse calculation is done for sell orders), is the NBBO quote midpoint five minutes after execution, one hour after execution, and at the end of the trading day minus the share-weighted order execution price. The performance difference is then divided by the share-weighted order execution price.

In Table 7, averages for each trader group are reported. In addition, differences between traders in the highest and lowest groups are reported, along with *t*-statistics, which indicate whether or not

[20] The traders in the lowest group use lit markets only, whereas traders in all other groups use both dark and lit markets.

the mean differences are significantly different from zero. Overall, the results indicate that large differences exist between traders who use dark trading the most versus the least and trader-level results are consistent with prior findings at the order-level. For example, those who have the highest (lowest) percentage of dark trading have marketable order execution submission sizes approximately 55% above (equal to) the average trade size in the marketplace. Traders who go dark the most (least) have lower (higher) price impacts and smaller (larger) fill rates on marketable order executions. For example, for traders with the highest (lowest) percentage of dark trading, the price impact and fill rate are 0.0025 (0.0421) and 0.8815 (0.9159), respectively. Traders with the highest (lowest) percentage of dark trading also exhibit significantly longer (shorter) execution times and better (worse) prices on marketable order executions. For example, for traders with the highest (lowest) percentage of dark trading, the effective spread percentage, price improvement percentage, and execution time are 0.0023 (0.0079), 0.0034 (−0.0018), and 78 (14), respectively. While those who use dark trading the most are more patient with marketable order execution, they also execute a larger portion of their overall trades passively. For example, traders who have the highest (lowest) percentage of dark trading execute non-marketable limit orders 57% (51%) of the time.

Those who have the highest percentage of dark trading appear more experienced and skillful at trading. For example, those who use dark trading the most are significantly more active. On average, they execute 24.7 million shares, 10,082 orders, and 14,420 trades. By contrast, traders with the lowest percentage of dark trading execute, on average, 991 thousand shares, 999 orders, and 1525 trades. The total number of days traded for those who use dark trading the most (least) is 186 (75).

Traders who use dark trading the most also exhibit greater trading diversity. For example, they use more trading venues, trade at more times of day, and use more order types. On the other hand, traders with the lowest percentage of dark trading use fewer trading venues and order types, and their trading is concentrated at certain times of day. For traders with the highest (lowest) percentage of dark trading, the market venue, time, and order type concentration measures are 0.3254 (0.5245), 0.0907 (0.1479), and 0.2618 (0.3496), respectively.

Performance differences also seem to exist between traders who use dark trading the most and the least. In order to proxy (we are using transaction data and do not have trader stock positions) for trading performance, fixed ex-post order execution times are used. Our approach is similar to that of Odean (1999) and others as described in the financial literature. The intuition is that, if market prices rise (decline) following buy (sell) orders, traders are subsequently performing well. Conversely, on the other hand, if market prices decline (rise) following buy (sell) orders, traders are subsequently not performing well. There are no theoretical guidelines for choosing an appropriate time horizon to measure ex-post performance. Casual observations of our data reveal that many traders are engaging in shorter-term trading strategies. A common time horizon used in financial studies for measuring information, trading costs, etc., is a five-minute interval (after execution); thus, we choose this time horizon. We also use alternative fixed time horizons of one hour and to the end of the trading day (similar to the price impact analysis). For each of the three time horizons, results indicate that traders who use dark trading more perform better. For example, for traders with the highest (lowest) percentage of dark trading, the five-minute, one-hour, and end-of-day performance measures are 0.0004 (−0.0006), 0.0005 (−0.0006), and 0.0005 (−0.0012), respectively. As with the other mean differences, the mean performance differences vary statistically from zero at the 1% level.

5. Conclusion

U.S. equities trade in multiple markets and traders have many choices of where to execute their orders. One way to distinguish between the different types of markets is whether the trading process is lit or dark. In lit (dark) markets, the trading interests of market participants are (not) displayed. Interest in dark trading has been rising recently as trading volume continues to migrate from lit to dark markets. In our paper, we obtain proprietary data from a U.S. broker-dealer and provide some insight into why traders choose dark (lit) markets.

The decision to trade in dark vs. lit markets appears, at least in part, to be driven by tradeoffs with respect to order execution quality dimensions. For example, we find that effective spreads are lower (higher) on dark (lit) marketable order executions and execution times are slower (faster) in the dark (lit) market. The price versus time tradeoff between dark and lit venues is analogous to the one that exists between the two main order types (see Cohen et al., 1981). For example, market (limit) orders are quick (slow) to execute but do so at a worse (better) price. Information also plays an important role in the decision to go dark. Informed traders are less likely to go dark because they all tend to trade around the same time and this makes it difficult to find a quick match in the dark (e.g., Zhu, 2014). Consistent with this, we find that lit marketable order executions are informative about future prices while dark orders are not. In addition, lit trades have higher fill rates than dark trades.

Market conditions, trader characteristics, and a variety of other factors also influence trader decision to go dark. In general, traders are more likely to execute in the dark when market conditions in the lit market are more challenging. For example, dark order execution is more likely to occur when the bid-ask spread is wider and market volatility is higher. Who is submitting the order also matters. Traders with greater experience and higher skill-level are much more likely to make use of dark trading.

Although many market participants, observers, and regulators have expressed concern about the rising presence of dark markets in U.S. equities, our results indicate that dark markets provide important benefits to traders that lit markets do not. From a trader perspective, perhaps the most significant benefit occurs with cost savings. For example, we find that more than 80% of dark orders are executed at a price better than the best price available in lit markets at the time of order submission. Whether or not the existence of dark markets operating alongside lit markets impedes other measures of market quality, such as price discovery, is not well understood, and is, therefore, an important area for future study in the existing market environment. It would also be valuable to update our analysis using more recent sample data. While all of the trading that we observe is automated, and dark pools operated by large wholesale market making firms (including the firm we observe) continue to account for a sizeable portion of trading volume in the current market environment, ongoing technological advances and the continual entry (exit) of market participants result in a trading landscape that is forever changing. For example, our study takes place before the rise of high frequency trading (HFT) in the marketplace. HFT and computerized strategies have greatly enhanced cross venue trading, as computers have become increasingly sophisticated at finding and comparing quotes across markets. Thus, ongoing research into dark trading is of interest.

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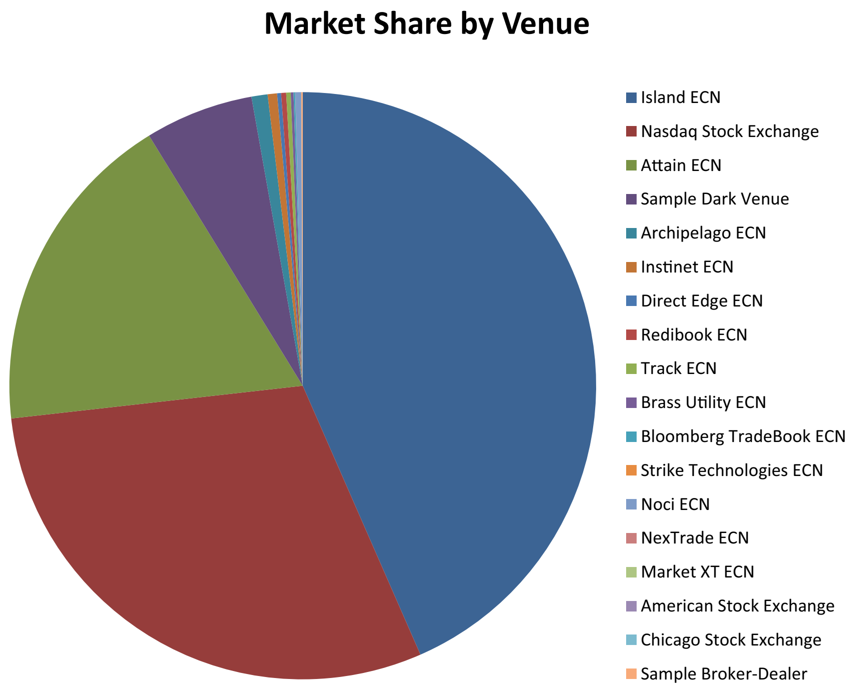

Fig. 5. Trading location. The figure depicts the percentage of sample trader activity that occurs in each market venue. Traders use 27 different trading systems in 18 market venues. The order execution data on individual stock traders are from a U.S. direct market access broker.

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Appendix A

Representativeness of sample data

The sample data represent approximately 0.41% of overall NASDAQ-listed share volume and 1.0% of share volume on those days on which traders are active on sample stocks. The firm's DMA client base consists of both institutional and retail traders who are geographically dispersed from the East Coast (New York) to the West Coast (California). A user identification code in the data allows us to trace activity to each individual trader. However, we are not able to identify the actual individual or institution behind each trade. From the trader-level identification code, we know that the average trader is active on 86 trading days and executes a total of 2031 orders (3042 trades) and 3,649,207 shares on 55 stocks.

In total, traders use 27 different trading systems across 18 market venues. The percentage of trading that occurs in each market venue is reported in Fig. 5. The Island ECN is the most frequently used venue.[21] Island's market share of sample trading is 43%, followed by NASDAQ (30%), Attain ECN (18%), and the dark venue (6%) which is used for marketable orders only.[22] In order to comply with certain regulatory requirements, Island chose not to display its limit order book on several AMEX-listed exchange-traded funds for a period of time during the sample (see Hendershott and Jones, 2005). As noted previously, our focus is on NASDAQ-listed stock trading only. For all of the stock trading that we observe, Island is considered a lit venue and its limit order book is available to market participants for viewing.

During our sample period, the market for NASDAQ-listed stocks is described in the financial literature as a marketplace between competing NASDAQ market makers and ECNs (e.g., Barclay et al., 2003; Goldstein et al., 2008). ECN market share is significant and on the rise over the sample. For example, Barclay et al. (2003) note that ECNs accounted for approximately 40% of NASDAQ-listed stock trading in August 2002 while Goldstein et al. (2008) find that three ECNs alone were accounting for approximately 40% of

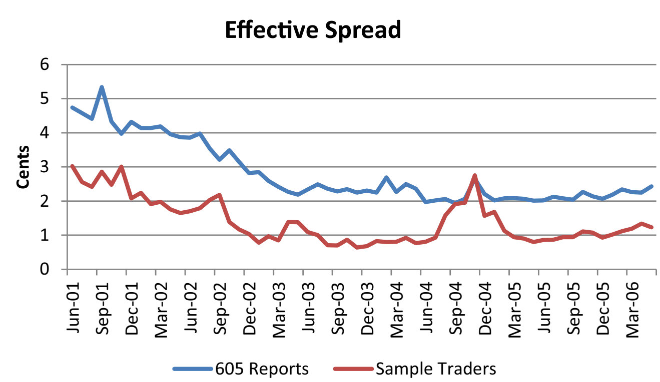

Fig. 6. Trading cost comparison. The figure depicts the average monthly dollar effective spread (marketable orders) for sample traders and U.S. market centers. Data from three sources are used to construct the figure results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker (2) Thomson Reuters tick data are used to obtain the NBBO for computing trader effective spreads; and (3) SEC Rule 605 data from VistaOne Regulatory Services are used to compute average effective spreads across market centers. The 605 data is for all eligible marketable orders (100–9999 shares), across all reporting market centers. The dollar effective spread for sample trader buy (sell) orders is twice the difference between the share-weighted order execution price (NBBO quote midpoint) and the NBBO quote midpoint (share-weighted order execution price) at the time of order submission. The dollar effective spread in the 605 data is based on the NBBO at the time of market center order receipt.

[21] Huang (2002) finds that Island quotes are often at the inside, update rapidly, and highly informative.

[22] Island and Attain were popular ECNs at times during our sample period. Island merged with Instinet ECN in 2002 (the two books operated independently after the merger for some time) and the combined entity, INET, was bought by NASDAQ in 2005. Attain was bought by Knight Capital Group in 2005 and renamed Direct Edge ECN. Direct Edge converted to a stock exchange in 2010 (EDGA and EDGX exchanges) and merged with BATS Global Markets in 2014. The BATS EDGA and EDGX Exchanges continue to operate as independent exchanges in the current market environment.

NASDAQ-listed stock trading from April 2003 until early 2004 (more than ten ECNs were in operation). Overall, approximately two-thirds of sample trading occurs on ECNs, which is a little higher than many estimates of ECN market share at times during our sample period. We suspect that this result is driven by the fact that our focus is on DMA traders who, unlike many other market participants, had the ability to access ECNs directly through the broker for trading.

Direct comparisons of sample market share by trading venue to overall market share by trading venue are not possible because ECN trades are not identifiable through public data sources. ECNs reported their trading anonymously through either NASDAQ or regional stock exchanges. However, we compute the percentage of shares traded in each stock market for each year in our sample period using publicly available tick data. NASDAQ is the dominant (reporting) market center, but ECN trades are often included under NASDAQ. The percentage of shares traded under NASDAQ for sample years is: 99% (1999), 98% (2000), 98% (2001), 91% (2002), 68% (2003), 52% (2004), 59% (2005), and 77% (2006). In 2002, pricing issues prompted several (but not all) of the ECNs to switch their trade reporting from NASDAQ to the regional stock exchanges. The sharp drop in NASDAQ market share after 2002 is reflective of the significant market share of ECNs. In 2005, NASDAQ purchased the INET ECN and NASDAQ's share of trading increased significantly.

We also compare the cost of trading between our sample traders and others in the marketplace. The average monthly dollar effective spread (marketable orders) is computed for sample traders and U.S. market centers using SEC Rule 605 report data obtained from VistaOne Regulatory Services. SEC Rule 605 requires market centers to make available to the public monthly reports containing uniform statistical measures of execution quality. The rule was adopted in November 2000, and firms began reporting to the public in June 2001. The 605 data that we use for analysis is for all eligible marketable orders (100–9999 shares) across all market centers, except Track ECN. The Track ECN reported several erroneous effective spread measures on their public 605 reports, and thus we excluded Track from the analysis.[23] While it is well known that transaction costs declined over the time period (particularly after decimalization), the sample traders pay a consistently lower effective spread (Fig. 6). We suspect that this result is driven by the fact that our focus is on DMA traders who have access to more sophisticated trading tools and services than the average market participant.

There is also a large increase in effective spreads around the end of 2004. The change occurs in both the 605 reports and sample trader data, but is more pronounced in the sample trader data. The spike in effective spreads reaches a high in November 2004, when the average effective spread rises to 2.7 cents in both the 605 reports and sample trader data. In part, the increase may be driven by a rise in market volatility. For example, from January through October 2004, the S&P 500 (NASDAQ composite) index remained in a fairly tight range and was up (down) 2.0% (−1.6%) overall. However, in the last two months of the year, the S&P 500 (NASDAQ composite) index surged 7.2% (10.2%). The average daily number of shares traded in the U.S. equity markets for the first (last) 10 (2) months was 1.7 (1.9) billion. Many market analysts attributed the end-of-year surge in stock prices to the result of the U.S. Presidential election. In November 2004, Republican President George W. Bush narrowly won re-election over Democrat John Kerry. Another reason for the increase in effective spreads could, in part, be due to the changing trading landscape. For example, in the fourth quarter of 2004, NASDAQ completed the integration of a popular ECN (Brut) into its trading operations. Some other major ECNs were acquired by exchanges and broker-dealers shortly thereafter in 2005. The DMA traders used ECNs frequently, and changes in the ECN landscape would presumably have a significant impact on their trading.

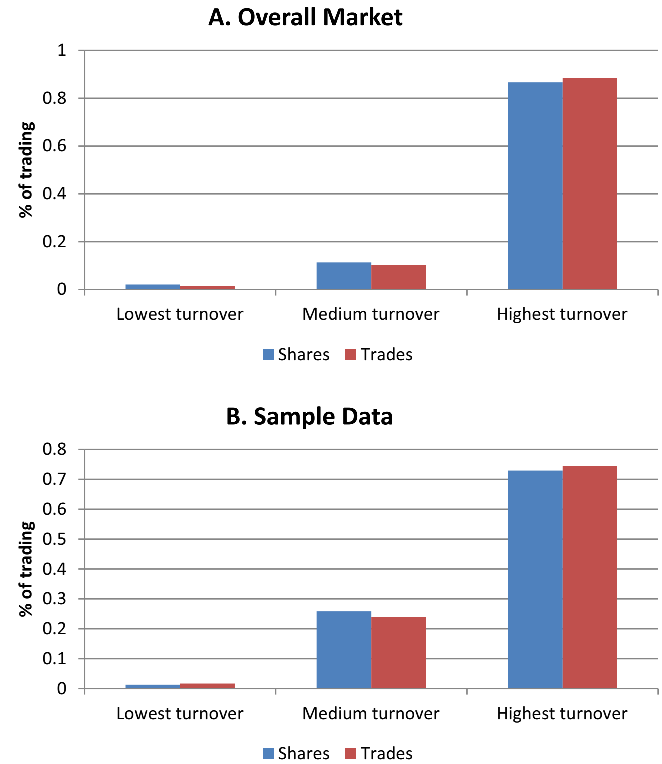

Fig. 7. Stock comparison. NASDAQ-listed stocks are sorted according to their average daily turnover ratios (shares traded/shares outstanding) over the sample period and then grouped into lowest turnover (30%), medium turnover (40%), and highest turnover categories (30%). In Fig. 3A (B), the percentage of NASDAQ (sample trader) trading activity occurring on stocks in each liquidity classification is reported. Data from two sources are used to construct figure results: (1) Order execution data on individual stock traders are from a U.S. direct market access broker and (2) CRSP data are used to obtain overall NASDAQ trading activity information about the stocks traded.

Finally, we compare trading activity patterns in the sample data with those in the overall marketplace. Trading activity patterns in the sample data are consistent with trading activity patterns in the market. For example, aggregate intraday trading activity follows a pattern similar to the well-documented general U-shaped market volume pattern. In other words, trading volume steadily declines from morning to midday and then increases progressively until the close (dark and lit intraday trading patterns are reported separately in Fig. 4). Moreover, the most actively traded stocks in our sample data are also those most actively traded in the overall marketplace. To see this, NASDAQ-listed stocks are sorted according to their average daily turnover ratios (shares traded/shares outstanding) over the sample period and then grouped into lowest turnover (30%), medium turnover (40%), and highest turnover categories (30%). The results are reported in Fig. 7.

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