# Diving Into Dark Pools*

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# Diving Into Dark Pools

**Abstract**

We study 2009 and 2020 dark trading for U.S. stocks. Dark trading is lower when volume is low, volatility high, and in periods of markets stress. Dark pools are more active for large caps, while internalization is more common for small caps. Traders use dark pools to jump the queue for large caps in 2009, and to avoid crossing the spread for small caps in both years. Internalization is higher when spreads are wide and depth is high. Dark pool trading improves spreads in 2009, but worsens market quality for large caps in 2020. We discuss explanations for the change.

## 1. Introduction

In its *Concept Release on Equity Market Structure* (SEC, 2010), the U.S. Securities and Exchange Commission (SEC) raises concerns about the consequences of a rising dark pool market share on public order execution quality and price discovery. More recently, in its *Staff Report on Equity and Options Market Structure Conditions in Early 2021* (SEC, 2021), the SEC raises concerns about the large amount of volume that is executed away from the lit markets by internalizing over-the-counter (OTC) market makers, particularly during periods of market stress. To help inform the regulatory debate, we use data from 2009 and 2020 to study dark trading. Specifically, we examine two main research questions. What factors influence order routing to dark pools and internalizing OTC market makers? Does dark trading affect market quality?

There are several reasons for why institutional traders may want to avoid displaying their orders in continuous limit order markets. Order display invites imitation, potentially reducing the alpha of the underlying investment strategy. Displayed orders also invite front running by broker-dealers as well as by opportunistic traders, resulting in higher trading costs. Moreover, institutional traders worry about the risk of trading against informed order flow, especially order flow from proprietary trading desks. *Regulation National Market System (NMS)* (SEC, 2005) opened the door for broker-operated non-displayed liquidity venues, so called dark pools. Dark pools have limited or no pre-trade transparency reducing the problems of imitation and front running. They also control access, potentially reducing the risks of facing informed order flow. Finally, they offer participants opportunities to trade inside the lit market spread.[1] Trades in dark pools represent less than 10% of U.S. share volume in 2009 and about 14% in 2020.[2]

While our focus is on dark pools, these venues are not the only way in which trading occurs away from lit exchanges. OTC market makers internalize roughly 24% of U.S. share volume in 2020. This is mainly orders routed to OTC market makers by retail brokerage firms, but OTC market makers also interact with institutional order flow. We incorporate internalization by OTC market makers throughout the analysis. Moreover, we control for trading in lit venues that compete with the listing exchange. This allows us to study the complex ways in which dark trading may affect market quality.

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[1] See Mittal (2008) for a discussion of dark pool characteristics.

[2] Rosenblatt Securities, Inc. started tabulating monthly share volume for dark pools in its Trading Talk publication in 2008 and TABB Group started its Liquidity Matrix publication in 2007. Since 2014, the Financial Industry Regulatory Authority (FINRA) collects Alternative Trading System level data on trading volume on a weekly basis, and from 2016 the data include trades by OTC market makers.

Our 2009 data come from a survey conducted by the Securities Industry and Financial Market Association (SIFMA) on our behalf. SIFMA solicited daily stock-level dark pool share-volume data from all their members operating dark pools. Participation was voluntary, and SIFMA in the end obtained data from eleven dark pools. The SIFMA sample allows us to examine dark pool activity for over 3,000 stocks. For 2009, the only publicly available data on dark trading are the trades reported to one of the Trade Reporting Facilities (TRFs) which aggregates dark pools and trades internalized by OTC market makers. We use this information to proxy for 2009 internalized trades by subtracting SIFMA reported volume from TRF reported volume, recognizing that this measure includes the dark pools that chose not to report their trades to SIFMA. We supplement the 2009 self-reported data with weekly Financial Industry Regulatory Authority (FINRA) OTC Transparency data for 2020. The 2020 data are comprehensive, and we are able to study trading activity in Alternative Trading Systems (ATSs) and internalized by OTC market makers (Non-ATSs) for over 2,900 stocks.

Our samples each include a dramatic decline in the stock market and elevated uncertainty, associated with the Great Financial Crisis in 2009 and the COVID pandemic in 2020, followed by a steady recovery. This allows us not only to study how dark trading has changed over time, but also to examine the role of dark trading during periods of market stress. The increase in the CBOE Volatility Index (VIX) was particularly dramatic in March 2020, and we find that the results are sensitive to including this period. Therefore, we report results for 2020 both overall and excluding the period February 15 - April 15, 2020 (ex-COVID sample).

Dark trading overall is relatively stable in each sample year despite the tumultuous stock market, but it does exhibit an increasing trend in 2009. We find that dark pools are more active for large capitalization firms than for small capitalization firms, while OTC market makers internalize more for small capitalization than for large capitalization firms. Consequently, we control for firm by quarter fixed effects throughout our analyses.

We first examine how order routing to dark venues depends on market conditions, such as price, volume, and volatility, as well as on instruments for order book characteristics. For small caps, consistently across our sample periods, order routing to dark pools increases when the book is less competitive (proxied by depth in 2009 and by both spread and depth in 2020), the relative tick size is large and trading activity is high, suggesting that traders value the advantage of sourcing liquidity on dark venues when the lit market is illiquid due to either low depth or wide spreads.

For large caps, how traders route orders to dark pools changes over our sample periods. In 2009, dark pool market share for large caps is higher when the book is more competitive, suggesting the ability to jump the long queue at the inside of the order book is particularly valuable for large caps, especially when the tick size is large. By contrast, in 2020 order routing to dark pools for large caps is unrelated to the state of the book, except during the COVID period when traders seem to use dark pools to avoid crossing the wide spread and the opportunity to execute within the quoted spread is more important.

Consistently across stocks and samples, we find that OTC market makers internalize more orders when depth is high. In 2009 we find evidence that the market share of OTC market makers is also higher when spreads are wide. This evidence suggests that payments for order flow arrangements are more profitable for internalizing market makers when spreads are wide, and a higher depth in the lit market means that OTC market makers can more easily offset order imbalances. Taken together, these results also show that the effect of market conditions and order book characteristics on market shares differ between categories of dark trading, as well as across stocks within a particular category.

We investigate how dark trading affects market quality using a simultaneous equation system where we instrument for dark trading to account for the fact that market quality and dark trading are jointly determined. We document that aggregate dark trading leads to lower spreads in 2009, but does not significantly affect our market quality measures in 2020. Separating the two forms of dark trading, we find that both higher dark pool market share and more internalization by OTC market makers lead to lower spreads in 2009. This is generally true for subsamples by firm size as well as overall. By contrast, we find no effect of dark trading on short-term volatility in 2009. In the later sample, more dark pool trading leads to higher short-term volatility overall, and both wider spreads and higher short-term volatility for the ex-COVID sample. By examining the subsamples by size, we show that the negative effect of dark pool trading on market quality derives from large capitalization stocks. We find no evidence that more internalization affects market quality in 2020.

Finally, we study whether dark trading plays a different role during periods of market stress, defined as the first six months of each year, and days (weeks) with low returns, high selling pressure, or high volatility. The market shares of dark pools and OTC market makers are generally lower during periods of market stress. In 2009, higher dark trading (of either type) during days when markets are under stress leads to narrower spreads and lower short-term volatility. By contrast, higher dark pool trading leads to wider spreads and higher short-term volatility during weeks with low returns and high volatility in 2020.

These differences in the effects of dark trading -- between types of dark trading, across stocks, and between sample periods -- highlight the complex ways that dark trading affects market quality for U.S. stocks. They illustrate that it can be misleading to focus on one form of fragmentation, on one part of the cross-section of stocks, or on one specific time-period. By comparing the 2009 and the 2020 sample periods, we see that changing market conditions, the development of new venues, as well as the practices of market participants can significantly affect inference regarding the role dark trading plays in markets. We speculate that the difference between the two samples arises because more proprietary order flow, High Frequency Traders (HFTs), and informative retail order imbalances reach dark pools in 2020, and that these venues have become less attractive for institutional traders as a result.

This paper contributes to the literature on dark pools in several ways.[3] Our study is the first broad cross-sectional study documenting dark trading in U.S. equity markets. The evidence we present suggests that studying aggregate dark trading instead of its components can lead to very different conclusions (Degryse, De Jong, and Van Kervel, 2015). Prior studies have emphasized that different types of dark pool pricing mechanisms (Foley and Putniņš, 2016) and dark pool trade sizes (Comerton-Forde and Putniņš, 2015) may have different effects on market quality, and we show that there are also differences between trades internalized by OTC market makers and dark pool trades (Kwan, Masulis, and McInish, 2015). Prior work has focused on the effect of dark pools on market quality for Large capitalization securities, missing the important cross-sectional variation documented in our paper (e.g., Comerton-Forde and Putniņš, 2015; Degryse, De Jong, and Van Kervel, 2015; and Foley and Putniņš, 2016). Finally, we show that the nature of dark trading and its effect on market quality have changed significantly in recent years.

The paper proceeds as follows. Section 2 describes our samples and provides descriptive statistics. How firm and order book characteristics influence order routing is discussed in Section 3. Section 4 studies the relationship between dark trading and measures of market quality. Market stress is the focus of Section 5. We discuss the results in Section 6 and Section 7 concludes.

## 2. Data and descriptive statistics

SIFMA solicited daily data on stock-level dark pool share volume for the 2009 calendar year from all their members operating dark pools. The reporting was voluntary, and SIFMA collected data on daily single-counted share volume from eleven dark pools. The data are daily share volume per security for each of the eleven dark pools, but the data include no names of the dark pools. Our agreement with SIFMA precludes us from study the data for individual (or groups of) dark pools. Therefore, we are unable to report results for individual dark pools, or results divided into groups of dark pools by the type of ownership or by the execution algorithm.[4] Online Appendix Figure A1 shows that our SIFMA raw data represent

[3] We discuss the extensive existing literature on fragmentation in Section 3 of the Online Appendix.

[4] Foley and Putniņš (2016) using Canadian data find that dark pools that enable traders to supply two-sided liquidity inside the lit market spread improve lit market quality, while those that execute at the midpoint have no effect on

between 47% and 60% of dark volume as reported by Rosenblatt, Inc. in their *Let There Be Light* publication (Gawronski and Schack, 2010). We screen the SIFMA dark pool data as described in Section 1 of the Online Appendix, which results in a sample with a cross-section of 3,098 securities. We aggregate the daily share volume across reporting venues into a stock-day series (*DP*). We use DTAQ to calculate daily total dark share volume reported to one of the TRFs (*TRF*), and lit competing share volume (*COMP*) as share volume reported to one of the transparent venues that compete with the listing exchange.[5] All registered exchanges can trade all U.S. stocks through unlisted trading privileges. Hence, for each listing exchange, there were as many as a dozen lit competing venues. There is no data source for internalized trades in 2009, so we proxy for internalized trades (*INT*) by subtracting dark pool share volume from TRF share volume for each stock-day. Note that while this measure includes primarily internalized trades, it also includes the dark pools that did not report to SIFMA. Finally, we express each measure of fragmentation as a fraction of consolidated share volume.

To compare our original 2009 SIFMA data to a more recent period, we download data from FINRA for 2020. Since 2014, FINRA has been publishing security-level weekly OTC Transparency data for ATSs, and FINRA augmented the data to include weekly data for individual OTC market makers grouped together under the Non-ATS header in 2016.[6] We screen the FINRA data as described in Section 2 of the Online Appendix, which results in a 52-week sample with a cross-section of 2,902 securities. For each stock and week, we aggregate the ATS share volume into a variable *ATS*, and the volume reported by OTC market makers into a variable *Non-ATS* and label the sum of these two as *FINRA.* The advantage of the FINRA OTC Transparency data is that it covers all dark pools and all internalizing OTC market makers. The drawback is that data are only available weekly, and we expect to have less power as a result. We use the SEC's Market Information Data Analytics System (MIDAS) to calculate 2020 weekly share volume for lit competing venues as share volume reported to one of the transparent venues that compete with the listing exchange, and express each measure as a fraction of consolidated share volume.

Figure 1 illustrates the variation in the three daily dark market shares averaged across stocks for 2009 (Panel A), and in the three weekly market shares averaged across stocks for 2020 (Panel B). We superimpose the VIX and the S&P 500 index values in each panel. Both years display a very large stock market decline followed by a rapid recovery in the first six months, and a calmer stock market in the second half of the year. Volatility spikes during the rapid stock market decline in the first half, particularly during

market quality. By contrast, Comerton-Forde, Malinova, and Park (2018) and IIROC (2015) find no significant effect of either type of dark pool activity on market quality using the same data.

[5] TRF trades appear with exchange code "D" in DTAQ data.

[6] For details, see https://www.finra.org/filing-reporting/otc-transparency .

2020. Therefore, we also analyze a restricted 2020 ex-COVID sample where we exclude nine weeks between February 15 and April 15, 2020. Dark fragmentation is much less volatile.[7] It increases gradually for the 2009 sample, but there is no noticeable secular trend in 2020.

Figure 1 hides significant cross-sectional variation in dark trading. We visualize this variation in Figure 2 where we plot time-series average measures of dark trading against the natural logarithm of previous year-end market capitalization, *log(Size)*, for 2009 (Panel A) and 2020 (Panel B). Overall dark trading is declining in *log(Size)* regardless of sample period. The next two plots in each panel show that there is a clear difference between dark pool trading and internalization. While internalization (*INT* and *Non-ATS*) is declining in *log(Size)*, dark pool trading (*DP* and *ATS*) is increasing in *log(Size)*. Hence, internalization is higher for small capitalization stocks than for large capitalization stocks on average, and the opposite is true for dark pool trading. The overall cross-sectional patterns are very similar across the two years, despite the fact that the data sources are very different and that we do not have comprehensive dark pool data for 2009. Figures 1 and 2 suggest that we should follow Degryse, De Jong, and Van Kervel (2015) and use stock-by-quarter fixed effects in our panel regressions to control for the slow moving trend and the significant cross-sectional variation in fragmentation.

We draw information on size and daily market conditions from CRSP, including market capitalization, share volume, closing stock price, and volatility (defined as (high-low)/high based on quotes). We also compute daily market quality measures from DTAQ for 2009. We draw daily market quality measures from the WRDS Intraday Indicators for 2020. To match our weekly FINRA data for 2020, we average the daily market condition and market quality data to create a weekly panel. To reduce the influence of outliers, we impose further screens on the data. We exclude stock-days where there is no reported consolidated volume in CRSP, where there are fewer than 20 trades per day in TAQ or WRDS Intraday Indicators, and we exclude early closing days around holidays. Finally, we drop stock-days (stock-weeks) where the SIFMA (FINRA) reported dark volume exceeds the consolidated volume as reported in CRSP.

Our market quality measures include stock-level daily time-weighted National Best Bid Offer (NBBO) quoted spreads, share-weighted effective half-spreads, and the standard deviation of mid-quote returns measured over 15-minute (quote-update) intervals for 2009 (2020).[8] Short-term volatility is a measure of trading frictions, and a market with lower volatility is more efficient. We multiply this variable

[7] There is a large spike in early 2020 for the three market shares. Our results are robust to excluding this week.

[8] WRDS Intraday Indicators do not include 15-minute measures of standard deviation based on mid-quote returns. We also repeated all our analyses for the variance ratio, and this variable is unaffected by dark trading for both years.

by 10,000 so it is in basis points. We express quoted and effective spreads as a percentage of the mid-quote. We measure depth computed as the time-weighted average bid and offer depths in shares at the NBBO. To address the significant skewness in the data, we follow the literature and take the natural logarithm of both market conditions and market quality measures in our regression analyses.[9]

Table 1 summarizes the descriptive statistics for our stock-day 2009 sample in Panel A, for our stock-week 2020 overall sample in Panel B and for our stock-week 2020 ex-COVID sample in Panel C. The median 2009 firm size is $483 million, volume is 270 thousand shares, stock price is $13.71, and volatility is 6.18%. The median 2020 firm size for the overall (ex-COVID) sample is $1.0 ($1.1) billion, volume is 1.9 (1.8) million shares, stock price is $22.34 ($22.80), and volatility is 4.62% (3.99%). Thus, the median firm is larger, has higher volume, a higher stock price, and lower volatility in 2020 (especially for the ex-COVID sample) compared to 2009. Despite this, we find that the median firm faces worse market quality in 2020 than in 2009. The median 2009 quoted spread is 24.78 basis points, effective half-spread is 7.72 basis points, depth is 474 shares, and standard deviation of 15-minute mid-quote returns is 48.11 basis points. The median 2020 quoted spread for the overall (ex-COVID) sample is 34.42 (31.42) basis points, the effective half-spread is 9.68 (8.75) basis points, depth is 282 (281) shares, and standard deviation of mid-quote returns is 4.08 (3.62) basis points (not directly comparable to 2009 where we have 15-minute returns). As expected, the 2020 ex-COVID sample has not only lower volatility (as measured by the intraday range) and lower standard deviation of returns, but also lower spreads than the full year sample.

It is well known that U.S. equity trading is highly fragmented (see O'Hara and Ye (2011) and the references therein). The fragmentation measures for our samples are reported in the bottom third of each panel in Table 1. *TRF* (*FINRA*) represents 30.5% (35.2%) of share volume while trades reported to competing exchanges (*COMP*) represents 28.5% (31.2%) of share volume for the median firm in 2009 (2020).[10] This means that overall fragmentation has increased substantially, and the listing exchange captures a smaller fraction of trading activity in 2020 compared to 2009. Internalized trading - *INT* (*Non-ATS*) - represents 23.6% (19.2%) of share volume for the median firm in 2009 (2020). This does not mean that internalization is declining. Recall that *INT* for 2009 comprises internalized trades, but also trades executed in dark pools that did not voluntarily report to SIFMA. The dark pool market share - *DP* (*ATS*) - for the median firm is 6.0% (14.2%) in 2009 (2020). Since the SIFMA sample represents roughly half of

[9] Comerton-Forde and Putniņš (2015), Degryse, De Jong, and Van Kervel (2015), and Foley and Putniņš (2016) take the natural logarithm of market quality and firm characteristics. Furthermore, we Winsorize market quality measures daily at 1% and 99% to deal with significant outliers. Online Appendix Table A1 reports descriptive statistics in logs.
[10] As the breakdown of fragmentation is very similar in the 2020 samples, we only report in parenthesis statistics for the overall 2020 sample.

all dark trading in 2009 (see Online Appendix Figure A1), it appears that dark pool trading has increased somewhat. Finally, we note that the level of dark trading in both our samples is higher than the 25% figure reported by Degryse, De Jong, and Van Kervel (2015) for European stocks in 2009 (dark pools, internalization, and over-the-counter). Dark trading for Australia in 2012 is 18% (dark pools and block trades) according to Comerton-Forde and Putniņš (2015), and it was 8.5% for Canada that same year according to Foley and Putniņš (2016).

It is clear from Table 1 that both samples span stocks with very different firm characteristics, market quality, and levels of dark trading. We believe this very diverse set of stocks will help us better understand the full role of dark trading in securities markets. In our analysis of dark trading, we control for competition from lit venues (*COMP*) as suggested by Degryse, De Jong, and Van Kervel (2015).

## 3. Order routing

When deciding where to send an order, a smart order router takes into account asset-, order-, and market-level characteristics as inputs, and uses this information to predict the fill probability for each venue. The characteristics "include all the factors that may influence fill rates: each exchange's market share, the state of the limit order book (e.g., the depth of each market at the inside price), trading volume, price level, volatility, asset type…" (Bacidore, 2020, p. 162). Data availability necessitates that we focus on a parsimonious specification to capture the main aspects of the order-routing process. We proxy for the state of the limit order book using NBBO depth and the inside quoted spread. Clearly, order routing decisions affect the limit order book, and we therefore use the lagged NBBO depth and the lagged inside quoted spread as instruments for the endogenous contemporaneous limit order book characteristics. We capture the market conditions by including price, share volume, and the intraday range defined as the (High-Low)/High. Since the tick size is constant at one cent for all our sample stocks, the stock price maps into the relative tick size (a high price means a low relative tick size).

To examine how order routing ($OR_{i,t}$) varies with order book characteristics, we run the following IV/2SLS daily panel regressions:

$$log(Quoted\ spread)_{i,t} = a_i\, d_q + b_{1,1}\, log(Quoted\ spread)_{i,t-1} + b_{1,2}\, log(Depth)_{i,t-1} + c_1\, X_{i,t} + e_{i,t} \quad (1)$$

$$log(Depth)_{i,t} = a_i\, d_q + b_{2,1}\, log(Quoted\ spread)_{i,t-1} + b_{2,2}\, log(Depth)_{i,t-1} + c_2\, X_{i,t} + e_{i,t} \quad (2)$$

$$OR_{i,t} = a_i\, d_q + \beta_1\, log(Quoted\ spread)_{i,t} + \beta_2\, log(Depth)_{i,t} + \gamma\, X_{i,t} + e_{i,t} \quad (3)$$

where $X_{i,t}$ is a vector of control variables that captures the market conditions: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$, we control for firm by quarter fixed effects ($a_i\, d_q$), and standard errors are clustered by stock and day. Table 2 reports the results for the second stage regressions in equation (3).[11] The first stage regressions (Online Appendix Table A2.1) for 2009 show that the lagged instruments for both own-effects are positive and significant ($b_{1,1}$ = 0.3678$^{***}$ and $b_{2,2}$ = 0.3424$^{***}$). The cross-effects are negative and small ($b_{1,2}$ = -0.0107$^{***}$ and $b_{2,1}$ = -0.0192$^{***}$), but significant. For the 2020 full sample, only the own-effects are positive and significant ($b_{1,1}$ = 0.3306$^{***}$ and $b_{2,2}$ = 0.2743$^{***}$). For the 2020 ex-COVID sample, only the own-effect for depth is positive and significant ($b_{2,2}$ = 0.2325$^{***}$), while for spread the own-effect is positive and significant only for Small stocks ($b_{1,1}$ = 0.1885$^{***}$).

Our variables *TRF* (2009) and *FINRA* (2020) capture aggregate order routing to dark venues. However, as discussed in Section 2, this data consists of two broad categories of dark trades, those that execute in dark pools and trades internalized by OTC market makers. For completeness, we also report results for order routing to lit competing exchanges. Access to lit competing venues enables liquidity providers to bypass time-priority on the listing exchange.

*TRF* order routing in 2009 is increasing in both our instruments for quoted spread and depth. However, when the aggregate *TRF* is decomposed into dark pools and internalization, order routing to dark pool is negatively related to both our metrics of market quality, whereas internalization is positively related to both spread and depth, which is puzzling as it is unclear whether routing to dark pools or internalizing OTC market makers are related to more or less liquid books.

*FINRA* order routing is unrelated to the book characteristics for the 2020 sample, but it is increasing in the spread for the 2020 ex-COVID sample. However, when we decompose the aggregate *FINRA* into dark pool trading and internalization by OTC market makers, the picture changes substantially. Order routing to dark pools is higher when the book is illiquid and the opposite is true for routing to internalizing OTC market makers. Order routing to lit competing venues is decreasing in both quoted spread and depth in 2009, whereas in both the 2020 samples it is unrelated to the book characteristics. Furthermore, we find that volume is consistently positively related to dark trading and negatively related to order routing to lit competing venues, but the effects of volatility and price change substantially between 2009 and 2020.

To understand the mechanisms that explain the aggregate results, and why they differ between 2009 and 2020, we need to investigate order routing at the most granular level available. We therefore sort our roughly three thousand stocks on previous year-end market capitalization and divide them into terciles (Small, Medium, and Large). We also separately analyze the stocks that are part of the S&P 500 index.

[11] The results are robust to using lagged instruments directly in equation (3), and estimating the panel regressions using OLS (see, Online Appendix Tables A3.1, A3.2, and A3.3).

Table 3 shows that in 2009 for Large caps - and more generally for the S&P 500 stocks - order routing to dark pools increases when the book is liquid as reflected in NBBO spread and depth. Jumping the long queues on the limit order book motivates traders to route to dark pools for Large caps as predicted by Buti, Rindi, and Werner (2017). For Small caps the opposite holds, and order routing to dark pools is strongly negatively related to NBBO depth. This suggests that for Small caps shallow books motivate traders to seek liquidity in dark pools.

For the 2020 ex-COVID sample, Large caps are unrelated to the state of the book, whereas the effect for Small caps gets stronger and order routing to dark pools increases not only when depth is shallow but also when the spread is large.[12] These results confirm that the desire to avoid crossing the spread is an important driver for order flow in Small caps. Note that once we add the nine COVID weeks back into the sample, orders are routed to dark pools when the book is illiquid not only for Small caps, but also for Large caps.

The market conditions also significantly affect order routing. Order routing to dark pools is increasing in volume and this result holds across stocks terciles and sample periods, consistent with the idea that investors seek alternative liquidity venues when trading activity is high. The effect of volatility is more complex. Order routing to dark pools is lower when volatility is high in 2009 and for the entire 2020 sample, whereas it is unrelated with volatility for the 2020 ex-COVID sample. This suggests that, while execution uncertainty and adverse selection costs due to stale trading (Aquilina, Foley, O'Neill, and Ruf, 2021) were a concern for dark venues during periods of high volatility in 2009, and during the 2020 COVID crash, those concerns have attenuated in 2020 overall, probably as a result of improvements in dark venue execution speeds. As a result, volatility is less of a deterrent to use dark pools in 2020 than it was in 2009. Finally, order routing to dark pools decreases in price: hence it increases with relative tick size in 2009 and - especially for Small caps - in the more recent 2020 ex-COVID sample, while it disappears if we add the turbulent weeks of the COVID period in 2020. Two possible mechanisms may be at work. First, when the relative tick size is large crossing the spread to execute a market order is more expensive and therefore opting for dark pools executing inside the NBBO may be more desirable. Second, when the relative tick size is large the queues at the top of the limit order book become longer and jumping the queues by routing orders to dark pools becomes an attractive order submission strategy.[13] Table 3 shows that dark pool order

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[12] As mentioned before (Table A2.1 in the Online Appendix), this result should be taken with caution as for Large caps the lagged NBBO spread value is a weak instrument for the state of the book in the 2020 ex-COVID sample.

[13] Yao and Ye (2018) show that an increase in the relative tick size increases rents for liquidity provision and lengthens the queue at the BBO.

routing is positively related with depth for Large caps whereas it is negatively related for Small caps, and we therefore conjecture that it is primarily the second mechanism that is at work for Large caps.

Turning to internalization, Tables 2 and 3 show that order routing to OTC market makers is increasing in NBBO depth and this result holds across all terciles and sample periods. This means that the main effect at work over time and across different stocks is that OTC market makers are more likely to internalize orders when they can lay off the resulting inventory against a deep book. Results for spread are more complex. In 2009, the desire to avoid crossing wide spreads is an important driving force for routing trades to OTC market makers. However, this effect virtually disappears in the 2020 samples. When including the nine weeks of extreme COVID related volatility, results become noisy and insignificant: for example, it is hard to explain why order routing to internalizing OTC market makers decreases in spread only for Small caps in the 2020 overall sample.[14] In 2009, market conditions also matter for order routing to OTC market makers and they receive more order flow when volatility is low and trading activity is high – as was the case for dark pools, but the results are noisier in the more recent sample.

Finally, order flow to lit competing venues is generally decreasing in both the quoted spread and depth in 2009, which is consistent with the idea that bypassing time-priority is more valuable when the listing exchange's order book is more competitive (Foucault and Menkveld, 2008). In contrast to dark fragmentation, order flow to lit competing venues is decreasing in volume and increasing in volatility, while it shows no significant correlation to the relative tick size. Thus, it appears that informed traders benefit from being able to sweep the possibly stale limit order books across venues when markets are more volatile and trading activity is low (Chakravarty, Pankaj, Upson, and Wood, 2012). Order book characteristics are generally unrelated to order flow to competing venues in 2020.

Taken together our results on order routing are as follows. Consistently across our sample periods, for Small caps order routing to dark pools increases when the book is illiquid, the relative tick size is large, there is less uncertainty, and high trading activity signals to traders that they may find liquidity in dark pools. In 2009, dark pools are mainly used for Large caps to jump the long queues in deep books, especially when the relative tick size is high. By contrast, in 2020, order routing to dark pools for Large caps is unrelated to the state of the book, and traders instead use dark pools to avoid crossing the wide spread

[14] Notice that for Small caps, OTC market makers internalize more orders when volatility as measured by the intraday range is high, while the sign on volatility is the opposite for all other subsamples. Therefore, we conjecture that the Small cap result on spread arises because wide quoted spreads coincide with high volatility (Online Appendix Table A2.1), and this causes the IV/2SLS to load any quoted spread effect on the volatility control for Small caps. Evidence supporting this conjecture is in Online Appendix Table A3.3 where we instead use OLS. Narrow lagged quoted spreads still lead to more internalizing by OTC market makers, but the magnitude is much smaller and there is no significant effect of the volatility control variable.

during the COVID period.[15] Similar results as for Large caps hold overall for the S&P 500 sample. Consistently across stocks and samples, we find that OTC market makers internalize more orders when depth is high, and they can more easily lay off the resulting inventory in lit markets. Results for lit competing venues are intriguing for 2009 as investors resort to lit competing venues when the book spread is narrow, possibly undercutting time priority, but no significant results persist in 2020. We discuss possible reasons for the changing pattern of fragmentation between our sample periods in Section 6.

## 4. Dark trading and market quality

A central question for regulators is whether dark trading has any detrimental effects on measures of market quality, such as quoted spreads, effective spreads, and short-term volatility. Traders decide whether to submit an order to a dark venue or to the public limit order book based on observing the depth and the quoted spread as well as their information about the value of the stock. Therefore, to investigate the effects of dark trading on market quality we have to take into account the fact that dark trading is endogenous. We estimate two-stage least squares instrumental variables (IV/2SLS) panel-regressions, where we instrument for dark trading as well as competition from lit venues in an attempt to control for endogeneity following Hasbrouck and Saar (2013). We also include an instrument for market-wide market quality to control for reverse causality following, e.g., Degryse, DeJong, and Van Kervel (2015) and Comerton-Forde and Putniņš (2015).

As the power of the IV/2SLS method depends on the quality of the instruments, we need to find good instruments for dark market shares. Hasbrouck and Saar (2013) propose using the average low latency trading in other stocks during the same time-period as an instrument for low latency trading in a particular stock when evaluating the impact of low latency trading on market quality. We follow their suggestion and use average across stocks of dark market share on day *t* as an instrument for the dark market share in stock *i*. The idea is that, if dark trading has a significant market-wide component, a measure of market-wide average of dark market share will correlate with firm-level dark trading. However, to be a good instrument, we also need to ensure that our market-wide average is uncorrelated with the error term in equation (6) defined below. Excluding the firm itself from the market-wide average eliminates a clear source of correlation, and by also excluding firms in the same industry and firms that belong to the same index we reduce the correlation that may arise because of common industry- or index-based trading strategies. Therefore, we exclude stock *i* and require the other stocks (*Noti*) to have a market capitalization in the same

[15] In Section 5 we further discuss order routing in periods of market stress.

size tercile (Large, Medium, Small) as stock *i*.[16] Furthermore, following Hasbrouck and Saar (2013), we exclude stocks that are in the same four-digit SIC code or in the same major index (S&P 500, Nasdaq 100) as firm *i* from *Noti*. We use the same method to create instruments for each of our market shares. Finally, we also create instruments for market quality measures using the same approach.[17] Specifically, we define $Y_{Noti,t}$ as the day *t* average market quality measure $Y_{i,t}$ across stocks in the same size tercile excluding stock *i*, but that are not in same four digit SIC code, and not in same index (S&P 500 and/or Nasdaq 100).

The IV/2SLS panel regressions take the following form:

$$DARK_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1\, Z_{i,t} + e_{1,i,t} \tag{4}$$

$$COMP_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2\, Z_{i,t} + e_{2,i,t} \tag{5}$$

$$Y_{i,t} = \alpha_i\, d_q + \beta_1\, DARK_{i,t} + \beta_2\, COMP_{i,t} + \boldsymbol{\gamma}\, Z_{i,t} + e_{4,t} \tag{6}$$

where $Y_{i,t}$ is a market quality measure, and $DARK_{i,t}$, is the market share of *TRF* trading for 2009 and the market share of *FINRA* reported trading for 2020, and $COMP_{i,t}$ is the market share of lit competing venues expressed as a percentage of consolidated volume. $Z_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$, $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $DARK_{Noti,t}$, and $COMP_{Noti,t}$ where *Noti,t* again stands for the day *t* average across stocks in the same size group as stock *i*, but that are Not in same four digit SIC code, and Not in same index (S&P 500 or Nasdaq 100).

We report results from the second stage of (6) in Table 4 for each of our market quality measures: *log(Quoted spread)*, *log(Effective half-spread)*, and *log(StD returns)*. The first stage regressions (Online Appendix Table A4.1) for 2009 show that the lagged instruments for own-effects are positive and significant. For example, when $Y_{i,t}$ is the quoted spread, $b_{1,1} = 0.8981^{***}$ and $b_{2,2} = 0.9449^{***}$. The cross-effects are smaller ($b_{1,2} = -0.0320$ and $b_{2,1} = 0.0245^{**}$), and only the second one is significant. For the 2020 overall and ex-COVID samples, both the own-effect and cross-effect for $DARK_{Noti,t}$ are insignificant, but the coefficient on $COMP_{Noti,t}$ is significant both as an own effect ($b_{2,2} = 0.9693^{***}$ and $b_{2,2} = 0.9765^{***}$, respectively) and as a cross effect ($b_{2,1} = 0.8111^{***}$ and $b_{2,1} = 0.7295^{***}$).

Starting with 2009, results in Panel A Table 4 show that dark trading leads to lower quoted and effective half-spreads but does not affect short-term volatility significantly. The effect of lit competition

[16] The idea behind the size grouping is that we have observed that there are systematic differences in dark pool trading across subsamples.

[17] Hasbrouck and Saar (2013) were able to use the spreads for other markets quoting the same security in their analysis of low latency orders on the Nasdaq. We unfortunately cannot follow their strategy because dark pools do not disseminate quotes.

on quoted spreads and short-term volatility is insignificant. The controls are all significant: as expected, spreads and short-term volatility are increasing in relative tick size (decreasing in price), and increasing in volatility as measured by the intraday range. Quoted spreads are decreasing in volume as expected, but both effective half-spreads and short-term volatility are increasing in volume.

Turning now to the 2020 samples, results in Panel B and C show that dark trading does not significantly affect any market quality measure. By contrast, lit competition is associated with lower quoted and effective half-spreads but has no significant effect on short-term volatility. With the exception of price for the quoted spread regressions, the control variables are significant also for 2020. As expected, spreads and short-term volatility are increasing in volatility. While quoted and effective half-spreads are decreasing in volume as expected, short-term volatility is increasing in volume.

Even if overall dark trading does not have detrimental effects on market quality, it is possible that one of the dark trading types - dark pools or internalization by OTC market makers - could adversely affect market quality. Dark pools specialize in Large caps, while OTC market makers are more active in Small caps (Figure 2), and this may lead to differences in the cross-section. It is also possible that dark trading is particularly detrimental for Small caps, where fragmentation and information asymmetries are more likely to affect market quality. We therefore further explore whether the effect of dark trading on market quality varies by the type of venue (dark pool or internalized by OTC market makers) or by size.

When we decompose *DARK* into *DP* and *INT* for the 2009 sample, the IV/2SLS panel regressions take the following form:

$$DP_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1\, Z_{i,t} + e_{1,i,t} \tag{7}$$

$$INT_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2\, Z_{i,t} + e_{2,i,t} \tag{8}$$

$$COMP_{i,t} = a_i\, d_q + b_3\, W_{i,t} + c_3\, Z_{i,t} + e_{3,i,t} \tag{9}$$

$$Y_{i,t} = \alpha_i\, d_q + \beta_1\, DP_{i\,i,t} + \beta_2\, INT_{i\,i,t} + \beta_3\, COMP_{i,t} + \boldsymbol{\gamma}\, Z_{i,t} + e_{4,t} \tag{10}$$

where $Z_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$, $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $DP_{Noti,t}$, $INT_{Noti,t}$, and $COMP_{Noti,t,}$ and $Noti,t$ again stands for the day $t$ average across stocks in the same size group as stock $i$, but that are Not in same four digit SIC code, and Not in same index (S&P 500 or Nasdaq 100). For the 2020 samples, we replace *DP* with market share of *ATS*s and *INT* with market share of *Non-ATSs*.

The results of the second stage estimation are in Table 5 Panel A for the 2009 sample and in Panels B and C for the 2020 samples.[18] The first stage results are in Online Appendix Table A5.1 for quoted spread and the results are similar for the other market quality variables. They show that the instruments for the own-effects are positive and highly significant in 2009 (coefficient on $DP_{Noti,t}$ is 0.8855***, $INT_{Noti,t}$ is 0.9253***, and $COMP_{Noti,t}$ is 0.9428***). In the 2020 samples, only the instruments for the own-effects in the *ATS* and *COMP* equations are significant but the cross-effects are significant for all equations, including the *Non-ATS* equation (for the 2020 overall sample coefficient on $ATS_{Noti,t}$ is 0.9624***, $Non\text{-}ATS_{Noti,t}$ is 0.0092, and $COMP_{Noti,t}$ is 0.9652***; while for the 2020 ex-COVID sample coefficients are 0.8999***, 0.0262 and 0.9669***, respectively).

For 2009, a higher dark pool market share leads to narrower quoted and effective half-spreads. A higher internalized market share also leads to narrower quoted spreads, and there is a negative coefficient in the effective half-spread regression but it is not significant at conventional levels. Neither form of dark trading affects short-term volatility. Hence, both types of dark trading lead to improved market quality on average in 2009. By contrast, we find no evidence that either form of dark trading affects spreads in the overall 2020 sample, and a higher dark pool market share leads to higher short-term volatility in this sample. In addition, we find that dark pool trading leads to wider effective half-spread for the 2020 ex-COVID sample. The coefficients on the control variables are significant and have the same signs as they did in Table 4.

We examine whether the beneficial effects of both types of dark trading on market quality in 2009, and the negative effect on effective half-spread in the 2020 ex-COVID sample and on short-term volatility in both the 2020 samples, derive from certain groups of stocks by conducting splits by size. The results are in Table 6.[19] Panel A covers the results for 2009. The beneficial effects of dark pools for quoted spreads are evident for all subsamples. Internalization by OTC market makers is beneficial for quoted spreads for all but the subsample of Small caps where the coefficient is insignificant. Similarly, the beneficial effects of dark pools for effective half-spreads are evident for all but the S&P 500 subsample where the coefficient is insignificant. Higher internalization by OTC market makers leads to lower effective half-spreads for Large caps and S&P 500 stocks, but the coefficient is insignificant for the remaining subsamples. Finally, there is no significant effect of either higher dark pool trading or internalization on short-term volatility for any subsample. The results for the 2020 overall sample are in Panel B, and show that there are no significant

[18] Note that the results for lit competition do not change qualitatively when we split dark trading into dark pools and internalization by OTC market makers. Therefore, we do not discuss these results again.

[19] The first stage results are in Online Appendix Table A6.1 for quoted spread. Results are similar for the other market quality variables.

effects on spreads of either higher dark pool trading or internalization by OTC market makers for any subsample. Note, however, that for the 2020 ex-COVID sample, the evidence shows that more dark pool trading leads to wider spreads for Large caps and to significantly higher short-term volatility both for Large caps and S&P 500 stocks.[20]

In sum, we find that both types of dark trading lead to lower spreads in 2009, but that dark pool trading leads to wider spreads for Large caps in the 2020 ex-COVID sample. We find no evidence that higher dark trading of either type affects short-term volatility in 2009, but we do find that higher dark pool market share leads to higher short-term volatility for Large caps in 2020. To further investigate why our results change over the two sample periods, in Section 5 we show the effects of dark fragmentation during periods of market stress and in Section 6 we provide a comprehensive discussion of our results.

## 5. Market stress

Our samples cover two tumultuous periods in global financial markets, the Great Financial Crisis in 2009 and the start of the COVID pandemic in 2020. Did the dramatic market moves and the high levels of uncertainty during the first halves of 2009 and 2020 imply a different relationship between dark trading and market quality? More generally, does dark trading have detrimental effects on market quality in periods of market stress?

Figure 1 suggests that the first half of each year *(H1)* was a period of market stress. We consider several other indicators of market stress at the stock level, including the lowest tercile of individual stock returns *(ret_low)*, the lowest tercile of stock-specific buy-order imbalances (*bs_low*), and the highest decile of volatility *(vol_extr)*. We instead use the highest tercile of volatility (*vol_high*) for the 2020 sample due to the limited time-series. Since our indicator variables are another way of capturing days (weeks) with extreme volatility, we drop the intraday range from these regressions. Moreover, since these days (weeks) are likely associated with extreme prices, we also drop the stock price as a control variable. We continue controlling for volume and for stock fixed effects.

[20]Degryse, De Jong, and Van Kervel (2015) argue that it is important to allow for non-linear effects of fragmentation on measures of market quality. We replicate the analysis in Table 4 and Table 5 allowing the effect of dark trading to affect market quality in a non-linear way (by including a squared term). Overall, we do not find significant effects except for dark trading on the short-term volatility for 2009 (Online Appendix Tables A8.1 and A8.2).

Table 7 reports the results of regressions of *DP* and *INT* on indicators of market stress for 2009 in Panel A, and of *ATS* and *Non-ATS* on indicators of market stress for 2020 in Panel B. We estimate the following panel regression of market shares ($MS_{i,t}$) using OLS:

$$MS_{i,t} = \alpha_i d_q + \beta I^{Stress} + \gamma \, log(Volume)_{i,t} + e_{i,t} , \tag{11}$$

where $I^{Stress}$ is a stock-specific indicator for market stress as discussed above. Full results are in Online Appendix Table A7, while Table 7 focuses on the coefficient $\beta$ on our market stress indicators. Both dark pool trading and internalization are lower during periods of market stress in 2009 for all our indicators of market stress except selling pressure. For 2020, we find that both types of dark trading are lower when returns are low. Trading reported by OTC market makers is lower also in the first half of the year when the pandemic caused the stock market to roil and when short-term volatility is high. By contrast, there is more dark pool trading when short-term volatility is high. This result is consistent with Zhu (2014): when volatility becomes extreme thus worsening substantially the lit spread, investors optimally choose to go dark rather than crossing the spread in the lit market. Results for selling pressure are more nuanced: while in 2009 high selling pressure induced traders to route orders to internalizing OTC market makers instead of to dark pools or lit competing venues to manage their inventories, in 2020 they seem to opt for the lit competing venues.[21] This might be because in 2020 we capture the peak of the COVID volatility period (see the VIX pattern in Figure 1). With the exception of weeks with high short-term volatility in 2020, these results show that traders route fewer orders to dark pools and that OTC market makers internalize less when markets are under stress.

Even though overall less volume executes in dark venues during periods of market stress, it is possible that the fact that any orders leave the lit market during these periods is harmful, and could worsen market quality exactly when needed the most. To examine whether different forms of dark trading, controlling for lit competition, have a harmful effect on spreads and short-term volatility, we estimate the panel regression in equations (7)-(10) above for periods of market stress. We drop the intraday range and stock price as control variables as discussed above, but continue controlling for volume and use stock fixed effects (but not quarter fixed effects). The results are in Table 8.

Regardless of market stress subsample, in 2009 more dark trading – through dark pools or internalizing OTC market makers - leads to lower quoted and effective half-spreads, and to lower short-

[21] For example, Chiyachantana, Jain, Jiang, and Wood (2004) show that traders face asymmetric price impact for their buy and sell orders in bull versus bear markets, thus presumably increasing concerns about inventory management costs when facing imbalance pressure.

term volatility even if the coefficient of *vol_extr* is not always significant.[22] A higher market share of lit competing venues also generally contributes to better market quality. Hence, there is no evidence based on our 2009 data that more dark trading, whether through dark pools or OTC market makers, leads to worse market quality in periods of market stress.

The picture is quite different for 2020. While there is no detrimental effect of dark pool trading during the first half of the year, we find that more dark pool trading leads to wider quoted spreads when returns are low and in particular when short-term volatility is high. This result is line with Zhu (2014) where high volatility diverts traders to the dark pools to avoid crossing the large spread thus worsening the spread on the lit market. More dark pool trading during periods of high volatility also leads to wider effective half-spreads and higher short-term volatility. By contrast, more trading by OTC market makers leads to lower effective half-spreads and lower volatility during weeks when volatility is high. More lit competing volume leads to lower quoted and effective half-spreads, but only when returns are low and not during other periods of market stress. The 2020 market stress evidence thus shows that dark pool trading leads to wider spreads and higher short-term volatility, not just on average as shown in Table 5 and for Large caps as shown in Table 6, but also for periods of market stress on average.

## 6. Discussion

Our results show that dark trading is generally beneficial for market quality in 2009, but we find evidence suggesting a detrimental effect of dark pool trading, particularly for Large caps, in 2020. There are several potential explanations for the discrepancy between the results, and we discuss these in turn in this section.

One possible explanation is that the FINRA data is weekly, and the lower frequency may contribute to the lack of power to detect significant effects of dark trading on market quality for the 2020 samples, both on average when examining aggregate dark trading and for trades internalized by OTC market makers. The FINRA *Non-ATS* data is particularly noisy, and this may explain why we find no significant effects of trades reported by OTC market makers in any of our tests.[23] It is also possible that the noisy *Non-ATS* data causes problems for estimating the effect of dark pool trading on market quality. However, dropping the *Non-ATS* category from the analyses in Tables 5 and 6 does not change the conclusion so this does not appear to be the explanation (Online Appendix Tables A5.2 and A6.2). For dark pool trading, the lack of

[22] These results are robust to defining low returns as the lowest decile of returns for each stock.

[23] FINRA *Non-ATS* includes an aggregate of smaller OTC market makers under the heading "De Minimis Firms." Their reporting appears to be much less consistent than that of the individually reported OTC market makers. For example, their reported volume often exceeds consolidated volume.

power appears to be mostly an issue with Small and Medium caps. We do find consistently harmful effects of dark pool trading for the subsample of Large caps suggesting that at least for these stocks, we are able to pin down the effect of dark pool trading on market quality.

Another possibility is that the 2009 SIFMA data only covers the dark pools that voluntarily reported their trading volume, and that the "good" dark pools selected to report their trading activity while those that had a negative impact on market quality did not participate in the survey. To address this concern, we create a subset of the dark pools that existed in 2009, and still are operating in 2020. We do not know if these dark pool survivors were in the original SIFMA sample, but we know for sure that dark pools that started operating after 2009 were not. We add the new dark pools to the *Non-ATS* subsample, creating a similar aggregate measure that we have for 2009. We then repeat our analysis to study the effect of these two "pseudo" forms of dark trading on market quality for our 2020 sample. The results show that neither the dark pool survivors nor the combined *Non-ATS* plus new dark pools aggregate has any effect on market quality for any of the subsamples by size (Online Appendix Table A6.3). Hence, while the trading that takes place through dark pool survivors appears to be less harmful than that of dark pool trading on average, we do not find that the dark pool survivors are beneficial for market quality. We conclude that the selection induced by self-selection is unlikely to explain the differences we observe between 2009 and 2020.

Other possible explanations relate to the fact that the mix of orders executed in dark pools have changed significantly between 2009 and 2020. Three particular trends deserve mention in this regard: proprietary trading, HFTs, and retail trading activity. We discuss each in turn. Dark pools' main selling point was originally that they gave institutional traders the opportunity to execute large trades without causing markets to move against them. They explicitly screened out order flow that could be toxic such as proprietary traders and HFTs. Quoting former SEC Commissioner Luis A. Aguilar:[24] "Dark pools initially portrayed themselves as havens from predatory traders." He continued: "They achieved this, in part, by excluding high-frequency traders, who supposedly use brute speed to front run institutional investors' large orders." As competition for order flow increased, dark pool operators started welcoming (albeit not always openly) both proprietary traders and HFTs, recognizing that they provide additional liquidity and increase the probability of execution.[25] However, since some HFTs use sophisticated pinging strategies to detect hidden orders, and proprietary traders may front-run large orders, allowing them access to dark pools may

[24] https://www.sec.gov/news/statement/shedding-light-on-dark-pools.html.

[25] In 2014, the New York Attorney General sued Barclays for its dark pool operations, specifically for misstating the level of HFT activity in its dark pool, thus defrauding investors. In January 2016, Barclays agreed to pay a fine of $35 million to the SEC and $70 million to the New York Attorney General for its misconduct related to the dark pool.

reduce the benefit of these venues for institutional traders (Korajczyk and Murphy, 2018; Van Kervel and Menkveld, 2019).

The second trend is the dramatic rise in retail trading activity that took place in 2020 as the U.S. went into lockdown sequestering most everyone at home. Retail brokerages experienced tremendous growth in accounts, as well as in trading activity, as individuals turned to the stock market for entertainment and distraction. For example, retail broker Robinhood had 13 million users at the end of 2020, up 30% from 2019.[26] Virtu Financial, one of the largest OTC market makers, estimates that retail represented over 30% of trading in late 2020, up from about 17% at the beginning of the year.[27] Brokers route retail orders to an OTC market maker, a dark pool, or to an exchange for execution. Retail orders typically receive price improvement of say 0.1 cents per share relative to the NBBO when internalized by an OTC market maker, and this fact means that a proxy for retail trading is the volume of sub-penny executions. While the traditional view was that retail traders are uninformed, evidence using this proxy suggest that their order imbalances predict future returns (Boehmer, Jones, Zhang, and Zhang, 2021). In practice, OTC market makers absorb retail order imbalances only when they have access to offsetting institutional orders, either via their own Single Dealer Platforms (SDPs) such as Citadel Connect or in dark pools (Barardehi, Bernhardt, Da, and Warachka, 2022).[28] During 2020, retail traders had an adversely affected stock liquidity during periods of market stress, timed their trades well relative to future returns, and generated an alpha (e.g., Ozik, Sadka, and Shen, 2021; Pagano, Sedunof, and Velthuis, 2021; Welch, 2021). We conjecture that an increasing volume of potentially market moving retail order imbalances likely reached dark pools in 2020, both directly when routed by retail brokers, and indirectly as OTC market makers laid off order imbalances.

In sum, the mix of order flow that reaches dark pools likely includes both more proprietary orders, orders from HFTs and more retail order imbalances in 2020 compared to 2009. Research suggests that these types of order flow move prices and potentially contribute to short-term volatility. Hence, dark pools have gone from being venues where institutional traders could find liquidity while avoiding broadcasting

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[26] Robinhood was not alone in experiencing strong growth in retail accounts. Fidelity had 26 million retail accounts at the end of 2020, up 17% from a year earlier, and Charles Schwab had 30 million active accounts, up 13% from a year earlier (net of acquisitions of TD Ameritrade and USAAs investment management company).

[27] Virtu Financial, Inc., 2020 annual report (https://2020annualreport.virtu.com/home/default.aspx ), and McCrank, J., Factbox: The U.S. retail trading frenzy in numbers, *Reuters*, Jan 29, 2021(https://www.reuters.com/article/us-retail-trading-numbers/factbox-the-u-s-retail-trading-frenzy-in-numbers-idUSKBN29Y2PW).

[28] SDPs are not ATSs according to the current rules, and they therefore do not report to FINRA. FINRA recently proposed to expand OTC equity trading data published on FINRA's website to include SPD trading (Regulatory Notice 18-28).

their trading intentions, to venues where they face an increasing amount of pinging and front running from proprietary traders and HFTs, and market moving order flow from retail investors. We conjecture that dark pools are less attractive to institutional traders in 2020 compared to 2009. This is consistent with the aggregate data - the market share of dark pools has declined from 14.5% in 2016 to 10.1% in 2020, while trading internalized by OTC market makers has increased from 22.1% to 31.2%. This trend has continued, and dark pools represent 8.1% while OTC market makers represent 37.2% of volume in 2021.[29] Our weekly data does not permit us to study the mix of traders in dark pools, but it is clearly a topic of interest for future research.

## 7. Conclusions

We study dark trading based on 2009 and 2020 data. Each sample includes roughly 3,000 stocks and covers a tumultuous period in U.S. stock markets, related to the Great Financial Crisis in 2009 and the COVID pandemic in 2020, respectively. This permits us to study dark trading for different stocks (Small and Large caps), of different types (dark pools and internalized trades), and during periods of market stress. It also allows us to examine whether dark trading plays a different role in 2020 compared to 2009.

The picture that emerges is that dark trading activity differs systematically across stocks and between dark pools and internalization by OTC market makers. For example, dark pools are more active for large caps, while OTC market makers internalize more for small caps. OTC market makers internalize more when spreads are wide and depth is high so they can more easily lay off order imbalances in the lit market. By contrast, how the dark pool market share depends on the order book changes between samples for large caps. In the earlier sample, traders in large caps use dark pools to jump the queue when the order book is competitive, in the later sample they instead use dark pools to avoid crossing a wide spread. The effect of dark trading on market quality has also changed. A higher dark pool market share leads to lower quoted and traded spreads and does not affect short-term volatility in the early sample. By contrast, we find that a higher dark pool market share leads to wider spreads and higher short-term volatility for large caps in the later sample. Similarly, more internalization by OTC market makers leads to improved spreads in the early sample, but does not affect market quality in the later sample.

While a full explanation for these changes is beyond the scope of the current paper, we speculate that the difference we observe between the two samples arises because proprietary order flow, HFTs, and

[29] Hadiaris, J., Cowen Market Structure: Retail Trading – What's going on, what may change, and what can you do about it? March 23, 2021. (https://www.cowen.com/insights/retail-trading-whats-going-on-what-may-change-and-what-can-institutional-traders-do-about-it/ )

retail order imbalances reach dark pools in recent years, and that these venues have become less attractive for institutional traders as a result. This conjecture is consistent with statements from the former SEC Commissioner Luis A. Aguilar[30] and with the recent decline in dark pool trading. Taken together, the evidence we present shows that dark trading is evolving over time, and we believe that research based on more granular recent data is needed to better understand what role it will play going forward.

[30] Op cit.

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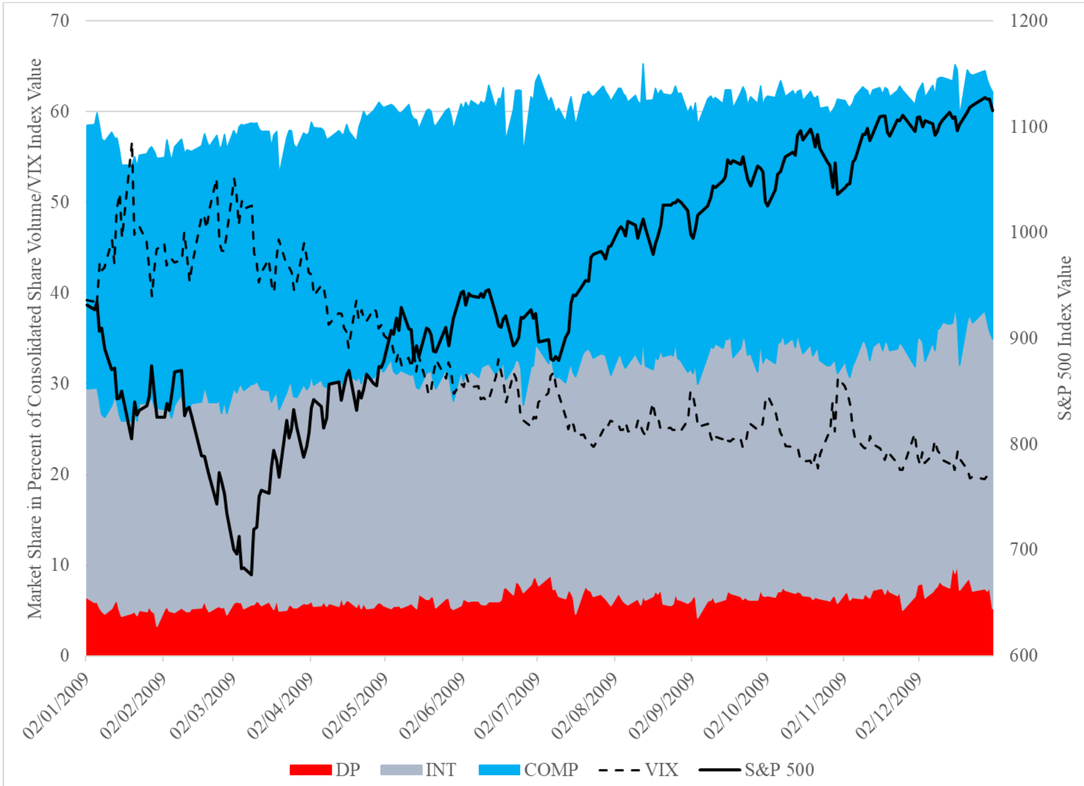
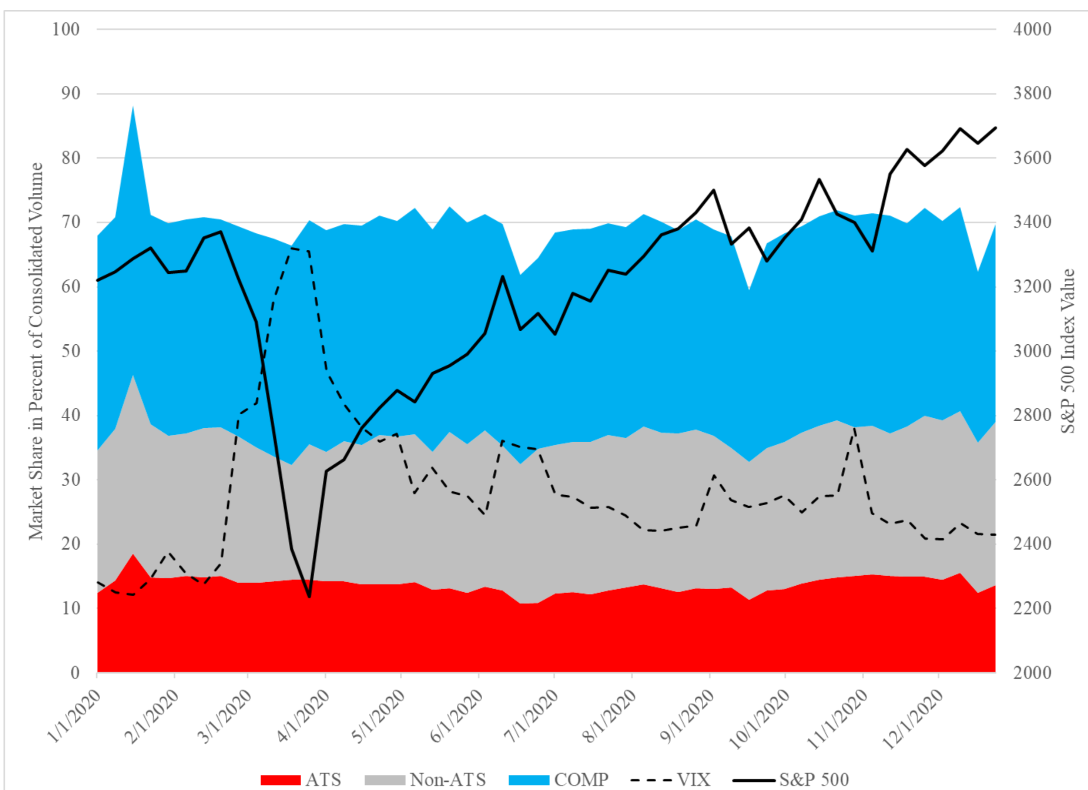
## Figure 1. Fragmentation over Time

The figure reports daily average market shares expressed in percent of consolidated share volume for three forms of fragmentation for 2009 in Panel A: *DP* is defined as SIFMA sample dark pool single-counted share volume; *INT* is defined as share volume reported to Trade Reporting Facilities (*TRF*) minus *DP*; and *COMP* is defined as share volume reported to lit venues excluding the exchange where the stock is listed. For 2020 in Panel B, *ATS* is defined as Alternative Trading Systems reporting to FINRA, *Non-ATS* are OTC market makers reporting to FINRA, and *COMP* is defined as for the 2009 sample. We plot the CBOE Volatility Index (VIX) on the left vertical axis, and the S&P 500 index on the right vertical axis.



## Figure 2. Dark Fragmentation by Size

**A.** 2009 sample dark fragmentation for *TRF*, *DP*, and *INT*.

**B.** 2020 sample dark fragmentation for *FINRA*, *ATS*, and *Non-ATS*.

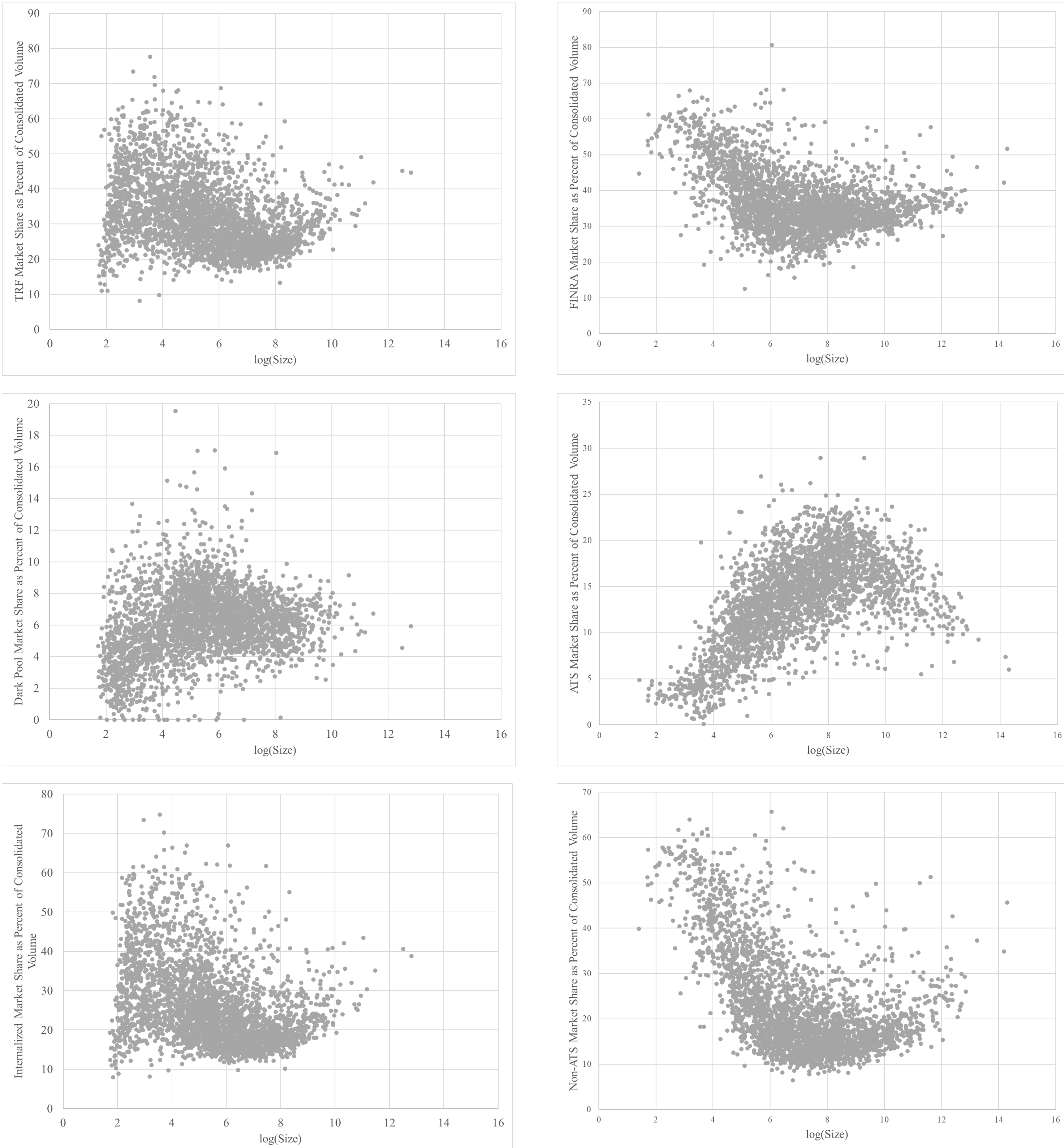


**Table 1. Descriptive Statistics**

The table reports descriptive statistics based on daily stock level data for the 2009 daily sample in Panel A, the 2020 overall weekly sample in Panel B, and the 2020 ex-COVID weekly sample where we exclude eight weeks of observations between February 15, 2020, and April 15, 2020, in Panel C. We obtain market capitalization in billion dollars, stock price in dollars, and *Volatility* is 100*(High-Low)/High from CRSP. For 2009, we use TAQ to calculate average daily: *Volume* as consolidated share volume divided by 1,000, time-weighted *Quoted spread* at the National Best Bid Offer (NBBO) and share-weighted *Effective half-spread* both in basis points of the mid-quote, *Depth* is the time-weighted shares at the NBBO, and *StD returns* is 10,000 times the standard deviation of 15-minute mid-quote returns. For 2020, we use CRSP and WRDS Intraday Indicators to calculate the average daily characteristics and market quality measures for each week. Note that *StD returns* for 2020 is 10,000 times the standard deviation of mid-quote returns. For 2009, fragmentation is measured as a fraction of TAQ consolidated volume, where *COMP* are lit competing venues with the main (listing) exchange, *TRF* is volume reported with "D" in TAQ, and *DP* are the SIFMA reporting dark pools, and *INT* is Internalized trades defined as *TRF- DP*. For 2020, fragmentation is measured as a fraction of WRDS Intraday Indicator reported daily consolidated volume aggregated to weekly data, where *COMP* are lit competing venues from MIDAS, *FINRA* is *ATS* and *Non-ATS* volume as reported to FINRA. Data are Winsorized at the 1st and 99th percentiles.

| **A. 2009 Sample** | N | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| Characteristics | | | | | | |
| *Size* | 3,098 | 3.345 | 13.856 | 0.157 | 0.483 | 1.699 |
| *Volume* | 3,098 | 1,756 | 11,296 | 74 | 270 | 1,017 |
| *Price* | 3,098 | 19.07 | 23.62 | 6.63 | 13.71 | 24.95 |
| *Volatility* | 3,098 | 6.77 | 3.13 | 4.60 | 6.18 | 8.37 |
| Market Quality | | | | | | |
| *Quoted spread* | 3,098 | 65.11 | 93.71 | 11.14 | 24.78 | 72.21 |
| *Effective half-spread* | 3,098 | 16.49 | 20.57 | 3.69 | 7.72 | 20.11 |
| *Depth* | 3,098 | 884 | 1,258 | 319 | 474 | 881 |
| *StD returns* | 3,098 | 68.15 | 27.68 | 48.11 | 63.80 | 82.88 |
| Fragmentation | | | | | | |
| *TRF* | 3,098 | 0.324 | 0.098 | 0.250 | 0.305 | 0.380 |
| *DP* | 3,098 | 0.060 | 0.021 | 0.047 | 0.060 | 0.074 |
| *INT* | 3,098 | 0.263 | 0.102 | 0.187 | 0.236 | 0.312 |
| *COMP* | 3,098 | 0.279 | 0.053 | 0.244 | 0.285 | 0.317 |

**Table 1. Continued**

| **B. 2020 Sample** | N | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| Characteristics | | | | | | |
| *Size* | 2,902 | 9.565 | 50.210 | 0.243 | 1.021 | 4.126 |
| *Volume* | 2,902 | 5,953 | 12,527 | 589 | 1,925 | 5,305 |
| *Price* | 2,902 | 45.57 | 61.74 | 10.04 | 22.34 | 54.87 |
| *Volatility* | 2,902 | 4.99 | 1.85 | 3.63 | 4.62 | 6.13 |
| Market Quality | | | | | | |
| *Quoted spread* | 2,902 | 80.06 | 112.20 | 16.98 | 34.42 | 85.73 |
| *Effective half-spread* | 2,902 | 24.42 | 34.68 | 4.88 | 9.68 | 26.10 |
| *Depth* | 2,902 | 711 | 1,439 | 188 | 282 | 589 |
| *StD returns* | 2,902 | 10.73 | 15.34 | 2.01 | 4.08 | 12.10 |
| Fragmentation | | | | | | |
| *FINRA* | 2,902 | 0.369 | 0.084 | 0.312 | 0.352 | 0.409 |
| *ATS* | 2,902 | 0.137 | 0.047 | 0.108 | 0.142 | 0.170 |
| *Non-ATS* | 2,902 | 0.231 | 0.112 | 0.149 | 0.192 | 0.282 |
| *COMP* | 2,902 | 0.329 | 0.073 | 0.281 | 0.312 | 0.395 |

| **C. 2020 ex-COVID** | N | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| Characteristics | | | | | | |
| *Size* | 2,902 | 9.847 | 52.160 | 0.250 | 1.053 | 4.238 |
| *Volume* | 2,902 | 5,558 | 11,771 | 553 | 1,798 | 4,944 |
| *Price* | 2,902 | 46.96 | 63.91 | 10.20 | 22.80 | 56.24 |
| *Volatility* | 2,902 | 4.36 | 1.76 | 3.06 | 3.99 | 5.42 |
| Market Quality | | | | | | |
| *Quoted spread* | 2,902 | 72.41 | 102.80 | 15.17 | 31.42 | 77.85 |
| *Effective half-spread* | 2,902 | 21.98 | 31.38 | 4.36 | 8.75 | 23.90 |
| *Depth* | 2,902 | 717 | 1,482 | 189 | 281 | 584 |
| *StD returns* | 2,902 | 9.60 | 13.87 | 1.75 | 3.62 | 10.63 |
| Fragmentation | | | | | | |
| *FINRA* | 2,902 | 0.372 | 0.085 | 0.313 | 0.355 | 0.415 |
| *ATS* | 2,902 | 0.136 | 0.047 | 0.107 | 0.140 | 0.169 |
| *Non-ATS* | 2,902 | 0.235 | 0.113 | 0.153 | 0.199 | 0.289 |
| *COMP* | 2,902 | 0.327 | 0.074 | 0.278 | 0.309 | 0.394 |

**Table 2. Order Routing**

The table reports the results of regressions of *TRF*, *DP* and *INT*, and *COMP* (*FINRA, ATS*, *Non-ATS*, and *COMP*) on order book and firm characteristics. We estimate the following panel regression of market shares ($MS_{i,t}$) using IV/2SLS:[1]

$$(1)\quad log(Quoted\ spread)_{i,t} = \alpha_i\, d_q + \beta_{1,1}\, log(Quoted\ spread)_{i,t\text{-}1} + \beta_{1,2}\, log(Depth)_{i,t\text{-}1} + \boldsymbol{\gamma_1}\, X_{i,t} + e_{1,i,t}$$

$$(2)\quad log(Depth)_{i,t} = \alpha_i\, d_q + \beta_{2,1}\, log(Quoted\ spread)_{i,t\text{-}1} + \beta_{2,2}\, log(Depth)_{i,t\text{-}1} + \boldsymbol{\gamma_2}\, X_{i,t} + e_{2,i,t},$$

$$(3)\quad MS_{i,t} = \alpha_i\, d_q + \beta_{3,1}\, log(Quoted\ spread)_{i,t} + \beta_{3,2}\, log(Depth)_{i,t} + \boldsymbol{\gamma_3}\, X_{i,t} + e_{3,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. Equations (1) and (2) models the endogenous variables $log(Quoted\ spread)_{i,t}$ and $log(Depth)_{i,t}$ using their lagged values as instruments. Equation (3) uses the fitted values from the first stage regressions for the endogenous variables.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A. 2009 | | | | B. 2020 | | | | C. 2020 ex-COVID | | | |
| | *TRF* | *DP* | *INT* | *COMP* | *FINRA* | *ATS* | *Non-ATS* | *COMP* | *FINRA* | *ATS* | *Non-ATS* | *COMP* |
| *log(Quoted spread)* | 0.0168*** | -0.0065*** | 0.0208*** | -0.0253*** | 0.0061 | 0.0243*** | -0.0187** | -0.0038 | 0.0806** | 0.0582*** | 0.0213 | -0.0227 |
| | (0.0041) | (0.0020) | (0.0037) | (0.0032) | (0.0103) | (0.0086) | (0.0083) | (0.0091) | (0.0372) | (0.0206) | (0.0216) | (0.0219) |
| *log(Depth)* | 0.0125*** | -0.0060*** | 0.0196*** | -0.0066*** | 0.0050 | -0.0221*** | 0.0276*** | -0.0006 | 0.0085 | -0.0165*** | 0.0265*** | 0.0072 |
| | (0.0029) | (0.0012) | (0.0024) | (0.0017) | (0.0063) | (0.0040) | (0.0064) | (0.0061) | (0.0081) | (0.0056) | (0.0075) | (0.0072) |
| *log(Price)* | -0.0196*** | -0.0169*** | -0.0022 | 0.0025 | 0.0095 | -0.0064 | 0.0166** | -0.0043 | -0.0306** | -0.0276*** | -0.0012 | 0.0253** |
| | (0.0044) | (0.0022) | (0.0042) | (0.0034) | (0.0101) | (0.0057) | (0.0075) | (0.0082) | (0.0140) | (0.0084) | (0.0083) | (0.0098) |
| *log(Volatility)* | -0.0222*** | -0.0103*** | -0.0099*** | 0.0073*** | -0.0335*** | -0.0288*** | -0.0034 | 0.0122 | -0.0094 | -0.0146 | 0.0061 | -0.0143 |
| | (0.0013) | (0.0005) | (0.0011) | (0.0008) | (0.0087) | (0.0057) | (0.0071) | (0.0076) | (0.0125) | (0.0095) | (0.0075) | (0.0110) |
| *log(Volume)* | 0.0384*** | 0.0123*** | 0.0241*** | -0.0118*** | 0.0327*** | 0.0215*** | 0.0105** | -0.0129** | 0.0491*** | 0.0290*** | 0.0190*** | -0.0210** |
| | (0.0017) | (0.0005) | (0.0015) | (0.0008) | (0.0050) | (0.0033) | (0.0041) | (0.0053) | (0.0108) | (0.0073) | (0.0065) | (0.0078) |
| Observations | 693,453 | 693,453 | 693,453 | 693,453 | 143,774 | 143,774 | 143,774 | 143,774 | 118,055 | 118,055 | 118,055 | 118,055 |
| R-squared | 0.0363 | 0.0206 | 0.0181 | 0.0060 | 0.0308 | -0.0003 | 0.0028 | 0.0121 | 0.0072 | -0.0557 | 0.0055 | 0.0245 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[1] Note that R-squared can be negative for IV/2SLS estimation: https://www.stata.com/support/faqs/statistics/two-stage-least-squares/. We follow the literature and still report the R-squared, recognizing that it has no statistical meaning in the context of IV/2SLS.

**Table 3. Order Routing by Size**

The table reports the results of regressions of *DP* and *INT*, and *COMP (ATS*, *Non-ATS*, and *COMP*) on lagged instruments for subsamples by market capitalization, and for stocks that are part of the S&P 500 index. We estimate the following panel regression of market shares ($MS_{i,t}$) using IV/2SLS:

$$(1)\quad log(Quoted\ spread)_{i,t} = \alpha_i\, d_q + \beta_{1,1}\, log(Quoted\ spread)_{i,t-1} + \beta_{1,2}\, log(Depth)_{i,t-1} + \gamma_1\, X_{i,t} + e_{1,i,t}$$

$$(2)\quad log(Depth)_{i,t} = \alpha_i\, d_q + \beta_{2,1}\, log(Quoted\ spread)_{i,t-1} + \beta_{2,2}\, log(Depth)_{i,t-1} + \gamma_2\, X_{i,t} + e_{2,i,t}$$

$$(3)\quad MS_{i,t} = \alpha_i\, d_q + \beta_{3,1}\, log(Quoted\ spread)_{i,t} + \beta_{3,2}\, log(Depth)_{i,t} + \gamma_3\, X_{i,t} + e_{3,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. Equations (1) and (2) models the endogenous variables $log(Quoted\ spread)_{i,t}$ and $log(Depth)_{i,t}$ using their lagged values as instruments. Equation (3) uses the fitted values from the first stage regressions (1)-(2).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **A. 2009** | *DP* | | | | *INT* | | | | *COMP* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* | -0.0025 | -0.0066** | -0.0165*** | -0.0120*** | 0.0091* | 0.0392*** | 0.0211*** | 0.0103 | -0.0219*** | -0.0341*** | -0.0223*** | -0.0182** |
| | (0.0026) | (0.0033) | (0.0030) | (0.0035) | (0.0051) | (0.0057) | (0.0050) | (0.0070) | (0.0048) | (0.0045) | (0.0051) | (0.0075) |
| *log(Depth)* | -0.0182*** | -0.0118*** | 0.0055*** | 0.0064*** | 0.0246*** | 0.0155*** | 0.0270*** | 0.0253*** | -0.0090*** | 0.0007 | -0.0130*** | -0.0150*** |
| | (0.0020) | (0.0021) | (0.0012) | (0.0013) | (0.0043) | (0.0036) | (0.0029) | (0.0034) | (0.0033) | (0.0033) | (0.0021) | (0.0026) |
| *log(Price)* | -0.0180*** | -0.0242*** | -0.0098*** | -0.0053 | -0.0150*** | 0.0010 | 0.0316*** | 0.0214*** | 0.0132*** | -0.0011 | -0.0151*** | -0.0122 |
| | (0.0026) | (0.0035) | (0.0031) | (0.0039) | (0.0057) | (0.0056) | (0.0057) | (0.0076) | (0.0045) | (0.0046) | (0.0057) | (0.0087) |
| *log(Volatility)* | -0.0133*** | -0.0137*** | -0.0056*** | -0.0058*** | -0.0049** | -0.0162*** | -0.0115*** | -0.0091*** | 0.0083*** | 0.0100*** | 0.0052*** | 0.0046*** |
| | (0.0010) | (0.0008) | (0.0006) | (0.0007) | (0.0021) | (0.0014) | (0.0012) | (0.0015) | (0.0016) | (0.0011) | (0.0009) | (0.0012) |
| *log(Volume)* | 0.0114*** | 0.0168*** | 0.0138*** | 0.0144*** | 0.0101*** | 0.0384*** | 0.0373*** | 0.0363*** | -0.0055*** | -0.0198*** | -0.0166*** | -0.0184*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0009) | (0.0022) | (0.0018) | (0.0017) | (0.0023) | (0.0012) | (0.0011) | (0.0012) | (0.0016) |
| Observations | 199,964 | 244,210 | 249,279 | 106,785 | 199,964 | 244,210 | 249,279 | 106,785 | 199,964 | 244,210 | 249,279 | 106,785 |
| R-squared | 0.0154 | 0.0291 | 0.0302 | 0.0360 | 0.0057 | 0.0417 | 0.0502 | 0.0587 | 0.0026 | 0.0142 | 0.0169 | 0.0258 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 3. Continued.**

| B. 2020 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *ATS* | | | | *Non-ATS* | | | | *COMP* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* | 0.0134** | 0.0193 | 0.0273*** | 0.0238*** | -0.0452*** | -0.0020 | 0.0023 | 0.0139 | 0.0076 | -0.0040 | -0.0173 | -0.0339* |
| | (0.0053) | (0.0142) | (0.0087) | (0.0086) | (0.0144) | (0.0148) | (0.0116) | (0.0197) | (0.0097) | (0.0100) | (0.0117) | (0.0174) |
| *log(Depth)* | -0.0220*** | -0.0290*** | -0.0142** | -0.0078 | 0.0098 | 0.0423*** | 0.0220*** | 0.0319*** | -0.0013 | -0.0009 | 0.0146 | -0.0020 |
| | (0.0050) | (0.0067) | (0.0063) | (0.0072) | (0.0101) | (0.0110) | (0.0082) | (0.0096) | (0.0088) | (0.0109) | (0.0092) | (0.0094) |
| *log(Price)* | -0.0083 | -0.0078 | -0.0057 | -0.0040 | -0.0119 | 0.0368*** | 0.0312*** | 0.0302 | 0.0131 | -0.0117 | -0.0256** | -0.0317* |
| | (0.0057) | (0.0093) | (0.0085) | (0.0090) | (0.0126) | (0.0102) | (0.0098) | (0.0182) | (0.0125) | (0.0091) | (0.0115) | (0.0174) |
| *log(Volatility)* | -0.0219*** | -0.0302*** | -0.0319*** | -0.0309*** | 0.0235*** | -0.0101 | -0.0315*** | -0.0413** | 0.0004 | 0.0130 | 0.0389*** | 0.0515*** |
| | (0.0037) | (0.0085) | (0.0087) | (0.0102) | (0.0085) | (0.0108) | (0.0112) | (0.0198) | (0.0074) | (0.0094) | (0.0126) | (0.0180) |
| *log(Volume)* | 0.0135*** | 0.0264*** | 0.0315*** | 0.0310*** | 0.0044 | 0.0205*** | 0.0128* | 0.0055 | 0.0010 | -0.0289*** | -0.0371*** | -0.0357*** |
| | (0.0023) | (0.0058) | (0.0066) | (0.0079) | (0.0048) | (0.0061) | (0.0072) | (0.0124) | (0.0048) | (0.0078) | (0.0099) | (0.0132) |
| Observations | 38,315 | 50,243 | 54,905 | 21,143 | 38,315 | 50,243 | 54,905 | 21,143 | 38,315 | 50,243 | 54,905 | 21,143 |
| R-squared | 0.0016 | 0.0062 | 0.0124 | 0.0059 | -0.0010 | 0.0087 | 0.0473 | 0.0806 | -0.0045 | 0.0515 | 0.0656 | 0.0363 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

| C. 2020 ex-COVID | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *ATS* | | | | *Non-ATS* | | | | *COMP* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* | 0.0198** | 0.0699** | 0.0847* | 0.0853 | 0.0015 | 0.0326* | 0.0278 | 0.0139 | 0.0022 | -0.0105 | -0.0569 | -0.1617 |
| | (0.0077) | (0.0317) | (0.0502) | (0.0893) | (0.0194) | (0.0192) | (0.0504) | (0.0197) | (0.0136) | (0.0198) | (0.0616) | (0.2729) |
| *log(Depth)* | -0.0211*** | -0.0157* | -0.0113 | -0.0245* | 0.0150 | 0.0414*** | 0.0200 | 0.0319*** | 0.0057 | 0.0094 | 0.0230 | 0.0107 |
| | (0.0066) | (0.0086) | (0.0094) | (0.0122) | (0.0132) | (0.0126) | (0.0135) | (0.0096) | (0.0093) | (0.0119) | (0.0150) | (0.0209) |
| *log(Price)* | -0.0205*** | -0.0325** | -0.0278 | -0.0310 | 0.0223** | 0.0032 | -0.0360* | -0.0413** | 0.0108 | 0.0272** | 0.0501** | 0.0886 |
| | (0.0046) | (0.0132) | (0.0191) | (0.0338) | (0.0091) | (0.0081) | (0.0191) | (0.0198) | (0.0077) | (0.0107) | (0.0240) | (0.1009) |
| *log(Volatility)* | -0.0103 | -0.0160 | -0.0236 | -0.0275 | -0.0297** | 0.0126 | 0.0350*** | 0.0302 | -0.0018 | -0.0127 | -0.0373** | -0.0553 |
| | (0.0078) | (0.0152) | (0.0177) | (0.0186) | (0.0136) | (0.0110) | (0.0106) | (0.0182) | (0.0134) | (0.0130) | (0.0176) | (0.0371) |
| *log(Volume)* | 0.0143*** | 0.0386*** | 0.0502** | 0.0607 | 0.0119** | 0.0274*** | 0.0241 | 0.0055 | -0.0012 | -0.0372*** | -0.0575** | -0.0963 |
| | (0.0030) | (0.0131) | (0.0221) | (0.0453) | (0.0053) | (0.0070) | (0.0182) | (0.0124) | (0.0056) | (0.0097) | (0.0234) | (0.1184) |
| Observations | 31,402 | 41,213 | 45,173 | 17,406 | 31,402 | 41,213 | 45,173 | 21,143 | 31,402 | 41,213 | 45,173 | 17,406 |
| R-squared | -0.0015 | -0.0787 | -0.1637 | -0.2844 | 0.0125 | 0.0145 | 0.0120 | 0.0806 | 0.0058 | 0.0750 | 0.0371 | -0.8746 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 4. Dark and Lit Market Shares and Market Quality**

The table reports the results of analyzing the relationship between market shares and market quality. We estimate the following three-equation panel regression model market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1) \quad DARK_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1\, X_{i,t} + e_{1,i,t}$$

$$(2) \quad COMP_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2\, X_{i,t} + e_{2,i,t}$$

$$(3) \quad Y_{i,t} = \alpha_i\, d_q + \beta_1\, DARK_{i,t} + \beta_2\, COMP_{i,t} + \gamma\, X_{i,t} + e_{3,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, $log(Volume)_{i,t}$, and $Y_{Noti,t}$. $W_{i,t}$ is a vector that includes: $DARK_{Noti,t}$ and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). For 2009*, DARK = TRF* and for 2020, *DARK = FINRA*. The first stage regressions based on equations (1)-(2) are reported in Online Appendix Table A4.1. The second stage IV/2SLS regressions in equation (3) use the fitted value from the first stage regressions (1)-(2).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | A. 2009 | | | B. 2020 | | | C. 2020 ex-COVID | | |
| | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* |
| *DARK* | -0.8245*** | -0.6014*** | -0.0075 | 1.6147 | 1.9497* | 0.3808 | 0.9722 | 1.0382 | 0.6813 |
| | (0.1428) | (0.1346) | (0.1546) | (1.3370) | (1.1634) | (0.9149) | (1.3555) | (0.6678) | (0.6328) |
| *COMP* | -0.2933* | -0.6234*** | 0.1134 | -2.5903** | -2.8322** | -0.9996 | -2.0078* | -1.9342*** | -1.0432* |
| | (0.1739) | (0.2136) | (0.1759) | (1.2042) | (1.0602) | (0.9030) | (1.1192) | (0.6563) | (0.5703) |
| *log(Price)* | -0.3915*** | -0.4740*** | -0.0407*** | 0.027 | -0.0837* | -0.1726*** | 0.0486 | -0.1023** | -0.0879** |
| | (0.0123) | (0.0142) | (0.0130) | (0.0366) | (0.0481) | (0.0415) | (0.0416) | (0.0428) | (0.0404) |
| *log(Volatility)* | 0.1933*** | 0.1926*** | 0.5130*** | 0.4247*** | 0.4279*** | 0.3509*** | 0.3374*** | 0.3687*** | 0.3037*** |
| | (0.0044) | (0.0041) | (0.0046) | (0.0393) | (0.0209) | (0.0253) | (0.0252) | (0.0163) | (0.0162) |
| *log(Volume)* | -0.1069*** | 0.0140*** | 0.1002*** | -0.3015*** | -0.2737*** | -0.1460*** | -0.2656*** | -0.2268*** | -0.1508*** |
| | (0.0059) | (0.0053) | (0.0061) | (0.0528) | (0.0456) | (0.0364) | (0.0543) | (0.0266) | (0.0268) |
| $Y_{Noti}$ | 0.4819*** | 0.3480*** | 0.4520*** | 0.9770*** | 0.7997*** | 0.8216*** | 0.9808*** | 0.6566*** | 0.7398*** |
| | (0.0237) | (0.0292) | (0.0197) | (0.0716) | (0.1071) | (0.0644) | (0.0830) | (0.0666) | (0.0451) |
| Observations | 696,594 | 695,821 | 696,653 | 146,667 | 146,665 | 146,647 | 120,948 | 120,947 | 120,934 |
| R-squared | 0.173 | 0.070 | 0.4539 | 0.439 | 0.152 | 0.5493 | 0.2187 | -0.0079 | 0.1408 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 5. Dark Pool/ATS, Internalization/Non-ATS, Lit Market Shares and Market Quality**

The table reports the results of analyzing the relationship between market shares and market quality for all stocks. We estimate the following four-equation panel regression model for market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1)\quad DP_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1\, X_{i,t} + e_{1,i,t}$$

$$(2)\quad INT_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2\, X_{i,t} + e_{2,i,t}$$

$$(3)\quad COMP_{i,t} = a_i\, d_q + b_3\, W_{i,t} + c_3\, X_{i,t} + e_{3,i,t}$$

$$(4)\quad Y_{i,t} = \alpha_i\, d_q + \beta_1\, DP_{i,t} + \beta_2\, INT_{i,t} + \beta_3\, COMP_{i,t} + \gamma\, X_{i,t} + e_{4,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$, $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $DP_{Noti,t}$, $INT_{Noti,t}$, and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). For 2020, *DP = ATS* and *INT = Non-ATS*. The first stage regressions (1)-(3) are reported in Online Appendix Table A5.1. The second stage regressions (4) use the fitted value from the first stage regressions (1)-(3) of the endogenous variables.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | A. 2009 | | | B. 2020 | | | C. 2020 ex-COVID | |
| | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* |
| *DP/ATS* | -1.3099*** | -1.1811*** | -0.1307 | 2.5974 | 1.6542 | 3.4465** | 4.4923 | 3.7893** | 3.3695** |
| | (0.1951) | (0.2376) | (0.2156) | (2.1593) | (2.0392) | (1.5449) | (3.3272) | (1.7666) | (1.5351) |
| *INT/Non-ATS* | -0.5894*** | -0.3235* | 0.0525 | 0.3338 | 2.2154 | -1.8781 | -2.4859 | -0.8410 | -1.1503 |
| | (0.1514) | (0.1771) | (0.1543) | (4.9263) | (3.8585) | (2.1085) | (7.4185) | (2.0022) | (2.1784) |
| *COMP* | -0.2393 | -0.5594** | 0.1231 | -2.5175* | -2.7948*** | -1.3087* | -2.3714 | -2.4443*** | -1.4832** |
| | (0.1641) | (0.2261) | (0.1758) | (1.3004) | (0.8478) | (0.7211) | (1.5269) | (0.7399) | (0.6111) |
| *log(Price)* | -0.3896*** | -0.4718*** | -0.0404*** | 0.0233 | -0.0786 | -0.2014*** | 0.0582 | -0.1324** | -0.0964* |
| | (0.0122) | (0.0140) | (0.0129) | (0.0483) | (0.1020) | (0.0618) | (0.0583) | (0.0527) | (0.0497) |
| *log(Volatility)* | 0.1911*** | 0.1895*** | 0.5121*** | 0.4202*** | 0.4225*** | 0.3714*** | 0.3601*** | 0.3980*** | 0.3267*** |
| | (0.0043) | (0.0041) | (0.0046) | (0.0444) | (0.0285) | (0.0223) | (0.0298) | (0.0300) | (0.0227) |
| *log(Volume)* | -0.1070*** | 0.0144*** | 0.1004*** | -0.2882*** | -0.2736*** | -0.1465*** | -0.2506** | -0.2338*** | -0.1583*** |
| | (0.0053) | (0.0052) | (0.0059) | (0.0819) | (0.0566) | (0.0333) | (0.1145) | (0.0306) | (0.0327) |
| $Y_{Noti}$ | 0.4878*** | 0.3568*** | 0.4532*** | 0.9248*** | 0.8242** | 0.6626*** | 0.9502*** | 0.4661** | 0.6533*** |
| | (0.0229) | (0.0290) | (0.0195) | (0.2098) | (0.3379) | (0.1516) | (0.1436) | (0.1879) | (0.1039) |
| Observations | 696,594 | 695,821 | 696,653 | 146,667 | 146,665 | 146,647 | 120,948 | 120,947 | 120,934 |
| R-squared | 0.188 | 0.075 | 0.4540 | 0.516 | 0.123 | 0.2033 | -0.7547 | -0.5558 | -0.2649 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 6. Dark Pool/ATS, Internalization/Non-ATS, Lit Market Shares and Market Quality by Size**

The table reports the results of analyzing the relationship between market shares and market quality for subsamples by market capitalization. We estimate the following four-equation panel regression model for market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1) \quad DP_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1\, X_{i,t} + e_{1,i,t}$$

$$(2) \quad INT_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2\, X_{i,t} + e_{2,i,t}$$

$$(3) \quad COMP_{i,t} = a_i\, d_q + b_3\, W_{i,t} + c_3\, X_{i,t} + e_{3,i,t}$$

$$(4) \quad Y_{i,t} = \alpha_i\, d_q + \beta_1\, DP_{i,t} + \beta_2\, INT_{i,t} + \beta_3\, COMP_{i,t} + \gamma\, X_{i,t} + e_{4,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$, $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $DP_{Noti,t}$, $INT_{Noti,t}$, and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). For 2020, *DP* = *ATS* and *INT* = *Non-ATS*. The first stage regressions (1)-(3) are reported in Online Appendix Table A6.1. The second stage regressions (4) use the fitted value from the first stage regressions (1)-(3) of the endogenous variables.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **A. 2009** | $Y_{i,t}$ = *log(Quoted spread)* | | | | $Y_{i,t}$ = *log(Effective half-spread)* | | | | $Y_{i,t}$ = *log(StD returns)* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *DP* | -1.0866*** | -1.1747*** | -1.0780*** | -0.9402** | -1.3539*** | -1.1544*** | -0.7792** | -0.9596 | 0.1764 | 0.1276 | -0.7749* | -1.2325* |
| | (0.2591) | (0.2372) | (0.3479) | (0.4214) | (0.3490) | (0.2394) | (0.3784) | (0.6567) | (0.1966) | (0.2286) | (0.4294) | (0.6511) |
| *INT* | -0.2477 | -0.7548*** | -0.9697*** | -1.0480*** | -0.1443 | -0.3940* | -0.8809*** | -0.9220** | 0.1922 | 0.1431 | 0.0166 | -0.2456 |
| | (0.1782) | (0.1847) | (0.2159) | (0.2881) | (0.2476) | (0.2263) | (0.2979) | (0.4396) | (0.1556) | (0.1992) | (0.2821) | (0.3582) |
| *COMP* | -0.2072 | -0.3288 | -0.4501* | -0.5329 | -0.4029* | -0.6680** | -1.1655*** | -1.6678** | -0.2742* | 0.1439 | 0.8288** | 0.8869** |
| | (0.1899) | (0.2540) | (0.2659) | (0.3317) | (0.2389) | (0.3073) | (0.4445) | (0.7487) | (0.1459) | (0.2586) | (0.3444) | (0.4266) |
| *log(Price)* | -0.3608*** | -0.3821*** | -0.4344*** | -0.5392*** | -0.4169*** | -0.5117*** | -0.4992*** | -0.5366*** | -0.0226* | -0.0267* | -0.0643*** | -0.0846*** |
| | (0.0162) | (0.0190) | (0.0241) | (0.0340) | (0.0195) | (0.0161) | (0.0227) | (0.0314) | (0.0118) | (0.0153) | (0.0216) | (0.0300) |
| *log(Volatility)* | 0.3153*** | 0.1516*** | 0.0831*** | 0.0531*** | 0.2888*** | 0.1594*** | 0.0867*** | 0.0528*** | 0.5985*** | 0.4917*** | 0.4318*** | 0.4009*** |
| | (0.0066) | (0.0063) | (0.0044) | (0.0057) | (0.0074) | (0.0047) | (0.0053) | (0.0087) | (0.0055) | (0.0061) | (0.0073) | (0.0100) |
| *log(Volume)* | -0.1272*** | -0.0980*** | -0.0702*** | -0.0469*** | -0.0095 | 0.0158** | 0.0840*** | 0.1120*** | 0.0931*** | 0.0882*** | 0.1366*** | 0.1763*** |
| | (0.0060) | (0.0078) | (0.0077) | (0.0100) | (0.0065) | (0.0071) | (0.0108) | (0.0170) | (0.0040) | (0.0092) | (0.0128) | (0.0168) |
| $Y_{Noti}$ | 0.3909*** | 0.5494*** | 0.5754*** | 0.4323*** | 0.2947*** | 0.3141*** | 0.4496*** | 0.5157*** | 0.3929*** | 0.5001*** | 0.4600*** | 0.4468*** |
| | (0.0291) | (0.0320) | (0.0351) | (0.0430) | (0.0374) | (0.0335) | (0.0489) | (0.0735) | (0.0201) | (0.0241) | (0.0253) | (0.0296) |
| Observations | 201,001 | 245,243 | 250,350 | 107,237 | 200,614 | 245,030 | 250,177 | 107,168 | 201,002 | 245,250 | 250,401 | 107,265 |
| R-squared | 0.2595 | 0.1751 | 0.2039 | 0.262 | 0.0548 | 0.1098 | 0.1224 | 0.1506 | 0.4086 | 0.4565 | 0.4918 | 0.5068 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 6. Continued.**

| B. 2020 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_{i,t}$ = log(Quoted spread) | | | | $Y_{i,t}$ = log(Effective half-spread) | | | | $Y_{i,t}$ = log(StD returns) | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *ATS* | -1.2035 | 2.5242 | 4.5543* | 14.0634 | -2.3550 | -1.8407 | 3.1264* | 7.9742 | -0.0107 | 4.5230 | 3.5207** | 5.7772 |
| | (6.8377) | (7.8653) | (2.5428) | (28.2960) | (10.5478) | (15.6181) | (1.7185) | (9.3659) | (4.2221) | (4.1793) | (1.6390) | (5.1784) |
| *Non-ATS* | 2.9283 | 0.4072 | -6.2617 | -26.1819 | 4.9635 | 11.6387 | -2.4194 | -10.5860 | 2.0785 | -4.7182 | -4.8788 | -7.9586 |
| | (8.9757) | (30.7526) | (8.8547) | (57.6560) | (9.4925) | (40.6304) | (4.7445) | (14.5756) | (2.6624) | (10.1632) | (4.3774) | (7.6472) |
| *COMP* | -3.2092 | -2.5054 | -3.1643** | -5.8480 | -5.2094 | -4.2456 | -2.6305*** | -4.3078 | -2.5924 | -0.8540 | -1.6501 | -2.4466 |
| | (7.3808) | (7.2960) | (1.4958) | (8.9162) | (6.7964) | (6.7920) | (0.8941) | (3.6900) | (2.1968) | (2.5247) | (1.0819) | (2.3172) |
| *log(Price)* | 0.0204 | 0.0243 | 0.1952 | 0.3326 | 0.0844 | 0.0755 | 0.0021 | -0.1068 | -0.1389 | -0.1364 | -0.0822 | -0.1805 |
| | (0.3477) | (0.2802) | (0.2047) | (0.6526) | (0.5474) | (0.7746) | (0.0534) | (0.2120) | (0.1319) | (0.1123) | (0.1033) | (0.1610) |
| *log(Volatility)* | 0.4023*** | 0.3584* | 0.2450 | -0.3384 | 0.3430 | 0.2849 | 0.3556*** | 0.2312 | 0.2550*** | 0.3525*** | 0.3544*** | 0.3188* |
| | (0.1404) | (0.2099) | (0.2478) | (1.5659) | (0.2567) | (0.3603) | (0.0852) | (0.2475) | (0.0749) | (0.0368) | (0.1044) | (0.1592) |
| *log(Volume)* | -0.2544*** | -0.3421 | -0.2878** | -0.4497 | -0.2480*** | -0.5738 | -0.2280*** | -0.2874 | -0.1458*** | -0.0888 | -0.1639** | -0.2190 |
| | (0.0894) | (0.8950) | (0.1217) | (0.4773) | (0.0697) | (1.0425) | (0.0623) | (0.1896) | (0.0198) | (0.2730) | (0.0660) | (0.1404) |
| $Y_{Noti}$ | 0.7067 | 1.0126 | 1.0947*** | 1.0110 | 0.9493 | 1.6853 | 0.7649*** | 0.3670 | 0.8057*** | 0.6124 | 0.6403*** | 0.5143 |
| | (0.5093) | (0.9821) | (0.2014) | (0.9660) | (0.9270) | (3.5374) | (0.2523) | (0.7212) | (0.2066) | (0.6079) | (0.1851) | (0.3487) |
| Observations | 39,099 | 51,279 | 55,989 | 21,560 | 39,097 | 51,279 | 55,989 | 21,560 | 39,085 | 51,272 | 55,989 | 21,560 |
| R-squared | -0.912 | 0.521 | -0.237 | -10.067 | -3.372 | -7.527 | 0.186 | -2.294 | -0.3291 | -0.9594 | -0.0481 | -0.7139 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

| C. 2020 ex-COVID | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_{i,t}$ = log(Quoted spread) | | | | $Y_{i,t}$ = log(Effective half-spread) | | | | $Y_{i,t}$ = log(StD returns) | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *ATS* | 2.2321 | 5.1721 | 5.6124** | 13.3753 | 3.0410 | 4.0300 | 4.0840** | 7.9931 | 0.4224 | 4.8592 | 3.2276*** | 3.6788** |
| | (2.1161) | (8.2829) | (2.1125) | (15.2771) | (2.0525) | (2.5933) | (1.6008) | (6.5106) | (2.4659) | (4.1648) | (0.9663) | (1.6255) |
| *Non-ATS* | -0.7537 | -3.8992 | -5.6417 | -13.5405 | -0.0713 | -1.3031 | -2.5961 | -5.1088 | 1.2744 | -4.7981 | -1.9805 | -1.1528 |
| | (1.7209) | (20.6311) | (8.9817) | (23.9465) | (0.5469) | (3.3606) | (3.4256) | (6.9409) | (1.0993) | (9.4063) | (2.8166) | (1.9221) |
| *COMP* | -0.6109 | -2.5195 | -3.5137** | -6.5292 | -1.7885*** | -2.5556** | -2.7296*** | -4.2902* | -1.9599** | -1.3490 | -1.5920** | -1.9234*** |
| | (1.3884) | (2.4534) | (1.4933) | (5.0722) | (0.5691) | (0.9991) | (0.9209) | (2.5443) | (0.9674) | (1.5336) | (0.5967) | (0.6227) |
| *log(Price)* | -0.1040 | 0.1256 | 0.3560 | 0.7037 | -0.1793** | -0.0988 | 0.0471 | 0.0289 | -0.1330* | -0.0045 | 0.0609 | 0.0189 |
| | (0.1062) | (0.1330) | (0.3570) | (1.0705) | (0.0832) | (0.0720) | (0.0842) | (0.1672) | (0.0779) | (0.0971) | (0.0990) | (0.0752) |
| *log(Volatility)* | 0.4354*** | 0.3524** | 0.1332 | -0.1988 | 0.4506*** | 0.3853*** | 0.2488*** | 0.1253 | 0.2371*** | 0.3811*** | 0.3106*** | 0.3047*** |
| | (0.0427) | (0.1352) | (0.2800) | (0.8746) | (0.0326) | (0.0692) | (0.0897) | (0.2084) | (0.0400) | (0.0914) | (0.0811) | (0.0649) |
| *log(Volume)* | -0.2137*** | -0.2672 | -0.3254* | -0.6229 | -0.2050*** | -0.2695*** | -0.2331*** | -0.3268* | -0.1281*** | -0.1115 | -0.1862*** | -0.1857*** |
| | (0.0193) | (0.4938) | (0.1792) | (0.3879) | (0.0180) | (0.0709) | (0.0648) | (0.1748) | (0.0181) | (0.2191) | (0.0574) | (0.0569) |
| $Y_{Noti}$ | 0.6218*** | 1.0990*** | 1.0405*** | 0.9140 | 0.5309*** | 0.5864** | 0.4081* | -0.0891 | 0.7577*** | 0.7577*** | 0.5271*** | 0.4145*** |
| | (0.0554) | (0.2720) | (0.2061) | (0.6475) | (0.0758) | (0.2877) | (0.2058) | (0.6081) | (0.0544) | (0.2271) | (0.0995) | (0.1094) |
| Observations | 32,184 | 42,251 | 46,254 | 17,823 | 32,183 | 42,251 | 46,254 | 17,823 | 32,174 | 42,247 | 46,254 | 17,823 |
| R-squared | 0.1376 | -1.7095 | -1.8620 | -8.9688 | -0.1803 | -0.9490 | -1.0150 | -2.3090 | -0.2684 | -2.7206 | -0.3494 | -0.1514 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 7. Market Stress and Dark and Lit Market Shares**

The table reports the results of regressions of *DP* and *INT* on indicators of market stress for 2009, in Panel A and of *ATS* and *Non-ATS* on indicators of market stress for 2020 in Panel B. We estimate the following panel regression of market shares ($MS_{i,t}$) using OLS:

$$MS_{i,t} = \alpha_i\, d_q + \beta\, I^{Stress} + \gamma\, log(Volume)_{i,t} + e_{i,t}\,,$$

where $I^{Stress}$ is a stock-specific indicator for the first two quarters (*H1*), the lowest tercile of individual stock returns *(ret_low)*, and the lowest tercile of stock-specific buy-order imbalances (*bs_low*). For 2009 (2020), we sample the highest decile (tercile) of individual stock volatility, *vol_extr (vol_high)*. Full results are provided in Online Appendix Table A7.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | **A. 2009** | | | **B. 2020** | |
| | *DP* | *INT* | *COMP* | *ATS* | *Non-ATS* | *COMP* |
| *I = H1* | -0.0124*** | -0.0283*** | 0.0017 | 0.0029 | -0.0136*** | 0.0168*** |
| | (0.0011) | (0.0019) | (0.0013) | (0.0038) | (0.0048) | (0.0054) |
| *I= ret_low* | -0.0037*** | -0.0059*** | 0.0006 | -0.0029** | -0.0072*** | -0.0006 |
| | (0.0007) | (0.0013) | (0.0007) | (0.0013) | (0.0017) | (0.0018) |
| *I = bs_low* | -0.0010*** | 0.0042*** | -0.0019*** | -0.0044*** | -0.0036*** | 0.0111*** |
| | (0.0003) | (0.0007) | (0.0004) | (0.0012) | (0.0011) | (0.0019) |
| *I = vol_extr* | -0.0116*** | -0.0155*** | -0.0022** | | | |
| | (0.0006) | (0.0013) | (0.0009) | | | |
| *I= vol_high* | | | | 0.0047** | -0.0104** | 0.0065* |
| | | | | (0.0020) | (0.0047) | (0.0034) |
| Controls | YES | YES | YES | YES | YES | YES |
| Firm FE | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 8. Market Shares and Market Quality in Periods of Market Stress**

The table reports the results of regressions of Quoted and Effective spreads on indicators of market stress for 2009, in Panel A, and for 2020, in Panel B. We estimate the following panel regression of market shares ($MS_{i,t}$) using IV/2SLS:

$$(1) \quad DP_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1\, X_{i,t} + e_{1,i,t}$$

$$(2) \quad INT_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2\, X_{i,t} + e_{2,i,t}$$

$$(3) \quad COMP_{i,t} = a_i\, d_q + b_3\, W_{i,t} + c_3\, X_{i,t} + e_{3,i,t}$$

$$(4) \quad Y_{i,t} = \alpha_i\, d_q + \beta_1\, DP_{i,t} + \beta_2\, INT_{i,t} + \beta_3\, COMP_{i,t} + \gamma\, X_{i,t} + e_{4,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$ and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $DP_{Noti,t}$, $INT_{Noti,t}$, and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). For 2020, *DP* = *ATS* and *INT* = *Non-ATS*. The second stage regressions (4) use the fitted value from the first stage regressions (1)-(3) of the endogenous variables. Market stress periods are: the first two quarters (*H1*), the lowest tercile of individual stock returns *(ret_low)*, and the lowest tercile of stock-specific buy-order imbalances (*bs_low*). For 2009 (2020), we sample the highest decile (tercile) of individual stock volatility, *vol_extr (vol_high)*.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **A. 2009** | $Y_{i,t}$ = log(Quoted spread) | | | | $Y_{i,t}$ = log(Effective half-spread) | | | | $Y_{i,t}$ = log(StD returns) | | | |
| | *H1* | *ret_low* | *bs_low* | *vol_extr* | *H1* | *ret_low* | *bs_low* | *vol_extr* | *H1* | *ret_low* | *bs_low* | *vol_extr* |
| *DP* | -1.4871*** | -1.0091*** | -1.1675*** | -0.7007** | -1.2870*** | -1.0044*** | -1.2241*** | -0.4878 | -1.5007*** | -0.9676*** | -0.8524*** | -0.6642 |
| | (0.2311) | (0.2646) | (0.2577) | (0.2888) | (0.2999) | (0.3158) | (0.2923) | (0.4512) | (0.2687) | (0.2277) | (0.1780) | (0.5399) |
| *INT* | -0.2866** | -1.0257*** | -1.3631*** | 0.0104 | -0.1881 | -0.8969*** | -0.8783*** | 0.1595 | -0.7134** | -0.7283*** | -1.0528*** | 0.0399 |
| | (0.1253) | (0.1679) | (0.1889) | (0.3253) | (0.1842) | (0.1888) | (0.1998) | (0.2576) | (0.3578) | (0.2225) | (0.2187) | (0.3611) |
| *COMP* | -0.4059*** | 0.0331 | -0.4480** | -0.0560 | -1.0376*** | -0.4521** | -0.5522*** | -0.9762*** | -0.6728*** | -0.6674*** | -0.7427*** | -0.5349** |
| | (0.1364) | (0.1843) | (0.1850) | (0.2205) | (0.2076) | (0.2253) | (0.2096) | (0.3111) | (0.1869) | (0.1968) | (0.1849) | (0.2686) |
| *log(Volume)* | -0.0998*** | -0.1122*** | -0.1003*** | -0.1232*** | 0.0261*** | 0.0232*** | 0.0217*** | 0.0374*** | 0.2089*** | 0.1947*** | 0.1733*** | 0.1999*** |
| | (0.0062) | (0.0057) | (0.0066) | (0.0099) | (0.0067) | (0.0062) | (0.0067) | (0.0084) | (0.0111) | (0.0066) | (0.0071) | (0.0108) |
| $Y_{Noti}$ | 0.8936*** | 0.9200*** | 0.9277*** | 0.7820*** | 0.8072*** | 0.8164*** | 0.8431*** | 0.6755*** | 0.8823*** | 0.8463*** | 0.8923*** | 0.4679*** |
| | (0.0147) | (0.0182) | (0.0201) | (0.0252) | (0.0219) | (0.0226) | (0.0226) | (0.0290) | (0.0216) | (0.0200) | (0.0167) | (0.0283) |
| Observations | 341,859 | 233,943 | 233,976 | 69,231 | 341,412 | 233,767 | 233,807 | 69,158 | 341,859 | 233,999 | 233,997 | 69,237 |
| R-squared | 0.3056 | 0.3101 | 0.2454 | 0.3521 | 0.0803 | 0.1184 | 0.1145 | 0.0470 | 0.2472 | 0.3821 | 0.3742 | 0.1792 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table 8. Continued.**

| B. 2020 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_{i,t}$ = *log(Quoted spread)* | | | | $Y_{i,t}$ = *log(Effective half-spread)* | | | | $Y_{i,t}$ = *log(StD returns)* | | | |
| | *H1* | *ret_low* | *bs_low* | *vol_high* | *H1* | *ret_low* | *bs_low* | *vol_high* | *H1* | *ret_low* | *bs_low* | *vol_high* |
| *ATS* | -0.0232 | 4.0580** | 4.5235 | 10.1089*** | -1.4955* | 1.9940 | 2.1741 | 6.2900*** | -2.4471** | 1.6395 | 0.9477 | 7.3868*** |
| | (1.0925) | (1.6072) | (2.9989) | (3.3351) | (0.7556) | (1.5049) | (1.5690) | (1.4479) | (1.1258) | (1.7083) | (1.7871) | (2.2719) |
| *Non-ATS* | -2.9879* | -2.9225 | -7.9555 | -8.8091* | 0.0340 | 0.4225 | -1.6477 | -4.6493** | -2.7477 | -2.5195 | -4.1004* | -7.9909*** |
| | (1.6606) | (3.7037) | (9.1517) | (5.0390) | (1.1235) | (3.2030) | (1.9815) | (2.2460) | (1.6560) | (2.9541) | (2.3987) | (2.5421) |
| *COMP* | 0.7615 | -3.0749*** | -1.2737 | -5.8588 | -0.1149 | -3.1172*** | -1.8256* | -2.9970* | 1.7482 | -1.4933 | -0.3363 | -0.9788 |
| | (1.2378) | (1.0691) | (2.3984) | (3.6811) | (0.8490) | (0.8585) | (1.0186) | (1.5648) | (1.2140) | (1.0868) | (1.2590) | (2.7098) |
| *log(Volume)* | -0.0359 | -0.1569*** | -0.0059 | -0.1384 | -0.0644** | -0.1708*** | -0.0699 | -0.0587 | 0.0548 | -0.0630 | 0.0354 | 0.0381 |
| | (0.0461) | (0.0557) | (0.1694) | (0.0972) | (0.0309) | (0.0537) | (0.0449) | (0.0493) | (0.0415) | (0.0464) | (0.0508) | (0.0619) |
| $Y_{Noti}$ | 1.1088*** | 1.0581*** | 0.9288** | 0.6740** | 1.2139*** | 1.1370*** | 1.0453*** | 0.5556*** | 1.1076*** | 0.9559*** | 0.8738*** | 0.1827 |
| | (0.0974) | (0.1986) | (0.4001) | (0.2925) | (0.0805) | (0.2156) | (0.1292) | (0.1532) | (0.1041) | (0.1663) | (0.1190) | (0.1768) |
| Observations | 74,139 | 50,792 | 50,641 | 47,957 | 74,137 | 50,792 | 50,639 | 47,956 | 74,123 | 50,789 | 50,631 | 47,950 |
| R-squared | 0.3573 | -0.0753 | -1.8301 | -4.1119 | 0.5431 | 0.2221 | 0.1699 | -1.9246 | 0.2402 | 0.2073 | -0.1987 | -5.5483 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

# Online Appendix:

# Diving Into Dark Pools

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and

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Date: January 2022

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## 1. SIFMA data

We first benchmark the raw SIFMA data against the monthly total share volume in dark pools as reported by Rosenblatt, Inc. in their monthly *Let There Be Light* publication. This publication bases its reported statistics on self-reported data from dark pools, and is the only source for information on dark pool activity for our sample period. Figure A1 Panel A shows that the SIFMA data mirrors the monthly time series variation in the Rosenblatt share volume closely. Figure A1 Panel B shows that the SIFMA data covers roughly half of the Rosenblatt share volume. Specifically, the market share of the dark pools submitting data for our study increases from 47% in January to 60% in December of dark volume as reported by Rosenblatt, Inc. Finally, Figure A1 Panel C shows that dark pool share volume as reported in the SIFMA (Rosenblatt) data represents 3.65 (7.74) percent of consolidated volume in January, and 6.10 (10.15) percent of consolidated volume in December.

The raw SIFMA data covers 10,178 unique securities and the coverage by individual dark pools ranges from a low of 5,646 to a high of 8,251 securities. In order to merge the SIFMA data with NYSEs Trade and Quote (TAQ) data and with data from the Center for Research in Securities Prices (CRSP), we screen the data following standard practice. We first exclude ticker symbols with suffixes (e.g., preferred, warrants, non-voting, etc.) and the ticker symbols with a fifth character (unless also in CRSP as A, B, or K). Second, we exclude securities that are not common stocks (CRSP SHRCD 10 or 11). As we need to merge CRSP with the SIFMA data, we also exclude 87 stocks with missing ticker symbols in CRSP and 49 stocks with duplicate stock identifiers for the same ticker symbol. Moreover, we exclude stocks with price above $1,000 and we screen out stocks with a price below $1.00 and less than 5,000 shares average volume. Finally, we exclude AMEX listed stocks. Our final SIFMA sample consists of 3,098 stocks with non-zero dark pool volume for at least one day in 2009.

## 2. FINRA data

The raw FINRA data covers 27,167 unique securities. We merge the FINRA data with data from MIDAS and CRSP, and exclude 23,874 securities that have missing ticker symbols in CRSP. We then exclude 24 ticker symbols with suffixes (e.g., preferred, warrants, non-voting, etc.) and the ticker symbols with a fifth character (unless also in CRSP as A, B, or K). Next, we exclude one security that is not common stocks (SHRCD 10 or 11) covered by CRSP. Finally, we exclude 366 securities with prices higher than $1,000 or lower than $1.00 dollars. Our FINRA sample consists of 2,902 stocks with non-zero dark pool volume for at least one week in 2020.

## 3. Theory and Empirical Literature

This section provides a brief and selective overview of the related theoretical and empirical literature.

### 2.1 Dark Pools

There is considerable heterogeneity across dark pools in terms of both ownership and execution protocols, but they all lack pre-trade transparency, they execute orders at or inside the lit market quotes, and they control access through subscriber agreements.

Consider how a dark venue interacts with a limit order book as modeled by, e.g., Buti, Rindi, and Werner (2017). The lack of pre-trade transparency has both negative and positive consequences for potential users of the dark venue. The fact that an order submitter cannot see if there is liquidity on the other side in a dark pool increases the non-execution costs for a limit order submitter, and results in price uncertainty for a market order submitter. Both features discourage subscribers from routing their order to a dark pool. However, executions in dark pools occur at prices at or inside the lit market quotes, which is beneficial to a market order submitter because it enables the trader to avoid crossing the spread, and therefore reduces the price opportunity cost. The ability to route orders to a dark pool is also beneficial to limit order submitters, because it allows them to access a finer price grid and therefore reduces the amount they have to price improve to gain priority. This feature is particularly helpful when the queues at the lit market inside quotes are long, when the tick-to price ratio is high (price is low), and when the spread is constrained by the tick size, so that limit order submitters extensively migrate to the dark market, decreasing the price uncertainty of the dark pool.

Information asymmetries can also affect subscribers' desire to use dark pools. Because both market and limit orders convey information as emphasized by, e.g., Kaniel and Liu (2006), Riccò, Rindi and Seppi (2020) and Rosu (2020), it could be beneficial for subscribers to use the dark pool either to reduce order exposure or to reduce price impact. This may encourage traders to use dark pools, particularly if they are trading based on private information and want to minimize their price impact (Ye and Zhu, 2019). However, as Zhu (2014) emphasizes, if informed traders are concerned about the lower execution probability that a dark pool may offer compared to a lit market where market makers offer liquidity at the first level of the book, they may instead prefer to trade in the lit maker rather than in the dark pool.[1]

[1] Furthermore, because dark pools are subscriber-based, they can discourage informed order flow and may even exclude brokers that have a history or routing orders with significant price impact to their venue. This further discourages the use of dark pools when there are significant information asymmetries.

Several models also make predictions about what the effect of more dark pool trading is on market quality and price discovery. Buti, Rindi, and Werner (2017) emphasize that the effects of dark pool trading depend on the liquidity of the stock. They show that the effect on lit market quality of higher dark pool activity depends on which type of orders leave the order book for the dark pool. In their model, the order book opens empty, and mostly limit orders move to the dark pool worsening the lit market spread. However, as liquidity builds up, market orders start migrating to the dark dampening the negative effect on the lit market spread. Therefore, their analysis suggests that for large and liquid stocks, predominantly market orders move to the dark pool and that this improves the lit market spread, whereas for illiquid stocks mostly limit orders move to the dark pool resulting in wider lit market spread.

When considering information asymmetries, the predictions are mixed. Zhu (2014) shows that dark pool trading improves price discovery. In his quote-driven model insiders trade off price improvement and the risk of no execution, and because they all trade on the same side of the market, they face a higher no execution risk in the dark pool as opposed to the lit market where market makers provide infinite liquidity. Therefore, insiders trade more in the lit market than in the dark pool, thus improving price discovery and worsening liquidity - adding adverse selection costs to the spread. In Ye and Zhu (2019) dark pool trading instead results in impaired price discovery. In their order-driven model, orders submitted to the lit market have a price impact whereas orders submitted to the dark do not move the price directly. Therefore, informed traders trade less aggressively on the lit market and this effect is stronger when the information is more valuable. Overall, the existing theory on the effects of dark pool trading on price discovery offers predictions that crucially depend on whether the lit market is quote- or order-driven. In addition, both Zhu (2014) and Ye and Zhu (2019) assume that insiders cannot choose to trade via limit orders, whereas the most recent empirical literature, i.e., Brogaard, Hendershott and Riordan (2019) and Garriot and Riordan (2020), shows that insiders using limit orders may significantly contribute to price discovery.

### 2.2 Internalized order flow

While the popularity of dark pools has risen steadily since their introduction, the bulk of dark trading is still retail order flow that is internalized by market makers. Internalizing market makers match order flow coming from the customers of retail brokerage firms at prices no worse than the prevailing lit market spread. Retail brokerage firms are in turn encouraged to direct retail orders to market makers in return for incentives, so called payment for order flow. The practice is to pay for retail market order and marketable limit orders, but not for liquidity-providing limit orders.

There is an extensive literature on payment for order flow, and early work focused on the fact that these arrangements were a way for market makers to offer price improvement when prices are discrete.

Chordia and Subrahamanyam (1995) and Kandel and Marx (1999) show that payment for order flow is higher when the tick size is larger in models of competing market makers. By contrast, Parlour and Rajan (2003) develop a model with a zero tick size where a market maker who pays for retail market orders also handles customer limit orders. They show that the value of the paid-for market order is lower if the order trades against the book instead of the market maker's quotes. Hence, the value of the incoming market order depends on the state of the market maker's limit order book. The market order is worth more if the book is empty, in other words if the spread is wide.

Easley, Kiefer and O'Hara (1996) argue that payment-for-order flow arrangements enable market makers to cream-skim the order flow, effectively screening out informed orders. Cream-skimming leaves a disproportionate amount of informed orders on the lit market, increasing the adverse selection facing liquidity suppliers, and market quality deteriorates as a result. However, since the proportion of informed orders is higher, price discovery is also faster (Kyle, 1985). Bloomfield and O'Hara (1998) find that the more order flow is preferenced, the wider are the spreads based on experimental evidence. Even without information asymmetries, payment for order flow affects spreads. Kandel and Marx (1999) find that higher payment for order flow is associated with wider spreads in equilibrium and Parlour and Rajan (2003) show that payment for order flow arrangements in equilibrium lead to wider spreads and higher trading costs for market orders.

### 2.3 Lit competing venues

All registered exchanges can trade all U.S. stocks, regardless of on which exchange they are listed, through what is called unlisted trading privileges. What factors are important in determining the market share of lit competing venues? One major feature that makes lit competing venues attractive is that they enable liquidity providers to bypass time-priority on the listing exchange (Foucault and Menkveld, 2008). This is clearly more important when the listing exchange's limit order book has long queues at the inside spreads, when the spread is more constrained by the tick size, and when the relative tick size is large. Hence, we expect the market share of lit competing venues to be higher for actively traded liquid stocks.

Theoretical models have shown that fragmentation may increase the number of liquidity providers (e.g., Biais, Martimort, and Rochet, 2000), enhancing competition between liquidity suppliers which helps improve market quality. Similarly, fragmentation can lead to increased competition between trading venues (e.g., Foucault and Menkveld, 2008) resulting in improved market quality. On the other hand, fragmentation may harm liquidity and price discovery by increasing search costs and this may decrease competition between trading venues (e.g., Yin, 2005).

### 2.4 Empirical Evidence

Few prior studies have examined how stock liquidity affects dark pool market shares. Ready (2014) studies monthly volume by stock in three dark pools: Liquidnet, POSIT, and Pipeline during June 2005-September 2007. He finds that the market share of these dark pools is less than one percent of consolidated volume, and that dark pool volume is concentrated in liquid stocks (low spreads, high share volume) consistent with Buti, Rindi, and Werner (2017). Kwan, Masulis and McInish (2015) are able to distinguish between five different types of dark venues based on a random sample of 116 U.S. stocks in 2011.[2] They document that four of the five dark venue-types have higher market shares in stocks that are constrained by the tick size. Moreover, they find that dark pools have higher market share when depth is higher for tick-constrained stocks. For unconstrained stocks, dark pool market shares are instead lower when depth is higher.

By contrast, there is more evidence on the effects of information asymmetries on dark pool market share but the results are mixed. Ye and Zhu (2019) show that during the weeks with Schedule 13D trades dark pool trades increase confirming their model predictions that market share of dark pool increases with informed trading. On the contrary, Menkveld, Yueshen and Zhu (2017) show that when the urgency to trade increases around VIX shocks, macroeconomic data releases, and firm's earnings surprises, dark pool market share decreases because agents are attracted by the higher immediacy of lit venues. Similarly, Reed, Samadi and Sokobin (2020) show that information-motivated traders, proxied for by short sellers, prefer to exploit their information advantage on regular exchanges rather than on dark pools, especially when their information is short-lived, in line with Zhu (2014).

Early evidence on the effect of dark trading on market quality was inconclusive in part because data on dark pools was unavailable. In Congressional testimony, Dr. Hatheway (Nasdaq OMX) argued that when stocks experienced "dark" trading in excess of 40 percent of total volume, execution quality began to deteriorate. Similarly, Weaver (2014) argued that dark trading is associated with a reduction in market quality. In contrast, O'Hara and Ye (2011) found that fragmentation of trading generally reduced transactions costs and improved execution speed. These contradictory results are perhaps not surprising as the researchers relied on proxies for dark trading. Both Weaver (2014) and O'Hara and Ye (2011) used volume reported to the Trade Reporting Facilities (TRFs) as a general proxy for dark trading. The Nasdaq

[2] These are: dark-electronic communication networks (DARK-ECN), block crossing venues (BLOCK), ping destinations (PING), retail market makers (INTERNALIZE), and an unclassified residual category (OTHER).

OMX study referred to in the Congressional testimony (Hatheway, 2009) used TRF volume minus BATS and DirectEdge as a proxy for dark pools, but this data still included internalized order flow.

Several authors have examined the effect of crossing networks on market quality and price discovery with mixed results. Gresse (2006) finds that crossing networks have a very limited market share and do not have a detrimental effect on the liquidity of the continuous market. Naes and Odegaard (2006) find that institutional orders sent first to crossing networks and then to the continuous market obtain lower realized execution costs for the crossed component, but not necessarily for the entire order. Conrad, Johnson, and Wahal (2003) find that institutional orders executed in crossing networks have lower realized execution costs and that traders use the continuous market to trade their exhaust. Fong, Madhavan, and Swan (2004) find no evidence of a liquidity drain away from the continuous market when traders can trade in a crossing network.

Others have explored the effect of dark pools on market quality and price discovery, but again the evidence is mixed. Brandes and Domowitz (2010) and Buchanan, Tse, Vincent, Lin and Kumar (2011) study dark pool trading in Europe and find that increased participation of dark pools enhances the price discovery process. Relying on a broader definition of dark trading including both dark pools and internalized trades, Degryse, de Jong, and van Kervel (2015) find that fragmentation is beneficial for the liquidity of 52 Dutch stocks as long as trading is transparent, but that dark trading has a detrimental effect on liquidity. Hatheway, Kwan and Zhen (2017) show instead that dark trading has a detrimental effect on the market quality of U.S. stocks, since dark pools segregate order flow based on asymmetric information risk. Nimalendran and Ray (2014) study data from one U.S. dark pool, and find that trading in the dark venue is associated with wider lit market spreads and price impacts. Several recent studies examine the effects of dark pools by using the large exogenous decrease to dark pool trading following the implementation of the SEC's Tick Size Pilot Program. Brogaard and Pan (2021) show that dark pool trading increases information acquisition for small stocks. Farley, Kelley and Puckett (2017) observe minimal changes in trading costs and informational efficiency after the reduction in dark trading. Albuquerque, Song and Yao (2020) suggest that dark pool trading improves intraday informational efficiency.

A strand of the literature has explored whether dark trading is elevated around earnings announcements. For example, Balakrishnan and Taori (2017) document that dark pool trading increases in the week of earnings announcements (as well as analyst recommendation revision), and that pre-news week trading happens in dark pools where proprietary flow is allowed. They also find that post-earnings-announcement drift (PEAD) is stronger for stocks with higher levels of dark pool trading, suggesting that dark pools delay price discovery. Gkougkousi and Landsman (2019) find that abnormal dark market share increases significantly in the weeks prior to, during, and following earnings announcements. Cox (2020) finds that both dark and lit market fragmentation increase around earnings announcements, but also documents that dark fragmentation reduces the level of PEAD for stocks with positive earnings surprises, suggesting that dark pools facilitate price discovery. Thomas, Zhang and Zhu (2021) find that under-reaction to earnings announcements increases with dark trading, suggesting that dark pools slow down price discovery. However, Brogaard and Pan (2021) find that dark pool trading leads to greater pre-emption of upcoming earnings news, generating a larger association between pre-announcement abnormal returns and upcoming earnings surprises, and smaller price reactions to earnings surprises at the announcement. In other words, the literature agrees that dark trading is elevated around earnings announcements, but the evidence on PEAD is inconclusive; some authors find that dark trading expedites price discovery, while others find that price discovery is slowed down when dark trading is elevated.

Finally, researchers have attempted to distinguish between dark trading in venues that operate as continuous opaque order books and periodic crossing-networks executing block trades. Comerton-Forde and Putniņš (2015) study the largest 500 Australian stocks and find that non-block dark trading widens quoted spreads, and that high-levels are harmful for price discovery. By contrast, block-crossing networks are not detrimental for price discovery. Exploiting restrictions in dark trading in Canada in 2012 (and Australia in 2013), Foley and Putniņš (2016) study the constituents of the TSX 250 index and find that dark limit order markets are beneficial for market quality and informational efficiency, but find no effect for mid-point crossing systems.[3]

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[3] Comerton-Forde, Malinova, and Park (2018) study the same Canadian rule change and show that the requirement that dark orders receive price improvement relative to lit market quotes caused brokers to route retail order flow away from dark venues to the lit venues with the lowest fee.

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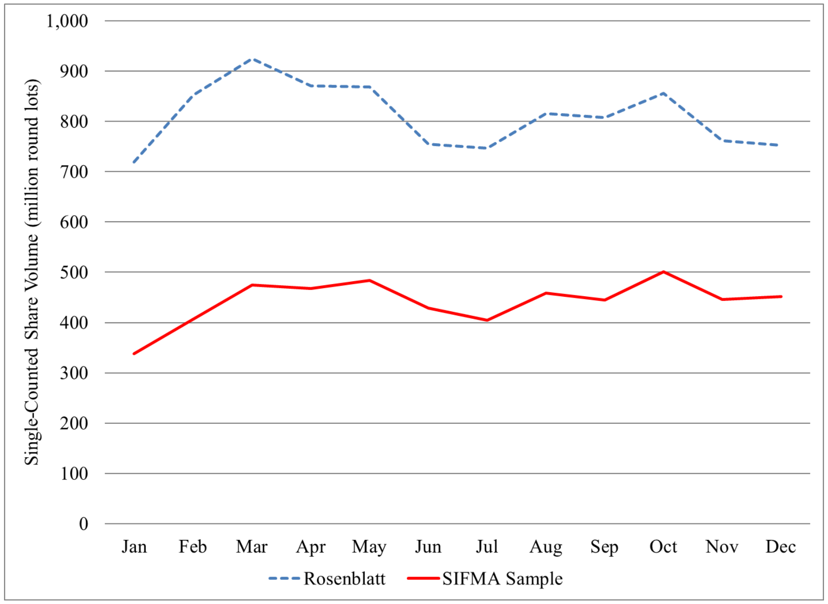
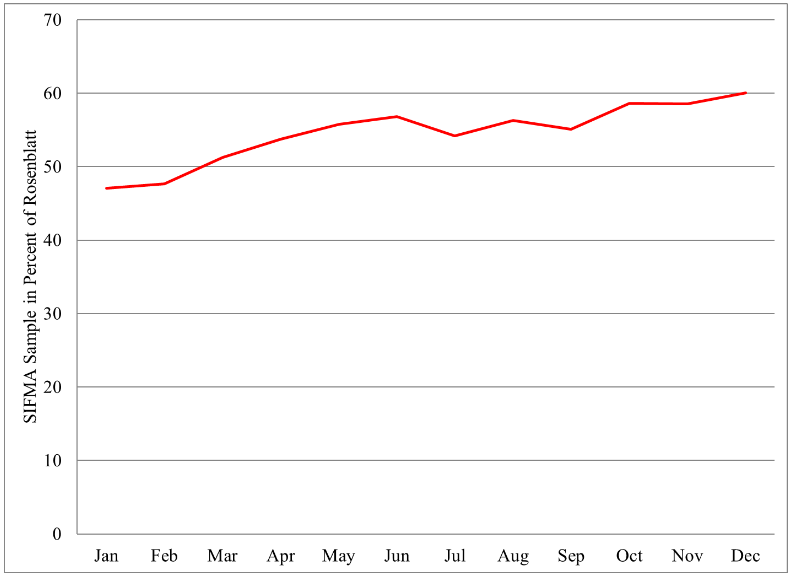
**Figure A1. SIFMA Sample Compared to Rosenblatt**

This figure reports monthly SIFMA sample dark pool trading activity compared to dark pool trading activity as reported by Rosenblatt Securities Inc. in their *Let There Be Light* publication. Panel A reports SIFMA single-counted share volume for 11 dark pools and single-counted share volume for 32 dark pools as reported by Rosenblatt. Panel B captures the fraction of Rosenblatt reported share volume that is reflected in the SIFMA sample. Panel C reports the market shares of the SIFMA sample and Rosenblatt sample relative to consolidated volume adjusted for double-counting as reported by Rosenblatt.



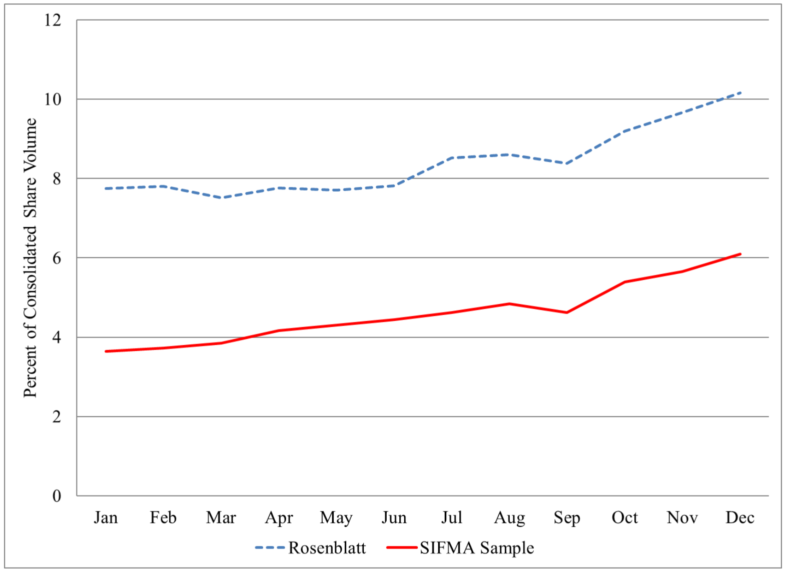



**Table A1. Descriptive Statistics in logs**

The table reports descriptive statistics based on daily stock level data for the 2009 daily sample in Panel A and the 2020 weekly sample in Panel B. We obtain market capitalization in million dollars, stock price in dollars, and Volatility is 100*(High-Low)/High from CRSP. For 2009, we use TAQ to calculate average daily: Volume as consolidated share volume, time-weighted *Quoted spreads* and share-weighted *Effective half-spreads* both in basis points of the mid-quote, and *StD returns* is 10,000 times the standard deviation of 15-minute mid-quote returns. For 2020, we calculate average weekly: Volume as consolidated share volume, time-weighted *Quoted spreads* and share-weighted *Effective half-spreads* both in basis points of the mid-quote, and *StD returns* is 10,000 times the standard deviation of mid-quote returns from daily WRDS Intraday Indicators. All characteristics and market quality data is expressed in natural logarithms. For 2009, market shares are measured as a fraction of TAQ consolidated volume, where *COMP* are lit competing venues with the main (listing) exchange, *TRF* is volume reported with "D" in TAQ, and *DP* are the SIFMA reporting dark pools, and *INT* is internalized trades defined as *TRF-DP*. For 2020, market shares are measured as a fraction of WRDS Intraday Indicator reported daily consolidated volume aggregated to weekly data, where *COMP* are lit competing venues from MIDAS, *FINRA* is volume of *ATS* and *Non-ATS* volume as reported to *FINRA*. Market quality and Fragmentation data are Winsorized at the 1st and 99th percentiles.

| **A. 2009 Sample** | N | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| Characteristics | | | | | | |
| *log(Size)* | 696,686 | 6.492 | 1.679 | 5.282 | 6.322 | 7.534 |
| *log(Volume)* | 696,686 | 12.530 | 1.960 | 11.160 | 12.510 | 13.890 |
| *log(Price)* | 696,686 | 2.584 | 0.923 | 1.939 | 2.664 | 3.262 |
| *log(Volatility)* | 696,686 | 1.662 | 0.643 | 1.237 | 1.668 | 2.094 |
| Market Quality | | | | | | |
| *log(Quoted spread)* | 696,627 | 3.155 | 1.174 | 2.265 | 3.05 | 3.933 |
| *log(Effective half-spread)* | 695,854 | 1.947 | 1.046 | 1.169 | 1.805 | 2.604 |
| *log(StD returns)* | 696,686 | 4.007 | 0.586 | 3.61 | 4.005 | 4.395 |
| Fragmentation | | | | | | |
| *TRF* | 696,686 | 0.316 | 0.144 | 0.212 | 0.291 | 0.394 |
| *DP* | 696,686 | 0.062 | 0.055 | 0.025 | 0.048 | 0.081 |
| *INT* | 696,686 | 0.253 | 0.138 | 0.155 | 0.220 | 0.318 |
| *COMP* | 696,686 | 0.284 | 0.095 | 0.224 | 0.287 | 0.344 |

| **B. 2020 Sample** | N | mean | sd | p25 | p50 | p75 |
|---|---|---|---|---|---|---|
| Characteristics | | | | | | |
| *log(Size)* | 146,702 | 6.975 | 2.085 | 5.453 | 6.941 | 8.337 |
| *log(Volume)* | 146,702 | 14.200 | 1.948 | 13.090 | 14.380 | 15.510 |
| *log(Price)* | 146,702 | 3.105 | 1.248 | 2.249 | 3.110 | 4.011 |
| *log(Volatility)* | 146,699 | 1.437 | 0.605 | 1.047 | 1.442 | 1.838 |
| Market Quality | | | | | | |
| *log(Quoted spread)* | 146,702 | 3.541 | 1.282 | 2.640 | 3.447 | 4.392 |
| *log(Effective half-spread)* | 146,700 | 2.380 | 1.212 | 1.476 | 2.201 | 3.183 |
| *log(StD returns)* | 146,682 | 1.470 | 1.316 | 0.552 | 1.331 | 2.361 |
| Fragmentation | | | | | | |
| *FINRA* | 146,702 | 0.367 | 0.120 | 0.284 | 0.348 | 0.432 |
| *ATS* | 146,702 | 0.137 | 0.066 | 0.092 | 0.134 | 0.177 |
| *Non-ATS* | 146,702 | 0.230 | 0.140 | 0.127 | 0.187 | 0.295 |
| *COMP* | 146,702 | 0.329 | 0.092 | 0.269 | 0.325 | 0.396 |

**Table A2.1. First Stage Regressions for Table 2 and 3 and Online Appendix Table A2.2**

The table reports the results of regressions of *log(Quoted spread)* and *log(Depth)* on lagged instruments in Panels A and D (B and E) for 2009 (2020) and for the ex-COVID 2020 sample in Panels C and F. We estimate the following panel regression using OLS:

$$(1)\quad log(Quoted\ spread)_{i,t} = \alpha_i\, d_q + \beta_{1,1}\, log(Quoted\ spread)_{i,t-1} + \beta_{1,2}\, log(Depth)_{i,t-1} + \gamma_1\, X_{i,t} + e_{1,i,t}\ ,$$

$$(2)\quad log(Depth)_{i,t} = \alpha_i\, d_q + \beta_{2,1}\, log(Quoted\ spread)_{i,t-1} + \beta_{2,2}\, log(Depth)_{i,t-1} + \gamma_2\, X_{i,t} + e_{2,i,t}\ ,$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **A. 2009** | | | | | **B. 2020** | | | | | **C. 2020 ex-COVID** | | | | |
| | *log(Quoted Spread)* | | | | | *log(Quoted Spread)* | | | | | *log(Quoted Spread)* | | | | |
| | All | Small | Medium | Large | S&P 500 | All | Small | Medium | Large | S&P 500 | All | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* $_{t-1}$ | 0.3678*** | 0.3099*** | 0.3971*** | 0.4663*** | 0.4797*** | 0.3306*** | 0.2527*** | 0.3142*** | 0.3719*** | 0.3538*** | 0.1661 | 0.1885*** | 0.1617 | 0.1431 | 0.0827 |
| | (0.0060) | (0.0055) | (0.0084) | (0.0174) | (0.0269) | (0.0918) | (0.0361) | (0.1161) | (0.1233) | (0.1292) | (0.1115) | (0.0471) | (0.1385) | (0.1479) | (0.1425) |
| *log(Depth)* $_{t-1}$ | -0.0107*** | 0.0026 | -0.0117*** | -0.0326*** | -0.0301*** | 0.0201 | 0.0100 | 0.0277 | 0.0614 | 0.0539 | -0.0061 | -0.0018 | -0.0021 | -0.0295 | 0.0024 |
| | (0.0023) | (0.0018) | (0.0038) | (0.0051) | (0.0051) | (0.0173) | (0.0098) | (0.0277) | (0.0384) | (0.0394) | (0.0183) | (0.0086) | (0.0337) | (0.0424) | (0.0440) |
| *log(Price)* | -0.2960*** | -0.2881*** | -0.2787*** | -0.3246*** | -0.3608*** | -0.2070* | -0.2297*** | -0.2292 | -0.2045 | -0.2754* | 0.0050 | -0.0693 | 0.0518 | 0.0689 | -0.0130 |
| | (0.0109) | (0.0115) | (0.0145) | (0.0209) | (0.0265) | (0.1050) | (0.0839) | (0.1379) | (0.1489) | (0.1563) | (0.1554) | (0.1144) | (0.2100) | (0.2010) | (0.2035) |
| *log(Volatility)* | 0.1783*** | 0.2795*** | 0.1468*** | 0.0952*** | 0.0684*** | 0.5559*** | 0.4977*** | 0.5415*** | 0.6449*** | 0.6955*** | 0.3664*** | 0.3967*** | 0.3477*** | 0.3637*** | 0.3640*** |
| | (0.0030) | (0.0049) | (0.0037) | (0.0034) | (0.0040) | (0.0515) | (0.0328) | (0.0660) | (0.0880) | (0.1112) | (0.0220) | (0.0180) | (0.0325) | (0.0287) | (0.0370) |
| *log(Volume)* | -0.1068*** | -0.1148*** | -0.1078*** | -0.0876*** | -0.0710*** | -0.2575*** | -0.2179*** | -0.2789*** | -0.3526*** | -0.4144*** | -0.2636*** | -0.2152*** | -0.2987*** | -0.3505*** | -0.4116*** |
| | (0.0020) | (0.0030) | (0.0025) | (0.0030) | (0.0039) | (0.0306) | (0.0182) | (0.0485) | (0.0828) | (0.1291) | (0.0318) | (0.0157) | (0.0545) | (0.0781) | (0.1202) |
| *Constant* | 3.8653*** | 4.2282*** | 3.7908*** | 3.4768*** | 3.2728*** | 5.7630*** | 5.9463*** | 6.1332*** | 6.7592*** | 8.1429*** | 6.1530*** | 6.1485*** | 6.5664*** | 6.9438*** | 8.0396*** |
| | (0.0485) | (0.0474) | (0.0674) | (0.1184) | (0.1622) | (0.7629) | (0.2859) | (0.9823) | (1.4826) | (2.3558) | (0.7616) | (0.3420) | (0.9878) | (1.2007) | (1.7397) |
| Observations | 693,453 | 199,964 | 244,210 | 249,279 | 106,785 | 143,774 | 38,315 | 50,243 | 54,905 | 21,143 | 118,055 | 31,402 | 41,213 | 45,173 | 17,406 |
| R-squared | 0.9748 | 0.8930 | 0.9283 | 0.9602 | 0.9679 | 0.9622 | 0.9242 | 0.8989 | 0.9088 | 0.8630 | 0.9642 | 0.9255 | 0.8945 | 0.9075 | 0.8534 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table A2.1. Continued.**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | **D. 2009** | | | | | **E. 2020** | | | | | **F. 2020 ex-COVID** | | |
| | | | *log(Depth)* | | | | | *log(Depth)* | | | | | *log(Depth)* | | |
| | All | Small | Medium | Large | S&P 500 | All | Small | Medium | Large | S&P 500 | All | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* $_{t-1}$ | -0.0192*** | -0.0005 | -0.0362*** | -0.0703*** | -0.1280*** | -0.0219 | 0.0160 | -0.0284 | -0.0259 | -0.0221 | 0.0064 | 0.0334** | 0.0053 | -0.0084 | -0.0087 |
| | (0.0056) | (0.0050) | (0.0085) | (0.0161) | (0.0308) | (0.0230) | (0.0154) | (0.0299) | (0.0258) | (0.0271) | (0.0149) | (0.0151) | (0.0208) | (0.0104) | (0.0117) |
| *log(Depth)* $_{t-1}$ | 0.3424*** | 0.2107*** | 0.3547*** | 0.5189*** | 0.5154*** | 0.2743*** | 0.1936*** | 0.2855*** | 0.4690*** | 0.5429*** | 0.2325*** | 0.1703*** | 0.2641*** | 0.3908*** | 0.4005*** |
| | (0.0098) | (0.0057) | (0.0107) | (0.0185) | (0.0215) | (0.0153) | (0.0125) | (0.0228) | (0.0305) | (0.0430) | (0.0221) | (0.0182) | (0.0312) | (0.0401) | (0.0422) |
| *log(Price)* | -0.1828*** | -0.1813*** | -0.1343*** | -0.1859*** | -0.2316*** | -0.3674*** | -0.4514*** | -0.3336*** | -0.1853*** | -0.2519*** | -0.3297*** | -0.4084*** | -0.2863*** | -0.1564*** | -0.2956*** |
| | (0.0057) | (0.0061) | (0.0063) | (0.0112) | (0.0172) | (0.0419) | (0.0388) | (0.0531) | (0.0576) | (0.0721) | (0.0310) | (0.0365) | (0.0462) | (0.0373) | (0.0515) |
| *log(Volatility)* | -0.4143*** | -0.3413*** | -0.4429*** | -0.5139*** | -0.6491*** | -0.1566*** | -0.1540*** | -0.1445*** | -0.1494*** | -0.1663*** | -0.1516*** | -0.1648*** | -0.1540*** | -0.1285*** | -0.1281*** |
| | (0.0183) | (0.0169) | (0.0192) | (0.0451) | (0.0616) | (0.0139) | (0.0159) | (0.0172) | (0.0243) | (0.0279) | (0.0121) | (0.0185) | (0.0173) | (0.0165) | (0.0137) |
| *log(Volume)* | 0.0632*** | 0.1242*** | 0.0642*** | -0.0670*** | -0.1575*** | 0.1463*** | 0.1331*** | 0.1637*** | 0.1780*** | 0.1494*** | 0.1462*** | 0.1312*** | 0.1677*** | 0.1804*** | 0.1622*** |
| | (0.0033) | (0.0034) | (0.0036) | (0.0073) | (0.0120) | (0.0073) | (0.0083) | (0.0123) | (0.0128) | (0.0139) | (0.0079) | (0.0085) | (0.0136) | (0.0143) | (0.0123) |
| *Constant* | 4.7255*** | 4.5371*** | 4.6738*** | 6.0297*** | 8.1216*** | 3.5894*** | 4.3808*** | 3.1070*** | 1.2155*** | 1.5049*** | 3.6158*** | 4.3949*** | 2.9281*** | 1.4421*** | 2.2584*** |
| | (0.0813) | (0.0623) | (0.1073) | (0.2539) | (0.3769) | (0.1746) | (0.1337) | (0.2838) | (0.3133) | (0.5049) | (0.2282) | (0.1806) | (0.3227) | (0.3577) | (0.3904) |
| Observations | 693,512 | 199,965 | 244,217 | 249,330 | 106,813 | 143,774 | 38,315 | 50,243 | 54,905 | 21,143 | 118,055 | 31,402 | 41,213 | 45,173 | 17,406 |
| R-squared | 0.8643 | 0.6672 | 0.9033 | 0.9411 | 0.9473 | 0.9185 | 0.7804 | 0.9435 | 0.9693 | 0.9777 | 0.9288 | 0.7965 | 0.9512 | 0.9791 | 0.9864 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table A2.2. Dark Order Routing by Size**

The table reports the results of regressions of *TRF (FINRA*) on lagged instruments. We estimate the following panel regression of market shares ($MS_{i,t}$) using IV/2SLS:

$$(1)\quad log(Quoted\ spread)_{i,t} = \alpha_i\, d_q + \beta_{1,1}\, log(Quoted\ spread)_{i,t-1} + \beta_{1,2}\, log(Depth)_{i,t-1} + \boldsymbol{\gamma_1}\, X_{i,t} + e_{1,i,t}\ ,$$

$$(2)\quad log(Depth)_{i,t} = \alpha_i\, d_q + \beta_{2,1}\, log(Quoted\ spread)_{i,t-1} + \beta_{2,2}\, log(Depth)_{i,t-1} + \boldsymbol{\gamma_2}\, X_{i,t} + e_{2,i,t}\ ,$$

$$(3)\quad MS_{i,t} = \alpha_i\, d_q + \beta_{3,1}\, log(Quoted\ spread)_{i,t} + \beta_{3,2}\, log(Depth)_{i,t} + \boldsymbol{\gamma_3}\, X_{i,t} + e_{3,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. Equations (1) and (2) models the endogenous variables $log(Quoted\ spread)_{i,t}$ and $log(Depth)_{i,t}$ using their lagged values as instruments. Equation (3) uses the fitted values from the first stage regressions for the endogenous variables.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **A. 2009** | | *TRF* | | |
| | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* | 0.0110** | 0.0349*** | 0.0051 | -0.0017 |
| | (0.0053) | (0.0068) | (0.0064) | (0.0080) |
| *log(Depth)* | 0.0028 | 0.0031 | 0.0325*** | 0.0317*** |
| | (0.0046) | (0.0045) | (0.0031) | (0.0036) |
| *log(Price)* | -0.0349*** | -0.0232*** | 0.0221*** | 0.0161** |
| | (0.0057) | (0.0064) | (0.0062) | (0.0080) |
| *log(Volatility)* | -0.0224*** | -0.0314*** | -0.0173*** | -0.0149*** |
| | (0.0021) | (0.0017) | (0.0014) | (0.0015) |
| *log(Volume)* | 0.0249*** | 0.0570*** | 0.0515*** | 0.0508*** |
| | (0.0025) | (0.0020) | (0.0019) | (0.0024) |
| Observations | 199,964 | 244,210 | 249,279 | 106,785 |
| R-squared | 0.0155 | 0.0737 | 0.0792 | 0.0928 |
| Firm#Quarter FE | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table A2.2. Continued.**

| B. 2020 | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *FINRA* | | | |
| | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* | -0.0299* | 0.0179 | 0.0298** | 0.0377** |
| | (0.0159) | (0.0146) | (0.0127) | (0.0180) |
| *log(Depth)* | -0.0132 | 0.0132 | 0.0080 | 0.0245* |
| | (0.0097) | (0.0105) | (0.0115) | (0.0127) |
| *log(Price)* | -0.0207* | 0.0286* | 0.0248* | 0.0261 |
| | (0.0116) | (0.0154) | (0.0125) | (0.0167) |
| *log(Volatility)* | -0.0015 | -0.0415*** | -0.0639*** | -0.0722*** |
| | (0.0086) | (0.0128) | (0.0128) | (0.0185) |
| *log(Volume)* | 0.0192*** | 0.0477*** | 0.0448*** | 0.0366*** |
| | (0.0052) | (0.0085) | (0.0082) | (0.0114) |
| Observations | 38,315 | 50,243 | 54,905 | 21,143 |
| R-squared | 0.0199 | 0.0430 | 0.0448 | 0.0557 |
| Firm#Quarter FE | YES | YES | YES | YES |

| C. 2020 ex-COVID | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *FINRA* | | | |
| | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* | 0.0253 | 0.1043** | 0.1111 | 0.1573 |
| | (0.0194) | (0.0467) | (0.0887) | (0.2586) |
| *log(Depth)* | -0.0084 | 0.0241* | 0.0091 | 0.0136 |
| | (0.0132) | (0.0143) | (0.0178) | (0.0254) |
| *log(Price)* | -0.0025 | -0.0312 | -0.0638* | -0.0915 |
| | (0.0088) | (0.0186) | (0.0331) | (0.0972) |
| *log(Volatility)* | -0.0411*** | -0.0039 | 0.0110 | 0.0347 |
| | (0.0114) | (0.0220) | (0.0200) | (0.0338) |
| *log(Volume)* | 0.0282*** | 0.0675*** | 0.0742** | 0.0890 |
| | (0.0058) | (0.0174) | (0.0329) | (0.1130) |
| Observations | 31,402 | 41,213 | 45,173 | 17,406 |
| R-squared | 0.0312 | 0.0033 | -0.0651 | -0.3584 |
| Firm#Quarter FE | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A3.1. Order Routing (OLS)**

The table reports the results of regressions of *DP*, *INT*, and *COMP (ATS*, *Non-ATS*, and *COMP*) on lagged instruments. We estimate the following panel regression of market shares ($MS_{i,t}$) using OLS:

$$MS_{i,t} = \alpha_i\, d_q + \beta_1\, log(Quoted\ spread)_{i,t\text{-}1} + \beta_2\, log(Depth)_{i,t\text{-}1} + \boldsymbol{\gamma}\, X_{i,t} + e_{i,t}\ ,$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | A. 2009 | | | | B. 2020 | | | | C. 2020 ex-COVID | | | |
| | *TRF* | *DP* | *INT* | *COMP* | *FINRA* | *ATS* | *Non-ATS* | *COMP* | *FINRA* | *ATS* | *Non-ATS* | *COMP* |
| *log(Quoted spread)* $_{-1}$ | 0.0059*** | -0.0023*** | 0.0073*** | -0.0092*** | 0.0019 | 0.0085*** | -0.0068** | -0.0013 | 0.0134*** | 0.0096** | 0.0037 | -0.0037 |
| | (0.0015) | (0.0007) | (0.0014) | (0.0012) | (0.0034) | (0.0031) | (0.0032) | (0.0029) | (0.0050) | (0.0042) | (0.0027) | (0.0027) |
| *log(Depth)* $_{-1}$ | 0.0041*** | -0.0020*** | 0.0065*** | -0.0020*** | 0.0015 | -0.0056*** | 0.0072*** | -0.0002 | 0.0015 | -0.0042*** | 0.0060*** | 0.0018 |
| | (0.0010) | (0.0004) | (0.0009) | (0.0006) | (0.0018) | (0.0010) | (0.0017) | (0.0016) | (0.0020) | (0.0012) | (0.0016) | (0.0017) |
| *log(Price)* | -0.0297*** | -0.0124*** | -0.0165*** | 0.0127*** | 0.0064 | -0.0034 | 0.0104 | -0.0032 | -0.0118 | -0.0089 | -0.0025 | -0.0168 |
| | (0.0038) | (0.0018) | (0.0038) | (0.0029) | (0.0093) | (0.0051) | (0.0069) | (0.0078) | (0.0130) | (0.0073) | (0.0079) | (0.0102) |
| *log(Volatility)* | -0.0215*** | -0.0104*** | -0.0098*** | 0.0040*** | -0.0309*** | -0.0119*** | -0.0181*** | 0.0102* | -0.0024 | -0.0038 | 0.0026 | 0.0159*** |
| | (0.0010) | (0.0004) | (0.0008) | (0.0006) | (0.0068) | (0.0028) | (0.0052) | (0.0052) | (0.0048) | (0.0031) | (0.0037) | (0.0058) |
| *log(Volume)* | 0.0374*** | 0.0126*** | 0.0232*** | -0.0095*** | 0.0319*** | 0.0120*** | 0.0193*** | -0.0120*** | 0.0292*** | 0.0113*** | 0.0173*** | -0.0140*** |
| | (0.0015) | (0.0004) | (0.0013) | (0.0007) | (0.0038) | (0.0020) | (0.0026) | (0.0038) | (0.0041) | (0.0022) | (0.0028) | (0.0045) |
| *Constant* | -0.0848*** | -0.0270*** | -0.0412* | 0.4051*** | -0.0760 | -0.0035 | -0.0688 | 0.5000*** | -0.0568 | 0.0004 | -0.0538 | 0.5582*** |
| | (0.0244) | (0.0078) | (0.0220) | (0.0126) | (0.0620) | (0.0359) | (0.0432) | (0.0534) | (0.0726) | (0.0467) | (0.0413) | (0.0630) |
| Observations | 693,512 | 693,512 | 693,512 | 693,512 | 143,774 | 143,774 | 143,774 | 143,774 | 118,055 | 118,055 | 118,055 | 118,055 |
| R-squared | 0.4946 | 0.1967 | 0.5236 | 0.3457 | 0.5728 | 0.5961 | 0.7005 | 0.7005 | 0.5966 | 0.6096 | 0.7130 | 0.7113 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table A3.2. Dark and Lit Order Routing by Size (OLS)**

The table reports the results of regressions of *TRF* and *COMP (FINRA* and *COMP*) on lagged instruments. We estimate the following panel regression of market shares ($MS_{i,t}$) using OLS:

$$MS_{i,t} = \alpha_i d_q + \beta_1 log(Quoted\ spread)_{i,t-1} + \beta_2 log(Depth)_{i,t-1} + \gamma X_{i,t} + e_{i,t}\ ,$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$.

| **A. 2009** | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *TRF* | | | | *COMP* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* $_{-1}$ | 0.0034** | 0.0138*** | 0.0001 | -0.0049 | -0.0068*** | -0.0136*** | -0.0095*** | -0.0068* |
| | (0.0016) | (0.0027) | (0.0030) | (0.0040) | (0.0015) | (0.0018) | (0.0024) | (0.0036) |
| *log(Depth)* $_{-1}$ | 0.0006 | 0.0007 | 0.0167*** | 0.0164*** | -0.0020*** | 0.0007 | -0.0060*** | -0.0072*** |
| | (0.0010) | (0.0016) | (0.0019) | (0.0021) | (0.0007) | (0.0012) | (0.0011) | (0.0014) |
| *log(Price)* | -0.0390*** | -0.0343*** | 0.0038 | -0.0037 | 0.0226*** | 0.0081** | -0.0012 | 0.0041 |
| | (0.0050) | (0.0049) | (0.0056) | (0.0068) | (0.0039) | (0.0034) | (0.0046) | (0.0065) |
| *log(Volatility)* | -0.0198*** | -0.0267*** | -0.0229*** | -0.0224*** | 0.0038*** | 0.0049*** | 0.0055*** | 0.0068*** |
| | (0.0013) | (0.0013) | (0.0012) | (0.0015) | (0.0010) | (0.0009) | (0.0008) | (0.0010) |
| *log(Volume)* | 0.0240*** | 0.0534*** | 0.0488*** | 0.0459*** | -0.0041*** | -0.0161*** | -0.0137*** | -0.0148*** |
| | (0.0022) | (0.0016) | (0.0017) | (0.0022) | (0.0010) | (0.0009) | (0.0010) | (0.0014) |
| *Constant* | 0.2313*** | -0.2602*** | -0.5271*** | -0.4953*** | 0.2785*** | 0.4917*** | 0.5694*** | 0.5931*** |
| | (0.0281) | (0.0275) | (0.0321) | (0.0448) | (0.0142) | (0.0180) | (0.0247) | (0.0358) |
| Observations | 199,965 | 244,217 | 249,330 | 106,813 | 199,965 | 244,217 | 249,330 | 106,813 |
| R-squared | 0.3711 | 0.4195 | 0.4973 | 0.5957 | 0.1948 | 0.2839 | 0.4170 | 0.4335 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES |

| **B. 2020** | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *FINRA* | | | | *COMP* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* $_{-1}$ | -0.0078* | 0.0052 | 0.0109** | 0.0128*** | 0.0019 | -0.0012 | -0.0068** | -0.0120*** |
| | (0.0042) | (0.0055) | (0.0041) | (0.0041) | (0.0024) | (0.0033) | (0.0033) | (0.0035) |
| *log(Depth)* $_{-1}$ | -0.0029 | 0.0043 | 0.0056 | 0.0153** | -0.0002 | -0.0004 | 0.0058 | -0.0029 |
| | (0.0019) | (0.0033) | (0.0054) | (0.0066) | (0.0016) | (0.0031) | (0.0041) | (0.0046) |
| *log(Price)* | -0.0079 | 0.0201 | 0.0173 | 0.0095 | 0.0119 | -0.0105 | -0.0248** | -0.0219 |
| | (0.0109) | (0.0135) | (0.0120) | (0.0138) | (0.0107) | (0.0082) | (0.0104) | (0.0135) |
| *log(Volatility)* | -0.0143** | -0.0337*** | -0.0459*** | -0.0501*** | 0.0044 | 0.0110 | 0.0255*** | 0.0283*** |
| | (0.0064) | (0.0087) | (0.0078) | (0.0085) | (0.0042) | (0.0066) | (0.0072) | (0.0075) |
| *log(Volume)* | 0.0239*** | 0.0449*** | 0.0357*** | 0.0246*** | -0.0008 | -0.0280*** | -0.0284*** | -0.0219** |
| | (0.0036) | (0.0065) | (0.0055) | (0.0073) | (0.0031) | (0.0059) | (0.0073) | (0.0089) |
| *Constant* | 0.2366*** | -0.3435*** | -0.2863*** | -0.1551 | 0.2353*** | 0.7490*** | 0.8673*** | 0.8479*** |
| | (0.0436) | (0.1086) | (0.1028) | (0.1429) | (0.0286) | (0.0841) | (0.1217) | (0.1578) |
| Observations | 38,315 | 50,243 | 54,905 | 21,143 | 38,315 | 50,243 | 54,905 | 21,143 |
| R-squared | 0.5373 | 0.5106 | 0.4942 | 0.5021 | 0.4814 | 0.6324 | 0.7782 | 0.7983 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table A3.2. Continued**

| C. 2020 ex-COVID | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *FINRA* | | | | *COMP* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* $_{-1}$ | 0.0045 | 0.0170* | 0.0158** | 0.0129* | 0.0006 | -0.0016 | -0.0083** | -0.0135** |
| | (0.0037) | (0.0094) | (0.0070) | (0.0069) | (0.0025) | (0.0037) | (0.0041) | (0.0056) |
| *log(Depth)* $_{-1}$ | -0.0015 | 0.0061 | 0.0003 | 0.0058 | 0.0010 | 0.0025 | 0.0107* | 0.0039 |
| | (0.0022) | (0.0041) | (0.0053) | (0.0077) | (0.0016) | (0.0032) | (0.0055) | (0.0058) |
| *log(Price)* | -0.0394*** | -0.0054 | 0.0172 | 0.0286 | -0.0042 | -0.0159 | -0.0448*** | -0.0564*** |
| | (0.0106) | (0.0194) | (0.0187) | (0.0213) | (0.0120) | (0.0120) | (0.0152) | (0.0188) |
| *log(Volatility)* | 0.0090** | 0.0014 | -0.0245*** | -0.0360*** | 0.0107** | 0.0222*** | 0.0264*** | 0.0284*** |
| | (0.0044) | (0.0080) | (0.0066) | (0.0075) | (0.0041) | (0.0081) | (0.0087) | (0.0103) |
| *log(Volume)* | 0.0217*** | 0.0404*** | 0.0369*** | 0.0264*** | -0.0009 | -0.0325*** | -0.0334*** | -0.0280** |
| | (0.0038) | (0.0071) | (0.0064) | (0.0082) | (0.0033) | (0.0069) | (0.0085) | (0.0104) |
| *Constant* | 0.2216*** | -0.3071** | -0.3096** | -0.2273 | 0.2561*** | 0.7971*** | 1.0011*** | 1.0606*** |
| | (0.0445) | (0.1298) | (0.1239) | (0.1696) | (0.0315) | (0.0959) | (0.1430) | (0.1876) |
| Observations | 31,402 | 41,213 | 45,173 | 17,406 | 31,402 | 41,213 | 45,173 | 17,406 |
| R-squared | 0.5645 | 0.5357 | 0.5184 | 0.5288 | 0.5005 | 0.6489 | 0.7882 | 0.8070 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table A3.3. Dark Pool/ATS and Internalized/Non-ATS Order Routing by Size (OLS)**

The table reports the results of regressions of *DP* and *INT (ATS* and *Non-ATS*) on lagged instruments. We estimate the following panel regression of market shares ($MS_{i,t}$) using OLS:

$$MS_{i,t} = \alpha_i\, d_q + \beta_1\, log(Quoted\ spread)_{i,t-1} + \beta_2\, log(Depth)_{i,t-1} + \gamma\, X_{i,t} + e_{i,t}\ ,$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **A. 2009** | | *DP* | | | | *INT* | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* $_{-1}$ | -0.0008 | -0.0022* | -0.0081*** | -0.0066*** | 0.0028* | 0.0150*** | 0.0080*** | 0.0017 |
| | (0.0008) | (0.0013) | (0.0014) | (0.0017) | (0.0016) | (0.0023) | (0.0024) | (0.0035) |
| *log(Depth)* $_{-1}$ | -0.0038*** | -0.0041*** | 0.0034*** | 0.0036*** | 0.0052*** | 0.0051*** | 0.0133*** | 0.0127*** |
| | (0.0004) | (0.0008) | (0.0007) | (0.0007) | (0.0009) | (0.0012) | (0.0017) | (0.0019) |
| *log(Price)* | -0.0110*** | -0.0172*** | -0.0072*** | -0.0051* | -0.0260*** | -0.0169*** | 0.0109** | 0.0013 |
| | (0.0022) | (0.0026) | (0.0024) | (0.0028) | (0.0052) | (0.0045) | (0.0051) | (0.0063) |
| *log(Volatility)* | -0.0107*** | -0.0131*** | -0.0082*** | -0.0081*** | -0.0068*** | -0.0125*** | -0.0145*** | -0.0143*** |
| | (0.0006) | (0.0007) | (0.0005) | (0.0006) | (0.0012) | (0.0011) | (0.0010) | (0.0013) |
| *log(Volume)* | 0.0094*** | 0.0168*** | 0.0148*** | 0.0142*** | 0.0121*** | 0.0352*** | 0.0337*** | 0.0316*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0008) | (0.0019) | (0.0014) | (0.0016) | (0.0022) |
| *Constant* | 0.0225*** | -0.0402*** | -0.1196*** | -0.1405*** | 0.2251*** | -0.2041*** | -0.4019*** | -0.3535*** |
| | (0.0083) | (0.0130) | (0.0136) | (0.0176) | (0.0249) | (0.0252) | (0.0283) | (0.0415) |
| Observations | 199,965 | 244,217 | 249,330 | 106,813 | 199,965 | 244,217 | 249,330 | 106,813 |
| R-squared | 0.1661 | 0.1873 | 0.2558 | 0.2997 | 0.4063 | 0.4145 | 0.4906 | 0.6036 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **B. 2020** | | *ATS* | | | | *Non-ATS* | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* $_{-1}$ | 0.0030** | 0.0069 | 0.0105** | 0.0086* | -0.0113*** | -0.0018 | 0.0003 | 0.0042 |
| | (0.0014) | (0.0043) | (0.0042) | (0.0047) | (0.0042) | (0.0039) | (0.0039) | (0.0055) |
| *log(Depth)* $_{-1}$ | -0.0041*** | -0.0077*** | -0.0050* | -0.0029 | 0.0014 | 0.0120*** | 0.0105*** | 0.0181*** |
| | (0.0008) | (0.0019) | (0.0026) | (0.0036) | (0.0019) | (0.0031) | (0.0039) | (0.0047) |
| *log(Price)* | -0.0015 | -0.0025 | -0.0087 | -0.0086 | -0.0059 | 0.0232** | 0.0267*** | 0.0183 |
| | (0.0040) | (0.0074) | (0.0089) | (0.0099) | (0.0103) | (0.0088) | (0.0091) | (0.0142) |
| *log(Volatility)* | -0.0118*** | -0.0156*** | -0.0121** | -0.0131** | -0.0005 | -0.0173** | -0.0333*** | -0.0370*** |
| | (0.0019) | (0.0036) | (0.0046) | (0.0052) | (0.0055) | (0.0065) | (0.0059) | (0.0076) |
| *log(Volume)* | 0.0076*** | 0.0162*** | 0.0194*** | 0.0200*** | 0.0156*** | 0.0279*** | 0.0159*** | 0.0045 |
| | (0.0013) | (0.0037) | (0.0044) | (0.0052) | (0.0029) | (0.0040) | (0.0047) | (0.0076) |
| *Constant* | 0.0287* | -0.0350 | -0.0840 | -0.1203 | 0.2115*** | -0.3018*** | -0.1977** | -0.0325 |
| | (0.0146) | (0.0639) | (0.0899) | (0.1110) | (0.0407) | (0.0630) | (0.0804) | (0.1485) |
| Observations | 38,315 | 50,243 | 54,905 | 21,143 | 38,315 | 50,243 | 54,905 | 21,143 |
| R-squared | 0.4827 | 0.4892 | 0.5460 | 0.5747 | 0.6215 | 0.5762 | 0.6094 | 0.6700 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A3.3. Continued.**

| C. 2020 ex-COVID | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *ATS* | | | | *Non-ATS* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Quoted spread)* $_{-1}$ | 0.0030* | 0.0112* | 0.0122* | 0.0073 | 0.0008 | 0.0055 | 0.0038 | 0.0057 |
| | (0.0017) | (0.0058) | (0.0070) | (0.0077) | (0.0037) | (0.0042) | (0.0047) | (0.0085) |
| *log(Depth)* $_{-1}$ | -0.0036*** | -0.0043* | -0.0069** | -0.0096** | 0.0026 | 0.0109*** | 0.0070 | 0.0153** |
| | (0.0010) | (0.0022) | (0.0032) | (0.0039) | (0.0022) | (0.0033) | (0.0043) | (0.0058) |
| *log(Price)* | -0.0030 | -0.0079 | -0.0160 | -0.0213 | -0.0359*** | 0.0024 | 0.0338*** | 0.0499*** |
| | (0.0055) | (0.0103) | (0.0130) | (0.0141) | (0.0112) | (0.0113) | (0.0111) | (0.0148) |
| *log(Volatility)* | -0.0092*** | -0.0058 | 0.0044 | 0.0032 | 0.0204*** | 0.0082 | -0.0285*** | -0.0392*** |
| | (0.0020) | (0.0048) | (0.0054) | (0.0062) | (0.0041) | (0.0056) | (0.0058) | (0.0070) |
| *log(Volume)* | 0.0073*** | 0.0151*** | 0.0184*** | 0.0217*** | 0.0136*** | 0.0246*** | 0.0179*** | 0.0046 |
| | (0.0014) | (0.0042) | (0.0048) | (0.0055) | (0.0031) | (0.0043) | (0.0054) | (0.0082) |
| *Constant* | 0.0273 | -0.0535 | -0.0516 | -0.0666 | 0.1980*** | -0.2459*** | -0.2514*** | -0.1579 |
| | (0.0177) | (0.0787) | (0.1091) | (0.1270) | (0.0411) | (0.0654) | (0.0871) | (0.1469) |
| Observations | 31,402 | 41,213 | 45,173 | 17,406 | 31,402 | 41,213 | 45,173 | 17,406 |
| R-squared | 0.5019 | 0.5106 | 0.5651 | 0.6033 | 0.6433 | 0.5924 | 0.6246 | 0.6840 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table A4.1.    First Stage Regressions for Lit and Dark Market Shares and Market Quality**

The table reports the results of the first stage regressions used to estimate the relationship between market shares and market quality. We estimate the following three-equation panel regression model market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1)\quad DARK_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1\, X_{i,t} + e_{1,i,t}$$

$$(2)\quad COMP_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2\, X_{i,t} + e_{2,i,t}$$

$$(3)\quad Y_{i,t} = \alpha_i\, d_q + \beta_1\, DARK_{i,t} + \beta_2\, COMP_{i,t} + \gamma\, X_{i,t} + e_{3,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, $log(Volume)_{i,t}$, and $Y_{Noti,t}$. $W_{i,t}$ is a vector that includes: $DARK_{Noti,t}$ and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). For 2009, *DARK* = *TRF* and for 2020, *DARK* = *FINRA*. The second stage results are reported in Table 4.

| **A. 2009** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Y = log(Quoted spread)* | | *Y= log(Effective half-spread)* | | *Y = log(StD returns)* | |
| | *TRF* | *COMP* | *TRF* | *COMP* | *TRF* | *COMP* |
| *log(Price)* | -0.0435*** | 0.0177*** | -0.0461*** | 0.0176*** | -0.0462*** | 0.0185*** |
| | (0.0025) | (0.0016) | (0.0026) | (0.0016) | (0.0025) | (0.0016) |
| *log(Volatility)* | -0.0161*** | 0.0019*** | -0.0158*** | 0.0020*** | -0.0147*** | 0.0014*** |
| | (0.0007) | (0.0005) | (0.0007) | (0.0005) | (0.0007) | (0.0005) |
| *log(Volume)* | 0.0378*** | -0.0097*** | 0.0380*** | -0.0098*** | 0.0385*** | -0.0100*** |
| | (0.0012) | (0.0006) | (0.0012) | (0.0006) | (0.0012) | (0.0006) |
| $TRF_{Noti}$ | 0.8981*** | 0.0245** | 0.8945*** | 0.0175* | 0.8585*** | 0.0377*** |
| | (0.0346) | (0.0116) | (0.0262) | (0.0095) | (0.0271) | (0.0094) |
| $COMP_{Noti}$ | -0.032 | 0.9449*** | -0.0456 | 0.9433*** | 0.0137 | 0.9230*** |
| | (0.0419) | (0.0189) | (0.0339) | (0.0186) | (0.0347) | (0.0177) |
| $Y_{Noti}$ | -0.0254*** | 0.0127*** | -0.0371*** | 0.0119*** | -0.0318*** | 0.0135*** |
| | (0.0049) | (0.0025) | (0.0035) | (0.0021) | (0.0026) | (0.0013) |
| *Constant* | -0.2059*** | 0.0403** | -0.2026*** | 0.0616*** | -0.1668*** | 0.0334*** |
| | (0.0307) | (0.0162) | (0.0211) | (0.0116) | (0.0212) | (0.0114) |
| Observations | 696,653 | 696,653 | 696,653 | 696,653 | 696,653 | 696,653 |
| R-squared | 0.504 | 0.356 | 0.504 | 0.356 | 0.5044 | 0.3557 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A4.1. Continued.**

| B. 2020 | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Y = log(Quoted spread)* | | *Y = log(Effective half-spread)* | | *Y = log(StD returns)* | |
| | *FINRA* | *COMP* | *FINRA* | *COMP* | *FINRA* | *COMP* |
| *log(Price)* | -0.0021 | 0.0142*** | -0.0239*** | 0.0159*** | -0.0113 | 0.0152*** |
| | (0.0143) | (0.0044) | (0.0078) | (0.0047) | (0.0116) | (0.0046) |
| *log(Volatility)* | -0.0179*** | 0.0054*** | -0.0073** | 0.0045** | -0.0149*** | 0.0049*** |
| | (0.0052) | (0.0018) | (0.0032) | (0.0017) | (0.0039) | (0.0017) |
| *log(Volume)* | 0.0354*** | -0.0046*** | 0.0354*** | -0.0046*** | 0.0351*** | -0.0046*** |
| | (0.0023) | (0.0017) | (0.0027) | (0.0017) | (0.0026) | (0.0017) |
| $FINRA_{Noti}$ | 0.0317 | -0.0009 | 0.0376** | -0.0014 | 0.0404** | -0.0017* |
| | (0.0193) | (0.0009) | (0.0172) | (0.0010) | (0.0201) | (0.0009) |
| $COMP_{Noti}$ | 0.8111*** | 0.9693*** | 0.7907*** | 0.9708*** | 0.8662*** | 0.9643*** |
| | (0.1035) | (0.0103) | (0.1124) | (0.0115) | (0.0922) | (0.0100) |
| $Y_{Noti}$ | -0.0396** | 0.0029 | -0.0844*** | 0.0065*** | -0.0600*** | 0.0051** |
| | (0.0191) | (0.0019) | (0.0099) | (0.0024) | (0.0160) | (0.0022) |
| *Constant* | -0.2079* | 0.0123 | -0.0535 | -0.0004 | -0.2317*** | 0.0116 |
| | (0.1054) | (0.0239) | (0.0606) | (0.0243) | (0.0590) | (0.0226) |
| Observations | 146,667 | 146,667 | 146,667 | 146,667 | 146,667 | 146,667 |
| R-squared | 0.591 | 0.738 | 0.595 | 0.738 | 0.5922 | 0.7376 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES |

| C. 2020 ex-COVID | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | *Y = log(Quoted spread)* | | *Y = log(Effective half-spread)* | | *Y = log(StD returns)* | |
| | *FINRA* | *COMP* | *FINRA* | *COMP* | *FINRA* | *COMP* |
| *log(Price)* | 0.0042 | 0.0102* | -0.0111 | 0.0113** | -0.0001 | 0.0107* |
| | (0.0108) | (0.0052) | (0.0097) | (0.0056) | (0.0122) | (0.0054) |
| *log(Volatility)* | -0.0097*** | 0.0041* | -0.0050 | 0.0038* | -0.0080** | 0.0039* |
| | (0.0034) | (0.0021) | (0.0031) | (0.0021) | (0.0031) | (0.0021) |
| *log(Volume)* | 0.0362*** | -0.0049** | 0.0353*** | -0.0048** | 0.0354*** | -0.0048** |
| | (0.0024) | (0.0020) | (0.0028) | (0.0020) | (0.0026) | (0.0020) |
| $FINRA_{Noti}$ | 0.0718 | -0.0004 | 0.0869** | -0.0016 | 0.0814* | -0.0016 |
| | (0.0448) | (0.0013) | (0.0386) | (0.0015) | (0.0443) | (0.0011) |
| $COMP_{Noti}$ | 0.7295*** | 0.9765*** | 0.7542*** | 0.9742*** | 0.7607*** | 0.9728*** |
| | (0.1214) | (0.0113) | (0.1070) | (0.0114) | (0.1115) | (0.0102) |
| $Y_{Noti}$ | 0.0031 | -0.0010 | -0.0739** | 0.0047* | -0.0212 | 0.0021 |
| | (0.0216) | (0.0017) | (0.0312) | (0.0027) | (0.0271) | (0.0022) |
| *Constant* | -0.4222*** | 0.0447 | -0.1355 | 0.0228 | -0.3506*** | 0.0345 |
| | (0.1045) | (0.0277) | (0.1095) | (0.0295) | (0.0771) | (0.0266) |
| Observations | 120,948 | 120,948 | 120,948 | 120,948 | 120,948 | 120,948 |
| R-squared | 0.6113 | 0.7533 | 0.6130 | 0.7533 | 0.6115 | 0.7533 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A4.2. Dark and Lit Market Shares and Market Quality by Size**

The table reports the results of analyzing the relationship between market shares and market quality for subsamples by market capitalization. We estimate the following three-equation panel regression model market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1) \quad DARK_{i,t} = a_i \, d_q + b_1 \, W_{i,t} + c_1 \, X_{i,t} + e_{1,i,t}$$

$$(2) \quad COMP_{i,t} = a_i \, d_q + b_2 \, W_{i,t} + c_2 X_{i,t} + e_{2,i,t}$$

$$(3) \quad Y_{i,t} = \alpha_i \, d_q + \beta_1 DARK_{i,t} + \beta_2 COMP_{i,t} + \boldsymbol{\gamma} \, X_{i,t} + e_{3,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, $log(Volume)_{i,t}$, and $Y_{Noti,t}$. $W_{i,t}$ is a vector that includes: $DARK_{Noti,t}$ and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). For 2009, *DARK* = *TRF* and for 2020*, DARK* = *FINRA*. The second stage IV/2SLS regressions in equation (3) uses the fitted value from the first stage regressions (1)-(2).

| A. 2009 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_{i,t}$ = *log(Quoted spread)* | | | | $Y_{i,t}$ = *log(Effective half-spread)* | | | | $Y_{i,t}$ = *log(StD returns)* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *DARK* | -0.3882** | -0.9222*** | -1.0121*** | -1.0118*** | -0.3326 | -0.7080*** | -0.8436*** | -0.9341** | 0.1914 | 0.1367 | -0.2790 | -0.5623* |
| | (0.1864) | (0.1638) | (0.1813) | (0.2524) | (0.2283) | (0.1443) | (0.2314) | (0.3827) | (0.1524) | (0.1708) | (0.2315) | (0.3109) |
| *COMP* | -0.2705 | -0.3713 | -0.4605* | -0.5254 | -0.4601* | -0.7576*** | -1.1551*** | -1.6711** | -0.2724* | 0.1428 | 0.7667** | 0.8345** |
| | (0.1982) | (0.2593) | (0.2666) | (0.3260) | (0.2421) | (0.2755) | (0.4271) | (0.7363) | (0.1458) | (0.2573) | (0.3388) | (0.4160) |
| *log(Price)* | -0.3612*** | -0.3837*** | -0.4344*** | -0.5389*** | -0.4134*** | -0.5166*** | -0.4992*** | -0.5367*** | -0.0220* | -0.0267* | -0.0638*** | -0.0866*** |
| | (0.0164) | (0.0193) | (0.0241) | (0.0341) | (0.0198) | (0.0168) | (0.0228) | (0.0319) | (0.0119) | (0.0152) | (0.0219) | (0.0310) |
| *log(Volatility)* | 0.3214*** | 0.1523*** | 0.0829*** | 0.0528*** | 0.2978*** | 0.1616*** | 0.0865*** | 0.0528*** | 0.5990*** | 0.4919*** | 0.4325*** | 0.4029*** |
| | (0.0064) | (0.0063) | (0.0044) | (0.0056) | (0.0072) | (0.0049) | (0.0052) | (0.0085) | (0.0055) | (0.0060) | (0.0073) | (0.0096) |
| *log(Volume)* | -0.1312*** | -0.0958*** | -0.0696*** | -0.0468*** | -0.0160** | 0.0188** | 0.0842*** | 0.1121*** | 0.0925*** | 0.0881*** | 0.1384*** | 0.1763*** |
| | (0.0066) | (0.0079) | (0.0077) | (0.0100) | (0.0065) | (0.0075) | (0.0109) | (0.0170) | (0.0042) | (0.0094) | (0.0131) | (0.0168) |
| $Y_{Noti}$ | 0.3753*** | 0.5473*** | 0.5743*** | 0.4335*** | 0.2885*** | 0.2996*** | 0.4506*** | 0.5152*** | 0.3931*** | 0.5000*** | 0.4553*** | 0.4404*** |
| | (0.0295) | (0.0326) | (0.0356) | (0.0433) | (0.0390) | (0.0342) | (0.0496) | (0.0739) | (0.0202) | (0.0242) | (0.0255) | (0.0299) |
| Observations | 201,001 | 245,243 | 250,350 | 107,237 | 200,614 | 245,030 | 250,177 | 107,168 | 201,002 | 245,250 | 250,401 | 107,265 |
| R-squared | 0.277 | 0.151 | 0.197 | 0.265 | 0.055 | 0.094 | 0.127 | 0.150 | 0.4076 | 0.4563 | 0.4939 | 0.5086 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A4.2. Continued.**

| B. 2020 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_{i,t}$ = log(Quoted spread) | | | | $Y_{i,t}$ = log(Effective half-spread) | | | | $Y_{i,t}$ = log(StD returns) | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *DARK* | 1.3624 | 2.1216 | 0.9673 | -0.5493 | 2.7465 | 3.1279 | 0.9416 | 0.0800 | 1.5906* | 0.5805 | -0.1365 | -0.6756 |
| | (1.7607) | (2.4697) | (1.2140) | (1.1684) | (2.2821) | (2.3256) | (1.0357) | (0.9638) | (0.9410) | (1.7407) | (1.2502) | (1.1510) |
| *COMP* | -2.2815 | -2.9303 | -2.3699** | -1.7169* | -4.3298 | -3.7039* | -1.9407** | -1.5185 | -2.4424* | -1.1528 | -0.6026 | -0.3859 |
| | (2.2147) | (2.2127) | (1.0104) | (1.0150) | (2.8388) | (2.0927) | (0.8995) | (0.9948) | (1.3882) | (1.6174) | (1.0693) | (1.0323) |
| *log(Price)* | -0.0300 | 0.0097 | 0.0507 | 0.1484** | -0.0263 | -0.0717 | -0.0107 | -0.0042 | -0.1562** | -0.1149** | -0.1143** | -0.1080** |
| | (0.0941) | (0.0482) | (0.0562) | (0.0650) | (0.1601) | (0.0747) | (0.0344) | (0.0520) | (0.0742) | (0.0495) | (0.0496) | (0.0518) |
| *log(Volatility)* | 0.4451*** | 0.3724*** | 0.4014*** | 0.2809*** | 0.4407*** | 0.3850*** | 0.3908*** | 0.3379*** | 0.2817*** | 0.3200*** | 0.4077*** | 0.3820*** |
| | (0.0216) | (0.0703) | (0.0668) | (0.0794) | (0.0208) | (0.0310) | (0.0441) | (0.0589) | (0.0184) | (0.0413) | (0.0651) | (0.0764) |
| *log(Volume)* | -0.2505*** | -0.3942** | -0.3056*** | -0.1891*** | -0.2555*** | -0.4078*** | -0.2198*** | -0.1157** | -0.1519*** | -0.1704 | -0.1276* | -0.0514 |
| | (0.0410) | (0.1614) | (0.0668) | (0.0505) | (0.0516) | (0.1517) | (0.0588) | (0.0503) | (0.0226) | (0.1134) | (0.0703) | (0.0529) |
| $Y_{Noti}$ | 0.6182*** | 1.0660*** | 1.2261*** | 1.3670*** | 0.7252*** | 0.9639*** | 0.9321*** | 0.8979*** | 0.7644*** | 0.9237*** | 0.8480*** | 0.8673*** |
| | (0.1034) | (0.0974) | (0.0614) | (0.1002) | (0.2156) | (0.2446) | (0.0743) | (0.0790) | (0.0709) | (0.1206) | (0.0530) | (0.0597) |
| Observations | 39,099 | 51,279 | 55,989 | 21,560 | 39,097 | 51,279 | 55,989 | 21,560 | 39,085 | 51,272 | 55,989 | 21,560 |
| R-squared | 0.155 | 0.344 | 0.718 | 0.773 | -1.130 | -0.366 | 0.551 | 0.545 | -0.1279 | 0.5338 | 0.7311 | 0.7874 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

| C. 2020 ex-COVID | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_{i,t}$ = log(Quoted spread) | | | | $Y_{i,t}$ = log(Effective half-spread) | | | | $Y_{i,t}$ = log(StD returns) | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *DARK* | -0.0684 | 1.4432 | 1.2133 | 0.3108 | 0.4928 | 1.1750 | 1.0036 | 0.8641 | 1.1732* | 0.0561 | 0.6617 | 0.7820 |
| | (0.8424) | (1.8734) | (1.1935) | (1.4808) | (0.3839) | (0.9121) | (0.7855) | (0.8444) | (0.6666) | (1.6028) | (0.8314) | (0.6012) |
| *COMP* | -0.7418 | -2.2938 | -2.2322** | -2.1241* | -1.7809*** | -1.9787** | -1.6860** | -1.6566* | -2.0358** | -0.6243 | -0.7735 | -0.9255* |
| | (1.0792) | (1.5188) | (0.9238) | (1.2014) | (0.6003) | (0.8945) | (0.6740) | (0.8430) | (0.9862) | (1.3249) | (0.6187) | (0.4774) |
| *log(Price)* | -0.0865 | 0.0986 | 0.1325 | 0.1817 | -0.1545** | -0.0664 | 0.0077 | -0.0213 | -0.1347* | -0.0041 | 0.0163 | 0.0023 |
| | (0.0812) | (0.0631) | (0.0973) | (0.1455) | (0.0703) | (0.0631) | (0.0561) | (0.0858) | (0.0750) | (0.0611) | (0.0568) | (0.0616) |
| *log(Volatility)* | 0.4026*** | 0.2963*** | 0.3195*** | 0.2433** | 0.4149*** | 0.3298*** | 0.3262*** | 0.2712*** | 0.2494*** | 0.2978*** | 0.3691*** | 0.3478*** |
| | (0.0156) | (0.0354) | (0.0597) | (0.0934) | (0.0148) | (0.0241) | (0.0335) | (0.0476) | (0.0169) | (0.0300) | (0.0384) | (0.0379) |
| *log(Volume)* | -0.2061*** | -0.3437*** | -0.3230*** | -0.2408*** | -0.1932*** | -0.2699*** | -0.2066*** | -0.1233** | -0.1333*** | -0.1332 | -0.1508** | -0.0878** |
| | (0.0204) | (0.1260) | (0.0797) | (0.0829) | (0.0121) | (0.0579) | (0.0513) | (0.0498) | (0.0183) | (0.1063) | (0.0568) | (0.0410) |
| $Y_{Noti}$ | 0.6342*** | 1.0665*** | 1.0947*** | 1.2599*** | 0.6095*** | 0.7889*** | 0.6590*** | 0.5019*** | 0.7518*** | 0.8728*** | 0.6516*** | 0.5781*** |
| | (0.0368) | (0.1053) | (0.1142) | (0.1586) | (0.0471) | (0.1062) | (0.0738) | (0.1216) | (0.0412) | (0.0834) | (0.0587) | (0.0558) |
| Observations | 32,184 | 42,251 | 46,254 | 17,823 | 32,183 | 42,251 | 46,254 | 17,823 | 32,174 | 42,247 | 46,254 | 17,823 |
| R-squared | 0.3614 | 0.1753 | 0.3327 | 0.4498 | 0.0804 | -0.0274 | 0.0622 | 0.0594 | -0.2639 | 0.2286 | 0.2529 | 0.2617 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in pare

*** p<0.01, ** p<0.05, * p<0.1

**Table A5.1. First Stage Regressions for *log(Quoted Spread)* IV/2SLS Regressions in Table 5**

The table reports the results of the first stage regressions of *DP* and *INT* on the instruments $DP_{Noti}$, $INT_{Noti}$, *and* $COMP_{Noti}$, control variables, and $log(Quoted\ Spread)_{Noti}$, for 2009, in Panel A and of *ATS* and *Non-ATS* on the instruments $ATS_{Noti}$, $Non\text{-}ATS_{Noti}$, *and* $COMP_{Noti}$, control variables, and $log(Quoted\ Spread)_{Noti}$ for 2020 (2020 ex-COVID) in Panel B (C). We estimate the following panel regression of market shares ($MS_{i,t}$) using OLS:

$$MS_{i,t} = \alpha_i\, d_q + \beta_1\, DP_{Noti,t} + \beta_2\, INT_{Noti,t} + \beta_3\, COMP_{Noti,t} + \beta_4 log(Quoted\ spread)_{Noti,t} + \boldsymbol{\gamma}\, X_{i,t} + e_{i,t}\ ,$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$ $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$,. We include market quality measures $Y_{Noti,t}$ as a control where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (SP500 and/or Nasdaq 100). For 2020, *DP = ATS* and *INT = Non-ATS*.

| | (1) | (2) | (3) | | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|---|
| | A. 2009 | | | | B. 2020 | | | C. 2020 ex-COVID | | |
| | *DP* | *INT* | *COMP* | | *ATS* | *Non-ATS* | *COMP* | *ATS* | *Non-ATS* | *COMP* |
| *log(Price)* | -0.0062*** | -0.0367*** | 0.0179*** | *log(Price)* | -0.0021 | -0.0021 | 0.0142*** | -0.0020 | 0.0021 | 0.0101* |
| | (0.0010) | (0.0024) | (0.0016) | | (0.0024) | (0.0132) | (0.0044) | (0.0021) | (0.0085) | (0.0052) |
| *log(Volatility)* | -0.0088*** | -0.0061*** | 0.0019*** | *log(Volatility)* | -0.0080*** | -0.0083* | 0.0054*** | 0.0148*** | 0.0201*** | -0.0049** |
| | (0.0003) | (0.0006) | (0.0005) | | (0.0012) | (0.0048) | (0.0018) | (0.0011) | (0.0021) | (0.0020) |
| *log(Volume)* | 0.0122*** | 0.0240*** | -0.0098*** | *log(Volume)* | 0.0145*** | 0.0205*** | -0.0046*** | -0.0072*** | -0.0010 | 0.0041* |
| | (0.0003) | (0.0010) | (0.0006) | | (0.0009) | (0.0021) | (0.0017) | (0.0015) | (0.0034) | (0.0021) |
| $DP_{Noti}$ | 0.8855*** | -0.0609** | 0.0448*** | $ATS_{Noti}$ | 0.9624*** | 0.3000* | 0.0096 | 0.8999*** | 0.3140** | 0.0242 |
| | (0.0128) | (0.0271) | (0.0149) | | (0.0461) | (0.1689) | (0.0255) | (0.0314) | (0.1554) | (0.0219) |
| $INT_{Noti}$ | 0.0108 | 0.9253*** | 0.0146 | $Non\text{-}ATS_{Noti}$ | 0.0028** | 0.0092 | -0.0011 | 0.0028 | 0.0262 | -0.0014 |
| | (0.0110) | (0.0283) | (0.0135) | | (0.0013) | (0.0136) | (0.0008) | (0.0018) | (0.0332) | (0.0012) |
| $COMP_{Noti}$ | -0.0041 | -0.0138 | 0.9428*** | $COMP_{Noti}$ | 0.0605** | 0.2691** | 0.9652*** | 0.0764*** | 0.2075* | 0.9669*** |
| | (0.0116) | (0.0290) | (0.0189) | | (0.0229) | (0.1018) | (0.0135) | (0.0170) | (0.1160) | (0.0151) |
| $log(Quoted\ spread)_{Noti}$ | 0.0017 | -0.0271*** | 0.0127*** | $log(Quoted\ spread)_{Noti}$ | 0.0017 | -0.0404** | 0.0029 | 0.0082*** | -0.0023 | -0.0009 |
| | (0.0015) | (0.0034) | (0.0025) | | (0.0021) | (0.0178) | (0.0020) | (0.0014) | (0.0206) | (0.0017) |
| *Constant* | -0.1241*** | -0.0756*** | 0.0418*** | *Constant* | -0.2115*** | 0.0020 | 0.0122 | -0.2407*** | -0.1629* | 0.0450 |
| | (0.0098) | (0.0218) | (0.0161) | | (0.0195) | (0.0936) | (0.0240) | (0.0185) | (0.0967) | (0.0278) |
| Observations | 696,653 | 696,653 | 696,653 | Observations | 146,667 | 146,667 | 146,667 | 120,948 | 120,948 | 120,948 |
| R-squared | 0.217 | 0.531 | 0.356 | R-squared | 0.614 | 0.704 | 0.738 | 0.6265 | 0.7141 | 0.7533 |
| Firm#Quarter FE | YES | YES | YES | Firm#Quarter FE | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A5.2. 2020 ATS and Lit Market Shares and Market Quality (Dropping Non-ATS)**

The table reports the results of analyzing the relationship between market shares and market quality. We estimate the following three-equation panel regression model for market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1) \quad ATS_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1 X_{i,t} + e_{1,i,t}$$

$$(2) \quad COMP_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2 X_{i,t} + e_{2,i,t}$$

$$(3) \quad Y_{i,t} = \alpha_i\, d_q + \beta_1\, ATS_{i,t} + \beta_2\, COMP_{i,t} + \boldsymbol{\gamma}\, X_{i,t} + e_{3,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$ , $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $ATS_{Noti,t}$ and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). The second stage regressions (3) use the fitted value from the first stage regressions (1)-(2) of the endogenous variables.

| | (1) | (2) | (3) |
|---|---|---|---|
| | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* |
| *ATS* | 2.7087** | 2.6868*** | 2.5467*** |
| | (1.1716) | (0.9525) | (0.8518) |
| *COMP* | -2.4332*** | -2.4066*** | -1.7956*** |
| | (0.6865) | (0.6590) | (0.4715) |
| *log(Price)* | 0.0216 | -0.1366*** | -0.1704*** |
| | (0.0474) | (0.0309) | (0.0342) |
| *log(Volatility)* | 0.4178*** | 0.4341*** | 0.3747*** |
| | (0.0287) | (0.0184) | (0.0192) |
| *log(Volume)* | -0.2825*** | -0.2413*** | -0.1734*** |
| | (0.0219) | (0.0188) | (0.0163) |
| $Y_{Noti}$ | 0.9110*** | 0.6312*** | 0.7879*** |
| | (0.0707) | (0.0294) | (0.0362) |
| Observations | 146,667 | 146,665 | 146,647 |
| R-squared | 0.5193 | 0.3005 | 0.4473 |
| Firm#Quarter FE | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A6.1. First Stage Regressions by Size for *log(Quoted Spread)* IV/2SLS Regressions in Table 6**

The table reports the results of the first stage regressions of *DP* and *INT* on the instruments $DP_{Noti}$, $INT_{Noti}$, *and* $COMP_{Noti}$, control variables, and *log(Quoted Spread)*$_{Noti}$, for 2009, in Panel A and of *ATS* and *Non-ATS* on the instruments $ATS_{Noti}$, $Non\text{-}ATS_{Noti}$, and $COMP_{Noti}$ , control variables, and *log(Quoted Spread)*$_{Noti}$ for 2020 in Panel B. We estimate the following panel regression of market shares ($MS_{i,t}$) using OLS:

$$MS_{i,t} = \alpha_i d_q + \beta_1 DP_{Noti,t} + \beta_2 INT_{Noti,t} + \beta_3 COMP_{Noti,t} + \beta_4 log(Quoted\ spread)_{Noti,t} + \gamma X_{i,t} + e_{i,t} ,$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$ $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$,. We include market quality measures $Y_{Noti,t}$ as a control where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (SP500 and/or Nasdaq 100). For 2020, *DP = ATS* and *INT = Non-ATS*.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **A. 2009** | *DP* | | | | *INT* | | | | *COMP* | | | |
| | *Small* | *Medium* | *Large* | *S&P 500* | *Small* | *Medium* | *Large* | *S&P 500* | *Small* | *Medium* | *Large* | *S&P 500* |
| *log(Price)* | -0.0045*** | -0.0074*** | -0.0066*** | -0.0038** | -0.0397*** | -0.0420*** | -0.0216*** | -0.0299*** | 0.0139*** | 0.0203*** | 0.0195*** | 0.0285*** |
| | (0.0016) | (0.0016) | (0.0014) | (0.0019) | (0.0041) | (0.0036) | (0.0033) | (0.0043) | (0.0027) | (0.0026) | (0.0030) | (0.0047) |
| *log(Volatility)* | -0.0096*** | -0.0107*** | -0.0071*** | -0.0071*** | -0.0049*** | -0.0073*** | -0.0106*** | -0.0100*** | 0.0029*** | 0.0015* | 0.0032*** | 0.0043*** |
| | (0.0005) | (0.0005) | (0.0004) | (0.0005) | (0.0012) | (0.0008) | (0.0007) | (0.0010) | (0.0010) | (0.0008) | (0.0006) | (0.0008) |
| *log(Volume)* | 0.0087*** | 0.0162*** | 0.0148*** | 0.0137*** | 0.0131*** | 0.0356*** | 0.0341*** | 0.0316*** | -0.0043*** | -0.0158*** | -0.0143*** | -0.0151*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0007) | (0.0015) | (0.0012) | (0.0011) | (0.0017) | (0.0009) | (0.0008) | (0.0007) | (0.0010) |
| $DP_{Noti}$ | 0.8914*** | 0.9241*** | 0.7802*** | 0.6264*** | -0.0482 | -0.1144*** | -0.1207* | -0.1821* | 0.0445* | 0.0624*** | 0.1103*** | 0.1737** |
| | (0.0246) | (0.0166) | (0.0259) | (0.0435) | (0.0372) | (0.0410) | (0.0669) | (0.0957) | (0.0244) | (0.0216) | (0.0346) | (0.0692) |
| $INT_{Noti}$ | 0.0072 | 0.0235* | 0.0123 | 0.001 | 0.8678*** | 1.0136*** | 0.9267*** | 0.8987*** | 0.0424*** | -0.0283* | 0.031 | 0.0721 |
| | (0.0115) | (0.0125) | (0.0194) | (0.0331) | (0.0341) | (0.0313) | (0.0471) | (0.0715) | (0.0136) | (0.0162) | (0.0324) | (0.0677) |
| $COMP_{Noti}$ | 0.0047 | -0.0143 | -0.0024 | 0.0276 | 0.0562* | -0.0694 | -0.026 | 0.0619 | 0.8966*** | 0.9780*** | 0.9693*** | 0.9858*** |
| | (0.0130) | (0.0147) | (0.0241) | (0.0386) | (0.0292) | (0.0420) | (0.0533) | (0.0796) | (0.0247) | (0.0243) | (0.0426) | (0.0897) |
| *log(Quoted spread)*$_{Noti}$ | 0.0067*** | -0.0003 | -0.0074*** | -0.0043 | -0.0182*** | -0.0318*** | -0.0381*** | -0.0522*** | 0.001 | 0.0148*** | 0.0279*** | 0.0454*** |
| | (0.0021) | (0.0021) | (0.0025) | (0.0040) | (0.0048) | (0.0053) | (0.0054) | (0.0079) | (0.0035) | (0.0036) | (0.0048) | (0.0096) |
| *Constant* | -0.0970*** | -0.1572*** | -0.1524*** | -0.1639*** | 0.0609* | -0.1846*** | -0.2795*** | -0.2258*** | 0.0163 | 0.0971*** | 0.0764** | 0.0231 |
| | (0.0142) | (0.0129) | (0.0163) | (0.0257) | (0.0313) | (0.0308) | (0.0390) | (0.0606) | (0.0222) | (0.0201) | (0.0318) | (0.0620) |
| Observations | 201,002 | 245,250 | 250,401 | 107,265 | 201,002 | 245,250 | 250,401 | 107,265 | 201,002 | 245,250 | 250,401 | 107,265 |
| R-squared | 0.183 | 0.209 | 0.276 | 0.319 | 0.413 | 0.426 | 0.507 | 0.624 | 0.204 | 0.295 | 0.434 | 0.458 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table A6.1. Continued.**

| B. 2020 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *ATS* | | | | *Non-ATS* | | | | *COMP* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Price)* | -0.0024 | 0.0000 | -0.0014 | -0.0014 | -0.0247** | 0.0105 | 0.0205 | 0.0057 | 0.0194* | 0.0070** | 0.0071 | 0.0130 |
| | (0.0041) | (0.0043) | (0.0040) | (0.0060) | (0.0122) | (0.0142) | (0.0144) | (0.0185) | (0.0100) | (0.0034) | (0.0058) | (0.0096) |
| *log(Volatility)* | -0.0102*** | -0.0145*** | -0.0075*** | -0.0088*** | 0.0102** | -0.0101* | -0.0273*** | -0.0331*** | 0.0031 | 0.0014 | 0.0184*** | 0.0240*** |
| | (0.0015) | (0.0024) | (0.0024) | (0.0031) | (0.0039) | (0.0051) | (0.0060) | (0.0079) | (0.0028) | (0.0020) | (0.0030) | (0.0040) |
| *log(Volume)* | 0.0081*** | 0.0212*** | 0.0258*** | 0.0273*** | 0.0175*** | 0.0307*** | 0.0170*** | 0.0070 | 0.0021 | -0.0154*** | -0.0145*** | -0.0084* |
| | (0.0010) | (0.0018) | (0.0018) | (0.0027) | (0.0025) | (0.0031) | (0.0039) | (0.0051) | (0.0024) | (0.0018) | (0.0029) | (0.0043) |
| $ATS_{Noti}$ | 0.5015*** | 1.1284*** | 1.1197*** | 0.9241*** | 0.3980* | 0.3178 | 0.1930 | 0.3904 | 0.0986 | 0.0972 | -0.1064 | -0.1859 |
| | (0.0852) | (0.0826) | (0.0945) | (0.1368) | (0.2096) | (0.2082) | (0.1949) | (0.2481) | (0.1681) | (0.0634) | (0.1373) | (0.2130) |
| $Non\text{-}ATS_{Noti}$ | 0.0018 | 0.0020 | 0.0047* | 0.0095*** | 0.0130 | 0.0016 | 0.0094 | 0.0107 | 0.0051 | 0.0103*** | -0.0150*** | -0.0209*** |
| | (0.0032) | (0.0020) | (0.0024) | (0.0031) | (0.0175) | (0.0150) | (0.0098) | (0.0090) | (0.0048) | (0.0023) | (0.0040) | (0.0065) |
| $COMP_{Noti}$ | -0.0322 | 0.0789 | 0.1400*** | 0.1941*** | 0.5394*** | 0.2679** | 0.1019 | 0.0188 | 0.6732*** | 1.0614*** | 1.0282*** | 0.9626*** |
| | (0.0407) | (0.0527) | (0.0436) | (0.0677) | (0.1236) | (0.1147) | (0.1573) | (0.1948) | (0.0842) | (0.0374) | (0.0572) | (0.0908) |
| $log(Quoted\ spread)_{Noti}$ | -0.0017 | 0.0020 | 0.0041 | 0.0035 | -0.0608*** | -0.0301 | -0.0167 | -0.0108 | -0.0025 | 0.0051 | -0.0004 | -0.0081 |
| | (0.0029) | (0.0053) | (0.0041) | (0.0057) | (0.0147) | (0.0191) | (0.0183) | (0.0238) | (0.0046) | (0.0032) | (0.0061) | (0.0081) |
| *Constant* | -0.0408* | -0.3241*** | -0.4394*** | -0.4806*** | 0.1880** | -0.2542** | -0.1253 | 0.0754 | -0.0296 | 0.1402*** | 0.2290*** | 0.2015* |
| | (0.0217) | (0.0400) | (0.0457) | (0.0696) | (0.0839) | (0.1011) | (0.1093) | (0.1402) | (0.0316) | (0.0328) | (0.0674) | (0.1127) |
| Observations | 39,099 | 51,279 | 55,989 | 21,560 | 39,099 | 51,279 | 55,989 | 21,560 | 39,099 | 51,279 | 55,989 | 21,560 |
| R-squared | 0.482 | 0.523 | 0.601 | 0.638 | 0.630 | 0.580 | 0.609 | 0.669 | 0.501 | 0.704 | 0.830 | 0.844 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

| C. 2020 ex-COVID | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *ATS* | | | | *Non-ATS* | | | | *COMP* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *log(Price)* | -0.0010 | 0.0002 | 0.0010 | -0.0010 | -0.0249** | 0.0059 | 0.0392*** | 0.0463** | 0.0110 | 0.0110*** | -0.0025 | -0.0158 |
| | (0.0054) | (0.0031) | (0.0038) | (0.0066) | (0.0104) | (0.0089) | (0.0127) | (0.0172) | (0.0121) | (0.0040) | (0.0051) | (0.0109) |
| *log(Volatility)* | 0.0079*** | 0.0220*** | 0.0270*** | 0.0315*** | 0.0164*** | 0.0305*** | 0.0217*** | 0.0082 | 0.0028 | -0.0174*** | -0.0188*** | -0.0146*** |
| | (0.0012) | (0.0018) | (0.0019) | (0.0026) | (0.0025) | (0.0030) | (0.0037) | (0.0052) | (0.0025) | (0.0022) | (0.0031) | (0.0043) |
| *log(Volume)* | -0.0094*** | -0.0140*** | -0.0026 | -0.0027 | 0.0161*** | 0.0009 | -0.0309*** | -0.0408*** | 0.0060* | 0.0022 | 0.0125*** | 0.0188*** |
| | (0.0017) | (0.0024) | (0.0027) | (0.0036) | (0.0035) | (0.0044) | (0.0057) | (0.0068) | (0.0030) | (0.0026) | (0.0038) | (0.0053) |
| $ATS_{Noti}$ | 0.4140*** | 1.0406*** | 1.0396*** | 0.8219*** | 0.4211** | 0.3970** | 0.1113 | 0.4213 | 0.0483 | 0.1145 | 0.0573 | 0.0640 |
| | (0.0870) | (0.0785) | (0.0814) | (0.1207) | (0.1915) | (0.1775) | (0.2235) | (0.2758) | (0.1576) | (0.0794) | (0.1270) | (0.2063) |
| $Non\text{-}ATS_{Noti}$ | 0.0002 | -0.0008 | 0.0076* | 0.0128** | 0.0395 | 0.0119 | 0.0261 | 0.0274 | 0.0028 | 0.0061 | -0.0111** | -0.0176* |
| | (0.0046) | (0.0045) | (0.0045) | (0.0050) | (0.0353) | (0.0315) | (0.0289) | (0.0265) | (0.0071) | (0.0069) | (0.0049) | (0.0091) |
| $COMP_{Noti}$ | -0.0019 | 0.1123** | 0.1433*** | 0.1838*** | 0.4998*** | 0.1601 | 0.1170 | 0.0147 | 0.6592*** | 1.0597*** | 0.9990*** | 0.8997*** |
| | (0.0408) | (0.0419) | (0.0393) | (0.0604) | (0.1138) | (0.1132) | (0.1715) | (0.1937) | (0.0816) | (0.0464) | (0.0591) | (0.0954) |
| $log(Quoted\ spread)_{Noti}$ | -0.0003 | 0.0159*** | 0.0136** | 0.0156** | -0.0213 | 0.0160 | 0.0026 | -0.0050 | 0.0027 | 0.0010 | -0.0159*** | -0.0184* |
| | (0.0051) | (0.0043) | (0.0051) | (0.0074) | (0.0175) | (0.0185) | (0.0231) | (0.0322) | (0.0049) | (0.0050) | (0.0054) | (0.0098) |
| *Constant* | -0.0465* | -0.3955*** | -0.5053*** | -0.5929*** | 0.0282 | -0.4254*** | -0.3525*** | -0.1469 | -0.0369 | 0.1717*** | 0.3953*** | 0.4655*** |
| | (0.0273) | (0.0340) | (0.0480) | (0.0721) | (0.0862) | (0.0998) | (0.1072) | (0.1568) | (0.0302) | (0.0414) | (0.0629) | (0.1058) |
| Observations | 32,184 | 42,251 | 46,254 | 17,823 | 32,184 | 42,251 | 46,254 | 17,823 | 32,184 | 42,251 | 46,254 | 17,823 |
| R-squared | 0.4988 | 0.5439 | 0.6190 | 0.6618 | 0.6481 | 0.5941 | 0.6237 | 0.6839 | 0.5211 | 0.7273 | 0.8466 | 0.8596 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A6.2. 2020 ATS and Lit Market Shares and Market Quality by Size (Dropping Non-ATS)**

The table reports the results of analyzing the relationship between market shares and market quality for subsamples by market capitalization. We estimate the following three-equation panel regression model for market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1) \quad ATS_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1 X_{i,t} + e_{1,i,t}$$

$$(2) \quad COMP_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2 X_{i,t} + e_{2,i,t}$$

$$(3) \quad Y_{i,t} = \alpha_i\, d_q + \beta_1 ATS_{i,t} + \beta_2 COMP_{i,t} + \boldsymbol{\gamma}\, X_{i,t} + e_{3,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$, $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $ATS_{Noti,t}$ and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). The second stage regressions (3) use the fitted value from the first stage regressions (1)-(2) of the endogenous variables.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_{i,t}$ = *log(Quoted spread)* | | | | $Y_{i,t}$ = *log(Effective half-spread)* | | | | $Y_{i,t}$ = *log(StD returns)* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *ATS* | 0.7659 | 2.6294* | 3.2954*** | 2.9912* | 2.4590* | 2.6676** | 2.5073*** | 2.9433* | 2.1183 | 2.7761*** | 2.2339*** | 1.8564* |
| | (1.1671) | (1.4095) | (1.1291) | (1.6237) | (1.3822) | (1.2074) | (0.8684) | (1.5101) | (1.5688) | (0.9741) | (0.8130) | (1.0660) |
| *COMP* | -0.7902* | -2.4101*** | -3.5809*** | -4.0751*** | -1.6517*** | -2.3936*** | -2.7064*** | -3.3295*** | -0.8071* | -1.9704*** | -2.0071*** | -2.0476*** |
| | (0.4205) | (0.8524) | (0.8427) | (1.0902) | (0.5468) | (0.8802) | (0.6527) | (0.9945) | (0.4595) | (0.5610) | (0.5757) | (0.7021) |
| *log(Price)* | -0.0939 | 0.0279 | 0.0690 | 0.1446** | -0.2013*** | -0.1399*** | -0.0058 | -0.0103 | -0.2439*** | -0.1164** | -0.1289*** | -0.1298*** |
| | (0.0624) | (0.0691) | (0.0481) | (0.0668) | (0.0683) | (0.0454) | (0.0358) | (0.0567) | (0.0822) | (0.0466) | (0.0351) | (0.0353) |
| *log(Volatility)* | 0.4446*** | 0.3558*** | 0.4168*** | 0.3962*** | 0.4689*** | 0.3880*** | 0.3977*** | 0.4121*** | 0.2994*** | 0.3512*** | 0.4645*** | 0.4821*** |
| | (0.0233) | (0.0351) | (0.0337) | (0.0525) | (0.0224) | (0.0258) | (0.0276) | (0.0505) | (0.0248) | (0.0230) | (0.0236) | (0.0327) |
| *log(Volume)* | -0.2243*** | -0.3304*** | -0.3680*** | -0.3185*** | -0.2109*** | -0.2793*** | -0.2549*** | -0.2123*** | -0.1320*** | -0.2112*** | -0.2149*** | -0.1482*** |
| | (0.0143) | (0.0462) | (0.0421) | (0.0599) | (0.0163) | (0.0406) | (0.0330) | (0.0506) | (0.0183) | (0.0292) | (0.0292) | (0.0380) |
| $Y_{Noti}$ | 0.5384*** | 0.9997*** | 1.2006*** | 1.3343*** | 0.4591*** | 0.6751*** | 0.8858*** | 0.8534*** | 0.6328*** | 0.8921*** | 0.8183*** | 0.8153*** |
| | (0.0376) | (0.0847) | (0.0586) | (0.0867) | (0.0358) | (0.0448) | (0.0515) | (0.0876) | (0.0413) | (0.0490) | (0.0480) | (0.0611) |
| Observations | 39,099 | 51,279 | 55,989 | 21,560 | 39,097 | 51,279 | 55,989 | 21,560 | 39,085 | 51,272 | 55,989 | 21,560 |
| R-squared | 0.5464 | 0.5192 | 0.6328 | 0.6951 | 0.2399 | 0.2533 | 0.4528 | 0.4246 | 0.2726 | 0.4143 | 0.6770 | 0.7761 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table A6.3. 2020 Surviving Dark Pools, Internalization, Lit Market Shares and Market Quality**

The table reports the results of analyzing the relationship between market shares and market quality for All stocks (Panel B) and subsamples by market capitalization (Panel C). We estimate the following four-equation panel regression model for market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1) \quad ATS\_survivors_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1 X_{i,t} + e_{1,i,t}$$

$$(2) \quad (Non\text{-}ATS{+}ATS\_new)_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2 X_{i,t} + e_{2,i,t}$$

$$(3) \quad COMP_{i,t} = a_i\, d_q + b_3\, W_{i,t} + c_3 X_{i,t} + e_{3,i,t}$$

$$(4) \quad Y_{i,t} = \alpha_i\, d_q + \beta_1 ATS\_survivors_{\,i,t} + \beta_2 (Non\text{-}ATS{+}ATS\_new)_{i,t} + \beta_3\, COMP_{i,t} + \boldsymbol{\gamma}\, X_{i,t} + e_{4,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$, $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $ATS\_survivors_{Noti,t}$, $(Non\text{-}ATS{+}ATS\_new)_{Noti,t}$, and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). The second stage regressions (4) use the fitted value from the first stage regressions (1)-(3) of the endogenous variables.

| **A. Survivors** | *Market Share of Market-wide volume* | **B. All Stocks** | (1) $Y_{i,t}$ = *log(Quoted spread)* | (2) $Y_{i,t}$ = *log(Effective half-spread)* | (3) $Y_{i,t}$ = *log(StD returns)* |
|---|---|---|---|---|---|
| BIDS BIDS ATS | 0.0076 | *ATS_survivors* | 2.1264 | 1.5247 | 3.6672** |
| BLKX INSTINET BLOCKCROSS | 0.0020 | | (1.5234) | (2.5031) | (1.6311) |
| CBLC CITIBLOC | 0.0003 | *Non-ATS+ATS_new* | 1.0863 | 2.2424 | -1.4086 |
| CROS CROSSFINDER | 0.0120 | | (3.2444) | (3.5188) | (1.7679) |
| EBXL LEVEL ATS | 0.0076 | *COMP* | -2.5142* | -2.8096*** | -1.1396 |
| ITGP POSIT | 0.0027 | | (1.3856) | (0.9804) | (0.7782) |
| KCGM VIRTU MATCHIT ATS | 0.0024 | *log(Price)* | 0.0271 | -0.0777 | -0.1916*** |
| LATS THE BARCLAYS ATS | 0.0055 | | (0.0396) | (0.0956) | (0.0587) |
| LQNA LIQUIDNET H2O ATS | 0.0021 | *log(Volatility)* | 0.4201*** | 0.4214*** | 0.3674*** |
| LQNT LIQUIDNET NEGOTIATION ATS | 0.0011 | | (0.0445) | (0.0267) | (0.0224) |
| MSPL MS POOL (ATS-4) | 0.0080 | *log(Volume)* | -0.2937*** | -0.2742*** | -0.1445*** |
| MSRP MS RPOOL (ATS-6) | 0.0027 | | (0.0725) | (0.0597) | (0.0340) |
| MSTX MS TRAJECTORY CROSS (ATS-1) | 0.0044 | $Y_{Noti}$ | 0.9522*** | 0.8335** | 0.6585*** |
| SGMT SIGMA X2 | 0.0119 | | (0.1592) | (0.3596) | (0.1541) |
| UBSA UBS ATS | 0.0259 | | | | |
| XIST INSTINET CROSSING | 0.0001 | | | | |
| | | | | | |
| Survivors Total | 0.0962 | Observations | 146,667 | 146,665 | 146,647 |
| ATS Total | 0.1278 | R-squared | 0.5011 | 0.1168 | 0.3420 |
| Survivors/ATS Total | 0.7532 | Firm#Quarter FE | YES | YES | YES |

**Table A6.3. Continued.**

| C. By Size | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Yi,t = log(Quoted spread)* | | | | $Y_{i,t}$ *= log(Effective half-spread)* | | | | $Y_{i,t}$ *= log(StD returns)* | | | |
| | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 | Small | Medium | Large | S&P 500 |
| *ATS_survivors* | -0.0337 | 2.0357 | 4.7978 | 11.0924 | 0.0756 | -0.5018 | 3.3508 | 8.4707 | 1.4436 | 3.9293* | 4.6118* | 7.3996 |
| | (2.1851) | (1.9783) | (3.0896) | (19.2142) | (6.3605) | (7.8742) | (2.8181) | (11.9710) | (3.2836) | (2.2359) | (2.4336) | (6.5978) |
| *Non-ATS+ATS_new* | 1.9229 | 2.5671 | -4.9829 | -15.8665 | 3.4806 | 6.9682 | -1.7412 | -7.9417 | 1.5691 | -2.1015 | -4.5506 | -7.0986 |
| | (3.2878) | (12.7190) | (7.5012) | (29.5143) | (5.0135) | (15.0948) | (4.9492) | (13.0760) | (1.5938) | (3.9684) | (4.0549) | (6.6035) |
| *COMP* | -2.5788 | -3.0929 | -2.3673 | -2.4355 | -4.5183 | -3.9540 | -2.2782*** | -2.9651 | -2.3829 | -1.0501 | -1.1717 | -1.5726 |
| | (3.3400) | (5.3314) | (1.6223) | (3.4889) | (4.0621) | (3.8077) | (0.8335) | (2.3338) | (1.5130) | (1.5676) | (1.0720) | (1.6183) |
| *log(Price)* | -0.0177 | 0.0038 | 0.2103 | 0.2842 | 0.0043 | -0.0105 | -0.0011 | -0.1325 | -0.1587* | -0.1173 | -0.0698 | -0.1962 |
| | (0.1369) | (0.1641) | (0.2200) | (0.4264) | (0.2863) | (0.2925) | (0.0529) | (0.2336) | (0.0854) | (0.0777) | (0.1119) | (0.1732) |
| *log(Volatility)* | 0.4262*** | 0.3746** | 0.2459 | -0.1950 | 0.3975*** | 0.3246** | 0.3639*** | 0.2473 | 0.2763*** | 0.3479*** | 0.3502*** | 0.3011* |
| | (0.0352) | (0.1490) | (0.2403) | (1.0174) | (0.1230) | (0.1493) | (0.0840) | (0.2352) | (0.0451) | (0.0323) | (0.1040) | (0.1628) |
| *log(Volume)* | -0.2505*** | -0.4086 | -0.2538* | -0.2482 | -0.2490*** | -0.4795 | -0.2137*** | -0.2068* | -0.1494*** | -0.1365 | -0.1448* | -0.1765* |
| | (0.0524) | (0.4916) | (0.1455) | (0.1537) | (0.0518) | (0.4497) | (0.0738) | (0.1140) | (0.0186) | (0.1348) | (0.0727) | (0.1017) |
| $Y_{Noti}$ | 0.6548*** | 1.0839** | 1.0710*** | 1.0260 | 0.8184 | 1.3569 | 0.7314** | 0.2776 | 0.7651*** | 0.7202** | 0.5664** | 0.4113 |
| | (0.1967) | (0.4645) | (0.2274) | (0.7766) | (0.5298) | (1.5508) | (0.3565) | (0.9579) | (0.1333) | (0.2965) | (0.2401) | (0.4459) |
| Observations | 39,099 | 51,279 | 55,989 | 21,560 | 39,097 | 51,279 | 55,989 | 21,560 | 39,085 | 51,272 | 55,989 | 21,560 |
| R-squared | -0.1078 | 0.2436 | 0.1277 | -3.1666 | -1.5622 | -2.3955 | 0.3287 | -1.1143 | -0.1010 | 0.1580 | 0.0357 | -0.4220 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A7. Market Shares and Market Stress (Full Table, Excerpt in Table 7)**

The table reports the results of regressions of *DP* and *INT* on indicators of market stress for 2009 in Panel A, and of *ATS* and *Non-ATS* on indicators of market stress for 2020 in Panel B. We estimate the following panel regression of market shares ($MS_{i,t}$) using OLS:

$$MS_{i,t} = \alpha_i\, d_q + \beta\, I^{Stress} + \gamma\, log(Volume)_{i,t} + e_{i,t},$$

where $I^{Stress}$ is a stock-specific indicator for the first two quarters (*H1*), the lowest tercile of individual stock returns *(ret_low)*, and the lowest tercile of stock-specific buy-order imbalances (*bs_low*). For 2009 (2020), we sample the highest decile (tercile) of individual stock volatility, *vol_extreme (vol_high)*.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **A. 2009** | | *I = H1* | | | *I = ret_low* | | | *I = bs_low* | | | *I = vol_extr* | |
| | *DP* | *INT* | *COMP* | *DP* | *INT* | *COMP* | *DP* | *INT* | *COMP* | *DP* | *INT* | *COMP* |
| *I* | -0.0124*** | -0.0283*** | 0.0017 | -0.0037*** | -0.0059*** | 0.0006 | -0.0010*** | 0.0042*** | -0.0019*** | -0.0116*** | -0.0155*** | -0.0022** |
| | (0.0011) | (0.0019) | (0.0013) | (0.0007) | (0.0013) | (0.0007) | (0.0003) | (0.0007) | (0.0004) | (0.0006) | (0.0013) | (0.0009) |
| *log(Volume)* | 0.0078*** | 0.0180*** | -0.0034*** | 0.0068*** | 0.0157*** | -0.0032*** | 0.0066*** | 0.0155*** | -0.0032*** | 0.0078*** | 0.0170*** | -0.0030*** |
| | (0.0004) | (0.0011) | (0.0007) | (0.0004) | (0.0012) | (0.0007) | (0.0004) | (0.0012) | (0.0007) | (0.0004) | (0.0012) | (0.0007) |
| *Constant* | -0.0295*** | 0.0414*** | 0.3254*** | -0.0219*** | 0.0590*** | 0.3244*** | -0.0211*** | 0.0575*** | 0.3252*** | -0.0345*** | 0.0421*** | 0.3219*** |
| | (0.0046) | (0.0139) | (0.0094) | (0.0051) | (0.0152) | (0.0093) | (0.0052) | (0.0152) | (0.0093) | (0.0051) | (0.0152) | (0.0095) |
| Observations | 696,686 | 696,686 | 696,686 | 696,686 | 696,686 | 696,686 | 696,686 | 696,686 | 696,686 | 696,686 | 696,686 | 696,686 |
| R-squared | 0.134 | 0.475 | 0.272 | 0.123 | 0.465 | 0.272 | 0.122 | 0.465 | 0.272 | 0.126 | 0.466 | 0.272 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **B. 2020** | | *I = H1* | | | *I = ret_low* | | | *I = bs_low* | | | *I = vol_high* | |
| | *ATS* | *Non-ATS* | *COMP* | *ATS* | *Non-ATS* | *COMP* | *ATS* | *Non-ATS* | *COMP* | *ATS* | *Non-ATS* | *COMP* |
| *I* | 0.0029 | -0.0136*** | 0.0168*** | -0.0029** | -0.0072*** | -0.0006 | -0.0044*** | -0.0036*** | 0.0111*** | 0.0047** | -0.0104** | 0.0065* |
| | (0.0038) | (0.0048) | (0.0054) | (0.0013) | (0.0017) | (0.0018) | (0.0012) | (0.0011) | (0.0019) | (0.0020) | (0.0047) | (0.0034) |
| *log(Volume)* | 0.0060*** | 0.0144*** | -0.0019 | 0.0063*** | 0.0142*** | -0.0011 | 0.0065*** | 0.0141*** | -0.0022 | 0.0060*** | 0.0141*** | -0.0014 |
| | (0.0016) | (0.0030) | (0.0027) | (0.0016) | (0.0031) | (0.0028) | (0.0017) | (0.0032) | (0.0029) | (0.0016) | (0.0029) | (0.0028) |
| *Constant* | 0.0501** | 0.0326 | 0.3473*** | 0.0482** | 0.0311 | 0.3446*** | 0.0454* | 0.0311 | 0.3555*** | 0.0504** | 0.0328 | 0.3460*** |
| | (0.0229) | (0.0422) | (0.0380) | (0.0229) | (0.0433) | (0.0400) | (0.0240) | (0.0449) | (0.0415) | (0.0228) | (0.0417) | (0.0399) |
| Observations | 146,702 | 146,702 | 146,702 | 146,702 | 146,702 | 146,702 | 146,702 | 146,702 | 146,702 | 146,702 | 146,702 | 146,702 |
| R-squared | 0.491 | 0.635 | 0.625 | 0.491 | 0.634 | 0.617 | 0.492 | 0.633 | 0.620 | 0.4920 | 0.6343 | 0.6178 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A8.1. Lit and Non-Linear Dark Market Shares and Market Quality**

The table reports the results of analyzing the relationship between market shares and market quality. We estimate the following four-equation panel regression model market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1) \quad TRF_{i,t} = a_i\, d_q + b_1\, W_{i,t} + c_1\, X_{i,t} + e_{1,i,t}$$

$$(2) \quad TRF^2_{i,t} = a_i\, d_q + b_2\, W_{i,t} + c_2\, X_{i,t} + e_{2,i,t}$$

$$(3) \quad COMP_{i,t} = a_i\, d_q + b_3\, W_{i,t} + c_3\, X_{i,t} + e_{3,i,t}$$

$$(4) \quad Y_{i,t} = \alpha_i\, d_q + \beta_1\, TRF_{i,t} + \beta_2\, TRF^2_{i,t} + \beta_3\, COMP_{i,t} + \gamma\, X_{i,t} + e_{4,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, $log(Volume)_{i,t}$, and $Y_{Noti,t}$. $W_{i,t}$ is a vector that includes: $TRF_{Noti,t}$, $TRF^2_{Noti,t}$, and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). For 2020, *TRF = FINRA*. The second stage IV/2SLS regressions in equation (4) uses the fitted value from the first stage regressions (1)-(3).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | A. 2009 | | | B. 2020 | | | C. 2020 ex-COVID | | |
| | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* |
| *TRF/FINRA* | -1.8217*** | -0.9036 | -1.4481** | -36.6539 | -142.9499 | 30.4343 | -244.1437 | 61.0849 | 19.1716 |
| | (0.5435) | (0.6301) | (0.7309) | (144.5626) | (1,243.7316) | (55.9501) | (1,939.7762) | (242.4674) | (20.5844) |
| *$TRF^2$/$FINRA^2$* | 1.5369* | 0.4729 | 2.2778** | 50.8004 | 191.0820 | -38.7343 | 324.7554 | -79.2867 | -23.2540 |
| | (0.7833) | (0.9430) | (1.0068) | (189.5086) | (1,645.6841) | (73.8928) | (2,552.1460) | (324.1019) | (26.8728) |
| *COMP* | -0.2284 | -0.5998*** | 0.2192 | -5.4262 | -12.4159 | 0.6201 | -20.1950 | 2.2906 | -0.2138 |
| | (0.1625) | (0.2190) | (0.1804) | (9.7603) | (84.4034) | (4.0034) | (139.6881) | (18.3550) | (1.2957) |
| *log(Price)* | -0.3871*** | -0.4720*** | -0.0293** | 0.1038 | 0.2827 | -0.2659 | 0.1605 | -0.1837 | -0.1299* |
| | (0.0123) | (0.0144) | (0.0120) | (0.2952) | (3.2540) | (0.1996) | (1.0945) | (0.4231) | (0.0755) |
| *log(Volatility)* | 0.2011*** | 0.1950*** | 0.5243*** | 0.5339 | 0.7929 | 0.3092** | 1.2897 | 0.1462 | 0.2561*** |
| | (0.0056) | (0.0062) | (0.0051) | (0.3687) | (3.1901) | (0.1232) | (7.3286) | (0.9236) | (0.0692) |
| *log(Volume)* | -0.1139*** | 0.0117* | 0.0884*** | -0.4735 | -0.8927 | -0.0519 | -1.4071 | 0.0491 | -0.1091 |
| | (0.0063) | (0.0068) | (0.0051) | (0.5832) | (5.4718) | (0.2351) | (8.4976) | (1.2313) | (0.0806) |
| $Y_{Noti}$ | 0.4754*** | 0.3488*** | 0.4589*** | 1.1165** | 1.4613 | 0.6527* | 1.7159 | 0.3198 | 0.5373*** |
| | (0.0236) | (0.0289) | (0.0190) | (0.4899) | (6.0317) | (0.3685) | (6.5142) | (1.5308) | (0.1772) |
| Observations | 696,594 | 695,821 | 696,653 | 146,667 | 146,665 | 146,647 | 120,948 | 120,947 | 120,934 |
| R-squared | 0.2004 | 0.0683 | 0.4188 | -6.2261 | -99.2205 | -2.6321 | -465.8843 | -28.1016 | -1.8280 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

**Table A8.2. Non-Linear Dark Pool/ATS, Internalization/Non-ATS, and Lit Market Shares and Market Quality**

The table reports the results of analyzing the relationship between market shares and market quality. We estimate the following six-equation panel regression model for market quality measures ($Y_{i,t}$) using IV/2SLS:

$$(1)\quad DP_{i,t} = a_i\, d_q + b_1 W_{i,t} + c_1 X_{i,t} + e_{1,i,t}$$

$$(2)\quad DP^2_{i,t} = a_i\, d_q + b_2 W_{i,t} + c_2 X_{i,t} + e_{2,i,t}$$

$$(3)\quad INT_{i,t} = a_i\, d_q + b_3 W_{i,t} + c_3 X_{i,t} + e_{3,i,t}$$

$$(4)\quad INT^2_{i,t} = a_i\, d_q + b_4 W_{i,t} + c_4 X_{i,t} + e_{4,i,t}$$

$$(5)\quad COMP_{i,t} = a_i\, d_q + b_5 W_{i,t} + c_5 X_{i,t} + e_{5,i,t}$$

$$(6)\quad Y_{i,t} = \alpha_i\, d_q + \beta_1 DP_{i,t} + \beta_2 DP^2_{i,t} + \beta_3 INT_{i,t} + \beta_4 INT^2_{i,t} + \beta_5 COMP_{i,t} + \gamma X_{i,t} + e_{6,i,t}$$

where $X_{i,t}$ is a vector of control variables that includes: $Y_{Noti,t}$, $log(Price)_{i,t}$, $log(Volatility)_{i,t}$, and $log(Volume)_{i,t}$. $W_{i,t}$ is a vector that includes: $DP_{Noti,t}$, $DP^2_{Noti}$, $INT_{Noti,t}$, $INT^2_{Noti}$, and $COMP_{Noti,t}$ where *Noti,t* stands for the day *t* average across stocks in the same size group, but that are Not in same four digit SIC code, and Not in same index (S&P 500 and/or Nasdaq 100). For 2020, *DP* = *ATS* and *INT* = *Non-ATS*. The second stage regressions (6) use the fitted value from the first stage regressions (1)-(5).

**Table A8.2. Continued.**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | | A. 2009 | | | B. 2020 | | | C. 2020 ex-COVID | |
| | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* | $Y_{i,t}$ = *log(Quoted spread)* | $Y_{i,t}$ = *log(Effective half-spread)* | $Y_{i,t}$ = *log(StD returns)* |
| *DP/ATS* | -3.2388 | 1.1823 | -2.4671 | -6.6900 | 1.2985 | -16.7102 | -46.9958 | -25.0811 | -16.9267 |
| | (1.9873) | (2.1959) | (2.0940) | (17.2525) | (12.9121) | (15.7797) | (50.9051) | (16.1607) | (19.3895) |
| $DP^2/ATS^2$ | 10.0140 | -10.8440 | 12.2621 | 25.5031 | -0.5991 | 58.4871 | 143.8807 | 80.8903* | 55.4317 |
| | (9.1180) | (10.4446) | (10.1274) | (55.5725) | (42.5694) | (50.9582) | (150.8151) | (47.2805) | (56.4383) |
| *INT/Non-ATS* | -1.3755*** | -1.2884* | -0.5899 | -0.0467 | -17.7837 | 17.4310 | 71.6859 | 29.7396 | 37.2262 |
| | (0.4761) | (0.7302) | (0.6599) | (23.4561) | (21.4436) | (23.7420) | (79.1201) | (25.9299) | (29.5750) |
| $INT^2/Non\text{-}ATS^2$ | 1.3711* | 1.5703 | 1.2376 | 4.2123 | 36.0299 | -31.4379 | -123.8012 | -50.5074 | -64.5934 |
| | (0.7653) | (1.1556) | (0.9862) | (44.6266) | (39.1833) | (44.9148) | (142.5169) | (46.4878) | (52.6686) |
| *COMP* | -0.1461 | -0.6177*** | 0.2424 | -3.4184* | -4.4031*** | -0.9328 | 2.3843 | -0.6350 | 1.3005 |
| | (0.1544) | (0.2293) | (0.1891) | (1.8702) | (1.5260) | (2.0019) | (6.6606) | (2.3832) | (2.5823) |
| *log(Price)* | -0.3897*** | -0.4666*** | -0.0334*** | 0.4500*** | 0.4404*** | 0.3884*** | -0.1189 | -0.1713** | -0.1801 |
| | (0.0130) | (0.0147) | (0.0125) | (0.0259) | (0.0443) | (0.0342) | (0.2151) | (0.0847) | (0.1165) |
| *log(Volatility)* | 0.2020*** | 0.1916*** | 0.5232*** | 0.0428 | -0.0549 | -0.1704** | 0.2822** | 0.3708*** | 0.2742*** |
| | (0.0063) | (0.0079) | (0.0069) | (0.0372) | (0.0736) | (0.0640) | (0.1094) | (0.0480) | (0.0531) |
| *log(Volume)* | -0.1138*** | 0.0104 | 0.0914*** | -0.3393** | -0.3902*** | -0.0798 | 0.1020 | -0.0965 | 0.0348 |
| | (0.0054) | (0.0071) | (0.0058) | (0.1548) | (0.1195) | (0.1586) | (0.4921) | (0.1604) | (0.1722) |
| $Y_{Noti}$ | 0.4745*** | 0.3510*** | 0.4658*** | 1.0146*** | 0.7879*** | 0.8594*** | 1.1437*** | 0.6876*** | 0.7184*** |
| | (0.0239) | (0.0282) | (0.0200) | (0.0560) | (0.1684) | (0.1191) | (0.2293) | (0.1849) | (0.1497) |
| Observations | 696,594 | 695,821 | 696,653 | 146,667 | 146,665 | 146,647 | 120,948 | 120,947 | 120,934 |
| R-squared | 0.1924 | 0.0525 | 0.4053 | -0.0607 | -4.9949 | -2.5689 | -70.7329 | -13.3034 | -21.2714 |
| Firm#Quarter FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1