Intermarket Competition: Evidence from Trading Venue Short Sales *

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ABSTRACT

Theory suggests that the impact of dark pools will depend in part on where the informed trade. Using a novel collection of off-exchange trade data, I study where short sellers exploit their well-documented information advantage. I find that short sales comprise a greater proportion of exchange trading than dark pool trading. I find stronger evidence of return predictability for exchange short sales relative to dark pool short sales. In periods leading up to unscheduled negative corporate news releases, I find evidence of increased exchange short sales. I find evidence of increased exchange short sale return predictability prior to news releases.

JOB MARKET PAPER

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Theory suggests that as trading fragments, both the liquidity of individual markets and the ability of trading to aggregate information can be affected. Providing an efficient price and liquidity are fundamental functions of financial markets in their broader roles of facilitating risk sharing and the efficient allocation of capital (see Fama, 1970; and O'hara, 1999; among others). The rise of dark pools has contributed substantially to the increase in fragmentation of U.S. equity trading. Formerly a small and obscure set of trading venues, dark pools are now hosting approximately 17% of trading volume while a stock can trade in over 40 venues.[1]

In this paper, I examine how dark pools change the way trading aggregates information and impact liquidity on stock exchanges. Empirical research on dark pools and fragmentation generally focuses on empirical measures of liquidity and price efficiency and arrives to mixed results (see O'hara and Ye, 2011; Buti, Rindi, and Werner, 2011; and Weaver, 2014; among others). I employ an alternative empirical strategy which is guided by the theory of intermarket competition. Informed traders in these models trade in a way that maximizes the value of their information (as in Kyle, 1985 and other models of strategic trade) while facing a tradeoff between potentially incurring lower transaction costs in a dark pool against having a higher probability of trade on exchange (see Hendershott and Mendelson, 2000; Ye, 2011; and Zhu, 2014; among others). Theory suggests that the impact of dark pools on market liquidity and efficiency will depend in part on where the informed trade, or whether dark pools induce segmentation of informed trade. Consequently, I focus on a relatively primitive question: where do the informed trade?

An empirical challenge in this institutional setting is that methods commonly used to identify informed trade can not be well-applied. For example, the Hasbrouck (1995) information share examines the lead/lag relationship between venue trade prices, but dark pool trades are executed at exchange quoted prices by design. The Easley, Kiefer, O'hara, and Paperman (1996) probability of informed trading which relies on identifying the initiating side of a trade is also difficult to apply in this setting.[2] In addition, data comprehensively identifying dark pool trading in U.S. equities has not been readily available. I use a novel collection of identified dark pool trade-level data, a database of corporate news releases, and short sale trade-level data for an alternative, but time-

[1]See, "Dark Pools Confront More Transparent Future Amid Threats", Bloomberg, 9/17/2014.

[2]It is difficult correctly identify the exact timing of off-exchange transactions and many dark pool trades take place at the midpoint of the National Best Bid and Offer, so price tests can not be well-applied.

honored notion of informed trading. Specifically, I examine where short sellers exploit their well-documented information advantage.

Non-exchange trading venues otherwise known as dark pools offer potentially lower transaction costs than exchanges. Dark pools don't publicly display orders and often match orders at prices inside the exchanges' prevailing best bid and ask (National Best Bid and Offer, or the NBBO).[3] Many of these orders are "pegged" to a reference price, such as the midpoint of the NBBO.[4] However, dark pool orders are less likely to be filled relative to exchange orders. Dark pools are often characterized by the fact that they "passively" cross the orders of buyers and sellers at prices at and within the NBBO by rule. Dark pools "passively" cross orders because the NBBO is determined at traditional stock exchanges whose quotes are both publically displayed and contribute to the construction of the NBBO.[5] In contrast to exchanges, if there is not contra-side interest in a dark pool for an order at prices at and within the NBBO, trade won't take place.[6] Dark pools are separate venues and not fully integrated with stock exchanges. Consequently, dark pool order flow may never enter the traditional stock exchanges where reference prices are determined.

In this paper, I ask three questions. Where do the informed trade? Where are short sales most informed? Where do the informed trade when private information is short lived? When examining where the informed trade, I find that short sales comprise 54.06% of exchange trading volume and 45.31% of dark pool trading volume. When examining where short sales are most informed, I find that stocks which are heavily shorted in dark pools and on exchanges underperform corresponding lightly shorted stocks by a four-factor adjusted value-weighted average of 0.53% and 0.89% over the

[3]Off-exchange trades are reported to public data feeds after execution with a delay. With that said, the absence of pre-trade transparency in itself may change the nature of the public information set relative to the case where all trades and orders are hosted on "lit" markets (for example, see the experimental studies of Flood, Huisman, Koedjik, and Maheiu, 1999; Bloomfield, O'Hara, and Saar, 2015; and Madhavan, 2000 for empirical results). However, it is important to emphasize that the notion and nature of order flow segmentation are the main focus of this paper. The presence of dark pools in U.S. market structure has different implications than the presence of "hidden" orders on exchanges. In the case of hidden exchange orders, other types of exchange order flow can still trade against hidden order flow, unlike dark pool order flow.

[4]A midpoint pegged order can be explained as follows: as the midpoint of the NBBO changes, the order price also changes to the prevailing midpoint of the NBBO.

[5]An exception to this is Lava Flow ECN, which for some time provided quotes through the FINRA Alternative Display Facility (ADF).

[6]Marketable order imbalances on exchanges will result in trading at a new price level and a change in the NBBO.

following 20 trading days (6.41% and 10.70% annualized), respectively. At higher frequency, midquote excess returns after exchange short sales are 0.32, 0.83, and 1.50 basis points (3.78% annualized) lower than corresponding post-dark pool short sale returns over post-trade horizons of 30 minutes, two hours, and one trading day, respectively. In order to understand where the informed trade when private information is short-lived, I study trading surrounding a sample of corporate news events. Since the arrival date of scheduled news known to the public in advance, uninformed traders may lower exposures to reduce adverse selection risk and pre-announcement trading may be reflective of belief heterogeneity (see Lee, Mucklow, and Ready, 1993; Sarkar and Schwartz, 2009; and Baruch, Panayides, and Venkataraman, 2015). However, uninformed traders likely do not know when unscheduled news will arrive. When I separate corporate news releases into scheduled and unscheduled events, I find that dark pools only capture an increased proportion of trading when the arrival of news is scheduled. Furthermore, I find relatively stronger evidence of increased exchange short selling on the trading day prior to unscheduled negative news arrival. I also only find evidence of increased 20 day cross-sectional return predictability of exchange short sellers on the trading day prior to news releases. In contrast to Engelberg, Reed, and Ringgenberg (2012), I do not find evidence of increased 20 day cross-sectional return predictability of short sellers in dark pools or on exchanges on news release days.

I further disaggregate the dark pools in the sample into dark pools characterized by large trade sizes (Block Dark Pools), dark pools characterized by smaller trade sizes than Block Dark Pools and a large percentage of trades occurring inside the NBBO (Midpoint Dark Pools), and dark pools characterized by smaller trade sizes than Block Dark Pools and a relatively small percentage of trades occurring inside the NBBO (Non-Midpoint Dark Pools). I find that short sales comprise 15.35%, 42.82%, and 48.37% of Block Dark Pools, Midpoint Dark Pools, and Non-Midpoint Dark Pools trading volume, respectively. I find the strongest evidence of short sale cross-sectional daily return predictability of the dark pools I study in Non-Midpoint Dark Pools, then Midpoint Dark Pools, then Block Dark Pools. At higher frequency, Midpoint Dark Pools exhibit the least intraday post-short sale return predictability.

There are several implications of my results. I provide new support for the theory of intermarket competition. My results also complement empirical papers on dark pools and fragmentation which focus on empirical measures of liquidity and arrive to mixed results. To the extent that the sample of dark pools examined in this paper and short sellers are representative, my results suggest that dark pools as a group induce segmentation of informed trade. Theory suggests that as relatively more informed trade is executed on exchanges and relatively more uninformed trade is executed in dark pools, there will be less noise accompanying informed order flow on exchanges. This suggests that the presence of dark pools may result in increased price efficiency with regard to information acquired. Dark pools may also result in less exchange liquidity since there is more information asymmetry remaining in exchange order flow. My results also may suggest that the off-exchange venues that may stand to lose the most market share from the implementation of a trade-at rule also appear to be inducing the least segmentation of the dark pools I study.[7]

My results also provide a better understanding how information is incorporated into equity prices in markets where a stock can trade in over 40 venues. More specifically, while a number of recent studies have examined which short sellers are informed and how short sellers obtain their information advantage, my results provide insight into where short sellers exploit their information advantage. There has also been research that has debated whether news resolves asymmetric information or creates it; my results provide evidence that in today's high frequency markets, asymmetric information is resolved faster with news releases.

The balance of this paper proceeds as follows: Section I reviews the relevant literature, Section II discusses the collection of data employed in this study, empirical methodology, and results. Section III concludes.

I. Literature

A. Where the Informed Trade

A number of studies examine where the informed trade in equity markets, debt markets, and their respective contingent claims. This literature helps us understand how information becomes incorporated into asset prices, an issue of longstanding interest to both the efficient markets and rational expectations literatures. Stephan and Whaley (1990), Mayhew, Sarin, and Shastri (1995), Easley, O'Hara, and Srinivas (1998), Chakravarty, Gulen, and Mayhew (2004), and Pan and Poteshman (2006), among others examine trading in equities and equity options and results are mixed with regard to where the

[7]The Lucas critique aside.

informed trade. Hasbrouck (2003) examines trading in U.S. equity index markets and finds that E-mini S&P 500 futures contribute the most to intraday price discovery of the markets examined. Acharya and Johnson (2007) examines trading in credit default swaps in relation to equities and finds evidence of informed trading in credit default swaps. My study provides a more nuanced understanding of how information enters the U.S. equity market by examining the trading and return predictability of short sellers on exchanges and in dark pools.

B. Fragmentation and Pre-Trade Transparency

Fragmentation and pre-trade transparency are two relevant issues when considering dark pools. While there has been a shift towards more transparency in financial markets, the recent growth of dark pools in the U.S. equity market is an exception to this trend. Milgrom and Weber (1982) analyzes the setting of a common value auction and shows that bid transparency increases competition. Baruch (2005) shows that making the limit order book transparent also increases competition. With regard to fragmentation, Pagano (1989) analyzes fragmentation across two markets in an endowment economy and shows that traders are attracted to venues where others trade. For more on fragmentation and pre-trade transparency, see Madhavan (2000) and Comerton-Forde and Putnins (2015), *inter alia*.

C. Intermarket Competition

In theory of intermarket competition, informed traders choose where to trade in order to maximize the value of their information. Ye (2011) and Zhu (2014) both model the coexistence of a "dark pool" (more generally a passive crossing platform) alongside a "lit" venue and arrive to different conclusions. In these models, traders weigh a tradeoff between the potential of not obtaining a trade execution in the dark pool against incurring higher transaction costs on exchange. Ye (2011) extends the Kyle (1985) framework in order to examine the choice of venue of an informed trader and finds that the informed trader will choose to split his order between the dark pool and exchange, trading less aggressively on the exchange and revealing less of his information relative to Kyle (1985). Consequently, the presence of dark pools will reduce market volatility and price discovery. Zhu (2014) presents a Glosten and Milgrom (1985) - like model which allows both informed traders and liquidity traders to choose their trading venue.[8] Since informed traders are more likely to have correlated orders and cluster on the heavy side of the market, they suffer from increased execution risk relative to liquidity traders. Consequently, relatively more informed traders will choose to trade on exchange while relatively more liquidity traders will choose to trade in the dark pool. With less noise accompanying informed demand and supply on the exchange, exchange prices will become more informative, though this coincides with less exchange liquidity.[9]

Furthermore, Zhu (2014) and Hendershott and Mendelson (2000) examines the coexistence of different types of trading venues and the notion of "information horizon", by examining the case where private information is relatively short lived. Hendershott and Mendelson (2000) models a dealer market and "crossing network" which can be thought of as an exchange and dark pool. This paper finds that informed traders with short lived private information will be more likely trade on exchange than informed traders with long lived private information. Zhu (2014) finds that all else equal, a shorter horizon of private information can cause more aggressive use of dark pools by informed traders. In the spirit of Myers and Majluf (1984), Menkveld, Yueshen, and Zhu (2015) formalizes a "pecking-order hypothesis" of trading venues. This study examines a setting of symmetrically informed traders who choose between trading on a "lit" venue that guarantees execution, a "midpoint matching dark pool" which executes trades at the exchange midpoint, but doesn't guarantee execution if there are order imbalances, and a "non-midpoint matching dark pool" which is run by a single competitive liquidity provider. If trading needs become more urgent, exchanges will be at the top of the pecking order.

[8]The assumption of traders self-selecting which trading venue to use has recently been called into question. Brokers often execute trades on behalf of clients and have discretion on how to submit orders. O'Donoghue (2015) analyzes delegated order routing in the presence of payments for order flow and finds that the delegation of order routing is non-trivial. Battalio, Corwin, and Jennings (2015) empirically finds that several retail brokerages route order flow in a manner that appears to maximize order flow payments, which may result in worse execution quality for their customers. Barclays has also been accused of routing a disproportionate amount of their smart order router order flow to their dark pool, LX, in order to build its market share of trading volume. This may suggest that similar issues may exist for institutional order routing. See, "Five Questions on the Barclays Dark Pool Lawsuit", Wall Street Journal, 6/26/2014. These issues suggest that not only do customers often delegate the choice of trading venue to their brokers, but that the incentives of the broker and customer may not be aligned. While I attempt to explain motivations of traders, theory suggests that the equilibrium outcome of where order flow gets executed in the aggregate still has implications for market quality and efficiency regardless of motivation.

[9]Buti, Rindi, and Werner (2015) also models intermarket competition without asymmetric information.

Empirically, Conrad, Wahal, and Johnson (2003) examines institutional order data and finds that orders executed in Alternative Trading Systems (ATSs, U.S. regulatory term for non-exchange trading venues) save 13 cents per share. Ye (2010) finds bid-ask spread costs in dark pools are 20% lower and that orders have a fill rate of 4% in NYSE stocks. Tuttle (2013) finds that ATSs fill 0.69% of orders in a more recent sample. Easley, Kiefer, and O'Hara (1998) examines trading on the New York Stock Exchange and Cincinnati Stock Exchange. Hendershott and Jones (2005) studies an ATS's decision to "go dark" in order to examine the impact of pre-trade opacity in several Exchange Traded Funds (ETFs). O'Hara and Ye (2011) finds that increased fragmentation of trading (due in part to increased off-exchange trading) improves market quality. Buti, Rindi, and Werner (2011) uses a sample of 11 self-reporting dark pools at a daily frequency to examine the relationship between the share of trading done in dark pools and measures of market quality and price informativeness and finds that dark pools improve market quality, but have a complex relationship with price discovery. Weaver (2014) uses a sample of all off-exchange trading and finds that off-exchange trading harms market quality. Comerton-Forde and Putnins (2015) uses data from Australia (which is a smaller market with a different institutional setup) and finds that some dark pool trading can be good for price discovery, but too much dark pool trading will harm it. Hatheway, Kwan, and Zheng (2014) argues that dark pools harm both market quality and price informativeness.

The results of these studies have disagreed to some extent. An issue when examining the relationship between the share of dark pool trading and measures of market quality and efficiency in order to make causal inferences is that they're jointly determined, along with other endogeneity issues. Some of these studies attempt to correct for these issues in order to make causal inferences, but this is a difficult task, especially in the U.S. where there hasn't been any major regulatory changes which have only affected off-exchange trading over this span. Furthermore, there have been other significant changes in U.S. equity market structure that have coincided with the growth of dark pools and may confound inferences. For example, the recent increase in trading done in dark pools has been accompanied in part by an increase in algorithmic and high frequency trading which also may also have affected market quality and efficiency.[10] My study complements the literature by employing an alternative empirical approach. I do this with, to my knowledge, the largest and most comprehensive sample of identified dark

[10]For example, see Hendershott, Jones, and Menkveld (2011) and Conrad, Wahal, and Xiang (2015).

pool trading in NYSE and NASDAQ listed stocks to date.

Fleming and Nguyen (2014) examines where the informed trade between the limit order book and "workup" functionality for U.S. government securities trading on the BrokerTec electronic trading platform. This functionality has pre-trade opacity and passive pricing. However, BrokerTec only supports trading exclusively in a limit order book or the workup process at a given point in time. In equity markets, traders can submit orders to both types of venues simultaneously. Furthermore, the institutional information structure of treasury markets is not typically associated with insider information. My study provides a different setting for testing the theory of intermarket competition and contributing to our understanding of equity market structure. In a contemporaneous effort to mine, the empirical portion of Menkveld, Yueshen, and Zhu (2015) examines the dynamic inter-relation between trading in different venues using a high frequency, one month panel of 117 NASDAQ-listed stocks to find support for the predictions of the "pecking order hypothesis" set forth in the theoretical portion of the study. While doing so, Menkveld, Yueshen, and Zhu (2015) examines all off-exchange trading and focuses on the behavior of "high frequency traders" as classified by NASDAQ. One concern when attempting to use the equilibrium outcome of a trade print to make inferences about trading venue preferences is that the outcome of a trade may not capture the nature of order routing before a trade execution. This is because a trade print does not necessarily reflect the first choice of venue of a trader. My approach is complementary as it examines a larger panel of identified dark pool trading at a lower frequency, covers a more recent sample period, focuses on a large group of identified dark pools rather than attempting to confront the greater complexity of all off-exchange trading, uses a larger and more diverse sample of corporate news, and examines the behavior of short sellers rather than high frequency traders. Furthermore, my study's main focus is to find support for all of the theory of intermarket competition, especially theory which is rooted in information economics.

D. Short Sellers as Informed Traders

Boehmer, Jones, and Zhang (2008) explains our understanding of short sellers with bravado, "Throughout the financial economics literature, short sellers occupy an exalted place in the pantheon of investors as rational, informed market participants who act to keep prices in line". Diamond and Verrecchia (1987) provides a theoretical explanation as to why short sellers may be informed. This paper illustrates that when short selling is relatively costly (because short sellers can not use the full proceeds of their short sales), short sellers will be relatively informed traders. Miller (1977), Duffie, Garleanu, and Pedersen (2002), and Hong, Scheinkman, and Xiong (2006) show that prices may diverge from fundamental values when short selling is constrained. Empirically, research has studied the return predictability of short sellers. Using both short interest and short volume data, Asquith, Pathak, and Ritter (2005), Diether, Lee, and Werner (2009), and Boehmer, Huszar, and Jordan (2010), among others show that heavily shorted stocks underperform lightly shorted stocks. Boehmer, Jones, and Zhang (2008) examines which short sales are informed using a panel of NYSE order data with trader type classifications. Using a higher frequency panel of short-sales, Comerton-Forde, Jones, and Putnins (2015) finds that intraday raw returns after marketable short sales are negative.

A more recent literature has examined how short sellers obtain their information advantage. Some research conjectures that short sales are related to well-known asset pricing anomalies (see Dechow, Hutton, Meulbroek, and Sloan, 2001 and Hanson and Sunderam, 2014, among others) or results from strategically trading against buyers (see So and Wang, 2014 and Arif, Ben-Rephael, and Lee, 2015). Another established explanation of the short sellers' information advantage comes from a group of studies that examine short selling surrounding corporate news releases. Christophe, Ferri, and Angel (2004), Christophe, Ferri, and Hsieh (2010), Karpoff and Lou (2010), and Boehmer, Jones, and Zhang (2012) find evidence of increased short selling prior to announcements of earnings, equity analyst ratings changes, announcements of firm misconduct, and "cash flow" news, respectively. Engelberg, Reed, and Ringgenberg (2012) studies short selling around news events and not only finds evidence of increased short selling in the days leading up to negative news, but that much of return predictability of short sellers occurs on news release days. I take a notion of informed trading from this literature and contribute to our understanding of short sellers by studying where short sellers exploit their information advantage.

E. Corporate News and Information Asymmetry

Corporate news has long been associated with asymmetric information. While conventional wisdom in information economics models public and private information as substitutes and suggests that news announcements reduce information asymmetry (see Kyle, 1985; Glosten and Milgrom, 1985; Korajczyk, Lucas, and McDonald, 1991; and Diamond and Verrecchia, 1987; among others), more recent studies argue that news may create information asymmetry. The general intuition behind the latter view is that news releases may lead to differential interpretations by traders based on variation in the distribution of information processing skill or capacity (e.g. Kandel and Pearson, 1995 and Hong and Stein, 1999, among others). Engelberg (2008) and Demers and Vega (2008) find that "soft" information can be predictive of post announcement returns and provide opportunities for informed trade by superior information processors. Engelberg, Reed, and Ringgenberg (2012) finds that a disproportionate amount of short sellers' return predictability coincides with news release days. I use corporate news releases to identify firm-specific information events, which may reflect instances in which private information exists and is short lived to find support for one or more mechanisms in the intermarket competition literature. Furthermore my results provide evidence regarding whether public news resolves or creates information asymmetry.

II. Methodology and Results

As discussed in Section I, Zhu (2014) predicts that the introduction of a dark pool will result in relatively more informed traders on exchange. Consequently I examine short sales and their return predictability.

I translate this prediction into two sets of tests which examine where the informed trade and where short sales are most informed. To align my research design with theory of intermarket competition, I separate and aggregate trading into representative venues; trading in dark pools and trading on exchanges. I only consider stocks that trade in both dark pools and on exchanges in my sample.[11,12]

[11]There are no stocks that trade exclusively in dark pools.

[12]In contrast to some empirical asset pricing and return predictability papers, I'm not advocating that the returns that accrue to short sales in my sample represent an implementable strategy to any investor. I simply want to examine the relative return predictability of dark pool and exchange short sales in order to understand how information is incorporated in equity prices.

A. Data

The sample employed in this study consists of media reportable trading for the disaggregated FINRA Trade Reporting Facilities Data (TRF), the RavenPack news release database, Center for Research in Security Prices (CRSP) daily stock data, short sale data obtained from the exchanges and FINRA, Security Information Processor (SIP) NBBO data, FINRA Order Audit Trail System (OATS) data, and NYSE Trade and Quote (TAQ) data. The sample period spans August 2012 through June 2014. I consider trading during regular trading hours (9:30:00 through 16:00:00 EST).[13] Kwan, Masulis, and McInish (2014) shows that dark pools lose a significant amount of market share when stock prices drop below one dollar and the minimum exchange tick size drops below one cent; consequently, I remove stocks that had a daily closing price below one dollar at some point in the sample. I am left with a sample of 3,148 stocks, 1,343,458 stock-day observations, and 70,993 news events. After filtering out overlapping news events, 24,334 news events remain.[14] In this paper, I focus on trading, which is an outcome of the order routing process.

A.1. Trade Reporting Facilities

Trade Reporting Facilities data are collected by FINRA for regulatory purposes. The TRF data contain U.S. stock transactions that are effected otherwise than on an exchange. FINRA requires that these trades be reported as soon as practicable but within 10 seconds, although the timestamp of execution is also provided by submitting party. While trades reported to the TRF appear in public data sources such as TAQ, all non-exchange trading is reported the same way. Consequently, one is not able to differentiate dark pool trading from other types of non-exchange trading using TAQ or other high frequency public data sources.[15] These disaggregated data allow me to identify dark pool trading. More importantly, I am able to identify and classify individual venues. The sample is constructed using the approach of Kwan, Masulis, and McInish (2014), but the data used in my study span a larger panel of stocks and to my knowledge, contains a more comprehensive set of identified dark pools for NASDAQ listed stocks. Furthermore, in contrast to Kwan, Masulis, and McInish (2014), these data allow me to

[13] The majority of dark pools in my sample do not host after hours trading.

[14] In parts of the analysis, I remove ten days from the sample that correspond to options expiration or "witching days" due to irregular changes in trading volume.

[15] Other types of off-exchange trading may include internalization, among other types of trading.

identify dark pool trading for non-NASDAQ listed stocks. The final sample consists of trade level data for 24 dark pools. The sample of dark pools in this paper host up to 16% of total trading by the end of the sample, which is close to recent estimates that dark pool trading now comprises 17% of total trading volume (see Footnote 2). As of the second calendar quarter of 2014, the dark pools in my sample comprise nine of the top ten and 17 of the top 20 non-Alternative Display Facility ATSs reporting to FINRA in terms of volume traded and comprise approximately 85% of ATS volume reported to FINRA for ATSs of interest.[16]

A.2. RavenPack Corporate News Releases

RavenPack is a leading provider of real-time news and sentiment analytics in finance. It provides a database of corporate news releases accompanied by analytics. I consider categorized press releases, full articles, news flashes, and hot news flashes from the Dow Jones Newswire. Ravenpack provides a timestamp of when the story was received by RavenPack, which coincides with when the news is released. If a story is released after 16:00:00, I consider the following trading day to be the event day. RavenPack provides a relevance score that determines how relevant a story is to a given company. RavenPack categorizes news releases into several categories ranging from conventional categories such as earnings to less frequently occurring news events such as labor issues covering events including executive resignations. To avoid overlapping news events and allay concerns of multicollinearity, I remove news events in a given stock that are within 15 calendar days of another news event for the same stock after presenting descriptive statistics. RavenPack also classifies categorized news as scheduled or unscheduled. RavenPack provides a sentiment score based on analytics that in some cases attempts to account for market expectations; however, like Engelberg, Reed, and Ringgenberg (2012), I opt to evaluate news based on the event day market reaction as it may better

[16] To allay concerns regarding the sensitivity of these data, I aggregate ATSs into categories so that the specific practices of any one ATS are not revealed.

reflect a divergence from the market's prior expectations.[17,18]

A.3. Other Sources

The CRSP US Stock Database contains daily market and corporate action data for securities with primary listings on NYSE, NYSE MKT, and NASDAQ. I use stock data for U.S. listed common stocks (CRSP share codes 10 and 11; Exchange codes 1, 2, and 3) with positive market capitalization.

The TAQ database contains intraday trade and quote data for securities listed on NYSE Group exchanges as well as NASDAQ issues. I calculate trading volume during regular trading hours by summing trade sizes, after filtering out trades with a price of less than zero and with a correction indicator other than zero in TAQ. I also use the Daily TAQ NBBO files appended by more NBBO records from the quotes files in order to compute midquote returns.[19] I use the TAQ "master files" in order to merge CRSP, RavenPack, short sale data, and TAQ and subsequently merge with the TRF data.

Short sale trade level data and daily short sale volume totals are obtained from the exchanges and FINRA. In the majority of cases, I am able to obtain trade level files and examine trading during regular trading hours. I am only able to obtain files at a daily frequency from NYSE Arca. National Stock Exchange (NSX) trade level short sale data is missing for January of 2014, so I use the daily frequency data for that month.[20] I am also missing short sale data for the CBSX, which ceased operations in early 2014.[21] I

[17]Results are qualitatively similar when I sign news with RavenPack's sentiment score and available in the web appendix.

[18]Similarly to Keim, Massa, and von Beschwitz (2013) I consider stories with a relevance score of 100 in order to reduce noise. RavenPack also provides novelty scores in order to link multiple stories that cover the same event. I use stories with novelty scores of 100 in order to filter out redundant news releases similarly to Engelberg, Reed, and Ringgenberg (2012) which applies an algorithm to accomplish the same task. If multiple news releases regarding the same topic occur on same day, I treat them as one news event. Following Engelberg, Reed, and Ringgenberg (2012), I exclude categories that have less than 999 stories in the sample. Furthermore, I filter out categories of stories relating to market activity, such as the "technical analysis", "prices", and "trading" categories since they don't represent corporate events. I remove stories regarding "insider-trading" because they comprise roughly half of the categorized news events and cluster in time and I would be required to drop the majority of them and other news events had I not initially filtered them out. Finally, I remove stories regarding "revenues" and "investor relations" because they are typically in close proximity to earnings announcements.

[19]In order to remove spurious quotes, I inspect end of minute NBBO midquotes which represented a 20% log return from their previous level and manually remove them if I deem them to be spurious (if they immediately revert).

[20]The NSX hosted less than one percent of trading in January 2014.

[21]The CBSX stopped providing short sale data on their website after June 2011 and represented less than one percent of total trading volume in January 2013.

report results for short sales that are not marked as exempt from the alternative uptick rule; which is activated after large stock price fluctuations and requires that short sellers transact at prices above the national best bid. In line with the short sales literature, I filter out exempt short sales to better identify informed short sales.[22] Short sales marked as exempt comprise roughly 6.0% of total short sale volume in the sample.[23]

The SIPs link the U.S. equity markets by processing and consolidating all protected quotes and trades from contributing trading venues. I obtain NBBOs from the UTP SIP and CQS SIP NBBO files for NASDAQ and NYSE Group listed stocks, respectively. I filter out NBBO records that correspond to locked and crossed markets.

TRF execution timestamps are only at a one second frequency, so in order to look at trade prices in dark pools relative to the outstanding NBBO, I use a sample of TRF data that is merged with OATS data with millisecond timestamps. OATS is an integrated audit trail of order, quote, and trade information for all NMS stocks and OTC equity securities. FINRA uses this audit trail system to recreate events in the life cycle of orders and more completely monitor the trading practices of member firms. In the sample, approximately 75% of trading in the TRF is successfully matched to OATS.

B. Descriptive Statistics

Stock level summary statistics for variables of interest are presented in Table I.

<Insert Table I>

Panel A presents the mean, median, 1st and 99th percentiles, and standard deviation for the number of novel news events per stock-day, the percentage of trading volume executed in dark pools, the percentage of exchange trading volume that was sold short, the percentage of dark pool trading volume that was sold short, and average market capitalization of the stocks over the sample. Dark pool trading comprises 13.1% of a stock's trading volume on average over the sample. Exchange short sales represent 45.7%

[22]Results are qualitatively similar when I consider exempt short sales and available upon request.

[23]There are a broad set of exemptions from the alternative uptick rule, including a broker dealer indicating that they conducted their own price test and certain very narrowly defined types of arbitrage activity, among others. For more on the alternative uptick rule and exemptions, see http://www.sec.gov/rules/final/2010/34-61595.pdf.

of a stock's exchange trading volume on average.[24] Short sale volume executed in dark pools represents 37.0% of a stock's dark pool trading volume on average. The stock level dark pool short ratio and its exchange counterpart are statistically distinguishable.

Panel B presents frequency counts of the number of novel news events in the sample by category. There are 11 categories in total. This panel suggests that there is a wide sample of types of news events, many of which have been studied individually in the financial economics literature.[25]

To gain an understanding of the temporal nature of aggregate dark pool trading and short sales over the sample, the time series of the share of daily total trading volume executed in dark pools (black solid line), the share of total exchange volume that was sold short (grey dashed line), and the share of dark pool trading volume that was sold short (black dashed line) across all stocks in the sample are presented in Figure 1.

<Insert Figure 1>

Exchange short sale volume represents slightly more than half of exchange trading volume throughout the sample while dark pool short sale volume comprises slightly less than half of dark pool trading volume throughout most of the sample. This is likely due not only to an increasing amount of longer horizon short selling in equity markets and reduced shorting contraints (see Hanson and Sunderam, 2014) but also to an increase in high frequency trading in equity markets.[26,27] While I do not observe the position

[24]I standardize the sample of exchange short sales by total TAQ Daily Volume for exchange codes not equal to "D", which corresponds to off-exchange trading.

[25]I confirm that unsigned returns are significantly larger and these days and results are available in the web appendix.

[26]There is both theoretical and empirical evidence which suggest that high frequency traders are informed. Foucault, Hombert, and Rosu (2015) develops a model with "high frequency speculators" and finds that both their relatively high frequency trading and lower frequency inventory accumulation will be informed. Using data on high frequency traders as identified by NASDAQ, Brogaard, Hendershott, and Riordan (2014) finds that high frequency traders trade in the direction of permanent price changes and opposite temporary price changes. Carrion (2013) also studies the inventory accumulation activity of high frequency traders on the NASDAQ and finds that they have market-timing ability. In the web appendix, I show that stock-day percentages of trading volume sold short do not sort with stock day cancel to trade ratios (a proxy of high frequency trading) especially meaningfully. On the other hand, stock-month percentages of trading volume sold short do monotonically sort with stock-month ratios of short interest to shares outstanding (a proxy of lower frequency short selling).

[27]Comerton-Forde, Jones, and Putnins (2015) finds that exchange short sales partially consist of limit orders. Several models including: Kaniel and Liu (2006), Goettler, Parlour, and Rajan (2009), Boulatov and George (2013), and Baruch, Panayides, and Venkataraman (2015), among others find that under some conditions, informed traders will use limit orders and Baruch, Panayides, and Venkataraman (2015) empirically finds that informed sellers are more likely to use limit orders than informed buyers.

closing activity of short sellers, Jones, Reed, and Waller (2015), Boehmer, Duong, and Huszar (2015), and Von Beschwitz and Massa (2015) study daily short position data find a mean short position duration of weeks over recent samples. To study higher frequency short sales strategies, I also examine the intraday return predictability of venue short sales.

Dark pool trading volume comprises as much as 16% of trading volume at the end of the sample. This percentage is close to recent estimates that dark pools host 17% of trading volume (see Footnote 2). Short sales in dark pools represent a smaller proportion total short volume relative to the percentage of total trading volume in dark pools. The share of volume sold short in dark pools is statistically distinguishable from its exchange counterpart. These results suggest that dark pools host a different composition of traders than exchanges.

The relative stability of these series is in contrast with previous research using less recent sample periods. In Figure 1 of Zhu (2014), the share of trading volume executed in dark pools had been significantly trending upward. The share of trading volume being sold short is also significantly trending upward in the commonly used Reg-SHO sample which spans 2005 through 2007. This may be evidence that equity trading is approaching an equilibrium level of short sales and dark pool trading, which makes this study's sample a better setting for testing theory. I reject the null of a unit-root in Augmented Dickey-Fuller tests for all four series presented in Figure 1.

C. Dark Pool Categories

In addition to the main empirical design of this paper, I further disaggregate the dark pools in my sample into three groups. While there are several dimensions across which dark pools may differ, I infer classifications from the data. There have been episodes of dark pools misleading customers with regard to their business practices.[28] Inferring dark pool categories from the data may teach us the most about these institutions. For example, Kirilenko, Kyle, Samadi, and Tuzun (2014) infers trader categories from account level audit trail data to learn about the ecosystem of the E-mini S&P 500 Futures Contract.

I classify the dark pools in my sample using two characteristics: the percentage

[28] For example, Pipeline Financial Group Inc. and Barclays have both been accused of misleading customers with regard to the practices of their dark pools. See, "Pipeline's Chairman, Chief Are Said to Leave Dark-Pool Firm After Scandal", Bloomberg, November 15, 2011 and Footnote 10.

of trades inside the NBBO and trade size. There are both theoretical and practical reasons to classify dark pools along these dimensions. Menkveld, Yueshen, and Zhu (2015) conjectures that there is a pecking order of trading venues, specfically exchanges, midpoint dark pools, and non-midpoint dark pools. Furthermore, the SEC is considering implementing a trade-at rule which would require that off-exchange trades which cannot significantly improve upon exchanges' best price be routed to exchanges. This type of order flow is likely most reflected in non-midpoint dark pool trading. Since I am unable to obtain millisecond timestamps for trading in two dark pools, I classify the remaining 22 into Block Dark Pools (4), Non-Midpoint Dark Pools (11), and Midpoint Dark Pools (7). Block Dark Pools are characterized by having larger trade sizes. Midpoint Dark Pools are characterized by having smaller trade sizes than Block Dark Pools and a high relative proportion of trades inside the NBBO and at the NBBO midpoint. Non-Midpoint Dark Pools are characterized by having smaller trade sizes than Block Dark Pools, and a lower relative proportion of trades inside the NBBO and at the NBBO midpoint compared to Midpoint Dark Pools.

Statistically, Block Dark Pools, Midpoint Dark Pools, and Non-Midpoint Dark Pools host 0.57%, 3.86%, and 8.88% of trading volume and 15.35%, 42.82%, and 48.37% of their trading volume are short sales, respectively. Of the trades matched to OATS, 82.42%, 44.51%, and 21.66% of Block Dark Pools, Midpoint Dark Pools, and Non-Midpoint Dark Pools trade prints are at the prices equal to the NBBO Midpoint, respectively. Of the trades matched to OATS, 87.18%, 57.83%, and 33.08% of Block Dark Pools, Midpoint Dark Pools, and Non-Midpoint Dark Pools trade prints are at prices inside the NBBO, respectively. The averages of the category constituent venues' average trade sizes of Block Dark Pools, Midpoint Dark Pools, and Non-Midpoint Dark Pools are 9702 shares, 247 shares, and 183 shares, respectively.[29]

In the web appendix I also show that the main results are qualitatively similar for relatively idiosyncratic deviations from the standard dark pool design. According to regulatory filings, some dark pools offer a discrete-time cross in addition to a continuous cross. Some dark pools allow "pool clubbing" where users will indicate that they only want to trade against certain types of accounts. Some dark pools allow participants to send non-binding conditional orders which are displayed to some other market participants or dark pool operators themselves will display some orders or send non-binding "indications of interest". Some dark pools offer crossing at a volume weighted average

[29]For more information regarding these categories, see the web appendix.

price (VWAP) in addition to crossing at and within the NBBO.[30]

D. Where are Short Sales Most Informed?

In this section, I examine where short sales are most informed. Stated alternatively, I examine where short sales exhibit the most return predictability cross-sectionally and at higher frequency.

Following Boehmer, Jones, and Zhang (2008), among others, if short sellers are informed in a given trading venue, then the stocks they heavily short should underperform the stocks they lightly short. Intuitively, this line of research asks how good short sellers are at relative valuation. I first adopt a portfolio approach to measure cross-sectional differences in trading venue short sales and future returns. I begin by sorting stocks by shorting flow measures and type of trading venue. As in Boehmer, Jones, and Zhang (2008) and Engelberg, Reed, and Ringgenberg (2012), each day, I sort stocks into quintiles based on trading venue shorting volume standardized by the corresponding trading venue volume.[31] After stocks are sorted into quintiles each day, I construct value-weighted portfolios for the following 20 trading days. This process is repeated each trading day which results in overlapping 20 day holding period returns. To address this overlap, I employ a variant of the calendar-time approach used in Jegadeesh and Titman (1993) and Boehmer, Jones, and Zhang (2008), among others. Each trading day's portfolio return is the simple average of 20 different daily portfolio returns and 1/20 of the portfolio is effectively rebalanced each day. Formally, the daily return of a portfolio is:

$$R_{p,t} = \frac{1}{20} \sum_{k=1}^{20} Q_{t-k}^{i,p} w_{t-1}^{i,p} R_{i,t}, \tag{1}$$

[30]One mechanism that I can not sharply empirically identify is the fact that dark pools have different sets of participants, and that these participant lists are non-nested across dark pools. While this may be the limiting case of the tradeoff between transactions costs and probability of trade where $P(Trade) = 0$ for some traders in one, or multiple dark pools. This may affect my unconditional results (which can be thought of as a level), it is less likely to affect my news results (which can be thought of as a change).

[31]The choice of scaling trading venue short sale volume by the corresponding venue total trading venue volume is deliberate. If I were to scale by an alternative variable, such as total trading volume, then the cross-sectional variation in the share of total trading executed in dark pools would also enter the variable of interest, confounding inferences regarding the hypotheses of this paper. The choice to scale by total trading volume is in line with the short sales literature and is motivated by the fact that large firms are characterized by having relatively more lendable shares for short sales (see Boehmer, Jones, and Zhang, 2008, among others).

Where $Q_{t-k}^{i,p}$ is an indicator variable set to one if and only if the i^{th} security is assigned to portfolio p based on trading venue short selling activity on day $[t-k]$; $w_{t-1}^{i,p}$ are market capitalization weights on day $t-1$; and $R_{i,t}$ is the raw return of stock i on day t. Average daily calendar-time returns are reported in percent multiplied by 20 (to state returns in approximately monthly terms), with t-statistics based on an i.i.d. daily time series as in Boehmer, Jones, and Zhang (2008). I control for systematic risk and momentum with the standard Carhart (1997) time series regression:

$$R_t - R_{rf,t} = \alpha + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \epsilon_t, \qquad (2)$$

Raw returns of trading venue short sale portfolios and the alphas by venue type from Equation 2 are reported in Table II. Panel B presents results across various portfolio holding horizons.

<Insert Table II>

Results suggest that short sellers are good at relative valuation, and may be better at avoiding undervalued stocks (consistent with Boehmer, Jones, and Zhang, 2008, among others). Where the results for exchange short sales and dark pool short sales diverge the most is the degree of cross-sectional return predictability. Heavily shorted stocks in dark pools underperform corresponding lightly shorted stocks by a four-factor adjusted average 0.53% over the following 20 trading days. While these returns are non-trivial, they are slightly more than half of the corresponding returns for portfolios formed on exchange short sales: 0.89% (10.70% annualized). The spread of exchange and dark pool long-short portfolios has an annualized alpha of 4.29% which is statistically significant. While there is some evidence of informed short selling taking place in dark pools, I interpret these results as evidence that there is a relatively lower degree of informed short selling taking place in dark pools relative to on exchanges.[32] For the 20 day holding horizon, the long-short alphas for Block, Midpoint, and Non-Midpoint alphas are 0.18%, 0.29%, and 0.55%, respectively (t-stats of 1.59, 2.01, and 4.45, respectively). Block Dark Pool short selling does not appear to be informed while Non-Midpoint Dark Pools, whose observables are closest to those of exchanges, appear to have the most informed short

[32]Results are qualitatively similar when I consider equal weighted portfolios. Results are available in the web appendix.

selling of the dark pools.[33] In Panel B, I find that the return predictability of short sellers decays to some extent as the holding horizon becomes longer for all types of trading venues, though results are qualitatively similar for different holding horizons.

I next examine the cross-sectional relationship between trading venue short sales and future returns of stocks using a regression based approach in order to simultaneously control for multiple characteristics. As in Boehmer, Jones, and Zhang (2008) and Engelberg, Reed, and Ringgenberg (2012), I employ a variant of the Fama and MacBeth (1973) procedure. Specifically, I estimate 452 daily cross-sectional regressions which eventually are of the form:

$$Ret_{i,t+1:t+20} = \alpha + \beta_1 Short_{i,t} + \beta' \mathbf{X} + \epsilon_{i,t}, \tag{3}$$

where the dependent variable is the 20 day cumulative raw or adjusted return of stock i starting on day $t+1$ (skipping one day after measuring shorting activity), $Short_{i,t}$ is either stock-day exchange short volume divided by corresponding exchange trading volume ($\frac{ExShortVol}{ExVol}$) or dark pool short volume divided by corresponding dark pool trading volume ($\frac{DPShortVol}{DPVol}$); and $\mathbf{X}$ is a vector of control variables including the stock's previous month book-to-market value and natural log of size (calculated as in Fama and French, 1993). Adjusted returns are calculated using the 125 size, book-to-market, and momentum porfolios introduced in Daniel, Grinblatt, Titman, and Wermers (1997) and series are all standardized to have a zero mean each day.[34,] I use a Fama-MacBeth approach of taking the time series mean of daily parameter estimates, with Newey-West (1987) standard errors (using 20 lags) as in Boehmer, Jones, and Zhang (2008) and Engelberg, Reed, and Ringgenberg (2012). Results are presented in Table III. Panel A presents results for exchange short sales and Panel B presents results for dark pool short sales. In Panel C, I incorporate the disaggregated dark pool types into the Fama MacBeth approach, eventually including all venue short sales in the same specification. Each row corresponds to a separate specification. I exclude Block Dark Pools because they don't host trades in a large number of stocks.[35]

[33] Not enough stocks are traded in Block Dark Pools each day to populate all five portfolios, so I form two portfolios, consisting of the most and least shorted stocks in Block Dark Pools.

[34] Results are qualitatively similar when I adjust for risk with lagged quarterly Fama and French (1993) three-factor model loadings and available upon request.

[35] Results are qualitatively similar when I include Block Dark Pools and available upon request.

<Insert Table III>

Both dark pool and exchange short sales are related to future returns. However, the magnitude of the coefficients for exchange short sales are roughly twice the size of their dark pool short sales counterparts. The parameter estimate series for $\frac{ExShortVol}{ExVol}$ is statistically distinguishable from its dark pool counterpart. After including controls, this gap persists. Interestingly, t-statistics for dark pool short sale coefficients are slightly larger than their exchange counterparts. I interpret this as further evidence that informed short selling is concentrated on exchanges. In Panel C, when venue short sales are included in the same specification, the estimate for Midpoint Dark Pools becomes statistically insignificant (coefficient of -0.065, t-statistic of -1.21). The estimate for exchange short sales is larger than that of Non-Midpoint Dark Pools and both are statistically significant (coefficients of -1.177 and -0.408, respectively). These results suggest that exchange short sales provide the most incremental explanatory power of returns, then Non-Midpoint dark pools, while Midpoint Dark Pools do not contain any incremental explanatory power of returns.

Comerton-Forde, Jones, and Putnins (2015) makes the point that since some short sellers employ high-frequency trading strategies, understanding the behavior of short sellers in today's markets requires observations at intraday horizons. Consequently, I examine the return predictability of short sales by trading venue at higher frequency. Due to computational and data limitations, I perform the proceeding intraday analyses on a stratified sample of 439 stocks over a sample spanning September 2012 through June 2014. The 439 stock sample consists of 152 stocks randomly selected from each size tercile, 76 of these stocks being NYSE Group listed and 76 being NASDAQ listed. Several stocks were removed due to consistently spurious quotes, leaving 439 stocks. The list of stratified tickers is available in the web appendix.[36]

Adapting the approach of Comerton-Forde, Jones, and Putnins (2015) to my setup, I take two types of executed trading venue order flow, exchange and dark pool, and for each stock I aggregate each type of executed order flow over five-minute intervals. The five-minute sampling frequency has significance in the realized volatility literature for being relatively robust to microstructure noise while still capturing economically meaningful variation (see Liu, Sheppard, and Patton, 2015, among others). For calculating returns,

[36]In some of these analyses, I do not separate Block Dark Pool trading because there is not consistent enough trading in the stratified sample.

I use the midquote that is in effect at the end of each five-minute interval. Figure 2 presents the average cumulative excess log midquote returns (in basis points) pooled over all stocks and five-minute intervals, weighted by dollar volume of the particular sale type.[37] Post-trade cumulative midquote excess returns are presented for horizons of up to one trading day.

<Insert Figure 2>

Exchange (grey dashed line) post trade excess returns are consistently lower than their dark pool (black solid line) counterparts. To determine whether the patterns in this figure are statistically significant, I adapt the panel regression approach of Comerton-Forde, Jones, and Putnins (2015) to my setting. More formally for a time horizon k following trade in stock i in 5-minute interval t, I regress the cumulative post-trade midpoint excess return $r_{i,t,t+k}$ (in basis points) on indicator variables separately for all dark pool short sales, $\mathbb{1}_{DP}$, and possible stock fixed effects, respectively:

$$r_{i,t,t+k} = \alpha_i + \beta_1 \mathbb{1}_{DP} + \epsilon_{i,t} \tag{4}$$

The indicator variables are configured to allow direct tests of differences between exchange and dark pool short sales. Model 1 has a fixed intercept no fixed effects while Model 2 has stock fixed effects. Standard errors are clustered by five minute intervals. Observations are weighted by dollar volume.[38] The base case in this regression is exchange short sales. I examine post-trade horizons of five minutes, 30 minutes, two hours, and one trading day. Results are presented in Table IV.

<Insert Table IV>

Panel A presents results for all dark pools. Cumulative post-trade log returns after exchange short sales are negative for horizons longer than 30 minutes and continue to drift downward. After one trading day, cumulative post exchange short sales are 1.501

[37]Comerton-Forde, Jones, and Putnins (2015) makes the point that dollar weighting better reflects the performance of short sellers. When I weigh trades equally, results are qualitatively similar and available in the web appendix.

[38]Results are qualitatively similar when I weigh trades equally and available in the web appendix.

basis points (3.78% annualized) lower than their dark pool counterparts. Cumulative dark pool post-short sale log returns are statistically distinguishable from their exchange counterparts for post-trade horizons longer than five minutes. Both dark pool and exchange short sales are followed by consistently downward drifting cumulative returns. In Panel B, I separate dark pools into Midpoint and Non-Midpoint Dark Pools and results are qualitatively similar. Non-Midpoint Dark Pool post-trade returns are lower than those of Midpoint dark pools. Results are quantitatively similar for specifications with stock-fixed effects.

Biais, Hillion, and Spatt (1995), among others note that order flow is persistent and Menkveld, Yueshen, and Zhu (2015) documents cross-dependencies between venue type trading. While conditioning on short sales in a single five minute interval most closely reflects the performance of short sellers, I also study the dynamic relationship among venue short sales and returns. I follow Comerton-Forde, Jones, and Putnins (2015) by implementing a variant of the Hasbrouck (1991) "information content of trade" vector autoregressive framework to my trading partition. For each stock, I estimate the following system over the entire sample period:

$$\begin{aligned}
x_t^{EX} &= \mu^{EX} + \sum_{i=1}^{5} \phi_i^r r_{t-i} + \sum_{i=1}^{5} \phi_i^{EX} x_{t-i}^{EX} + \sum_{i=1}^{5} \phi_i^{DP} x_{t-i}^{DP} + \epsilon_t^{EX} \\
x_t^{DP} &= \mu^{DP} + \sum_{i=1}^{5} \theta_i^r r_{t-i} + \sum_{i=1}^{5} \theta_i^{EX} x_{t-i}^{EX} + \sum_{i=1}^{5} \theta_i^{DP} x_{t-i}^{DP} + \epsilon_t^{DP} \\
r_t &= \mu + \sum_{i=1}^{5} \lambda_i^r r_{t-i} + \sum_{i=1}^{5} \lambda_i^{EX} x_{t-i}^{EX} + \sum_{i=1}^{5} \lambda_i^{DP} x_{t-i}^{DP} + \epsilon_t^r,
\end{aligned} \tag{5}$$

where t denotes the five-minute interval and individual stock subscripts are suppressed.[39] x^{EX} and x^{DP} denote exchange and dark pool dollar volumes in a given five-minute interval. r_t is the excess log midquote return. I estimate five lags of each variable.[40] A separate estimation is conducted for each stock over the sample and coefficients and impulse response functions are averaged across all stocks. To make the impulse responses more comparable across volume types, the magnitude of each volume shock is set equal to the standard deviation of unanticipated exchange short volume. Fig-

[39]For reasons related to data limitations and methodological considerations discussed above, I do not estimate this system in trade time or at higher frequency.

[40]For a subsample of stocks in this sample, five lags was the most common BIC-minimizing lag length.

ure 3 presents equally weighted impulse response functions of excess midquote returns after trading venue short sale shocks over one trading day.

<Insert Figure 3>

The left vertical axis measures cumulative post exchange short sale shock returns and the right vertical axis measures post dark pool short sale shock returns. Post exchange short sale shock returns (grey solid line) are 0.854 basis points (2.15% annualized) lower than corresponding post dark pool short sale returns (black dashed line) after one trading day.[41]

Collectively, the unconditional evidence suggests that short sales and their return predictability are relatively concentrated on exchanges relative to dark pools.[42] This finding is consistent with the prediction of Zhu (2014) that the introduction of a dark pool to the market structure will induce segmentation of informed trade.

E. Intermarket Competition and Information Horizon

I next ask where do the informed trade when private information is short lived. The theory of intermarket competition suggests that if private information is short lived, or when traders may have a shock to their need for immediacy, then traders' choice of venue may change. Furthermore, the news releases in the sample are established in the literature as containing firm-specific, value relevant news. Consequently, news releases provide a more concrete, identifiable sample of events associated with firm-specific information and short lived information.

[41] Results are qualitatively similar when I consider orthogonalized IRFs.

[42] Treynor (1981), Perold (1988), and Edwards and Wagner (1993), among others illustrate that the concept of transaction costs is multifaceted. In my setting, shares for short sales are borrowed at the account level, not the trading venue level, so trading venues do not directly affect shorting costs. While I can't empirically measure *explicit* transactions costs (such as fees) across trading venues, they do not affect inferences regarding how trading incorporates information into equity prices. Differential *Implicit* transaction costs across venues such as bid-ask spread costs, market impact, and opportunity costs may bias my return predictability results if, for example, dark pool short sales are executed at systematically higher prices than exchange short sales intraday. In the web appendix, I show that the stock-day volume weighted average prices that dark pool and exchange short sellers pay on average are not statistically distinguishable from one another suggesting that dark pool short sales aren't systematically executed at higher trade prices than exchange short sales intraday. However, this result need not imply that dark pools provide cost savings as I do not observe parent orders.

As discussed in Section I, Menkveld, Yueshen, and Zhu (2015) predicts that exchanges will capture a greater proportion of trading volume if there is a shock to traders' need for immediacy. Hendershott and Mendelson (2000) predicts that informed traders with short lived information will use exchanges and Zhu (2014) predicts that all else equal, a shorter information horizon will result in more aggressive use of dark pools by informed traders. Consequently, I examine whether dark pools capture an increased proportion of trading volume and whether there is evidence of increased short selling and short sale return predictability surrounding corporate news events.

To examine how trading in dark pools responds to news events for the five days surrounding news releases.[43] I adopt a panel multi-regression approach where I vary the timing of the dependent variable relative to the news event. Specifically, I estimate five panel regressions of the form:

$$\frac{DPVol_{i,t}}{Vol_{i,t}} = \alpha_i + \alpha_m + \beta_1 VIX_{t-1} + \beta_2 \mathbb{1}_{News_{i,t}} + \epsilon_{i,t}, \tag{6}$$

where $\frac{DPVol_{i,t}}{Vol_{i,t}}$ is the stock-day outcome variable, the share of trading volume executed in dark pools for a given stock-day, α_i denotes stock fixed effects, and α_m denotes month fixed effects. $\mathbb{1}_{News_{i,t}}$ represents an indicator variable that takes the value of one if a news event occurs, and zero otherwise. Menkveld, Yueshen, and Zhu (2015) show that the share of trading taking place in dark pools responds to VIX shocks, so I include the lagged level of the VIX to control for expected market volatility. I use stock and month fixed effects to control for heterogeneity across firms and aggregate confounders.

In Panels B and C, I separate news events into scheduled and unscheduled releases and present the coefficients of interest. Since the arrival date of scheduled news known to the public in advance, uninformed traders may lower exposures to reduce adverse selection risk before scheduled corporate events (see Lee, Mucklow, and Ready 1993). Baruch, Panayides, and Venkataraman (2015) argues that examining unscheduled corporate news releases provides a better setting for studying informed trading as uninformed traders likely do not know when unscheduled news will arrive. Similarly, Sarkar and Schwartz (2009) finds that unscheduled corporate news announcements are preceeded by relatively more market sidedness than scheduled macroeconomic announcements. Du and Zhu (2014) also analyzes optimal trading frequency in dynamic double auctions and

[43] I confirm that trading volume does not significantly increase until the day prior to news releases and results are available upon request.

shows that the nature of news arrival has non-trivial implications for market design. After separating news events, I am left with 13,776 scheduled events and 10,394 unscheduled events. Results are presented in Table V.

<Insert Table V>

Consistent with Menkveld, Yueshen, and Zhu (2015), I find that the share of trading executed in dark pools is both negatively associated with the VIX. However, the share of trading in dark pools generally increases around corporate news events, starting one day before the news release. After positive news, the share of trading done in dark pools reverts to its unconditional mean after day $t + 2$; however, after negative news, there is a larger increase in dark pool share (0.897% relative to the stock-level mean of 13.1%) on the news day and slower reversion back to the unconditional mean. The volatility literature tells us that bad news results in higher volatility than good news, which Black (1976) coins the "leverage effect" (also see Nelson, 1991 and Engle and Ng, 1993, *inter alia*). Volatility is generally associated with adverse selection in the market microstructure literature (for example, see Van Ness, Van Ness, and Warr, 2001, among others). Exchange bid-ask spreads also likely widen during these periods (see Lee, Mucklow, and Ready, 1993). Consequently, this finding is consistent with Zhu (2014) which predicts that all else equal, an increase in adverse selection will result in more use of a dark pool. In Panels B and C, I find that the increased proportion of trading done in dark pools around news events is primarily for scheduled news events.

Christophe, Ferri, and Angel (2004), Christophe, Ferri, and Hsieh (2010), Karpoff and Lou (2010), and Boehmer, Jones, and Zhang (2012) find evidence of increased short selling prior to negative news announcements. I add to these findings by examining whether there is evidence of increased venue short sales prior to news releases with a difference-in-differences-like approach similar to that of Engelberg, Reed, and Ringgenberg (2012), where I vary the timing of the dependent variable relative to the news event. Specifically, I estimate three panel regressions of the form:

$$\frac{Short_{i,t}}{Vol_{i,t}} = \alpha_i + \alpha_m + \beta_1 \mathbb{1}_{Exchange_{i,t}} + \beta_2 \mathbb{1}_{News_{i,t}} + \beta_3 (\mathbb{1}_{Exchange_{i,t}} \times \mathbb{1}_{News_{i,t}}) + \beta' \mathbf{X} + \epsilon_{i,t}, \quad (7)$$

Where $\frac{Short_{i,t}}{Vol_{i,t}}$ is the outcome variable (stock-day venue short volume divided by corresponding total trading volume in percent) for stock i on day t, $\mathbb{1}_{Exchange}$ denotes an indicator variable which is equal to one if the outcome variable is the ratio of exchange short sales to exchange volume (making the base case the ratio of dark pool short sales to dark pool volume), $\mathbb{1}_{News_{i,t}}$ represents an indicator variable that takes the value of one if a news event occurs, and zero otherwise, and the interaction term: $(\mathbb{1}_{Exchange} \times \mathbb{1}_{News_{i,t})}$ is the variable of interest, measuring the incremental response of exchange short sales to dark pool short sales prior to and on the day of news releases. If short sellers are informed, then there should be increased shorting prior to the release of negative news. Diether, Lee, and Werner (2008) finds that not only do short sellers predict returns, but that short sellers respond to past returns. The two lags for returns (in percent) are introduced to control for the return responding behavior of short sellers. α_i and α_m again denote stock and month fixed effects, respectively. Results are presented in Table VI.

<Insert Table VI>

In Panel A, I find an increase of the ratio of both dark pool short ratios and exchange short ratios on the day before negative news releases. In Panel B, I find that both exchange and dark pool short ratios increase preceding scheduled negative news, though dark pool short ratio increases by more than exchange short ratio.[44] I interpret the findings for scheduled news releases are consistent with Zhu (2014) who predicts that a short horizon of private information will result in more aggressive use of the dark pool by informed traders. As mentioned above, the literature posits that unscheduled news provides the best sample of events for examining informed trading. In Panel C, I find that dark pool short ratio does not increase on the day before unscheduled news releases, but the exchange short ratio increases by 1.514% (relative to stock-level mean of 45.7%.[45] This result is consistent with the predictions of Hendershott and Mendelsen (2000) and Menkveld, Yueshen, and Zhu (2015). For a better understanding of how these magnitudes relate to returns, I conduct an exercise similar to that of Engelberg, Reed, and Ringgenberg (2012), where I form equal weighted long-short portfolios similarly to above for dark pool and exchange short sales, conditioning on a stock both being in the most or least shorted quintile and having an imminent news release the following trading

[44] I confirm that the increase in exchange short ratio is statistically significant by examining exchange trading on its own, results are available upon request.

[45] In the web appendix, I show that total trading volume also increases on the day before news releases.

day.[46] Figure 4 presents the cumulative percentage returns of equal-weighted long-short portfolios conditioning on just venue short sales and portfolios conditioning on venue short sales and a news release being imminent.

<Insert Figure 4>

The spread between exchange and dark pool short sale cross-sectional return predictability increases when also conditioning on news being imminent, regardless of the sign of the news. I interpret this finding as evidence that there is relatively weak evidence of news-informed short selling dark pools relative to such trading on exchanges.[47]

I next expand upon the Fama-MacBeth analysis in Table III, including a separate set of news indicator and interaction terms for news event days to statistically test whether short sellers return predictability changes on or before the day of either type of these news releases. Results are presented in Table VII. Engelberg, Reed, and Ringgenberg (2012) finds that a disproportionate amount of short sellers' 20 day return predictability comes on news release days, which suggests that short sellers are skilled information processors rather than more traditional informed traders.

<Insert Table VII>

The results for exchange short sales in Panel A corroborate the other findings in this paper. The interaction term for exchange short sales on the day prior to news is significantly negative (statistically significant at the 10 or 5 percent level) for all relevant specifications. These results suggest that there is an increase in the 20 day return predictability of exchange short sales on the day prior to the release of news. I find no evidence of increased return predictability around the news for dark pool short sales in Panel B, which is consistent with the notion that dark pool trading is less informed. Furthermore there is no increase in 20 day return predictability on news release days.

[46]Results are qualitatively similar when I form value-weighted portfolios and available in the web appendix.

[47]With these results, there is still the possibility that firm specific, time varying confounders are causing a change in short sales and dark pool share around news rather than the news itself. For example, there are studies discussed in Section I that suggest short sellers may be trading on well-known asset pricing anomalies; however, asset pricing anomalies are also typically slow moving and unlikely to affect short sales precisely before news releases.

The 20 day return predictability of trading venue short sales does not increase on news days. This result contrasts with that of Engelberg, Reed, and Ringgenberg (2012). A potential explanation for this result is the growth in news-based high frequency trading and improvements in news analytics technology (for example, Keim, Massa, and von Beschwitz, 2013 shows that the introduction of more advanced news analytics results in faster stock price reaction to news releases). These results suggest that asymmetric information does not persist after news news releases in my sample.

III. Conclusion

In this study, I examine trading in 24 dark pools. To the extent that the results of this paper are representative, they suggest that dark pools may host a different group of investors than exchanges and in turn, induce a degree of order flow segmentation. Consistent with the mechanism of Zhu (2014), as relatively more informed trade is executed on exchanges and relatively more uninformed trade is executed in dark pools, there may be less noise accompanying informed supply and demand on exchanges. This may result in increased price efficiency of markets with regard to information acquired, though this may result in lower liquidity on exchange as there is more information asymmetry in the remaining exchange order flow. The approach of this study focuses on short sellers and does not examine other potential sources of informed trade such as long-only investors with potentially longer lived information. Inferences could be different if long-only investors are both informed and disproportionately use dark pools for their informed trading. However, some of the institutional investors literature has been rather skeptical of long investors' information advantage (see Daniel, Grinblatt, Titman, and Wermers, 1997 and Lewellen, 2011). Also, a comprehensive database of institutional investor trade level data does not exist, so any analysis using this type of data may be subject to selection bias. By studying short sales, I am able to construct a nearly comprehensive database of their position opening activity.

This study focuses on dark pools (formally known as Alternative Trading Systems) which host slightly less than half of off-exchange trading in the sample. It is important to note that off-exchange trading consists of more than dark pools. For example, off-exchange trading can result from internalization and other types of transactions. Addressing all of the different types of off-exchange trading is beyond the scope of this paper due to data limitations. However, Tuttle, 2014, presents some useful facts regarding this issue. In the web appendix I show that off-exchange short sales in total comprise less of off-exchange trading volume and exhibit less return predictability than the identified dark pool short sales I study. Although this paper focuses on the specific issue of trading venue short sales, it raises questions regarding payment for order flow in off-exchange trading. In some ways, the order flow segmentation of order flow that may be induced by dark pools can be likened to the concept of "cream-skimming" as described in Easley, Kiefer, and O'hara (1996), among others. Cream-skimming in this context refers to the concept of market participants or venues purchasing uninformed order flow to trade against. This practice could ultimately affect the liquidity of other venues as they are left with a greater amount of information asymmetry in their remaining orders.

While strong statements about welfare are clearly beyond the scope of this empirical study; dark pools may reduce transaction costs of the investors who use them. However, as dark pools capture more order flow, exchanges may become less liquid, increasing transaction costs for the investors who use exchanges. It's not clear that the improvement in exchange market quality in the absence of dark pools will offset the reduced transactions costs dark pool users may incur. Consequently, eliminating dark pools may not be a pareto improvement. Welfare implications of price informativeness are likely more nuanced as Stiglitz (2014) suggests. Ultimately, regulators will have to weigh the impact of a regulation on market price efficiency against the impact of the regulation on market liquidity and the price improvement enjoyed by users of dark pools.

While the segmentation of order flow in financial markets may improve the informational efficiency of prices, in rational expectations models with endogenous and costly information acquisition, markets instantaneously and at least partially convey information and the supply of informed traders adjusts to provide sufficient compensation for information collection; see (Grossman and Stiglitz, 1980 and Verrecchia, 1982, among others) The Grossman-Stiglitz (1980) Paradox suggests that if markets instantaneously and fully convey information from the informed to the uninformed, then there would not be sufficient compensation for anyone to obtain information. Since the market would only convey only costless information, the market would be uninformative despite reflecting all the information that had been acquired.

References

Acharya, Viral V. and Timothy C. Johnson, 2007, Insider Trading in Credit Derivatives, *Journal of Financial Economics*, 84, 110-141.

Admati, Anat R., and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies*, 1, 1, 3-40.

Arif, Salman, Azi Ben-Rephael, and Charles M.C. Lee, 2015, Do Short-Sellers Profit from Mutual Funds? Evidence from Daily Trades, *Working Paper*.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short Interest, Institutional Ownership, and Stock Returns, *Journal of Financial Economics*, 78, 243-276.

Baruch, Shmuel, 2005, Who Benefits from an Open Limit-Order Book?, *Journal of Business*, 78, 4, 1267-1306.

Baruch, Shmuel, Marios A. Panayides, and Kumar Venkataraman, 2015, Informed Trading and Price Discovery Before Corporate Events, *Working Paper*.

Battalio, Robert, Shane Corwin, and Robert Jennings, 2015, Can Brokers Have it All? On the Relation Between Make-Take Fees & Limit Order Execution Quality, *Working Paper*.

Biais, Bruno, Pierre Hillion, and Chester Spatt, 1995, An empirical analysis of the limit order book and the order flow in the Paris Bourse, *Journal of Finance*, 50, 5, 1655-1689.

Black, Fischer, 1976, Studies of Stock Price Volatility Changes, *Proceedings of the 1976 Meetings of the American Statistical Association*, 171-181.

Bloomfield, Robert, Maureen O'Hara, and Gideon Saar 2015, Hidden Liquidity: Some New Light on Dark Trading, *Journal of Finance*, 70, 5, 2227-2274.

Boehmer, Ekkehart, Truong X. Duong, and Zsuzsa R. Huszar, 2015, Short covering trades, *Working Paper*.

Boehmer, Ekkehart, Zsuzsa R. Huszar, and Bradford D. Jordan, 2010, The Good News in Short Interest, *Journal of Financial Economics*, 96, 2, 2010.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2008, Which Shorts Are Informed?, *Journal of Finance*, 63, 2, 491-527.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2012, What Do Short Sellers Know?, *Working Paper*.

Boulatov, Alex, and Thomas J. George, 2013, Hidden and displayed liquidity in securities markets with informed liquidity providers, *Review of Financial Studies*, 26, 8, 2096-2137.

Buti, Sabrina, Barbara Rindi, and Ingrid M. Werner, 2011, Diving into Dark Pools, *Working Paper*.

Buti, Sabrina, Barbara Rindi, and Ingrid M. Werner, 2015b, Dark Pool Trading Strategies, Market Quality, and Welfare, *Working Paper*.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance*, 52, 1, 57-82.

Chakravarty, Sugato, Huseyin Gulen, and Stewart Mayhew, 2004, Informed Trading in Stock and Option Markets, *Journal of Finance*, 59, 3, 1235-1258.

Christophe, Stephen E., Michael G. Ferri, and Jim Angel, 2004, Short-Selling Prior to Earnings Announcements, *Journal of Finance*, 59, 4, 1845-1875.

Christophe, Stephen E., Michael G. Ferri, and Jim Hsieh, 2010, Informed Trading Before Analyst Downgrades: Evidence from Short Sellers, *Journal of Financial Economics*, 95, 1, 85-106.

Comerton-Forde, Carole, Charles M. Jones, and Talis J. Putnins, 2015, Shorting at Close Range: A Tale of Two Types, *Journal of Financial Economics*, Forthcoming.

Comerton-Forde, Carole and Talis J. Putnins, 2015, Dark Trading and Price Discovery, *Journal of Financial Economics*.

Conrad, Jennifer, Kevin M. Johnson, and Sunil Wahal, 2003, Institutional Trading and Alternative Trading Systems, *Journal of Financial Economics* 70, 1, 99-134.

Conrad, Jennifer, Sunil Wahal, and Jin Xiang, 2015, High-frequency quoting, trading, and the efficiency of prices, *Journal of Financial Economics*, 116, 2, 271-291.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based benchmarks, *Journal of Finance*, 52, 3, 1035-1058.

Dechow, Patricia M., Amy P. Hutton, and Lisa Meulbroek, and Richard G. Sloan, 2001, Short-Sellers, Fundamental Analysis, and Stock Returns, *Journal of Financial Economics*, 61, 1, 77-106.

Diether, Karl B., Kuan-Hui Lee, and Ingrid M. Werner, 2008, Short-Sale Strategies and Return Predictability, *Review of Financial Studies*, 22, 2, 575-607.

Demers, Elizabeth A. and Clara Vega, 2008, Soft Information in Earnings Announcements: News or Noise?, *International Finance Discussion Papers 951, Board of Governors of the Federal Reserve System.*

Diamond, Douglas W. and Robert E. Verrecchia, 1987, Constraints on Short-Selling and Asset Price Adjustment to Private Information, *Journal of Financial Economics*, 18, 2, 277-311.

Diamond, Peter A., 1971, A Model of Price Adjustment, *Journal of Economic Theory* 3, 2, 156-168.

Du, Songzi and Haoxiang Zhu, 2014, Welfare and Optimal Trading Frequency in Dynamic Double Auctions, *Working Paper.*

Duffie, Darrell, Nicolae Garleanu, and Lasse Heje Pedersen, 2002, Securities Lending, Shorting, and Pricing, *Journal of Financial Economics*, 66, 2, 307-339.

Easley, David, Nicholas M. Kiefer, and Maureen O'Hara, 1996, Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow, *Journal of Finance*, 51, 3, 811-833.

Easley, David, Nicholas M. Kiefer, and Maureen O'Hara, 1996, Liquidity, Information, and Infrequently Traded Stocks, *Journal of Finance*, 51, 4, 1405-1436.

Easley, David, Maureen O'Hara, and P. S. Srinivas, 1998, Option Volume and Stock Prices: Evidence on Where Informed Traders Trade, *Journal of Finance*, 53, 2, 431-465.

Engelberg, Joseph E., 2008, Costly Information Processing: Evidence from Earnings Announcements, *Working Paper.*

Engelberg, Joseph E., Adam V. Reed, and Matthew C. Ringgenberg, 2012, How Are Shorts Informed?: Short Sellers, News, and Information Processing, *Journal of Financial Economics*, 105, 2, 260-278.

Engle, Robert F. and Victor K. Ng, 1993, Measuring and Testing the Impact of News on Volatility, *Journal of Finance*, 48, 5, 1749-1778.

Fama, Eugene F. and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics*, 33, 3-56.

Fama, Eugene F., 1970, Efficient Capital Markets: A Review of Theory and Empirical Work, *Journal of Finance*, 25, 2, 383-417.

Fama, Eugene F. and James D. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy*, 81, 3, 607-636.

Fleming, Michael and Giang Nguyen, 2014, Order Flow Segmentation and the Role of Dark Trading in the Price Discovery of U.S. Treasury Securities, *Working Paper.*

Flood, Mark D., Ronald Huisman, Kees G. Koedijk, and Ronald J. Maheiu, 1999, Quote Disclosure and Price Discovery in Multiple-Dealer Financial Markets, *Review of Financial Studies*, 12, 1, 37-59.

Foucault, Thierry, Johan Hombert, and Ioanid Rosu, 2015, News Trading and Speed, *Journal of Finance*, Forthcoming.

Glosten, Lawrence R. and Paul R. Milgrom, 1985, Bid, Ask and Transaction Prices in a Specialist Market, *Journal of Financial Economics*, 14, 71-100.

Goettler, Ronald L., Christine A. Parlour, and Uday Rajan, 2009, Informed traders and limit order markets, *Journal of Financial Economics*, 93, 1, 67-87.

Grossman, Sanford J. and Joseph E. Stiglitz, 1980, On the Impossibility of Informationally Efficient Markets, *American Economic Review*, 70, 3, 393-408.

Hanson, Samuel G. and Adi Sunderam, 2014, The Growth and Limits of Arbitrage: Evidence from Short Interest, *Review of Financial Studies*, 27, 4, 1238-1286.

Hasbrouck, Joel, 1991, Measuring the information content of stock trades, *Journal of Finance*, 46, 1, 179-207.

Hasbrouck, Joel, 1995, One Security, Many Markets: Determining Contributions to Price Discovery, *Journal of Finance*, 50, 4, 1175-1199.

Hasbrouck, Joel, 2003, Intraday Price Formation in U.S. Equity Index Markets, *Journal of Finance*, 58, 6, 2375-2400.

Hatheway, Frank, Amy Kwan, and Hui Zheng, 2014, An Empirical Analysis of Market Segmentation on U.S. Equities Markets, *Working Paper.*

Hendershott, Terrence and Charles M. Jones, 2005, Island Goes Dark: Transparency, Fragmentation, and Regulation, *Review of Financial Studies*, 18, 3, 744-793.

Hendershott, Terrence and Haim Mendelson, 2000, Crossing Networks and Dealer Markets, *Journal of Finance*, 47, 5, 247-270.

Hong, Harrison, Jose Scheinkman, and Wei Xiong, 2006, Asset Float and Speculative Bubbles, *Journal of Finance*, 61, 3, 1073-1117.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance*, 48, 1, 65-91.

Jones, Charles, Adam V. Reed, and William Waller, 2015, Revealing Shorts: An Examination of Large Short Position Disclosures, *Working Paper.*

Kaniel, Ron and Hong Liu, 2006, So What Orders Do Informed Traders Use?, *Journal of Business*, 79, 4, 1867-1913.

Karpoff, Jonathan M. and Xiaoxia Lou, 2010, Short Sellers and Financial Misconduct, *Journal of Finance*, 65, 5, 1879-1913.

Kandel, Eugene and Neil Pearson, 1995, Differential Interpretation of Public Signals and Trade in Speculative Markets, *Journal of Political Economy*, 103, 4, 831-872.

Keim, Donald B., Massimo Massa, and Bastian von Beschwitz, 2013, Media-Driven High Frequency Trading: Evidence from News Analytics, *Working Paper.*

Kirilenko, Andrei A., Albert S. Kyle, Mehrdad Samadi, and Tugkan Tuzun, 2014, The Flash Crash: The Impact of High Frequency Trading on an Electronic Market, *Working Paper.*

Kwan, Amy, Ronald Masulis, and Thomas H. McInish, 2014, Trading Rules, Competition for Order-Flow and Market Fragmentation, *Journal of Financial Economics*, 115, 2, 330-348.

Korajczyk, Robert A. and Lucas D. McDonald, 1991, The Effect of Information Releases on the Pricing and Timing of Equity Issues, *Review of Financial Studies*, 4, 4, 685-708.

Kyle, Albert S., 1985, Continuous Auctions and Insider Trading, *Econometrica*, 53, 6, 1315-1335.

Lewellen, Jonathan, 2011, Institutional Investors and the Limits of Arbitrage, *Journal of Financial Economics*, 102, 62-80.

Liu, Lily, Kevin Sheppard, and Andrew Patton, 2015, Does Anything Beat 5-Minute RV? A Comparison of Realized Measures Across Multiple Asset Classes, *Journal of Econometrics*, 187, 1, 293-311.

Madhavan, Ananth, 2000, Market Microstructure: A Survey, *Journal of Financial Markets*, 3, 205-258.

Mayhew, Stewart, Atulya Sarin, and Kuldeep Shastri, 1995, The Allocation of Informed Trading Across Related Markets: An Analysis of the Impact of Changes in Equity-Option Margin Requirements, *Journal of Finance*, 50, 5, 1635-1653.

Menkveld, Albert J., Bart Zhou Yueshen, and Haoxiang Zhu, 2015, Shades of Darkness: A Pecking Order Theory of Trading Venues, *Working Paper.*

Milgrom, Paul R. and Robert J. Weber, 1982, A Theory of Auctions and Competitive Bidding, *Econometrica* 50, 5, 1089-1122.

Miller, Edward M., 1977, Risk Uncertainty, and The Divergence of Opinion, *Journal of Finance*, 32, 4, 1151-1168.

Lee, Charles M.C., Belinda Mucklow, Mark J Ready, 1993. Spreads, depths and the impact of earnings information: an intraday analysis, *Review of Financial Studies* 6, 2, 345-374.

Myers, Stewart C. and Nicholas S. Majluf, 1984, Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have, *Journal of Financial Economics* 13, 2, 187-221.

Nelson, Daniel B., 1991, Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica*, 59, 2, 347-370.

Newey, Whitney K. and Kenneth D. West, 1987, A Simple, Positive, Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 55, 3, 703-708.

O'hara, Maureen, 1999, Making Market Microstructure Matter, *Financial Management*, 28, 2, 83-90.

O'hara, Maureen and Mao Ye, 2011, Is market fragmentation harming market quality?, Journal of Financial Economics, 100, 3, 459-474.

O'Donoghue, Shawn M., 2015, The Effect of Maker-Taker Fees on Investor Order Choice and Execution Quality in U.S. Stock Markets, *Working Paper*.

Pagano, Marco, 1989, Trading Volume and Asset Liquidity, *Quarterly Journal of Economics*, 104, 255-274.

Pan, Jun and Allen M. Poteshman, 2006, The Information in Option Volume for Future Stock Prices, *Review of Financial Studies*, 19, 3, 871-908.

Perold, Andre F., 1998, The Implemenation Shortfall: Paper Versus Reality, *Journal of Portfolio Management*, 14, 3, 4-9.

Sarkar, Asani and Robert A. Schwartz, 2009, Market Sidedness: Insights into Motives for Trade Initiation, *Journal of Finance*, 64, 1, 375-423.

So, Eric C. and Sean Wang, 2014, News-Driven Return Reversals: Liquidity Provision Ahead of Earnings Announcements, *Journal of Financial Economics* 114, 1, 20-35.

Stephan, Jens A. and Robert E. Whaley, 1990, Intraday Price Change and Trading Volume Relations in the Stock and Stock Option Markets, *Journal of Finance*, 45, 1, 191-220.

Stiglitz, Joseph E., 2014, Tapping the Brakes: Are Less Active Markets Safer and Better for the Economy?, *Address presented at the Federal Reserve Bank of Atlanta 2014 Financial Markets Conference.*

Treynor, Jack, 1981, What does it take to win the trading game?, *Financial Analysts Journal*, 37, 55-60,

Tuttle, Laura, 2013, Alternative Trading Systems: Description of ATS Trading in National Market System Stocks, *SEC DERA Staff White Paper.*

Tuttle, Laura, 2014, OTC Trading: Description of Non-ATS OTC Trading in National Market System Stocks, *SEC DERA Staff White Paper.*

Van Ness, Bonnie F., Robert A. Van Ness, and Richard S. Warr, 2001, How Well Do Adverse Selection Components Measure Adverse Selection?, *Financial Management*, 30, 77-98.

Verrecchia, Robert E., 1982, Information Acquisition in a Noisy Rational Expectations Economy, *Econometrica*, 50, 6, 1415-1430.

Von Beschwitz, Bastian and Massimo Massa, 2015, Why Do Short Sellers Like Qualitative News, *Journal of Financial and Quantitative Analysis*, Forthcoming.

Wagner, Wayne H., and Mark Edwards, 1993, Best Execution, *Financial Analysts Journal*, 49, 1, 65-71.

Weaver, Daniel G., 2014, The Trade-At Rule, Internalization, and Market Quality, *Working Paper.*

Ye, Mao, 2010, Non-Execution and Market Share of Crossing Networks, *Working Paper.*

Ye, Mao, 2011, A Glimpse into the Dark: Price Formation, Transaction Cost and Market Share of the Crossing Network, *Working Paper.*

Zhu, Haoxiang, 2014, Do Dark Pools Harm Price Discovery?, *Review of Financial Studies*, 27, 3, 747-789.

Table I: Summary Statistics

Panel A: Stock level statistics	Mean	Median	1st Percentile	99th Percentile	Standard Deviation
Novel news events per firm-day	0.060	0.044	0.010	0.277	0.090
Exchange short vol./Exchange vol.	0.457	0.481	0.182	0.617	0.099
Dark pool short vol./Dark pool vol.	0.370	0.372	0.123	0.587	0.101
Dark pool vol./Total vol.	0.131	0.138	0.025	0.234	0.046
Market capitalization ($ mm)	$5,018	$721	$15	$77,943	$21,243

Panel B: News Categories	*N*
Acquisitions and Mergers	4564
Analyst Ratings	12420
Assets	1683
Credit	1426
Credit Ratings	5405
Dividends	3060
Earnings	22834
Equity Actions	5814
Labor issues	6023
Partnerships	999
Products and Services	6765

The database has 1,343,458 stock-day observations over the period spanning August 2012 through June 2014 and contains 3,148 securities. Panel A provides summary statistics at the stock level. I consider all related news releases in one day to be one news event. *Novel news events per stock-day* is a count of news events per stock-day for a given stock. *Exchange short vol./Exchange vol.* is exchange short sale volume divided by exchange trading volume for a given stock over the sample. *Dark pool short vol./Dark pool vol.* is dark pool short sale volume divided by dark pool trading volume for a given stock over the sample. *Dark Pool vol./Total vol.* is total dark pool volume divided by total trading volume for a given stock over the sample. Market capitalization is a stock sample average calculated from CRSP. Panel B contains summary statistics on the frequency of news events from each news category in the sample.

Table II: Portfolio Raw Returns and Carhart Alphas Based on Recent Trading Venue Short Sales

Panel A: Raw Returns and Carhart Alphas by Venue Type

	Exchange		All Dark Pools		Block		Midpoint		Non-Midpoint	
Portfolio	Raw Return	Alpha	Raw Return	Alpha	Raw Return	Alpha	Raw Return	Alpha	Raw Return	Alpha
1 (least shorted)	2.429	0.764	2.123	0.412	1.710	0.027	1.985	0.239	2.122	0.420
		(6.83)		(4.34)		(0.50)		(2.07)		(4.47)
2	1.919	0.223	1.681	-0.021			1.573	-0.109	1.750	0.044
		(1.96)		(-0.22)				(-1.05)		(0.55)
3	1.591	-0.089	1.688	-0.006			1.751	0.055	1.623	-0.067
		(-1.12)		(-0.12)				(0.95)		(-1.27)
4	1.644	-0.078	1.628	-0.099			1.641	-0.089	1.639	-0.088
		(-1.29)		(-1.62)				(-1.45)		(-1.52)
5 (most shorted)	1.640	-0.128	1.656	-0.122	1.578	-0.148	1.730	-0.050	1.659	-0.134
		(-1.49)		(-1.39)		(-1.45)		(-0.58)		(-1.57)
Long-Short	0.789	0.891	0.467	0.534	0.132	0.175	0.254	0.288	0.463	0.554
		(5.72)		(4.28)		(1.59)		(2.01)		(4.45)
Spread with Exchange Long-Short			0.322	0.357	0.658	0.716	0.535	0.603	0.326	0.338
				(2.85)		(4.18)		(4.13)		(2.56)

Panel B: Long-Short Carhart Alphas by Venue Type over Different Holding Horizons

	Exchange		All Dark Pools		Block		Midpoint		Non-Midpoint	
Horizon	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat
10	1.153	(6.77)	0.701	(5.20)	0.118	(0.90)	0.382	(2.45)	0.815	(6.06)
20	0.891	(5.72)	0.534	(4.28)	0.175	(1.59)	0.288	(2.01)	0.554	(4.45)
40	0.784	(5.82)	0.554	(5.26)	0.045	(0.47)	0.261	(2.03)	0.578	(5.47)
60	0.606	(4.69)	0.428	(4.30)	−0.074	(−0.79)	0.157	(1.20)	0.419	(4.26)

This table presents portfolio raw returns and Carhart (1997) alphas from regressions that examine the performance of value-weighted portfolios based on short sales measures over the period spanning August 2012 through June 2014. Results are presented for portfolios formed on the ratio of exchange short volume to exchange volume, total dark pool short volume to total dark pool volume, Block Dark Pool short volume to Block Dark Pool Volume, Midpoint Dark Pool Short Volume to Midpoint Dark Pool Volume, and Non-Midpoint Dark Pool short volume to non-Midpoint Dark Pool volume. After forming portfolios, value-weighted portfolios are held for the following 20 trading days. This process is repeated each trading day, so that each trading day's portfolio return is an average of 20 different portfolios, with 1/20 of the portfolio rebalanced each day. Panel presents long-short portfolio alphas for portfolios with holding horizons of 10, 20, 40, and 60 days. Daily calendar-time returns and Carhart (1997) four-factor alphas are reported in percent multiplied by 20 to reflect an approximately monthly return, with t-statistics based on the daily time series presented in parentheses.

Table III: Cross-sectional Relation Between Monthly Percentage Returns and Trading Venue Short Sales

Panel A: Exchange Short Sales

	Raw Returns		Adjusted Returns	
	[1]	[2]	[3]	[4]
Intercept	2.113	2.113	0.119	0.120
	(3.92)	(3.92)	(2.18)	(2.20)
$\frac{ExShortVol}{ExVol}$	−1.518	−1.226	−1.294	−1.151
	(−4.02)	(−2.95)	(−3.10)	(−3.42)
Size		−0.057		−0.031
		(−0.63)		(−1.05)
Book to Market		0.274		−0.013
		(1.09)		(−0.08)

Panel B: Dark Pool Short Sales

	Raw Returns		Adjusted Returns	
	[1]	[2]	[4]	[5]
Intercept	2.112	2.113	0.119	0.121
	(3.92)	(3.92)	(2.20)	(2.22)
$\frac{DPShortVol}{DPVol}$	−0.821	−0.683	−0.735	−0.676
	(−6.98)	(−5.84)	(−6.03)	(−6.64)
Size		−0.085		−0.057
		(−0.99)		(−1.62)
Book to Market		0.282		−0.006
		(1.12)		(−0.04)

Panel C: By Venue Type

Intercept	Exchange	Midpoint	Non-Midpoint	Size	Book to Market
1.524	−1.100			−0.061	−0.031
(3.36)	(−4.36)			(−2.28)	(−0.17)
1.694		−0.371		−0.098	−0.033
(3.69)		(−5.65)		(−3.53)	(−0.19)
1.834			−0.765	−0.093	−0.034
(3.95)			(−6.37)	(−3.39)	(−0.19)
1.726	−0.765	−0.077	−0.514	−0.067	−0.035
(3.76)	(−2.86)	(−1.46)	(−4.17)	(−2.45)	(−0.20)

This table presents results of Fama and MacBeth (1973) regressions examining the relation between returns, short sales by type of trading venue over the period spanning August 2012 through June 2014. For each model, I run 452 daily cross-sectional regressions and calculate the time series mean of the daily coefficient estimates, and obtain t-statistics using Newey-West (1987) standard errors with 20 lags. Dependent variables are the cumulative raw returns or Daniel, Grinblatt, Titman, and Wermers (1997) adjusted returns over the following 20 trading days. In panels A and B, each column corresponds to a different specification. $\frac{ExShortVol}{ExVol}$ is the ratio of short sales volume executed on exchanges to total trading volume executed on exchanges for a given stock-day. $\frac{DPShortVol}{DPVol}$ is the ratio of total dark pool short sales volume to dark pool trading volume for a given stock-day. In Panel C, raw returns are used, dark pools are disaggregated into Midpoint and Non-Midpoint Dark Pools, and each row corresponds to a separate specification. Size (the natural log of stock market capitalization) and Book-to-Market are calculated as in Fama and French (1993). Explanatory variables are standardized to have a mean of zero each day. T-statistics are presented in parentheses.

Table IV: Post-Short Sale Midquote Cumulative Excess Returns Measured through Varying Post-Trade Horizons

	5 Minutes		30 Minutes		2 Hours		1 Trading Day	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Panel A: All Dark Pools								
Intercept	0.433***		0.373		−0.515		−3.863***	
Dark Pool	−0.027	−0.007	0.274*	0.322**	0.712***	0.830***	1.378***	1.501***
Panel B: By Dark Pool Type								
Intercept	0.433***		0.373		−0.515		−3.863***	
Midpoint	−0.023	0.013	0.372*	0.410**	1.261***	1.290***	2.865***	2.585***
Non-Midpoint	−0.017	−0.009	0.261*	0.300*	0.560***	0.688***	0.980***	1.217***

This table presents interval-level regression estimates, for which the dependent variable is the midquote post-trade excess cumulative log returns measured in basis points over various post-trade horizons. Trades are aggregated into five minute intervals and weighted by dollar volume. Dark Pool, Midpoint and Non-Midpoint are indicator variables that take the value of one for all Dark Pool short sales, Midpoint Dark Pool short sales, and Non-Midpoint Dark Pool short sales, respectively (the base case is Exchange short sales). Log returns are de-meaned. Standard errors are clustered by five minute intervals. Model 1 does not include fixed effects and Model 2 includes stock fixed effects.***,** , and * indicate statistical significance for a coefficient estimate at the 1, 5, and 10 percent level, respectively. This sample is a stratified sample of 439 stocks during September 2012 through June 2014.

Table V: Regression Analysis of Dark Pool-Volume Ratio Surrounding News Events

	Event time of the dependent variable				
Panel A: $\frac{DPVol}{Vol}$	$t-2$	$t-1$	t	$t+1$	$t+2$
Panel A1: All News					
VIX_{t-1}	−0.093***	−0.093***	−0.093***	−0.092***	−0.092***
News Event	0.040	0.216***	0.575***	0.372***	0.223***
N	1,315,325	1,315,325	1,315,325	1,315,325	1,315,325
R^2	27%	27%	27%	27%	27%
Panel A2: Positive News					
VIX_{t-1}	−0.093***	−0.093***	−0.093***	−0.093***	−0.093***
News Event	0.122	0.336***	0.573***	0.281***	0.186*
N	1,315,325	1,315,325	1,315,325	1,315,325	1,315,325
R^2	27%	27%	27%	27%	27%
Panel A3: Negative News					
VIX_{t-1}	−0.093***	−0.093***	−0.093***	−0.092***	−0.092***
News Event	0.034	0.165	0.897***	0.619***	0.405***
N	1,315,325	1,315,325	1,315,325	1,315,325	1,315,325
R^2	27%	27%	27%	27%	27%
Panel B: $\frac{DPVol}{Vol}$*, Scheduled News*	$t-2$	$t-1$	t	$t+1$	$t+2$
Panel B1: All News	0.018	0.347***	0.929***	0.589***	0.372***
Panel B2: Positive News	0.194	0.490***	0.958***	0.434***	0.345***
Panel B3: Negative News	0.001	0.251*	1.152***	0.905***	0.647***
Panel C: $\frac{DPVol}{Vol}$*, Unscheduled News*	$t-2$	$t-1$	t	$t+1$	$t+2$
Panel C1: All News	0.078	0.041	0.083	0.072	0.011
Panel C2: Positive News	0.000	0.106	−0.045	0.049	−0.059
Panel C3: Negative News	0.099	−0.009	0.392**	0.048	−0.067

This table presents results of panel data regressions that examine dark pool volume surrounding news events over the period spanning August 2012 through June 2014. In each regression in Panel A, the dependent variable is daily stock dark pool trading volume divided by total daily volume (in percent) and the independent variable of interest is an indicator variable that takes the value of one if a news story occurs and zero otherwise. Panel A1 presents results for all news events, Panel A2 presents results for positive news events, and Panel A3 presents results for negative news events. In Panels B and C, news events are separated into scheduled and unscheduled events, respectively and coefficients of interest are presented. I define a news event as positive (negative) if the news announcement day return is in the top (bottom) quintile of return for that day, respectively. In each panel I examine five separate regressions that vary the timing of the dependent variable relative to the news event to examine short volume changes around news event. For example, $t-2$ indicates that the news release indicator variable is equal to one two days before a news event. All regressions include stock and month fixed effects and the lagged VIX close. ***,** , and * indicate statistical significance for a coefficient estimate at the 1,5, and 10 percent level, respectively.

Table VI: Venue Short Sales Surrounding Around News Events

	Event time of the dependent variable		
Panel A: All	$t-2$	$t-1$	t
Panel A1: All			
Return_{t-1}	0.307***	0.307***	0.307***
Return_{t-2}	0.126***	0.126***	0.126***
Exchange	4.352***	4.356***	4.347***
News	−0.477***	0.244	−0.881***
Exchange × News	0.513**	0.296	0.787***
N	2,538,884	2,538,884	2,538,884
R^2	21%	21%	21%
Panel A2: Negative			
Exchange	4.358***	4.361***	4.356***
News	−0.577**	0.807***	−2.423***
Exchange × News	0.498	0.008	0.923**
Panel B: Scheduled	$t-2$	$t-1$	t
Panel B1: All			
Exchange	4.361***	4.366***	4.36***
News	−0.261	0.883	−0.669***
Exchange × News	−0.011	−0.532	0.106
Panel B2: Negative			
Exchange	4.361***	4.364***	4.36***
News	−0.514	1.318***	−1.919***
Exchange × News	0.083	−0.859*	0.041
Panel C: Unscheduled	$t-2$	$t-1$	t
Panel C1: All			
Exchange	4.352***	4.351***	4.348***
News	−0.761***	−0.556**	−1.11***
Exchange × News	1.181***	1.358***	1.671***
Panel C2: Negative			
Exchange	4.358***	4.358***	4.356***
News	−0.716	−0.122	−3.376***
Exchange × News	1.315**	1.636**	2.63***

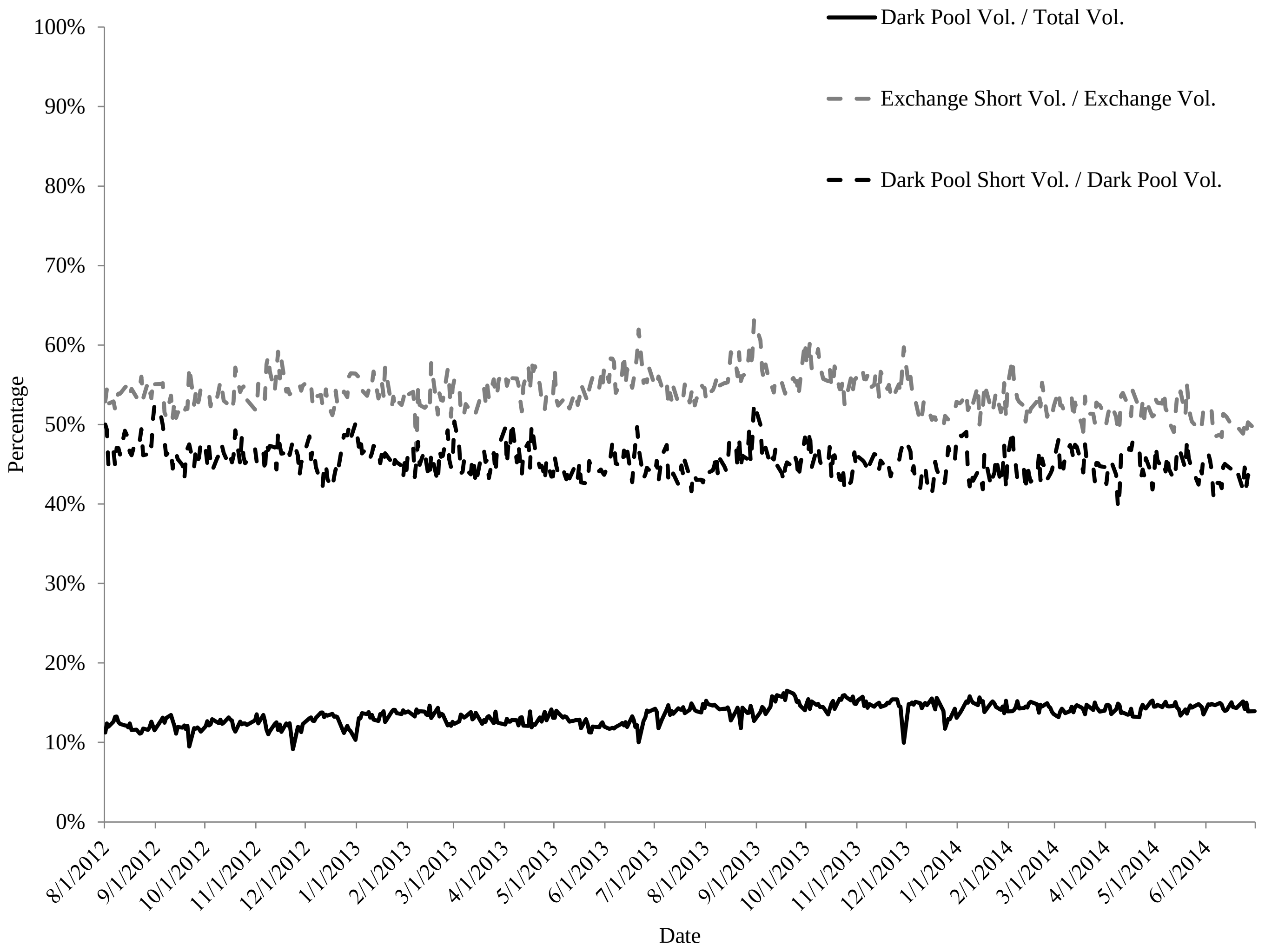
This table presents results of panel data regressions that examine trading venue short sales leading up to and including news events over the period spanning August 2012 through June 2014. Each subpanel corresponds to a separate regression. In each regression, the dependent variable is daily stock trading venue short sale volume divided by total daily venue volume (in percent) and the independent variables of interest are an indicator variable that takes the value of one if a news story occurs and zero otherwise (News), another indicator variable that equals one if exchange trading is being considered (Exchange), making dark pool trading the base case, and the interaction term of "News" and "Exchange". Panel A presents results for all news events, Panel B presents results for scheduled news events, and Panel C presents results for unscheduled news events. I define a news event as positive (negative) if the news announcement day return is in the top (bottom) quintile of return for that day, respectively. In each panel I examine three separate regressions that vary the timing of the dependent variable relative to the news event to examine short volume changes around news event. For example, $t-2$ indicates that the news release indicator variable is equal to one two days before a news event. All regressions include stock and month fixed effects. Since estimates for control variables, R^2, and the number of observations do not vary much across specifications, I only report them in Panel A1. ***,** , and * indicate statistical significance for a coefficient estimate at the 1,5, and 10 percent level, respectively.

Table VII: Cross-sectional Relation Between Monthly Percentage Returns, Trading Venue Short Sales, and News Arrival

	Raw Returns		Adjusted Returns	
Panel A: Exchange Short Sales	[1]	[2]	[3]	[4]
Intercept	2.111	2.110	0.117	0.117
	(3.92)	(3.91)	(2.16)	(2.17)
$\frac{ExShortVol}{ExVol}$	−1.498	−1.206	−1.274	−1.130
	(−3.90)	(−2.87)	(−3.02)	(−3.31)
$News_{t-1}$	0.063	0.085	0.102	0.103
	(0.62)	(0.87)	(1.11)	(1.10)
$\frac{ExShortVol}{ExVol} \times News_{t-1}$	−1.269	−1.408	−1.395	−1.466
	(−1.85)	(−2.06)	(−1.99)	(−2.13)
$News_t$	−0.182	−0.158	−0.153	−0.150
	(−1.57)	(−1.40)	(−1.26)	(−1.23)
$\frac{ExShortVol}{ExVol} \times News_t$	−0.298	−0.181	0.043	0.068
	(−0.45)	(−0.27)	(0.06)	(0.09)
Size		−0.057		−0.031
		(−0.63)		(−1.05)
Book to Market		0.273		−0.015
		(1.08)		(−0.09)
	Raw Returns		Adjusted Returns	
Panel A: Dark Pool Short Sales	[1]	[2]	[3]	[4]
Intercept	2.110	2.111	0.117	0.119
	(3.92)	(3.91)	(2.18)	(2.19)
$\frac{DPShortVol}{DPVol}$	−0.815	−0.679	−0.730	−0.672
	(−6.83)	(−5.68)	(−5.94)	(−6.53)
$News_{t-1}$	0.059	0.077	0.105	0.107
	(0.58)	(0.77)	(1.13)	(1.13)
$\frac{DPShortVol}{DPVol} \times News_{t-1}$	0.245	0.161	0.228	0.148
	(0.72)	(0.49)	(0.62)	(0.41)
$News_t$	−0.204	−0.180	−0.153	−0.144
	(−1.75)	(−1.61)	(−1.42)	(−1.35)
$\frac{DPShortVol}{DPVol} \times News_t$	−0.119	0.014	−0.123	−0.065
	(−0.34)	(0.04)	(−0.33)	(−0.18)
Size		−0.085		−0.057
		(−0.99)		(−1.62)
Book to Market		0.281		−0.008
		(1.11)		(−0.05)

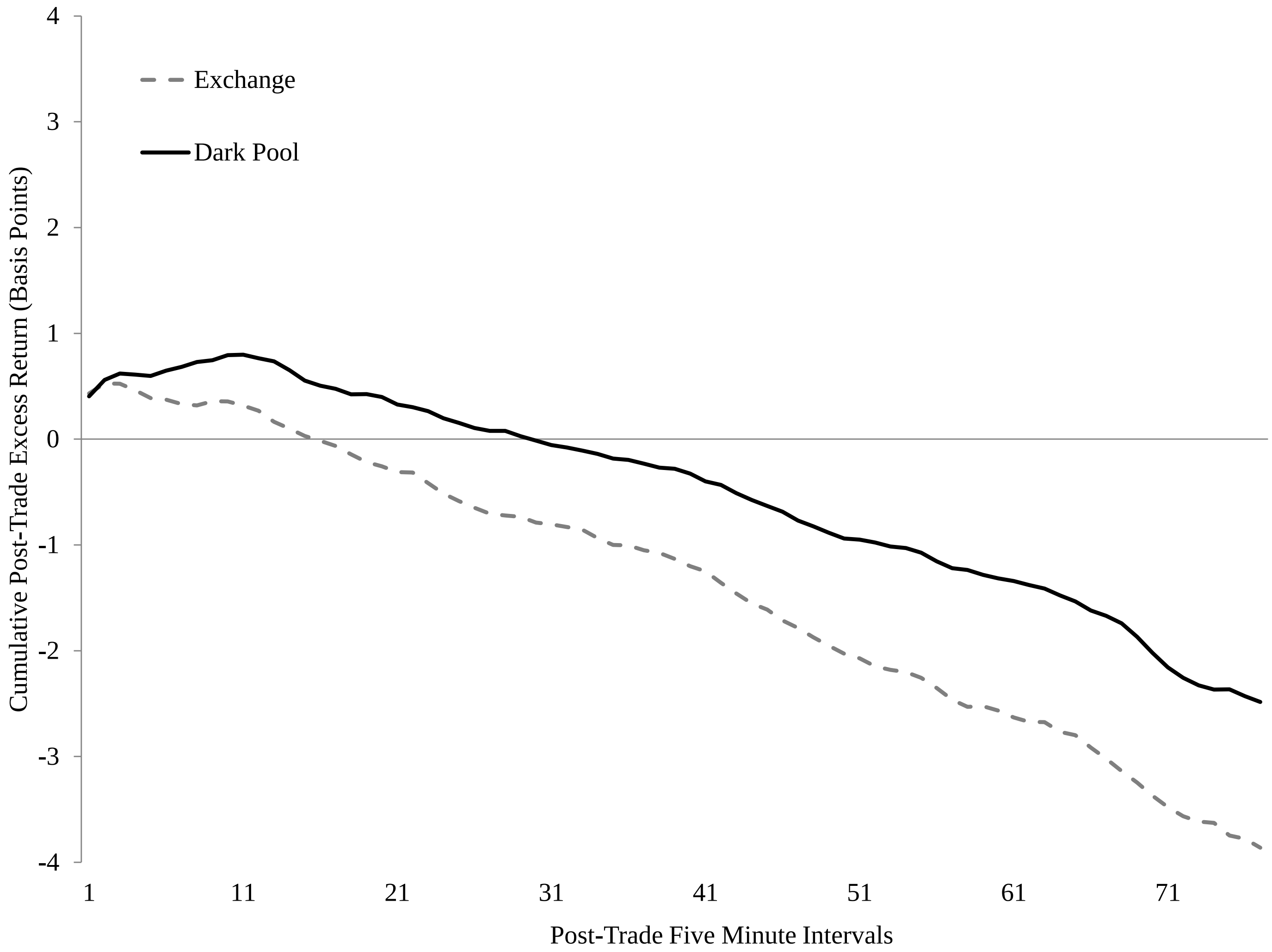
This table presents results of Fama and MacBeth (1973) regressions examining the relation between returns, short sales by type of trading venue, and news events over the period spanning August 2012 through June 2014. For each model, I run 452 daily cross-sectional regressions and calculate the time series mean of the daily coefficient estimates, obtain t-statistics using Newey-West (1987) standard errors with 20 lags. Dependent variables are the cumulative raw returns or Daniel, Grinblatt, Titman, and Wermers (1997) adjusted returns over the following 20 trading days. $\frac{ExShortVol}{ExVol}$ is the ratio of short sales volume executed on exchanges to total trading volume executed on exchanges for a given stock-day. $\frac{DPShortVol}{DPVol}$ is the ratio of total dark pool short sales volume to dark pool trading volume for a given firm-day. $News_{t-1}$ and $News_t$ are indicator variables that equal one if there is a coporate news release for a given firm on the following and current day, respectively. Size (the natural log of firm market capitalization) and Book-to-Market are calculated as in Fama and French (1993). Explanatory variables are standardized to have a mean of zero each day. T-statistics are presented in parentheses.

Figure 1: Aggregate Dark Pool and Short Sales Share of Trading Volume



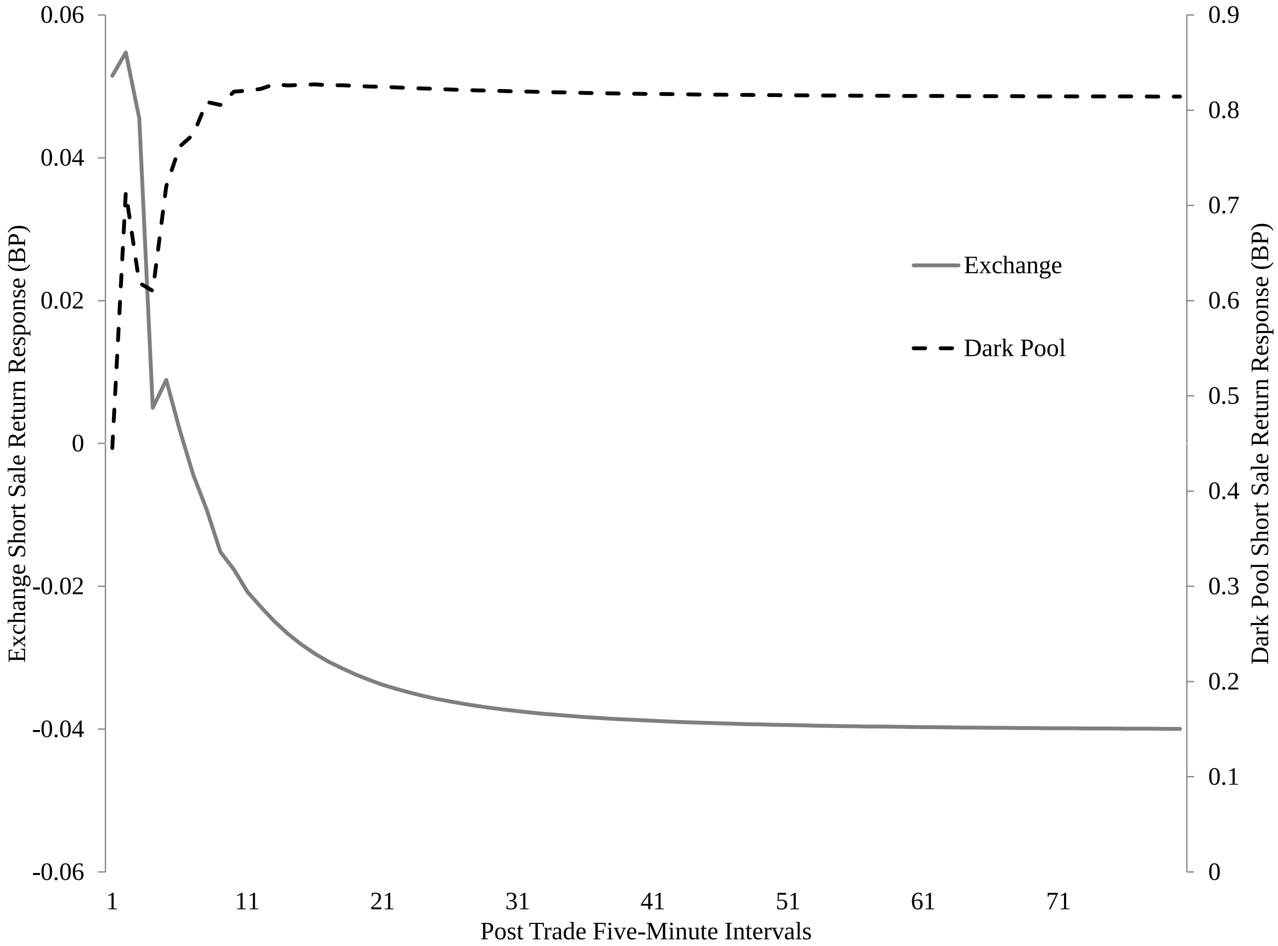
Time series of shares of various types of aggregate trading volume across all stocks in the 3,148 stock sample over a sample period spanning August 2012 through June 2014. *Exchange Short vol./Exchange vol.* is total daily exchange short sale volume divided by total daily exchange trading volume across all firms in the sample. *Dark Pool vol./Total vol.* is total daily dark pool volume divided by total daily trading volume across all firms in the sample. *Dark Pool short vol./Total Short vol.* is total daily dark pool short sale volume divided by total daily short sale volume across all firms in the sample. *Dark Pool short vol./Dark pool vol.* is total daily dark pool short sale volume divided by total daily dark pool trading volume across all firms in the sample.

Figure 2: Average Cumulative Midquote Excess Returns after Venue Short Sales



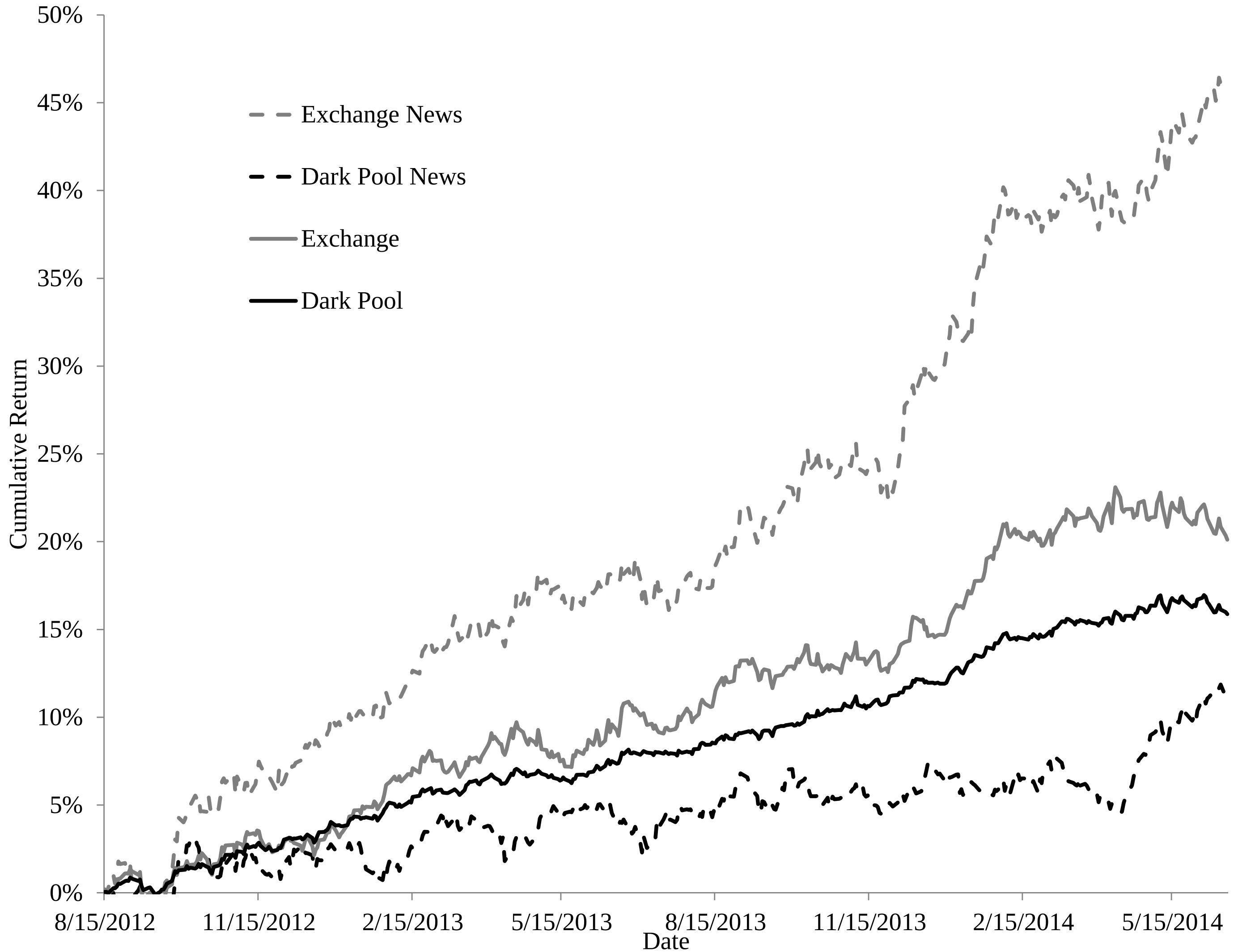
This figure presents average cumulative log returns (in basis points) after exchange (grey dashed line) and dark pool (black dashed line) short sales, respectively. Log-returns are excess returns (de-meaned) and trades are aggregated into five minute intervals and dollar weighted. This sample consists trading for a stratified sample of 439 stocks over September 2012 through June 2014. The horizontal axis is the number of five-minute intervals after a short sale took place and the vertical axis is the cumulative log return of the short sales.

Figure 3: Cumulative Return Response to Venue Short Sale Shocks



This figure presents the equally weighted cumulative impulse response functions estimated from a vector autoregression of excess stock midquote returns (in basis points) to exchange short sale (grey solid line) and dark pool short sale (black dashed line) shocks, respectively. Log-returns are excess returns (de-meaned) and short sales are measured in dollar volume and aggregated into five minute intervals. The horizontal axis measures the number of five-minute intervals after a short sale shock. The left vertical axis measures cumulative return responses after exchange short sale shocks and the right vertical axis measures corresponding returns after dark pool short sale shocks. The magnitude of each short sale shock is equal to the standard deviation of unanticipated exchange short sale dollar volume. This sample consists trading for a stratified sample of 439 stocks over September 2012 through June 2014. The horizontal axis is the number of five-minute intervals after a short sale took place and the vertical axis is the cumulative log return of the short sales.

Figure 4: Cumulative Long-Short Portfolio Returns conditioning on Venue Short Sales and News Events



This figure presents cumulative returns from quintile long/short portfolios formed by conditioning on venue short sales or venue short sales and news events being imminent the following day. These equal-weighted portfolios are then held for 20 days and portfolio formation process is repeated each day. The grey line presents cumulative percentage returns for the long-short portfolio formed on exchange short sales, the grey dashed line presents returns for the long-short portfolio formed on exchange short sales and news events, the black line presents returns for the long-short portfolio formed on dark pool short sales, and the black dashed line presents returns for the long-short portfolio formed on dark pool short sales and news events.