

Two Essays on Dark Trading

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**Ryan Zebadiah Farley
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ABSTRACT

This dissertation examines the effect of two hallmarks of modern market structure, dark trading and fragmentation. The first chapter looks at the effects of dark trading on market quality on an ordinary trading day. Our research design is predicated on a regulatory pilot spearheaded by the Securities and Exchange Commission. We leverage this setting to examine what happens to liquidity and price efficiency following a large negative exogenous shock to dark trading. The second chapter investigates the effects of dark trading and fragmentation on the resiliency of stocks facing an aggregate market shock. Prior literature has found cross sectional variation, based on the characteristics of liquidity suppliers, regarding what happens to market quality during a market downturn. However, due to prior data limitations we do not know how stock resiliency is affected by where a stock trades. Using newly available public data provided by FINRA, I characterize the locus of trading for all stocks across dark and lit trading venues (termed the “liquidity map”) and use this information to explain cross sectional variation in market quality following a negative shock to the aggregate market.

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INTRODUCTION

Two prominent features of US equity markets are dark trading and fragmentation. Over the past two decades, dark trading is estimated to have grown from 5% to 40% of volumes. As volumes have migrated off exchange, trading has also become increasingly disperse over a fragmented marketplace. For example, in 1993 NYSE executed 79% of shares in listed firms, but only 30% in recent years, with the remaining volumes spread over 14 exchanges, 32 dark pools, 12 internalizers, and countless other brokers in the upstairs market (based on executions during December of 2018). Regulators view the proliferation of dark trading and fragmentation as a serious concern, despite ambiguity within academic research as to how these facets of market structure effect investing outcomes.

The first chapter of this dissertation examines the effects of dark trading on market quality on a typical trading day. Our research design leverages a regulatory pilot spearheaded by the Securities and Exchange Commission. Within this setting, we isolate our analysis to one provision of the pilot (Trade-At) to examine how a large negative exogenous shock to dark trading impacts market quality.

The second chapter investigates the effects of dark trading and fragmentation on the resiliency of stocks facing an aggregate market shock. Prior literature has found cross sectional variation in liquidity dislocations during a market downturn based on characteristics of liquidity suppliers. However, the effects of where a stock trades on its resiliency is unknown due to data limitations. Concerns about dark trading and market fragmentation prompted regulators to make a highly granular dataset available that discloses dark trading statistics. My study is the first to ask what we can learn about stock resiliency from where stocks trade. This question was

previously unanswerable using public data. I fill this gap in the literature using publicly available data provided by FINRA to map out individual stock patterns and use these characteristics to explain cross sectional variation in liquidity dislocations following a negative shock to the aggregate market.

**CHAPTER I: DARK TRADING VOLUME AND MARKET QUALITY:
A NATURAL EXPERIMENT**

Abstract

We exploit an exogenous shock to dark trading volume in order to identify the effect of dark trading on market quality. Following a 34% reduction in dark trading volume, we find that the cost of trade (e.g., effective spreads, realized spreads, price impact, and quoted spreads) does not change. While our findings stand in contrast to those of prior studies, a number of supplemental tests confirm that conflicting inferences cannot be attributed to different stock samples or time periods. Our research highlights the benefit of structured experimentation from the Securities and Exchange Commission (SEC) for understanding causal effects in capital markets.

Keywords: Market Fragmentation, Microstructure, Market Efficiency

JEL codes: G1

* All authors are from Haslam College of Business, University of Tennessee. Email: rfarley1@vols.utk.edu; ekk@utk.edu; pucketta@utk.edu. Kelley received funding for this work as a Home Federal Bank Scholar. We thank Sabrina Buti, Mao Ye, Stephen Jurich, Satchit Sagade, Chaojun Wang, and seminar participants at Eastern Carolina University, the Financial Management Association meeting in San Diego, James Madison University, the Mid-Atlantic Research Conference at Villanova University, St. Louis University, the Southern Finance Association meeting in Asheville, University of Paris-Dauphine, and University of Tennessee for their helpful comments. All errors are our own.

Introduction to Chapter I

Dark trading, which occurs on platforms that do not display orders prior to execution, accounts for roughly one-third of all equity trading volume in U.S. markets.² Yet as dark venues aggressively compete for market share and traders decide how best to fulfill the fiduciary task of order routing, basic questions regarding the consequences of trading “in the dark” remain unanswered. The current lack of understanding fuels an intense policy debate concerning market structure. Regulatory bodies worldwide, tasked with protecting overall trader welfare, are considering and/or implementing policies to curb the use of dark venues. For example, European policymakers restricted dark trading to 8% of overall trading volume via MiFID II rules beginning in March 2018.³ At the current time, regulators in the United States, Australia, Canada, and Hong Kong are debating similar policies.

Economic theory offers opposing predictions for how dark trading might influence market outcomes. Theoretical models argue that dark trading may damage overall market quality (e.g., wider spreads, higher volatility, and less efficient prices) by segmenting informed from uninformed order flow (Admati and Pfleiderer, 1998; Madhavan 1995; Zhu, 2014). Bolton, Santos, and Scheinkman (2016) offer the similar message that cream-skimming (i.e., selectively routing uninformed order flow to dark venues) is harmful. Likewise, the availability of dark venues may detract from liquidity externalities that arise in a centralized market (Mendelson, 1987). On the other hand, the proliferation of dark trading might enhance the overall quality of equity markets

² Dark venues include more than 60 different alternative trading systems (ATS) and internalized trades at hundreds of broker-dealers. Statistics on dark trading volume are obtained from BATS Global Markets for the month of July, 2017: https://www.bats.com/us/equities/market_share/. Recent reports from the TABB Group point to a higher fraction of dark trading volume (44.9%), but include hidden orders in lit markets in this total: <https://research.tabbgroup.com/report/v15-034-tabb-equity-digest-q2-2017>

³ See discussion in Davies and Sirri (2017). – p, 28.

by increasing competition across venues (Economides, 1996; Hendershott and Mendelson, 2000) or amongst informed liquidity suppliers (Boulatov and George, 2013). Dark venues may also inhibit predatory trading activity by allowing traders to hide their intentions (Harris, 1997).

Ultimately, the question of how dark trading affects market quality is an empirical one. While the question is both relevant and straightforward, answers are not. The central problem is identification, since trading on dark versus lit venues is the endogenous outcome of a complex trading landscape. Simply put, traders choose execution strategies that may include routing orders to dark venues based on expectations of trading costs, future market conditions, and many unobservable constraints. So while empirical studies use various econometric corrections to obtain inference (e.g., instrumental variables, selection bias corrections, etc.), one must recognize the inherent difficulty in establishing a causal relation within the “complex ecosystem” in which securities trade.⁴ Not surprisingly, the body of empirical research lacks a cohesive message. Degryse, de Jong, and van Kervel (2014), Weaver (2014), Comerton-Forde and Putnins (2015), Hathaway, Kwan, and Zheng (2017; hereafter “HKZ”) find evidence of increased transactions costs and diminished market quality as dark trading volumes rise. In stark contrast, O’Hara and Ye (2011), Jiang, McInish, and Upson (2012), Buti, Rindi, and Werner (2016), Foley and Putnins (2016), and others associate greater levels of dark trading volume with significant improvements in transactions costs, price efficiency, and execution speeds.

Our contribution lies squarely on identification. We exploit a large exogenous shock to dark trading that arises from the SEC’s ‘Tick Size Pilot’ enacted in October 2016. The pilot,

⁴ Staff of the Division of Trading and Markets, U.S. Securities and Exchange Commission, “Equity Market Structure Literature Review, Part I: Market Fragmentation,” (available at <http://www.sec.gov/marketstructure/research/fragmentation-lit-review-100713.pdf>)

designed to examine liquidity for smaller firms, increases the tick size (to one nickel) for stocks in three randomly assigned treatment groups and holds constant the trading environment of an equal number of control firms. Our experiment detracts from the pilot's primary focus and instead utilizes a nuanced distinction between two of the pilot's treatment groups – Group 2 (G2) and Group 3 (G3). While the pilot restricts quoting and trading to nickel increments for stocks in treatment groups G2 and G3 alike, it imposes an additional restriction on stocks in G3. This additional restriction, commonly called the *Trade-At* rule, prohibits a venue from executing a trade at the National Best Bid or Offer quote unless it is the venue displaying that quote. Instead, it must either offer a five-cent price improvement or route the order to the venue with the best quote.⁵ Since dark facilities do not display quotes, the provision reduces the competitive position and market share of these venues.

We summarize our experiment in three pictures that describe G2 and G3 stocks during the forty trading days surrounding October 2016, when the Pilot was implemented in a staggered fashion. Figure 1 (Appendix C) reveals that the average fraction of stock-level trading on dark venues drops by four standard deviations, from 35% to 23% in G3 stocks. In contrast, dark trading in group G2 rises slightly.⁶ Figure 2 displays a similar plot for effective spreads, a common measure of transactions costs. Despite the large shock to dark trading around the event, there is no discernible change in the difference in effective spreads between the two groups of stocks. Finally, Figure 3 plots a market quality measure based on variance ratios, which changes only slightly

⁵ In Appendix A, we provide an example of how *Trade-At* affects order routing.

⁶ A negative spike in dark trading is observable for both treatment and control stocks during the pre-pilot period depicted in Figure 1. The spike coincides with the third Friday of September, known as "Triple Witching Day", when derivatives expire for equities and equity indices. The steep drop in the share of dark trading is driven by a large increase in overall trading (52.13%) that dominates a modest increase in dark trading (5.31%).

around implementation. On their face, these results suggest that trading on dark venues has a largely benign effect on overall market quality.

We test the veracity of our ‘inference from pictures’ using formal statistical tests. Specifically, we implement a difference-in-difference framework in which G3 stocks serve as the “treatment” group and G2 stocks are the “control” group. For each stock, we construct daily firm-level observations over the twenty days before and the twenty days after the pilot’s staggered implementation during October 2016. The dependent variables that we analyze include spread measures – effective spread, quoted spread, realized spread, and price impact – along with an intra-day variance ratio to evaluate price efficiency.

Our regressions provide no evidence that the large exogenous shift in dark trading volume causes a change in effective or quoted spreads. When investigating the components of the effective spread – the realized spread and price impact – we find a similar result. In fact, the only variable that appears affected is the variance ratio. The variance ratio measure for G3 increases by 0.0185 (t -statistic=1.81) when compared to G2. This marginally significant change is modest evidence of a loss to price efficiency following restrictions on dark trading.

We conduct a rigorous set of exercises to demonstrate the validity of our experiment. First, we verify that stocks in groups G2 and G3 are similar across a number of characteristics (i.e., firm size, trading volume, share price, etc.). We then offer statistical evidence that differences in dark trading and our market quality variables between groups G2 and G3 are stable during the period leading up to the Pilot’s enactment. This evidence confirms the parallel trends assumption, which is key for inference in differences-in-differences analyses.

We next demonstrate that the pilot does not meaningfully alter other stock characteristics that possibly correlate with market quality. The treatment effect (i.e. “*Trade-At*”) on variables such as turnover, trade size, and price is economically small and typically statistically insignificant. Motivated by recent work from Comerton-Forde, Gregoire, and Zhong (2018), we also investigate the treatment effect on inverted venues. These authors argue the sub-penny price improvement offered by inverted-fee venues is particularly attractive when similar execution opportunities are not available in the dark. We show that even though the inverted venue share of total trading volume increases for G3 stocks, the majority of this change is attributable to trades that shift from dark to lit venues being proportionally allocated across all lit venues. We also show a large drop in dark trading but no significant change to market quality among stocks where the tick size constraint did *not* bind. This results mitigates concerns over a confounding inverted fee venue effect because Comerton-Forde, Gregoire, and Zhong (2018) argue those venues are less important for non-tick constrained stocks.

In closely related work, Comerton-Forde, Malinova, and Park (2018) analyze Canada’s minimum price improvement rule that was imposed in 2012. Using proprietary trader-type data, these authors show that the rule mainly redirected retail order flow from a single dark pool (that resembles a U.S. retail wholesale execution venue) to the lit market with the lowest take fee. In essence, the rule forced the previously-segmented retail order flow back into the lit markets; consequently, liquidity providers shifted to lit markets as well. The latter result improved lit depth, though in aggregate, liquidity was largely unaffected. Devani, Anderson, and Zhang (2015) reach similar conclusions and also note there was no change in measures of informational efficiency.⁷

⁷ Foley and Putnins (2016) use publicly available data to study the same minimum price improvement rule, and they argue that dark trading improves liquidity. However, Comerton-Forde, Malinova, and Park (2018) show in their

Our main insights and contribution are incremental to those gleaned from the Canadian rule change. The U.S. tick pilot program contained an exemption by which wholesalers and exchange retail liquidity program participants could price improve retail orders by a half penny from the best bid or offer for stocks in both our treatment and control groups. A second exemption allowed venues to price blocks of at least 50,000 shares or \$100,000 trades at the best bid or offer and at penny increments. Thus, unlike the migration of retail flow that occurred in Canadian stocks, we expect the tick pilot to redirect *non-block institutional volume* from dark to lit venues. As such, our analysis complements that of Comerton-Forde, Malinova, and Park (2018) and Devani, Anderson, and Zhang (2015) to suggest *Trade-At* rules have an immaterial effect on market quality.

We investigate the robustness of our results in several ways. First, we include control variables in our difference-in-difference regressions that aim to capture order characteristics related to expected trading costs. Second, because prior studies have found differential effects for dark trading when looking at different subsamples of stocks, we parse our sample along multiple stock characteristics and repeat the difference-in-difference analysis. Specifically, we divide stocks in our sample by market capitalization, quoted spread, turnover, fragmentation across lit venues, and whether the tick size constraint is binding. Finally, we exploit newly disclosed FINRA data to decompose dark trading into that occurring on Alternative Trading Systems (ATS) and non-ATS venues. While we find a few subsamples with economically and statistically weak evidence that dark trading either harms or improves market quality, the common message is that

Online Appendix that this conclusion is driven by the inclusion of six to twelve relatively illiquid stocks and obfuscated by the potential mis-classification of one-sided versus two-sided markets.

given the size of the shock to dark trading, detectable changes to transaction costs and price efficiency are marginal at best.

We reconcile our results with others in the literature who conclude dark trading deteriorates liquidity. Notably, HKZ (2017) use a 2-stage procedure to control for selection bias and find that a 10% rise in dark volume leads to a 9.2% increase in effective spreads. Our message is quite different as we find a larger shock to dark trading has no effect on liquidity. One possibility is that our different sample period and sample of stocks (our sample is skewed towards smaller stocks) are responsible for the stark difference in conclusions. With this in mind, we replicate HKZ during both their original sample period using their sample of stocks and during our sample period using our sample of stocks. In both replications we find results that are quantitatively and qualitatively similar to those reported by HKZ. Thus, our differences with HKZ are not driven by our stock sample or time period. Rather, they are more reasonably attributable to differences in our respective identification strategies. Our work and replication highlights the inherent difficulty in selecting instruments and the importance of structured experimentation from the Securities and Exchange Commission (SEC) for understanding causal effects in capital markets.

An important caveat is in order. Dark venues are typically associated with both a lack of pre-trade transparency and a finer pricing grid (*e.g.*, subpenny executions) when compared to lit exchanges.⁸ The nature of our experiment isolates the effect of pre-trade transparency because stocks in both groups are subject to the same five-cent pricing grid. We view this as a strength of our approach because any study of market structure that isolates individual aspects provides a cleaner set of guidelines for regulators and those who experiment with future market design. In

⁸ It is worth noting that post-trade transparency differs also, in that while all trades are publically disseminated in real-time, only lit trades are reported with a specific venue where the execution occurred.

this sense, our analysis is complementary to studies such as Kwan, Masulis, and McInish (2015), who analyze tick size changes on lit exchanges as a stock's price moves above and below one dollar, and Comerton-Forde, Gregoire, and Zhong (2018), who highlight the role of inverted fee venues, as those papers can better speak to finer changes in the pricing grid.

The remainder of our paper proceeds as follows: Section II reviews the SEC's tick size pilot, Section III summarizes our data, Sections IV and V discuss our research design and results, and Section VI concludes.

Natural Experiment: SEC Tick Size Pilot

The 2012 Jumpstart Our Business Startups Act ("JOBS Act") directed the SEC to assess how decimalization affects the liquidity and trading of smaller capitalization companies. The directive stems from a concern that decimalization reduced incentives to make markets, produce sell-side research, and underwrite public offerings in smaller firms. Advocates of a wider minimum tick size argue that under such a policy market making would be more profitable, sell side analysts would increase coverage, and institutions would be more likely to invest in smaller firms. In response, the SEC implemented the "Tick Size Pilot" in October of 2016, which increased quoting and trading increments from \$0.01 to \$0.05 for randomly selected samples of small- and mid-capitalization stocks. Rindi and Werner (2017) discuss the background leading up to the SEC's tick size pilot program and provide a comprehensive analysis of pilot stocks verses controls. They show that stocks with increased tick sizes have greater quoted and effective spreads but also increased depth.

Stratifying by market capitalization, volume weighted average price, and average daily volume, the pilot randomly assigns approximately 2,400 stocks to a control group and three treatment groups⁹:

- Treatment Group 1 (G1) - stocks must be quoted in nickel increments;
- Treatment Group 2 (G2) – same treatment as G1, plus stocks must also *trade* in nickel increments or at a half-nickel midpoint.
- Treatment Group 3 (G3) – same treatment as G2, plus stocks are subject to the *Trade-At provision*, which prohibits a venue from executing a trade at the “Best Protected Bid” (NBB) or “Best Protected Offer” (NBO) unless it is displaying that quote.¹⁰

The treatments for G1 and G2 clearly align with the JOBS Act directive as they change the pricing grid from pennies to nickels. In contrast, the additional treatment effect in Group 3, commonly known as a *Trade-At* provision, specifies that any trading venue not displaying protected quotes (*e.g.* all dark venues) cannot execute at the inside quote (NBB or NBO) – effectively shifting trade from dark to lit venues.¹¹

We exploit the nuanced *difference between Group 3 and Group 2 stocks* to identify an exogenous shock to dark trading volume. Dark venues’ inability to execute trades at the prevailing inside quote coupled with the coarser pricing grid (improvements to the inside quote must be at least five cents) should result in a significant transfer of trading volume from dark to lit trading venues. Moreover, comparing effects between Groups 3 and 2 holds constant the pricing grid, thus isolating any pure “dark trading” effect. The exogenous shift in trading volume, random

⁹ The complete SEC Tick Size Pilot plan is available at <https://www.sec.gov/rules/sro/nms/2015/34-74892-exa.pdf>

¹⁰ Appendix A provides three examples of *Trade-At* from the SEC implementation plan.

¹¹ There are several exemptions from *Trade-At*, all of which generally follow exemptions to RegNMS Rule 611 (“trade-through”). *Trade-At* exemptions include block trades, fractional shares, trades during a locked market or self-help condition, trades part of a non “regular way” contract (*i.e.* not settled T+3), and stop trades. In addition, retail price improvement is exempt from pilot trading rules provided the inside quote is improved by at least a half penny. However, it is unclear how any of these exemptions might bias inference from our study.

assignment of stocks into treatment groups, and the existence of a suitable counterfactual group (G2) present an unparalleled opportunity to study the *causal* effects of dark trading on market quality.

From the onset, controversy surrounded the inclusion of a *Trade-At* provision in the Tick Size Pilot. The SEC noted very clearly the relevance of the *Trade-At* provision when directing exchanges and FINRA to submit a tick pilot plan:

The Commission believes that if trading volume in Test Group Two Pilot Securities moves to undisplayed trading centers, then including the trade-at requirement in Test Group Three could test whether trading remains on lit venues and what impact, if any, the migration of trading from lit venues to dark venues would have on liquidity and market quality for the Pilot Securities... (SEC, 2014, p. 36846).

As exchanges have long advocated tests involving a *Trade-At* provision (Lynch, 2015), it is perhaps not surprising the Pilot included this feature. Operators of dark pools naturally voiced strong opposition:

We see no connection between the goal of the Pilot – widening tick sizes to determine the impact on small cap issuers and their securities – and the imposition of a Trade-At Requirement which is simply a measure to increase market share for [lit] exchanges (SIFMA, 2014).

As we show in Figure 1, the drop in dark trading market share was indeed large, swift, and long-lasting.

Data

Sample Construction

A stock's eligibility for the Pilot program was determined over a “measurement” period from April 4 until September 2, 2016 in accordance with the following criteria:

- National Market System (NMS) common stocks trading publicly for at least six months prior to the beginning of the pilot
- Market capitalization of no greater than \$3 billion
- Closing price of at least \$2.00 on the last day of the measurement period
- Closing price of at least \$1.50 on each day during the measurement period
- Average daily volume (*ADV*) of no greater than one million shares
- Volume weighted average price (*VWAP*) of at least \$2.00

On September 3, 2016, the SEC published a list of 2,398 stocks that met the eligibility requirements and assigned each stock to three different tercile groups based on market capitalization, volume weighted average price, and average daily volume. These tercile assignments produce 27 unique fractile portfolios.¹² Stocks were then randomly drawn from these fractile portfolios and assigned to one of the three mutually exclusive treatment groups (targeting 400 stocks in each group) as described in Section II. The random draw also forced the same distribution across listing exchanges within treatment groups. The result was group assignments for 2,395 stocks in the pilot, with 400 in one treatment group and 398 in the other two treatment groups. Remaining stocks comprised the control group.

We obtain a daily list of Pilot stocks, their corresponding group assignments (*i.e.* control group, G1, G2, or G3), and the effective date for each record from the listing exchanges (NYSE and NASDAQ).¹³ From the list, we retain only G3 and G2 stocks and identify 789 unique firms

¹² Portfolios containing less than ten stocks were combined with other portfolios containing under ten stocks until each portfolio contained at least ten stocks.

¹³ Listing exchanges provide daily lists that reflect any updates to the sample groups that might arise from mergers, delistings, etc. A list of pilot stocks is also available from FINRA: www.finra.org/industry/tick-size-pilot-program.

during the period from September 2, 2016 until November 29, 2016.¹⁴ After matching each firm's ticker symbol with CRSP to obtain exchange listing, sharecode, shares outstanding, and trading volume, we filter the sample to include only common shares (sharecode=10 or 11), leaving 667 unique firms.

We gather data necessary to construct measures of market quality (spreads, price impact, and variance ratios) as well as several control variables used in our regressions from the NYSE's daily millisecond trade and quote data (TAQ). To ensure the integrity of the TAQ data, we match trades and quotes following Holden and Jacobsen (2014) and exclude all trades executed before 9:30 am or after 4:00 pm, as well as those associated with the opening or closing auctions.¹⁵ We also exclude executions exempt from the RegNMS Rule 611 (also known as the trade through rule), because these trades are not necessarily related to the prevailing quote at the time of the trade.¹⁶ After requiring sufficient TAQ data to compute market quality measures each day, we are left with 660 firms in the final sample, of which 327 are from group G3 and 333 are from group G2.

We identify dark venue executions as those with exchange code 'D' in TAQ.¹⁷ This 'flagged' dark trading volume includes all trading within dark pools (i.e. registered alternative trading systems, ATS) as well as internalized trades at broker-dealers.¹⁸ To assess the prevalence

¹⁴ Dates for our study are chosen to ensure four weeks of market data before and after the staggered implementation of the 'Tick Size Pilot', which occurred from October 3 to 31, 2016.

¹⁵ Trades that occur outside of the regular trading session are coded in TAQ with trade condition T or U. Auction trades are coded with trade conditions O and 6 on all exchanges except for NYSE. For NYSE listed securities the first and last regular session trades, which are not stop orders, executed with exchange code "N" identify NYSE auction trades.

¹⁶ For example: stop, derivatively priced and prior reference price trades.

¹⁷ This measure excludes executions against hidden orders on exchanges.

¹⁸ We retain RegNMS exempt trades since these reflect trader decisions and without them we would have an incomplete picture of order flow allocation. Thus our measure encompasses all regular trading session transactions executed against undisplayed trading interest away from any exchange.

of dark trading volume for each stock and day, we calculate the dollar value traded in dark venues scaled by total traded dollar value (*DarkTrading*). This proportion based measure, which serves as our primary independent variable of interest, is common in empirical studies of U.S. stocks (e.g. O'Hara and Ye, 2011; Hatheway, Kwan, and Zheng, 2017). Degryse, De Jong, and Van Kervel (2015) compute a similar measure to analyze dark trading in Dutch stock. Market Quality Measures

To assess market quality, we calculate daily spread measures and variance ratios using intraday trade and quote data from TAQ. Our spread measures include both quoted and effective spreads. We compute quoted spread (*QS*) as:

$$QS = \frac{NBO_t - NBB_t}{midpoint_t}, \quad (1)$$

where *NBO* and *NBB* reflect the national best offer and bid price respectively, and *midpoint* is a simple average of the two. For each stock-day, we compute a time-weighted average of the quoted spread to ensure that longer persisting spreads are more heavily weighted than fleeting quotes.

While quoted spreads are often viewed as an accurate estimate of the cost of small market orders (Anand, et al, 2012), we also proxy for the realized cost of trade by calculating effective spreads. The effective spread (*ES*) compares the execution price of a trade to the prevailing midpoint at the time of trade, as follows:

$$ES = 2 * \frac{abs(price_t - midpoint_t)}{midpoint_t} \quad (2)$$

If the midpoint is a “fair price”, then the effective spread measures a trader’s willingness to pay for immediacy.

We decompose the effective spread into the realized spread (RS) and price impact (PI).

$$RS = BuySell * 2 * \frac{price_t - midpoint_{t+s}}{midpoint_t} \quad (3)$$

$$PI = BuySell * 2 * \frac{midpoint_{t+s} - midpoint_t}{midpoint_t} \quad (4)$$

In the above equations, $price$ is the price of an execution, $midpoint$ is the average of the NBO and NBB , t is the time a trade occurred, and $BuySell$ equals 1 (-1) if the trade is buyer (seller) initiated following the Lee and Ready (1991) algorithm.¹⁹

Realized spreads compare the execution price at time t with the midpoint at a later time ($t + s$). We choose 5 minutes for s , which is a common choice in the literature (see, *e.g.*, Hendershott, Jones, and Menkveld, 2011). This variable is a proxy for compensation to market makers or other liquidity providers. The other component of the effective spread, price impact, captures a given trade’s effect on the stock price. The comparison of a future midpoint to the prevailing midpoint at the time of the trade allows us to infer the permanent price change attributable to a given trade. For each firm-day, we compute dollar-weighted averages for effective spread, realized spread, and price impact.

The final measure that we construct, the variance ratio, focuses on how efficiently stock prices incorporate new information. To the extent that stock prices fully and immediately impound

¹⁹ We modify the Lee and Ready (1991) algorithm following the DTAQ procedure outlined in Holden and Jacobsen (2014). Specifically, we lag quote observations by one microsecond, exclude quotes that indicate a locked or crossed market, and supplement the NBBO file using the daily quote file.

new information, one should expect stock returns to follow a random walk and the variance in returns to scale linearly over time. Under these assumptions, the variance ratio (VR) serves as a viable proxy for price efficiency (Lo and MacKinlay, 1988). Specifically, we look at the ratio between 30-minute and 15-minute return variances as in O'Hara and Ye (2011):

$$VR = abs(\frac{Ret_var30}{2*Ret_var15} - 1) \quad (5)$$

We capture the variance of midpoint returns over 30 (15) minute periods as Ret_var30 (Ret_var15). If prices follow a random walk, the variance of 30-minute returns should be twice that of 15-minute returns, and VR should be zero.

Given the nature of microstructure measures, throughout our analysis we winsorize all continuous variables at the 2.5th and 97.5th percentiles of the relevant sample.²⁰ We include a comprehensive list of all variable definitions in Appendix B.

Summary Statistics

In Table 1 (Appendix D) we present pooled summary statistics for our treatment and control stocks.

Variables are measured during the twenty trading days before the 'Tick Size Pilot' began on October 3, 2016. In this period, pilot stocks and their corresponding groups were publicly known, but the various treatment effects had not yet been imposed. We calculate a time series average measure for each stock over the twenty-day period and report the cross-sectional average across all stocks in the sample. Average trade size, dark block trades, depths, market capitalization, traded value, and $VWAP$ are reported as dollar values.

²⁰ Results are qualitatively and quantitatively consistent when winsorizing at the 1st and 99th percentiles.

Table 1 confirms that sample stocks are small- to mid-capitalization firms with mean and median market capitalization of \$614 million and \$346 million, respectively. Stock price (*VWAP*) has a mean of \$22.10 and an interquartile range of \$8.60 to \$29.72. Nasdaq-listed firms account for 73% of the sample and 26% of firms are listed on the NYSE. The average trade size for our sample stocks is \$2,555. Quoted spreads average 80 basis points (\$0.12), while the average effective spread is 50 basis points (\$0.07). We also find that dark trading accounts for a sizeable fraction of sample firms' trading activity and is consistent with commonly-cited estimates for all stocks. The mean (median) value for the percentage of dark trading volume is 34% (32%) with an interquartile range of 26% to 41%.

Empirical Analysis

Research Design

Our research design exploits differential treatments across groups G2 and G3 in the 'Tick Size Pilot'. This setting naturally lends itself to a difference-in-difference framework since the only difference between the two groups is the *Trade-At* provision imposed on G3. Thus, any effects purely derived from the *Trade-At* provision should be detectable by differencing market quality measures between groups G3 and G2. Henceforth, we refer to G3 stocks as "treated" stocks, G2 stocks as "control" stocks, and the post-implementation period as the "treatment" period.

In our main analysis below, we estimate the following regression model using daily stock-level data:

$$Y_{i,t} = \beta_0 + \beta_1 TA_i + \beta_2 Post_t + \beta_3 TA_i * Post_t + \gamma X_{i,t} + \epsilon_{i,t}$$

Variables designed to measure aspects of market quality (e.g., quoted spreads, effective spreads, etc.) are represented by Y . Stocks in the treatment group (G3) have TA equal to one and control

stocks (G2) have TA equal to zero. The indicator variable $Post$ equals one after the ‘Tick Size Pilot’ is implemented and zero otherwise. Thus, our coefficient of interest, β_3 , captures the marginal effect of treatment on G3 stocks. The vector X contains a set of control variables we expand upon below. To the extent that stocks’ assignment to G2 and G3 is random, the vector of control variables should not be necessary. Because the ‘Tick Size Pilot’ was implemented in staggered fashion between October 3 and October 31, 2016, we drop observations during the implementation period and consider the twenty trading days prior to October 3 as the pre-period and the twenty trading days following October 31 as the post period.²¹

Parallel Trends Analysis

Because clean identification is critical for valid inference, we conduct a rigorous set of exercises to demonstrate the validity of our experiment. The first question we address is whether stocks across the treatment (G3) and control (G2) groups systematically differ. The stratified random sampling method employed by the SEC to assign stocks into various groups provides reasonable confidence that stocks across these groups are similar. Nevertheless, we empirically test for differences across G3 and G2 during the twenty trading days leading up to the treatment period, and present our results in Table 2.

Table 2, Panel A shows that *DarkTrading* is similar across treated and control stocks at 34.4% and 34.0%, respectively (p-value of the difference = 0.66). We also compare characteristics used by the SEC in the stratified random sampling procedure (*i.e.* market capitalization, traded volume, and price). Mean differences of these variables confirm that the SEC’s random assignment effectively controls for these variables - none are significantly different across groups. We report

²¹ We drop the shortened trading day on the Friday after Thanksgiving, November 25th, 2016.

differences in mean values of other trading environment variables in Panel B and our main market quality measures (*e.g.*, effective spreads, quoted spreads, etc.) in Panel C. Only four of the twelve variables tested show marginally significant differences – dark block trades, effective spread, price impact, and quoted spread. For example, percentage effective spreads in G3 are stocks, and differences for both effective and quoted spreads are significant at the ten percent level.

While the mean values for several of our variables of interest differ between groups (*e.g.*, effective and quoted spreads), our tests do not require (for valid inference) these levels to be identical during the pre-treatment period. What is required is that these variables display parallel trends during the pre-treatment period – *i.e.*, the differences across groups are stable (Roberts and Whited, 2013). Visual inspection of Figures 1-3 suggests this to be the case for our main independent variable, *DarkTrading*, and two key market quality variables, effective spread and variance ratio. In particular, we are interested in the green line that plots the difference between treatment (G3) and control (G2) groups over the pre-treatment period.

We formally analyze these trends by estimating the model:

$$Y_{i,t} = \alpha_0 + \alpha_1 TA_i + \sum_{\tau \in (-3, -1)} \phi_\tau W_\tau + \sum_{\tau \in (-3, -1)} \lambda_\tau W_\tau * TA_i + \epsilon_{i,t} \quad (7)$$

where TA equals one for treatment stocks (G3) and zero for control stocks (G2), and W_τ references a time dummy variable for each of the three weeks prior to the pilot period (the intercept captures the fourth week). For our purposes, the most important coefficient estimates in the regression are the interactions between TA and the week indicators (W).²² Since the estimate for α_1 captures the

²² Hastings (2004) uses a similar framework to analyze trends in gasoline prices around the vertical integration between retail gas stations and refiners.

average difference between groups, insignificant interaction terms (λ) would indicate constant trends across groups in each week during the pre-Pilot period. As reported in Table 3, this is indeed what we find. Across both dependent and independent variables of interest, we only find one interaction coefficient (out of the eighteen that are tested) that is statistically different from zero. For example, while *DarkTrading* drops and spreads increase during the third week prior to the Pilot (as indicated by the significant W_{-3} term), the changes are similar across groups G3 and G2—the $W_{-3} * TA$ interaction term is insignificant. Overall, our findings suggest both that the SEC tick size pilot does not suffer from any obvious sample selection issues, and that it satisfies the requirements for parallel trends.

Main Analysis

The most striking feature of Figure 1 is that *DarkTrading* for treated stocks (G3) drops from 35% of value traded to about 23% on the first day of the pilot regime. In stark contrast, *DarkTrading* for control stocks (G2) increases slightly. To put the magnitude of this shock into context, we note that the time-series standard deviation of *DarkTrading* is 3% during the pre-period. Thus, the treatment represents a shock exceeding four standard deviations. In addition to being large in magnitude, the difference in dark trading, between treatment and control, persists through the end of the 20-day window. We estimate our main differences-in-differences specification using *DarkTrading* as the dependent variable and present the results in the first column of Table 4. The effect of treatment on the treated is contained within the coefficient estimate for $TA * Post$. Consistent with Figure 1, the interaction coefficient reveals dark trading in G3 dropped by 12.1% (p-value<0.001). This move represents approximately a 34% decline from pre-treatment levels and validates our identification strategy. Moreover, if dark trading has any

impact on market quality, we deem a shock of this size more than sufficiently powerful to uncover the effect.

The sharp contrast between Figure 1 and Figures 2 and 3 succinctly summarizes our main message. Simply put, the shock to dark trading at the Pilot's initiation is not mirrored by any meaningful economic change to market quality metrics. Figure 2 shows effective spreads widen, which is not surprising given the five-fold increase to the minimum tick size for each group. More importantly, spreads change to a similar degree for both groups. Likewise, Figure 3 shows little change to the variance ratio for either treatment or control samples. Overall these graphs present clear visual evidence of a shock to dark trading, but little indication of differential impacts to market quality between treatment and control.

We estimate Equation (6) with market quality measures as the dependent variable and present the results in the remainder of Table 4. The second through sixth columns of the table report coefficient estimates from Equation (6) with no controls, where our dependent variables include effective spread (*ES*), quoted spread (*QS*), price impact (*PI*), realized spread (*RS*), and the variance ratio (*VR*). Consistent with the findings of Rindi and Werner (2017), effective and quoted spreads rise for treated and control stocks after quotes and trades are required to occur in nickel increments. The point estimates for the *Post* dummy coefficient are 17.8 basis points and 25.4 basis points for effective and quoted spreads, respectively. However, our primary interest is the coefficient on *TA * Post*, which describes the unique effect of *Trade-At*. Confirming the patterns in Figures 1 and 2, the introduction of *Trade-At* leads to a precipitous decline in dark trading volume but no discernible effect on effective or quoted spreads. The interaction coefficients are -0.47 basis points and 2.97 basis points, both indistinguishable from zero.

We also investigate the components of the effective spread – the realized spread and price impact. The dramatic shift in dark trading could potentially affect either. Changes in competition for liquidity provision would likely manifest in realized spread, which is commonly viewed as a proxy for market making profit. Forced pooling of informed and uninformed order flow could drive changes in price impact, a common proxy for adverse selection. The results in Table 4 reveal, however, that neither measure is affected by the negative shock to dark trading. While realized spread and price impact increase statistically for each group of stocks, the coefficients on $TA * Post$ are both insignificant. The only market quality variable that appears to be affected is the variance ratio, which increases by 0.0173 (t -statistic=1.88) for G3 when compared to G2. While this change is only marginally significant, this is modest evidence of a loss to price efficiency following restrictions on dark trading.

These main results are surprising in light of the intense policy debate on dark trading. The sharp exogenous drop in dark trading has no impact on the cost of trade. These results stand in stark contrast to those in HKZ (2017), who argue dark trading is detrimental to overall market quality. They are somewhat more in line with O'Hara and Ye's (2011) message that dark trading has neutral to slight positive economic effect on market quality.

While our primary regressions produce valid inference under the assumption that stock assignments to G3 and G2 are random, we attempt to bolster confidence in our tests by including a number of control variables in our difference-in-difference specification. Control variables include market capitalization, price, and trade size, which O'Hara and Ye (2011) show to be related to dark trading, and trading volume, which is known to be related to spread measures. We note that the SEC stratified the sample based on three of these four variables, so the sample selection

already accounts for them in part. We also follow HKZ and select additional control variables that aim to capture inputs to trading decisions.

Variables that might influence the trading decision include the existence of large blocks of liquidity (*DarkBlocks*), volatility (*Volatility*), and asymmetric information (*PIN*). The potential to trade against a block in dark venues might attract order flow. If there are any systematic relationships between the expected cost of an order and the availability of dark block liquidity, we must control for block trades (*DarkBlock*) to avoid attributing such effects to dark trading in general. Another important factor that may influence order routing is trading risk, broadly defined as the risk that orders will execute at disadvantaged prices due to adverse selection or the combination of poor timing and extensive volatility. Orders that are riskier to trade typically generate higher implementation costs. If traders route more orders to lit venues when trading risk is high, then a relationship between risk and transaction costs could be erroneously attributed to dark trading. HKZ emphasize that these controls directly influence inferences, so we include their measures to control for trading risk. The first is a volatility measure (*Volatility*) and the second is the probability of informed trading (*PIN*). The construction of all additional control variables is detailed in Appendix B.

The remaining five columns on the right side of Table 4 report the same difference-in-difference regression with the addition of controls discussed above. With added control variables, our results are nearly identical. We still find no impact to trading costs with a modest reduction in price efficiency, though only marginally significant. These findings imply dark trading has no discernible impact on the cost to trade.

Potential Confounding Effects

While our results show that the dramatic change in dark trading has no impact on market quality, we also consider alternative explanations for the mostly insignificant results. For example, it is possible that dark trading affects market quality, but the large shock we study also influences other aspects of the trading landscape that generate equivalent but offsetting effects. We explore the possibility of confounding effects by estimating Equation (6) for a host of trading characteristics as the dependent variable. We report the results in Table 5, which contrasts the sharp drop in dark trading volume to changes in other important variables that might be related to market quality.

For ease of comparison, we again display the estimates for *DarkTrading* in the first column of Table 5, Panel A. Subsequent columns reveals no significant treatment effect ($TA * Post$) for stock price (*VWAP*). While *Turnover* and *TradeSize* are associated with a statistically significant treatment effect, the economic magnitude of the change is quite small. Specifically, *Turnover* decreases by about 4 basis points relative to the control group, from a pre-treatment average of 59 basis points. Trade size for the treated group declines significantly by \$93 compared to the control group (the pre-treatment average is \$2,841). Juxtaposed against the drop in dark trading volume, these effects are quite small in magnitude and unlikely to materially change market quality.

A more specific concern is that *Trade-At* alters the competitive landscape among lit venues, as discussed in the introduction. Comerton-Forde, Gregoire, and Zhong (2018) describe how inverted fee venues' gain a competitive advantage by offering potential sub-tick price improvements, particularly when the tick size is discrete and dark trading is constrained. Indeed, they show that inverted venue share increased for the *Trade-At* group under the Tick Pilot and

argue that any effect of dark trading on market quality may be confounded by an inverted venue share effect.²³ In Figure 4, Panel A, we corroborate this result by showing inverted venue trading as a share of total trading increases substantially for group G3 relative to G2. We estimate (6) and show in Table 5, Panel B that inverted fee venue share (*InvShare_all*) increases by 3.35%, and this change is statistically significant.

However, this finding may arise mechanically from the dramatic decline in trading on dark venues. If trading that shifts from dark to lit venues is simply allocated across various lit venues according to their pre-Pilot market share, every lit venue's post-Pilot share of total trading will increase. Whether the shift in trading from dark to lit venues is *disproportionately* allocated to inverted venues is an important empirical question that might affect our inferences. To address this issue, we compute inverted venue trading as a fraction of lit exchange volume (*InvShare_lit*). We plot daily values of this variable for groups G3 and G2 around the Pilot in Figure 4, Panel B. The relative change in the re-computed inverted venue share is visually smaller than the shift depicted in Panel A.

We test for statistical differences by estimating (6) with inverted share of lit trading (*InvShare_lit*) as the dependent variable. The coefficient estimate is approximately cut in half to 1.61%. While statistically significant, the coefficient's economic magnitude is small relative to the similar coefficient explaining dark trading. The change in inverted share is $(1.61\% / 12.42\% =) 13\%$ of its pre-Pilot mean. We also note that both groups G3 and G2 have a substantial increase in inverted share of lit trading as the coefficient estimate for the *Post* dummy is 9.33% and highly significant, which represents a $(9.33\% / 12.00\% =) 78\%$ increase relative to the pre-Pilot mean.

²³ Cox, Van Ness, and Van Ness (2017) find that trades and orders migrate from maker-taker to inverted fee venues for stocks with tick size increases.

Thus, any competitive advantage of inverted venues appears more manifest by the increased tick size that occurs for both groups, where trades must occur at nickel increments or greater than through an incremental effect of *Trade-At*. We associate the first order effect of *Trade-At* with changes to dark volume, not to inverted venue competitiveness. We revisit the importance of inverted fee venues in our Subsample Analysis in section below.

A second specific concern is that researchers have found a positive relationship between lit fragmentation and liquidity (Degryse, De Jong, and Van Kervel, 2015). If *Trade-At* induces a reallocation of orders among lit venues (inverted venue effects aside), such that relative market shares change, then confounding inferences could emerge. The extent to which trading activity amongst lit venues changes is an empirical question. To offer a more holistic glimpse of how *Trade-At* affects trade dispersion across lit markets, we estimate the model with lit fragmentation (*Fragmentation*) and the number of lit venues (*LitVenues*) as dependent variables. Our fragmentation measure is similar to the Herfindahl metric in Degryse, De Jong, and Van Kervel (2015).²⁴ We calculate an inverse Herfindahl Index using the market share of dollar volume per displayed venue. The lower bound of this measure (one) indicates all trades occurred within a single venue, while the upper bound is the number of lit venues and would indicate equal market share across them.

For the *Fragmentation* measure, the interaction coefficient is 0.10 and statistically significant at the 5% level, indicating trading becomes slightly more disperse on lit venues. This effect is economically small, as the point estimate is about one-eighth of the standard deviation

²⁴ Degryse, De Jong, and Van Kervel (2015) use one minus the HHI calculation, whereas we use one divided by HHI. Our modification allows for an intuitive interpretation of the variable as trading split evenly across n venues will have a value of n .

reported in Table 1. The *LitVenues* result is similarly small, but opposite in direction. While the number of lit venues show a significant drop, the economic magnitude of 0.08 fewer lit venues is economically trivial. For a trade-based fragmentation measure (not reported), the coefficient on $TA * Post$ is economically quite small and statistically indistinguishable from zero. We interpret the regressions in Table 5, Panel B as evidence that treatment reduced dark trading and that whatever order flow was reallocated among lit venues did not materially alter the relative allocation of trades among lit exchanges. Collectively, the results in this section enforce the feasibility of using the *Trade-At* pilot as a natural experiment and bolster our conclusion that dark trading has no causal effect on market quality.

Replication of HKZ

Earlier studies have been limited to drawing inferences about dark trading without the benefit of a natural experiment. Without an exogenous shock, these studies have attempted to control for potential endogeneity in the form of reverse causality and selection bias. O’Hara and Ye (2011) employ a two-stage Heckman selection model. HKZ augment this method by adding variables to control for traders’ expectations regarding trading risk. Importantly, the inference obtained by HKZ is starkly different than ours – that dark trading harms market quality.

Given the differences in our findings, we explore the possibility that differences either in the time period or the sample of stocks considered (our sample is skewed towards smaller stocks) are responsible for the stark difference in conclusions. Specifically, we replicate HKZ during both their original sample period using their sample of stocks and during our sample period using our sample of stocks. For the replication in our sample period, we pool G3 and G2 stocks during the pre-pilot period. As in HKZ, we estimate both a simple OLS regression and a two-stage Heckman

procedure. While results are similar across both specifications, we concentrate our discussion on the Heckman procedure in the interest of brevity.

The first stage of the Heckman selection model is a probit model that predicts *DarkTrading* and includes independent variables that might influence the trading decision such as *DarkBlocks*, volatility (*Volatility*), and the probability of informed trading (*PIN*). This first stage facilitates the calculation of an inverse mills ratio that, when included in the second stage, corrects for the possibility that traders allocate their orders between lit and off exchange venues based on the difficulty of the order. We present the results in Table 6. For both the OLS model and the two-stage model, *DarkTrading* loads highly significant and positive, implying dark trading increases effective spreads. To interpret marginal effects, a 10% shock to *DarkTrading* predicts effective spread will increase 4.46 bps. In both replications, the estimated marginal effect is almost identical (both quantitatively and qualitatively) to that reported by HKZ. Thus, our differences with HKZ *cannot* be driven by our stock sample or time period. Rather, they are more reasonably attributable to differences in our respective identification strategies.

This comparison of methods highlights the challenge of empirical research within the trading landscape. While OLS analyses likely produce biased coefficient estimates because of endogeneity problems, the Heckman correction model may not sufficiently mitigate these concerns. For the Heckman correction to be correctly specified, there must be at least one unique regressor in the first stage regression that is correlated with the suspect variable (e.g. dark trading) but does not incrementally affect the second stage dependent variable (e.g. effective spreads). Our work and replication highlights the inherent difficulty in selecting instruments and the importance of structured experimentation from the SEC for understanding causal effects in capital markets.

As beneficiaries of such pilot programs, we hope regulators continue to make use of natural experiments to shed light on causal relationships within market microstructure.

Subsample Analysis

Previous studies show differential effects from dark trading in subsamples. Despite our sample being limited to smaller stocks, there is a chance the relationship between dark trading and market quality is concentrated in one particular set of stocks, and pooling all stocks introduces noise that prevents precise inferences. In this section, we analyze subsamples of stocks based a number of stock characteristics to sharpen our tests.

Trading Environment Subsamples

O'Hara and Ye (2011) find that their main results, from a 2008 sample of dark trading, are not homogeneous across listing exchanges or market capitalization subsamples. Similarly, HKZ report that stocks with wide versus narrow quoted spreads respond differently to dark trading volume. In an effort to flesh out our result, we divide stocks into terciles based on a number of different stock characteristics such as firm size, quoted spread, and trading activity. We sample these variables over the second quarter of 2016, which precedes the announcement of the Pilot groupings.

We estimate regression Equation (6) for the top and bottom tercile groups of each variable and present the coefficient for the interaction term ($TA*Post$) in Table 7. As before, we also present the interaction coefficient for *DarkTrading* in the first column to reveal the magnitude of the shock. In each subsample that we analyze, treatment stocks exhibit a substantial drop in *DarkTrading* relative to control stocks ranging from about -10% to about -13%. Thus, in all cases, we expect the shock to provide sufficient power to detect effects on our outcome variables.

Subsamples based on firm size (*MktCap*) and *QuotedSpread* reveal almost no evidence of changes in effective or quoted spreads following the shock to dark trading volume. While liquidity coefficients are uniformly negative for high turnover stocks and mainly positive for low turnover stocks, only three of the eight coefficients are statistically significant (two are significant only at the 10% level). Taken together, these various subsample results lack any cohesive message.

We also consider variation in the lit trading environments across stocks. Such variation may matter because the shock to dark trading that we exploit effectively pushes activity from dark to lit markets, and prior research argues that certain lit market characteristics affect market quality. Degryse, De Jong, and Van Kervel (2015) associate lit market fragmentation with greater depth and tighter spreads in their sample of Dutch stocks. They argue that competition across visible limit order books and the commensurate increase in the number of liquidity suppliers drives these improvements. We split the sample according to *Fragmentation*, which is an inverse Herfindahl Index of trading across lit venues. Stocks in the top *Fragmentation* tercile are those for which pre-pilot lit market trading was most dispersed. Degryse et al's conclusion suggests an improvement to liquidity in the top *Fragmentation* group because dark trading will shift to a highly competitive lit market. The results in Table 7 are directionally consistent with this prediction, though none of the changes to liquidity measures for high *Fragmentation* stocks are statistically significant. In contrast, for the low *Fragmentation* group spreads significantly increase after the shock. Thus, when volume shifts from dark venues to highly concentrated lit markets, liquidity degrades, also consistent with the competition story.

Another prominent feature of modern lit markets is the proliferation of inverted fee venues. By offering sub-penny rebates to liquidity demanders, these venues facilitate trades within the

NBBO at a finer pricing grid. This fee structure is particularly attractive under a *Trade-At* rule that effectively precludes dark executions at the NBBO. Comerton-Forde, Gregoire, and Zhong (2018) report that inverted venue market share indeed increases for G3 stocks, especially for stocks where the nickel tick is a binding constraint, and they associate instrumented inverted venue trading with better liquidity and informational efficiency. We divide our sample into stocks where the nickel constraint does and does not bind. We assign to the binding tick size group stocks with average quoted spread below five cents during the second quarter of 2016, and we assign all others to the non-binding group.

Comparing our results for the binding and non-binding groups offers relevant insights. We see from Table 7 that effective spreads fall by about 6 bps (t -statistic=1.93), and changes in realized spreads are also statistically significant at the 10% level. But since Comerton-Forde, Gregoire, and Zhong (2018) argue that liquidity improvements arising from inverted fee venues are concentrated in the binding tick constraint stocks, it is difficult to disentangle whether the drop in effective spreads that we document can be attributed to a reduction in dark trading or an increase in trading on inverted venues. Fortunately, the non-binding group provides a cleaner picture. The finer pricing grid offered by inverted fee venues is less important for these stocks, so analyzing this subsample highlights a large shock to dark trading (approximately -11.6%) while mitigating concerns of a confounding inverted fee venue effect. The results for this subsample are consistent with the overall message from the full sample that dark trading has little meaningful effect on market quality; coefficients differ in sign across measures, and only one (price impact) is statistically significant at the 10% level.

Decomposing Dark Trading Variable

Our analysis thus far treats all dark trading as homogenous. This choice follows other papers studying U.S. data (e.g., O’Hara and Ye, 2011 and HKZ) and stems from the fact that TAQ data identifies trades that occur off the lit exchanges (Exchange Code = “D”) with no clarification on where they execute. Degryse, de Jong, and van Kervel (2015) similarly categorize dark trading in Dutch stocks. Because numerous types of off-exchange trading venues exist - dark pools, internalizers who purchase retail order flow, and broker-dealers facilitating institutional block trades – this treatment of the data might add noise if the effect of dark trading varies across venue types.

Several studies of non-U.S. dark trading that have the ability to utilize more granular data, either explicitly or implicitly reference dark pools. A key example is Comerton-Forde and Putnins (2015), who analyze dark trading in Australia. Since payment for order flow is prohibited in Australia and these authors account separately for block-size trading, the dark order flow they study likely resembles that in U.S. dark pools. These authors conclude that high levels of non-block dark trading are harmful to market quality, while low levels are either beneficial or benign. In our final analysis, we exploit a new dataset to study stocks where dark pool activity is most prevalent.

FINRA began releasing weekly execution volume by stock for every ATS in the U.S on May 12, 2014 and similar data for non-ATS venues on April 4, 2016. We download these datasets and compute two new weekly variables, *DarkTrading_ATS* and *DarkTrading_nonATS* that decompose a weekly version of our main *DarkTrading* variable.²⁵ The former is share volume

²⁵ We explore the accuracy of our *DarkTrading* decomposition by comparing the difference between weekly trades reported by FINRA (ATS plus non-ATS trades) to TRF trades as reported by TAQ (including opening and closing

across all ATS platforms scaled by total share volume from TAQ, and it proxies for trading in dark pools. The latter, defined as non-ATS share volume scaled by total TAQ share volume, captures internalized retail and institutional flow.

On average, ATS and non-ATS venues both contribute meaningfully to dark trading. The pre-pilot means of *DarkTrading_ATS* and *DarkTrading_nonATS* are 13.6% and 22.6%; the respective standard deviations are 9.2% and 18.9%. Figure 5, Panel A displays *DarkTrading_ATS* for treatment and control stocks during the four weeks before and after the pilot implementation. The x-axis of this figure represents weeks rather than days (as in Figure 1) since the FINRA ATS data is aggregated to the weekly level. Panel B displays an analogous plot for *DarkTrading_nonATS*. One clear result is that both types of dark trading fall dramatically around the Pilot. Compared to the control group, stocks in the treatment group experience a 6.5% drop in *DarkTrading_ATS* and a 5.1% drop in *DarkTrading_nonATS*.

We attempt to isolate the effect of trading in dark pools using two sorting variables. First, we split sample into terciles according to *DarkTrading_ATS*, once again using data from the second quarter of 2016. Comerton-Forde and Putnins (2015) identify a “tipping point” of around ten percent, above which dark trading is harmful. Thus, insofar as our *DarkTrading_ATS* sort separates stocks on either side of a similar tipping point, we hypothesize the shock to dark trading will harm market quality in the top tercile group and improve market quality in the bottom tercile group. We present mean values of relevant variables for each subsample in Table 8, Panel A. The tercile sort produces meaningful separation in dark pool trading. Average *DarkTrading_ATS* in the

auction trades and trades outside of regular trading session hours). For our sample of 660 stocks, the difference between the two averages 0.17% of weekly trading volume and has a standard deviation of 0.34%.

top and bottom tercile groups is 20.5% and 8.9%, respectively, so stocks in the two subsamples straddle the tipping point inferred by Comerton-Forde and Putnins (2015).

We estimate a weekly version of the difference-in-difference regression from Equation (6) for the top and bottom tercile groups and present the coefficient for the interaction term ($TA*Post$) in Table 8, Panel B. As before, we present the interaction coefficient for *DarkTrading* in the first column to reveal the magnitude of the shock, and now also include results for *DarkTrading_ATS* and *DarkTrading_nonATS*. Stocks in both the top and bottom terciles experience about a 6% drop in *DarkTrading_ATS*, which should be sufficiently powerful to detect market quality effects. For the high *DarkTrading_ATS* stocks, the signs on each liquidity measure are consistent with market quality improvements, but only the coefficient for realized spread is statistically significant. In contrast, for the low *DarkTrading_ATS* group, changes to effective spread, quoted spread, and price impact are all positive, and the change is statistically significant for quoted spread and price impact.

Similar shocks to ATS and non-ATS trading within each subsample may contribute to the weak statistical significance reported above. In our second tercile split, we attempt to isolate the shock to ATS trading. Here, we split according the ratio of *DarkTrading_ATS* to *DarkTrading_nonATS*. We again present mean values of relevant variables within subsamples in Table 8, Panel A. Average *DarkTrading_ATS* is 19.6% for top tercile stocks and 9.3% for those in the bottom tercile. The weekly differences-in-differences analysis that is presented in Panel B reveals different shocks to ATS and non-ATS trading for stocks within the top and bottom tercile groups. In the top tercile, ATS trading falls by 7.7% while non-ATS trading only falls by 3.6%. In

contrast, ATS trading within the bottom tercile drops 5.6% compared to the non-ATS drop of 7.6%.

Table 8, Panel B shows, however, that the market quality changes with ATS/non-ATS terciles resemble those in the *DarkTrading_ATS* terciles both in magnitude and statistical significance. Thus, even in subsamples that prior literature suggests will contain the strongest market quality effects, our tests fail to detect material changes. Our overall conclusion from the subsample analyses in Tables 7 and 8 is that while the tick pilot generated massive shocks to trading on dark venues, market quality effects are economically and statistically benign.

Chapter I Conclusion

Our main message is that a large shift in trading from dark to lit venues around the 2016 Tick Size Pilot had no meaningful impact on standard measures of market quality. This finding should inform policy makers worldwide in the midst of ongoing discussion of the potential benefits and dangers of dark trading. The academic literature to date lacks a cohesive empirical voice, no doubt due to the endogenous nature of trade routing decisions, as well the fact that dark venues, in addition to lacking pre-trade transparency, often utilize a more granular pricing grid than is available in lit markets. We circumvent these concerns by exploiting an exogenous shock to dark trading that, when compared to the appropriate counterfactual, is distinct from any differences in the pricing grid.

We acknowledge our insignificant results have alternative interpretations. For example, the shift in dark trading may result in countervailing and roughly offsetting effects on market quality. However, when we analyze changes in other trading characteristics (*e.g.*, turnover, inverted venue share of lit trading, and the dispersion of trading across lit venues) that may relate to market quality,

we find that such changes, when statistically significant, are economically modest compared to the drastic shift in dark trading. Thus, while we cannot rule out a perfectly offsetting effect, we find this interpretation less plausible than the simple message that dark trading is mostly benign.

It is important to note the conclusion that dark trading is largely innocuous to market quality does not imply that it is either inconsequential or uninteresting. For the 327 G3 firms over the twenty days following the Pilot's implementation, aggregate dark trading drops by about \$4.5 billion from its level during the twenty days prior to the pilot. From the perspective of dark pool operators and exchanges alike, the ultimate destination of these trades and policies that alter this flow are quite meaningful as it determines who receives rents from market-making. Moreover, since trading algorithms often employ top-level choices of whether to include dark venues, frictions that alter the myriad of routing decisions may prove costly by way of implementation.

Finally, our insignificant results prompt additional analysis at the trader level. None of the various metrics we calculate represent sufficient statistics for the welfare of a representative trader. Data at the trader level would be useful in this regard as one could construct measures that better describe realized investor experience. The work of Jones and Lipson (2001) examining how the change from eighths to sixteenths affected institutional trading costs offers a useful template. We encourage future researchers to follow this path.

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Appendices: Chapter I

Appendix A: Example of *Trade-At*

Example 1

Across all (lit) markets for security ABC, the highest bid price is \$20.00 and the lowest offer price is \$20.10. Exchange1 is displaying a bid to buy 100 shares at \$20.00. Exchange2 is displaying a bid to buy 100 shares at \$19.95. There are no other displayed quotes from buyers.

Meanwhile, DarkPool1, which as a dark venue does not display quotes, has an order to buy 800 shares of ABC at \$20.00 and an order to sell 800 shares at \$20.10. DarkPool1 receives an order to sell 100 shares of ABC at the market price. Since dark venues do not display quotes, DarkPool1 must either execute the 100 share sell order at \$20.05 or route the order to a trading that is currently displaying the highest quoted bid price. Given the two orders at DarkPool1, in order to execute the 100 share sell order, the dark pool would need to buy 100 shares at \$20.05 and sell 100 shares at \$20.00, resulting in a \$5.00 loss. As a result, DarkPool1 is unable to fill 100 shares by partially filling their buy order against the 100 share sell order. If the stock was not subject to the *Trade-At* provision, DarkPool1 could have filled the order rather than execution taking place on an exchange venue.

Under the same conditions, if DarkPool1 received an order to sell 300 shares at the market, DarkPool1 could execute 200 shares, after routing 100 shares to Exchange1. This is because, after routing an order to sell 100 shares to Exchange1, there are no other bids quoted at \$20.00. Once DarkPool1 fulfills its *Trade-At* obligation to route orders to sell as many shares as are currently bid at the lowest quoted price, DarkPool1 can execute the remaining shares with their own buy orders at \$20.00.

Appendix B. Variable Definitions

	Variable	Description	Source
	<i>DarkTrading</i>	Dollar value traded in undisplayed markets (identified in TAQ as execution destination equals 'D'), divided by total consolidated dollar value traded. Measure is at the stock day level using all trades executed during the regular trading session.	TAQ
	<i>AskDepth</i>	Average value of interest quoted at the national best offer price (NBO), during the regular trading session, calculated as the daily time-weighted mean per stock.	TAQ
	<i>BidDepth</i>	Average value of interest quoted at the national best bid price (NBB), during the regular trading session, calculated as the daily time-weighted mean per stock.	TAQ
Variables of interest	<i>ES</i>	<i>Effective spread</i> . Calculated as the absolute value of twice the difference between execution price and the prevailing midpoint (trades exempt from RegNMS rule 611 are excluded). Dollar-weighted averages are calculated for each stock-day. Expressed either in dollars or as a percentage scaled by the prevailing midpoint.	TAQ
	<i>PI</i>	<i>Price impact</i> . Calculated as a buy/sell indicator multiplied by twice the difference between execution price and prevailing midpoint five minutes after the trade. Dollar-weighted averages are calculated for each stock-day. Expressed either in dollars or as a percentage scaled by the prevailing midpoint at the time of execution.	TAQ
	<i>QS</i>	<i>Quoted spread</i> . Calculated as the NBO minus NBB, for each consolidated quote observed. Time-weighted averages are computed for each-stock day. Expressed either in dollars or as a percentage scaled by the prevailing midpoint.	TAQ
	<i>RS</i>	<i>Realized spread</i> . Calculated as a buy/sell indicator multiplied by twice the difference between midpoint five minutes after the trade and the prevailing midpoint at execution time. Dollar-weighted averages are calculated for each stock-day. Expressed either in dollars or as a percentage scaled by the prevailing midpoint at the time of execution.	TAQ

Variable	Description	Source
<i>VR</i>	<i>Variance ratio</i> . Calculated as absolute value of the daily mean ratio of variance of 30 second midpoint returns divided by twice the variance of 15 second midpoint returns, minus one.	TAQ
<i>DarkBlocks</i>	Measure of day stock level block trades in undisplayed markets, calculated as the sum of dollar value of block trades, where block trades are any regular session execution valued at greater than the top 1% of trades evaluated over the period of April 1st through June 30th 2016. When used as a regressor we follow Hatheway, Kwan, & Zheng (2017) and scale by total dollar volume traded in dark venues.	TAQ
<i>DarkTrading_ATS</i>	Calculated as total shares traded across all ATS venues scaled by total share volume, measured per stock week.	FINRA, TAQ
<i>DarkTrading_nonATS</i>	Calculated as total shares traded across dark venues that are not registered ATS venues scaled by total share volume, measured per stock week.	FINRA, TAQ
<i>InvShare_lit</i>	Measure of trading at venues with inverted fees, i.e. liquidity suppliers pay a fee on executions and liquidity demanders receive a rebate. Calculated as the dollar value traded in inverted markets (during our sample period BATS-Y, EDGA, and Nasdaq BX are the only inverted venues in operation), divided by total consolidated dollar value traded across all displayed trading venues. Measure is at the stock day level using all trades executed during the regular trading session.	TAQ
<i>InvShare_all</i>	Measure of trading at venues with inverted fees, i.e. liquidity suppliers pay a fee on executions and liquidity demanders receive a rebate. Calculated as the dollar value traded in inverted markets (during our sample period BATS-Y, EDGA, and Nasdaq BX are the only inverted venues in operation), divided by total consolidated dollar value traded. Measure is at the stock day level using all trades executed during the regular trading session.	TAQ

Variable	Description	Source
<i>MktCap</i>	Market capitalization is the product of shares outstanding and daily closing price, for pre period evaluations, we use the last market capitalization available from CRSP in June 2016. When used as a regressor, we take the natural log.	CRSP
<i>NYSE</i>	Dummy variable set to one if a stock is listed on the NYSE as of October 31, 2016.	CRSP
<i>LitVenues</i>	Number of lit venues with trades.	TAQ
<i>PIN</i>	Measure of ex-ante trading risk from asymmetric information that estimates the probability of informed trading (Pin) following Easley, Kiefer, & O'Hara (1997). Trades are categorized as buyer or seller initiated following Lee & Ready (2001), quotes and trades are matched following Holden & Jacobsen (2014), and trades exempt from RegNMS rule 611 are excluded.	TAQ
<i>TradeSize</i>	Dollar value executed scaled by number of trades executed, measured at a stock day level. When used as a regressor, we follow Hatheway, Kwan, & Zheng (2017) and scale by the average trade size per stock over the pre-pilot period.	TAQ
<i>TradedValue</i>	Sum of dollar value executed. When used as a regressor, we take the natural log.	TAQ
<i>Trades</i>	Count of number of executions.	TAQ
<i>Turnover</i>	Measures daily trading activity per stock, calculated as the sum of shares executed divided by shares outstanding.	CRSP, TAQ
<i>UninfSupply</i>	Proxied using the share of stock day order imbalances not explained by stock day returns. Calculated as the residual from a pooled regression over all stock days for a given period, regressing absolute dollar value imbalances on absolute returns, following Hatheway, Kwan, & Zheng (2017).	CRSP, TAQ

Variable	Description	Source
<i>Volatility</i>	Proxied using the daily mean per stock of standard deviations of midpoint returns using the prevailing quote at each second over the 30 seconds following each trade during the regular trading session (excluding trades exempt from RegNMS rule 611), following Hatheway, Kwan, & Zheng (2017).	TAQ
<i>VWAP</i>	Volume weighted average prices are calculated using all executions during the regular trading session, scaling dollar value executed by shares executed.	TAQ

Appendix C. Chapter I Figures

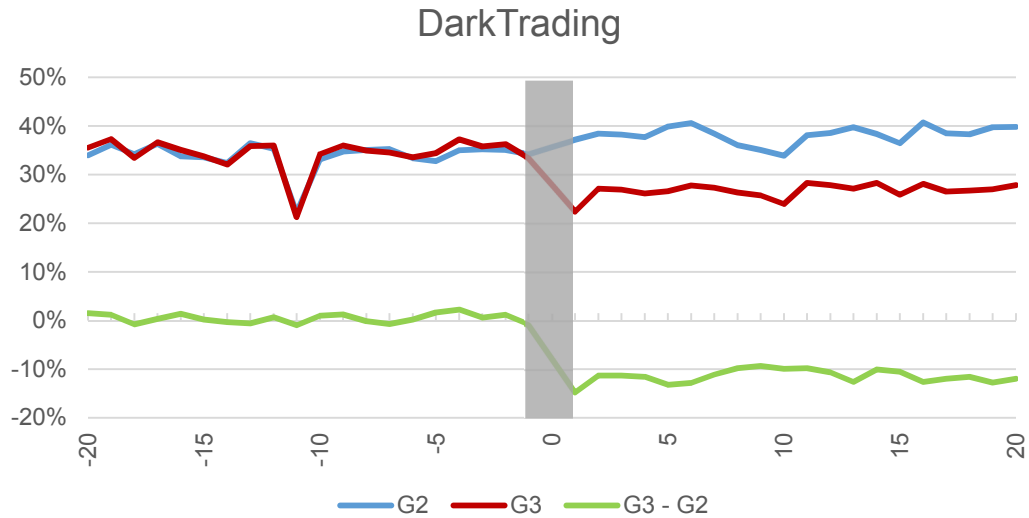


Figure 1. The effect of Trade-At on dark trading.

This figure plots the mean share of dollar volume executed in dark trading venues for our control and treatment stocks. G2 represents our control stocks and G3 represents our treatment group. We also plot the difference in variance ratio, between control and treatment groups. The tick size pilot was implemented gradually from October 1st until October 31st, which was the first trading day in which the pilot is fully enacted. We drop the implementation period from our data but present this period by a gray vertical bar. The plot is in calendar time, tracking 20 days up until implementation begins, and 20 days subsequent to the pilot being fully implemented. Variables are defined in Appendix B, *DarkTrading* is winsorized at 2.5th and 97.5th percentiles.

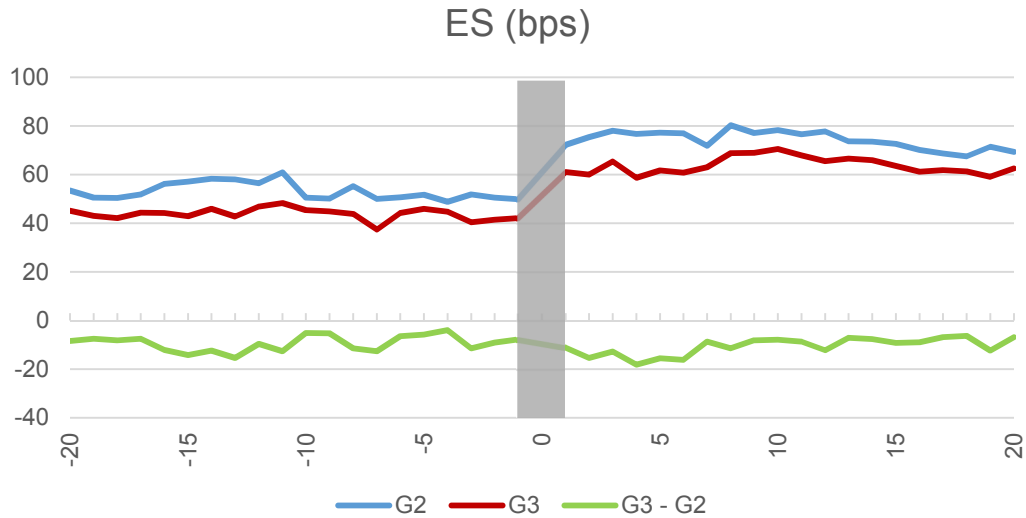


Figure 2. The effect of Trade-At on transaction costs.

This figure plots the mean effective spread of stocks for our control and treatment stocks. G2 represents our control stocks and G3 represents our treatment group. We also plot the difference in variance ratio, between control and treatment groups. The tick size pilot was implemented gradually from October 1st until October 31st, which was the first trading day in which the pilot is fully enacted. We drop the implementation period from our data but present this period by a gray vertical bar. The plot is in calendar time, tracking 20 days up until implementation begins, and 20 days subsequent to the pilot being fully implemented. Variables are defined in Appendix B, effective spreads are winsorized at 2.5th and 97.5th percentiles.

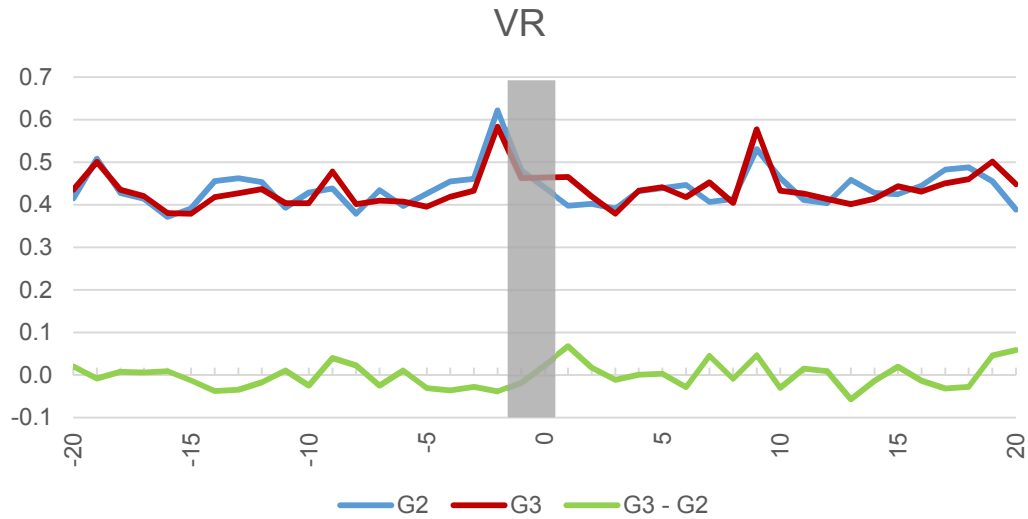


Figure 3. The effect of Trade-At on price efficiency.

This figure plots the mean variance ratio of stocks for our control and treatment stocks. G2 represents our control stocks and G3 represents our treatment group. We also plot the difference in variance ratio, between control and treatment groups. The tick size pilot was implemented gradually from October 1st until October 31st, which was the first trading day in which the pilot is fully enacted. We drop the implementation period from our data but present this period by a gray vertical bar. The plot is in calendar time, tracking 20 days up until implementation begins, and 20 days subsequent to the pilot being fully implemented. Variables are defined in Appendix B, variance ratios are winsorized at 2.5th and 97.5th percentiles.

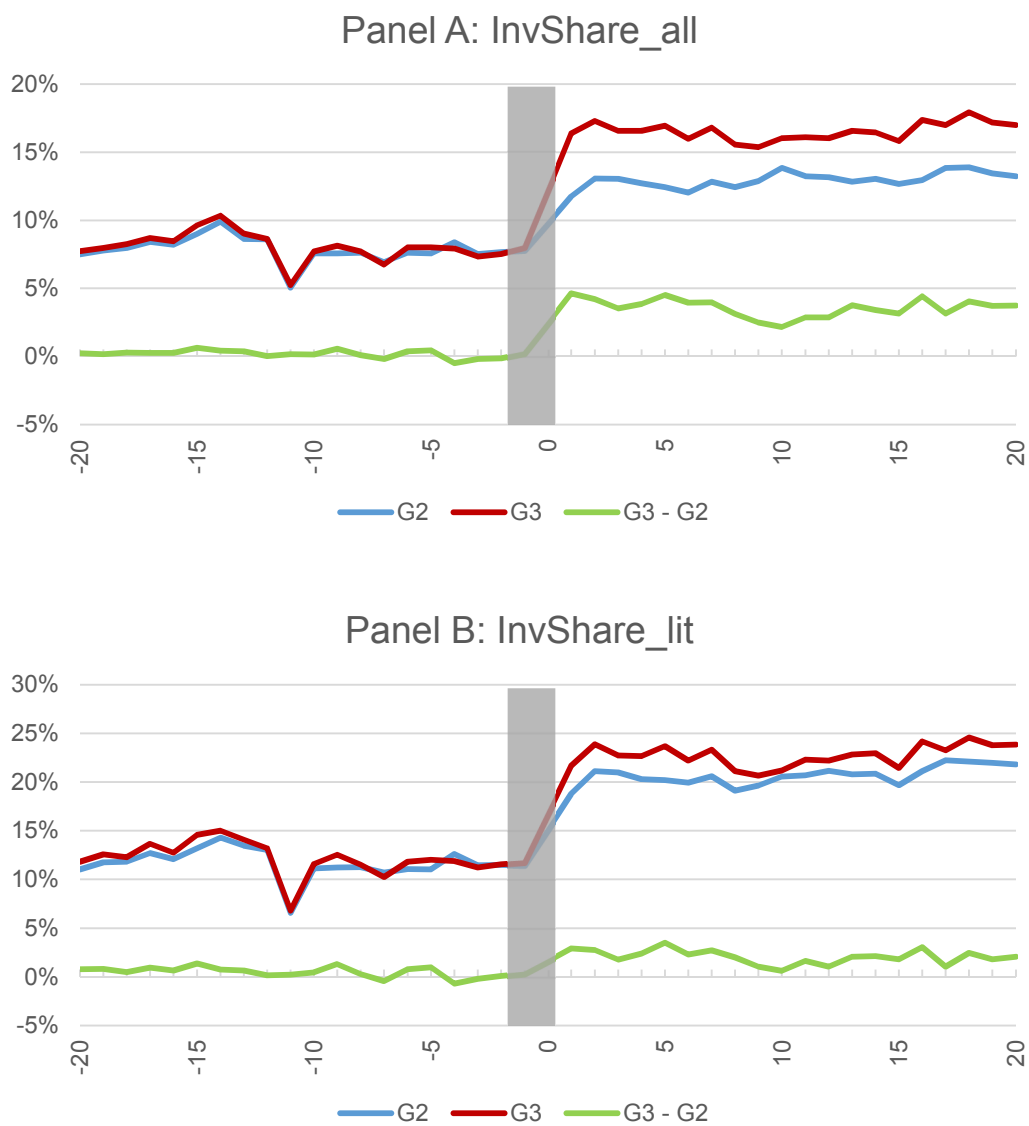


Figure 4. Comparing the effects of Trade-At between dark and inverted trading.

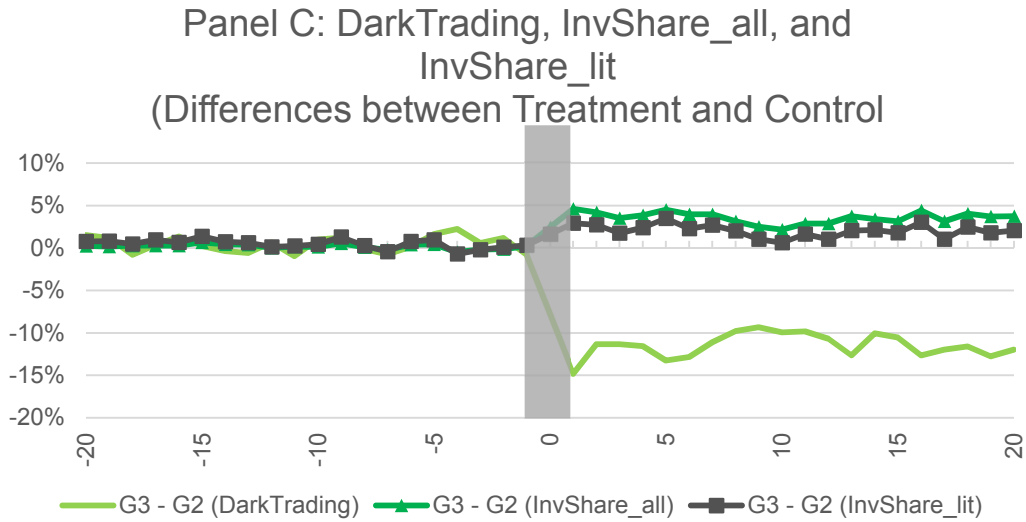


Figure 4, continued.

Panel A plots the share of dollar volume executed on inverted venues scaled by total value traded (*InvShare_all*). Panel B plots the share of dollar volume executed on inverted venues scaled by all lit executions (*InvShare_lit*). Panel C plots differences between control and treatment groups for: DarkTrading, *InvShare_all*, and *InvShare_lit*. G2 represents our control stocks and G3 represents our treatment group. We also plot the difference between control and treatment groups. The pilot was implemented gradually from October 1st until October 31st, the first trading day in which the pilot is fully enacted. We drop the implementation period but presented this period by a gray vertical bar. The plot is in calendar time, tracking 20 days up until implementation begins, and 20 days subsequent to the pilot being fully implemented. Variables are defined in Appendix B and winsorized at 2.5th and 97.5th percentiles.

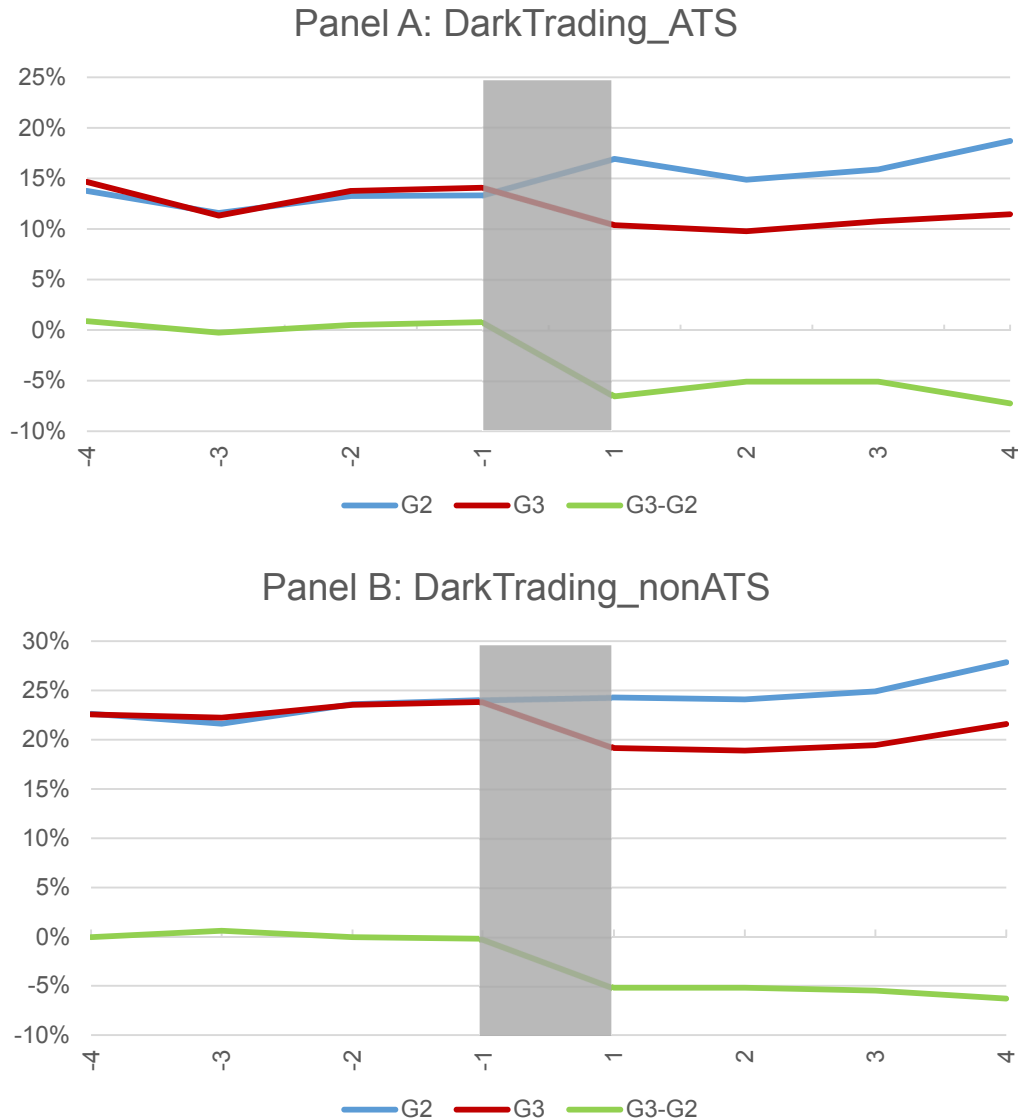


Figure 5. The effect of TradeAt on segments within dark trading.

Panel A plots the proportion of share volume executed on ATS venues scaled by total shares traded (*DarkTrading_ATS*). Panel B plots the proportion of share volume executed on non-ATS dark venues scaled by total shares traded (*DarkTrading_nonATS*). G2 represents our control AAstocks and G3 represents our treatment group. We also plot the difference between control and treatment groups. The pilot was implemented gradually from October 1st until October 31st, the first trading day in which the pilot is fully enacted. We drop the implementation period but present this period by a gray vertical bar. The plot is in calendar time, tracking four weeks up until implementation begins, and four weeks subsequent to the pilot being fully implemented. Variables are defined in Appendix B.

Appendix D: Chapter I Tables

Table 1. Summary Statistics

Panel A	N	Mean	Std Dev	Q1	Median	Q3
<i>MktCap</i>	660	613,526	629,410	121,684	345,767	946,020
<i>NYSE</i>	660	0.26	0.44	0.00	0.00	1.00
<i>Trades</i>	660	1,473	1,590	213.575	926.65	2,313
<i>TradedValue</i>	660	4,716,634	6,613,603	301,926	1,876,548	6,033,475
<i>Turnover</i>	660	0.0058	0.0051	0.0020	0.0044	0.0076
<i>VWAP</i>	660	22.10	18.14	8.60	17.02	29.72
Panel B	N	Mean	Std Dev	Q1	Median	Q3
<i>DarkTrading</i>	660	0.3418	0.1053	0.2648	0.3178	0.4076
<i>DarkBlocks</i>	660	541,044	835,776	36,106	200,068	679,413
<i>Fragmentation</i>	660	3.25	0.88	2.64	3.22	3.90
<i>InvShare_lit</i>	660	0.1176	0.0469	0.0805	0.1282	0.1508
<i>InvShare_all</i>	660	0.0787	0.0363	0.0477	0.0876	0.1059
<i>TradeSize</i>	660	2,555	1,722	1,282	2,131	3,249
Panel C	N	Mean	Std Dev	Q1	Median	Q3
<i>ES (bps)</i>	660	49.90	65.05	9.51	20.53	61.02
<i>ES (\$)</i>	660	0.07	0.09	0.02	0.03	0.08
<i>QS (bps)</i>	660	79.76	100.18	16.80	35.84	96.85
<i>QS (\$)</i>	660	0.12	0.15	0.03	0.06	0.14
<i>PI (bps)</i>	660	19.00	16.70	7.54	12.85	25.27
<i>RS (bps)</i>	660	29.33	49.31	1.52	5.12	34.84
<i>VR</i>	660	0.4363	0.0835	0.3815	0.4345	0.4899

This table reports summary statistics for the cross-section of stocks from the SEC's tick pilot that we study, Pilot groups G2 and G3. The variable *MktCap* and the *NYSE* dummy are measured as of June 30, 2016. All other variables are first averaged at the stock level over the 20 day period before the pilot (September 2nd through the 30th, 2016). Variables are winsorized at 2.5th and 97.5th percentiles, and defined in Appendix B.

Table 2. Treatment and Control Differences, Pre-Pilot Period

Panel A	G2	G3	G3 - G2	
	(N = 333)	(N = 327)		
	Mean	Mean	Diff	p-value
<i>DarkTrading</i>	0.3395	0.3440	0.0045	0.656
<i>MktCap</i>	579,141	648,542	69,402	0.157
<i>TradedValue</i>	4,352,297	5,087,656	735,359	0.141
<i>VWAP</i>	21.55	22.65	1.09	0.319

Panel B	G2	G3	G3 - G2	
	(N = 333)	(N = 327)		
	Mean	Mean	Diff	p-value
<i>TradeSize</i>	2474	2638	164	0.220
<i>DarkBlocks</i>	476,904	606,361	129,456**	0.047
<i>Fragmentation</i>	3.23	3.27	0.04	0.600
<i>InvShare_lit</i>	0.1153	0.1199	0.0046	0.211
<i>InvShare_all</i>	0.0778	0.0796	0.0018	0.522

Panel C	G2	G3	G3 - G2	
	(N = 333)	(N = 327)		
	Mean	Mean	Diff	p-value
<i>ES (bps)</i>	54.73	44.98	-9.75*	0.054
<i>QS (bps)</i>	87.29	72.10	-15.18*	0.051
<i>PI (bps)</i>	20.28	17.69	-2.59**	0.046
<i>RS (bps)</i>	32.33	26.26	-6.07	0.114
<i>VR</i>	0.4403	0.4323	-0.01	0.222
<i>AskDepth (\$)</i>	6,032	6,280	248	0.396
<i>BidDepth (\$)</i>	5,746	6,084	338	0.205

This table reports univariate analysis of stock traits over four weeks prior to pilot launch, comparing our control group (G2) with the *Trade-At* treatment group (G3). For all variables except *MktCap*, which is sampled on June 30, 2016, the sample includes daily stock-level observations from the 20 day period prior to pilot launch (September 2nd through the 30th, 2016). Variables are winsorized at 2.5th and 97.5th percentiles, and defined in Appendix B. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 3. Pre-Pilot Trends

	<i>DarkTrading</i>	<i>ES</i>	<i>QS</i>	<i>PI</i>	<i>RS</i>	<i>VR</i>
<i>TA</i>	0.0079 (0.0091)	-7.78* (4.60)	-12.41* (7.20)	-2.71* (1.43)	-3.77 (3.58)	0.0064 (0.0122)
<i>W-3</i>	-0.0306*** (0.0045)	4.19** (1.65)	4.7* (2.46)	3.01*** (0.93)	1.07 (1.68)	0.0030 (0.0119)
<i>W-2</i>	-0.0065 (0.0052)	-3.16* (1.82)	-3.17 (2.69)	1.25 (1.10)	-4.21** (1.70)	(0.0084) (0.0111)
<i>W-1</i>	-0.0064 (0.0055)	-4.49** (1.86)	-4.03 (2.79)	0.09 (1.03)	-3.76** (1.77)	0.0636*** (0.0128)
<i>TA * W-3</i>	-0.0080 (0.0066)	-1.96 (2.24)	-0.29 (3.10)	-0.3 (1.27)	-2.42 (2.28)	(0.0259) (0.0167)
<i>TA * W-2</i>	0.0004 (0.0072)	1.87 (2.54)	2.39 (3.58)	-0.37 (1.40)	1.99 (2.43)	(0.0065) (0.0168)
<i>TA * W-1</i>	0.0011 (0.0076)	2.5 (2.53)	4.16 (3.84)	0.92 (1.36)	0.62 (2.46)	(0.0375)** (0.0178)
<i>Intercept</i>	0.3492*** (0.0066)	48.79*** (3.47)	78.22*** (5.41)	19.14*** (1.13)	28.11*** (2.64)	0.4276*** (0.01)
Observations	12,610	12,610	12,610	12,610	12,610	12,610
R-squared	0.008	0.005	0.004	0.004	0.002	0.005

This table reports estimates of Equation (7) by regressing the dependent variables in the top row on indicator variables for stocks assigned to the treatment group (*TA*), week fixed effects for all four of the five day periods before the pilot began (*W*), and interactions between the treatment indicator variable and each week fixed effect. The sample includes stock-day observations for the 20-day period prior to the Pilot (September 2nd through September 30th, 2016). The weekly dummy indicators W_k for $k = 1, 2, 3$ refer to observations k weeks prior to the Pilot. Variables are winsorized at 2.5th and 97.5th percentiles, and defined in Appendix B. Standard errors are clustered on firm and date, and appear in parentheses. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 4. Impact of Trade-At on Market Quality

	<i>DarkTrading</i>		<i>ES</i>		<i>QS</i>		<i>PI</i>		<i>RS</i>		<i>VR</i>		<i>ES</i>		<i>QS</i>		<i>PI</i>		<i>RS</i>		<i>VR</i>	
<i>Post</i>	0.0363	***	17.75	***	25.39	***	9.21	***	7.75	***	-0.0068		18.34	***	27.43	***	7.94	***	9.96	***	-0.0101	
	(0.0080)		(2.04)		(3.15)		(0.95)		(1.55)		(0.0151)		(1.88)		(3.06)		(0.85)		(1.59)		(0.0148)	
<i>TA</i>	0.0063		-7.2	*	-10.87	*	-2.66	**	-3.74		-0.0109	**	-3.4	*	-4.84		-1.43	*	-1.22		-0.0124	**
	(0.00)		(4.17)		(6.56)		(1.27)		(3.02)		(0.0054)		(2.05)		(3.26)		(0.79)		(1.68)		(0.0053)	
<i>TA * Post</i>	-0.1206	***	-0.47		2.97		0.68		-1.66		0.0173	*	0.18		4.02		1.4293		-2.04		0.0160	*
	(0.00)		(2.42)		(3.79)		(1.17)		(1.83)		(0.0094)		(2.14)		(3.43)		(1.07)		(1.66)		(0.0092)	
<i>DarkBlocks</i>													-5.45	**	-11.63	***	-7.65	***	5.45	**	0.0252	**
													(2.56)		(4.05)		(1.28)		(2.17)		(0.0119)	
<i>Volatility</i>													3.28	***	4.68	***	1.77	***	0.94	***	0.0001	
													(0.21)		(0.32)		(0.13)		(0.14)		(0.0001)	
<i>MktCap</i>													-5.52	***	-8.77	***	-6.78	***	1.08		-0.0101	*
													(1.88)		(2.91)		(0.85)		(1.32)		(0.0056)	
<i>PIN</i>													182.25	***	261.67	***	30.78	***	132.3	***	-0.0827	**
													(19.59)		(31.59)		(7.54)		(16.55)		(0.0417)	
<i>VWAP</i>													-5.26	**	2.26		-4.43	***	-0.65		0.0011	
													(2.40)		(3.58)		(0.83)		(1.77)		(0.0046)	
<i>TradeSize</i>													5.93	**	13.16	***	4.8	***	1.64		-0.0081	
													(2.50)		(3.87)		(1.20)		(2.14)		(0.0112)	
<i>TradedValue</i>													-10.32	***	-20.44	***	2.09	***	-12.75	***	0.0149	***
													(1.06)		(1.61)		(0.44)		(0.88)		(0.0028)	
<i>Intercept</i>	0.3383	***	47.96	***	77.63	***	20.23	***	26.41	***	0.4419	***	269.03	***	459.92	***	121.73	***	157.47	***	0.4449	***
	(0.0088)		(3.20)		(4.92)		(1.02)		(2.26)		(0.0124)		(30.18)		(46.38)		(12.40)		(23.39)		(0.0834)	

Table 4, continued.

	<i>DarkTrading</i>	<i>ES</i>	<i>QS</i>	<i>PI</i>	<i>RS</i>	<i>VR</i>	<i>ES</i>	<i>QS</i>	<i>PI</i>	<i>RS</i>	<i>VR</i>
<i>Observation</i>	24,657	24,657	24,657	24,657	24,657	24,657	24,657	24,657	24,657	24,657	24,657
<i>R-squared</i>	0.064	0.02	0.019	0.025	0.006	0.001	0.622	0.646	0.309	0.42	0.007

This table reports estimates of a difference in difference model as in Equation (6). We regress the dependent variables in the top row on indicator variables for dates after the pilot is implemented (*Post*), stocks assigned to the treatment group (*TA*), and the interaction between these indicator variables (*TA * Post*), which represents the effect of treatment on the treated. Observations span 20 days before and after pilot implementation, September 2nd through November 29th, 2016, excluding the staggered implementation from October 1st through October 30th. Variables are winsorized at 2.5th and 97.5th percentiles, and defined in Appendix B. Standard errors are clustered on firm and date, and appear in parentheses. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 5. Impact of the Trade-At Provision

Panel A	<i>DarkTrading</i>	<i>Turnover</i>	<i>TradeSize</i>	<i>VWAP</i>
<i>Post</i>	0.0363*** (0.0080)	0.0011*** (0.0003)	257** (85)	1.07*** (0.20)
<i>TA</i>	0.0063 (0.0008)	0.0001 (0.0004)	158 (134)	1.28 (1.54)
<i>TA * Post</i>	-0.1206*** (0.0045)	-0.0004* (0.0002)	-93*** (19)	-0.18 (0.32)
<i>Intercept</i>	0.3383*** (0.0088)	0.0059*** (0.0003)	2,598*** (140)	22.84*** (1.06)
Observations	24,657	24,657	24,657	24,657
R-squared	0.064	0.006	0.004	0.001
Panel B	<i>InvShare all</i>	<i>InvShare lit</i>	<i>Fragmentation</i>	<i>LitVenues</i>
<i>Post</i>	0.0539*** (0.0027)	0.0933*** (0.0046)	0.61*** (0.09)	0.32*** (0.03)
<i>TA</i>	0.0013 (0.0027)	0.0042 (0.0034)	0.01 (0.06)	0.09 (0.13)
<i>TA * Post</i>	0.0335*** (0.0028)	0.0161*** (0.0004)	0.1** (0.04)	-0.08* (0.04)
<i>Intercept</i>	0.0811*** (0.0028)	0.12*** (0.0042)	3.31*** (0.09)	8.35*** (0.09)
Observations	24,657	24,657	24,657	24,657
R-squared	0.273	0.271	0.070	0.006

This table reports estimates of a difference in difference model as in Equation (6). We regress the dependent variables in the top row on indicator variables for dates after the pilot is implemented (*Post*), stocks assigned to the treatment group (*TA*), and the interaction between these indicator variables (*TA * Post*). Thus the effect of treatment on the treated is the estimated coefficient on *TA * Post*. Observations span 20 days before and after pilot implementation, September 2nd through November 29th, 2016, excluding the staggered implementation from October 1st through October 30th. Variables are winsorized at 2.5th and 97.5th percentiles, and defined in Appendix B. Standard errors are clustered on firm and date, and appear in parentheses. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 6. OLS and Heckman Correction Estimates - Impact of Dark Trading on Transaction Costs

	OLS	Heckman Correction	
	<i>ES</i>	<i>DarkTrading</i> (First Stage)	<i>ES</i> (Second Stage)
<i>IMR</i>			8.89
			-10.71
<i>DarkTrading</i>	42.29***		44.61***
	-6.52		-7.2
<i>DarkBlocks</i>	-10.99***	0.89***	-5.79
	-3.26	-0.15	-7.23
<i>Volatility</i>	28,463.94***	-27.85	28,399.42***
	-2,907.84	-17.66	-2,934.64
<i>PIN</i>	207.39***	0.75***	211.82***
	-23.16	-0.2	-24.14
<i>VWAP</i>	3.98***	-0.03*	3.27*
	-1.54	-0.02	-1.78
<i>TradeSize</i>	10.49***	-0.07	10.41***
	-3.46	-0.2	-3.6
<i>TradedValue</i>	-12.26***	-0.01	-12.53***
	-1.03	-0.01	-1.1
<i>MktCap</i>		-0.17***	
		-0.02	
<i>UninfSupply</i>		-1.02***	
		-0.11	
<i>Constant</i>	140.88***	2.94***	134.03***
	-14.06	-0.37	-15.31
Observations	12,610	12,610	12,610
R-squared	0.608	0.418	0.608

This table reports estimates of the relationship between dark trading and transaction costs over the 20 day period before the tick size pilot was implemented (September 2nd through September 30th, 2016). The first column estimates an OLS model. The second column reports estimates of the first-stage of the Heckman correction model, where the dependent variable is the inverse normal of *DarkTrading*. The third column mirrors the OLS specification with the exception of including the inverse mills ratio (*IMR*) estimated in the first-stage Heckman regression (correcting for sample selection). Both columns one and three use effective spread as the dependent variable. Variables are as defined in Table 1. Variables are winsorized at 2.5th and 97.5th percentiles, and defined in Appendix B. Standard errors appear in parentheses, and for the first and third column are clustered on firm and date. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 7. Stock Trait Subsamples and the Impact of Dark Trading on Market Quality

		<i>DarkTrading</i>	<i>ES</i>	<i>QS</i>	<i>PI</i>	<i>RS</i>	<i>VR</i>
<i>MktCap</i>	Top	-0.0994*** (0.0091)	-1.1573 (1.0810)	-0.6563 (1.4495)	-0.9088 (0.6966)	-0.0486 (0.4587)	0.0478** (0.0205)
	Bottom	-0.1336*** (0.0066)	0.7300 (3.4930)	6.9977 (5.5717)	3.0064* (1.7744)	-3.5031 (2.8483)	0.0016 (0.0111)
<i>Quoted spread</i>	Top	-0.1316*** (0.0101)	0.8332 (5.5201)	8.7357 (9.2328)	5.9359** (2.7775)	-7.2993* (4.4107)	0.0207* (0.0123)
	Bottom	-0.1062*** (0.0064)	-1.6286 (1.3485)	-0.3404 (1.8089)	-1.4400* (0.8511)	-0.2136 (0.6712)	0.0395*** (0.0136)
<i>Turnover</i>	Top	-0.1189*** (0.0064)	-4.9848* (3.0213)	-2.4170 (4.1575)	-1.7137 (1.4180)	-3.1551* (1.8569)	0.0155 (0.0158)
	Bottom	-0.1244*** (0.0085)	5.2065 (5.1182)	9.7073 (8.6520)	6.1465** (2.4493)	-2.5961 (4.4614)	0.0058 (0.0126)
<i>Fragmentation</i>	Top	-0.1226*** (0.0071)	-5.3634 (3.3308)	-3.0669 (5.0263)	-2.0633 (1.6111)	-2.7026 (2.2234)	0.0115 (0.0165)
	Bottom	-0.1063*** (0.0079)	10.8291** (4.5878)	18.6797** (7.5374)	7.3076*** (2.2793)	0.9797 (3.8550)	0.0125 (0.0118)
<i>Nickel bind</i>	True	-0.1309*** (0.0060)	-6.4317* (3.3310)	-4.6358 (4.9878)	-1.8328 (1.4288)	-4.3316* (2.4577)	0.0193 (0.0158)
	False	-0.1157*** (0.0056)	2.4699 (2.6307)	6.5052 (4.4563)	2.7672* (1.4902)	-1.7016 (2.1915)	0.0151 (0.0106)

This table reports coefficient estimates of the effect of treatment on the treated ($TA*Post$) based on daily difference-in-difference regressions. The time period covers September 2nd through November 29th 2016, excluding October. Additional regressors, omitted for brevity, include indicator variables for the post period ($Post$) and selection into the treatment group (TA). In regressions using market quality dependent variables control variables are included identical to Table 4. The top row contains the dependent variable for each regression. The first column lists the stock traits used to split the sample. For each trait there is a row reporting estimates obtained in regressions limited to stocks in the *Top* (*Bottom*) tercile for that trait. The only exception is the row labelled *Nickelbind*, which divides the sample into stocks with an average quoted spread above (below) a nickel, denoted as True (False). Subsamples were formed using cross-sectional means calculated over the second quarter of 2016. Variables are winsorized at 2.5th and 97.5th percentiles, and defined in Appendix B. Standard errors are clustered on firm and date, and appear in parentheses. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 8. Dark Heterogeneity and the Impact of Dark Trading on Market Quality

Panel A		DarkTrading		DarkTrading_ATS		DarkTrading_nonATS		DarkTrading_ATS / DarkTrading_nonATS		
DarkTrading_ATS	Top			0.3736		0.2051		0.1665		1.644
	Middle			0.3465				0.1905		1.058
	Bottom			0.4439		0.0894		0.3501		0.429
DarkTrading_ATS / DarkTrading_nonATS	Top			0.3337		0.1956		0.1364		1.802
	Middle			0.3538		0.1579		0.1929		0.986
	Bottom			0.4765		0.0943		0.3777		0.344

Panel B		DarkTrading		DarkTrading_ATS		DarkTrading_nonATS		ES		QS		PI		RS		VR	
DarkTrading_ATS	Top	-0.1248 (0.0075)	***	-0.0636 (0.0073)	***	-0.0622 (0.0088)	***	-4.2931 (2.6438)		-1.3049 (4.5140)		-0.9865 (1.2546)		-4.0182 (1.8726)	**	0.0095 (0.0119)	
	Bottom	-0.1270 (0.0084)	***	0.0598 (0.0050)	***	0.0611 (0.0142)	***	6.8774 (5.2868)		14.3520 (8.4414)	*	6.5867 (2.5291)	**	-0.5501 (4.0085)		0.0112 (0.0162)	
DarkTrading_ATS / DarkTrading_nonATS	Top	-0.1115 (0.0071)	***	-0.0769 (0.0079)	***	-0.0358 (0.0026)	***	-3.1560 (1.8323)	*	-3.8298 (2.8299)		-1.6086 (0.9102)	*	-2.1250 (1.3642)	*	0.0367 (0.0105)	
	Bottom	-0.1373 (0.0095)	***	-0.0560 (0.0062)	***	0.0760 (0.0144)	***	6.3580 (5.4274)		15.7865 (8.6087)	*	7.4055 (2.6141)	** *	-3.1010 (4.2519)		0.0084 (0.0124)	

This table reports mean statistics for heterogeneity within dark trading and coefficient estimates for subsamples based on dark trading heterogeneity. Panel A reports means for the proportion of all trading taking place in all dark venues (*DarkTrading*), only ATS dark venues (*DarkTrading_ATS*), only non-ATS dark venues (*DarkTrading_nonATS*), and the ratio of ATS to non-ATS dark trading (*DarkTrading_ATS / DarkTrading_nonATS*). Means are reported for each subsample of stocks, terciles formed on the variable in the first column. Panel B reports coefficient estimates for the effect of treatment on the treated (*TA*Post*) based on difference-in-difference regressions. Regression of *DarkTrading_ATS* and *DarkTrading_nonATS* use stock week observations over the last four weeks in September preceding the pilot, and first four weeks after the pilot was fully implemented. All other models use stock day observations over the period September 2nd - November 29th 2016, excluding October. Additional regressors, omitted for brevity,

Table 8, continued.

include indicator variables for the post period (*Post*) and selection into the treatment group (*TA*). In regressions using market quality dependent variables control variables are included identical to Table 4. The top row contains the dependent variable for each regression. The first column lists stock traits used to split the sample. For each trait a row reports estimates obtained in regressions limited to stocks in the *Top (Bottom)* tercile for that trait. Subsamples were formed using cross-sectional means calculated over the second quarter of 2016. Variables are winsorized at 2.5th and 97.5th percentiles defined in Appendix B. Standard errors appear in parentheses, clustered on firm and date or week. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels.

CHAPTER II
DARK TRADING, FRAGMENTATION AND TAIL EVENTS

Ryan Farley

Abstract

Using newly released data from FINRA, I characterize the locus of trading for all stocks across dark and lit trading venues (termed the “liquidity map”). I then investigate whether a stock’s “liquidity map” affects its resiliency during extreme market declines. Stocks with more fragmented volumes are associated with narrower spreads and lower volatility. The magnitudes of these effects are two to three times stronger for fragmentation among dark pool venues compared to lit fragmentation. Consistent with a competition story, reductions in transaction costs are driven by lower realized spread among more fragmented stocks. Dark pool volumes are also associated with more liquidity and less volatility. Conversely, dark volumes traded away from dark pools relate to increased volatility. In tests limited to variables available before the FINRA data, I find that earlier proxies for dark trading and fragmentation yield incomplete or erroneous inferences. Thus my results underscore the benefits of regulatory efforts to make dark trading more transparent.

Keywords: Market Fragmentation, Microstructure, Market Efficiency

JEL codes: G1

Introduction to Chapter II

Investors care most about liquidity when it is scarce, for example when liquidating assets in a market downturn. During a market decline, liquidity can suddenly dry up, increasing price volatility (Brunnermeier & Pedersen 2008). Depressed asset prices tighten capital constraints on intermediaries as the value of their holdings decline, resulting in margin calls, leading to further reductions in liquidity supply (Comerton-Forde, Hendershott, Jones, Moulton, & Seasholes 2010). When less liquidity is supplied by intermediaries, stocks with more liquidity provided by institutional investors fare better during a market shock (Anand, Irvine, Puckett, & Venkataraman 2013). Meanwhile falling prices induce redemptions of mutual fund shares, and as portfolio managers decide which stocks to sell, herding causes incremental reductions to prices and liquidity (Dennis & Strickland 2002). The response to market shocks by economic agents is an important determinant of how stocks weather a downturn. However, we know comparatively little about how market structure impacts the propagation of an aggregate shock in the cross section.

Dark trading and fragmentation are pervasive facets of modern market structure. In 1993, the NYSE executed 79% of shares in listed firms, but only 30% in recent years as trading has become increasingly disperse across a fragmented marketplace.²⁶ Conversely, “dark trading” (i.e. trades executed away from exchanges) has grown over the same period, now accounting for over one third of US equity trading volumes.²⁷ Within dark trading there are currently 46 registered Alternative Trading System venues (ATS), commonly referred to as “dark pools”.²⁸ Dark pools execute about 15% of trading volumes, but on a given week some stocks transact in as many as 39

²⁶ In my sample period, NYSE market share of NYSE listed firms is 29.78%. Historical estimates come from the SEC’s 1994 report, “Market 2000” (<https://www.sec.gov/divisions/marketreg/market2000.pdf>).

²⁷ In the past two decades it is estimated dark trading volumes rose from 5% to 40% (Angel Harris, & Spatt 2015).

²⁸ As of February 28th, 2019 (<http://www.finra.org/industry/equity-ats-firms>).

dark pools while other stocks transact in none. Given the cross sectional variation and prevalence of dark trading and fragmentation, it is certainly possible that trading heterogeneity impacts how stocks weather aggregate market shocks. Dark trading and fragmentation may stabilize markets during downturns, by increasing competition between liquidity suppliers within and across trading venues. Alternatively, higher search costs in dark markets may cause stocks typically trading across a host of dark venues to be worse off during times of market stress. Searching more venues delays execution, increasing uncertainty, as more time allows prices to move further from levels that induced a decision to trade. My study attempts to test these competing theories to learn about the effects of dark trading and fragmentation in the cross section of stocks for extreme down days on the market.

Overall my findings indicate that dark trading and fragmentation can help explain how market shocks impact individual securities. I find that on big down days in the aggregate market, when market returns are below two standard deviations of the mean, stocks with greater fragmentation are more liquid and less volatile. Estimated benefits are two to three times larger for fragmentation among dark venues. Moreover, greater execution volumes in dark pools are also tied to lower volatility and trading costs. Liquidity improvements are driven by reductions to realized spread, consistent with benefits deriving from increased competition. Interestingly, performing the same analysis using proxies available to earlier researcher yields different inferences, underscoring the importance of accounting for heterogeneity within dark trading.

This study is the first to my knowledge to examine this research question, and is made possible by a public dataset provided by FINRA (a US regulator of broker dealers), which

attributes trading volumes to individual dark pools at the stock-venue level.²⁹ Earlier work proxied for dark trading and fragmentation using aggregate dark volumes (O'Hara & Ye 2011; Hatheway, Kwan, & Zheng 2017) or dispersion among lit venues (Degryse, De Jong, & van Kervel 2015; Haslag & Ringgenberg 2016).³⁰ However, these proxies are indirect and noisy for measuring variation within dark trading or fragmentation among dark venues. As a result, prior studies were unable to leverage the considerable cross sectional variation in where dark trading occurs (Ready 2014; Buti, Rindi, & Werner 2017; among others) to explain market quality outcomes. Given a more nuanced picture of where stocks trade, we can better understand how market structure affects market efficiency.

Where a stock trades could influence market quality, because market mechanisms and counterparties vary greatly among dark trading venues (Tuttle 2013; Tuttle 2014; Farley, Kelley, & Puckett 2019). Given the heterogeneity in dark venues and cross sectional variation in where stocks trade, if the location of trading is persistent, it is feasible for past information mapping out trading volumes to explain how stocks fare during aggregate market shocks. I confirm there is considerable persistence in variables describing where stocks are traded.³¹

To examine the effects of dark trading and fragmentation under a negative market shock, I construct a “liquidity map” for each stock in my sample by calculating variables that describe proportional volumes over different market segments, and dispersion within them. For proportional measures, I calculate market shares of trading volumes in a given segment of the dark

²⁹ FINRA began providing this and other data on dark trading as of May 12, 2014 (<http://www.finra.org/industry/otc-%28ats-%26-non-ats%29-transparency>).

³⁰ Dark volumes are coded with exchange “D” in public trade data feeds, but without attribution to any specific dark venue. Conversely, lit venues report trades to the same feed using their unique exchange code.

³¹ In autoregressive analysis of sample stocks, the average AR1 coefficients for variables describing where a stock trades range from 0.94 to 0.96.

market scaled by total executed shares. Specifically, I use dark trading venue attribution data from FINRA to separate dark trading into dark pool volumes and what I term “elevator” volumes (comprised of upstairs trading and internalization). Additionally, I calculate an inverse Herfindahl-based measure to quantify fragmentation overall, among exchange venues (“lit fragmentation”), and dark pools (“dark fragmentation”).³² In the spirit of Dennis & Strickland (2002) and Hameed, Kang, & Viswanathan (2010), I identify event days of extreme market decline when returns to the CRSP value-weighted index are more than two standard deviations below the sample period mean.³³ For each event, I construct a pre-event window from five weeks up until one week prior to the event. Liquidity map variables and controls for stock characteristics are measured over the pre-event window, and used to explain liquidity, volatility, and returns on event days. I also analyze returns over periods subsequent to event days. Within this setting, using lagged regressors mitigates the concern of simultaneity bias to infer causal relationships between a stock’s liquidity map and its resilience in facing a market decline.

My primary empirical tests regress market quality measures on a stock’s liquidity map. I find evidence of benefits associated with dark trading and fragmentation. Additionally, by comparing results using variables from before the FINRA data was available with FINRA’s more granular data, I find that aggregated dark trading volumes provide an incomplete picture. When using the share of aggregate dark volumes, available to earlier work, I find dark trading increases spreads and volatility. However, by isolating volumes to dark pool executions, I draw the opposite inference. I estimate a one standard deviation increase in dark pool volumes reduces effective

³² This fragmentation measure, based on dispersion of trading volumes, follows: Bennett & Wei (2006); Nguyen, Van Ness, & Van Ness (2007); Degryse, De Jong, & van Kervel (2015); and others.

³³ Results are qualitatively similar when considering alternative definitions of extreme market declines, such as declines to: the CRSP equal-weighted index, overnight returns to SPY, and intraday returns of sample stocks.

spread during a market decline by 1.58 to 1.85 basis points (bps) and is related to lower volatility. Conversely, dark trading outside of dark pools (e.g. high frequency trading internalization and bilateral negotiations) is positively related to illiquidity costs and volatility. These findings suggest it is necessary to examine individual aspects of the dark market in order to avoid potentially deleterious policy prescriptions. Consistent with this proposition, in addition to looking at the size of segments of the dark market I also study dispersion within them.

More fragmented stocks are more liquid and less volatile during times of market stress. However, using fragmentation measures available before the FINRA data underestimates the benefits. In regressions of market quality measures on both lit and dark fragmentation, the effects of dark fragmentation are estimated to be two to three times the magnitude of lit fragmentation. For example, a one standard deviation increase to dark (lit) fragmentation corresponds to a 2.54 (1.05) bps reduction to effective spread. Reductions in effective spread are driven by declines in realized spread, consistent with competition reducing profits from liquidity provision.

In analysis on price dislocations, I find evidence that more fragmented stocks experience larger price declines on days the aggregate market experiences a large decline. In subsequent analysis, I find limited evidence this price response is consistent with investor overreaction in smaller firms. Overall my findings provide strong evidence that market structure matters for how a stock weathers a market decline and the return process that follows.

A considerable number of studies examine implications of the heterogeneity documented among liquidity providers (Acharya & Viswanathan 2011), but this paper is the first to my knowledge to study effects of heterogeneity within dark trading and fragmentation during periods

of market stress.³⁴ Given the reduced fees and enhanced rebates provided by exchanges to obligatory market makers, when they scale down liquidity provision during a market decline (Comerton-Forde, Hendershott, Jones, Moulton, & Seasholes 2010), there is a more even playing field to supply liquidity (Clark-Joseph, Ye, & Zi 2017). Increased urgency among investors and reduced participation by obligatory market makers, offers revenue opportunities for voluntary liquidity providers (Anand, Irvine, Puckett, & Venkataraman 2013). I view my results as complementary to this story. I find that stocks with higher dark pools volumes and stocks with more fragmented trading offer greater liquidity and less volatility in times of stress. Conversely, while higher search costs might be expected from dark trading due to reduced execution probability (Zhu 2014), I do not find evidence of search frictions reducing liquidity or increasing volatility during market declines (Duffie, Garleanu, & Pedersen 2007). My contribution hinges on new data about dark trading volumes, made available in an effort by regulators to increase the transparency of dark trading. Thus, my findings illustrate how this initiative provides a valuable opportunity to improve our understanding of how market structure impacts investment outcomes.

The remainder of the paper is organized as follows. Section 2 discusses background information on current market structure. Section 3 explains the details of my sample and measures. Section 4 discusses my empirical analysis. Section 5 presents robustness tests, and Section 6 concludes.

Market Structure

The defining characteristic of dark trading is that, whereas traders can observe the prices and sizes available to trade against in exchanges (“lit venues”), trading interest is completely

³⁴ A contemporaneous working paper, Felez-Vinas (2018), offers complementary results, finding lit fragmentation improves quoted spread and depth within the context of adverse market conditions. Dark trading is outside the scope of her study which is focused on impacts to the consolidated order book from additional quoting venues.

unobservable in dark venues. Dark trading is comprised of two segments. ATs (also known as “dark pools”) and the over-the-counter (OTC) market. Dark pools execute trades by matching compatible orders within their undisclosed electronic limit order book. Regulators require that a firm be a broker-dealer to operate a dark pool, however some operators register as such without conducting other business typical to brokers (e.g. trading on behalf of clients). Most dark pools match orders electronically based on price-size-time priority, while lit venues prioritize orders by price-time-size. Though originally marketed to institutional investors interested in trading large orders with other institutions, in recent years average trade sizes have decreased in dark pools while potential counterparties broadened to include broker-dealers, retail investors, and high frequency trading firms (HFT).³⁵ While dark pools receive the lion’s share of press coverage, the majority of dark trading takes place in the OTC market. Historically, the term “OTC” has been used to describe unlisted stocks, Nasdaq-listed stocks, trading off-exchange, trading off-exchange but not in a dark pool, and upstairs market trading.³⁶ To avoid this confusion, I instead adopt the term “elevator” for trades occurring away from lit and dark pool venues. Thus, elevator describes a combination of trading via manual human interaction in upstairs markets and automated “internalizing” by HFTs.

The more modern segment of the elevator market encompasses internalizer venues operated by HFTs. Internalizers use high speed, sophisticated short horizon trading algorithms to consider whether or not to expend capital to execute against each new order as it arrives. The economics involved mirror the capital commitment transactions of traditional market makers. However, the decision whether to commit capital leverages a comprehensive view of firm

³⁵ Dark pools can limit access to their venue and discuss counterparty “quality” in marketing materials. For example, Luminex (<https://luminextrading.com/how-it-works/>)

³⁶ FINRA’s view on the term OTC: <https://www.finra.org/investors/unraveling-mystery-over-counter-trading>

inventory and market conditions across asset classes. A significant share of executions on internalizer venues come from payment-for-order-flow arrangements with large retail brokerages, and most retail executions are against HFT internalizers (Comerton-Forde, Malinova & Park 2018 and others). The remainder of elevator trading occurs in the upstairs market with very different mechanisms and counterparties.

In the upstairs market, trading is accomplished via bilateral bargaining. Brokers either “shop” client orders to find offsetting trading interest among other institutional customers, or provide liquidity from their own inventory. The defining trait of the upstairs market is transacting via communication between humans away from any exchange. While trading in upstairs markets is quite different from internalizer venues, distinguishing between these types of trades is limited with available data.

Dark trades are reported to the public through an intermediary called a trade reporting facilities (TRF). In terms of post trade transparency, while all trades are reported in real time, only executions in lit venues disclose the specific venue where a transaction takes place. Historically, the operators of these TRFs, NYSE and Nasdaq, did not distinguish between off-exchange trades and executions from their own order books. This meant researchers were completely unable to observe dark trading. In 2008, regulators began requiring TRFs to report dark trades using the destination code “D” to distinguish dark trades from other transactions. This level of granularity facilitated initial research in the area (O’Hara & Ye 2011). However, since researchers had no ability to observe venue allocations within dark trading, researchers treated it as a homogenous market segment. In 2014, FINRA undertook an initiative to increase the transparency of dark trading. This initiative resulted in the first highly granular, publicly available dataset that details where dark trading takes place.

Data

My sample begins with the universe of NYSE and Nasdaq listed CRSP common stocks (share codes 10 and 11) with available data on event days. Event days are defined as any trading day where there is a negative two sigma move in the aggregate market.³⁷ I proxy for the aggregate market using the CRSP value-weighted index, which has a mean return of 0.028% over my sample period. Based on this event criteria, there are 43 event days where the CRSP value-weighted index declines by more than my cutoff (-1.630%). I exclude stocks with a volume-weighted average price (VWAP) below \$3.00 or above \$999.00 over a four week pre-event period prior to a given event day. Stocks that have traded less than 10 days during a pre-event period are also excluded. All analysis relies on TAQ data to calculate liquidity measures and variables describing a stock's trading environment over the pre-event period. Thus, stocks without sufficient TAQ data for relevant time periods are also dropped. The data required to attribute dark trading volumes to specific market segments and trading venues became available from FINRA as of May 12th, 2014. My main regression model requires lagged data as far back as five weeks prior to a given event date. As a result, my sample period covers June 16th, 2014 to December 31st, 2018. The resulting sample is an unbalanced panel covering 3,398,449 stock- days, comprised of 4,129 unique firms. Definitions for all variables are available in Appendix A.

My main data comes from a transparency initiative undertaken by the US Financial Industry Regulatory Authority (FINRA). The data became available as of May 12th, 2014 motivated by concerns that dark trading was too opaque and potentially harmful. FINRA provides the number of trades and shares executed per stock-week for every US dark pool. FINRA also

³⁷ This is slightly more conservative than Hameed, Kang, & Viswanathan (2010) who use 1.5 standard deviations as their cutoff criteria for significant market down days.

provides “elevator” market volumes, but it is not possible to distinguish between HFT internalizers from the upstairs market. This is because often the largest share of elevator volumes come from venues that execute less than 200 trades in a given stock-week. FINRA aggregates these trades and categorizes them as “de minimis” without attributing specific trading venues. Despite this limitation, venue level dark pool volumes provide considerable insight.

Figure 6 (Appendix B) demonstrates the granularity of the FINRA data compared to data available to earlier work. Panel A presents proportional volumes per market segment for four stocks during for the week of June 16th, 2014. NYSE’s Trade & Quote data (TAQ) facilitates calculating venue level volumes, but only for lit venues. While all dark trades are included in TAQ and disseminated publicly in real time, they are labelled as dark without disclosing a specific venue. The purple portions of the pie charts analogously represents aggregate dark volumes. Before the FINRA data was available, all that could be observed in TAQ was the difference between lit (yellow) and dark (purple) volumes. With the data from FINRA, heterogeneity within dark trading is now observable. In bar charts corresponding to a given pie chart, I use the FINRA data to disaggregate dark trading into dark pool and elevator volumes, blue and red respectively. For example, 33% and 20% of volumes for HSP and MKL respectively traded in the dark with two thirds executed in dark pools and the remaining third in elevator venues. Before the FINRA data there was no way to differentiate between the portions of dark trading taking place in dark pools versus elevator venues.

In Panel B, I present venue level market shares within dark pool volumes, none of which is observable via TAQ. Here we see HSP had notably higher volumes in half a dozen or so of the 33 dark pools where it traded, with at most 2.22% of total volumes from any one venue.

Meanwhile, MKL had 40% of dark pool volumes from only one of the 25 dark pools where it traded. Before the FINRA data was available none of this nuance was observable.

To measure a stock's liquidity map I calculate variables describing proportional market shares of different market segments and dispersion within them. Aggregate dark trading volumes come from TAQ which I scale by total volumes to measure aggregate dark trading (*DarkTrd*). I decompose dark volumes between dark pools (*DarkPool*) and elevator markets (*Elev*) by summing volumes from FINRA, by total volumes in TAQ.³⁸ Dispersion measures use an HHI-based method:

$$FRAG = 1 / \sum (\frac{shares_i}{\sum(shares_i)})^2 \quad (1)$$

Thus, *FRAG* is the inverse of the sum of squared market shares within a given market segment, such that the lower bound is one (for completely consolidated trading), and the upper bound is the number of venues that exist (implying perfectly uniform volumes).³⁹ I calculate this measure over all lit and dark pool venues (*Frag*), only lit venues (*FragLit*), and only dark pool venues (*FragDark*). FINRA data reports at the stock-week level, while TAQ reports at the stock-day level. Therefore, merging this data requires aggregating daily TAQ data at the weekly level. Thus all liquidity map variables are constructed at the stock-week level (e.g. *FragLit* uses lit venue market shares for a given week calculated using daily TAQ data).⁴⁰

Panel A of Table 9 provides summary statistics for liquidity map variables, grouped by NYSE market capitalization quintile. The first three columns detail proportional measures,

³⁸ Elevator data is only available from FINRA starting April 6th, 2016. In earlier periods I infer this variable by subtracting dark pool volumes from aggregate dark trading.

³⁹ Rather than subtracting the HHI concentration by one as in Degryse, De Jong, & van Kervel (2015) and Haslag & Ringgenberg (2016), by dividing one by HHI concentration (following Fidessa 2006) I allow lit and dark fragmentation to take on different ranges, reflecting the existence of many more dark pools than exchanges.

⁴⁰ There are some stock-weeks where reconciling volume statistics between TAQ and FINRA appear erroneous. I filter out stock-weeks where dark pool or elevator volumes exceed off-exchange volumes reported by TAQ (1% of observations). I also filter out stock-weeks where the sum of dark pool and elevator volumes exceed aggregated dark volumes reported by TAQ if the difference is at least five percent of total traded shares (2% of observations).

followed by three measures of fragmentation. While *DarkTrd* can be calculated using only TAQ data, *DarkPool* and *Elev* are only observable using the FINRA data. Similarly, out of my fragmentation measures, only *FragLit* could be observed using TAQ data while *Frag* and *FragDark* require data from FINRA. By looking at how these liquidity map variables relate to firm size, it is apparent that the FINRA data reveals considerable nuance not available using TAQ data alone.

Consistent with previous findings, Table 9 shows that in my sample dark trading accounts for 36.26% of volumes, with 14.97% from dark pools and 23.22% from elevator markets.⁴¹ Using TAQ data, it was already possible to observe that aggregate dark volumes decrease as size increases. However using the FINRA data, we learn the relationship between dark pool shares and size appears non-linear while elevator volumes have an inverse relationship with size (similar to aggregate dark trading). For the smallest stocks, two thirds of dark trading takes place in elevator markets. For larger stocks, the split between dark pools and elevator venues is much more even. Meanwhile, the positive relation between *FragLit* and size was observable using only TAQ data, though with the FINRA data, we learn there is much more variation in *FragDark* between size quintiles. Beyond motivation to control for size in regression analysis, these statistics offer evidence of systematic differences between these variables.

Dependent variables are constructed to measure market quality. Liquidity and volatility measures use TAQ and daily returns come from CRSP. My main measure of liquidity is effective spread. If the midpoint is a “fair price”, then effective spread measures a trader’s willingness to pay for immediacy, calculated as:

⁴¹ For example, Menkveld et al. (2017) reports that of the third of volumes executed in dark venues, dark pools account for about 15% of total volumes.

$$ES = 2 * \frac{abs(price_t - midpoint_t)}{midpoint_t} \quad (2)$$

I also decompose effective spread into price impact (*PI*) and realized spread (*RS*), typical proxies for liquidity costs related to adverse selection and profits to liquidity suppliers, respectively:

$$PI = BuySell * 2 * \frac{midpoint_{t+s} - midpoint_t}{midpoint_t} \quad (3)$$

$$RS = BuySell * 2 * \frac{price_t - midpoint_{t+s}}{midpoint_t} \quad (4)$$

In the above equations, price is the price of an execution, midpoint is the average of the *NBO* and *NBB*, *t* is the time a trade occurred, and *BuySell* equals 1 (-1) if the trade is buyer (seller) initiated following the Lee and Ready (1991) algorithm. Specifically, I follow Holden and Jacobsen (2014) using one microsecond lags for matching quotes and trades, and incorporating TAQs quote file with their NBBO file. I use 30 second lags to compute *PI* and *RS*. Therefore, my liquidity variables capture dollar-weighted stock-day averages for effective spread, price impact, and realized spread. I measure stock-day volatility as the standard deviation of returns over all executions in a regular trading session. Abnormal returns use DGTW benchmarks, relying on CompuStat data to form book-to-market portfolios.

In Panel B of Table 9, I present traits and market quality measures of sample stocks. The mean stock has a market capitalization of nearly \$6B, with a standard deviation of \$25B. In this broad group of firms, 37% are listed on NYSE, with the average stock trading over 7,000 times a day, executing over \$53B in volumes. The median effective spread is 17.96 bps or \$0.036, compared to quoted spreads of 32.23 bps or \$0.064. Similar to statistics concerning size, liquidity measures exhibit large standard deviations and positive skew. Volatility is also positively skewed,

with mean and medians of 0.30% and 0.11% respectively. Looking at the cross section over the entire sample period provides a reference point for trading conditions on event days.

Table 10 presents descriptive statistics on event dates, i.e. days when the market experiences a negative two-sigma event. Statistics pertaining to all event dates are presented in Panel A. Panel B presents mean values aggregated by year. The value-weighted market return on event days is -1.93%, slightly smaller than the -2% criteria for extreme market declines in Dennis & Strickland (2002). Compared to liquidity measures over the entire sample period in Table 9, median effective and quoted spread are nearly doubled on event days, as is volatility. Additionally, in Table 9 market quality variables exhibit significant positive skewness, but on event days the distribution appears much more symmetrical. Trading costs and volatility are lower in the third quartiles on event days compared to typical days from Table 9. However, compared to Table 9, the first quartile of spreads and volatility is much higher on event days. Panel B indicates spreads, volatility and returns look fairly consistent for event days falling in different years. Also, there is evidence of event clustering, with 10 (20) event dates in 2016 (2018).

Since FINRA's dark trading data facilitates novel measures of a stock's liquidity map (where it trades), it is worth considering how these variables relate to earlier proxies and other aspects of the trading environment. Table 11 presents correlation coefficients across liquidity map, market quality, and stock trait variables. Earlier work proxied for dark trading and fragmentation with the proportion of aggregate dark trading (*DarkTrd*). However, correlations are weak and negative between *DarkTrd* and fragmentation measures with estimates of -0.22, -0.01, and -0.22 for *Frag*, *FragLit*, and *FragDark* respectively. Another proxy used in prior work is *FragLit*. This proxy is highly correlated with *Frag* and *FragDark*, with coefficients of 0.76 and 0.45. The strong correlation between *FragLit* and *Frag* is to be expected, since the lit market shares used to calculate

FragLit are included in the calculation of *Frag*. There is also strong correlation between fragmentation measures and dark pool trading. However, the correlation between aggregate dark trading (*DarkTrd*) and dark pool volumes (*DarkPool*) is only 0.10. There is a much stronger correlation of 0.69 between *DarkTrd* and *Elev*, indicating that studies proxying for dark trading using aggregate measures like *DarkTrd* may be drawing inferences about the effects of elevator markets rather than dark pools. Additionally, *Elev* is negatively correlated to all fragmentation measures. In terms of market quality, it is notable that spreads and volatility are negatively correlated with *DarkPool* and fragmentation, but positively correlated with *DarkTrd* and *Elev*. This correlation matrix provides additional support to believe more granular measures of dark trading and fragmentation could yield incremental understanding of their effects, motivating a more rigorous regression based framework.

Analysis & Results

My empirical strategy uses lagged measures of a stock's liquidity map and control variables to explain: liquidity, volatility, and abnormal returns on days of extreme market decline:

$$Y_{i,t} = \beta_1 \mathbf{LiqMap}_{i,t-1} * \mathbf{Evt}_t + \beta_2 \mathbf{LiqMap}_{i,t-1} + \beta_3 \mathbf{Evt}_t + \gamma \mathbf{Z}_{i,t-1} + \alpha_i + \epsilon_{i,t} \quad (5)$$

Where Y is the dependent variable for stock i at time t , $\mathbf{LiqMap}$ is a vector of variables describing where a stock traded over the pre-event period, $\mathbf{Evt}$ is an indicator variable equal to one on event dates and zero otherwise, $\mathbf{Z}$ is a vector of control variables measured over the pre-event period, α is stock fixed effects, and ϵ is the residual. Similar to Hameed, Kang, & Viswanathan (2010), my panel includes all dates in the sample period and my variables of interest are interaction terms between $\mathbf{Evt}$ and liquidity map variables. These interaction terms capture the incremental effects of a given liquidity map variable, conditional on a negative two-sigma event. Therefore,

coefficients on standalone liquidity map variables estimate the unconditional relationship between the dependent variable and a given dimension of the liquidity map. For ease of interpretation, all liquidity map variables are standardized with a mean of zero and standard deviation of one. Thus, coefficient estimates describe the marginal effect of a one standard deviation increase in a given variable of interest. For example, *DarkTrd* coefficients estimate the unconditional relationship with the dependent variable, while *DarkTrd X Evt* captures the incremental effects of *DarkTrd* conditional on extreme market decline.

My vector of control variables is typical to the literature. *Mktcap* proxies for firm size, *Price* is calculated as the volume-weighted average price (VWAP), *TrdSz* is the average value of trades, *Turnover* is shares traded scaled by shares outstanding, and all except *Mktcap* are pre-period means. Additionally, I include contemporaneous returns to the CRSP value-weighted index (*CRSP*) to account for variations in the magnitude of market declines (results are quantitatively consistent without inclusion). Finally, all standard errors reported are clustered on firm and date.

To construct the pre-period window, I begin at the start of the trading week five weeks prior to each date in the sample period. Then I calculate the mean of each variable over the subsequent four trading weeks and ignore the week immediately preceding a given date.⁴² The resulting unbalanced panel dataset includes stock-day level dependent variables on a given date with mean values of explanatory variables calculated using data from the previous fifth through second weeks, but not the closest prior week.

Liquidity

In Table 12, I present estimates on the effects of a stock's liquidity map on effective spread. First, let us consider the results using proportional measures available before the FINRA data. In

⁴² Except for market capitalization which is measured on the first day of the pre-period.

column one we see the unconditional relation between spreads and *DarkTrd*, aggregate dark volumes, is negative and economically small (0.53 bps). This is consistent with the findings of O'Hara & Ye (2011). However, the interaction term (*DarkTrd X Evt*) is positive and significant, indicating a one standard deviation increase in aggregate dark trading increases effective spread by 1.82 bps on large down days. Using the data from FINRA, in columns two and three, I decompose dark trading into its two market segments (*DarkPool* and *Elev*) and find very different results. *DarkPool* is positive and insignificant in an unconditional context, but the interaction term *DarkPool X Evt* indicates that conditional on an extreme market decline, a one standard deviation increase in dark pool volumes reduces effective spread by 1.85 bps. Column three shows a negative insignificant estimate on *Elev* and a positive and significant coefficient for the variable of interest, *Elev X Evt*, of 6.08 (t-stat of 2.08). In column four, I include both *DarkPool*, *Elev*, and their corresponding interaction terms. The coefficients decrease in magnitude but directional estimates are consistent with beta estimates of -1.58 for *DarkPool X Evt* (t-stat of -4.89) and 4.20 for *Elev X Evt* (t-stat of 1.82) respectively. These results on effective spread indicate that heterogeneity within dark trading has differential effects on liquidity and that using *DarkTrd* as a proxy could provide erroneous inference. Using only TAQ data, these results would be limited to inferences regarding *DarkTrd*, and the improvements to liquidity associated with *DarkPool* would be unobservable.

Columns five through eight examine the effects of fragmentation. All three measures of fragmentation have a negative significant relation to effective spread, both unconditionally and in the context of market declines. When lit fragmentation is alone, in column six, the variable of interest is estimated to indicate a -2.46 bps (t-stat of -5.87) reduction to effective spread. The comparable estimate for dark fragmentation in column seven is -3.43 (t-stat of -5.53). When lit and dark fragmentation are included together, the estimated beta on *FragLit X Evt* drops to a range

of -1.05 (t-stat of -4.24) to -1.14 (t-stat of -4.61), and *FragDark X Evt* ranges from -2.54 (t-stat of -4.98) to -2.83 (t-stat of -5.15).⁴³ This analysis consistently indicates that fragmentation reduces trading costs during a large market decline. Moreover, the benefits of fragmentation depend on the types of venues considered, as the magnitude of coefficients on *FragDark X Evt* is more than twice that of *FragLit X Evt*. Thus, it appears without the FINRA data, using lit fragmentation to proxy for overall or dark pool fragmentation would underestimate the benefits. Finally, in column nine I include lit and dark fragmentation alongside *DarkPool* and *Elev* volume measures. Interaction terms for *DarkPool* and *Elev* lose statistical significance while lit and dark fragmentation remain significant with coefficient estimates falling only slightly to -1.05 and -2.54 bps respectively.⁴⁴ The negative, significant relationship on large down days between effective spread and dark fragmentation is stable throughout Table 12. Additionally, the beta estimate on *FragDark X Evt* (-2.54) is economically significant, representing a 6.10% (15.76%) reduction in transaction costs from the sample mean (median) of 46.39 bps (17.96 bps). Overall dark pool volumes and dispersion among them seem to improve liquidity during a market drop, and there is some evidence that elevator trading increases effective spread.⁴⁵ Conversely, before the FINRA data my results would indicate that dark trading harms liquidity and lit fragmentation is beneficial.

To search for a feasible mechanism by which dark trading and fragmentation affects liquidity I decompose effective spread into price impact (a proxy for adverse selection costs) and realized spread (a proxy for profits to liquidity providers). Table 13 presents these results for price

⁴³ When combining *FragLit* and *FragDark* in the same model, estimates on standalone terms stay largely the same (betas of 0.10 and -2.40, and t-stats of 0.69 and -15.66), with a slight reduction to the marginal effects of *FragLit*.

⁴⁴ In an unconditional setting, the estimated coefficient on *DarkPool* becomes 0.07 (t-stat of 0.58), *Elev* becomes -0.61 (t-stat of -0.001), and coefficients on *FragLit* and *FragDark* increase slightly to 0.08 and -2.42 (with t-stats of 0.50 and -16.44).

⁴⁵ Notional versus relative calculations of effective and quoted spread yields qualitatively similar results.

impact and Table 14 for realized spread. For price impact, estimated relations largely mirror the results in Table 12. However, t-stats are softened for interaction terms on *DarkPool* and *Elev*, and all beta coefficients drop in magnitude. For example, beta estimates on the variable of interest for *DarkPool* range from -0.33 (t-stat of -2.70) to -0.39 (t-stat of -2.83), but fall to -0.03 (t-stat of -0.26) when alongside fragmentation variables. Meanwhile for *Elev*, coefficients on the variable of interest range from 0.91 (t-stat of 1.50) to 1.37 (t-stat of 1.75) without fragmentation variables, and 1.31 (t-stat of 1.86) in column nine. In terms of fragmentation, variables of interest indicate significant negative relationships with price impact. When it is the only variable of interest, the coefficient estimate of *FragLit X Evt* is -0.548 (t-stat of -3.54), but falls to -0.268 (t-stat of -2.37) once *FragDark* is added to the model. The estimate on *FragDark X Evt* is -0.73 (t-stat of -3.42) when alone, and ranges from -0.52 (t-stat of -2.84) to -0.60 (t-stat of -3.14) in specifications that include *FragLit*.

For realized spread, directional inferences mirror Table 12 and beta estimates are much larger in magnitude compared to Table 13. Estimates on the variable of interest for dark fragmentation are stable over all specifications, with a beta of -2.37 (t-stat of -5.22) when alone, and a range of -1.81 (t-stat of -4.73) to 1.96 (t-stat of -4.67) when alongside lit fragmentation. Interaction terms for lit fragmentation are negative and statistically significant throughout, but smaller in magnitude than dark fragmentation. The interaction term on *DarkPool* indicates lower realized spread, but estimates are no longer statistically significant when alongside fragmentation variables. Meanwhile models that include *Elev*, show statistically insignificant coefficients on the variable of interest, except for column three (significant only at the 10% level). The directional relationships estimated in Table 14 agree with those estimated in Table 13, implying dark trading and fragmentation have complimentary effects on price impact and realized spread. Additionally,

all the interaction terms in Table 14 are larger in magnitude compared to Table 13. The notably stronger estimates for realized spread versus price impact are consistent with improved trading conditions via increased competition. Conversely without the FINRA data, estimates on *DarkTrd* would imply dark trading reduces liquidity due to increased rent extraction by liquidity providers.

In addition to analysis using effective spread to proxy for illiquidity costs, I estimate the same models with quoted spread as the dependent variable and get similar results. In untabulated results on quoted spread, *DarkTrd* is linked to a significant 2.90 bps increase during market declines, but with regressions using *DarkPool* and *Elev* the former is negative and significant and the latter is positive and insignificant. In untabulated regressions of quoted spread, once both lit and dark fragmentation are included, lit fragmentation becomes insignificant but dark fragmentation is linked to a significant reduction in spreads of 5.07 to 5.37 bps.

Volatility

In addition to liquidity, volatility is a major concern for investors during turbulent markets. Table 15 presents results from regressions with volatility as the dependent variable. Column one shows what conclusions were available before the FINRA data. The variable of interest, *DarkTrd* $\times$ *Evt* has a coefficient estimate of 1.03 (t-stat of 3.15).⁴⁶ However, when *DarkTrd* is decomposed into *DarkPool* and *Elev* using the FINRA data, only *DarkPool* is statistically significant with coefficient estimates indicating *DarkPool* (*Elev*) reduces (exacerbates) volatility. The *DarkPool* interaction term has beta estimates ranging from -0.96 to -1.21, all significant.⁴⁷ Meanwhile, estimates for the interaction on *Elev* are statistically insignificant ranging from 3.94 to 5.98. Within

⁴⁶ The unconditional relationship between *DarkTrd* and volatility is estimated to be 0.75 (t-stat of 4.85).

⁴⁷ Beta estimates on the standalone term *DarkPool* range from -0.43 to -0.49 and are statistically significant. Meanwhile, estimates for the unconditional relationship between volatility and *Elev* are marginally significant and range from 2.56 to 2.82

my setting of high volatility episodes, stocks with higher dark pool volumes have relatively lower volatility.

In columns five through eight, results consistently indicate fragmentation reduces volatility unconditionally and incrementally given a market decline. The magnitude of *FragDark X Evt* is consistent and ranges from -2.09 to -2.26, while the interaction term on *FragLit* drops from -1.95 to -0.93 once lit and dark fragmentation are both included in the model. Once both proportional and dispersion measures of the liquidity map are included together, estimated effects from fragmentation sustain but estimates for *DarkPool* and *Elev* terms change. Interaction terms on *DarkPool* are no longer significant and flip positive, while the *Elev* interaction increases to 4.92 and becomes significant at the 5% level.⁴⁸ While some volatility results using proportional measures are tenuous, it is worth noting using *DarkTrd* alone would yield contrary inference. Moreover, while *FragLit* was available to earlier work before the FINRA data and estimates indicate it reduces volatility similar to *FragDark*, these results offer different policy prescriptions. For example, finding benefits from *FragLit* without being able to assess *FragDark* would not assuage concerns that proliferation of dark pools is detrimental to market quality. Additionally, leveraging the FINRA data indicates that benefits from dark fragmentation are stronger than those from lit fragmentation. In summary, during market turbulence when volatility is high across the asset class, highly fragmented stocks exhibit less volatile prices.

Price Effects

To examine how a stock's liquidity map affects price dislocation I regress DGTW abnormal returns on the same model, presented in Table 16. In analysis limited to variables

⁴⁸ Unconditional estimates for *DarkPool* and *Elev* are both positive and significant at the 1% level.

available in TAQ, the interaction term on aggregate dark trading has an estimated effect of increasing abnormal returns by 10 bps. However using the FINRA data, I estimate the coefficient on *DarkPool X Evt* as negative indicating a 10 to 20 bps lower abnormal return, while *Elev X Evt* loads positive indicating a 90 to 130 bps positive abnormal return. Like my earlier analysis, results on abnormal returns indicates that using aggregated dark trading alone would not provide insight into dark pool effects and may generate erroneous inference. Dark fragmentation is associated with 30 to 40 bps negative abnormal return, whereas lit fragmentation is tied to a 20 bps negative return that softens to 10 bps once *FragDark* variables are included. In the full specification only fragmentation variables retain statistical significance.

Conditional on market declines, dark pool volumes and fragmentation are tied to more negative abnormal returns. When both variables are included in the same model, only the relationship with fragmentation sustains. In terms of how to interpret these findings, more negative abnormal returns on big down days could be indicative of an overreaction, or more efficient incorporation of negative information. If this is due to overreaction then prices should revert on subsequent days generating positive abnormal returns. Conversely, if the cause is more efficient information incorporation then abnormal returns over subsequent periods may still be negative but should be less so compared to less fragmented stocks and/or stocks with lower dark pool volumes.

To examine further, I perform an event time portfolio analysis, with the goal of isolating the relationship between abnormal returns and fragmentation from the relationship between abnormal returns and dark pool volumes. I begin by forming double sort decile portfolios and calculating the average abnormal returns to each portfolio on the event date and over the subsequent two, five, and ten trading days that follow. Portfolios are formed by sorting on pre-period variables for each of the 43 event dates. Then I calculate returns to each event date portfolio,

using value-weighting or equal-weighting, and calculate the mean return across event dates per decile (i.e. leaving 10 portfolios). These results are presented in Table 17. Panel A presents returns for portfolios formed by sorting on *FragDark* and then *DarkPool*. In Panel B I present the reverse, sorting first on *DarkPool* and then on *FragDark*. Thus, Panel A examines the relationship between *DarkPool* and abnormal returns following an event while controlling for *FragDark*, and Panel B explores the same relationship with *FragDark*, controlling for *DarkPool*.

If my results from regressions of abnormal returns are indicative of overreaction, then I expect portfolios of stocks with more volumes and fragmentation among dark pools to have positive buy-and-hold abnormal returns (BHAR) subsequent to event days. On the other hand, if results in Table 16 indicate more efficient incorporation of negative information, then I expect all portfolios to experience negative BHARs, but better relative performance from stocks with more volumes and fragmentation among dark pools.

Looking at Table 17, I do not see negative BHARs across all portfolios as I would expect if my results in Table 16 indicate that fragmentation is tied to more efficient information incorporation during market stress. Additionally there is no indication of a monotonic relationship between fragmentation and BHARs. However, for the most fragmented portfolio of stocks in Panel B of Table 17, there are positive and significant BHARs (15 bps over two days, 26 bps over five days, and 34bps over ten days). Value-weighted returns for the same portfolio are much smaller in magnitude and statistically insignificant (except for a two day window when BHARs are 5 bps, significant at the 10% level). Therefore, returns among smaller stocks are much larger for this portfolio. Results from this portfolio are consistent with an overreaction story, where highly fragmented smaller stocks are oversold during an extreme market decline and revert in subsequent days. However the lack of a monotonic relationship observable in Panel B, between BHARs and

fragmentation, detracts from this interpretation. At the other extreme, the decile of the least fragmented stocks has negative abnormal returns for equal-weighted portfolios. These negative returns are relatively large in magnitude and highly statistically significant over a ten day interval. Meanwhile, value-weighted returns for this portfolio are indistinguishable from zero. Thus, in a portfolio of the least fragmented stocks, smaller stocks exhibit much lower returns. Results from this portfolio are consistent with an underreaction story, where investors underestimate the impact of negative information on an event day leading to negative drift in the days that follow. However, if the cause is structural frictions impeding information incorporation (i.e. consistent with an information incorporation story), we would still observe negative drift for this portfolio subsequent to an event day. So while results for the top and bottom deciles in Panel B are consistent with an overreaction/underreaction story, it is not possible to rule out an explanation based on information incorporation. Moreover, in the absence of any monotonic relationship between BHARs and fragmentation, some alternative interpretation may also be plausible.

To summarize my findings, I find strong evidence of benefits to market quality from fragmentation and dark trading on days of extreme market decline. The strongest benefits come from fragmentation among dark pool venues. Additionally, there is clear indication that proxies available prior to FINRA's transparency data initiative may generate erroneous inference (*DarkTrd*) or an incomplete picture (*FragLit*). Thus, my findings also highlight benefits from regulatory efforts to improve trading transparency. There is also some evidence that within my setting, dark fragmentation and dark pool volumes are associated with more negative abnormal returns, but I fail to find strong evidence to explain this result as either overreaction or more efficient information incorporation.

In empirical microstructure, the unobservable intentions of traders and a complex landscape generate concerns about simultaneity bias. For example, traders consider market quality when choosing where to route their orders, so it is possible that market quality outcomes and trading venues are determined simultaneously. The use of lagged regressors and firm fixed effects attempts to address these concerns. Future liquidity and volatility cannot influence prior trading patterns. Thus, estimating marginal effects of where a stock trades during a pre-period window on contemporaneous market quality variables, mitigates the simultaneity bias problem. Additionally, the use of firm fixed effects mitigates endogeneity from omitted variable bias (for omitted variables that are time invariant). However, in the next section I present results of robustness tests focused on these and other potential issues.

Robustness

To confirm my results I perform a battery of robustness tests. These efforts focus on the validity of the setting, event criteria, research design, and the potential of event clustering to confound my results. Overall, my robustness tests support my findings.

To verify that my setting is picking up incremental effects during extreme market declines, I generate randomly selected placebo event dates and rerun my main regressions with this alternate definition of *Evt*. If liquidity map variables of interest (i.e. interaction terms) are generally found to be statistically insignificant, then falsification tests support the validity of my setting. In placebo regressions of effective spread, none of the interaction terms are statistically significant and coefficient estimates have much lower magnitudes than in Table 12 (e.g. *FragDark X Evt* ranges from 0.16 to 0.22 bps in falsification tests compared to -2.54 to -3.43 bps). Meanwhile, unconditional liquidity map estimates are similar to those in Table 12. In placebo tests with volatility as the dependent variable, interaction terms are also insignificant. Placebo tests of

abnormal returns also support the validity of my setting, with only one of 14 interaction terms across the nine model specifications is significant, and only marginally. Interestingly, beta estimates and t-stats on standalone liquidity map variables are similar in both placebo tests and my main analyses. While this falsification test demonstrates there is a difference between what I define as days of extreme market declines and randomly selected days, it is possible my findings are unique to my criteria of extreme declines.

To determine if my findings are unique to my definition of an extreme down day on the market, I test three other criteria: equal-weighted CRSP returns, overnight returns to SPY (i.e. open price on t versus close price on $t-1$), and intraday returns to a value-weighted index of stocks in my sample (i.e. close price on t versus open price on t). Results using event criteria based on the CRSP equal-weighted index with regressions of effective spread, volatility, and abnormal returns are very similar to those obtained when using value-weighted criteria. In regressions of effective spread on a model including proportional and dispersion based measures, *FragLit X Evt* has an estimated beta of -1.76 (t-stat of -5.45) and *FragDark X Evt* has a beta of -3.30 (t-stat of -5.29). Using the full specification in regressions of volatility yields betas of -0.73 (t-stat of -4.56) for *FragLit X Evt* and -1.85 (t-stat of -4.17) for *FragDark X Evt*. Beta estimates for regressions of abnormal returns also generates similar inferences, having magnitudes within 10 bps compared to those reported in Table 13.

Results using SPY overnight returns as event criteria in regressions of effective spread and volatility also agree my main results (though with increased coefficient magnitudes). For example, when effective spread (volatility) is the dependent variable, beta estimates are -1.76 (-1.35) for *FragLit X Evt* and -3.30 (-2.82) for *FragDark X Evt*. However, regressions of abnormal returns yields insignificant coefficients on variables of interest, except for *DarkPool X Evt* in models that

omit fragmentation. Coefficient estimates for *DarkPool X Evt* are 10 bps, significant at the 5% level when alone, and the 10% level when *Elev* is included.

Results using events based on intraday value-weighted returns to my sample stocks are also consistent with my main analyses. In regressions of effective spread on models including proportional and dispersion based liquidity map variables, *FragLit X Evt* (*FragDark X Evt*) indicates narrower spreads by 1.27 (2.48) bps. In comparable tests with volatility as the dependent variable, *FragLit X Evt* (*FragDark X Evt*) has an estimated beta of -1.01 (-1.85) with a t-stat of -5.25 (-3.59). Results for abnormal returns imply a one standard deviation increase in *FragDark* implies negative abnormal return of 30 bps (p-value < 0.01) on a big down day, though no statistically significant relation is found for *FragLit*. Overall, these tests bolster confidence that my results are not peculiar to a particular definition of a market decline. However, it is also worth verifying aspects of my research design.

My model uses a panel setting with indicator and interaction terms to isolate incremental effects on big down days, however an alternative specification would be an event study setting that drops observations on days that are not qualifying events. To test if my results are robust to this dimension of my research design, I rerun my tests using only days of extreme market decline. In this alternative model, standalone liquidity map variables are my variables of interest, representing the incremental effects of fragmentation and dark trading during market stress. Within this setting, regressions of effective spread no longer find statistical significance among proportional variables, but estimates on fragmentation variables are very similar (with beta estimates of -0.83 for *FragLit* and -3.01 for *FragDark*, and t-stats of -2.07 and -6.68 respectively). One reason for the change in inferences regarding *DarkPool* and *Elev* could be reduced power (this setting loses 96.28% of observations). Another reason may be the inability of this model, using an event study setting, to

isolate unconditional effects from incremental effects of liquidity map variables on down days. In regressions of volatility, results for fragmentation variables are consistent (highly significant betas of -1.88 and -3.49 for *FragLit* and *FragDark* respectively). Coefficient estimates for *DarkPool* and *Elev* lose statistical significance in models that omit fragmentation. In the fully specified model, beta estimates indicate increased volatility from *DarkPool* (*Elev*), with a beta of 0.70 (12.67), significant at the 5% (1%) level. In analysis of abnormal returns, only *FragDark* is found to be statistically significant, indicating an incremental effect of -10 bps (p-value < 0.01). While the use of a full panel in my main analysis offers more powerful tests and controls for unconditional relationships, my results are largely robust to an alternative event study setting.

In addition to an event study setting, I also test alternative specifications of my panel model. Within the full panel, I re-run my main tests adding lags of my dependent variables. I also analyze a model using random effects (instead of fixed effects) with lags of my dependent variables. In all cases, my results are qualitatively and quantitatively consistent.

Lastly, I rerun my analysis dropping 2018 from my sample on the basis that 20 out of 43 event dates come in late 2018 during a period of prolonged market stress. Using lagged regressors means that under tighter clustering of event days, there is a greater likelihood of extreme down days contributing to my pre-period window, potentially confounding my results. However, this does not appear to be the case. Results without 2018 are consistent across analysis on effective spread, volatility, and abnormal returns. In summary, my main findings are robust to a variety of alternative specifications, definitions of event criteria, and concerns event clustering.

Chapter II Conclusion

On days of extreme market decline, more fragmented stocks are more liquid and less volatile. In this setting, fragmentation among dark pools is significantly more beneficial than

among lit venues. During a market decline, liquidity provision is more profitable and obligatory market makers supply less liquidity. My results may indicate this shift in incentives induces competition between and within trading venues, which improves trading conditions.

Earlier research was limited to indirect proxies of dark trading and fragmentation. Using a novel dataset of dark pool venue attribution from FINRA, I demonstrate that a more granular view into where stocks trade provides a greater understanding of the effects from dark trading and fragmentation. Regulatory concerns about these highly controversial facets of modern market structure may be misguided. If my analysis was limited to typical proxies from prior work (proportion of off-exchange trading and dispersion among exchange volumes), I would conclude that dark trading exacerbates illiquidity and volatility during market declines, and fragmentation among lit venues mitigates such trading conditions. However with direct measures of dark trading, I find dark pools have beneficial effects for liquidity and volatility. Additionally, fragmentation among dark pools makes stocks cheaper to trade and less erratic, and the benefits are two to three times those offered from lit fragmentation.

Results on price dislocations are more difficult to interpret than results on liquidity and volatility. If lower abnormal returns on big down days stem from improved information incorporation with more fragmented stocks, then these results indicate additional benefits from fragmentation, particularly among dark pools. However, if these lower abnormal returns are actually indicative of more fragile prices among more fragmented stocks, then these results offer a caveat to the benefits of dark trading and fragmentation. Overall I find some evidence consistent with investors overreacting to negative news for more fragmented stocks on days of extreme market decline.

Disaggregating dark trading volumes into individual market segments and venues allows researchers to tie investment outcomes to individual market mechanisms and counterparties. Given the disagreement in inference drawn from aggregated dark volumes versus more granular data, my results motivate subsequent work to isolate the effects of segments within elevator markets. HFT internalization and upstairs trading represent very different matching mechanisms and counterparties. Additional work is necessary to isolate the effects of these types of trading so regulators, practitioners, and academics can provide well informed policy prescriptions with the level of nuance that drives traders' order routing decisions.

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Appendices: Chapter II

Appendix A. Variable Definitions

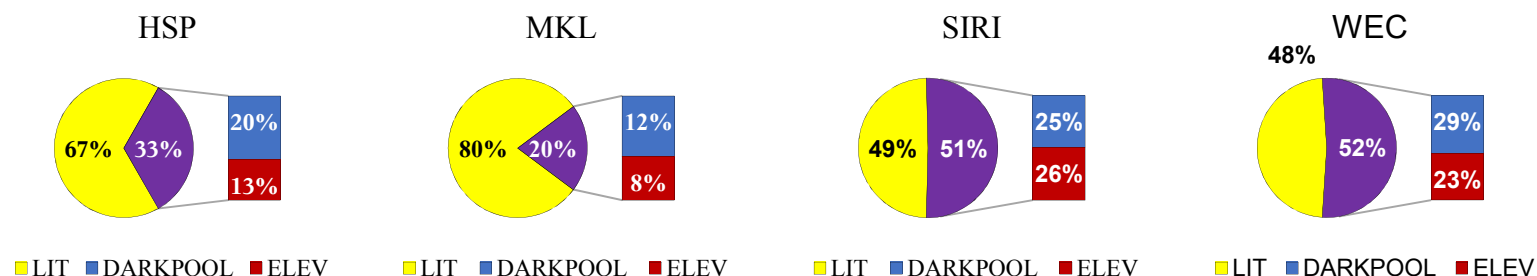
Variable	Description	Source
<i>Amihud</i>	Amihud illiquidity is calculated as the absolute value of return on day t , divided by value traded on day t .	CRSP, TAQ
<i>CRSP (EW)</i>	The daily return of the CRSP equal-weighted index.	CRSP
<i>CRSP (VW)</i>	The daily return of the CRSP value-weighted index.	CRSP
<i>DarkTrd</i>	Dollar value traded in undisplayed markets (identified in TAQ as execution destination equals 'D'), divided by total consolidated dollar value traded. Measure is at the stock day level using all trades executed during the regular trading session. When used as a regressor, it is aggregated over a given event pre-period, and normalized to have mean of zero and standard deviation of one.	TAQ
<i>DarkPool</i>	Calculated as total shares traded across all dark pool ("ATS") venues scaled by total share volume, measured per stock week. When used as a regressor, it is aggregated over a given event pre-period, and normalized to have mean of zero and standard deviation of one.	FINRA, TAQ
<i>Depth</i>	Dollar value of trading interest at the NBBO, calculated as an average of dollar value quoted at the NBB and the NBO.	TAQ
<i>Elev</i>	"Elevator" volumes are calculated as total shares traded across dark venues that are not registered ATS venues scaled by total share volume, measured per stock week. When used as a regressor, it is aggregated over a given event pre-period, and normalized to have mean of zero and standard deviation of one.	FINRA, TAQ
<i>ES</i>	<i>Effective spread</i> . Calculated as the absolute value of twice the difference between execution price and the prevailing midpoint (trades exempt from RegNMS rule 611 are excluded). Dollar-weighted averages are calculated for each stock-day. Expressed either in dollars or as a percentage scaled by the prevailing midpoint.	TAQ
<i>ESLag</i>	The average daily <i>ES</i> during the pre-event window.	TAQ
<i>Evt</i>	An indicator variable equal to one on days where the return to the CRSP value-weighted index is below two standard deviations of the mean over the sample period, June 16th, 2014 through December 31st, 2018.	CRSP
<i>Frag</i>	The inverse of a Herfindalh measure of market share concentration among exchanges and ATS venues. Market share per venue is assessed on a stock-week basis. When used as a regressor, it is aggregated over a given event pre-period, and normalized to have mean of zero and standard deviation of one.	FINRA, TAQ

Variable	Description	Source
<i>FragDark</i>	The inverse of a Herfindalh measure of market share concentration among ATS venues only. Market share per venue is assessed on a stock-week basis. When used as a regressor, it is aggregated over a given event pre-period, and normalized to have mean of zero and standard deviation of one.	FINRA
<i>FragLit</i>	The inverse of a Herfindalh measure of market share concentration among exchange venues only. Market share per venue is assessed on a stock-week basis. When used as a regressor, it is aggregated over a given event pre-period, and normalized to have mean of zero and standard deviation of one.	TAQ
<i>MktCap</i>	Market capitalization is the product of shares outstanding and daily closing price, for pre-period evaluations, I use market capitalization available from CRSP on the first day a stock trades during a given event pre-period. When used as a regressor, I take the natural log.	CRSP
<i>NYSE</i>	Dummy variable set to one if a stock is listed on the NYSE on the first day the stock trades during a given event pre-period.	CRSP
<i>PI</i>	<i>Price impact</i> . Calculated as a buy/sell indicator multiplied by twice the difference between execution price and prevailing midpoint thirty seconds after the trade. Dollar-weighted averages are calculated for each stock-day. Expressed either in dollars or as a percentage scaled by the prevailing midpoint at the time of execution.	TAQ
<i>PI_{Lag}</i>	The average daily <i>PI</i> during the pre-event window.	TAQ
<i>QS</i>	<i>Quoted spread</i> . Calculated as the NBO minus NBB, for each consolidated quote observed. Time-weighted averages are computed for each-stock day. Expressed either in dollars or as a percentage scaled by the prevailing midpoint.	TAQ
<i>Ret (raw)</i>	Daily raw returns taken from CRSP's daily file	CRSP
<i>RS</i>	<i>Realized spread</i> . Calculated as a buy/sell indicator multiplied by twice the difference between midpoints thirty seconds after the trade and the prevailing midpoint at execution time. Dollar-weighted averages are calculated for each stock-day. Expressed either in dollars or as a percentage scaled by the prevailing midpoint at the time of execution.	TAQ
<i>RS_{Lag}</i>	The average daily <i>RS</i> during the pre-event window.	TAQ
<i>TrdVal</i>	Sum of dollar value executed. When used as a regressor, I take the natural log.	TAQ

Variable	Description	Source
<i>Trds</i>	Count of number of executions.	TAQ
<i>TrdSz</i>	Dollar value executed scaled by number of trades executed, measured at a stock day level , scaled by 1,000 when used in regression analysis.	TAQ
<i>Turnover</i>	Measures daily trading activity per stock, calculated as the sum of shares executed divided by shares outstanding.	CRSP, TAQ
<i>Volatility</i>	Proxied using the daily mean per stock of standard deviations of intraday returns, where intraday returns are the rate of return between each consecutive trade (excluding trades exempt from RegNMS rule 611). Scaled by 10,000 for readability when used in regressions.	TAQ
<i>VolatilityLag</i>	The average daily <i>Volatility</i> during the pre-event window.	TAQ
<i>VWAP</i>	Volume weighted average prices are calculated using all executions during the regular trading session, scaling dollar value executed by shares executed.	TAQ

Appendix B: Chapter II Figures

Panel A



Panel B

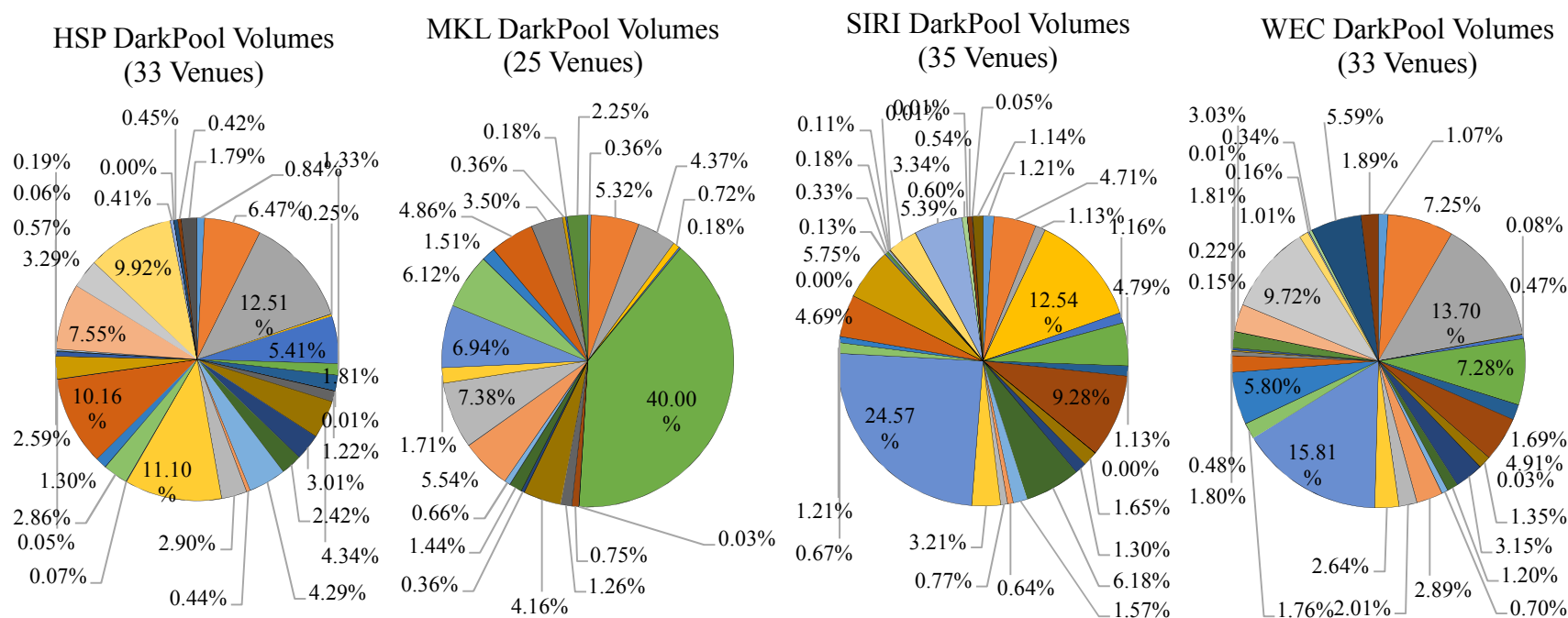


Figure 6. Cross Sectional Variation in Dark Trading

Diagrams illustrating the granularity provided by FINRA's dark trading transparency data. Panel A presents pie charts of market shares for dark (lit) venues in purple (yellow). Corresponding bar charts split dark trading into dark pool and elevator venues. Panel B presents market shares among dark pool venues.

Appendix C: Chapter II Tables

Table 9. Dark Trading & Fragmentation Summary Statistics

Panel A	Dark Trd	Dark Pool	Elev	Frag	Frag Lit	Frag Dark
<i>All</i>	36.26%	14.97%	23.22%	14.49	3.52	8.85
<i>Size</i>						
1	37.58%	13.39%	27.38%	11.96	3.21	7.15
2	29.50%	17.40%	15.73%	16.41	3.65	9.63
3	28.17%	17.56%	14.12%	17.74	3.88	10.05
4	27.71%	17.42%	13.91%	18.26	3.98	10.32
5	27.10%	15.39%	15.60%	18.72	3.99	10.83

Panel B	N	Mean	Std Dev	Q1	Median	Q3
<i>Stock Traits:</i>						
<i>MktCap (M)</i>	4,129	5,998.96	25,263.08	204.51	763.38	2,880.72
<i>NYSE</i>	4,129	0.37	0.48	0	0	1
<i>Price</i>	4,129	34.85	48.05	9.50	20.80	43.66
<i>Trds (k)</i>	4,129	7.01	13.73	0.68	2.57	7.45
<i>TrdVal (M)</i>	4,129	53.08	184.84	1.22	7.55	36.04
<i>Turnover</i>	4,129	0.010	0.021	0.004	0.006	0.011
<i>Market Quality:</i>						
<i>ES (bps)</i>	4,129	46.39	64.50	7.09	17.96	54.64
<i>ES (\$)</i>	4,129	0.071	0.103	0.018	0.036	0.076
<i>QS (bps)</i>	4,129	73.39	97.66	13.18	32.23	87.98
<i>QS (\$)</i>	4,129	0.123	0.174	0.032	0.064	0.132
<i>PI (bps)</i>	4,129	16.18	14.06	5.73	11.66	22.24
<i>RS (bps)</i>	4,129	29.11	49.82	1.06	5.44	32.04
<i>Volatility</i>	4,126	0.30%	0.50%	0.04%	0.11%	0.32%

This table reports summary statistics for dark trading and fragmentation variables by NYSE market capitalization quintile, from smallest to largest stocks. Panel A presents mean values for dark trading and fragmentation per quintiles formed on market capitalization using breakpoints from NYSE listed stocks. Panel B presents descriptive statistics on stock traits and market quality over the full sample. Spread and volatility measures are winsorized at the 1st and 99th percentile. Variables are as defined in Appendix A.

Table 10. Summary Statistics

Panel A	N	Mean	Std Dev	Q1	Median	Q3
<i>ES (bps)</i>	43	39.22	4.20	37.15	39.10	41.00
<i>ES (\$)</i>	43	0.079	0.012	0.069	0.077	0.088
<i>QS (bps)</i>	43	67.91	22.45	59.28	64.09	69.59
<i>QS (\$)</i>	43	0.150	0.052	0.117	0.125	0.181
<i>PI (bps)</i>	43	15.01	1.75	14.29	14.80	15.64
<i>RS (bps)</i>	43	23.20	2.69	21.68	23.20	24.60
<i>Vol</i>	43	0.24%	0.03%	0.22%	0.23%	0.26%
<i>Ret (raw)</i>	43	-2.29%	0.64%	-2.69%	-2.16%	-1.80%
<i>CRSP (VW)</i>	43	-1.93%	0.54%	-2.32%	-1.88%	-1.58%
<i>CRSP (EW)</i>	43	-2.30%	0.61%	-2.59%	-2.09%	-1.88%

Panel B	N	ES (bps)	ES (\$)	QS (bps)	QS (\$)	Volatility	Ret (raw)
<i>2014</i>	3	39.10	0.068	58.12	0.109	0.23%	-2.10%
<i>2015</i>	9	40.97	0.076	62.01	0.123	0.25%	-2.23%
<i>2016</i>	10	37.63	0.067	60.89	0.115	0.24%	-2.59%
<i>2017</i>	1	35.06	0.066	55.77	0.117	0.19%	-2.40%
<i>2018</i>	20	39.47	0.090	76.15	0.188	0.24%	-2.19%

This table reports summary statistics on event dates during the sample period, May 12, 2014 through December 31, 2018. Events are defined as dates when returns to the CRSP value-weighted index are below two standard deviations from the sample period mean. Panel A presents statistics aggregated across event dates. Panel B presents means of these statistics per year. All variables are measured at the daily level, spreads and volatility are winsorized at the 1st and 99th percentile. Variables are as defined in Appendix A.

Table 11. Correlation Matrix

	Frag	Frag Lit	Frag Dark	Dark Trd	Dark Pool	Elev	ES (bps)	QS (bps)	PI (bps)	RS (bps)	Amihud	Volatility	Mkt Cap	NYSE	Trds	Trd Val	Turnover
<i>FragLit</i>	0.76																
<i>FragDark</i>	0.65	0.45															
<i>DarkTrd</i>	-0.21	-0.01	-0.21														
<i>DarkPool</i>	0.40	0.33	0.42	0.11													
<i>Elev</i>	-0.42	-0.25	-0.39	0.73	-0.44												
<i>ES (bps)</i>	-0.50	-0.32	-0.58	0.39	-0.34	0.48											
<i>QS (bps)</i>	-0.50	-0.33	-0.58	0.35	-0.33	0.44	0.88										
<i>PI (bps)</i>	-0.32	-0.18	-0.36	0.29	-0.19	0.33	0.53	0.51									
<i>RS (bps)</i>	-0.45	-0.29	-0.52	0.33	-0.31	0.42	0.91	0.80	0.19								
<i>Amihud</i>	-0.13	-0.09	-0.15	0.09	-0.10	0.12	0.26	0.25	0.15	0.23							
<i>Volatility</i>	-0.52	-0.34	-0.59	0.38	-0.34	0.47	0.86	0.84	0.46	0.79	0.23						
<i>MktCap</i>	0.15	0.08	0.18	-0.09	-0.05	-0.04	-0.12	-0.13	-0.14	-0.09	-0.02	-0.13					
<i>NYSE</i>	0.65	0.60	0.29	-0.28	0.12	-0.32	-0.30	-0.30	-0.25	-0.25	-0.06	-0.31	0.14				
<i>Trds</i>	0.27	0.22	0.29	-0.08	-0.02	-0.05	-0.20	-0.21	-0.19	-0.16	-0.03	-0.21	0.68	0.18			
<i>TrdVal</i>	0.13	0.09	0.15	-0.05	-0.05	-0.01	-0.12	-0.12	-0.13	-0.09	-0.02	-0.13	0.77	0.10	0.85		
<i>Turnover</i>	0.06	0.08	0.08	0.05	0.00	0.03	-0.05	-0.06	0.00	-0.05	0.00	-0.06	-0.02	0.01	0.04	0.01	
<i>VWAP</i>	0.15	0.06	0.13	-0.26	0.07	-0.24	-0.21	-0.20	-0.21	-0.16	-0.05	-0.19	0.26	0.19	0.15	0.27	-0.01

This table reports Pearson correlation coefficients for variables within the pooled sample. Spreads and volatility are winsorized at the 1st and 99th percentile. Variables are as defined in Appendix A.

Table 12. Impact of Dark Trading and Fragmentation on Effective Spread on Days with Extreme Negative Market Returns

	Model								
	1	2	3	4	5	6	7	8	9
<i>DarkTrd X Evt</i>	1.820 *** (0.481)								
<i>DarkPool X Evt</i>		-1.850*** (0.351)		-1.578*** (0.323)					-0.201 (0.242)
<i>Elev X Evt</i>			6.423** (3.082)	4.195* (2.309)					3.987 (2.434)
<i>Frag X Evt</i>					-3.043*** (0.512)				
<i>FragLit X Evt</i>						-2.459*** (0.419)		-1.144*** (0.248)	-1.051*** (0.248)
<i>FragDark X Evt</i>							-3.426*** (0.619)	-2.826*** (0.549)	-2.538*** (0.510)
<i>DarkTrd</i>	-0.525*** (0.149)								
<i>DarkPool</i>		-0.218* (0.115)		-0.238** (0.115)					0.066 (0.114)
<i>Elev</i>			-0.473 (0.437)	-0.516 (0.449)					-0.613 (0.633)
<i>Frag</i>					-1.478*** (0.146)				
<i>FragLit</i>						-0.330** (0.149)		0.103 (0.149)	0.080 (0.159)
<i>FragDark</i>							-2.365*** (0.147)	-2.396*** (0.153)	-2.416*** (0.147)
<i>Evt</i>	3.385*** (0.654)	3.350*** (0.617)	3.349*** (0.627)	3.357*** (0.617)	3.324*** (0.648)	3.495*** (0.647)	3.246*** (0.630)	3.317*** (0.635)	3.329*** (0.634)
<i>Mktcap</i>	-7.448*** (0.776)	-7.301*** (0.771)	-7.288*** (0.771)	-7.316*** (0.771)	-6.947*** (0.760)	-7.247*** (0.770)	-7.346*** (0.753)	-7.348*** (0.751)	-7.360*** (0.752)
<i>Price</i>	-2.628*** (0.770)	-2.554*** (0.773)	-2.554*** (0.773)	-2.558*** (0.773)	-2.862*** (0.769)	-2.650*** (0.772)	-2.436*** (0.764)	-2.432*** (0.762)	-2.444*** (0.761)
<i>TrdSz</i>	0.126*** (0.030)	0.114*** (0.029)	0.117*** (0.029)	0.115*** (0.029)	0.103*** (0.029)	0.113*** (0.029)	0.135*** (0.036)	0.135*** (0.036)	0.138*** (0.036)

Table 12, continued.

	Model								
	1	2	3	4	5	6	7	8	9
<i>Turnover</i>	-19.320*** (3.210)	-19.418*** (3.236)	-19.398*** (3.239)	-19.412*** (3.233)	-19.135*** (3.189)	-19.299*** (3.215)	-18.868*** (3.071)	-18.890*** (3.074)	-18.869*** (3.069)
<i>CRSP (VW)</i>	1.013 (15.541)	1.211 (15.609)	1.270 (15.586)	1.182 (15.610)	1.538 (15.616)	1.321 (15.647)	1.107 (15.950)	1.034 (15.960)	0.956 (15.967)
<i>VolatilityLag</i>	0.697*** (0.019)	0.695*** (0.019)	0.696*** (0.019)	0.695*** (0.019)	0.689*** (0.019)	0.694*** (0.019)	0.700*** (0.019)	0.700*** (0.019)	0.701*** (0.019)
<i>Firm FEs</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	3,398,451	3,398,451	3,398,451	3,398,451	3,398,451	3,398,451	3,390,551	3,390,551	3,390,551
<i>R-squared</i>	0.710	0.710	0.710	0.710	0.710	0.710	0.711	0.711	0.711

This table reports estimates for regressions of effective spread on variables describing a stock's liquidity map, an indicator variable (Evt) equal to one on event dates and zero otherwise, interaction terms, and control variables. Events are defined as dates when returns to the CRSP value-weighted index are below two standard deviations from the sample period mean. Interaction terms are the variables of interest, calculated by multiplying Evt by liquidity map variables describing dark trading and trading dispersion. Liquidity map variables are normalized to mean zero with standard deviation of one. Variables are as defined in Appendix A. Spreads and volatility are winsorized at the 1st and 99th percentile. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are clustered by event date and firm, and presented in parentheses

Table 13. Impact of Dark Trading and Fragmentation on Price Impact on Days with Extreme Negative Market Returns

	Model								
	1	2	3	4	5	6	7	8	9
<i>DarkTrd X Evt</i>	0.477*** (0.172)								
<i>DarkPool X Evt</i>		-0.391*** (0.138)		-0.332*** (0.123)					-0.027 (0.104)
<i>Elev X Evt</i>			1.372* (0.783)	0.909 (0.606)					1.310* (0.704)
<i>Frag X Evt</i>					-0.737*** (0.187)				
<i>FragLit X Evt</i>						-0.548*** (0.155)		-0.268** (0.113)	-0.246** (0.113)
<i>FragDark X Evt</i>							-0.729*** (0.213)	-0.603*** (0.192)	-0.522*** (0.184)
<i>DarkTrd</i>	-0.393*** (0.055)								
<i>DarkPool</i>		0.146*** (0.046)		0.131*** (0.047)					-0.004 (0.046)
<i>Elev</i>			-0.567* (0.340)	-0.506 (0.314)					-1.088*** (0.419)
<i>Frag</i>					0.349*** (0.054)				
<i>FragLit</i>						0.686*** (0.061)		0.733*** (0.063)	0.725*** (0.066)
<i>FragDark</i>							-0.178*** (0.065)	-0.313*** (0.067)	-0.313*** (0.064)
<i>Evt</i>	1.663*** (0.303)	1.663*** (0.296)	1.662*** (0.298)	1.665*** (0.297)	1.670*** (0.298)	1.656*** (0.300)	1.659*** (0.294)	1.637*** (0.294)	1.642*** (0.295)
<i>Mktcap</i>	-2.256*** (0.238)	-2.111*** (0.238)	-2.138*** (0.238)	-2.128*** (0.238)	-2.183*** (0.236)	-2.165*** (0.236)	-2.154*** (0.233)	-2.212*** (0.230)	-2.244*** (0.230)
<i>Price</i>	-2.109*** (0.263)	-2.041*** (0.263)	-2.048*** (0.263)	-2.047*** (0.263)	-1.986*** (0.262)	-1.919*** (0.259)	-2.063*** (0.262)	-1.930*** (0.257)	-1.954*** (0.256)
<i>TrdSz</i>	0.027** (0.012)	0.020* (0.011)	0.020* (0.011)	0.021* (0.011)	0.022* (0.011)	0.024** (0.012)	0.041*** (0.013)	0.049*** (0.014)	0.054*** (0.015)

Table 13, continued.

	Model								
	1	2	3	4	5	6	7	8	9
<i>Turnover</i>	3.743*** (1.067)	3.680*** (1.054)	3.678*** (1.055)	3.691*** (1.055)	3.605*** (1.041)	3.498*** (1.010)	3.702*** (1.058)	3.533*** (1.012)	3.562*** (1.016)
<i>VolatilityLag</i>	0.083*** (0.004)	0.082*** (0.004)	0.082*** (0.004)	0.083*** (0.004)	0.083*** (0.004)	0.085*** (0.004)	0.083*** (0.004)	0.085*** (0.004)	0.086*** (0.004)
<i>Firm FEs</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	3,397,917	3,397,917	3,397,917	3,397,917	3,397,917	3,397,917	3,390,060	3,390,060	3,390,060
<i>R-squared</i>	0.314	0.314	0.314	0.314	0.314	0.314	0.317	0.317	0.317

This table reports estimates for regressions of price impact on variables describing a stock's liquidity map, an indicator variable (Evt) equal to one on event dates and zero otherwise, interaction terms, and control variables. Events are defined as dates when returns to the CRSP value-weighted index are below two standard deviations from the sample period mean. Interaction terms are the variables of interest, calculated by multiplying Evt by liquidity map variables describing dark trading and trading dispersion. Liquidity map variables are normalized to mean zero with standard deviation of one. Variables are as defined in Appendix A. Spreads and volatility are winsorized at the 1st and 99th percentile. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are clustered by event date and firm, and presented in parentheses.

Table 14. Impact of Dark Trading and Fragmentation on Realized Spread on Days with Extreme Negative Market Returns

	Model								
	1	2	3	4	5	6	7	8	9
<i>DarkTrd X Evt</i>	1.135*** (0.360)								
<i>DarkPool X Evt</i>		-1.271*** (0.260)		-1.098*** (0.248)					-0.171 (0.193)
<i>Elev X Evt</i>			4.204* (2.342)	2.650 (1.834)					1.562 (2.258)
<i>Frag X Evt</i>					-2.011*** (0.404)				
<i>FragLit X Evt</i>						-1.657*** (0.287)		-0.752*** (0.154)	-0.696*** (0.158)
<i>FragDark X Evt</i>							-2.369*** (0.454)	-1.959*** (0.418)	-1.812*** (0.383)
<i>DarkTrd</i>	0.130 (0.123)								
<i>DarkPool</i>		-0.284*** (0.090)		-0.278*** (0.089)					0.187** (0.090)
<i>Elev</i>			0.403 (0.280)	0.331 (0.254)					1.221** (0.518)
<i>Frag</i>					-1.887*** (0.120)				
<i>FragLit</i>						-1.100*** (0.117)		-0.722*** (0.116)	-0.762*** (0.124)
<i>FragDark</i>							-2.153*** (0.117)	-2.031*** (0.119)	-2.071*** (0.115)
<i>Evt</i>	1.481*** (0.412)	1.444*** (0.392)	1.443*** (0.394)	1.448*** (0.391)	1.410*** (0.424)	1.587*** (0.412)	1.345*** (0.422)	1.435*** (0.424)	1.440*** (0.422)
<i>Mktcap</i>	-5.486*** (0.584)	-5.569*** (0.580)	-5.526*** (0.580)	-5.556*** (0.581)	-5.141*** (0.569)	-5.463*** (0.579)	-5.571*** (0.566)	-5.509*** (0.565)	-5.457*** (0.565)
<i>Price</i>	-0.244 (0.571)	-0.285 (0.573)	-0.274 (0.573)	-0.277 (0.573)	-0.655 (0.569)	-0.515 (0.574)	-0.186 (0.565)	-0.330 (0.566)	-0.307 (0.565)
<i>TrdSz</i>	0.094*** (0.023)	0.095*** (0.023)	0.096*** (0.023)	0.094*** (0.023)	0.080*** (0.023)	0.088*** (0.023)	0.101*** (0.026)	0.092*** (0.025)	0.087*** (0.025)

Table 14, continued.

	Model								
	1	2	3	4	5	6	7	8	9
<i>Turnover</i>	-22.685*** (3.449)	-22.659*** (3.430)	-22.651*** (3.439)	-22.671*** (3.433)	-22.299*** (3.353)	-22.347*** (3.350)	-22.161*** (3.278)	-21.993*** (3.230)	-21.999*** (3.236)
<i>CRSP (VW)</i>	-0.295 (9.076)	-0.677 (9.107)	-0.529 (9.089)	-0.625 (9.101)	-0.439 (9.251)	-0.609 (9.209)	-1.185 (9.476)	-1.235 (9.530)	-1.120 (9.508)
<i>VolatilityLag</i>	0.574*** (0.015)	0.574*** (0.015)	0.575*** (0.015)	0.574*** (0.015)	0.566*** (0.015)	0.570*** (0.015)	0.577*** (0.014)	0.575*** (0.014)	0.574*** (0.014)
<i>Firm FEs</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	3,397,917	3,397,917	3,397,917	3,397,917	3,397,917	3,397,917	3,390,060	3,390,060	3,390,060
<i>R-squared</i>	0.586	0.586	0.586	0.586	0.586	0.586	0.586	0.586	0.586

This table reports estimates for regressions of realized spread on variables describing a stock's liquidity map, an indicator variable (Evt) equal to one on event dates and zero otherwise, interaction terms, and control variables. Events are defined as dates when returns to the CRSP value-weighted index are below two standard deviations from the sample period mean. Interaction terms are the variables of interest, calculated by multiplying Evt by liquidity map variables describing dark trading and trading dispersion. Liquidity map variables are normalized to mean zero with standard deviation of one. Variables are as defined in Appendix A. Spreads and volatility are winsorized at the 1st and 99th percentile. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are clustered by event date and firm, and presented in parentheses.

Table 15. Impact of Dark Trading and Fragmentation on Volatility on Days with Extreme Negative Market Returns

	Model								
	1	2	3	4	5	6	7	8	9
<i>DarkTrd X Evt</i>	1.032*** (0.328)								
<i>DarkPool X Evt</i>		-1.206*** (0.297)		-0.958** (0.377)					0.268 (0.234)
<i>Elev X Evt</i>			5.977 (4.832)	3.942 (4.486)					4.916** (2.112)
<i>Frag X Evt</i>					-2.366*** (0.462)				
<i>FragLit X Evt</i>						-1.954*** (0.352)		-0.931*** (0.162)	-0.922*** (0.178)
<i>FragDark X Evt</i>							-2.782*** (0.621)	-2.264*** (0.556)	-2.086*** (0.522)
<i>DarkTrd</i>	0.754*** (0.110)								
<i>DarkPool</i>		-0.487*** (0.093)		-0.425*** (0.099)					0.314*** (0.091)
<i>Elev</i>			2.817* (1.501)	2.564* (1.398)					6.187*** (1.101)
<i>Frag</i>					-2.651*** (0.134)				
<i>FragLit</i>						-1.818*** (0.123)		-1.346*** (0.119)	-1.375*** (0.125)
<i>FragDark</i>							-2.788*** (0.136)	-2.545*** (0.136)	-2.613*** (0.131)
<i>Evt</i>	3.364*** (0.582)	3.316*** (0.573)	3.314*** (0.573)	3.326*** (0.575)	3.281*** (0.631)	3.514*** (0.631)	3.245*** (0.606)	3.374*** (0.634)	3.382*** (0.626)
<i>Mktcap</i>	-9.145*** (0.704)	-9.481*** (0.703)	-9.343*** (0.704)	-9.383*** (0.704)	-8.754*** (0.678)	-9.236*** (0.696)	-9.591*** (0.685)	-9.428*** (0.682)	-9.190*** (0.680)
<i>Price</i>	0.186 (0.675)	0.017 (0.679)	0.080 (0.678)	0.078 (0.678)	-0.464 (0.664)	-0.336 (0.676)	0.262 (0.668)	0.004 (0.667)	0.172 (0.663)
<i>TrdSz</i>	0.125*** (0.027)	0.143*** (0.029)	0.135*** (0.028)	0.130*** (0.027)	0.106*** (0.024)	0.121*** (0.026)	0.132*** (0.031)	0.110*** (0.028)	0.074*** (0.025)

Table 15, continued.

	Model								
	1	2	3	4	5	6	7	8	9
<i>Turnover</i>	-18.936*** (3.645)	-18.808*** (3.583)	-18.844*** (3.608)	-18.865*** (3.600)	-18.192*** (3.450)	-18.238*** (3.442)	-18.279*** (3.404)	-17.933*** (3.313)	-18.037*** (3.349)
<i>CRSP (VW)</i>	12.574 (12.259)	11.503 (12.365)	11.878 (12.274)	11.708 (12.336)	11.579 (12.542)	11.460 (12.791)	11.063 (12.896)	10.907 (13.195)	11.426 (13.099)
<i>Firm FEs</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	3,346,277	3,346,277	3,346,277	3,346,277	3,346,277	3,346,277	3,341,442	3,341,442	3,341,442
<i>R-squared</i>	0.661	0.660	0.660	0.661	0.662	0.662	0.663	0.663	0.664

This table reports estimates for regressions of volatility on variables describing a stock's liquidity map, an indicator variable (Evt) equal to one on event dates and zero otherwise, interaction terms, and control variables. Events are defined as dates when returns to the CRSP value-weighted index are below two standard deviations from the sample period mean. Interaction terms are the variables of interest, calculated by multiplying Evt by liquidity map variables describing dark trading and trading dispersion. Liquidity map variables are normalized to mean zero with standard deviation of one. Variables are as defined in Appendix A. Spreads and volatility are winsorized at the 1st and 99th percentile. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are clustered by event date and firm, and presented in parentheses.

Table 16. Impact of Dark Trading and Fragmentation on Abnormal Returns on Days with Extreme Negative Market Returns

	Model								
	1	2	3	4	5	6	7	8	9
<i>DarkTrd X Evt</i>	0.001*** (0.000)								
<i>DarkPool X Evt</i>		-0.002*** (0.000)		-0.001*** (0.000)					0.000 (0.000)
<i>Elev X Evt</i>			0.013*** (0.002)	0.009*** (0.003)					0.000 (0.003)
<i>Frag X Evt</i>					-0.003*** (0.000)				
<i>FragLit X Evt</i>						-0.002*** (0.000)		-0.001*** (0.000)	-0.001*** (0.000)
<i>FragDark X Evt</i>							-0.004*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
<i>DarkTrd</i>	0.000*** (0.000)								
<i>DarkPool</i>		0.000 (0.000)		0.000 (0.000)					0.000 (0.000)
<i>Elev</i>			-0.001*** (0.000)	-0.001*** (0.000)					-0.001* (0.000)
<i>Frag</i>					0.000 (0.000)				
<i>FragLit</i>						0.000 (0.000)		0.000* (0.000)	0.000 (0.000)
<i>FragDark</i>							0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
<i>Evt</i>	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
<i>Mktcap</i>	-0.001* (0.000)	-0.001* (0.000)	-0.001* (0.000)	-0.001* (0.000)	-0.001 (0.000)	-0.001* (0.000)	-0.001* (0.000)	-0.001* (0.000)	-0.001* (0.000)
<i>Price</i>	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
<i>TrdSz</i>	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000*** (0.000)

Table 16, continued.

	Model								
	1	2	3	4	5	6	7	8	9
<i>Turnover</i>	0.094*** (0.015)	0.094*** (0.015)	0.094*** (0.015)	0.094*** (0.015)	0.094*** (0.015)	0.094*** (0.015)	0.094*** (0.015)	0.094*** (0.015)	0.094*** (0.015)
<i>VolatilityLag</i>	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
<i>Firm FEs</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	3,031,215	3,031,215	3,031,215	3,031,215	3,031,215	3,031,215	3,025,720	3,025,720	3,025,720
<i>R-squared</i>	0.015	0.015	0.015	0.015	0.015	0.015	0.016	0.016	0.016

This table reports estimates for regressions of DGTW abnormal returns on variables describing a stock's liquidity map, an indicator variable (Evt) equal to one on event dates and zero otherwise, interaction terms, and control variables. Events are defined as dates when returns to the CRSP value-weighted index are below two standard deviations from the sample period mean. Interaction terms are the variables of interest, calculated by multiplying Evt by liquidity map variables describing dark trading and trading dispersion. Liquidity map variables are normalized to mean zero with standard deviation of one. Variables are as defined in Appendix A. Spreads and volatility are winsorized at the 1st and 99th percentile. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively. Standard errors are clustered by event date and firm, and presented in parentheses.

Table 17. Impact of Dark Trading and Fragmentation on Buy-and-hold Abnormal Returns Following Days with Extreme Negative Market Returns

Panel A	Frag Dark	Dark Pool	Raw Ret (VW)	BHAR [1,2] (VW)	BHAR [1,5] (VW)	BHAR [1,10] (VW)	Raw Ret (EW)	BHAR [1,2] (EW)	BHAR [1,5] (EW)	BHAR [1,10] (EW)
1	8.54	8.05%	-2.29%	0.04%	0.12%	0.13%	-2.35%	-0.04%	0.06%	0.03%
2	8.63	10.45%	-2.41%	-0.03%	-0.02%	-0.04%	-2.27%	0.00%	0.02%	-0.09%
3	8.69	11.86%	-2.37%	-0.05%	-0.02%	-0.03%	-2.26%	-0.01%	-0.08%	-0.18%***
4	8.73	13.07%	-2.40%	0.01%	0.08%	0.15%	-2.30%	-0.05%	-0.02%	-0.02%
5	8.76	14.22%	-2.48%	0.06%	0.13%	0.05%	-2.31%	0.02%	0.00%	-0.08%
6	8.78	14.77%	-2.34%	-0.04%	-0.09%	-0.17%	-2.28%	0.06%	0.02%	0.00%
7	8.81	16.72%	-2.46%	-0.01%	-0.16%**	-0.35%***	-2.28%	-0.05%	-0.23%***	-0.37%***
8	8.82	18.30%	-2.38%	0.07%	0.01%	-0.03%	-2.30%	0.00%	-0.15%**	-0.23%***
9	8.82	20.53%	-2.48%	0.02%	-0.08%	-0.23%**	-2.32%	-0.02%	-0.12%*	-0.24%***
10	8.81	25.88%	-2.43%	-0.02%	-0.17%	-0.42%***	-2.29%	-0.06%	-0.14%	-0.38%**
Panel B	Frag Dark	Dark Pool	Raw Ret (VW)	BHAR [1,2] (VW)	BHAR [1,5] (VW)	BHAR [1,10] (VW)	Raw Ret (EW)	BHAR [1,2] (EW)	BHAR [1,5] (EW)	BHAR [1,10] (EW)
1	5.03	15.54%	-2.07%	0.06%	-0.08%	-0.27%	-1.59%	-0.10%	-0.30%*	-0.64%***
2	6.76	15.40%	-2.29%	0.02%	0.13%	-0.04%	-1.97%	-0.03%	-0.15%	-0.38%***
3	7.57	15.36%	-2.43%	0.00%	-0.01%	-0.22%*	-2.13%	-0.01%	-0.08%	-0.16%
4	8.15	15.35%	-2.46%	-0.01%	-0.18%*	-0.28%**	-2.22%	0.00%	-0.12%**	-0.27%***
5	8.65	15.38%	-2.41%	-0.03%	-0.10%	-0.08%	-2.28%	-0.02%	-0.11%**	-0.15%**
6	9.12	15.43%	-2.45%	0.03%	-0.05%	0.02%	-2.42%	-0.03%	-0.05%	-0.12%
7	9.59	15.45%	-2.35%	-0.04%	-0.09%	-0.22%	-2.45%	-0.06%**	-0.09%*	-0.14%*
8	10.09	15.47%	-2.40%	0.01%	0.18%***	0.30%***	-2.54%	0.02%	0.05%	0.00%
9	10.69	15.53%	-2.35%	-0.08%**	-0.06%	-0.09%	-2.61%	-0.04%	-0.05%	-0.05%
10	11.71	15.55%	-2.38%	0.05%*	0.04%	-0.02%	-2.77%	0.15%**	0.26%**	0.34%***

This table reports mean values for fragmentation among dark pools, dark pool proportional volumes, raw event date returns, and buy-and-hold abnormal returns over various time intervals following event dates. Buy-and-hold abnormal returns are calculated over two, five, and ten day intervals subsequent to a given event date. Panel A presents these statistics by deciles formed by sorting stocks first on *FragDark*, and then *DarkPool*, on each event date. Panel B presents the same statistics for deciles formed by sorting stocks first on *DarkPool*, and then *FragDark* on each event date. Abnormal returns are calculated using DGTW expected returns. Mean returns are

Table 17, continued.

calculated on a value-weighted (VW) or equal-weighted (EW) basis for a given decile of stocks on a given event date, and then equally weighted across event dates. Variables are as defined in Appendix A. Statistical significance is denoted by *, **, and *** to indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, based on p-values comparing a given deciles' return with zero.

CONCLUSION

In this dissertation, I examine two highly controversial facets of modern market structure, dark trading and fragmentation. Research in this area has employed an array of statistical techniques to address the endogeneity that arises from a complex trading landscape. My contribution is made possible by leveraging opportunities provided by regulatory initiatives. Rather than using statistical corrections for endogeneity, my research relies on exogenous regulatory shocks and novel data for causal identification.

My first essay explores the effects of aggregate dark trading volumes on market quality for typical trading sessions. Empirically, we use the Security and Exchange Commission's (SEC) Tick Size Pilot Program to isolate a pilot provision which generates a significant negative exogenous shock to dark trading. Several earlier studies find strong positive effects on liquidity from dark trading, and several others find the opposite. However, in the presence of a large exogenous shock to dark trading, we find no significant impact on liquidity or price efficiency. These findings suggest regulatory concern may be misguided, given restrictions on dark trading in many developed markets.

In my second essay, I study how dark trading and fragmentation affect stock resiliency. There is a mature literature focused on how different economic agents explain cross sectional variation in how individual stocks fare during times of market stress. However, we know comparatively little about the direct effects from market structure in this setting. One reason for this gap in the literature was a lack of data about dark trading and fragmentation to investigate empirically. However, in a recent effort to increase transparency in dark trading, the Financial Industry Regulatory Authority (FINRA) began publishing highly granular data regarding

executions in dark trading venues. My empirical strategy identifies days of extreme market decline and uses FINRA's dark trading data to explain dislocations to liquidity, volatility, and price in the cross section. Contrary to inferences obtained using proxies available before FINRA's dark trading data, I find that stocks with greater dark pool volumes and fragmentation have relatively higher liquidity, lower volatility, and steeper price declines during a large down day on the market. My results offer evidence of benefits from dark trading and fragmentation that contradict concerns that dark trading and fragmentation make markets more fragile.

VITA

Ryan Z Farley was born and raised in New York, New York. He graduated from Staten Island Technical High School and received a full scholarship from Loyola University of New Orleans to pursue his undergraduate education. In May of 2001, he graduated with his Bachelor of Science degree from Loyola University in Computer Science. Later that year, Ryan returned to New York in search of employment opportunities.

Ryan began his career as a systems analyst with Abel Noser Corp., an institutional equity broker in New York's financial district. After obtaining his Series 7 license for registered representatives, Ryan moved on to join ITG Inc. where he managed two teams responsible for the firm's trading infrastructure, before switching roles to join ITG's International Sales & Trading desk. In this role, Ryan was responsible for sales of electronic trading products to US domiciled institutions trading in foreign markets. In 2009, Ryan left ITG to become a product manager with Deutsche Bank's equity division. At Deutsche Bank, Ryan was responsible for order and execution management products for US equities, later becoming global program manager of crossing networks, execution algorithms, and electronic trading. After an eleven year career in institutional trading, Ryan decided to pursue a career in academia and enrolled in graduate school at the University of Tennessee.

Following the completion of a Master's degree in Economics, Ryan joined the doctoral program at University of Tennessee's finance department in January of 2015. At the Haslam College of Business, Ryan developed knowledge and skills as an academic researcher, benefiting immensely from the instruction of Haslam's stellar faculty. Ryan's area of expertise is equity market structure and investments, and he will graduate with a Ph.D. in Business Administration

with a concentration in finance in August of 2019. During his doctoral study, Ryan worked closely with Dr. Andy Puckett and Dr. Eric Kelley. He is extremely grateful for their mentorship. Following graduation, Ryan will join the Department of Finance within the Haslam College of Business, to become director of the Torch Funds program providing experiential learning opportunities to undergraduate and graduate students pursuing careers in investments.