2019

The Effects of Market Fragmentation Around Corporate Events

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THE EFFECTS OF MARKET FRAGMENTATION AROUND CORPORATE EVENTS

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A DISSERTATION PRESENTED IN PARTIAL FULFILLMENT OF
REQUIREMENTS FOR THE DEGREE OF DOCTORATE OF
PHILOSOPHY IN BUSINESS ADMINISTRATION, DEPARTMENT OF FINANCE,
UNIVERSITY OF MISSISSIPPI

MAY 2019

ABSTRACT

In Part 1, I investigate the effects of market fragmentation in the liquidity formation of initial public offerings (IPOs). Recent exchange officials cite increases in market fragmentation as a hindrance to the liquidity formation in IPO trading. We find that IPOs are less fragmented at the start of IPO trading relative to later periods in the IPO secondary market. We also discover that more underpriced issues experience greater fragmentation, both lit and dark, at the start of IPO trading. Our study also examines the level of undisplayed liquidity in IPOs, finding more hidden trading at the start of IPO trading and in more underpriced issues. Finally, we provide evidence that algorithmic, hidden, and lit fragmented trading improve offering day IPO liquidity. In Part 2, I use the current fragmented market structure to test and an update theoretical limit order models on trading aggressiveness and order submissions around liquidity deadlines such as a stock's ex-dividend date. We use a stock's ex-dividend date as a deadline for liquidity traders to examine if dividend-seeking traders use dark and/or taker-maker venues as these two venues allow traders to bypass waiting costs and spread constraints to capture dividends. Our evidence indicates that taker-maker (dark) venue market share decreases (increases) on cum-dividend days, reverting once the stock trades ex-dividend. In Part 3, I use off-exchange retail trading data to examine the relevance of stock splits in attracting retail participation. Historically, stock splits help align prices in an optimal price range, resulting in disperse ownership and greater retail investor participation. We cite Minnick and Raman's (2014) contention that changes in direct retail ownership contribute to the decline in stock splits. We provide an empirical analysis of retail trading around stock splits, forward and reverse. Our results indicate a transitory increase (decrease) in both retail trading and retail trading imbalances around forward (reverse) splits. Our results cast doubt on the optimal price range hypothesis in that stock splits align prices to an optimal range and confirm the declining significance of stock splits in attracting permanent retail ownership.

DEDICATION

This dissertation is dedicated to my wife, Laura, for being my greatest supporter and friend throughout this process, and to my parents for always supporting me and instilling a strong desire to succeed.

ACKNOWLEDGEMENTS

I wish to thank Dr. Robert Van Ness for serving as my dissertation committee chairperson and for his advice and guidance throughout the PhD program. I would also like to thank the other members of my committee, Dr. Bonnie Van Ness, Dr. Kathleen Fuller, and Dr. Paul Johnson for their help and support through this process. I also offer a large and genuine thanks to the entire the finance faculty at the University of Mississippi for their support during my time in the PhD program. Finally, I wish to thank my fellow PhD students, past and present, for providing me the best environment possible for me to grow as a student.

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PART 1: THE DARK SIDE OF IPOS: EXAMINING WHERE AND WHO TRADES IN THE IPO SECONDARY MARKET

I. INTRODUCTION

This paper examines the levels of dark and lit fragmentation in initial public offerings (IPOs). Dark fragmentation or dark trading refers to off-exchange trading where order flow is either internalized by broker-dealers, matched via crossing networks, or executes over-the-counter. Dark trading allows subscribers to use anonymous, undisplayed orders away from the lit market. Dark trading venues such as dark pools provide investors both better execution costs and pre-trade anonymity yet higher execution risk. Menkveld, Yueshen, and Zhu (2017) recently document that overall dark trading accounts for nearly 30% of equity trading volume in the U.S.[1] Further, Buti, Rindi, and Werner (2017) document that over 50 alternative trading systems such as dark pools exist in the U.S. Lit fragmentation refers to the fragmentation of order flow across several open and publicly transparent limit order book exchanges such as the NYSE and NASDAQ. Lit trading is currently fragmented across 13 limit order book exchanges in the U.S., offering various fee- and rebate- model pricing venues. Gresse (2017) documents that for stocks in the S&P 500, nearly 50% of trade volume is executed away from their primary exchange. The literature studying both lit and dark fragmentation suggests that fragmented trading may affect market quality and liquidity formation in stocks.

Ellis, Michaely, and O'Hara (2000), Corwin, Harris, and Lipson (2004) and Bessembinder, Hao, and Zheng (2015) all document the importance of liquidity formation in IPO secondary

[1] Data provided by Fidessa shows that off-exchange or dark trading accounts for nearly 35% of daily volume in the U.S.

markets since liquid secondary markets help reduce the cost for market making, lower volatility, improve access in securing future capital, attract analyst coverage, and mitigate potential IPO failure. Two recent developments focus on the potential impact of market structure on IPO liquidity formation. In a presentation to the Securities and Exchange Commission, NASDAQ chairman, Robert Greifeld, suggests that increases in market fragmentation hinders the capital formation of small cap stocks, concluding that IPOs should have their own liquidity concentration program whereby the capital formation of the stock is less fragmented.[2] This sentiment is further mentioned in a Wall Street Journal article published on November 28th, 2017, where current NASDAQ chairman, Nelson Griggs, states:

"The current fragmented structure penalizes small companies for their low daily trading volumes; investors are deterred from making big bets on those companies because of the lack of liquidity to fill bigger trades. Concentrating disaggregated liquidity on one or two exchanges would allow investors to better source liquidity and make those stocks more attractive. Allowing issuers the choice to aggregate their liquidity on a single exchange—with limited exceptions—would result in better trading for the investors who believe in these companies."[3]

Another prominent exchange leader, NYSE President Thomas Farley, voiced a concern that both market fragmentation and undisplayed liquidity have made it more challenging to bring IPOs to market. In June 27th, 2017 testimony before the U.S. House of Representatives Committee Financial Services Capital Markets, Farley commented:

"Our markets have changed significantly over the past 10 years since the adoption of Regulation NMS. Equity markets are now intensely competitive and innovative. Unfortunately, these positive attributes have also brought with them added challenges of increased fragmentation,

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[2] See https://www.sec.gov/info/smallbus/acsec/acsec-050113-greifeld-slides.pdf
[3] See https://www.wsj.com/articles/a-more-concentrated-market-would-help-ipos-1511910303

lack of obligated liquidity provision, and a decrease in displayed liquidity, particularly in less liquid stocks…..We hear concern from NYSE listed companies and investors regarding increasing complexity and fragmentation in the U.S. equity markets, and the resulting challenge in finding sufficient liquidity….Smarter regulation of today's equity market structure will ease the burden for entrepreneurs and innovators to access the capital markets."

Despite the voiced concerns that fragmented markets as well as undisplayed liquidity hinders capital formation in IPOs, little evidence exists as to the current fragmentation of IPOs. Ellis, Michaely, and O'Hara (2000), Aggarwal (2000, 2003) and Corwin, Harris, and Lipson (2004) analyze the development of the secondary market for IPOs, providing insight as to how trading takes place around the offering and how firm characteristics impact IPO secondary market liquidity. Other studies including Ellis (2006), Edwards and Hanley (2010), and Chan (2010) look at who trades in IPOs as it relates to market makers, short sellers, and retail investors. However, no study contributes as to where IPO secondary market trading and liquidity formation occurs. Given the concerns of the current exchange presidents, we investigate and contribute to the literature as to the role of fragmentation and undisplayed liquidity in IPOs.

We focus on multiple issues related to IPO secondary market liquidity. First, we analyze the levels of dark and lit fragmentation in IPOs. The start of IPO trading is typically associated with high uncertainty and asymmetric information risk (Corwin, Harris, and Lipson, 2004). Further, the start of IPO trading is often accompanied with large trading volumes (Ellis, Michaely, and O'Hara, 2000). These abnormal trading conditions may have significant effects on the level of dark and lit fragmentation since the large trading volume around the offering date is likely to increase the probability of execution, particularly in dark trading venues (Buti, Rindi, and Werner, 2017). However, consistent with Menkveld, Yueshen, and Zhu's (2017) venue pecking order hypothesis, traders may prefer execution immediacy over the lower costs and price improvement provided by fragmented markets during a high uncertainty trading environment. We argue that the venue pecking order hypothesis applies to IPOs as IPOs are often associated with both large price moves and non-execution risk at the start of IPO trading. As a result, we expect lower levels of fragmented trading across both lit and dark venues at the start of IPO trading. Moreover, to the extent that uncertainty and informational asymmetries reduce in the IPO secondary market, fragmented trading is expected to increase as lower execution costs outweigh the benefits of execution immediacy. Second, we determine the levels of dark and lit fragmentation in IPOs, sorted on the level of IPO underpricing. Since underpriced or "hot" IPO issues are associated with even greater price uncertainty and asymmetric risk (see Rock, 1986; Amihud, Hauser, and Kirsh, 2003), markets are likely to fragment as traders seek other trading venues, particularly off-exchange, to reduce their exposure to adverse selection risk. In addition, the higher trading volumes associated with more underpriced IPO issues are likely to increase the execution probability for traders in dark venues (Buti, Rindi, and Werner, 2017). However, to the extent that the higher execution risk in underpriced IPOs (see Corwin, Harris, and Lipson, 2004), traders may prefer execution immediacy over execution costs, resulting in less fragmented trading in underpriced issues.

Third, we analyze the changes in algorithmic trading around IPOs. Ellul and Pagano (2006) assert that the asymmetric information environment associated with IPOs may induce investors to rely on other investors' trading behavior in determining their own strategy, resulting in a potential information cascade. Recently, Weller (2017) shows that algorithmic traders are more active in acquiring information around periods of high information asymmetry. Weller studies algorithmic trading around earnings announcements and finds that algorithmic trading deters information acquisition despite impounding information into prices. Fourth, we examine the levels of hidden liquidity in IPOs given the concerns that the lack of displayed liquidity hinders the liquidity formation of IPOs. Hidden liquidity or the ability to use hidden limit orders in the limit order book are likely targets of algorithmic or latent traders since Bloomfield, O'Hara, and Saar (2015) document that many algorithmic traders employ "pinging" strategies (i.e., placing and cancelling orders simply to discover hidden orders in the limit order book). To the extent that underpriced IPOs are associated with higher informational asymmetries, algorithmic traders (AT) may find it advantageous to trade in more underpriced IPOs to acquire pertinent information from hidden limit orders. Furthermore, we analyze if uncertainty in the IPO secondary market results in more algorithmic trading as algorithmic trading is associated with reducing search and monitoring frictions, primarily in periods of high uncertainty. We also determine if changes in the IPO secondary market result in traders switching between hidden limit orders and submitting orders to the dark venue.

Finally, we analyze the effects of market fragmentation, undisplayed trading, and algorithmic trading on market liquidity in IPOs. First, we investigate if these market innovations impact market liquidity for IPOs on the offering day. Second, we analyze if the impact of fragmentation, undisplayed liquidity, and algorithmic trading influence liquidity formation in the extended aftermarket. Our analysis examines both the offering day and extended aftermarket separately since changes in informational asymmetries as the IPO trades may affect the relation between IPO liquidity (i.e., transaction costs, price efficiency) and our measures of fragmented, undisplayed, and algorithmic trading.

Our main findings are summarized as follows: First, we find that IPOs are less fragmented at the start of IPO trading relative to the extended IPO secondary market as IPOs become more fragmented, both lit and dark, over time. Second, we show that more underpriced issues are associated with higher levels of both dark and lit fragmentation. For hot IPO issues, we find that off-exchange or dark trading accounts for nearly 30% of all executed volume on the offering date. This finding indicates that the large price moves and non-execution risks in underpriced issues are likely offset by the large trading volumes in underpriced issues, resulting in higher execution probabilities for traders in fragmented markets. Third, we provide evidence that dark and hidden trading are substitutes in the IPO secondary market. Although dark and hidden trading appear to complement one another around the offering date, the two forms of undisplayed trading exhibit inverse patterns in the IPO secondary market. Simultaneously, we show that algorithmic trading increases in post-IPO trading. The increases in both dark and algorithmic trading as well as the decrease in hidden trading are consistent with Degryse, Tombeur, and Wuyts (2015), who argue that both market and trading conditions impact the level of smart order router algorithmic trading which reduces the execution probability of hidden orders but connects more traders to dark venue. Fourth, we document that algorithmic trading is higher in underpriced issues – consistent with the notion that algorithmic traders are more active during periods of increased adverse selection risk. We also provide evidence that hidden, algorithmic, and lit fragmented trading improves offering day liquidity. Finally, we show that off-exchange or dark fragmentation adversely impacts IPO liquidity while lit fragmentation improves IPO liquidity in the extended aftermarket.

Overall, our study contributes to the literature in analyzing lit and dark fragmentation, particularly in IPOs. We argue that our findings are of interest to regulators and policymakers in understanding how IPOs trade in fragmented markets. Further, we suggest that our evidence provides new information to policymakers in understanding how undisplayed or opaque liquidity (i.e., dark and hidden trading) comprises IPO trading and impacts overall IPO liquidity.

II. HYPOTHESIS DEVELOPMENT

LIT FRAGMENTATION AND IPOS

The market fragmentation literature generally focuses on the positive and negative effects of market competition. Earlier studies such as Hamilton (1979) and Chowdhry and Nanda (1991) document that adverse selection risk increases with more decentralized trading. Other papers (Easley, Kiefer, and O'Hara, 1996; Bessembinder, 1997) demonstrate that new market competition results in more cream-skimming for order flow, resulting in greater adverse selection risk on the primary market. However, O'Hara and Ye (2011), Degryse, Tombeur, and Wuyts (2015), and Gresse (2017) provide evidence that market fragmentation has positive effects on liquidity including lower execution costs and greater trading depth. While these papers provide valuable contributions in understanding the consequences of market fragmentation, other studies outline why market fragment. Fong, Madhavan, and Swan (2001) provide answers as to why markets fragment, showing that institutional trading interest, liquidity constraints such as the bid-ask spread in the primary market, and the ability to execute large trades are determinants of why markets fragment. Further, Fong, Madhavan, and Swan suggests that continuous markets with the existence of the bid-ask spread presents a dilemma to traders. Traders with a low trading immediacy may prefer alternative markets that provide lower execution costs yet experience greater potential risk for nonexecution. Menkveld, Yeushen, and Zhu (2017) provide a similar explanation in analyzing how markets fragment or consolidate around urgency shocks. Menkveld et al. propose a venue pecking order hypothesis in which urgency or informational shocks force traders to sort through trading venues based on the level of execution immediacy and execution costs. They provide empirical evidence that trading consolidates to high-immediacy, high-cost lit trading venues during urgency shocks.

The unique trading environment associated in IPOs provides us the opportunity to examine how markets fragment. First, several IPO studies (Aggarwal, 2000, 2003; Ellis, Michaely, and O'Hara, 2000; Corwin, Harris, and Lipson, 2004) find that the initial trading volume over the first several days following an IPO is abnormally high. This is particularly evident in underpriced or hot IPO issues in which trading volumes can exceed the allocation shares (i.e., oversubscribed issues). Second, initial IPO trading is associated with high uncertainty and informational asymmetries, especially for hot IPOs. Together, we posit that these trading conditions may result in varying levels of lit fragmentation. Consistent with Menkveld, Yueshen, and Zhu's (2017) venue pecking order hypothesis, we suggest that the urgency to execute in the initial IPO secondary market results in less market fragmentation than in later periods of the IPO secondary market. Therefore, we expect the following prediction to hold:

H1: Lit fragmentation increases in the IPO secondary market.

Further, we posit that the large price moves and resulting nonexecution risks in underpriced or "hot" IPOs, results in less lit fragmentation as IPO investors restrict their trading intentions on immediacy as opposed to finding low-costs venues.

UNDISPLAYED LIQUIDITY AND IPOS

The initial IPO secondary market is often associated with higher levels of asymmetric information risk and uncertainty. In motivating our next hypotheses, we focus on the literature describing the relation between dark trading and high periods of uncertainty. First, Ye (2011) and

Zhu (2014) provide conflicting explanations as to the level of dark trading expected around periods of high uncertainty. Ye argues that informed traders experience a stronger incentive to conceal information in the dark pool during periods of high uncertainty. Ye concludes that increases in the fundamental value uncertainty increases the informed trader's activity in the dark pool and reduces her activity in the lit exchange. Conversely, Zhu suggests that due to execution risk faced by informed traders due to increases in competition in the dark venue, lit exchanges are more attractive to informed participants. Zhu accounts for the role of uncertainty by suggesting that an increase in volatility leads to increases in informed trading in dark venues but ultimately reduces dark venue market share since informed traders tend to cluster on the same side of the book and experience greater counterparty risk.

Ready (2014) provides empirical findings that indicate institutions are less likely to route orders to dark pools during period of higher uncertainty or adverse selection risk.[4] Likewise, Buti, Rindi, and Werner (2011; 2017) document that dark trading is negatively related to measures of uncertainty. Buti, Rindi, and Werner document that dark pool activity decreases in the limit order spread which serves as a proxy for trader valuation dispersion. Recently, Hatheway, Kwan, and Zheng (2017) find that stocks with higher adverse selection risk are associated with less dark trading activity. Hence, the theoretical and empirical evidence suggest that volatility and adverse selection risk increases execution risks in the dark venue, resulting in lower dark venue market share. Using the initial trading periods of IPOs as a setting of high adverse selection risk and volatility, we expect that dark trading increases as the level of uncertainty and adverse selection risk reduces in the IPO secondary market.

[4] Ye (2011), Buti, Rindi, and Werner (2011), and Menkveld et al. (2017) provide corroborating evidence that dark pool market share is inversely related with the level of uncertainty as measured by volatility.

To the extent that execution risk in the dark venues increases as informed traders cluster on the same side, we predict less dark trading on the offering date. However, as post-IPO asymmetric information risk and uncertainty reduces, counterparty risk in the dark venue declines, and dark trading market share increases. Therefore, we expect the following prediction to hold:

H2: Dark trading increases in the IPO secondary market.

While hypothesis two states that dark trading increases in the IPO secondary market as informational asymmetries and uncertainty is resolved, the literature analyzing the determinants of dark trading via limit order and trading volume suggests an alternative explanation. First, Buti, Rindi, and Werner (2017) argue that dark trading levels are an increasing function of both lit venue limit order book depth and trading volume. Examining limit order submissions in IPOs, Corwin, Harris, and Lipson (2004) document unusually high limit order book depth at the IPO offering date, extending several weeks beyond the offering date. Corwin, Harris, and Lipson mention, however, that limit order depth scaled to overall trading volume is relatively low in the early periods of the IPO secondary market. Likewise, both Ellis, Michaely, and O'Hara (2000) and Corwin, Harris, and Lipson document that IPOs are associated with unusually large trading volumes around the offering date. If IPOs, particularly underpriced IPOs, are characterized by both large trading volume and limit order depth then we predict dark trading to increase around the offering date, reducing in the post-IPO secondary market.

Hypothesis two focuses on how dark trading evolves in the IPO secondary market. We also address if dark trading levels vary in IPOs, conditioning on the level of IPO underpricing. To the extent underpriced issues engender greater volatility, price swings, and higher execution risks, then IPO traders may prefer trading immediacy offered by the lit venues, resulting in less dark trading. However, to the extent that dark venues enable traders to avoid certain adverse selection risks and to mitigate some informational exposure, dark venue market share may be larger in underpriced issues. Which of these determinants will dominate is an empirical question.

It is important to distinguish between hidden liquidity and dark liquidity. Hidden orders are limit orders that are placed on lit venues but are not visible to other participants. Harris (1996), Aitken, Berkman, and Mak (2001), De Winne and D'Hondt (2007), and Bessembinder, Panayides, and Venkataraman (2009) confirm the notion that hidden orders reduce the cost of order exposure and allow traders to disguise information. Boulatov and George (2013), however, demonstrate the hidden liquidity does not necessarily favor informed traders and hidden liquidity enhance market quality. Both Aitken et al. and Bessembinder et al. argue that despite the advantage of using hidden orders to disguise information, hidden orders are given low execution priority – exposing traders to higher execution risk as well as pick-off risk from faster traders. We explore the role of hidden liquidity in IPO trading since concealing value-relevant information is important for traders given the high uncertainty and asymmetric information risk associated with IPOs.[5]

We analyze if hidden trading on lit venues exhibit similar patterns to trading that takes place on dark venues around IPOs. Both Degryse, Tombeur, and Wuyts (2015) and Menkveld et al. (2017) provide evidence as to the interaction between hidden and dark liquidity. Degryse, Tombeur, and Wuyts show that while hidden and dark trading are substitutes, they are not perfect substitutes. Further, there are market conditions in which traders prefer hidden orders over accessing dark venues and vice versa. For example, Degryse, Tombeur, and Wuyts suggest that Menkveld, Yueshen, and Zhu's (2017) pecking order theory of trading venues can extend to hidden orders, where informed traders demanding a higher level of trading immediacy may prefer using

[5] Early studies such as Rock (1986) Gale and Stiglitz (1989) develop models accounting for the informational content of IPOs. Empirical studies such as Kim and Ritter (1999) and Hanley and Hoberg (2010) provide evidence as to how investors can properly evaluate the informational content of IPOs.

hidden orders on lit venues rather than using dark venues. If this relation holds for IPOs, then we expect that hidden activity comprises a considerable portion of overall trading activity around the offering date due to the high informational sensitivity surrounding the event.

As trading persists in the secondary market and adverse selection risk gradually declines, we expect that hidden order usage will decline. Further, as time extends beyond the offering date, hidden trading is likely to decline since the execution probability of hidden orders is directly related to overall trading volume (Degryse, Tombeur, and Wuyts, 2015). As trading volume in IPOs typically declines from offering day levels, hidden liquidity is also expected to decline. Degryse, Tombeur, and Wuyts further suggest an opposite pattern for dark trading, in which higher lit trading volume results in a decrease in execution probability in dark platforms consistent with our second hypothesis. Therefore, we expect an inverse relation between hidden and dark trading in the IPO secondary market, confirming that notion that the two forms of undisplayed trading are substitutes rather than complements.

H3: Hidden trading decreases in the IPO secondary market.

Consistent with our previous conjectures, we also analyze whether hidden trading levels depend on the level of IPO underpricing. Since hidden liquidity provides informed traders the ability to disguise value relevant information, we expect that underpriced issues experience higher levels of hidden liquidity. This expected relation follows from the notion that underpriced issues are associated with higher adverse selection risks.

ALGORITHMIC TRADING AND IPOS

We also analyze how algorithmic trading changes in the IPO secondary market relative to both changes in dark and hidden trading. Degryse, Tombeur, and Wuyts (2015) suggest that algorithmic trading levels vary with both dark and hidden trading. Specifically, Degryse, Tombeur, and Wuyts demonstrate that algorithmic traders using smart order routers may enhance competition on lit venues, reducing the execution probability for hidden limit orders. Concurrently, these smart order routers can tap into different venues connecting more traders to dark platforms. They conclude that the level of algorithmic trading should be positively (negatively) related to dark (hidden) trading. In this paper, we follow the pattern suggested by Degryse, Tombeur, and Wuyts, and expect that algorithmic trading has a direct (inverse) relation with dark (hidden) trading in the IPO secondary market.

H4: Algorithmic trading increases in the IPO secondary market.

Several theoretical studies (see Biais, Foucault, and Moinas, 2011; Martinez and Rosu, 2011) document that algorithmic trading is more informed than human trading. Hoffman (2013) shows that algorithmic traders are informed participants, quickly incorporating information into prices. Consistent with the notion that algorithmic trading is employed for strategic purposes, Weller (2017) documents that algorithmic traders increase their participation and acquire pertinent information around events associated with high informational risk. Weller analyzes AT strategies using a pre- and post- trading window around earnings announcement dates as a proxy for information risk.

Ellul and Pagano (2006) suggests that traders may have an incentive to capture information in formulating their own trading strategy in an IPO given the increased asymmetric information risk. To the extent that underpriced IPOs are associated with increases in asymmetric information risk, we expect that more underpriced issues to have higher levels of algorithmic trading since the profits from information acquisition are larger.

III. DATA AND METHODS

SAMPLE SELECTION & EMPIRICAL MEASURES

In Table 1, we provide a description of how we arrive at our final sample count. The initial sample consist of all IPOs between 2012 and 2016, totaling 920. Our initial list of IPO firms is obtained from the Field-Ritter IPO database including founding and offering dates. We merge our initial sample with the Market Information Data Analytics System (MIDAS) data on ticker symbol. After matching the initial sample list of IPOs with the list of tickers in MIDAS, the sample count reduces to 600. Further, we require that the starting dates in MIDAS to match the offering dates of the sample IPOs, reducing the sample to 538 IPOs. After excluding equity-carveouts, closed-end funds, ADRs, REITs, financials and utilities, offerings below $5, incompatible data between CRSP and MIDAS, the final sample count consists of 451 IPOs.

Table 2 provides a breakdown of the IPOs by primary listing exchange, industry classification, and year. We observe an increase of IPOs in 2013 and 2014 and consistent with the emerging growth company (EGC) classification of the Jumpstart Our Business Startups Act (JOBS Act) enacted in April 2012, most of the IPOs in the sample come from industries such as biotechnology, pharmaceutical, and other technology-based industries (i.e., SIC codes 28, 35, 73) that are likely to make use of the EGC classification.[6] Likewise, we find that many IPOs during the sample period use NASDAQ as the primary exchange. In Panel C, we report the offering

[6] Dambra, Field, & Gustafson (2015) document that biotechnology and pharmaceutical firms comprise the majority of the increase in IPO activity following the JOBS Act enactment. They argue these firm types are more inclined to take advantage of the changes in reporting and disclosure cost provisions.

characteristics of the sample firms. The mean (median) offering price is $14.58 ($15.00), while the mean (median) offer amount is $235.60 ($95.40) millions. The average underpricing as measured by the percentage change between the offering and closing price is 18.90%. The average firm age for our sample of IPOs is 17.6 years and the average underwriter rank is 7.93.

We examine both trades and trading volume for our sample of IPOs using MIDAS. The MIDAS database contains information on all orders for all listed securities across all U.S. exchanges. Further, the MIDAS database contains both trade and volume data on order cancellations, odd-lots, and displayed and hidden executed orders. The database covers stocks dating back to the start of 2012. We use this data to construct our measures of hidden trading, algorithmic trading, and lit fragmentation. First, we construct our measure of lit fragmentation using a Herfindahl-Hirschman Index (HHI, the sum of squared market shares) based on the reported daily trading volumes reported by all exchange venues in the MIDAS data. Following Degryse, De Jong, and Kervel (2015), we exclude dark trading volumes from the measure since we want to analyze lit and dark fragmentation separately. We adjust the measure by calculating *LitFrag* as 1 – HHI, so that higher (lower) numbers indicate more (less) fragmentation. Our measures of hidden trading are constructed using both hidden trades and hidden volume relative to the overall trades and volume executed in stock i on day t. Our first measure, *Hidden-to-Trade*, captures the proportion of executed hidden trades relative to all executed trades while *Hidden-to-Volume*, captures the relative frequency of hidden share volume to all trading volume. Thus, our hidden liquidity ratios reflect the number of trades that execute against hidden limit orders.

We use MIDAS to construct our four measures of algorithmic trading. First, we calculate *Cancel-to-Trade*, which represents the number of full or partial cancellations relative to the number of trades. To the extent that algorithmic traders submit and cancel a high volume of orders relative to executed orders, a high *Cancel-to-Trade* ratio is expected when algorithmic traders are active. Similarly, we calculate *Trade-to-Order*, which is a ratio capturing the number of trades executed relative to overall orders. We expect that a lower *Trade-to-Order* ratio indicates a higher presence of algorithmic trading. Our measure, *Trade-to-Order*, is the inverse of the order-to-trade ratio used in Hagstromer and Norden (2013) who show that latent traders tend to have higher order-to-trader ratios. Finally, we calculate *Odd-to-Trade*, which is the proportion of executed odd-lot trades to all trade executions and *Trade Size*, which is computed by scaling the executed share volume to the number of executed trades. These last two measures serve as proxies of algorithmic trading as O'Hara, Yao, and Ye (2014), Hendershott and Riordan (2013), and Menkveld (2014) document that algorithmic traders use odd lots and smaller trade sizes to conceal information. A higher (lower) *Odd-to-Trade* (*Trade Size*) measure indicates more algorithmic trading. Our measure of dark trading is derived from TAQ using exchange code 'D'. We scale the number of trades and trading volume reported via exchange code 'D' to the overall trades and trading volume reported on TAQ for the day. In verifying the number of trades and trading volume, we compare the overall the numbers reported on TAQ with those reported by CRSP. The numbers are not exact but are close. Similarly, we sum the number of trades and trading volume reported on MIDAS with those reported only for exchange code 'D' to verify that the total trading volume resembles the aggregate trading volume on CRSP. Our first measure, *Dark-to-Trade*, captures the proportion of executed dark trades relative to all executed trades while *Dark-to-Volume*, captures the relative frequency of dark venue share volume to all trading volume.

IV. RESULTS

FRAGMENTATION AND IPO UNDERPRICING

Our first objective is to compare where trading is taking place across IPOs conditional on the level of underpricing. Table 3 reports the univariate differences across IPO quartiles formed via the level of underpricing where quartile 1 (quartile 4) represents the least (most) underpriced issues. Throughout the paper, we denote IPOs that fall into the lowest quartile of underpricing as "cold", the highest quartile of underpricing as "hot". We refer to quartiles 2 and 3 as "cool" and "warm", respectively. First, we report in Panel A that IPO trading characteristics such as the percentage float, offer turnover, trading turnover, and our measure of volatility using the daily price range. In Panel A, we find that both offer (96.31%) and share turnover (30.43%) as well as volatility (15.83%) are higher in the most underpriced issues (i.e., quartile 4). In Panel B, we show that hidden trading as measured by *Hidden-to-Trade* is higher in the most underpriced IPOs (i.e., quartile 4) at 26.00%. Further, our measures of dark trading using both our trade ratio (29.19%) and volume ratio (29.05%) indicate that more underpriced IPOs experience more dark trading. This result contrasts with the venue pecking order hypothesis which suggests execution risk in the dark venue may deter overall dark trading activity during periods of high uncertainty. In Panel C, we show that more underpriced issues are highly fragmented, with issues in quartile 1 (quartile 4) having a *LitFrag* score of 63.91 (72.67). This result implies that despite increased asymmetric information risk in underpriced issues, trading does not consolidate as put forth by the venue pecking order hypothesis. Further, we show that algorithmic trading is higher in the most underpriced issues. In Panel C, we find that *Odd-to-Trade* (15.25%) is higher among the most underpriced quartile. We also report in Panel C, that *Trade-to-Order* (13.72%) is lowest in the most underpriced quartile, indicating that order submissions dominate the number of executed trades, consistent with algorithmic trading. Underpriced issues also have the highest *Cancel-to-Trade* (7.18) measure, indicating the underpriced issues experience more cancellations relative to the number of executed trades – another indication of algorithmic trading. Finally, underpriced issues have the lowest average *Trade Size* (175.67). Thus, our initial evidence supports the notion that underpriced issues are associated with higher levels of algorithmic trading.

In Figure 1, we provide a visual representation of how measures of hidden and dark trading vary across our quartiles sorted via underpricing. We show that both warm and hot IPOs contain a larger share of both hidden and dark trading activity relative to cool and cold IPOs on the offering date. In Panel A, we display the monotonic increase in hidden trading as a proportion of all reported trading. In Panel B, we provide a visual showing that dark trading levels are higher on the offering date for both warm and hot IPOs. Overall, Figure 1 indicates that the level of undisplayed liquidity is conditional of the level of IPO underpricing.

In Figure 2, we show both hot and warm IPOs are associated with higher levels of lit fragmentation on the offering date. Similarly, we show that the measures of algorithmic trading, for the most part, are higher in hot and warm IPOs. In Panel A, we show that underpriced issues are heavily fragmented on the offering day. Compared to less underpriced issues, both warm and hot issues experience greater market competition on the offering day. This result is not surprising given that both warm and hot IPOs are also fragmented in the level of off-exchange trading reported to dark venues that we document in Figure 1. In Panels B through D, we provide three measures related to our proxies of algorithmic trading. We do not report the visuals for *Trade Size* to save space although the results indicate that *Trade Size* monotonically decreases in underpriced issues. The visuals associated with Panels B through D indicate a higher presence of algorithmic trading as both *Odd-to-Trade* and *Cancel-to-Trade* measures are increasing underpriced issues. Overall, the panels in Figure 2 demonstrate that underpriced or "hot" IPO issues experience more algorithmic trading.

We next examine our first hypothesis that states lit fragmentation is lower at the start of IPO trading than in later periods of the IPO secondary market. To identify changes in lit fragmentation in the IPO secondary market, we compare the level of lit fragmentation on the offering day with the levels of lit fragmentation in the remaining first five trading days as well as the remaining first 60 trading days after the IPO. Table 4 provides the results from our analysis in determining how market fragmentation changes beyond the offering date. First, we show in Panel A that lit fragmentation is higher among hot IPOs. The higher amount of lit fragmentation in hot IPOs, relative to cold IPOs, persists throughout the first 60 trading days of the IPO. We also document that lit fragmentation increases for all IPOs throughout the first 60 trading days of the IPO. In Panel B, we report the difference in lit fragmentation between the offering date and the remaining periods. While there are no significant differences in lit fragmentation between the offering date and the early periods (i.e., day 5, 10, 20), we find that lit fragmentation is significantly higher in days 31-60 relative to the offering date.

In Figure 3, we provide the changes in lit fragmentation across all four IPO quartiles for the first 60 trading days following the IPO. We observe that both warm and hot IPOs are more fragmented than cold IPOs at the offering date. Further, the level of lit fragmentation remains consistent throughout the first 10 trading days of the IPO across all four quartiles of underpricing. However, after ten trading days, both cool and cold IPOs become more fragmented and resemble to some degree, the level of lit fragmentation experienced by both warm and hot IPOs in the later periods of trading. Overall, the evidence provided in Table 4 and Figure 3 support hypothesis one.

Table 4 and Figure 3 show that contrary to our expectation, lit fragmentation is higher among underpriced IPOs. We next control for firm- and trading-related characteristics that might explain the levels of lit fragmentation around the IPO offering date. The dependent variable, $LitFrag_i$, refers to our measure of lit fragmentation as defined earlier for stock i on the IPO offering date. We include two measures of IPO underpricing. The first measure, $Underpricing_i$, is a continuous measure of underpricing. Consistent with previous literature, we add one to the underpricing percentage and then take the natural log to transform the distribution. This transformation removes the skewness of the underlying distribution of our original underpricing variable. Our second measure of underpricing, $WarmIPO_i$, is a dummy variable that equals one if the IPO firm is in the highest tercile of IPO underpricing. Our firm-related controls include the IPOs firm size, firm age, price support dummy variable, and underwriter ranking. Firm $Size_i$ is computed by taking the natural log of the firm's fiscal year-end market capitalization as reported in Compustat. Firm Age_i is calculated by taking the natural log of one plus the firm's age, where the firm's age is derived by taking the difference between the firm's offering year and founding year. We include a control for price support, since Ellis, Michaely, and O'Hara (2000) show that underwriters often act in stabilizing and supporting IPO prices following the IPO. Consistent with Edwards and Hanley (2010), we construct the Price $Support_i$ dummy variable: if the IPO firm's first-day return is equal to zero, or if the IPO is in the top quartile for the percent of trades, using TAQ, executed at the offer price on the offering day. $Underwriter_i$ is the underwriter ranking associated with the IPO and is classified according to the Loughran and Ritter's (2004) updated 0-9 scale of the Carter and Manaster (1990) underwriter rankings. We also include other trading-related controls as Gresse (2017) documents that trading volume, price, and number of trading platforms in which trades occur can influence the levels of market fragmentation. $Volume_i$ is the natural log of the entire trading volume on the IPO offering day. Similar to Gresse, we construct $InversePrice_i$ which captures the relative tick size on the primary exchange. Finally, $Market\ Competition_i$ is the number of exchanges in which executed trades on the offering day. Equation (1) provides the full regression model. We also include IPO year and industry fixed-effects.

$$LitFrag_i=\alpha + \beta_1 Underpricing_i \text{ or } WarmIPO_i + \beta_2 Firm\ Size_i + \beta_3 Volume_i + \beta_4 InversePrice_i + \beta_5 Market\ Competition_i + \beta_6 Firm\ Age_i + \beta_7 Price\ Support_i + \beta_8 Underwriter_i + \varepsilon_i \quad (1)$$

The results in Table 5 confirm that underpriced issues are associated with greater lit fragmentation. In column (1), we find that a positive coefficient estimate, 0.0245, for $Underpricing_i$. In column (2), we also report a positive estimate, 0.250, for our dummy variable measure of underpricing, $WarmIPO_i$. As for our controls, we find that larger IPO firms experience greater lit fragmentation around the offering date. We also find in column (2) that older firms and those with more prestigious underwriters experience greater lit fragmentation. Further, we find that the parameter estimate for $Price\ Support_i$ is negative in both regressions. This result implies that price-supported IPOs, which need price stabilization from underwriters to prevent larger initial selloffs experience less market fragmentation across lit trading venues. Finally, the sign of the estimates for our trading-related controls $InversePrice_i$ and $Market\ Competition_i$ are the same as those presented in Gresse (2017). Overall, the results in Table 5 indicate that the level of underpricing influences the degree of lit fragmentation and both firm and IPO-related characteristics influence the level of fragmented trading around the offering date.

DARK AND HIDDEN TRADING IN IPOS

In this section, we focus on the level of dark and hidden trading in IPOs. We first compare the level of dark and hidden trading at the offering date with those of the remaining 60 trading days. To determine if dark and hidden trading evolves in the IPO secondary market, we compare the level of dark and hidden trading on the offering day with the levels of dark and hidden trading in the remaining first five trading days as well as remaining first 60 trading days after the IPO. First, we show in Panel A that dark trading as a percentage of all trades, *Dark-to-Trade*, and dark trading as a percentage of all share volume, *Dark-to-Volume,* account for 27.30% (25.74) of offering day trading activity. These ratios increase throughout the first five days of trading, peaking around day 10, where *Dark-to-Trade (Dark-to-Volume)* accounts for 41.38% (52.47%) of trading activity. Second, we report measures of hidden trading using trades, *Hidden-to-Trade*, and share volume, *Hidden-to-Volume*, account for 33.42% and 33.81% of offering date trading activity on lit venues. These ratios decrease throughout the first five days of trading, plateauing around day 10, where *Hidden-to-Trade (Hidden-to-Volume)* accounts for 25.93% (28.51%) of lit trading activity. In Panel B, we compare dark and hidden trading on the offering day with the remaining periods (i.e., day 5, day 10, day 20, days 31-60). Across all trading day comparisons, the differences are statistically significant. Across the entire set of IPOs, we find that relative to the offering date, dark trading increases 12.55% (7.78%) when measured five days (31-60 days) after the IPO. The difference in *Hidden-to-Trade (Hidden-to-Volume)* between the offering date and 31-60 days after the offering is 9.02% (7.87%), confirming that hidden trading declines in the IPO secondary market. Overall, the results indicate that dark and hidden trading experience inverse patterns in the IPO secondary market confirming the suggestion of Degryse, Tombeur, and Wuyts

(2015) that the dark and hidden trading are substitutes rather than complements. This finding is also consistent with the notion that traders may prefer hidden orders over submitting orders to the dark venue around the offering date since hidden orders offer greater immediacy during a period of high informational uncertainty. In sum, the findings provided in Table 6 indicate support hypotheses 2 and 3, in that hidden (dark) trading levels decrease (increase) in the IPO secondary market. Further, the results indicate that two forms of undisplayed liquidity appear to be substitutes rather than compliments in the IPO secondary market.

In Figure 4, we plot measures of dark and hidden trading in the first 60 days beyond the offering date.[7] The visual in Figure 4 depicts how hidden trading declines around the offering date while dark trading increases in the first 10 trading days following the offering, accounting for over 40% of all trading activity around day 10. The existence of high hidden limit order trading around the offering differs with prior evidence provided by Corwin, Harris, and Lipson (2004), who document that limit order cancellation rates are high at the start of IPO trading as both adverse selection and nonexecution risk outweigh the advantages of limit orders. Overall, the visual provided in Figure 4 illustrates that traders switch from hidden to dark orders as the IPO trades in the secondary market.

Our results indicate the dark and hidden trading act as substitutes in the IPO secondary market. We next analyze the relative use of dark and hidden trading on the offering date. Further, we analyze if asymmetric risk associated with underpriced issues are associated with higher levels of undisplayed trading on the offering day. The studies of Harris (1996) and Rindi (2008) posit that in periods of high adverse selection risk, traders are more inclined not to expose orders.

[7] Figure 2 depicts the changes in hidden and dark trading using the number of trades scaled to all trades reported that day. We also have the visual reporting the changes in hidden and dark trading using volume measures that are available upon request.

Gozluklu (2016) offers similar comments and suggests that in markets where the potential for high informational asymmetries exist, undisclosed orders may be used to compete for liquidity provision. Similarly, Buti and Rindi (2013) document that large traders are primary beneficiaries from “reserve” orders, which are partially hidden orders. Bloomfield, O’Hara, and Saar (2015) claim that hidden liquidity increases the trading profits for informed traders during periods of high private information sensitivity. Similarly, Yao (2017) shows that informed traders use hidden orders to their advantage, experiencing positive abnormal returns at the intraday level. These studies indicate support for the notion that hidden orders allow informed traders to disguise information. Further, Ellis et al. (2000), Aggarwal (2000, 2003), Corwin, Harris, and Lipson (2004), and Ellis (2006) all document that trading volume is very high in first two trading days following an initial public offering, accounting for nearly 70% of shares offered at issuance. To the extent that underpriced IPOs are associated with increased volume, hidden order traders are also likely to experience a higher probability of execution.

While our univariate results provide evidence that dark trading is higher among underpriced issues, we next account for firm-specific determinants to help control for the observed levels of hidden and dark trading in underpriced IPOs. Consistent with our earlier regression specification, we control for IPO firm-related characteristics such as the IPO firm’s size, firm age, underwriter ranking, and price support. We further control for trading volume, inverse price, and market competition as these variables are likely to influence the level of dark trading. Finally, we include our two separate measures of underpricing as the main independent variable. The full regression specification includes both IPO year and industry fixed-effects.

$$\text{Dark or Hidden Ratio}_i \quad (2)$$
$$= \alpha + \beta_1 \text{Underpricing}_i \text{ or WarmIPO}_i + \beta_2 \text{Firm Size}_i + \beta_3 \text{Volume}_i$$
$$+ \beta_4 \text{InversePrice}_i + \beta_5 \text{Market Competition}_i + \beta_6 \text{Firm Age}_i + \beta_7 \text{Price Support}_i + \beta_8 \text{Underwriter}_i + \varepsilon_i$$

The results in Table 7 corroborate our univariate findings in that more underpriced issues experience greater dark and hidden trading on the offering day. Both measures of dark trading, trades and volume ratios, are higher for underpriced IPOs. In columns (1) and (2), we show that the coefficient estimates for Underpricing_i (Warm IPO_i) are 0.1059 (0.0423), indicating that more underpriced issues have greater off-exchange or dark trading on the offering date. In columns (3) and (4), we provide similar results that underpriced IPOs are associated with higher levels of dark trading, measuring dark trading as the percentage of dark trades to all executed trades. In columns (5) through (8), we document that more underpriced issues possess higher levels of hidden trading, supporting the contention that traders are more inclined to conceal their trading intentions in IPO issues with greater informational uncertainty. The results for our control variables are notable. First, we report that hidden trading is negatively related inverse price. To the extent the inverse price captures transaction costs (see Keim and Madhavan, 1997), our results are consistent with the notion that the decision to hide liquidity is indirectly related to transaction costs. We also find that dark trading activity is inversely related to the level of price support while hidden trading, using volume measures, is positively related to price support. These results provide some indication that traders withdraw from the lit market for dark trading venues during weaker offerings, however, it appears that the hidden option enables traders to supply more liquidity for price-supported IPOs. This last finding is also consistent with the premise that price supported IPOs reduce the cost of submitting limit orders (Corwin, Harris, and Lipson, 2004). We also document that the IPO firm's age and underwriter ranking are not significant predictors of offering day undisplayed liquidity. In sum, the findings provided in Table 7 confirm our prediction that underpriced issues experience more undisplayed liquidity.

ALGORITHMIC TRADING IN IPOS

Our next set of tests analyzes the levels of algorithmic trading in IPOs. Similar to our set of tests examining how measures of fragmented and undisplayed trading change in the IPO secondary, we analyze how algorithmic trading evolves in the secondary market. Table 8 provides the comparison of algorithmic trading levels at the offering day against later periods in the IPO secondary market. Panel A shows that *Odd-to-Trade* and *Cancel-to-Trade* increase as the IPO trades in the secondary market, indicating that algorithmic trading is low around the IPO offering date relative to later periods in the secondary market. We also document in Panel A that the ratio, *Odd-to-Trade,* is 10.78% of offering day. The *Odd-to-Trade* ratio increases throughout the first 60 days of trading, indicating that algorithmic trading increases in the later IPO trading periods. We next report in Panel A that both *Trade-to-Order* and *Cancel-to-Trade* measures are 15.58% and 6.36 on the offering day. Further, the *Trade-to-Order* (*Cancel-to-Trade*) measure decreases (increases) throughout the first 60 days of trading, which implies that algorithmic trading levels are lower at the start of IPO trading only to increase in the later IPO trading periods. We also report in Panel A that *Trade Size* declines in the days following the offering, supporting the premise that as algorithmic trading activity increases in the later IPO trading periods, resulting in smaller executed trade sizes. In Panel B, we compare the measures of algorithmic trading on the offering day with the remaining periods (i.e., day five, day 10, day 20, days 31-60). The differences in the four algorithmic trading measures between the early and later IPO trading periods indicate that algorithmic trading is low in the initial IPO secondary market but increases in the following weeks and months after the offering day. For example, we discover that relative to the offering date, *Odd-to-Trade* increases 6.21% (15.17%) when measured five days (31-60 days) after the IPO across the entire set of IPOs. The difference in *Trade-to-Order* between the offering date (31-60 days) after the offering is 8.32% (10.75%), confirming that *Trade-to-Order* declines in the IPO secondary market. We also document the difference in *Cancel-to-Trade* between the offering date and the later trading periods, showing that *Cancel-to-Trade* increases 15.34 (18.81) in the five (31-60) days relative to the offering day. Likewise, we show that *Trade Size* decreases 47.89 (97.10) in the five (31-60) days relative to the offering day. Overall, the patterns exhibited by the four measures of algorithmic trading support our conjecture that increases in algorithmic trading coincide with increases in fragmentation in later trading periods of the IPO.

In Figure 5, we provide all four measures of algorithmic trading in the IPO secondary market, however, this time we include the first 180 trading days. The observed trends provided in Figure 5 show that *Odd-to-Trade* and *Cancel-to-Trade* ratios are low at the start of the IPO secondary market, increasing in the first several trading days after the offering. Interestingly, the observed pattern associated with *Cancel-to-Trade* contrasts with the limit order cancellation rate pattern in IPOs provided by Corwin, Harris, and Lipson (2004). Corwin, Harris, and Lipson show that limit order cancellations are high around the offering, declining significantly in the first 10 trading days. In Figure 5, we also report that both *Trade Size* and *Trade-to-Order* decline almost monotonically in the IPO secondary market. Our finding that *Trade-to-Order* peaks around the offering, declining in the following days also differs from the results of Corwin, Harris, and Lipson, who document that order submission (execution) rates are lower (higher) on the offering date. Corwin, Harris, and Lipson further show that order submission (execution) rates increase (decreases) in the following days – contrasting with the results we observe in Figure 5. Overall, the evidence provided in both Table 8 and Figure 5 indicate support for hypothesis 3 in that algorithmic traders increase their participation in the later periods of the IPO secondary market. Further, the patterns we document for hidden, dark, and algorithmic trading are consistent with Degryse, Tombeur, and Wutys (2015) who demonstrate the market conditions affect smart order route algorithmic strategies, which reduce the level of hidden trading yet provide traders greater access to the dark venue.

We next examine if the higher adverse selection risk in underpriced issues results in greater algorithmic trading activity. In Table 9, we provide the coefficient estimates from our multivariate test(s) where our four measures of algorithmic trading serve as the dependent variable. The full the model including the independent variables and fixed-effects are the same as described in equation (1). Corroborating our univariate findings, we discover that three of the four measures of algorithmic trading are directly related to the degree of IPO underpricing. In columns (1) and (2), we provide the estimates where *Odd-to-Trade* serves as the measure of algorithmic trading. In columns (1) and (2), we report the mean estimate of 0.0954 (0.0348) for Underpricing_i (Warm IPO_i). This finding implies that algorithmic trading is more pervasive in underpriced issues. Consistent with our expectation, we find the coefficient estimates for *Trade-to-Order* (*Trade Size*) are negative -0.0273 (-0.1834) when using the continuous measure of underpricing. This indicates that underpriced issues are associated with higher levels of algorithmic trading. Similar results hold when using the dummy variable measure of underpricing. The estimate for the *Cancel-to-Trade* ratio is insignificant using the continuous (dummy) measure of underpricing, suggesting that underpriced issues are not associated with high cancellation episodes that are typically associated with algorithmic trading. While this limits support for our prediction that underpriced IPOs induce algorithmic traders to capture fundamental information, we do confirm that odd lot executions, smaller trade sizes, and order submissions dominate underpriced IPOs, consistent with the likelihood of algorithmic trading.

FRAGMENTED, UNDISPLAYED, AND ALGORITHMIC TRADING ON IPO MARKET QUALITY

In this last section, we examine if our measures of fragmented, undisplayed, and algorithmic trading impact the market quality in IPOs. We first examine the effects of fragmentation and undisplayed trading on market quality by constructing a two-stage least squares analysis. We follow Gresse (2017) and employ similar instruments when constructing the first stage estimates for both dark and lit fragmentation. For all reported regressions, the measures of *Dark, LitFrag, and Hidden* are constructed using daily executed trading volume. In the first stage, we regress our measures of dark and hidden trading on the stock's market capitalization, trading volume, average trade size, relative tick size, number of actively competing markets with respect to executed trades, and the difference between the average trade size on the lit and dark venues. For lit fragmentation, the instruments remain the same except that we exclude the differential trade size measure. In the second stage, we regress measures of market quality which include two measures of transaction costs, quoted and effective spreads to help capture round-trip trading costs for investors. We also include price impact as a dependent variable to help measure the effects of market fragmentation on the price efficiency in IPOs.

In Table 10, we provide the second-stage coefficient estimates where our three measures of market quality serve as the dependent variable. The full second-stage model includes controls related to firm size, volume, volatility, underwriter ranking, firm age, and our measure of IPO underpricing. The second-stage model also includes year and industry fixed-effects. When analyzing the effects of market fragmentation on market quality beyond the offering day, we include both firm fixed-effects and cluster standard errors at the firm level. Table 10 provides the coefficient estimates for only the offering day. For each measure, we find that dark trading, $\widehat{Dark}$, has no effect on offering day market quality. However, we find evidence that both lit fragmentation and hidden trading are associated with both lower transaction costs and price impact. For instance, the we find that the coefficient estimate for $\widehat{LitFrag}$ is negative for all three measures of market quality, suggesting lit fragmentation is associated with lower offering day spreads and better price efficiency. Further, we show that the estimates for $\widehat{Hidden}$ are also negative for all three measure of market quality. This finding implies that hidden liquidity improves offering day market quality in IPOs. Our controls related to volatility and volume load as expected, however none of the firm-related IPO characteristics such as underwriter ranking, firm age, and underpricing have any impact on offering day liquidity. Hence, offering day liquidity is not influenced by offering characteristics that may serve as another source of uncertainty.

In Table 11, we provide the second-stage coefficient estimates where our three measures of market quality serve as the dependent variable, however, we replace our measures of undisplayed trading and market fragmentation with three of the four measures of algorithmic trading. We do not include trade size as a measure of AT since trade size serves as one of the instruments used to predict algorithmic trading. Likewise, we do not include the differences in trade size between lit and dark venues as an instrument in the first-stage. To allow the signs of all the coefficient estimates to imply the same effect on our dependent variable, we replace our measure of AT, *Trade-to-Order*, with the inverse. Thus, the coefficient estimates of all three measures of AT will have the same interpretation – a positive (negative) estimate implies that AT reduces (increases) market liquidity. The estimates provided in Table 11 show that all three measures of AT are associated with lower transaction costs on the offering day. For instance, $\widehat{\textit{Odd-to-Trade}}$ is negative for all three measures of market quality, indicating that increases in odd-lot trading associated with algorithmic trading activity is associated with lower spreads and more efficient prices on the IPO offering day. Consistent with the notion that algorithmic trading is associated with lower transaction costs, the coefficient estimates for both $\widehat{\textit{Cancel-to-Trade}}$ and $\widehat{\textit{Trade-to-Order}}$^ are also negative. As for the impact of AT on price efficiency, we find that both $\widehat{\textit{Odd-to-Trade}}$ and $\widehat{\textit{Trade-to-Order}}$^ are associated with lower price impact levels, implying better offering day price efficiency. Overall, these results are consistent with Hendershott, Jones, and Menkveld (2011), who document that algorithmic trading narrows spreads and reduces adverse selection risks (i.e., price impact).

In Table 12, we provide the second-stage coefficient estimates by analyzing the effects of market fragmentation and undisplayed trading on market liquidity in the extended aftermarket. To better analyze the effects fragmentation and undisplayed trading on market quality in the various IPO trading periods, we partition the sample into three stages: first week, weeks two through five, and weeks six through ten. We conduct this additional analysis since the level of informational asymmetries and adverse selection risks tend to evolve as the IPO trades, the effects of market fragmentation and undisplayed trading on market liquidity may vary. To save space, we report the only the coefficient estimates for our measures of fragmentation and undisplayed trading. The full model does include the same controls as those used in the offering day regressions. Table 12 provides some notable results. In Panel A, we find that apart from the offering day, the measures of lit fragmentation, $\widehat{\textit{LitFrag}}$, and hidden trading, $\widehat{\textit{Hidden}}$, have no significant effect on market quality in the first week of IPO trading. This finding indicates that despite improving offering day liquidity, the effects of lit fragmentation and hidden liquidity has no beneficial effect on IPO liquidity in the first week of trading. However, we find the coefficient estimate for $\widehat{Dark}$ is positive for all three measures of market quality, indicating the higher levels of dark trading increases both spreads and price impact in IPOs. This result is consistent with Zhu (2014) who documents that if dark trading venues reduce the number of uninformed trades in the lit market, both adverse selection risks and bid-ask spreads increase in the lit market. In Panel B, we find that hidden trading, $\widehat{Hidden}$, has no impact on market quality during next the four weeks of IPO trading. Consistent with the results provided in Panel A, we document that our measure of dark trading, $\widehat{Dark}$, is associated with wider transaction costs yet no effect on price impact. Thus, our results suggest that the adverse effects associated with dark trading continues in the first month of IPO trading. We also find in Panel B, that the coefficient estimate for lit fragmentation, $\widehat{LitFrag}$, is negative with respect to our two transaction costs measures, suggesting that lit fragmentation continues to improve market liquidity in the first month of IPO trading. Finally, in Panel C, we find that our two measures of undisplayed trading, $\widehat{Dark}$ and $\widehat{Hidden}$, increase transaction costs and price impact in the later IPO trading periods while lit fragmentation, $\widehat{LitFrag}$, reduces both transaction costs and price impact. Overall, Table 12 suggests higher levels of dark trading increase spreads throughout the later IPO trading periods and increase the price impact component of the bid-ask spread in the first week of IPO trading, suggesting the dark trading leads to greater illiquidity in the early stages of IPO trading. Conversely, we find that lit fragmentation reduces transaction costs and price impact in the later IPO trading periods.

In Table 13, we provide the second-stage coefficient estimates by analyzing the effects of algorithmic trading on market quality through the extended IPO aftermarket. In Panel A, we find little evidence that our measures of AT impact market quality in the first week of IPO trading, where only $\widehat{\textit{Cancel-to-Trade}}$ and $\widehat{\textit{Trade-to-Order}}$^ load significantly on effective spreads. Further the coefficient estimates for these two measures are economically smaller than those documented in Table 10 when analyzing the effects of AT on offering day market quality. We document similar evidence in Panel B in that algorithmic trading has a negligible impact on market quality in the following month of IPO trading. However, in Panel C, we find that the coefficient estimates for $\widehat{\textit{Odd-to-Trade}}$ and $\widehat{\textit{Trade-to-Order}}$^ are negative across all three measures of market quality, consistent with the notion that AT improves not only spreads but also reduces adverse selection risks – consistent with the findings of (Hendershott, Jones, and Menkveld, 2011). Interestingly, we show that the coefficient estimate for $\widehat{\textit{Cancel-to-Trade}}$ is positive for all three measures of market quality, implying that high cancellation activity is associated with wider spreads and greater adverse election risks. Hence, despite of two of the three measures supporting the contention that AT aids IPO liquidity, we interpret this last finding to suggest that algorithmic trading has mixed effects on liquidity in extended IPO aftermarket.

V. CONCLUSION

In this study, we analyze the market fragmentation of IPOs. We find that relative to the weeks and months after the IPO offering day, lit fragmentation is low at the start of IPO trading. Sorting on the level of underpricing, we find that more underpriced IPOs are associated with greater lit fragmentation. We also discover that off-exchange or dark fragmentation is higher among underpriced issues. We argue that the greater adverse selection risk in underpriced issues results in greater dark trading on the offering date.

We also analyze if traders use hidden limit orders to disguise relevant information around IPOs. We find evidence that underpriced IPOs are associated with greater hidden liquidity. We next determine the level of hidden liquidity in the IPO secondary market and show that hidden liquidity levels steadily decline in the IPO secondary market. Further, we document that measures of dark and hidden trading move in opposite directions in the early stages of the IPO secondary market. We interpret this finding as consistent with the argument that dark and hidden trading are substitutes rather than complements (Degryse, Tombeur, and Wuyts, 2015).

We next investigate how algorithmic trading comprises the initial IPO secondary market. Consistent with the notion that algorithmic traders engage in information acquisition around informational-sensitive events (Weller, 2017), we find that measures of algorithmic trading are higher among underpriced IPOs. Our evidence also reveals that measures of algorithmic trading are relatively low at the start of IPO market, increasing over the first several months. Over the first 60 trading days in the IPO secondary market, we show, consistent with Degryse, Tombeur, and

Wuyts (2015), that algorithmic trading is positively (negatively) related to the level of dark (hidden) trading as smart order router algorithms hinder execution probability of limit orders while allowing participants to tap into dark venues.

In the final part of our analysis, we examine the effects of market fragmentation, undisplayed trading, and algorithmic trading on IPO liquidity. Our results show that lit fragmentation, hidden trading, and algorithmic reduce both transaction costs and price impact levels of the offering day. Beyond the offering day, we find that dark trading is associated with higher levels of illiquidity in the later IPO trading periods. Conversely, we document that lit fragmentation is associated with reductions in transaction costs and price impact in the later IPO aftermarket.

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APPENDIX

APPENDIX 1: SAMPLE SELECTION

Table 1: Sample Selection

This table presents a breakdown of our sample selection. The first column provides the filters we apply in deriving our final sample of IPOs. The second column provides the number and percentage of firms representing our initial list of IPOs. The percentage of firms relative to the initial sample count is provided in parentheses.

Filter	*Number of Firms (Percentage)*
IPOs obtained from Field-Ritter IPO database between 2012 and 2016	920 (100)
Matching IPOs with MIDAS via ticker symbol	600 (65.2)
Compatible offering dates between Ritter IPO database and MIDAS	538 (58.5)
Excluding equity-carve outs, ADRs, REITs, financial and utility firms, offerings below $5, and compatible offering dates in CRSP	451 (49.0)

APPENDIX 2: SAMPLE DISTRIBUTION

Table 2: Sample Distribution

This table presents summary statistics for the data used in the study. Panel A displays the distribution of IPOs over our five-year sample period. In Panel A, we also provide the breakdown of IPOs by primary exchange listing, NYSE or NASDAQ. In Panel B, we provide the distribution of IPOs by industry where industry descriptions are based on two-digit SIC code. In Panel C, we provide summary statistics of the firm-related offering characteristics such as offer price, shares offered, share proceeds, firm age, underwriter reputation, expenses, and initial returns. Offering characteristics are obtained via NASDAQ and CRSP. Underwriter rank is obtained from the Carter and Manaster (1990) index.

Panel A. Distribution by Year and Primary Exchange

Year	*N*	*NYSE*	*NASDAQ*
2012	78	36	42
2013	113	46	67
2014	127	41	86
2015	80	22	58
2016	53	13	40
Total	451	158	293

Panel B. IPO Distribution by Industry

Industry name	*SIC Codes*	*N*
Oil and Gas	13	14
Food products	20	6
Chemical products	28	157
Manufacturing	30-34	5
Computer equipment & services	35, 73	118
Electronic equipment & services	36	22
Scientific instruments	38	21
Wholesale and retail trade	50-59	49
Entertainment services	70, 78, 79	12
Health services	80	10
All Others	10, 21-27, 29, 37	37
Total		451

Panel C. Offering Characteristics

	Mean	*Std*	*Q1*	*Median*	*Q3*
Offer Price ($)	14.58	5.62	11.00	15.00	18.00
Shares Offered ($M)	12.66	31.03	5.00	7.00	11.36
Offer Proceeds ($M)	235.60	923.51	64.00	95.40	172.50
Firm Age	17.61	21.42	7.00	10.00	18.00
Underwriter Rank	7.93	2.15	8.00	8.50	9.00
Firm Size (Ln)	13.00	1.14	12.15	12.95	13.77
Expenses ($M)	3.61	1.92	2.50	3.21	4.10
Offer_Close (%)	18.90%	30.66%	0.00%	10.00%	28.75%
Offer_Open (%)	17.11%	24.26%	0.67%	9.33%	26.20%
Open_Close (%)	1.43%	13.61%	-4.68%	0.00%	5.88%

APPENDIX 3: OFFERING DAY TRADING STATISTICS BY UNDERPRICING

Table 3: Offering Day Trading Statistics by Underpricing

This table provides the summary statistics and differences for offering day trading activity for our sample of IPOs sorted into quartiles via the level of initial underpricing. IPOs that experience the least (most) offering day underpricing are classified in the cold (hot) IPO quartile. In Panel A, we report the IPO offering characteristics. In Panel B, we report measures of dark and hidden trading. In Panel C, we report measures of lit fragmentation and algorithmic trading. Measures of hidden and algorithmic trading are obtained from MIDAS. Measures of dark trading are obtained through TAQ. The last column reports the differences in trading statistics between firms in the most underpriced quartile ("hot") and least underpriced quartile ("cold"). T-tests are conducted to confirm differences among the group means. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

	Cold IPOs (N=125)	*Cool IPOs (N=101)*	*Warm IPOs (N=112)*	*Hot IPOs (N=113)*	*Hot - Cold IPOs*
Panel A. IPO Offering Characteristics					
Number of IPOs	125	101	112	113	
Offer Price	$12.24	$14.47	$15.22	$16.62	
Offer Amount	$144,185,667	$476,454,310	$199,911,854	$156,805,468	
Offer_Close Return	-6.21%	3.81%	18.69%	60.37%	
Open_Close Return	-5.18%	-2.31%	4.41%	9.14%	
Offer_Open Return	-0.74%	6.74%	15.32%	47.89%	
Float	36.22%	35.48%	35.62%	29.95%	
Offer Turnover (%)	48.01	47.44	61.63	96.31	
Turnover (%)	16.93	16.42	19.54	30.43	
DailyRange (%)	10.96%	10.00%	11.31%	15.83%	
Panel. B Dark and Hidden Trading					
Hidden-to-Trade	23.43%	24.10%	24.45%	26.00%	3.77***
Hidden-to-Volume	18.50%	18.81%	17.39%	18.52%	1.31
Dark-to-Trade	25.47%	25.92%	28.70%	29.19%	4.47***
Dark-to-Volume	22.19%	24.95%	27.07%	29.05%	5.67***
Hidden Size	259.34	246.39	195.23	171.29	8.45***
Dark Size	304.24	457.26	254.37	237.74	3.63***
Panel C. Fragmentation and Algorithmic Trading					
LitFrag	63.91	66.95	70.49	72.67	7.84***
Odd-to-Trade	7.96%	8.94%	11.09%	15.25%	11.96***
Odd-to-Volume	1.54%	1.96%	2.80%	3.91%	13.22***
Trade-to-Order	16.90%	16.32%	15.30%	13.72%	5.71***
Cancel-to-Trade	5.81	6.23	6.40	7.18	2.45**
Trade Size	256.09	232.14	193.67	175.67	10.48***

APPENDIX 4: LIT FRAGMENTATION IN THE IPO SECONDARY MARKET

Table 4: Lit Fragmentation in the IPO Secondary Market

This table reports the trend analysis showing how lit fragmentation changes in the first 60 days of the IPO secondary market. We also report how measures of lit fragmentation vary across IPOs sorted into quartiles via the level of initial underpricing where the most (least) underpriced IPOs are referred to as "hot" ("cold"). In Panel A, we report the estimates of lit fragmentation for each of the first trading days and then for every other fifth day in the IPO secondary market in the first 30 days following the offering. We report days 31 through 60 as a composite average. In Panel B, we provide differences and t-statistics showing the differences in lit fragmentation across the later time periods relative to the offering date. Lit fragmentation is calculated via an inverted Herfindahl-Hirschman Index using trading volumes reported on each exchange from MIDAS. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

	Cold IPOs (N=125)	*Cool IPOs (N=101)*	*Warm IPOs (N=112)*	*Hot IPOs (N=113)*	*All IPOs (N=451)*	*Hot - Cold IPOs*
Panel A. Lit Fragmentation						
Day 1	63.91	66.95	70.49	72.67	68.42	8.76***
Day 2	65.25	67.85	72.72	75.06	70.19	9.80***
Day 3	65.28	66.53	73.34	75.40	70.21	10.13***
Day 4	62.38	65.30	73.41	75.57	69.06	13.20***
Day 5	64.48	67.03	72.25	75.05	69.66	10.57***
Day 10	65.68	68.63	70.17	74.00	69.59	8.32***
Day 15	63.84	67.33	71.16	72.41	68.65	8.57***
Day 20	66.64	68.53	72.18	74.10	70.37	7.47***
Day 25	68.66	72.53	72.32	74.09	71.83	5.44***
Day 30	70.64	70.79	73.03	73.70	72.07	3.03**
Day 31-60	69.91	71.71	73.11	74.90	72.42	4.98***
Panel B. Comparing Early IPO Secondary Market with the Remaining Weeks						
Day 1 vs.	-0.57	-0.08	-1.76	-2.38	-1.24	
Day 5	(0.35)	(0.03)	(1.52)	(2.23)**	(1.52)	
Day 1 vs.	-1.17	-1.68	-0.32	-1.33	-1.16	
Day 10	(0.96)	(0.84)	(0.23)	(1.30)	(1.41)	
Day 1 vs.	-2.73	-1.58	-1.69	-1.43	-1.95	
Day 20	(1.58)	(0.84)	(1.50)	(1.53)	(2.58)**	
Day 1 vs.	-6.00	-4.76	-2.62	-2.22	-4.00	
Days 31-60	(5.20)***	(3.94)***	(2.95)***	(3.06)***	(8.54)***	

APPENDIX 5: LIT FRAGMENTATION AND IPO UNDERPRICING

Table 5: Lit Fragmentation and IPO Underpricing

This table reports the results from estimating a fixed-effects regression equation for our sample of IPO firms on their respective offering date where the dependent variable, $LitFrag_i$ is calculated as one minus a Herfindahl-Hirschman Index using trading volumes reported on each exchange from MIDAS. The main independent variable in both regression specifications is the level of IPO underpricing, using either the continuous measure, $Underpricing_i$ or dummy variable measure, $WarmIPO_i$. Controls related to the IPO firm's size, firm age, price support, and underwriter ranking are included in the specification. We also include controls related to the IPO firm's trading volume, relative tick size (inverse price), and number of competing markets on the offering date. We further include both IPO year and industry fixed-effects. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	*Lit Fragmentation*	
	[1]	[2]
Underpricing	0.0245***	
	(4.01)	
Warm IPO		0.0250***
		(4.43)
Firm Size	0.0131***	0.0144***
	(3.72)	(4.45)
Volume	-0.0018	-0.0003
	(1.07)	(0.16)
Inverse Price	-0.6887***	-0.6994***
	(7.14)	(7.42)
Market_Competition	0.0251***	0.0304***
	(8.23)	(10.30)
Firm Age	0.0021	0.0065**
	(0.60)	(2.21)
Price Support	-0.0186*	-0.0310***
	(1.84)	(2.94)
Underwriter	0.0019	0.0021*
	(1.48)	(1.77)
Intercept	0.2446***	0.2003***
	(5.32)	(2.94)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Adjusted R^2	24.06%	32.11%

APPENDIX 6: DARK AND HIDDEN TRADING IN THE IPO SECONDARY MARKET

Table 6: Dark and Hidden Trading in the IPO Secondary Market

This table reports the trend analysis showing how measures of dark and hidden trading change in the first 60 days of the IPO secondary market. In Panel A, we report the estimates of dark and hidden trading for each of the first trading days and then for every other fifth day in the IPO secondary market in the first 30 days following the offering. We report days 31 through 60 as a composite average. In Panel B, we provide differences and t-statistics showing differences in dark and hidden trading across the later time periods relative to the offering date. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

	Dark-to-Trade	*Dark-to-Volume*	*Hidden-to-Trade*	*Hidden-to-Volume*
Panel A. Estimates of Dark, Hidden, and Fragmented Trading				
Day 1	27.30%	25.74%	33.42%	33.81%
Day 2	34.54%	40.84%	27.93%	31.51%
Day 3	37.29%	45.52%	27.20%	30.63%
Day 4	37.55%	45.86%	27.27%	31.31%
Day 5	39.85%	49.32%	27.17%	31.63%
Day 10	41.38%	52.47%	25.93%	28.51%
Day 15	40.55%	50.39%	26.10%	28.19%
Day 20	39.26%	50.03%	25.96%	28.59%
Day 25	38.81%	48.68%	26.71%	27.65%
Day 30	37.15%	47.89%	25.36%	26.62%
Day 31-60	35.08%	44.86%	24.40%	25.94%
Panel B. Comparing Early IPO Secondary Market with the Remaining Weeks				
Day 1 vs.	-12.55%	-23.58%	6.25%	2.18%
Day 5	(20.21)***	(26.77)***	(8.36)***	(2.44)**
Day 1 vs.	-14.08%	-26.73%	7.49%	5.30%
Day 10	(22.07)***	(31.01)***	(10.08)***	(6.14)***
Day 1 vs.	-11.95%	-24.29%	7.46%	5.22%
Day 20	(19.36)***	(27.82)***	(9.76)***	(5.98)***
Day 1 vs.	-7.78%	-19.12%	9.02%	7.87%
Days 31-60	(23.22)***	(28.58)***	(16.58)***	(13.23)***

APPENDIX 7: DARK AND HIDDEN TRADING AND IPO UNDERPRICING

Table 7: Dark and Hidden Trading and IPO Underpricing

This table reports the results from estimating a fixed-effects regression equation for our sample of IPO firms on their respective offering date where the dependent variable in columns (1) through (4) is a measure of dark trading using a ratio of dark trading to overall trading via volume or number of trades. The dependent variable in columns (5) through (8) is a measure of hidden trading using a ratio of hidden trading to overall trading via volume or number of trades. The main independent variable is underpricing measured via the natural log underpricing, Underpricing, or a dummy variable, Warm IPO, taking the value of 1 if the IPO is in the top quartile of underpriced IPOs. Year and industry fixed-effects are included. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	*Dark-to-Volume*		*Dark-to-Trade*		*Hidden-to-Volume*		*Hidden-to-Trade*	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Underpricing	0.1059***		0.0328**		0.0709***		0.0902***	
	(4.27)		(1.97)		(2.62)		(4.71)	
Warm IPO		0.0423***		0.0190**		0.0200		0.0219**
		(3.75)		(2.54)		(1.62)		(2.47)
Firm Size	0.0068	0.0073	0.0029	0.0031	-0.0158**	-0.0156**	-0.0250***	-0.0247***
	(1.01)	(1.08)	(0.64)	(0.69)	(2.16)	(2.11)	(4.81)	(4.67)
Volume	-0.0279***	-0.0268***	-0.0117***	-0.0113***	-0.0039	-0.0033	0.0124***	0.0131***
	(5.24)	(5.02)	(3.29)	(3.19)	(0.67)	(0.57)	(3.03)	(3.14)
Inverse Price	0.1325	0.0357	-0.1376	-0.1312	-0.5693***	-0.6850***	-0.5209***	-0.6897***
	(0.72)	(0.20)	(1.12)	(1.11)	(2.84)	(3.52)	(3.68)	(4.94)
Market_Competition	0.0067	0.0065	0.0012	0.0012	-0.0268***	-0.0270***	-0.0199***	-0.0202***
	(1.09)	(1.05)	(0.29)	(0.28)	(3.99)	(4.00)	(4.18)	(4.16)
Firm Age	-0.0046	-0.0054	0.0028	0.0029	0.0089	0.0079	-0.0010	-0.0025
	(0.75)	(0.88)	(0.69)	(0.72)	(1.33)	(1.18)	(0.21)	(0.52)
Price Support	-0.0306***	-0.0310***	-0.0292***	-0.0280***	0.0372***	0.0351***	-0.0102	-0.0136
	(2.93)	(2.94)	(4.17)	(3.99)	(3.26)	(3.05)	(1.26)	(1.65)
Underwriter	-0.0013	-0.0018	0.0004	0.0003	0.0042	0.0038	0.0003	-0.0006
	(0.57)	(0.77)	(0.24)	(0.20)	(1.63)	(1.47)	(0.00)	(0.32)
Intercept	0.3725***	0.3804***	0.2957***	0.2918***	0.8791***	0.8933***	0.7725***	0.7943***
	(2.96)	(3.00)	(3.50)	(3.47)	(6.40)	(6.47)	(7.94)	(8.01)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	26.87%	26.13%	29.17%	29.61%	34.83%	34.15%	53.75%	51.92%
No. of Obs	451	451	451	451	451	451	451	451

APPENDIX 8: ALGORITHMIC TRADING IN THE IPO SECONDARY MARKET

Table 8: Algorithmic Trading in the IPO Secondary Market

This table reports the trend analysis showing how measures of algorithmic trading change in the first 60 days of the IPO secondary market. In Panel A, we report the estimates of algorithmic trading for each of the first trading days and then for every other fifth day in the IPO secondary market in the first 30 days following the offering. We report days 31 through 60 as a composite average. In Panel B, we provide differences and t-statistics showing differences in algorithmic trading across the later time periods relative to the offering date. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

	Odd-to-Trade	*Trade-to-Order*	*Cancel-to-Trade*	*Trade Size*
Panel A. Estimates of Algorithmic Trading				
Day 1	10.78%	15.58%	6.36	215.08
Day 2	14.98%	13.59%	8.01	180.32
Day 3	15.77%	11.54%	11.91	173.76
Day 4	16.62%	9.92%	14.76	168.65
Day 5	16.98%	7.26%	21.74	167.19
Day 10	18.12%	6.10%	24.34	152.61
Day 15	18.20%	6.16%	24.51	142.23
Day 20	19.73%	6.14%	25.09	143.70
Day 25	22.22%	5.37%	25.14	129.79
Day 30	22.96%	5.46%	24.67	127.61
Day 31-60	25.95%	4.83%	25.21	117.97
Panel B. Comparing Early IPO Secondary Market with the Remaining Weeks				
Day 1 vs.	-6.21%	8.32%	-15.34	47.89
Day 5	(11.55)***	(24.29)***	(12.06)***	(9.86)***
Day 1 vs.	-7.34%	9.48%	-17.94	62.47
Day 10	(12.11)***	(29.92)***	(14.14)***	(14.47)***
Day 1 vs.	-8.95%	9.44%	-18.69	71.38
Day 20	(13.52)***	(30.35)***	(13.81)***	(15.89)***
Day 1 vs.	-15.17%	10.75%	18.81	97.10
Days 31-60	(23.46)***	(50.11)***	(16.41)***	(28.85)***

APPENDIX 9: ALGORITHMIC TRADING AND IPO UNDERPRICING

Table 9: Algorithmic Trading and IPO Underpricing

This table reports the regression results where the dependent variable is a measure of algorithmic trading. In columns (1) and (2), the dependent variable is the *Odd-to-Trade* ratio. In columns (3) and (4), the *Trade-to-Order* serves as the dependent variable. In columns (5) and (6), the *Cancel-to-Trade* ratio serves as the dependent variable. In columns (7) and (8), *Trade Size* is the dependent variable. The main independent variable in all the regressions is our measure of underpricing captured via the natural log of one plus underpricing, Underpricing, or a dummy variable, Warm IPO, taking the value of 1 if the IPO is in the top quartile of underpriced IPOs. Controls included firm size, return volatility, inverse price, market competition, firm age, price support dummy, and underwriter rank. Year and industry fixed-effects are included. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	*Odd-to-Trade*		*Trade-to-Order*		*Cancel-to-Trade*		*Trade Size*	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Underpricing	0.0954***		-0.0273**		0.9540		-0.1834***	
	(7.69)		(2.17)		(0.73)		(2.66)	
Warm IPO		0.0348***		-0.0151***		0.6801		-0.0610**
		(6.27)		(2.76)		(1.20)		(2.01)
Firm Size	-0.0021	-0.0011	0.0007	0.0004	-0.1354	-0.1213	0.0453***	0.0435***
	(0.72)	(0.39)	(0.25)	(0.14)	(0.45)	(0.41)	(2.86)	(2.74)
Volatility	0.0192***	0.0236***	0.0035	0.0032	0.3833	0.3639	-0.1079***	-0.1176***
	(4.84)	(6.01)	(0.86)	(0.82)	(0.92)	(0.90)	(4.89)	(5.49)
Inverse Price	-0.2755***	-0.3871***	0.1315	0.1310	-2.2857	-1.3153	3.5498***	3.8020***
	(3.14)	(4.52)	(1.48)	(1.55)	(0.25)	(0.15)	(7.29)	(8.14)
Market_Competition	-0.0101***	-0.0101***	-0.0070**	-0.0071**	0.4471	0.4532	0.0574***	0.0576***
	(3.68)	(3.62)	(2.51)	(2.55)	(1.56)	(1.58)	(3.77)	(3.77)
Firm Age	-0.0044	-0.0052*	0.0032	0.0031	-0.4964*	-0.4862	-0.0003	0.0015
	(1.53)	(1.77)	(1.09)	(1.07)	(1.66)	(1.63)	(0.02)	(0.10)
Price Support	-0.0048	-0.0047	0.0086*	0.0076	-0.2264	-0.1654	0.1261***	0.1271***
	(0.99)	(0.99)	(1.73)	(1.53)	(0.44)	(0.32)	(4.65)	(4.64)
Underwriter	-0.0003	-0.0007	0.0030***	0.0030***	-0.1305	-0.1300	-0.0107*	-0.0097
	(0.24)	(0.63)	(2.68)	(2.75)	(1.14)	(1.14)	(1.75)	(1.60)
Intercept	0.2960***	0.3232***	0.1274**	0.1279**	9.0302	8.7672	3.4938***	3.4320***
	(4.94)	(5.30)	(2.09)	(2.12)	(1.44)	(1.41)	(10.49)	(10.32)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	43.45%	40.91%	18.54%	19.12%	16.34%	16.53%	41.77%	41.33%
No. of Obs	451	451	451	451	451	451	451	451

APPENDIX 10: THE EFFECTS OF DARK, HIDDEN, AND LIT FRAGMENTATION ON IPO OFFERING DAY LIQUIDITY

Table 10: The Effects of Dark, Hidden, and Lit Fragmentation on IPO Offering Day Liquidity

This table reports the second-stage estimates where the dependent variable is one of our measures of market quality. In columns (1) through (3), the main independent variable is the $\widehat{Dark}$ ratio. In columns (4) through (6), the $\widehat{LitFrag}$ serves as the main independent variable. In columns (7) through (9), the $\widehat{Hidden}$ ratio serves as the main independent variable. $\widehat{Dark}$, $\widehat{LitFrag}$, and $\widehat{Hidden}$ are predicted values from a first-stage regression. Controls included firm size, return volatility, trading volume, underwriter rank, firm age, and underpricing. Year and industry fixed-effects are included. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

	Offering Day Market Quality								
Dependent Variable	Quoted Spread	Effective Spread	Price Impact	Quoted Spread	Effective Spread	Price Impact	Quoted Spread	Effective Spread	Price Impact
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
$\widehat{Dark}$	0.0026	-0.0003	0.0032						
	(0.99)	(0.12)	(1.02)						
$\widehat{LitFrag}$				-0.0074***	-0.0072***	-0.0048**			
				(3.90)	(3.40)	(2.16)			
$\widehat{Hidden}$							-0.0132**	-0.0170***	-0.0151**
							(2.51)	(2.77)	(2.40)
Ln(Mcap)	-0.0001	-0.0002	-0.0002	0.0009	-0.0002	-0.0001	-0.0002	-0.0003	-0.0003
	(0.74)	(1.08)	(1.27)	(0.57)	(0.11)	(0.45)	(1.00)	(1.50)	(1.43)
Ln(Volatility)	0.0029***	0.0022***	0.0025***	0.0031***	0.0024***	0.0027***	0.0032***	0.0026***	0.0029***
	(13.01)	(9.06)	(9.84)	(13.80)	(9.60)	(10.32)	(11.76)	(8.18)	(8.97)
Ln(Volume)	-0.0017***	-0.0013***	-0.0007***	-0.0018***	-0.0013***	-0.0008***	-0.0019***	-0.0014***	-0.0009***
	(10.43)	(7.26)	(3.58)	(13.96)	(9.11)	(5.36)	(12.33)	(8.05)	(5.08)
Underwriter	-0.0005***	-0.004***	-0.0000	-0.0004***	-0.0004***	0.0000	-0.0004***	-0.0004***	0.0001
	(8.10)	(6.80)	(0.12)	(7.50)	(6.18)	(0.17)	(5.77)	(4.27)	(0.79)
Ln(1+Age)	0.0000	0.0002	0.0001	0.0001	0.0002	0.0001	0.0001	0.0003	0.0002
	(0.29)	(1.06)	(0.55)	(0.53)	(1.29)	(0.67)	(0.55)	(1.26)	(0.76)
Ln(Underpricing)	-0.0003	-0.0007	-0.0008	0.0004	-0.0004	-0.0002	0.0008	0.0003	0.0005
	(0.43)	(0.96)	(0.99)	(0.63)	(0.56)	(0.25)	(1.12)	(0.39)	(0.60)
Constant	0.0418***	0.0368***	0.0241***	0.0432***	0.0372***	0.0256***	0.0523***	0.0491***	0.0363***
	(10.17)	(8.07)	(4.97)	(10.87)	(8.36)	(5.46)	(8.89)	(7.14)	(5.13)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.6915	0.5501	0.3662	0.6958	0.5502	0.3767	0.6148	0.3779	0.1768

APPENDIX 11: THE EFFECTS OF ALGORITHMIC TRADING ON IPO OFFERING DAY LIQUIDITY

Table 11: The Effects of Algorithmic Trading on IPO Offering Day Liquidity

This table reports the second-stage estimates where the dependent variable is one of our measures of market quality. In columns (1) through (3), the main independent variable is the $\widehat{Odd\text{-}to\text{-}Trade}$ ratio. In columns (4) through (6), the $\widehat{Cancel\text{-}to\text{-}Trade}$ serves as the main independent variable. In columns (7) through (9), the inverse $\widehat{Trade\text{-}to\text{-}Order}$^ ratio serves as the main independent variable. $\widehat{Odd\text{-}to\text{-}Trade}$, $\widehat{Cancel\text{-}to\text{-}Trade}$, and $\widehat{Trade\text{-}to\text{-}Order}$^are predicted values from a first-stage regression. Controls included firm size, return volatility, trading volume, underwriter rank, firm age, and underpricing. Year and industry fixed-effects are included. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	Quoted Spread	Effective Spread	Price Impact	Quoted Spread	Effective Spread	Price Impact	Quoted Spread	Effective Spread	Price Impact
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
$\widehat{Odd\text{-}to\text{-}Trade}$	-0.0242***	-0.0305***	-0.0263***						
	(2.82)	(3.21)	(2.76)						
$\widehat{Cancel\text{-}to\text{-}Trade}$				-0.0007***	-0.0007**	-0.0002			
				(2.68)	(2.52)	(1.08)			
$\widehat{Trade\text{-}to\text{-}Order}$^							-0.0410***	-0.0399***	-0.0190*
							(4.28)	(3.89)	(1.91)
Ln(Mcap)	0.0001	0.00002	-0.0000	0.0003	0.0002	-0.0007	0.0004*	0.0003	0.0003
	(0.47)	(0.13)	(0.05)	(1.17)	(0.73)	(0.29)	(1.91)	(1.27)	(0.14)
Ln(Volatility)	0.0034***	0.0028***	0.0031***	0.0034***	0.0027***	0.0027***	0.0029***	0.0022***	0.0026***
	(11.08)	(8.39)	(9.21)	(8.99)	(6.87)	(9.00)	(11.29)	(8.10)	(9.70)
Ln(Volume)^%	-0.0020***	-0.0016***	-0.0011***	-0.0024***	-0.0019***	-0.0010***	-0.0024***	-0.0019***	-0.0011***
	(11.46)	(8.27)	(5.54)	(7.69)	(5.87)	(3.94)	(11.46)	(8.43)	(4.99)
Underwriter	-0.0005***	-0.0004***	0.0000	-0.0005***	-0.0005***	-0.0000	-0.0005***	-0.0005***	-0.0000
	(6.83)	(5.64)	(0.11)	(5.70)	(5.08)	(0.28)	(7.67)	(6.68)	(0.55)
Ln(1+Age)	-0.0001	0.0001	-0.0001	-0.002	-0.0001	0.0000	0.0000	0.0001	0.0001
	(0.33)	(0.29)	(0.07)	(0.83)	(0.23)	(0.07)	(0.01)	(0.72)	(0.40)
Ln(Underpricing)	0.0028**	0.0027**	0.0026**	0.0006	-0.0001	-0.0002	0.0015*	0.0007	0.00027
	(2.33)	(2.10)	(1.96)	(0.66)	(0.15)	(0.30)	(1.91)	(0.84)	(0.33)
Constant	0.0457***	0.0404***	0.0284***	0.0484***	0.0423***	0.0271***	0.0339***	0.0281***	0.0212***
	(9.74)	(7.79)	(5.47)	(7.61)	(6.38)	(5.25)	(6.60)	(5.11)	(3.97)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.5968	0.4165	0.2671	0.3056	0.1082	0.3248	0.5734	0.4225	0.3211

APPENDIX 12: THE EFFECTS OF DARK, HIDDEN, AND LIT FRAGMENTATION ON EXTENDED IPO AFTERMARKET LIQUIDITY

Table 12: The Effects of Dark, Hidden, and Lit Fragmentation on Extended IPO Aftermarket Liquidity

This table reports the second-stage estimates where the dependent variable is one of our measures of market quality. In columns (1) through (3), the main independent variable is the $\widehat{Dark}$ ratio. In columns (4) through (6), the $\widehat{LitFrag}$ serves as the main independent variable. In columns (7) through (9), the $\widehat{Hidden}$ ratio serves as the main independent variable. $\widehat{Dark}$, $\widehat{LitFrag}$, and $\widehat{Hidden}$ are predicted values from a first-stage regression. Controls included firm size, return volatility, trading volume, underwriter rank, firm age, and underpricing. Year, industry, and firm fixed-effects are included. Standard errors are clustered at the firm-level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	Quoted Spread	Effective Spread	Price Impact	Quoted Spread	Effective Spread	Price Impact	Quoted Spread	Effective Spread	Price Impact
Panel A. Week 1									
$\widehat{Dark}$	0.0045*	0.0032**	0.0030**						
	(1.75)	(2.24)	(2.45)						
$\widehat{LitFrag}$				-0.0038	-0.0029	0.0003			
				(1.15)	(1.12)	(0.13)			
$\widehat{Hidden}$							0.0132	0.0107	0.0020
							(1.52)	(1.48)	(0.35)
Panel B. Weeks 2 – 5									
$\widehat{Dark}$	0.0047***	0.0057***	0.0007						
	(3.01)	(3.08)	(1.00)						
$\widehat{LitFrag}$				-0.0053**	-0.0038**	0.0008			
				(2.39)	(2.51)	(0.64)			
$\widehat{Hidden}$							-0.0056	-0.0026	0.0014
							(0.84)	(0.47)	(0.41)
Panel C. Weeks 6 – 10									
$\widehat{Dark}$	0.0036***	0.0035***	-0.0002						
	(3.35)	(4.83)	(0.48)						
$\widehat{LitFrag}$				-0.0126***	-0.0077***	-0.0046**			
				(3.35)	(3.04)	(2.48)			
$\widehat{Hidden}$							0.0457***	0.0322***	0.0141***
							(4.37)	(4.44)	(3.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 13: THE EFFECTS OF ALGORITHMIC TRADING ON EXTENDED IPO AFTERMARKET LIQUIDITY

Table 13: The Effects of Algorithmic Trading on Extended IPO Aftermarket Liquidity

This table reports the second-stage estimates where the dependent variable is one of our measures of market quality. In columns (1) through (3), the main independent variable is the $\widehat{\textit{Odd-to-Trade}}$ ratio. In columns (4) through (6), the $\widehat{\textit{Cancel-to-Trade}}$ serves as the main independent variable. In columns (7) through (9), the inverse $\widehat{\textit{Trade-to-Order}}$^ ratio serves as the main independent variable. $\widehat{\textit{Odd-to-Trade}}$, $\widehat{\textit{Cancel-to-Trade}}$, and $\widehat{\textit{Trade-to-Order}}$^ are predicted values from a first-stage regression. Controls included firm size, return volatility, trading volume, underwriter rank, firm age, and underpricing. Year, industry, and firm fixed-effects are included. Standard errors are clustered at the firm-level. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Dependent Variable	Quoted Spread	Effective Spread	Price Impact	Quoted Spread	Effective Spread	Price Impact	Quoted Spread	Effective Spread	Price Impact
				Panel A. Week 1					
$\widehat{\textit{Odd-to-Trade}}$	-0.0082	-0.0045	-0.0003						
	(1.16)	(0.84)	(0.06)						
$\widehat{\textit{Cancel-to-Trade}}$				-0.0001	-0.0001**	0.0000			
				(1.02)	(2.19)	(0.76)			
$\widehat{\textit{Trade-to-Order}}$^							-0.0001	-0.0001**	0.0000
							(1.58)	(2.15)	(0.44)
				Panel B. Weeks 2 – 5					
$\widehat{\textit{Odd-to-Trade}}$	-0.0030	-0.0001	-0.0002						
	(1.50)	(0.08)	(0.15)						
$\widehat{\textit{Cancel-to-Trade}}$				-0.0001	0.0000	0.0001**			
				(0.94)	(0.37)	(1.99)			
$\widehat{\textit{Trade-to-Order}}$^							0.0000	0.0000	0.0000
							(1.41)	(0.67)	(0.67)
				Panel C. Weeks 6 – 10					
$\widehat{\textit{Odd-to-Trade}}$	-0.0041***	-0.0025**	-0.0016**						
	(2.65)	(2.45)	(2.15)						
$\widehat{\textit{Cancel-to-Trade}}$				0.0002***	0.0001***	0.0001***			
				(3.34)	(2.96)	(2.86)			
$\widehat{\textit{Trade-to-Order}}$^							-0.0000**	-0.0000**	-0.0000**
							(2.41)	(2.24)	(2.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

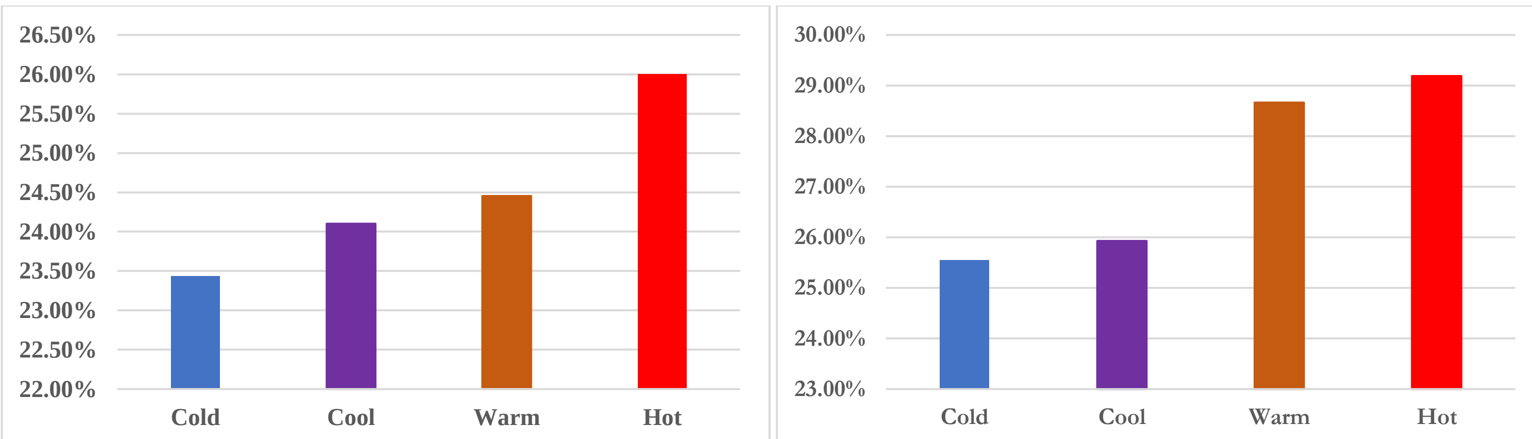
APPENDIX 14: HIDDEN AND DARK TRADING ON THE OFFERING DATE SORTED BY UNDERPRICING

Figure 1: Hidden and Dark Trading on the Offering Date Sorted by Underpricing

Figure 1 provides the level of hidden and dark trading on offering date for our sample of IPOs. Panel A provides the proportion of executed hidden trades to all executed trades on the offering date, sorted by underpricing quartiles. Panel B provides the proportion of executed dark or off-exchange trades to all executed trades on the offering date, sorted by underpricing quartiles. IPOs that experience the least (most) offering day underpricing are classified in the cold (hot) IPO quartile.

Panel A. Hidden-to-Trade

Panel B. Dark-to-Trade

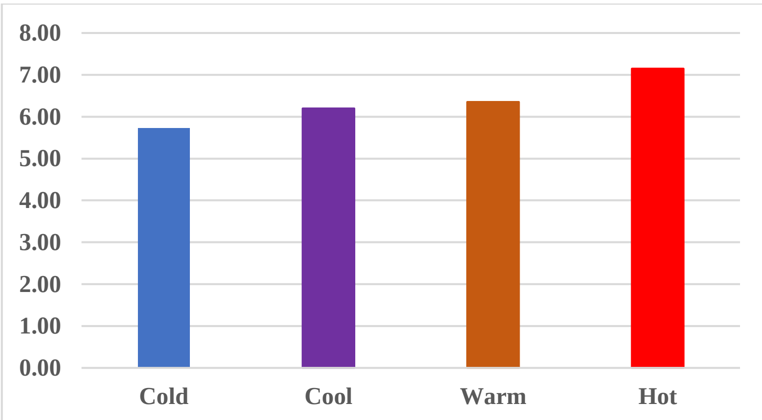


APPENDIX 15: FRAGMENTATION AND ALGORITHMIC TRADING ON THE OFFERING DATE BY UNDERPRICING

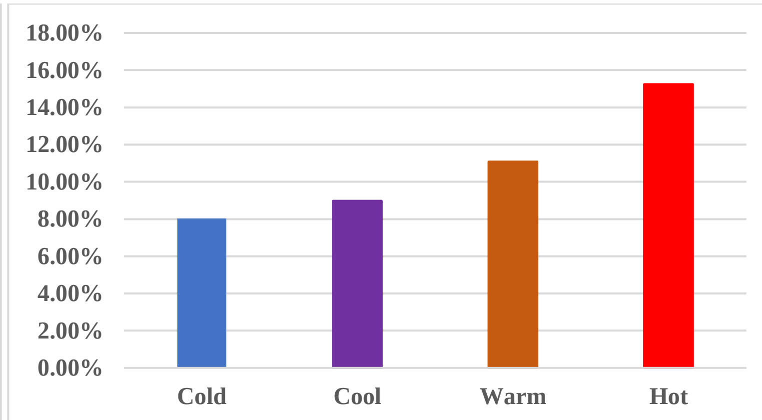
Figure 2: Fragmentation and Algorithmic Trading by Underpricing

Figure 2 reports the measures of lit fragmentation and three measures of algorithmic trading (trade size omitted). The visuals provided in Figure 2 reference the initial day trading statistics provided in Table 3. Results are reported for our sample of IPOs sorted into quartiles via the level of initial underpricing where "cold" ("hot) refer to the least (most) underpriced IPOs. Our measures of hidden, algorithmic trading, and lit fragmentation are obtained from MIDAS. Our measure of dark trading is calculated using TAQ data.

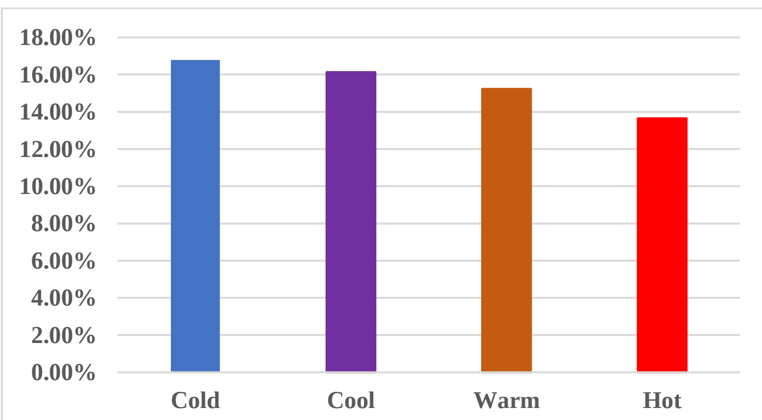
Panel A. Lit Fragmentation



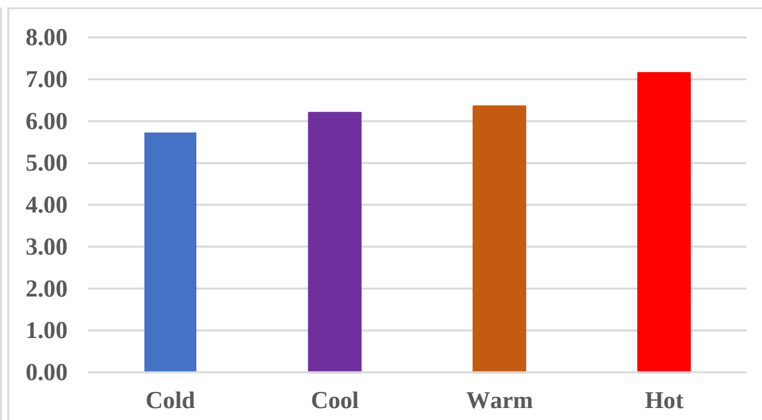
Panel B. Odd-to-Trade



Panel C. Trade-to-Order



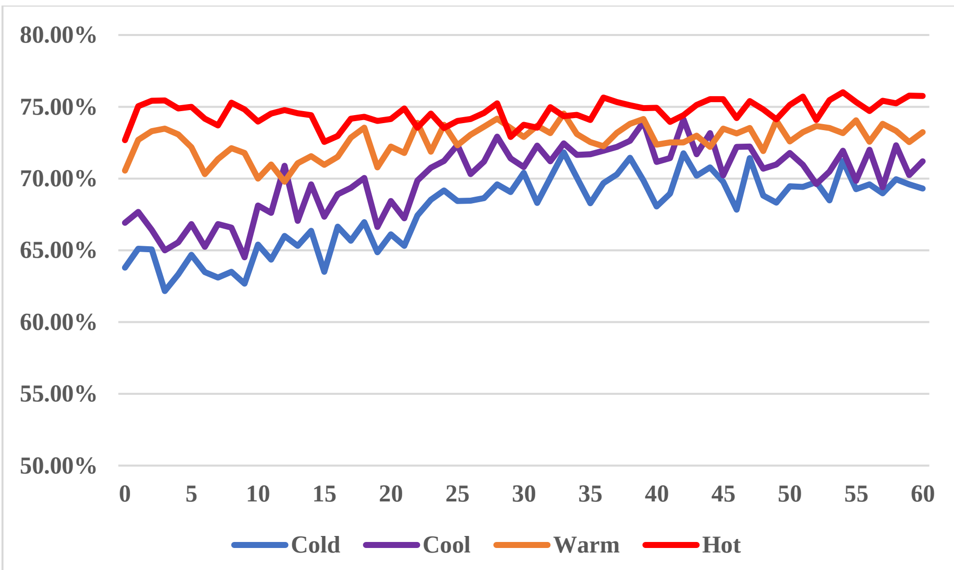
Panel D. Cancel-to-Trade



APPENDIX 16: LIT FRAGMENTATION AND THE IPO SECONDARY MARKET

Figure 3: Lit Fragmentation and the IPO Secondary Market

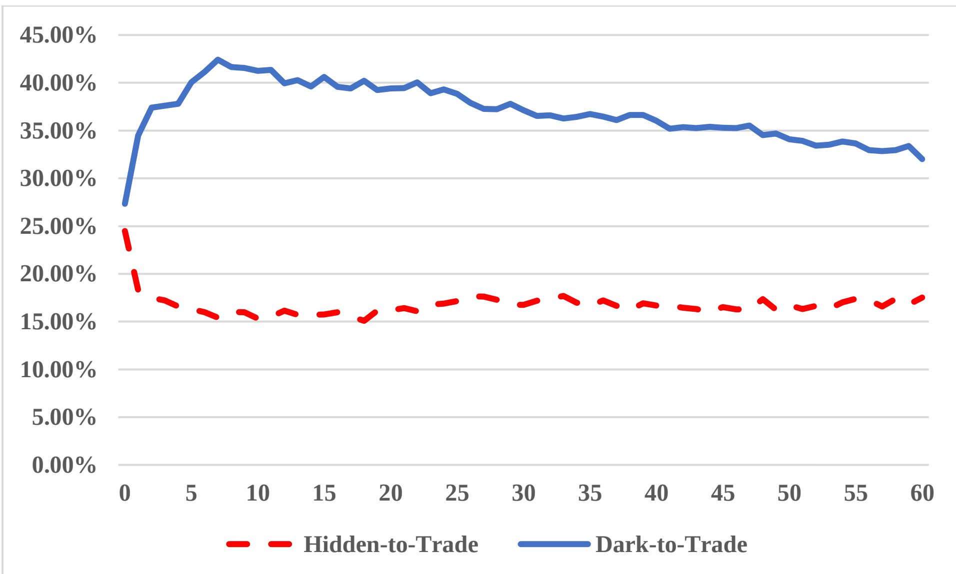
This figure shows the level of lit fragmentation in the first 60 trading days following the offering date. Results are reported as the average level of lit fragmentation for the group of IPOs within each quartile, formed via the level of initial underpricing. IPOs that experience the least (most) offering day underpricing are classified in the cold (hot) IPO quartile. Our measure of lit fragmentation is calculated via a an inverted Herfindahl-Hirschman Index using trading volumes reported for each exchange within MIDAS.



APPENDIX 17: HIDDEN AND DARK TRADING AND THE IPO SECONDARY MARKET

Figure 4: Hidden and Dark Trading and the IPO Secondary Market

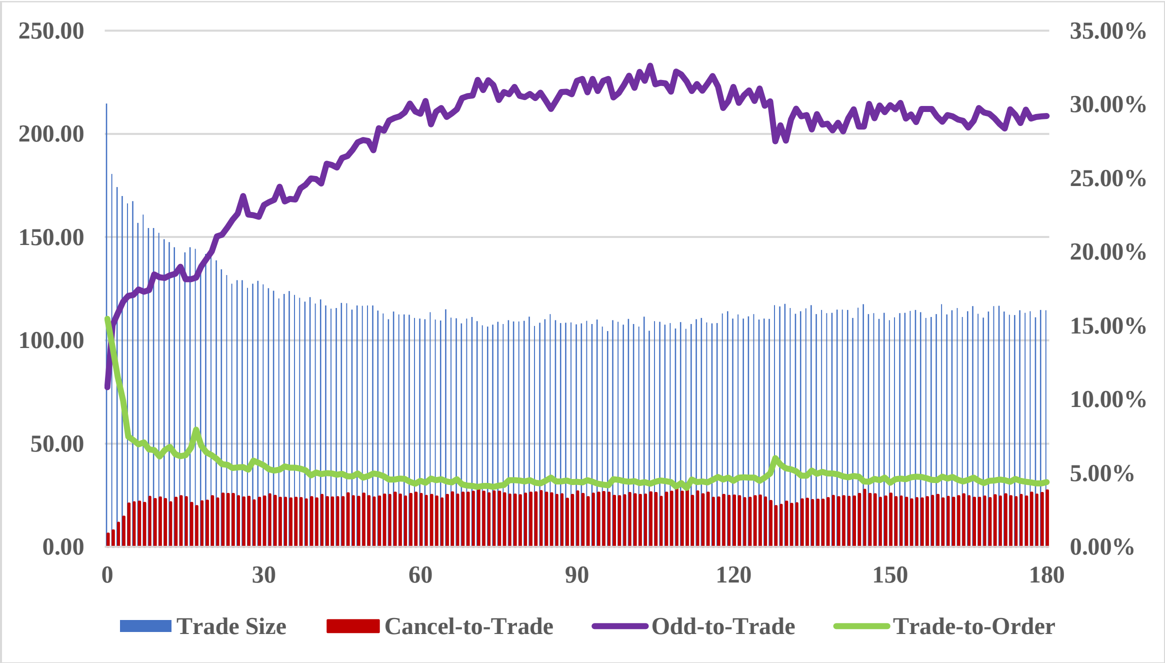
This figure reports the trend analysis between measures of hidden and dark trading for all IPOs in the first 60 days following the offering date. The solid (dashed) line denotes the level of dark (hidden) trading. Our measure of hidden (dark) trading is obtained from MIDAS (TAQ).



APPENDIX 18: ALGORITHMIC TRADING AND THE IPO SECONDARY MARKET

Figure 5: Algorithmic Trading and the IPO Secondary Market

This figure reports the trend analysis for the four measures of algorithmic trading for all IPOs in the first 180 days following the offering date. All measures are obtained via MIDAS.



PART 2: WHERE DOES EX-DIVIDEND TRADING OCCUR: A PECKING ORDER OF TRADING VENUES EXPLANATION OF DIVIDEND CAPTURE

I. INTRODUCTION

Dividend capture is the trading practice where traders buy the stock cum-dividend and sell the stock ex-dividend in attempt to capture the dividend income. Recently, Henry and Koski (2017) and Mortal, Paudel, and Silveri (2017) suggest that trading costs are relevant for ex-dividend trading. Henri and Koski posit that more skilled institutions – those better at obtaining lower execution costs, are more profitable than lesser-skilled institutions in capturing dividends. Mortal, Paudel, and Silveri examine if market frictions such as transaction costs impact price efficiency around the ex-dividend date. Mortal, Paudel, and Silveri account for both structural and regulatory changes that reduce transaction costs and improve price efficiency on the NASDAQ exchange. They also analyze the impact of market structure changes associated with the NASDAQ on the ex-dividend price-drop ratio (PDR), the ratio of the stock price change on the ex-dividend day relative to the distributed dividend amount, and find a decline in price-drop ratios for NASDAQ-listed stocks. Their findings indicate that both transactions costs and market structure affect the level of ex-dividend day activity.

To the extent transaction costs and market structure impact ex-dividend activity, we analyze if traders have a trading venue preference in capturing dividends. If waiting costs, order aggressiveness, and transaction costs determine the level of traders engaging in dividend-capture, then we expect changes in trading venue market share around the ex-dividend date. For example, if waiting costs associated with limit order queues increase on cum-dividend days, as suggested by Ainsworth and Lee (2014), then traders have incentives to bypass limit order queues to capture the dividend. Two trading venues in the current market structure allow traders to bypass the queue and become more aggressive in capturing the dividend: taker-maker and dark trading venues.

Currently, trading venues operate via two fee-and-rebate models: maker-taker and taker-maker. Maker-taker venues provide rebates to limit order submissions (i.e., liquidity suppliers) and charge fees to market order submissions (i.e., liquidity demanders). The maker-taker fee model is currently offered by 8 of the 13 U.S. exchanges (Comerton-Forde, Gregoire, and Zhang, 2018). Taker-maker venues are trading venues that enable traders to earn rebates on market order submissions and pay fees on limit order submissions. The taker-maker model effectively allows traders to bypass limit order queues by submitting aggressive market orders, providing traders rebates despite crossing the spread. As for limit order submissions on taker-maker venues, Comerton-Forde, Gregoire, and Zhong document that liquidity-supplying limit orders displayed on taker-maker venues will likely execute before limit orders submitted at the same price on maker-taker venues since the taker-maker fee model attracts a higher share of liquidity-taking market orders. Taker-maker models also attract aggressive liquidity-taking participants by providing faster and more certain execution at lower net trading costs. Currently three exchanges offer the taker-maker fee model (BATS-Y, BOSTON, and EDGA) and account for just under 15% (10%) of overall lit (total) market share.[8]

Dark trading venues are alternative trading platforms that allow subscribers to use anonymous, non-transparent orders that interact away from quoting exchanges (i.e., lit trading venues) at prices no worse than the current National Best Bid Offer (NBBO). Currently, over 30

[8] As of June 2018, the taker-maker venues account for 14.8% of the market share on "lit" trading venues. Including the trading activity of dark venues as part of the aggregate trading volume, the taker-maker venue accounts for 9.41%. Trading statistics for each exchange are provided at https://www.nasdaqtrader.com.

dark trading venues exists and together, account for over 30% of overall market share.[9] Trading in dark venues offers investors a tradeoff between better execution costs as well as pre-trade anonymity and higher execution risk. This tradeoff manifests since transacting in the dark requires the availability of a counterparty. Buti, Rindi, and Werner (2017) posit that longer waiting queues in the limit order book may trap market orders in the dark, forcing more aggressive traders to the dark venue. Zhu (2014) provides a theoretical model suggesting that liquidity orders in the dark face less execution risk as they are less correlated and less likely to cluster on one side of the book. Since dividend-capturing traders are trading for liquidity purposes as opposed to information signals, finding a counterparty is expected to be less problematic.

Our analysis centers around the limit order models developed by Foucault, Kadan, and Kandel (2005) and Rosu (2009), which suggest that patient (impatient) liquidity traders tend to submit limit (market) orders. Ainsworth and Lee (2014) argue that ex-dividend dates provide several advantages in testing the level of order aggressiveness and trading patience associated with these limit order models. First, the ex-dividend date is known in advance, providing a setting where liquidity traders instead of informed traders are more active. Second, the limit order models theorize that traders have subjective differences with regards to valuation, resulting in trading profits. As it relates to ex-dividend trading, the differential tax rates applied to income-seeking traders, not information, may affect valuation differences. Third, the ex-dividend date is likely to change the proportion of both patient and impatient traders, given the existence of dividend clienteles. Foucault, Kadan, and Kandel posit that the changes in the proportion of patient and impatient traders can impact market resiliency while Rosu argues that the change in

[9] Menkveld, Yueshen, and Zhu (2017) provide these trading statistics using data reported from Rosenblatt Securities.

the proportion of patient traders can result in overshooting prices and price impact. To the extent that the composition of patient and impatient traders adjusts around the ex-dividend date, both ex-day returns and price-drop ratios could change.

Consistent with Ainsworth and Lee (2014), we hypothesize that waiting costs will increase on the cum-dividend days and decrease on the ex-dividend day. The increases in waiting costs on the cum-dividend days will induce more competition from liquidity suppliers, increasing the limit order queue. This greater competition in the limit order book will also result in more aggressively-priced limit order submissions, and a reduction in the bid-ask spread consistent with the make-take phase model of Foucault, Kadan, and Kandel (2013). Once the trading deadline expires on the ex-dividend day, both waiting costs and aggressively-priced orders are expected to decrease, resulting in widening spreads. We hypothesize that the resulting increase in limit order competition and waiting costs on cum-dividend days will lead to more aggressive liquidity takers in the taker-maker venue due to the higher execution rates and the ability to use rebates to offset crossing the spread. Simultaneously, limit order traders (i.e., liquidity makers) can trade aggressively in taker-maker markets by simply paying the access fee and step in front on the limit order queue. Likewise, if the higher waiting costs and limit order competition narrows spreads in the cum-dividend days, then we expect less trading activity in maker-taker venues since the lower spreads marginalize liquidity supplier profits as well as execution rates. We also predict that dark trading venues provide aggressive traders another trading platform to bypass limit order queues in capturing dividends. To the extent that aggressive, liquidity traders increase their participation in the dark venue, counterparty risk will decrease, and fill rates in the dark venue will increase. Although our theoretical arguments suggest that both inverted, taker-maker venues and dark venues capture a larger share of cum-dividend trading, empirical evidence is warranted since both venues may also serve as substitutes for dividend-capturing traders.

We also analyze if retail traders increase their participation in dark venues to capture dividends. Broker-dealer dark pools are dark pools that allow brokers to facilitate retail customer orders in the dark venue. Buti, Rindi, and Werner (2017) document seven operating broker-dealer pools exist in the U.S, accounting for over 8% of equity volume in the U.S.[10] More importantly, dark venues may appeal to retail investors in obtaining cheaper execution costs in capturing the dividend. For example, SEC Rule 612 permits sub-penny pricing, which effectively allows brokers to jump in front of the NBBO by placing a slightly better offer, facilitating immediate execution (Comerton-Forde et al, 2018). This allows retail orders to avoid paying the penny spread since marketable orders are routed to off-exchange trading venues. Consistent with our earlier arguments that longer limit order queues, waiting costs, and transaction costs affect which trading venues obtain market share prior to the dividend, we expect that broker-dealers take advantage of sub-penny pricing opportunities in the dark venue, resulting in more retail trading and buying prior to the ex-dividend date.

If waiting costs, transaction costs, and order aggressiveness incentivize more trading in both taker-maker and dark trading venues on cum-dividend days, then we expect this relation to be more pronounced in stocks with higher transaction costs as both Kalay (1982) and Miller and Scholes (1982) suggest that transactions costs impact arbitragers seeking to profit around ex-dividend dates. Further, if stocks with higher dividend yields attract more liquidity traders then

[10] The numbers we cite are provided Buti, Rindi, and Warner (2017) and sourced from Rosenblatt Securities as of December 2012.

we expect more trading in taker-maker and dark trading venues than maker-taker venues prior to the ex-dividend date for those stocks.[11]

Using all ex-dividend dates for the universe of dividend-paying stocks in CRSP between January 2013 and September 2016, our findings indicate a significant increase in dark trading on cum-dividend days yet find a significant decrease in taker-maker trading on cum-dividend days, increasing once the stock trades ex-dividend. We suggest that the increase in taker-maker trading after the ex-dividend date is likely due to changes in spread constraints as the proportion of impatient and patient traders adjust. We also find that the decrease (increase) in taker-maker (dark) trading is more pronounced in stocks with higher dividend yields. This finding suggests that despite providing similar incentives to dividend-capturing traders, dark venues, not taker-maker venues, obtain a larger market share prior to the ex-dividend day. We argue this empirical finding supports the notion that these two venues, competing for order flow by offering investors away to bypass limit order queues and subvert sub-penny pricing restrictions, serve as substitutes.

This study contributes to multiple streams of literature. First, we contribute to the ex-dividend trading literature by providing evidence as to which trading venues are preferred by investors in capturing dividends.[12] Dubofksy (1992), Bali and Hite (1998), Frank and Jagannathan (1998), and Jakob and Ma (2004) document the importance of pricing grids and trading costs as determinants of ex-dividend trading activity, emphasizing the importance of market structure effects on ex-dividend day trading. We add to these studies by investigating if

[11] Rather than tests the effects of transaction costs and dividend yield separately, we suggest that a stock's dividend yield serves as an appropriate proxy for transaction costs. In unreported results, we find that spreads increase monotonically from low-yield stocks to high-yield stocks.

[12] Akmedov and Jakob (2010) investigate ex-dividend day trading activity between on- and off-exchange trading venues in Denmark, finding that the off-exchange average price trading affects the low price-drop ratios found on the on-exchange trading venue, Copenhagen Stock Exchange (CSE). However, the market structure between U.S. and Denmark fee models are not comparable.

trading venues offering investors the opportunity to bypass trading constraints (i.e., limit order queues and pricing grids) in capturing dividends. Second, we contribute to the literature investigating the impact of fee models and fragmentation on market activity. The two fee models, maker-taker and taker-maker provide different incentives and costs to both limit order and marketable order traders. We use the ex-dividend date as a deadline for liquidity traders to offer new insight into which trading venues and fee models attract greater market share. Third, our results indicate that highly fragmented stocks are associated with lower price-drop ratios (PDRs) although this relation reverses once we account for the stock's dividend yield. We interpret this finding that for high dividend yield stocks, market fragmentation increases the PDR closer to one, increasing price efficiency on the ex-day return. Fourth, we document that retail investor order imbalances, both in the number of trades and executed volume are positive on cum-dividend days, becoming negative on the ex-dividend day. This last finding conflicts with previous studies in several aspects. In contrast to Jakob and Ma (2003), we find that both measures of order imbalances are negative on the ex-dividend day. Further, our results do not support Frank and Jagannathan's (1998) dividend aversion contention that some investors, particularly retail investors, delay the purchase of a stock until the stock trades ex-dividend - our results indicate that order imbalances are significantly positive on cum-dividend days. Consistent with Jakob and Ma (2003), we find that ex-dividend day order imbalances contribute to a reduction in the PDR. However, the relation inverts once we interact our order imbalance measure with the stock's dividend yield.

II. LITERATURE REVIEW

Several studies analyzing ex-dividend trading suggests that market frictions such as trading costs and pricing grids impact the level of dividend capture. Kalay (1982) and Miller and Scholes (1982) suggest that transactions costs play a significant role in the level of ex-dividend trading behavior. Dubofksy (1992), Frank and Jagannathan (1998), Bali and Hite (1998), and Koski and Scruggs (1998) document the relevance of price discreteness and transaction costs as determinants of ex-dividend trading activity. The argument behind transactions costs impacting the level of dividend-capture is built on the premise that higher transaction costs hinder arbitrage trading profitability, reducing the incentive of short-term traders or arbitragers to obtain the dividend-paying stock. Naranjo, Nimalendran, and Ryngaert (2000) provide empirical evidence supporting the notion that higher transaction costs impedes traders from buying the dividend-paying stock. Graham, Michaely, and Roberts (2003) provide empirical findings failing to support the transactions cost model of ex-dividend trading. Likewise, Jakob and Ma (2004) analyze ex-dividend trading around changes in the minimum price increment, finding little support for the argument that transactions costs and price discreteness influence ex-dividend activity. Jakob and Ma (2005; 2007) examine the role of limit order adjustment on price-drop ratios. Their findings examine Dubofsky's explanation of ex-dividend day price drops. Dubofsky argues that automated ex-day limit order adjustment mechanically effects ex-dividend day stock price behavior. Henry and Koski (2017) demonstrate that skilled institutional traders, those able to execute trades at significantly lower costs, are better in capturing dividends than less-skilled institutional traders. Mortal, Paudel, and Silveri (2017) argue that transactions costs are relevant in determining price behavior around ex-dividend dates. The findings of Mortal, Paudel, and Silveri suggest that market frictions are relevant in understanding ex-dividend day trading activity.

III. HYPOTHESIS DEVELOPMENT

Our hypotheses are developed from the limit order book models provided by Foucault (1999), Foucault, Kadan, and Kandel (2005), and Rosu (2009) as well as the theoretical literature analyzing the liquidity cycles associated with fee venue pricing models – Colliard and Foucault (2012) and dark pools (Buti, Rindi, and Werner, 2017). First, the theoretical limit order book models provide a setting where informed trading is absent, and all trading is conducted by liquidity traders who place subjective valuations unrelated to information. Ex-dividend day trading provides an empirical setting where traders place differing valuations to accommodate potential differences in both tax and capital gains rates.

Foucault (1999) suggests the bid-ask spread will increase as the execution risk of limit orders increases. Foucault further argues that market orders will increase once a change occurs in the proportion of traders placing a higher subjective value on the stock. Ainsworth and Lee (2014) posit that the ex-dividend day provides a valuable setting where there is an increase in investors placing higher valuations on dividends. Foucault, Kadan, and Kandel (2005) develop an optimal order choice model involving the trade-off between execution immediacy and the delayed cost of execution. Their model suggests that when the market is dominated by patient (impatient) traders, limit (market) order submissions increase. When market orders dominate, a liquidity shock occurs, and spreads widen. When patient limit orders dominate, liquidity demand subsides, which lengthens the expected time to execution of limit orders. This increase in execution time in the limit order queue forces limit orders to price more aggressively. Rosu (2009) theorizes that limit orders are placed at different levels since traders need to be compensated for waiting. Similar to Foucault, Kadan, and Kandel, Rosu argues that impatient (patient) traders submit market (limit) orders. Rosu concludes that increases in liquidity competition results in lower bid-ask spreads and price impact, causing prices overreact. Central to both models is the absence of asymmetric information, which allows market frictions to manifest via the waiting costs and rent-seeking strategies of patient traders. Trading around the ex-dividend date provides an empirical setting to examine these theoretical implications since liquidity traders are more active than informed traders.

Colliard and Foucault (2012) account for the role of exchange fee models in discussing the relation between patient and impatient traders and order submissions. Colliard and Foucault develop five equilibriums for patient and impatient investors and the corresponding execution probability. The equilibrium that most resembles the ex-dividend trading setting described by Ainsworth and Lee (2014) is the first equilibrium type since impatient investors can act as makers or takers depending on fee structure and the execution rates across the two venues, while patient investors can be makers or takers depending on the state of the limit order book. In the existence of higher waiting costs and a pending deadline to capture the dividend, we posit that order placement becomes more aggressive on cum-dividend days, resulting in more market order submissions. We posit that impatient traders will submit market orders to the taker-maker venue to capture the dividend. Simultaneously, if patient, limit order traders desire higher execution probability, then patient traders will submit more limit orders to taker-maker venues since the execution rates increase in the presence of more liquidity-demanders (i.e., takers).[13] We expect higher fill rates for limit orders submitted to inverted venues as Battalio, Corwin, and Jennings (2016) demonstrate that limit orders submitted to high take fee venues (i.e., maker-taker venues) are associated with significantly lower fill rates than limit orders submitted to low take fee venues (i.e., taker-maker venues).

Figure 1 above provides the anticipated order flow for maker-taker and taker-maker venues around the ex-dividend date. Figure 1 shows that larger waiting costs and limit order queues provide incentives for traders to employ more aggressive orders and the taker-maker venue is the best venue for these traders due to faster execution, rebates, and lower net trading costs. Once the trading deadline expires on ex-dividend date, then both waiting costs and limit order queues decline and bid-ask spreads increase. Following the ex-dividend date, order aggressiveness declines and traders use more limit orders as the profits from supplying liquidity increases in the form of a larger bid-ask spread. Therefore, we hypothesize that taker-maker venues receive a higher market share on cum-dividend days, prior to the ex-dividend date.

H1: Taker-Maker fee venues experience greater market share on cum-dividend days.

Hypothesis 1 states that taker-maker fee venues offering rebates to aggressive market orders and higher execution probability for limit orders capture a greater market share prior to the ex-dividend day. An alternative explanation suggests taker-maker venues receive a higher market share following the ex-dividend date. Angel, Harris, and Spatt (2015) argue that larger

[13] Our argument mirrors the optimal order routing theory proposed by Maglaras, Moallemi, and Zheng (2012). Similar to Boehmer, Jennings, and Wei (2006), Maglaras et al. demonstrate that market orders gravitate towards markets with the lowest fees, while limit orders are submitted to the markets with the highest rebates and/or lowest execution waiting times. Maglaras, Moaellemi, and Zheng (2015) show that standing limit orders directed to high-fee venues experience lower execution quality and trade less frequently.

trading costs provide incentives for traders to jump the limit order queue by submitting more orders to taker-maker venues.[14] To the extent that waiting costs and patient traders keep spreads low prior to the ex-dividend date then traders may refrain from using the taker-maker venue since the price improvement incentive offered by the inverted venue is marginalized. Further, if waiting costs reduce and the proportion of patient and impatient traders adjust following the ex-dividend date then spreads will increase. The resulting wider spread will then encourage more participation in taker-maker venues to bypass the queue as liquidity competition increases as both Comerton-Forde, Gregoire, and Zhang (2018) and Cox, Van Ness, and Van Ness (2018) show that larger spreads associated with a wider tick size increase market share in taker-maker venues.

We next derive our hypothesis related to dark trading around ex-dividend dates. Consistent with our argument that the higher waiting costs and longer limit order queues increases the incentive for traders to bypass the queue by submitting more orders to taker-maker venues, we expect that dark trading venues provide another trading platform to bypass resting limit orders. Buti, Rindi, and Werner (2011) suggests that dark pools are more active the higher the level of competition in the lit limit order book. Buti, Rindi, and Werner argue that competition among liquidity suppliers due to a wider spread may encourage traders to submit more market orders to the dark to execute at the mid-quote rather than incur the wider spread in limit order book. However, a wider spread encourages patient, liquidity traders to submit orders to the limit order book on the lit venue as liquidity-supplying profits are greater. While these explanations provide conflicting predictions, Buti, Rindi, and Werner (2017) provide an updated

[14] Angel, Harris, and Spatt (2015) also note that when maker-taker and taker-maker venues offer the same quotes at the same price on the same side of the market, traders are incentivized to send marketable orders to taker-maker venues to receive the rebate. Hence, the execution probability for limit orders placed at the quote on taker-maker venues is larger than similar orders placed on the maker-taker venue.

theoretical model to account for continuous dark pool executions, where traders can choose to submit limit or market orders to either the lit limit order book or the dark venue. The model shows that when the limit order book starts empty, traders are more likely to submit limit orders, and it is limit orders that primarily migrate to the dark venue. Buti, Rindi, and Werner further argue that since dark pools typically trap market orders, reducing the available supply of liquidity demanders in the publicly transparent limit order book, execution rates for limit orders in the lit venue decline. Simultaneously, traders switch from limit orders to market orders. The model also shows that when the limit order book in the lit venue is deeper, then traders make greater use of market orders and it is market orders that primarily migrate to the dark venue. Comerton-Forde, Gregoire, and Zhang (2018) provide empirical evidence that liquidity demanders prefer dark venues as competition in the lit venue limit order book increases. Finally, the Buti, Rindi and Werner's model implies that trader's personal valuation of the asset will affect the perceived gain from trading and will motivate higher use of market orders.

Applying the theoretical model setting of Buti, Rindi, and Werner (2017) to the expected limit and market order submissions around the ex-dividend date, we posit that increasing competition among liquidity suppliers and a deeper limit order book will motivate more traders to submit market orders to the dark venue prior to the ex-dividend date. Absent of asymmetric information, the trader's higher valuation is solely on the dividend, creating another incentive to use market orders to capture the dividend. Formalizing our second hypothesis, we predict that the dark venue captures a larger share of aggressive, liquidity-demanding dividend traders prior to the ex-dividend date.

H2: Dark trading venues experience greater market share on cum-dividend days

We argue that the patient liquidity-supplying competition in the lit limit order book motivates more traders to use market orders in the dark venue to capture the dividend. However, execution rates for market orders in the dark venue depends on the availability of a counterparty. Further, since the execution probability of a market order in the dark venue is less than a market order in the lit venue, it is primarily limit orders that experience a higher execution probability in the dark venue than in the lit venue. Finally, if the bid-ask spread is a determinant of dark venue market share as suggested by Buti, Consonni, Rindi, Wen, and Werner (2015) and Kwan, Masulis, and McInish (2015), then lower expected spreads on cum-dividend days may mitigate any price improvement obtained in the dark venue. If this relation holds, then dark market share may decrease on cum-dividend days.

In this study, we have suggested that higher waiting costs, transactions costs, and order aggressive affect which trading venues obtain greater market share around the ex-dividend date, however, we next examine if the determinants of trading venue market share apply to the executions of retail trades in the dark. Dark pools such as broker dealer pools provide many retail customers the opportunity to obtain price improvement and bypass current limit order queues. Bartlett and McCrary (2015) document that SEC Rule 612 which permits trading at sub-penny prices, allows broker-dealers the opportunity to route retail marketable orders to the dark venue to avoid paying displayed spreads and bypass limit order queues. We argue that the trading deadline for liquidity-takers around the ex-dividend date to result in higher retail trading and buying activity in the dark venue. Thus, we expect that retail trades in the dark venue will increase on the cum-dividend days to bypass limit order queues. To the extent that retail trades in the dark venue are used to capture dividends, we expect an increase in retail trading prior to the ex-dividend date. We further posit retail trades to engage in buying (selling) behavior before (after) the ex-dividend date. Formalizing our third and final hypothesis, we predict that retail traders are net buyers (sellers) before (after) the ex-dividend day.

H3: Retail traders are buyers (sellers) before (after) the ex-dividend date

While it seems obvious that retail investors are likely net buyers prior to the ex-dividend date, Frank and Jagannathan (1998) put forth a dividend aversion hypothesis that argues investors defer trading until the stock is trading without dividend. They argue that some investors do not like dividends since dividends entail decision costs such as what do with received funds as well physically depositing or cashing dividend check. Frank and Jagannathan conclude that changes in the order imbalances between the last cum-dividend day and first ex-dividend can reduce the measured PDR. Jakob and Ma (2003) argue that while the dividend aversion hypothesis may not pose a dilemma for sophisticated institutional investors, small, retail traders are more likely to postpone their stock purchase until the ex-dividend date. Jakob and Ma (2003) provide supporting evidence that small, retail trade imbalances postpone stock purchases around the ex-dividend date and this behavior results in upward bias in the ex-day closing price and a decline in the PDR. We argue that technological changes that allow retail brokerages to directly deposit dividend distributions into a retail investor's account likely mitigates any potential dividend aversion costs. Thus, we expect that retail order imbalances will not contribute to ex-day price increases and a decline in the PDR.

As it relates to our discussion surrounding the pecking order of trading venues around the ex-dividend date, we next analyze whether changes in market fragmentation improve or impede price efficiency on the ex-dividend day. The literature cites that under the assumption the capital markets are perfect, the share price following a dividend distribution should fall by the exact amount of the dividend paid on a per share basis.[15] While tax-based theories suggests that tax differentials between capital gains and dividend income help explain ex-dividend price drops, other papers (Dubofsky, 1992; Jakob and Ma, 2004; and Akhmedov and Jakob, 2010) argue that microstructure effects could influence the ex-day pricing anomaly. In this study, we suggest that changes in both lit and dark fragmentation serve as another market friction that contributes to changes in the price drop ratio or PDR. The microstructure literature finds mixed evidence as to the effects of market fragmentation and price efficiency. O'Hara and Ye (2011) show that while fragmentation increases short-term volatility, they also provide evidence that the prices of small, fragmented stocks tend to be closer to a random walk. Comerton-Forde and Putnins (2015) find that higher levels of dark trading coincide with increases price discovery on the lit venue while Hatheway, Kwan, and Zhang (2017) document that dark venues contribute less to price discovery on the consolidated market. Therefore, it remains an empirical question as to the impact of lit and dark fragmentation on the level of price efficiency around the ex-dividend date. In this study, we examine the effects of lit market fragmentation (i.e., competition among limit order book exchanges) as well as off-exchange or dark market fragmentation on ex-day PDRs.

[15] Elton and Gruber (1970), Lakonishok and Vermaelen, (1986), and Michaely (1991) provide discussion on the impact of differential tax rates on ex-dividend activity.

IV. DATA AND METHODS

METHODS AND MEASURES

We classify dark trading in two ways, using the total number of trades and trading volume reported in exchange code "D" in TAQ. Exchange code "D" captures all off-exchange trading activity reported by the trade reporting facility (TRF) for stock i on day t. While this measure encompasses all trading taking place away from the lit venue and not specific to dark pools, other studies including Menkveld, Yueshen, and Zhu (2017) define dark trading using this data. We scale both the number of trades and trading volume reported in exchange code "D" to the total number of trades and trading volume reported in TAQ to create our two dark trading ratios. We use the Market Information Data Analytics System, MIDAS, in capturing both the level of trade executions and trading volume for all lit venues, including both the maker-taker and taker-maker venues. Since we scale the total trade and trading volumes reported for all maker-taker and taker-maker venues to all reported trade and trading volume, which includes dark trading, the constructed trading ratios for maker-taker and taker-maker venues are not perfectly inversely related.[16]

We identify retail trades in the dark venue using executions that receive small amounts of price improvement, typically less than a penny (Boehmer, Jones, and Zhang, 2017). These transactions usually take place just above or below a round penny. For example, we identify

[16] If taker-maker and maker-taker ratios were constructed using only report lit trades and trading volume, then the two measures would be inversely related (i.e., TM Ratio = 1 – MT Ratio). The correlation coefficient in market share measures between the maker-taker and taker-maker trading venues is -0.4990.

transactions as retail-initiated buys if the executed price is slightly below the round penny, and retail-initiated sells if the executed price is slightly above the round penny. If we let P_{it} equal the execution price in stock i at time t, then let Z_{it} = 100 * mod (P_{it}, 0.01) be the fraction of a penny associated with that execution price. Z_{it} can take on any value in the unit interval [0,1). We then classify retail buys if the transaction price falls in the (0.6, 1) Z_{it} interval and classify retail sells if the transaction price falls in the (0,0.4) Z_{it} interval. We compute buy-sell imbalances by scaling the difference between retail buy and sell trades (volume) to the total amount of executed retail trades (volume). We create a retail trading ratio by scaling all dark venue, retail executed trades to all executed trades for stock i on day t. We also construct retail trading ratio by scaling all executed retail share volume to all executed shares volume for stock i on day t. We verify our measures of retail trading with those of Boehmer, Jones, and Zhang, finding similar numbers.

DATA AND SAMPLE PERIOD

Sample construction includes all ordinary common stocks (CRSP share code 10 or 11) between January 2013 and September 2016. The beginning of the sample coincides with the introduction of the exchange data provided by MIDAS. We end the sample for all dividends in September to not conflict with changes to the tick size increment for the pilot firms associated with the SEC's Tick Size Pilot Program as the literature documents that increases in the minimum price increment may confound not only changes in market share across fee venues but also ex-dividend trading. For example, both Comerton-Forde, Gregoire, and Zhang (2018), Cox, Van Ness, and Van Ness (2018) show that increases in the tick size associated with the SEC's Tick Size Pilot results in greater market share for taker-maker fee venues. The dividend literature provides evidence that transaction costs and price discreteness affect ex-dividend trading as well as ex-day premiums and the price-drop ratio. We also require stocks in our sample to trade every day of the sample period and require that the stock have a share price greater than $5 for every day in sample period. We use CRSP to collect our sample of firms paying quarterly dividends during our sample period, using both CRSP and Nasdaq to verify ex-dividend dates. We also use CRSP to obtain control measures related to market capitalization, share turnover, price, price volatility, and dividend yield.

Table 1 reports statistics that describe the sample. Panel A reports the stock and trading characteristics of our sample. The average stock has a market capitalization of $12.18 billion and a price of $46.05. Price volatility, measured as the standardized daily range (see Diether, Lee, and Werner, 2009), is 2.33%. We also calculate share turnover using CRSP, dividing the daily trading volume by the number of shares outstanding. We obtain the retail ratio by scaling the total number of retail trades on TAQ to the total number of executed trades in TAQ. We create a similar ratio using retail volume. We find that the retail ratio, using scaled retail volume, is 6.83%. Note that this ratio reflects the retail trading taking place under exchange code "D" in TAQ and does not account for retail trading taking place on lit venues. We also report dividend characteristics such as the dividend paid, dividend yield, and the number of dividend increases and decreases. Finally, we document that the average dividend paid is 23 cents a share, with a yield of 0.6%.

V. RESULTS

MULTIVARIATE ANALYSIS

We construct a 21-day event window study around the ex-dividend date to examine abnormal levels of dark, taker-maker, and maker-taker venue trading activity. The 21-day event window allows us to examine the changes in dark, taker-maker, and maker-taker venue trading activity before and after the ex-dividend date while mitigating the potential effects of confounding events such as earnings announcements and/or stock splits that may affect trading venue preference.[17] We employ two measures of dark trading using our described dark ratio as well as a standardized dark trading ratio to account for conflicting motivations of dark trading. Similarly, we construct standardized measures of taker-maker and maker-taker in the 21-day event window around the ex-dividend date. For each standardized measure, we compute the ratios using the proportion of executed trades for each trading venue. We use a standardized measure as other studies (Lakonishok and Vermaelen, 1986; Koski and Scruggs, 1998; Blau, Fuller, and Van Ness, 2011) also employ a standardized trading measure around the ex-dividend date. We finally construct standardized measures of retail trading and retail trading imbalances around the ex-dividend date.

[17] Menkveld, Yueshen, and Zhu (2017) demonstrate that uncertainty surrounding earnings announcements results in market consolidation and a pecking order of trading venue preference. Yao and Ye (2014) demonstrate that stock splits induce changes in the relative tick size, resulting in changes in market share between maker-taker and taker-maker trading venues.

Table 2 reports the results for a 21-day window surrounding the ex-dividend date. We report not only the trading venue ratio and standardized trading venue ratio but also the market-adjusted return in the event window. Market-adjusted returns are calculated by deducting the CRSP equally-weighted index return (including distributions) from the stock's daily raw return. We conduct t-tests to determine whether the level of trading venue market share differs from zero for each trading day within the event window. In columns [2] and [3], we report the changes in maker-taker market share around the ex-dividend. In columns [4] and [5], we show the changes in taker-maker market share while in columns [6] and [7], we display the changes in dark trading around the ex-dividend day. In Table 2, we document that abnormal maker-taker market share levels peak on the ex-dividend date, 0.0289. The results in column [5] demonstrate that abnormal levels of taker-maker market share are lower on the cum-dividend days. Following the ex-dividend date, we find that taker-maker market share increases after the ex-dividend date. Hence, our earlier findings contrast with hypothesis 1 in that we show that taker-maker market share increases following the ex-dividend date. To the extent that aggressive dividend-capture traders seek a trading venue to bypass limit order queues and spread constraints prior to the ex-dividend date, our evidence suggests that taker-maker venues are not attracting this order flow. In column [7], we report that abnormal dark trading is higher on the cum-dividend days. Following the ex-dividend date, we find that abnormal dark trading levels decrease. Our finding that taker-maker (dark) venue market share decreases (increases) prior to the ex-dividend date only to revert following the ex-dividend date indicates that dark venues attract a larger share of dividend-capturing order flow, supporting hypothesis 2.

Figure 2 shows that visual changes in trading venue market share around the ex-dividend date. We report both the scaled and standardized measures of trading venue market share. In

Panel A, we show that maker-taker market share increases on the ex-dividend date, where both the regular and standardized measure peaks on the ex-day. For instance, the standardized maker-taker ratio peaks at 0.0289. In Panel B, we document that taker-maker market share increases following the ex-day. For example, we find that both the regular and standardized measure of taker-maker market share exhibits a sharp discontinuity before and after the ex-dividend date. The standardized measure ranges between -0.0400 and -0.0600 on the cum-dividend days, and ranges between 0.0250 and 0.0500 on the ex-dividend days. In Panel C, we provide the levels of dark trading market share around the ex-dividend date. The visual in Panel C indicates that dark venue market share peaks on the cum-dividend days, decreasing once the stock trades ex-dividend. Overall, the illustrations provided in Figure 3 indicate increases in dark venue market share when the stock trades cum-dividend while taker-maker venue market share increases when the stock trades ex-dividend.

In Table 3, we report changes in retail trading in dark venues around the ex-dividend date. Consistent with our expectation, we find that retail trading levels increase on cum-dividend days. We show that abnormal levels of retail trading (0.0483) peak on the day prior to the ex-dividend date. Following the ex-dividend date, we find that retail trading levels decline. In columns [4] through [7], we provide the changes in retail trading imbalances around the ex-dividend date. In column [5], we report that abnormal retail trading imbalances increase on the cum-dividend days, peaking on the last cum-dividend day, (*SOIBTRD* = 0.1014), indicating more retail buying prior to the ex-dividend date. After the ex-dividend date, we find that retail traders are net sellers, where all ex-dividend days in the event widow possess a negative order imbalance estimate. In column [7], we display the changes in abnormal retail trading imbalances using executed volume. The results in column [7] corroborate hypothesis 3 that retail traders in the dark venue are net buyers prior the ex-dividend date, supporting the contention that retail trades in dark venues are capturing dividends prior to the ex-dividend date.

Figure 3 shows the visual changes in retail trading around the ex-dividend date. In Panel A, we display that retail trading increases on the cum-dividend days, declining on the ex-dividend date. The standardized retail trading ratio peaks on the last cum-dividend day (0.0483), becoming statistically negative on the ex-dividend days. In Panels B and C, we provide the changes in retail trading imbalances. In Panel B, we show that retail trading imbalances using executed trades, OIBTRD, is positive and increasing on the cum-dividend days, only to decrease upon the ex-dividend day. In Panel C, we display the levels of retail trading imbalances using executed trade volume, OIBVOL. Consistent with the imbalance estimates provided in Panel B, we find that retail trading imbalances using executed trade volume peaks just prior to the ex-dividend date and becomes negative after the ex-dividend date. For example, we show that the standardized order imbalance measure peaks on the last cum-dividend day (0.1058), becoming negative and significant for all ex-dividend days. Overall, the visuals provided in Figure 3 indicate that retail trades in the dark are net buyers prior to the ex-dividend date.

MULTIVARIATE ANALYSIS

To evaluate if other factors impact the level of dark trading the ex-dividend date, we employ a multivariate regression framework. Consistent with Lakonishok and Vermaelen (1986), Hu and Tseng (2006), and Tseng and Hu (2013), we employ both our scaled measure as well a standardized measure of trading except in this study our measure of trading is the level of trading in dark, taker-maker, and maker-taker venues. Following Park and Lee (2014), we employ the standardized trading measure in a multivariate regression framework. In analyzing how dark and taker-maker trading activity changes around the ex-dividend date, we include five separate dummy variables to represent a five-day subset around the event date. For example, EX $_{t-2}$ (EX $_{t+2}$) takes the value of a 1 for the two trading days before (after) the ex-dividend date.

Our controls include firm size since previous literature suggests that the level of dark trading varies with firm size.[18] We also include a control for price since the availability of sub-penny pricing in both dark and taker-maker venues is less attractive for investors in stocks with high prices. This follows since the relative tick size is higher (lower) in lower (higher)-priced stocks which may motivate trading activity in dark and taker-maker venues to bypass lit venue tick constraints (Comerton-Forde, Gregoire, and Zhong, 2018). Further, we include controls for volatility and turnover. To the extent that share turnover measures the amount of liquidity in the market as suggested by Datar, Naik, and Radcliffe (1998), we expect that dark trading is likely to have a positive relation with turnover.[19] Finally, we include a control for volatility since research (see Ready, 2013; Zhu, 2014; Buti, Rindi, and Werner, 2017) suggest that volatility directly impacts the level of dark trading, while Garvey, Huang, and Wu (2016) suggest an inverse relation. Combining these controls, we estimate the following equation. We also include both stock and date fixed effects and cluster standard errors at the stock and date level. The dependent variable, Trading Venue_Ratio$_{i,t}$ refers to trading venue market share ratios associated with maker-taker, taker-maker, and dark trading venues. The full regression specification is provided below.

$$\text{Trading Venue\_Ratio}_{i,t} = \beta_0 + \beta_1 EX_{i,t-2} + \beta_2 EX_{i,t-1} + \beta_3 EX_{i,t} + \beta_4 EX_{i,t+1} + \beta_5 EX_{i,t+2} + \text{Controls}_{i,t} + \varepsilon_{i,t} \quad (1)$$

[18] Buti, Rindi, and Werner (2011) show that dark trading is higher among larger firms while the studies of Comerton-Forde and Putnins (2015) show that large cap stocks have lower levels of dark trading.
[19] Buti, Rindi, and Werner (2017) argue that dark trading is directly related with the overall trading frequency/volume in the stock.

Table 4 reports the results from regression equation [1]. In columns [1] and [2], the dependent variable is maker-taker market share. In column [2], we show that the standardized measures of maker-taker market share, *SMT Ratio*, is only significant on the ex-dividend day, 0.0310, indicating that maker-taker market share is highest on the ex-dividend day. In columns [3] and [4], we show that taker-maker market share levels are lower on cum-dividend days. In column [4], we report that the coefficient estimates for ExDay_{t-2} and ExDay_{t-1} are both negative. Similar results hold when the unstandardized measure of taker-maker market share serves as the dependent variable (see column 3). This finding indicates that taker-maker market share is significantly lower on cum-dividend days relative to the rest of the trading days in the sample period. In columns [5] and [6], we provide the coefficient estimates for the ex-dividend date dummy variables, where dark venue market share serves as the dependent variable. Consistent with our univariate results, we show that following the ex-dividend date, dark venue market share declines. In column [6], we show that all ex-dividend date dummy variables after the ex-dividend day are negative. For instance, the standardized dark trading ratio is -0.0329, -0.0215, and -0.0430 on ExDay_{t}, ExDay_{t+1}, and ExDay_{t+2}, confirming that dark trading market share is significantly negative following dividend distribution date. We further document that abnormal levels of dark venue market share are positive, 0.0258, on the last cum-dividend day, ExDay_{t-1}.The results provided in Table 4 confirm support for hypothesis 2 that dark venue market share increases prior to the ex-dividend date but do not support for hypothesis 1 in that taker-maker venue market share increases on the cum-dividend days.

We next analyze retail trading in multivariate framework. Following other studies such as Malmendier and Shanthikumar (2007), Lai and Teo (2008), and Park and Lee (2014), we use standardized trading imbalances using event window studies as well as in a multivariate regression framework. Consistent with our previous regression equation, we include controls related to firm size, price volatility, turnover, and price. We also include stock and date fixed-effects and cluster standard errors at the stock and date level. The dependent variable, $Retail\_Ratio_{i,t}$ refers to retail trading ratios as well as our measures of retail trading imbalances. The full regression specification is provided below.

$$Retail\_Ratio_{i,t} = \beta_0 + \beta_1 EX_{i,t-2} + \beta_2 EX_{i,t-1} + \beta_3 EX_{i,t} + \beta_4 EX_{i,t+1} + \beta_5 EX_{i,t+2} + Controls_{i,t} + \varepsilon_{i,t} \quad (2)$$

In Table 5, we provide the coefficient estimates from regression equation (2). In columns [1] and [2], we provide the coefficient estimates for the ex-dividend date dummy variables, where our measures of retail trading serve as the dependent variable. In column [1], we report positive coefficient estimates for each of the ex-dividend date dummy variables, $ExDay_{t-2}$ and $ExDay_{t-1}$, prior to the ex-dividend date. However, we also report that retail trading increases on the ex-dividend date. While this confirms that ex-dividend day is associated with increases in retail trading, however, once we standardized the retail trading measure, we find in column [2], that retail trading peaks only on the cum-dividend days prior to the ex-dividend date. Further, the standardized retail trading becomes negative on the ex-dividend date, $ExDay_t$, consistent with our expectation that retail trading participation recedes once the stock begins to trade without the dividend. In columns [3] and [4], we provide the estimates where our measure of retail trading imbalance using executed trades serves as the dependent variable. The results indicate that retail traders are net buyers on the cum-dividend days. For example, we report coefficient estimates of 0.0186 and 0.0240 for dummy variables, $ExDay_{t-2}$ and $ExDay_{t-1}$, in column [3]. In column [4], we provide estimates positive estimates for both $ExDay_{t-2}$ and $ExDay_{t-1}$, confirming that retail trading imbalances are positive prior to the ex-dividend date. In columns [3] through [6], we document that following the ex-dividend date, retail traders in the dark venue are net sellers. This last finding contrasts with Jakob and Ma (2003), who infer retail trading using order sizes, finding that small order buys outnumber the small order sells on the ex-dividend day. Overall, the evidence provided in Table 5 confirm hypothesis three in that retail trades which execute in dark venue are associated with dividend-capture trading behavior.

VI. ROBUSTNESS

DIVIDEND YIELD

Several studies show dividend-capture trading is directly related to the stock's dividend yield. First, Lakonishok and Vermaelen (1986) demonstrate that ex-dividend returns are affected by stocks with larger dividend yields, which are likely stocks that experience the largest demand by dividend capture traders. Michaely and Vila (1995; 1996) provide additional evidence that ex-dividend trading volume increases in the level of the stock's dividend yield. To address if investor's use of dark and taker-maker venues around the ex-dividend date is greater for high dividend-yield stocks, we use a 21-day event window, analyzing how dark and taker-maker market share varies across five quintiles formed via the stock's dividend yield. We interact the five ex-dividend day dummy variables with the stock's dividend yield. Consistent with our previous model specifications, we include controls such as firm size, price volatility, turnover, and price. We also include stock and date fixed-effects and cluster standard errors at the stock and date level. The dependent variable, Trading Venue_Ratio$_{i,t}$ refers to trading venue market share ratios associated with maker-taker, taker-maker, and dark trading venues. The full regression specification is provided below.

$$\text{Trading Venue\_Ratio}_{i,t} \tag{3}$$
$$= \beta_0 + \beta_1 EX_{i,t-2} + \beta_2 EX_{i,t-1} + \beta_3 EX_{i,t} + \beta_4 EX_{i,t+1} + \beta_5 EX_{i,t+2}$$
$$+ \beta_6 EX_{i,t-2}*Yield + \beta_7 EX_{i,t-1}*Yield + \beta_8 EX_{i,t}*Yield$$
$$+ \beta_9 EX_{i,t+1}*Yield + \beta_{10} EX_{i,t+2}*Yield + \beta_{11} Yield_i + Controls_{i,t} + \varepsilon_{i,t}$$

Table 6 reports the coefficient estimates from regression equation (3). In columns [1] and [2], we report the coefficient estimates for the ex-dividend date dummy variables as well as the interaction term accounting for the stock's dividend yield, where maker-taker market share serves as the dependent variable. We find in columns [1] and [2] that the stock's dividend yield has no significant effects on trading in maker-taker venues around the ex-dividend date. To the extent that higher dividend yield stocks are more desired by dividend-capturing traders, our results suggests that maker-taker venues are less attractive to those capturing dividends. In columns [3] and [4], we report estimates from regression equation (3) where measures of taker-maker venue market share serve as the dependent variable. In column [3], we find that the interaction terms prior to the ex-dividend date, $EX_{i,t-2}$*Yield and $EX_{i,t-1}$*Yield, are negative. We also report a negative coefficient estimate for the interaction term on the ex-dividend date, $EX_{i,t}$*Yield. These findings imply that for costly dividend arbitrage stocks such as those with higher dividend yields, there is less trading activity on taker-maker venues despite cost savings associated with these venues. We find similar evidence in column [4], where the standardized measure of taker-maker market share serves as the dependent variable. In columns [5] and [6], we show that the higher dividend yield results in more trading in the dark venues prior to the ex-dividend date. For instance, the coefficient estimates for $EX_{i,t-2}$*Yield and $EX_{i,t-1}$*Yield are 0.2438 and 0.4860 using the scaled dark trading ratio and 3.8353 and 6.0073 using the standardized dark trading ratio. These findings suggest that higher dividend-yield stocks motivate less (more) dividend-capture trading in the (taker-maker) dark trading venue.

Consistent with the premise that high-dividend yield stocks attract more dividend-capture trading, we expect a higher share of retail orders which execute in the dark for high-dividend yield stocks. Such a finding would corroborate Graham and Kumar (2006), who find that retail investor holdings indicate a preference for high dividend yield securities.[20] We address this relation by analyzing the proportion of retail-executed trades in the dark venue as well as the order imbalances of retail traders in the dark venue across stocks, sorted by dividend yield. To test this relation, we replace the trading venue ratios as the dependent variable in equation (3) with our measures of retail trading.

In Table 7, we provide estimates of retail trading and retail trading imbalances in the dark venue around the ex-dividend, accounting for the stock's dividend yield. In columns [1] and [2], we provide evidence that retail trading increases around the ex-dividend date for high-dividend yield stocks. We also show that retail trading peaks for high-dividend yield stocks on the last cum-dividend date, where the estimate for $EX_{i,t-1}$*Yield is positive, 0.3843 (12.9009), when the scaled (standardized) retail trading ratio serves as the dependent variable. This finding implies that high dividend yield stocks are associated with more dividend-capture activity by retail investors. In columns [3] and [4], we find that retail trade imbalances prior to the ex-dividend are increasing with the stock's dividend yield. For instance, the coefficient estimates for $EX_{i,t-2}$*Yield and $EX_{i,t-1}$*Yield are 2.3776 and 3.0578 using the scaled retail trading imbalance, OIBTRD. This result suggests that retail traders are stronger buyers of dividend-paying stocks on

[20] Another explanation is that retail investors tend to hold low-priced stocks. Low-priced, dividend-paying stocks are likely to have large dividend yields. To account for this confounding effect, we control for price in all our regression specifications.

cum-dividend days for high-dividend yield stocks. We provide corroborating evidence when the standardized measure of retail trading imbalance, SOIBTRD, serves as the dependent variable, the estimates for $EX_{i,t-2}$*Yield and $EX_{i,t-1}$*Yield are 9.4489 and 12.6101. In columns [5] and [6], we display the retail trading imbalances using executed trade volume, OIBVOL, which support our contention that high dividend yield stocks motivate more retail buying prior to the ex-dividend date. Consistent with our trading imbalance measures using trades which execute, we find that imbalances using executed trade volume is higher on the last two cum-dividend dates for high-dividend yield stocks. Finally, we show that measures of retail trading imbalances, using both executed trades and trade volume are negative following the ex-dividend date. This indicates that retail traders are less active in trading the stock once the dividend begins to trade without the dividend – consistent with dividend-capturing behavior. We conclude that the results provided in Table 7 confirm that the stock's dividend yield is a significant factor in retail trading participation and trading behavior in dark venues around the ex-dividend date.

Figure 4 shows the changes in retail trading imbalances around the ex-dividend date sorted by the stock's dividend yield. In Panel A, we provide the retail trading imbalances using trades which execute around the ex-dividend date. The visual in Panel A shows that retail trading imbalance, OIBTRD, increases on the cum-dividend days for high-dividend yield stocks (i.e., quintile 5). The retail trading imbalance for stocks in the next largest dividend-yield quintile exhibit similar patterns around the ex-dividend, although smaller in magnitude. This confirms that while moderately high-dividend yield stocks exhibit some retail dividend-capturing trading behavior, it is primarily the largest dividend-yield stocks that attracts more retail-oriented buying behavior on the cum-dividend days. In Panel B, we provide changes in retail trading imbalance using executed volume, OIBVOL. Consistent with Panel A, we show that retail trading imbalances increases on the cum-dividend days for high-dividend yield stocks. For instance, we document that the high-dividend yield quintile (i.e., blue line) is associated with the highest level of retail trading imbalance.

EFFECTS OF LIT AND DARK FRAGMENTATION ON PRICE-DROP RATIO

In this section, we examine whether fragmented stocks experience higher or lower price-drop ratio, PDR. We follow Mortal, Paudel, and Silveri (2017) and measure the PDR, as the difference between the closing price on the cum-dividend date and the closing price on the ex-dividend date, scaled by the dividend paid on a per share basis. The formal calculation is provided in equation (4) below:

$$\text{Price Drop Ratio (PDR)} = \frac{\text{Price}_{\text{cum}}\text{-Price}_{\text{ex}}}{\text{Dividend}} \tag{4}$$

In unreported results, the average PDR for our sample of firms is 0.4474 while the median PDR for our sample of firms is 0.4896. The average PDR in our sample is lower than that reported by Jakob and Whitby (2017) although their measure of PDR is adjusted for market returns on the cum-dividend price. After adjusting for the market-return on the cum-dividend price, the mean and median PDR is 0.5328 and 0.6243, which is closer to the numbers reported in their paper.[21]

We first examine the relation between our measures of fragmentation and the PDR. We define lit fragmentation as the fragmentation of order flow across publicly transparent limit order book exchanges. Our measure of lit fragmentation, LitFrag, is constructed using an inverted Herfindahl-Hirschman Index, using daily trading volumes reported by all trading venues reported

[21] The PDR totals reported in this paper are slightly lower than the mean (0.656) and median (0.715) reported by Jakob and Whitby (2017). One explanation for such differences are likely to attributed to sample periods as their study extends back to 1982 and stops at 2012.

in the Market Information Data Analytics System (MIDAS) database. The inverted index allows us to interpret that a higher index score implies greater lit fragmentation. Apart from analyzing the impact of market fragmentation on price drops, we also control for several possible variables that might influence the PDR. First, we control for the stock's dividend yield as tax-based dividend arguments suggest that varying dividend yields serve as a proxy for measuring tax clienteles. Second, we control for the stock's nominal price as Jakob and Whitby (2017) show that there is a negative relation between the nominal share price and the price drop ratio, suggesting the ex-dividend day prices are more efficient when the stock has a lower nominal share price. We also control for the nominal dividend paid per share as both Dubofsky (1992) and Bali and Hite (1998) argue that the dividend size is positively related with the PDR. We also include a spread measure as larger transaction costs may inhibit short-term arbitrage traders, resulting in PDRs to move further away from one. Conversely, when transaction costs are low, short-term dividend arbitrage traders will increase the PDR closer to one. Although Mortal, Paudel, and Silveri (2017) show that PDRs are comparable between NASDAQ and NYSE-listed stocks, we control for the stock's primary listing exchange to see if the listing exchange impacts the ex-day price drop. Finally, we control for the firm size and trading volume. We expect that more liquid stocks such as those with larger trading volumes stimulate short-term dividend arbitrage activity, resulting in enhanced price efficiency and a price-drop ratio closer to one. The specification includes both year and firm fixed-effects. The full regression specification is provided below in equation (5):

$$PDR_{i,t} = \beta_0 + \beta_1 Frag_{i,t} + \beta_2 Frag_{i,t}{*}Yield_i + \beta_3 Yield_i + Controls_{i,t} + \varepsilon_{i,t} \qquad (5)$$

Table 8 column (1) reports the coefficient estimate for our measure lit fragmentation, LitFrag. While the coefficient estimate is negative it is not statistically different from zero.

Consistent with our earlier analysis, we account for the influence of the stock's dividend yield. Thus, we include an interaction term LitFrag x Yield. In column (2), we report a negative coefficient estimate for LitFrag, however, the interaction term is positive. This result implies that in high dividend-yield stocks, higher levels of lit fragmentation increase the PDR, improving price efficiency. In column (3), we find higher levels of off-exchange or dark fragmentation reduces the PDR, a finding that suggests higher levels of dark fragmentation impedes the price efficiency mechanism on the ex-dividend day. In other words, it appears that increases in dark trading surrounding the ex-dividend date help explain the ex-day price anomaly. Consistent with our specification in column (2), we interact our measure of dark fragmentation with the stock's dividend yield. In column (4), we find that our interaction term DarkFrag x Yield is positive – a similar result to that found with the interaction term using our measure of lit fragmentation. Our results indicate that both lit and dark fragmentation appear to reduce the PDR, however, we also document that in high-dividend yield stocks, market fragmentation appears to increase the PDR, improving ex-day price efficiency. The coefficient estimate for the stock's nominal share price is negative, consistent with Jakob and Whitby (2017). Interestingly, we find that the estimate for trading volume, LnVol, is negative across all specifications, which contradicts the liquidity argument that liquidity facilitates arbitrage activity. Finally, we show that our transaction cost measure, Spread, is negatively related to the PDR, which is consistent with the transaction costs hypothesis that argues that stocks with higher transaction costs inhibit dividend capturing activity.

Aside from our analysis on the effects of market fragmentation on the ex-day PDR, we next examine the effects on the ex-day return. We replace the stock's ex-day PDR with the stock's ex-day return as the dependent variable. The stock's ex-day return refers to either the stock's raw return (including the dividend distribution) as well as its market-adjusted return, which we refer to as *AB Return*. To the extent that market fragmentation reduces the PDR, we expect both lit and dark fragmentation to be associated with higher ex-day returns. However, to the extent that the stock's dividend yield moderates the effects of market fragmentation leading to an increase the PDR, we expect that ex-day returns to increase as well. All other independent variables from equation (5) are the same. Likewise, both year and firm fixed-effects are included. The full regression specification is provided below in equation (6):

$$\text{Return}_{i,t} = \beta_0 + \beta_1 \text{Frag}_{i,t} + \beta_2 \text{Frag}_{i,t} {*} \text{Yield}_i + \beta_3 \text{Yield}_i + \text{Controls}_{i,t} + \varepsilon_{i,t} \qquad (6)$$

Table 9 provides the coefficient estimates from the equation (6). Consistent with our expectation, we find in higher dividend-yield stocks, higher levels of lit and dark fragmentation are associated with lower ex-day returns. For example, both columns (2) and (4) show that the coefficient estimate is negative for our interaction term, LitFrag x Yield. This indicates that for higher-dividend yield stocks, more fragmented stocks are associated with lower ex-day returns. In columns (6) and (8), we find that the parameter estimate is negative for our interaction term, DarkFrag x Yield. Notably, the estimates for LitFrag and DarkFrag are insignificant across all specifications, indicating that the two measures of fragmentation, alone, are not significant determinants of ex-day returns. Overall, the results provided in Table 8 and 9 indicate that conditional on the stock's dividend yield, higher levels of market fragmentation drive the PDR closer to one, resulting in lower ex-day returns. Finally, we document a positive coefficient estimate for Spread, consistent with the argument the stock's with larger spreads inhibit dividend arbitrage activity.

RETAIL TRADING IMBALANCES AND THE PRICE-DROP RATIO

In the final part of our analysis, we examine whether retail trading imbalances affect the PDR. According to Frank and Jagannathan (1998) and Jakob and Ma (2003), retail traders are subject dividend aversion behavior which argues that retail traders may delay the stock purchases until the stock trades ex-dividend, resulting in prices to close higher on the ex-dividend date. Although we have shown that retail traders are not only more active prior to the ex-dividend, they are also net buyers, particularly in the high-dividend yield stocks. Nonetheless, we test whether retail trading imbalances contribute to smaller or larger PDRs. In Table 10, we provide results showing that retail trading imbalances, OIBTRD, appear to result in lower PDRs, consistent with the findings of Jakob and Ma (2003). However, once we interact the retail trading imbalance with the stock's dividend yield, we document a positive coefficient for the term, OIBTRD x Yield. This finding indicates that in the higher dividend yield stocks, retail traders contribute to a higher PDR. In fact, the combined effects, conditional on the stock's dividend yield, indicate that retail traders increase not only the PDR but also improve ex-day price efficiency.

VII. CONCLUSION

We argue that the ex-dividend date influences which trading venues capture a larger share of dividend-capturing traders. We follow theoretical limit order models as well the literature on ex-dividend trading to suggests that certain trading venues (i.e., taker-maker and dark venues) are more attractive to dividend-capture traders. We posit that these two trading venues enable aggressive dividend-capture traders the opportunity to bypass limit order queues and offset transaction costs in capturing dividend-paying stocks. Finally, we argue that SEC Rule 612 allowing trading at sub-penny prices motivates broker-dealers to route retail marketable orders to dark venues as to avoid paying displayed spreads and bypass limit order queues.

Our univariate and multivariate analysis confirms that dark trading venues obtain higher market share prior to the ex-dividend date, confirming our expectation that dark trading venues provide an aggressive favorable platform in capturing dividends. However, our results indicate that taker-maker trading venues experience lower market share on cum-dividend days only to increase once the stock trades ex-dividend. We argue that the increase in taker-maker market share following the ex-dividend date is consistent with the contention that once the stock trades ex-dividend, spreads increase resulting in higher incentives for traders to use taker-maker venues to offset larger transaction costs and bypass the limit order queue. Additional tests confirm that retail trading in the dark venue increases on cum-dividend days. Further, our analysis shows that retail traders in dark venues are net buyers – consistent with dividend-capturing trading behavior. We further control for the stock’s dividend yield as an additional factor contributing to the changes in trading venue and retail trading activity. Our evidence suggests that the stock's dividend yield is a relevant factor in explaining how trading fragments around the ex-dividend date.

We also analyze if more fragmented stocks are associated with better ex-day price efficiency. Although we find that both lit and dark fragmentation are associated with a reduction in the PDR, once we account for the stock's dividend yield, we find that fragmented trading is associated with higher PDR and lower ex-day returns. This result is consistent the notion that fragmented trading, lit and dark, are associated with improving price efficiency. Finally, we address whether retail traders contribute to higher or lower PDRs as the dividend aversion hypothesis holds that certain traders delay their stock purchases following the dividend distribution date, driving up ex-day prices, and a lower PDR. Our results indicate that retail trading imbalances lower PDR, however, once conditioning on the stock's dividend yield, we show that retail trading imbalances increase the PDR. This last result indicates the retail traders improve ex-day price efficiency.

Our findings have a several implications. First, we show that the impending trading deadline associated with capturing dividends motivates more trading in dark venues on cum-dividend days. This results in less trading activity on lit venues on cum-dividend days. Second, we find that the higher subjective valuation associated with stock's dividend yield motivates more activity to the dark venues. Third, in contrast to the dividend aversion hypothesis, we show that retail trading in dark venues exhibit dividend-capture trading tendencies. Finally, we detail that fragmented stocks as well as off-exchange retail trading contribute the ex-day price drop anomaly.

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APPENDIX

APPENDIX 1: SUMMARY STATISTICS

Table 1: Summary Statistics

This table presents statistics that describe the sample. Panel A reports the following stock and trading characteristics. Market capitalization is the CRSP market cap in (000s). Price the daily closing price using the midpoint of the bid and ask. Price volatility is the difference between the daily high and daily low scaled by the daily high price. Turnover is measured by dividing the daily trade volume by the shares outstanding. Maker-taker and Taker-maker Ratios are computed using reported executed trades and trading volume in MIDAS. Maker-taker (Taker-maker) ratio is the daily maker-taker (taker-maker) volume scaled to by all daily trades. Dark trades are daily trade executions reported under exchange code “D” in TAQ. Dark ratio is the daily dark trades divided by daily trades. Retail ratio is computed by scaling all identified retail trades in exchange code “D” in TAQ to all reported trades. OIBTRD (OIBVOL) refer to the retail order imbalances using executed trades (volume). Panel B reports the statistics about the dividends. The amount of dividend and dividend yield are reported as well as the amount of the dividend change. Increases (decreases) are the positive (negative) difference between the recent dividend and the last dividend yield.

	Mean	Standard Deviation	Q1	Q3	N
	[1]	[2]	[3]	[4]	[5]
Panel A. Stock and Trading Characteristics					
Market Cap	12,183,918,000	35,590,498,000	662,190,280	83,899,684,500	1,671
Price	46.05	42.93	19.98	59.23	1,671
Price Volatility	0.0233	0.0153	0.0139	0.0280	1,671
Turnover	0.0071	0.0085	0.0030	0.0086	1,671
Maker-taker Ratio (Trades)	0.6468	0.0943	0.5983	0.7090	1,671
Maker-taker Ratio (Volume)	0.6084	0.1124	0.5517	0.6810	1,671
Taker-maker Ratio (Trades)	0.1217	0.0602	0.0859	0.1513	1,671
Taker-maker Ratio (Volume)	0.0859	0.0456	0.0588	0.1079	1,671
Dark Ratio (Trades)	0.2316	0.0856	0.1767	0.2666	1,671
Dark Ratio (Volume)	0.3057	0.1182	0.2282	0.3589	1,671
Retail Ratio (Trades)	0.0471	0.0634	0.0210	0.0474	1,671
Retail Ratio (Volume)	0.0683	0.0850	0.0282	0.0728	1,671
OIBTRD	-0.0219	0.2870	-0.1750	0.1429	1,671
OIBVOL	-0.0355	0.3598	-0.2381	0.1696	1,671
Panel B. Dividend characteristics					
Dividend paid	0.2304	0.1923	0.0200	1.0250	19,546
Dividend yield	0.0061	0.0042	0.0006	0.0262	19,546

APPENDIX 2: EVENT STUDY OF TRADING VENUE MARKET SHARE AROUND THE EX-DIVIDEND DAY

Table 2: Event study of Trading Venue Market Share Around the Ex-Dividend Day

Table 2 presents results from a 21-day event study around dividend ex-dividend day. Columns [2] and [3] report the results for maker-taker market share and standardized maker-taker market share. Columns [4] and [5] report the results for taker-maker market share and standardized taker-maker market share. Columns [6] and [7] report the results for dark market share and standardized dark market share. Column [1] reports the market-adjusted returns, which are obtained by subtracting CRSP equally-weighted index returns from the CRSP raw returns. We standardized each trading venue measure by calculating the difference between the venue ratio for stock i on day t and the average venue ratio and then divide this difference by the standard deviation of venue trading measure for stock i. The standardization procedure allows each stock to have a trading venue measure on each day that is similarly distributed with a zero mean and a unit variance. The t-tests tests whether the standardized trading venue measure is significantly different from zero. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Returns	*MT Ratio*	*Standardized MT Ratio*	*TM Ratio*	*Standardized TM Ratio*	*Dark Ratio*	*Standardized Dark Ratio*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
t-10, t-6	0.0286***	0.6452	-0.0008	0.1207	-0.0337***	0.2340	0.0287***
t-5	0.0675***	0.6449	0.0101	0.1204	-0.0444***	0.2347	0.0218***
t-4	0.0610***	0.6448	-0.0100	0.1198	-0.0486***	0.2354	0.0455***
t-3	0.0190	0.6452	0.0167**	0.1201	-0.0416***	0.2347	0.0065
t-2	0.0060	0.6453	0.0125*	0.1203	-0.0420***	0.2344	0.0102
t-1	-0.0098***	0.6453	0.0043	0.1196	-0.0538***	0.2351	0.0312***
Ex-Day	-0.0370***	0.6468	0.0289***	0.1217	-0.0022	0.2316	-0.0318***
t+1	0.0340***	0.6459	0.0073	0.1224	0.0137**	0.2317	-0.0205***
t+2	0.0236**	0.6453	0.0064	0.1235	0.0370***	0.2312	-0.0376***
t+3	-0.0138	0.6447	-0.0054	0.1230	0.0249***	0.2326	-0.0146**
t+4	0.0233*	0.6442	-0.0190***	0.1229	0.0306***	0.2329	-0.0014
t+5	0.0334***	0.6456	0.0020	0.1235	0.0355***	0.2309	-0.0350***
t+6,t+10	0.0046***	0.6445	-0.0104***	0.1233	0.0523***	0.2322	-0.0233***

APPENDIX 3: RETAIL TRADING AND RETAIL TRADING IMBALANCES AROUND EX-DIVIDEND DATES

Table 3: Retail Trading and Retail Trading Imbalances Around Ex-Dividend Dates

Table 3 presents results from a 21-day event study around dividend announcements. Columns [2] and [3] report the results for retail and standardized retail market share. Columns [4], and [5] report the results for retail order imbalances and standardized retail order imbalances using trade executions. Columns [6], and [7] reports the results for retail order imbalances and standardized retail order imbalances using executed trade volume. Column [1] reports the market-adjusted returns, which are obtained by subtracting CRSP equally-weighted index returns from the CRSP raw returns. Retail ratio (daily retail volume in dark venues divided by daily trade volume) is reported along with the standardized retail ratio. We standardized the retail trading measure by calculating the difference between the retail ratio for stock i on day t and the average retail ratio and then divide this difference by the standard deviation of the retail trading measuring for stock i. The standardization procedure allows each stock to have a dark measure on each day that is similarly distributed with a zero mean and a unit variance. The t-tests tests whether the standardized retail trading measure is significantly different from zero. The standardized procedure is also applied to retail order imbalances. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Returns	*Retail Ratio*	*Standardized Retail Ratio*	*OIBTRD*	*Standardized OIBTRD*	*OIBVOL*	*Standardized OIBVOL*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
t-10, t-6	0.0286***	0.0473	0.0017	-0.0178	0.0111***	-0.0262	0.0134***
t-5	0.0675***	0.0485	0.0100	-0.0178	0.0057	-0.0236	0.0251***
t-4	0.0610***	0.0483	0.0417***	-0.0125	0.0297***	-0.0230	0.0317***
t-3	0.0190	0.0488	0.0225***	-0.0095	0.0460***	-0.0205	0.0405***
t-2	0.0060	0.0487	0.0320***	-0.0038	0.0792***	-0.0100	0.0834***
t-1	-0.0098***	0.0483	0.0483***	0.0028	0.1014***	-0.0029	0.1058***
Ex-Day	-0.0370***	0.0471	-0.0175**	-0.0219	-0.0073	-0.0355	-0.0213***
t+1	0.0340***	0.0464	-0.0192***	-0.0277	-0.0431***	-0.0395	-0.0465***
t+2	0.0236**	0.0468	-0.0448***	-0.0292	-0.0347***	-0.0440	-0.0444***
t+3	-0.0138	0.0467	-0.0298***	-0.0377	-0.0724***	-0.0461	-0.0558***
t+4	0.0233*	0.0465	-0.0106	-0.0307	-0.0428***	-0.0438	-0.0398***
t+5	0.0334***	0.0459	-0.0308***	-0.0257	-0.0261***	-0.0388	-0.0338***
t+6,t+10	0.0046***	0.0473	-0.0019	-0.0228	-0.0186***	-0.0366	-0.0226***

APPENDIX 4: TRADING VENUE MARKET SHARE AROUND THE EX-DIVIDEND DAY

Table 4: Trading Venue Market Share Around the Ex-Dividend Day

This table reports the regression results from equation (1). The dependent variable refers to trading venue market share ratio, where trading venue refers to either maker-taker, taker-maker, and dark trading venues. We also use the standardized trading venue market share as the dependent variable. All trading venue market share ratios are measured for stock i on day t across the event window where EX_t is equal to one if day t is the ex-dividend date. Five separate dummy variables are included to capture the five days around the ex-dividend date. Other independent variables include firm size, price volatility, share turnover, and price. Both day and stock fixed effects are included in the regression. Standard errors are clustered at the firm and date level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Maker-Taker		*Taker-Maker*		*Dark*	
Dep Var. =	*MT Ratio*	*SMT Ratio*	*TM Ratio*	*STM Ratio*	*Dark Ratio*	*SDark Ratio*
	[1]	[2]	[3]	[4]	[5]	[6]
$ExDay_{t-2}$	0.0004	0.0157	0.0362***	-0.0457***	0.0012	0.0081
	(0.40)	(1.47)	(4.92)	(4.71)	(1.25)	(0.73)
$ExDay_{t-1}$	0.0005	0.0114	-0.0016**	-0.0592***	0.0017*	0.0258**
	(0.60)	(1.18)	(2.24)	(6.25)	(1.92)	(2.54)
$ExDay_t$	0.0007	0.0310***	-0.0022***	-0.0054	0.0009	-0.0329***
	(0.68)	(3.15)	(3.23)	(0.55)	(1.02)	(3.32)
$ExDay_{t+1}$	0.00087	0.0095	-0.0016**	0.0105	-0.0012	-0.0215**
	(0.85)	(0.89)	(2.28)	(1.02)	(1.33)	(1.96)
$ExDay_{t+2}$	0.0008	0.0126	0.0004	0.0332***	-0.0022***	-0.0430***
	(0.79)	(1.16)	(0.52)	(3.31)	(2.65)	(3.93)
$Size_t$	0.0006	0.0130***	0.0014**	-0.0032	-0.0089***	-0.0124***
	(0.44)	(4.75)	(2.08)	(1.50)	(8.62)	(4.75)
$Volatility_t$	0.0218***	0.1299***	0.0083***	-0.0900***	-0.0142***	-0.0808***
	(15.70)	(17.15)	(12.25)	(14.63)	(12.52)	(10.42)
$Turnover_t$	-0.2513***	-5.45***	-0.0076***	-4.1179***	0.2171***	9.0441***
	(3.85)	(14.75)	(8.04)	(8.77)	(3.80)	(14.39)
$Price_t$	0.0318***	0.0064	0.0342	-0.0129***	-0.0134***	0.0022
	(10.43)	(1.63)	(0.83)	(3.61)	(6.37)	(0.66)
Intercept	0.6120***	0.3324***	-0.0184***	-0.2282***	0.3512***	-0.206***
	(51.21)	(9.52)	(11.40)	(7.93)	(28.66)	(5.72)
Adjusted R^2	0.0705	0.0056	0.0552	0.0056	0.0763	0.0072
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 5: RETAIL TRADING AROUND EX-DIVIDEND DATE

Table 5: Retail Trading Around Ex-Dividend Date

This table reports the regression results from equation (2). The dependent variable refers to one of the measures of retail trading. In columns [1] and [2], the dependent variable refers to the ratio of retail trading to all reported trading. In columns [3] and [4], the dependent variable refers to retail order imbalances using executed trades while in columns [5] and [6], the dependent variable refers to retail order imbalances using executed trade volume. We also use the standardized trading retail trading and retail order imbalance as the dependent variable. All retail trading ratios are measured for stock i on day t across the event window where EX_t is equal to one if day t is the ex-dividend date. Five separate dummy variables are included to capture the five days around the ex-dividend date. Other independent variables include firm size, price volatility, share turnover, and price. Both day and stock fixed effects are included in the regression. Standard errors are clustered at the firm and date level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Retail Trading		*Trade Imbalance*		*Volume Imbalance*	
Dep Var. =	*Retail Trd*	*SRetail Trd*	*OIBTRD*	*SOIBTRD*	*OIBVOL*	*SOIBVOL*
	[1]	[2]	[3]	[4]	[5]	[6]
EX_{t-2}	0.0011***	0.0319***	0.0186***	0.0897***	0.0223***	0.0908***
	(3.12)	(2.73)	(7.60)	(9.44)	(7.69)	(10.09)
EX_{t-1}	0.0011***	0.0489***	0.0240***	0.1095***	0.0290***	0.1126***
	(3.12)	(4.29)	(10.14)	(11.66)	(9.68)	(12.15)
EX_t	0.0034***	-0.0179*	-0.0041*	-0.0011	-0.0067**	-0.0167**
	(7.79)	(1.72)	(1.75)	(-0.13)	(2.44)	(2.10)
EX_{t+1}	-0.0006**	-0.0206*	-0.0073***	-0.0386***	-0.0086***	-0.0441***
	(1.96)	(1.93)	(3.05)	(4.35)	(2.95)	(5.45)
EX_{t+2}	-0.0009***	-0.0511***	-0.0083***	-0.0294***	-0.0122***	-0.0402***
	(3.26)	(4.61)	(3.50)	(3.27)	(4.08)	(4.54)
$Size_t$	-0.0094***	-0.0056**	0.0116***	0.0006	0.0093***	-0.0000
	(13.70)	(2.14)	(11.06)	(0.36)	(10.24)	(0.03)
$Volatility_t$	-0.0083***	-0.0913***	0.0118***	0.0083*	0.0155***	-0.0013
	(9.18)	(11.86)	(5.79)	(1.82)	(7.20)	(0.35)
$Turnover_t$	-0.3291***	-0.8593	0.5367***	0.1936	0.7300***	0.1843
	(6.27)	(1.37)	(5.70)	(0.98)	(7.48)	(1.04)
$Price_t$	0.0007	-0.0076***	0.0033	-0.0002	0.0058***	-0.0012
	(0.70)	(2.73)	(1.42)	(0.14)	(2.64)	(0.69)
Intercept	0.1486***	-0.2429***	-0.1574***	0.0163	-0.1304***	-0.0063
	(18.61)	(6.77)	(12.47)	(0.78)	(10.93)	(0.50)
Adjusted R^2	0.1090	0.0032	0.0070	0.0011	0.0042	0.0012
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 6: TRADING VENUE MARKET SHARE AROUND THE EX-DIVIDEND DAY BY DIVIDEND YIELD

Table 6: Trading Venue Market Share Around the Ex-Dividend Day by Dividend Yield

This table reports the regression results from equation (3). The dependent variable refers to trading venue market share ratio, where trading venue refers to either maker-taker, taker-maker, and dark trading venues. We also use the standardized trading venue market share as the dependent variable. All trading venue market share ratios are measured for stock i on day t across the event window where EX_t is equal to one if day t is the ex-dividend date. Five separate dummy variables are included to capture the five days around the ex-dividend date. Five separate interaction terms are included to capture the effects of the stock's dividend yield around the ex-date. Other independent variables include firm size, price volatility, share turnover, and price. Both day and stock fixed effects are included in the regression. Standard errors are clustered at the firm and date level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Maker-Taker		*Taker-Maker*		*Dark*	
Dep Var. =	*MT Ratio*	*SMT Ratio*	*TM Ratio*	*STM Ratio*	*Dark Ratio*	*SDark Ratio*
	[1]	[2]	[3]	[4]	[5]	[6]
EX_{t-2}	0.0009	0.0203	-0.0005	-0.0209*	-0.0004	-0.0158
	(0.72)	(1.42)	(0.65)	(1.69)	(0.33)	(1.11)
EX_{t-1}	0.0022*	0.0271**	-0.0009	-0.0356***	-0.0014	-0.0116
	(1.68)	(1.99)	(1.04)	(2.88)	(1.14)	(0.79)
EX_t	0.0011	0.030**	-0.0007	0.0165	-0.0004	-0.0493***
	(0.94)	(2.43)	(0.91)	(1.39)	(0.42)	(4.06)
EX_{t+1}	0.0012	0.0138	0.0003	0.0043	-0.0015	-0.0274**
	(0.95)	(0.94)	(0.32)	(0.31)	(1.39)	(2.00)
EX_{t+2}	0.0007	0.0152	0.0010	0.0246*	-0.0017*	-0.0410***
	(0.57)	(1.07)	(1.29)	(1.95)	(1.71)	(3.04)
EX_{t-2} x Yield	-0.0776	-0.7369	-0.1662***	-3.9741***	0.2438**	3.8353***
	(0.71)	(0.47)	(2.84)	(3.38)	(2.27)	(2.70)
EX_{t-1} x Yield	-0.2664*	-2.5346	-0.2195***	-3.7849***	0.4860***	6.0073***
	(1.86)	(1.57)	(4.20)	(3.50)	(3.30)	(3.59)
EX_t x Yield	-0.0706	0.0083	-0.1374**	-3.5233***	0.2079**	2.6272**
	(0.76)	(0.01)	(2.42)	(3.09)	(2.40)	(2.33)
EX_{t+1} x Yield	-0.0479	-0.6832	0.0176	0.9882	0.0303	0.9509
	(0.49)	(0.46)	(0.27)	(0.66)	(0.36)	(0.78)
EX_{t+2} x Yield	0.0212	-0.4149	0.0712	1.3757	-0.0924	-0.3175
	(0.23)	(0.28)	(1.26)	(1.12)	(1.01)	(0.25)
Intercept	0.6216***	0.3265***	0.0370***	-0.2327***	0.3414***	-0.1958***
	(51.58)	(9.32)	(5.04)	(7.94)	(27.92)	(5.41)
Adjusted R^2	0.0734	0.0056	0.0553	0.0056	0.0810	0.0073
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 7: RETAIL TRADING AROUND THE EX-DIVIDEND DAY SORTED BY DIVIDEND YIELD

Table 7: Retail Trading Around the Ex-Dividend Day Sorted by Dividend Yield

This table reports the regression results from equation (3). The dependent variable refers to one of the measures of retail trading. We also use the standardized trading venue market share as the dependent variable. All trading venue market share ratios are measured for stock i on day t across the event window where EX_t is equal to one if day t is the ex-dividend date. Five separate dummy variables are included to capture the five days around the ex-dividend date. Five separate interaction terms are included to capture the effects of the stock's dividend yield around the ex-date. Other independent variables include firm size, price volatility, share turnover, and price. Both day and stock fixed effects are included in the regression. Standard errors are clustered at the firm and date level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Retail Trading		*Trade Imbalance*		*Volume Imbalance*	
Dep Var. =	*Retail Trd*	*SRetail Trd*	*OIBTRD*	*SOIBTRD*	*OIBVOL*	*SOIBVOL*
	[1]	[2]	[3]	[4]	[5]	[6]
EX_{t-2}	0.0006	-0.0024	0.0038	0.0308	0.0103**	0.0449***
	(1.16)	(0.14)	(0.76)	(1.56)	(2.12)	(2.70)
EX_{t-1}	-0.0013*	-0.0315	0.0050	0.0309	0.0144***	0.0498***
	(1.94)	(1.45)	(0.97)	(1.53)	(3.06)	(2.85)
EX_t	0.0025***	-0.0524***	-0.0001	0.0073	-0.0004	-0.0002
	(5.12)	(3.46)	(0.04)	(0.63)	(0.10)	(0.02)
EX_{t+1}	-0.0006	-0.0262*	-0.0003	-0.0058	-0.0039	-0.0258**
	(1.43)	(1.93)	(0.07)	(0.39)	(1.01)	(2.36)
EX_{t+2}	-0.0005	-0.0554***	0.0036	0.0146	-0.0020	-0.0010
	(1.18)	(4.11)	(0.86)	(1.02)	(0.45)	(0.08)
EX_{t-2} x Yield	0.0800	5.4992***	2.3776***	9.4489***	1.9174***	7.3638***
	(1.36)	(2.95)	(3.51)	(3.39)	(3.20)	(3.17)
EX_{t-1} x Yield	0.3843***	12.9009***	3.0578***	12.6101***	2.3455***	10.0851***
	(3.92)	(4.11)	(3.99)	(4.15)	(3.35)	(3.70)
EX_t x Yield	0.1379**	5.5338***	-0.6385**	-1.3580	-1.0135**	-2.6349**
	(2.42)	(3.17)	(2.00)	(1.13)	(2.47)	(2.09)
EX_{t+1} x Yield	-0.0121	0.8903	-1.14526**	-5.2512***	-0.7576	-2.9262**
	(0.25)	(0.72)	(2.24)	(2.68)	(1.58)	(2.06)
EX_{t+2} x Yield	-0.0654	0.7003	-1.9120***	-7.0490***	-1.6514***	-6.2830***
	(1.16)	(0.54)	(3.47)	(3.82)	(3.22)	(3.74)
Intercept	0.1403***	-0.2360***	-0.1825***	0.0189	-0.1499***	-0.0044
	(17.53)	(6.52)	(12.95)	(0.88)	(11.36)	(0.34)
Adjusted R^2	0.1175	0.0036	0.0098	0.0017	0.0053	0.0016
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 8: FRAGMENTATION AND PRICE-DROP RATIOS

Table 8: Fragmentation and Price-Drop Ratios

This table reports the regression results from equation (5). The dependent variable refers to the price-drop ratio, PDR, as provided in equation (4). The main independent variable is our measure of fragmentation, lit or dark. All fragmentation measures are calculated for stock i on day t, where t refers to the ex-dividend date. We interact our measure of fragmentation with the stock's dividend yield. We also include controls such as the stock's dividend yield, price, dividend, firm size, trading volume, spread, and exchange listing. Both year and stock fixed effects are included in the regression. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Dependent Variable = PDR	[1]	[2]	[3]	[4]
LitFrag	-0.7115	-1.1321*		
	(1.08)	(1.65)		
LitFrag x Yield		0.2058**		
		(2.09)		
DarkFrag			-1.2241***	-2.8336***
			(2.84)	(4.72)
DarkFrag x Yield				0.7898***
				(3.84)
Dividend Yield	-8.5272	-12.4670	-8.6984	-15.6322
	(0.49)	(0.71)	(0.50)	(0.89)
Price	-0.0089***	-0.0087***	-0.0088***	-0.0086***
	(2.76)	(2.66)	(2.71)	(2.66)
Dividend	0.5557	0.4843	0.5584	0.4979
	(1.19)	(1.03)	(1.19)	(1.06)
LnMcap	-0.2973	-0.0983	-0.3151	-0.0388
	(1.29)	(0.39)	(1.36)	(0.16)
LnVol	-0.2227***	-0.2252***	-0.1953**	-0.1912**
	(2.88)	(2.91)	(2.52)	(2.47)
Spread	-43.5228***	-43.7299***	-42.8505***	-44.0635***
	(3.22)	(3.24)	(3.17)	(3.26)
NASDAQ	1.3096	1.3060	1.3590	1.3570
	(1.31)	(1.30)	(1.36)	(1.36)
Intercept	8.3977**	5.9500	8.3578**	4.5945
	(2.34)	(1.57)	(2.34)	(1.24)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.1045	0.1046	0.1048	0.1055

APPENDIX 9: FRAGMENTATION AND EX-DAY RETURNS

Table 9: Fragmentation and Ex-Day Returns

This table reports the regression results from equation (6). The dependent variable refers to the ex-day return, where *Return* refers to the raw return and *AB Return* refers to the market-adjusted return on the ex-dividend date. The main independent variable is our measure of fragmentation, lit or dark. All fragmentation measures are calculated for stock i on day t, where t refers to the ex-dividend date. We interact our measure of fragmentation with the stock's dividend yield. We also include controls such as the stock's dividend yield, price, dividend, firm size, trading volume, spread, and exchange listing. Both year and stock fixed effects are included in the regression. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Dependent Variable	*Return*	*Return*	*AB Return*	*AB Return*	*Return*	*Return*	*AB Return*	*AB Return*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
LitFrag	-0.0029	0.0044	-0.0067	0.0007				
	(0.23)	(0.34)	(0.55)	(0.05)				
LitFrag x Yield		-0.0035*		-0.0036**				
		(1.93)		(1.97				
DarkFrag					0.0010	0.0179	-0.0027	0.0147
					(0.12)	(1.60)	(0.33)	(1.31)
DarkFrag x Yield						-0.0083**		-0.0085**
						(2.16)		(2.23)
Div Yield	0.3826	0.4504	0.3310	0.3997	0.3830	0.4560	0.3309	0.4057
	(1.17)	(1.37)	(1.02)	(1.22)	(1.17)	(1.39)	(1.02)	(1.24)
Intercept	-0.1453**	-0.1032	-0.1456**	-0.1029	-0.1473**	-0.1077	-0.1488	-0.1082
	(2.17)	(1.46)	(2.18)	(1.46)	(2.21)	(1.56)	(0.29)	(1.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.3122	0.3133	0.3133	0.3134	0.3122	0.3123	0.3133	0.3135

APPENDIX 10: RETAIL ORDER IMBALANCES AND PRICE-DROP RATIOS

Table 10: Retail Order Imbalances and Price-Drop Ratios

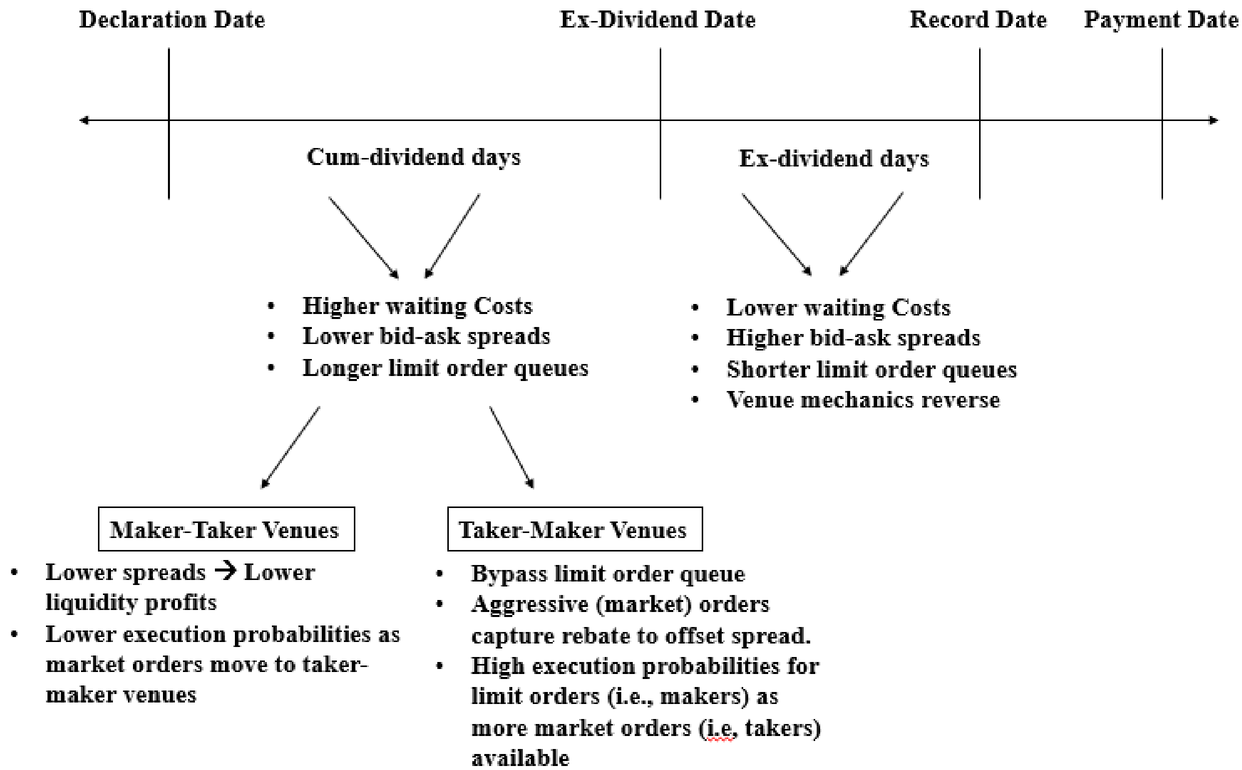
This table reports the regression results from equation (5) except we replace our measure of fragmentation with our measure of retail trading imbalance. The dependent variable refers to the price-drop ratio, PDR, as provided in equation (4). Our retail trading imbalance measure, OIBTRD, is calculated for stock i on day t, where t refers to the ex-dividend date. We interact our retail trading imbalance measure with the stock's dividend yield. We also include controls such as the stock's dividend yield, price, dividend, firm size, trading volume, spread, and exchange listing. Both year and stock fixed effects are included in the regression. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Dependent Variable = PDR	[1]	[2]
OIBTRD	-0.3357**	-0.7925***
	(2.20	(3.14)
OIBTRD x Yield		72.9626**
		(2.28)
Dividend Yield	-8.2106	-5.4515
	(0.47)	(0.31)
Price	-0.0089***	-0.0085***
	(2.75)	(2.63)
Dividend	0.5590	0.4182
	(1.19)	(0.89)
LnMcap	-0.2991	-0.2858
	(1.29)	(1.24)
LnVol	-0.2329***	-0.2338***
	(3.06)	(3.07)
Spread	-44.1952***	-44.3399***
	(3.27)	(3.28)
NASDAQ	1.3384	1.3398
	(1.34)	(1.34)
Intercept	7.8401**	7.6119**
	(2.20)	(2.13)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Adjusted R^2	0.1046	0.1049

APPENDIX 11: FEE VENUES AND EX-DIVIDEND TRADING

Figure 1: Fee Venues and Ex-Dividend Trading

Figure 1 provides the motivation for trading across fee models around the ex-dividend date. Limit order book queues, waiting costs, and bid-ask spreads are likely to motivate order placement before and after the ex-dividend date. We conclude this will motivate which fee venue, maker-taker vs. taker-maker, will attract a larger proportion of dividend-capture trading.

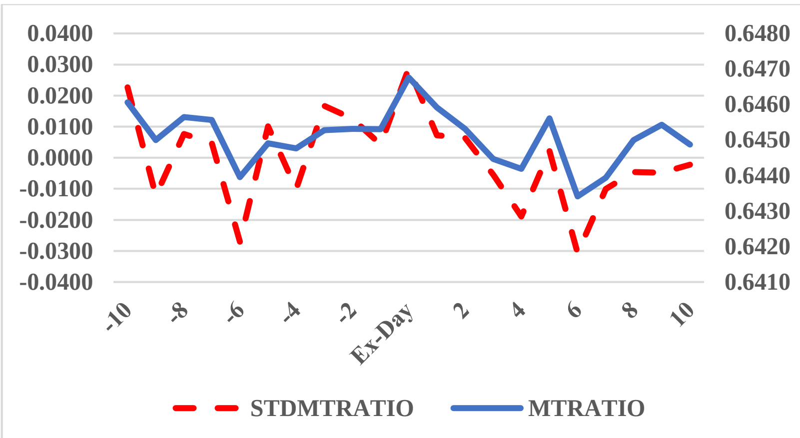


APPENDIX 12: TRADING VENUE MARKET SHARE AROUND THE EX-DIVIDEND DAY

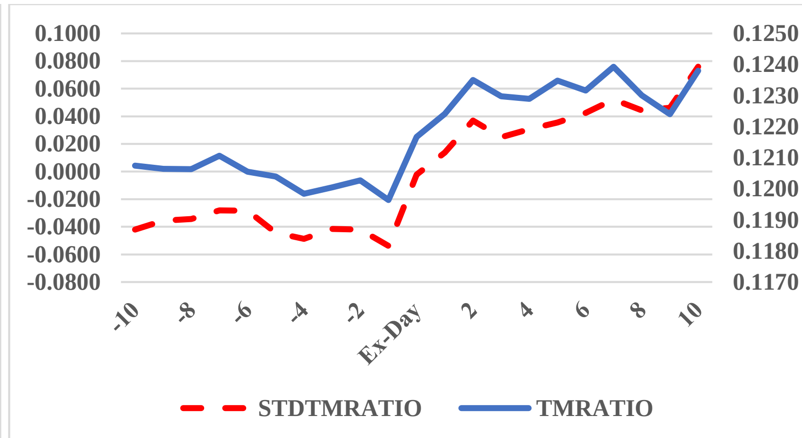
Figure 2: Trading Venue Market Share Around the Ex-Dividend Day

Figure 2 reports dark trading activity around the ex-dividend date across a 10-day event window. Panel A reports both the maker-taker trading ratio and standardized maker-taker ratio for all ex-dividend days. Panels B documents both the taker-maker trading ratio and standardized taker-maker ratio for all ex-dividend days. Panels C documents both the dark trading ratio and standardized dark trading ratio for all ex-dividend days.

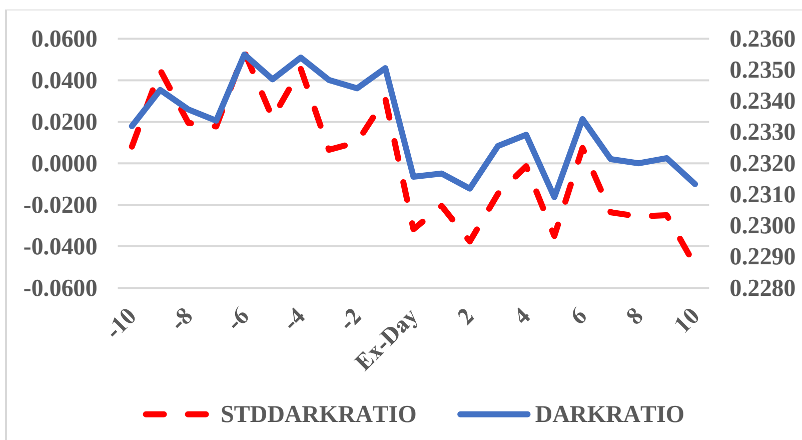
Panel A. Maker-Taker Trading Ratio



Panel B. Taker-Maker Trading Ratio



Panel C. Dark Trading Ratio

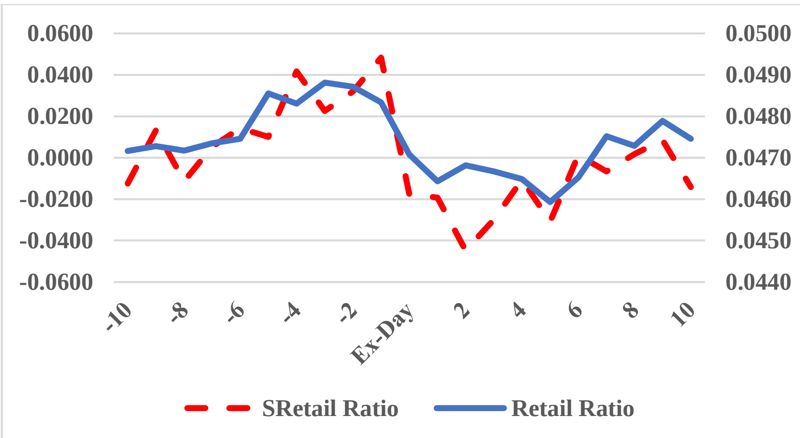


APPENDIX 13: RETAIL TRADING AROUND THE EX-DIVIDEND DAY

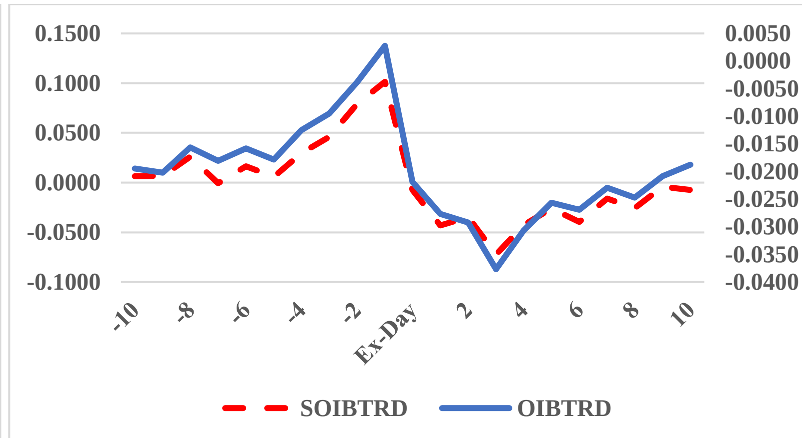
Figure 3: Retail Trading Around the Ex-Dividend Day

Figure 3 reports both the retail trading ratio and retail trading imbalances around dividend announcements. Panel A reports retail trading ratios around dividend announcements. Panels B and C reports retail trading imbalances, OIBTRD, across all (dividend vs. increase) dividend announcements. Panel D reports the retail trading imbalances, OIBTRD, across all dividend announcements sorted via the stock's dividend yield.

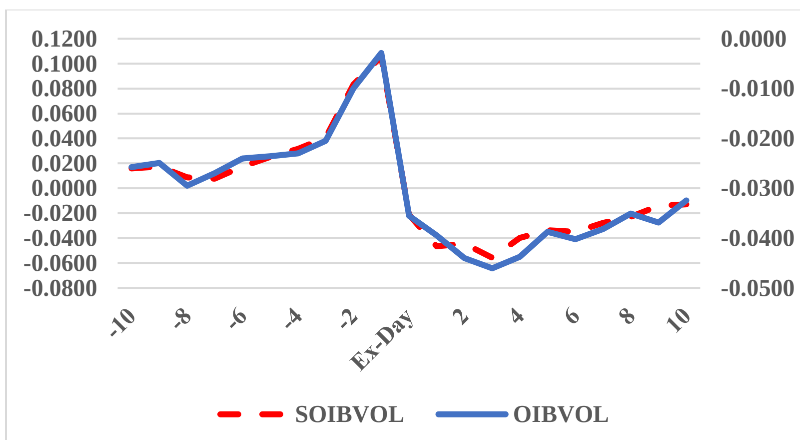
Panel A. Retail Trading Ratio



Panel B. OIBTRD



Panel C. OIBVOL

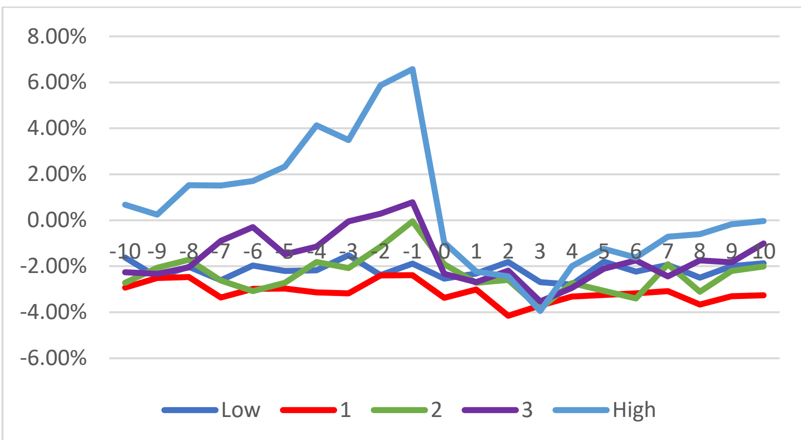


APPENDIX 14: RETAIL TRADING AROUND EX-DIVIDEND DATE BY DIVIDEND YIELD

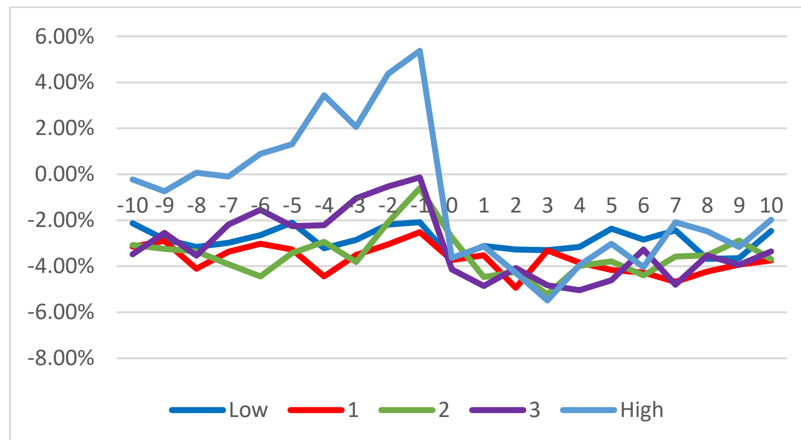
Figure 4: Retail Trading Around Ex-Dividend Date by Dividend Yield

Figure 4 reports both the retail trading ratio and retail trading imbalances around ex-dividend days. Panel A reports retail trading ratios around ex-dividend days. Panels B and C reports retail trading imbalances, OIBTRD, across all (dividend vs. increase) ex-dividend days. Panel D reports the retail trading imbalances, OIBTRD, across all ex-dividend days sorted via the stock's dividend yield.

Panel A. OIBTRD



Panel B. OIBVOL



PART 3: STOCK SPLITS AND RETAIL TRADING

I. INTRODUCTION

A May 26th, 2017 Wall Street Journal (WSJ) article, "Amazon's Brush With $1,000 Signals the Death of the Stock Split" cites Amazon's decision not to split their stock despite a share price closing near $1,000 as a signal that stock splits are dead.[22] The article documents that S&P 500 companies, in total, have accounted for less than 50 stock splits since 2010. Figure 1 shows the decline in the stock splits for S&P 500 companies.

The decline in the number of stock splits since 2010 is notable given that the average share price for stocks in the S&P 500 has been rising, coinciding with a "bull" market run over the same period. The WSJ article cites that among other explanations, that decades ago, companies considered stock splits as a method to keep shares affordable for retail investors. Despite no fundamental changes to the company following the stock splits, splits help generate excitement among retail investors, resulting in more trading. In recent years, however, individuals have moved away from direct ownership in equities and toward more diversified investments such as index funds.

Consistent with the notion that changes in retail investor ownership have contributed to the decline in the number of stock splits, Minnick and Raman (2014) confirm that one contributing factor to the declining number of stock splits is the decline in direct retail ownership of stocks. Their findings suggest that firms are less likely to benefit from a stock split since increasing the shareholder base and attracting more retail investors is more difficult as other

[22] Available at https://www.wsj.com/articles/amazons-brush-with-1-000-signals-the-death-of-the-stock-split-1495791009

investment options (i.e., mutual funds) exist for retail investors to diversify their holdings.[23] While Minnick and Raman provide evidence that changes in retail wealth and retail household income impact the firm's propensity to split, they do not examine if stock splits are relevant in attracting retail trading around the split date. In this study, we investigate retail trading activity using around stock splits to see if stock splits are relevant in attracting retail investors.

One historical view dating back to the early works of Copeland (1979), Baker and Gallagher (1980), and Baker and Powell (1993) suggests that stock splits align stocks prices in an optimal price range, resulting in a larger, dispersed shareholder base. A beneficiary from the post-split price reduction is the individual (i.e. retail) investor. In fact, numerous studies (Kryzanowski and Zhang, 1996; Schultz, 2000; Easley, O'Hara, and Saar, 2001; Angel, Brooks, & Mathew, 2004; Pavabutr and Sirodom, 2010) examine whether retail or small traders increase their participation around stock splits. Most of these papers rely on trade size as a proxy for retail trading. O'Hara, Yao and Ye (2014) document that changes to market structure such as increases in high-frequency trading reduce researchers' ability to proxy for retail trading using trade size and odd lot executions. In this study, we use a recently developed measure put forth by Boehmer, Jones, and Zhang (2018) to identify off-exchange retail trades around stock splits. Boehmer, Jones, and Zhang document that nearly 90% of orders placed with brokers received small price improvements and that these small price improvements typically occur off-exchange. Nonetheless, Boehmer, Jones, and Zhang argue that their measure captures an economically significant amount of retail trading activity.

Studies analyzing the impact of stock splits on retail investor clientele document that splits have a long-term impact on the degree of retail investor activity. For example,

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[23] Minnick and Raman (2014) cite the Dolley's (1933) viewpoint that retail investors purchase splitting stocks to diversify their holdings. See Minnick and Raman (2014) for studies confirming this viewpoint.

Kryzanowski and Zhang (1996) show that increases in small-board lot trading (i.e., trade values of less $10,000) following a split persist for nearly 120 trading days while large traders (i.e., trade values of at least $100,000) are less affected by the stock split. Likewise, Schultz (2000) shows that the trading activity of small traders extends for over two months following the split-date. Angel, Brooks, and Mathew (2004) find increases in activity of small-volume traders after the stock split date and confirm a long-term change increase in small-volume investors. Lipson and Mortal (2006) examine long-term liquidity effects post-stock split, finding that the average trade size declines considerably following the stock split, which they infer as a long-term increase in individual trading. These studies provide consistent evidence in support of the trading range hypothesis. We also examine if stock splits provide retail traders a favorable trading range, resulting in a long-term increase in retail trading. This expectation follows that post-split price levels do not revert to pre-stock split levels in the short-term, otherwise, the splitting stock underestimated the appropriate split factor to get prices back to a favorable range. To the extent that stock splits are no longer relevant in attracting retail participation, we expect that stock splits do not induce long-term retail participation.

We also analyze if reverse stock splits alter retail trading. Consistent with the premise that stock splits enable an optimal price range for retail traders, Bacon, Salandro, and Shin (1993) investigate managerial decisions to engage in a reverse split, finding that managers believe that reverse stock splits align stock prices to a more favorable range and increase their ownership base. Han (1995) documents that trading costs reduce and volume increases following reverse splits, supporting the notion that reverse splits enhance the liquidity of the stock. However, Han does not demonstrate if reverse splits directly impact the retail trading activity.

Several studies investigate post-split volatility effects of reverse splits.[24] Koski (2007) suggests that the decline in post-split volatility following reverse splits is attributed to the decline in noise traders, however, Koski does not directly identify retail trades. While reverse stock splits may move prices to an optimal range, many reverse stock splits may drive prices away from the low prices typically coveted by retail traders. Our identification of retail trades allows us to examine whether reverse splits increases or decreases retail trading activity.

We analyze nearly 700 combined forward and reverse splits between 2007 and 2016. We find that retail trading increases (decreases) around forward (reverse) splits. We also confirm that stock splits have only a transitory effect on retail trading. For example, we find that retail trading and retail trading imbalances increases in the several days around the split-date, subsiding in the subsequent 10 days. We further account for pre- and post-split price levels to determine if stock splits affect retail trading. We posit that forward stock splits with lower post-split prices and higher pre-split prices will have higher retail trading levels following the split-date. Our evidence shows that retail trading increases more for splits with higher pre-split prices but not for lower post-split prices. We also partition the sample of reverse splits by pre-split and post-split price levels, finding that higher post-split prices levels result in less retail trading following the split-date. Our results suggest that retail trading and trading behavior is affected by stock splits and is conditional on pre-split and post-split price levels. To the extent stock splits provide retail investors an optimal price, allowing for long-term retail trading participation, our results cast doubt on this optimal price hypothesis. Our findings do suggest that an optimal price range may exists depending on the pre- and post-split price levels associated with the forward and reverse splits. However, across all sample cuts, we find that the resulting change in retail participation

[24] Dravid (1987), Peterson and Peterson (1992), and Koski (2007) all analyze volatility effects associated with reverse splits.

subsides within 10 trading days of the split-date. This finding confirms the notion that stock splits are less significant in capturing greater retail demand.

We contribute to the literature in several ways. First, we contribute to the literature by providing an updated analysis of retail trading around stock splits, using a contemporary identification of retail traders. Second, we contribute to the literature as to the permanent effects of stock splits on retail trading by examining whether stock splits induce long-term or transitory retail trading. To the extent our findings indicate transitory retail investor participation, we provide evidence consistent with Minnick and Raman's (2014) assertion that the benefits of stocks splits have declined, in part, due to changes in retail investing. Third, we provide evidence as to the relation between retail trading around reverse splits. To the extent that retail trading declines following reverse splits, we argue reverse splits do not enable an optimal price but rather move prices away from the lower price levels preferred by retail investors.

II. HYPOTHESIS DEVELOPMENT

The optimal range hypothesis states that stock splits lower stock prices to an "optimal" range in order to attract more retail investors, as it makes it easier for investors to purchase in round lots (Baker and Gallagher, 1980; Lakonishok and Lev, 1987; Dyl and Elliott; 2006). The optimal range hypothesis also suggests that stock splits increase the firm's shareholder base, attracting greater retail clientele. However, some studies provide inconclusive evidence that stock splits adjust prices to an optimal range, increasing the firm's shareholder base. Lamoureux and Poon (1987) find increases in the number of transactions along with the number of shares traded but do not provide evidence as to changes in investor clienteles. Maloney and Mulherin (1992) document that stock splits increase the firm's shareholder base, specifically for institutional ownership, however, they do not directly test changes in retail ownership. Since these early findings, a host of studies document an increase in retail trading activity around stock splits.[25] Many of these studies use trade size and the number of odd lot trades as a proxy for retail activity. However, O'Hara, Yao, and Ye (2014) show that stealth traders and algorithmic traders use small-sized trades, including odd lot trades so that small traders are no longer considered retail traders.

While the literature suggests that stock splits may align prices to a favorable range, reverse splits may serve a similar purpose. Bacon, Salandro, and Shin (1993) investigate

[25] See Kryzanowski and Zhang, 1996; Muscarella and Vetsuypens, 1996; Schultz, 2000; Lipson, 2001; Easley et al., 2001; Kamara and Koski, 2001; Angel, Brooks, & Mathew, 2004; Kadapakkam et al., 2005; Pavabutr and Sirodom, 2010; and Kumar, Page and Spalt, 2012.

managerial decisions to engage in a reverse split, finding that managers believe that reverse splits align stock prices to a more favorable range and increase a firm's ownership base. Specifically, Bacon, Salandro, and Shin cite the managerial belief that despite driving prices upwards, the higher price resulting from the reverse split improves the marketability of the stock. Yet, many reverse splits are often conducted to avoid exchange delisting (Peterson and Peterson, 1992). Kim, Klein, and Rosenfeld (2008) show that over 63% of their sample of reverse-splitting firms engage in a reverse split to avoid exchange delisting. Further, Kim, Klein, and Rosenfield as well as Koski (2007) show that firms engaging in a reverse stock split to avoid delisting tend to be low-priced, smaller capitalized, and more volatile. Han and Kumar (2013) document that retail investors prefer stocks with lottery-like features such as lower market capitalization, low price, and high volatility. Similarly, Bali, Cakici, and Whitelaw (2011) argue that retail investors suffer from underdiversification and show a tendency for trading stocks with lottery-like features. Finally, Meng and Pantzalis (2018) examine turn-of-the-month effects and monthly retail investor liquidity around stock splits, finding that lower prices following a stock splits results in greater turn-of-the-month demand for stocks with lottery-like features. To the extent that reverse splits increase prices and reduce volatility (Koski, 2007), thereby reducing the lottery-like features of the stock, then we expect a decline in retail trading activity. We formalize our first hypothesis below.

H1: Retail trading increases (decreases) around forward (reverse) stock splits

We also examine the buy-sell imbalances of retail investors around stock splits. Previous stock split studies (Kryzanowski and Zhang, 1996; Schultz, 2000; Easley at al., 2001) show that retail investors are net buyers despite an overall rise in trading costs following the stock split. All three studies rely on the Lee-Ready (1991) trade classification algorithm in determining buy and sells. In this paper, we use Boehmer, Jones, and Zhang (2018) in classifying retail trading. Boehmer, Jones, and Zhang compare their buy-sell assignment to the trade sign of the Lee and Ready algorithm, finding that the trade signs match for nearly 90% of the observations. Hence, we expect that retail traders exhibit stronger buying tendencies around stock splits. To the extent that reverse splits drive prices away from preferred levels of retail traders, we expect retail sell trades to dominate retail buy trades. Therefore, we expect the following hypothesis to hold.

H2: Retail traders are net buyers (sellers) around forward (reverse) stock splits

While hypotheses 1 and 2 analyze if stock splits affect the level of retail trading as well as the trading behavior of retail investors, we next focus on the duration of retail investor activity following the stock split. To the extent that stock splits enable an optimal price range, allowing more retail traders the opportunity to transact in a stock at a lower price, then a stock split should have a sustaining effect on retail trading participation. Empirical evidence provided by Kryzanowski and Zhang (1996), Schultz (2000), Angel, Brooks, and Mathew (2004), and Lipson and Mortal (2006) confirm that stock splits impact retail traders beyond the split date, with some studies (i.e., Kryzanowski and Zhang, Schultz, and Lipson and Mortal) documenting effects lasting between two and four months following the split date.

One alternative explanation for stock splits is that they serve in attracting awareness about the firm. Consistent with signaling theory of stock splits, both Brennan and Copeland (1988), and Grinblatt, Masulis, and Titman (1984) argue that stock splits serve in attracting awareness to the firm. Huang, Liano, and Pan (2015) suggest that the stock split argument offered by Grinblatt et al. mirrors the attention-grabbing hypothesis of Barber and Odean (2007). Empirical evidence provided by Huang, Liano, and Pan shows that liquidity effects are short-lived around both the announcement and split date. They do not test, however, the liquidity effects associated with retail investors around the split date. Further, most of their sample period precedes many of the stock split studies in the literature and therefore, may not provide an accurate depiction of the changes in retail investor participation.[26]

Formalizing our third hypothesis, we reference Minnick and Raman (2014), who suggests that the decline in direct equity investment from retail investors implies fewer benefits to firms in splitting the stock in expanding the long-term shareholder base. Further, to the extent that retail traders no longer use stock splits to diversify their holdings as posited by Minnick and Raman, retail trading following a split could be short-lived. We posit that to the extent that retail trading participation increases following the stock split as suggested in hypothesis 1 and 2, we expect that this relation is transitory.

H3: Forward and reverse stock splits have only transitory effects on retail trading activity.

[26] Their sample period ranges back to 1960 and most of their sample firms come before market structure changes such as decimalization, increases in high frequency trading, and the decline of direct retail trading participation.

III. MEASURES AND METHODS

DATA AND SAMPLE SELECTION

Our measure of retail trading comes from Boehmer, Jones, and Zhang (2018), who measure retail trading in dark venues between 2010 and 2016. Our data allow us to examine retail trades dating back to 2004, however, Menkveld, Yueshen, and Zhu (2017) document that dark trades as defined by those reported to FINRA (code “D” in TAQ definition) are missing from May 2006 to February 2007 because TAQ data mixed trades reported to FINRA with some NASDAQ trades. Thus, we examine only stock splits taking place after February 2007 to mitigate any sample bias and data reporting errors. We obtain all stock and reverse splits from CRSP using distribution code 5523. Following the stock split literature, we filter out stock (reverse) splits that have a split factor less (greater) than 2 (0.5). For example, 3-for-2 stock splits (i.e., split factor = 1.5) and 2-for-3 reverse stock splits (i.e., split factor = 0.667) are excluded from the sample. We construct measures of retail trading and retail trading imbalances as well as standardized measures of retail trading imbalances. Applying these filters, we have 315 stock splits and 379 reverse splits.

Table 1 provides summary statistics for our sample. Panel A reports the number of splits, forward and reverse, for each year in our sample period. We find that most of the forward stock splits occur in the earlier years of our sample period. We also report the number of reverse splits occurring with a pre-split price below and above $1.00. Consistent with notion that most reverse splits are conducted to avoid delisting, we find that 75% of the reverse splits are conducted with a pre-split price below $1.00. In Panel B, we report the frequency of forward stock splits by split factor. Most of our forward stock splits have a split factor of 2-to-1. Panel B also reports the frequency of forward stock splits by pre-split price range and post-split price range. We find that nearly 95% of the forward stock splits have a pre-split price greater than $30 while over 60% of the forward stock splits have a post-split price greater than $30. In Panel C, we report the frequency of reverse splits by split factor. We show that nearly half of the reverse splits have a split factor between 6 and 10. We also report the frequency of reverse splits by their pre- and post-split price range, finding nearly half of the reverse splits have a post-split price ranging between $1 and $5.

Figure 2 shows that distribution of forward and reverse stock splits across the years in the sample period. In Panel A, we show that the frequency of forward splits is highest in the beginning of the sample period, while reverse splits peak toward the end of the sample period. In Panel B, we provide the distribution of reverse splits, grouped by their pre-split price level. We find that the frequency of reverse splits with a pre-split price greater than $1.00 is consistent in all years of the sample, however, we do find that frequency of reverse splits occurring with a pre-split price less $1.00 increases over the time-series.

We follow Boehmer, Jones, and Zhang (2018) to identify retail trading activity. Boehmer, Jones, and Zhang argue that their measure of retail trading accounts for a considerable amount of all retail trading activity. Boehmer, Jones, and Zhang suggests that nearly all retail orders are non-directed, giving the broker discretion on execution venue. Thus, brokers have autonomy in routing orders to off-exchange venues to receive some price improvement. Further, Boehmer, Jones, and Zhang cite 606 filings with several brokerage houses, finding that most retail investor orders (90%) receive some small price improvement. Finally, while the measure is limited to market orders and does not include possible retail limit orders limiting the scope of all retail trading activity, considering that most retail order flow is internalized or sold to wholesalers, we are confident that the proxy of off-exchange retail trading captures a significant portion of aggregate retail trading activity.[27]

Boehmer, Jones, and Zhang (2018) propose that one can identify retail trades in the dark venue by using executions that receive small amounts of price improvement, typically less than a penny. These transactions usually take place just above or below a round penny. For example, we identify transactions as retail-initiated buys if the executed price is slightly below the round penny, and retail-initiated sells if the executed price is slightly above the round penny. If we let P_{it} equal the execution price in stock i at time t, then let Z_{it} = 100 * mod (P_{it}, 0.01) be the fraction of a penny associated with that execution price. Z_{it} can take on any value in the unit interval [0,1). We then classify retail buys if the transaction price falls in the (0.6, 1) Z_{it} interval and classify retail sells if the transaction price falls in the (0,0.4) Z_{it} interval. We compute buy-sell imbalances by scaling the difference between retail buy and sell trades (volume) to the total amount of executed retail trades (volume). We create a retail trading ratio by scaling all dark venue, retail executed trades to all executed trades for stock i on day t. We also construct retail trading ratio by scaling all executed retail share volume to all executed shares volume for stock i on day t. We verify our measures of retail trading with those of Boehmer, Jones, and Zhang, finding similar numbers.[28]

[27] Boehmer, Jones, and Zhang (2018) show that their measure of retail trading accounts for nearly 3.68% of all executed trades. Our analysis shows that retail trading accounts for 3.68% of all executed trades.

[28] For example, we find that order imbalances using trades (volume) is -0.044 (-0.040). Boehmer, Jones, and Zhang (2018) report that order imbalances using trades (volume) is -0.038 (-0.032). However, comparing median values of order imbalance measures, our numbers are nearly identical (-0.028 vs. -0.027) to those of Boehmer, Jones, and Zhang.

$$\text{OIBTRD(VOL)}=\frac{\text{Retail Buy Trd (Vol)-Retail Sell Trd (Vol)}}{\text{Total Retail Trd (Vol)}} \quad (1)$$

Finally, to better evaluate if retail trading levels statistically differ from mean levels throughout our event window period, we construct a standardize retail trading measure for both our retail market share ratios as well as our order imbalances measures. To compute our standardized measures, we take the retail trading measure for stock *i* on day *t*, and then subtract the average retail trading measure for stock *i* across the event window period, and then divide this difference by the standard deviation in the retail trading measure for stock *i* over the event window period.

IV. EMPIRICAL RESULTS

UNIVARIATE ANALYSIS

In Table 2, we provide changes in retail trading around forward and reverse splits in our event window. In Panel A, columns (1) through (4) provide the changes in retail trading for forward splits while columns (5) through (8) provide the changes in retail trading around reverse splits. We show that following the stock split date, both standardized retail trading measures, constructed using either executed trades or trade volume, increase. Retail trading peaks on around split date, where both standardized measures are larger on the peak date than in the subsequent days. While retail trading levels remain positively elevated from their pre-split levels, the levels of retail trading following the split do not reflect a long-term change after the stock split. We show that retail trading declines following reverse splits. In column (8), we find that the standardized retail trading measure using executed trade volume declines following the stock splits.

In Panel B of Table 2, we partition the sample of reverse splits based on the pre-split price of $1 since many splits conducted below $1 are done so to avoid exchange delisting. Kwan, Masulis, and McInish (2015) argue that market structure changes for stocks priced around $1.00 present conflicting reasons for retail trading in the dark such as SEC Rule 612 which prohibits the displaying, ranking, or accepting orders priced at more than two decimal places for stocks priced at or above $1.00 by broker- dealers and exchanges. Specifically, they show that once a stock falls below $1.00, the minimum price increment falls from $0.01 to $0.001, resulting in a lower relative tick size. Kwan, Masulis, and McInish show that retail dark volume decreases once the stock price rises above $1.00, however, they also document that retail market share increases as the stock price goes above $1.00. In columns (1) through (4), we show that retail trading declines following reverse splits with a pre-split price less $1.00 The decline in retail trading supports the results of Kwan, Masulis, and McInish. The decreases in retail trading following the reverse stock split are also supportive of our arguments that reverse splits drive prices away from their lottery like features. In columns (5) through (8), we show that retail trading increases on the split date for reverse splits with a pre-split price above $1.00, however, the increase in retail trading is only transitory. The standardized estimates of retail trading are not significantly different from zero in the remaining days following the split.

MULTIVARIATE ANALYSIS

Our multivariate analysis regresses retail trading activity and trading imbalances on dummy date variables around the stock split date. We also control for the stock's daily market capitalization, volume, price, volatility, spread, split factor, and turnover. The same regression specification is applied to reverse splits; however, we partition the sample of reverse splits to account for Reg NMS rule 612. Reg NMS rule 612 (i.e., subpenny pricing rule) implies that when a stock falls below $1.00, the required minimum pricing increment for exchange trades decreases from a penny, or $0.01, to $0.0001. To account for this potential confounding influence on our measure of retail trading, we partition the reverse splits that take place with pre-split price below and above $1.00. By partitioning reverse splits based on the pre-split price above $1.00, we can make inferences about retail trading participation for reverse splits that are not influenced by Reg NMS rule 612. To further account for measurement errors, we divide the sample of reverse splits into pre-split and post-split price buckets (see Koski, 2007). We also include both industry and year fixed-effects and cluster standard errors at the stock level. The full model specification is provided in equation (2).

$$\text{Retail}_i = \beta_0 + \beta_1 \text{SplitDate}_{i,t-2} + \beta_2 \text{SplitDate}_{i,t-1} + \beta_3 \text{SplitDate}_{i,t} + \beta_4 \text{SplitDate}_{i,t+1} + \beta_5 \text{SplitDate}_{i,t+2} + \beta_6 \text{SplitDate}_{i,t+3,t+10} + \beta_7 \text{Controls}_i + \varepsilon_{i,t} \quad (2)$$

Table 3 provides the coefficient estimates from regression equation (2). In columns (1) and (2), we find that only the coefficient estimate for $\text{SplitDate}_{i,t+1}$ is positive, 0.0051 (0.0130), when retail trading is measured via executed trades (trade volume). The other stock split-date dummy variables are insignificant both before and after the split, indicating that the effective date of the stock split has no sustaining influence on retail trading. The transitory increases in retail trading following the stock split are consistent with the notion suggested by Minnick and Raman (2014) in that retail investors are less likely to use stock splits to diversify their holdings. In columns (3) and (4), we provide the results for all reverse splits. We find that following reverse stock splits, both retail trading measures, execute retail trades and retail volume, decline following the stock split date. Consistent with our conjecture that pre-stock split prices below and above $1.00 affect the level of retail trading activity, we find that retail trading decreases following reverse stock splits for those occurring with a pre-stock split price below $1.00. In column (6), we find that retail trading does not significantly change following reverse splits occurring with a pre-split price above $1.00. The lack of an increase in retail trading following a reverse stock split contrast with the argument that reverse stock splits improve the marketability of the stock, resulting in greater retail investor participation. Our results suggest that the reverse stock split forces prices away from the lower price levels preferred by retail investors.

Figure 3 provides the visual changes in retail trading around forward and reverse stock splits. In Panel A, we show the changes in retail trading levels using both our scaled and standardized measure of retail trading using executed trades. The visual in Panel A indicates that retail trading peaks on the stock split date, however, the abnormal levels of retail trading quickly decline in the 10 days after the stock split. In Panel B, we provide the changes in retail trading around the stock split using executed volume. Consistent with our results in Panel A, we find that forward stock splits induce a transitory increase in retail trading around the stock split date, only to subside in the subsequent 10 days. Thus, the visuals provided in Figure 3 illustrate that stock splits induce only a short-term effect on retail participation.

Figure 4 provides the visual changes in retail trading around forward and reverse stock splits. In Panel A, we show the changes in retail trading around all reverse stock splits. We find that a decline in retail trading leading around the stock split date. In fact, the standardized measure of retail trading becomes negative around the reverse stock split date. In Panel B, we provide similar evidence using executed trade volume. In Panel C, we show the changes in retail trading around reverse stock splits with a pre-stock split price less than \$1.00, finding that retail trading declines on the stock split date. While retail trading levels increase in the subsequent days after the stock split-date, the levels are well below those prior to the stock split. Panel D displays that for reverse stock splits with a pre-stock split price greater than \$1.00, we find that retail trading increases. The dashed line denotes that sharp increase in retail trading following the reverse stock split date. The results provided in Panels C and D indicate that reverse splits influence the level of retail trading yet are conditional on the pre-stock split price level around \$1.00.

Our analysis shows that forward (reverse) stock splits result in increases (decreases) in retail trading, consistent with hypothesis 1. We next address hypothesis 2 which states that forward (reverse) stock splits result in more (less) retail buying. Consistent with our previous model specification, we analyze the levels of retail trading around the split date, replacing our retail trading ratio with our measure of order imbalance, OIBTRD/OIBVOL, as the dependent variable. Following the studies of Malmendier and Shanthikumar (2007), Lai and Teo (2008), and Park and Lee (2014), we use a standardized imbalance measure, SOIBTRD/SOIBVOL, in our multivariate regressions. Columns (1) through (4) display the level of retail trade imbalances across the stock split date dummy variables for forward stock splits while columns (5) through (8) show the level of retail trade imbalances for reverse stock splits. We find that forward stock splits, retail traders are net buyers following the stock split. In column (1), the coefficient estimates for $SplitDate_{i,t+1}$, $SplitDate_{i,t+2}$, and $SplitDate_{i,t+3,t+10}$ are 0.1635, 0.0794, and 0.0292. The decline in the size estimates for the post-split date dummy variables indicate that beyond the effective date, retail traders exhibit less buying behavior. We provide similar results when measuring trade imbalances using executed volume as well as our standardized measures. In columns (5) and (6), we find that reverse stock splits induce more net retail selling following the split date. In column (5), the coefficient estimates for $SplitDate_{i,t+1}$, $SplitDate_{i,t+2}$, and $SplitDate_{i,t+3,t+10}$ are -0.0812, -0.0810, and -0.0467. The decline in the size estimates for the post-split date dummy variables indicate that beyond the effective date of the reverse stock split, retail traders exhibit less selling behavior. We find similar results using our measure of standardized trade imbalance, SOIBTRD, however, our results using volume-based imbalances measures yield insignificant results.

RESULTS BY PRE- AND POST-SPLIT PRICE LEVELS

In this section, we analyze the changes in retail trading activity around both forward and reverse stock splits accounting for pre- and post-stock split price levels. First, we analyze whether the post-stock split price levels affect the level of retail trading around forward stock splits. To the extent that lower post-stock split price results in greater retail participation, we expect that stocks with a post-stock split price less than $30 will have more retail trading following the split-date. We partition the sample of forward stock splits into two categories based on whether the post-stock split price is greater or less than $30, performing the same regression analysis from the previous section.

Table 5 reports the changes in retail trading around forward stock splits, grouped by their post-stock split price levels. In columns (1) through (4), we report the changes in retail trading levels around the split for forward stock splits with a post-stock split price less than $30 while columns (5) through (8) report the results for stocks with a post-split price greater than $30. We find that post-stock split price levels affect the level of retail trading, however, our results contrast with our conjecture that a lower post-stock split price level induces more retail trading. While we find that retail trading increases the day after the effective stock split-date for stock splits with a post-stock split price level below $30, we do not find higher levels of retail trading in the subsequent event window. Further, the coefficient estimate for $\text{Split}_{t+3,,t+10}$ is negative in both columns (1) and (2), suggesting that retail trading is lower than pre-stock split retail trading levels. In columns (5) and (8), we show that retail trading remains significantly higher than its post-stock split levels. The results in Table 5 indicate that retail trading around the stock split-date is moderated by post-stock split levels. To further test whether post-stock split price levels affect the level of retail trading activity around forward stock splits, we analyze retail trading imbalances around the stock split date for forward stock splits, grouped by post-stock split price levels.

We show in Table 6 that retail trading imbalances are positive around the stock split-date for forward stock splits, regardless of post-stock split price levels. The coefficient estimates for Split_{t+1} are positive for all imbalance measures across all forward stock splits. However, we find that the coefficient estimates for Split_{t+2} and $\text{Split}_{t+3,,t+10}$ remain positive for retail trading imbalance measures only for forward stock splits with a post-stock split price greater than \$30. Our finding that retail trading activity, both participation and buying behavior, is transitory for forward stock splits less than \$30, indicates support for the contention that retail traders are not using splitting of stocks to diversify their holdings. Further, our results indicate that an optimal price range – one in which results in greater long-term retail participation, is conditional on post-stock split price levels, particularly for higher-priced stocks.

To further examine whether retail trading participation around forward stock splits is affected by price levels, we account for pre-stock split price levels. Over 95% of our forward stock splits have a pre-stock split price greater than \$30. To facilitate comparison across pre-stock split prices, we partition our sample of forward stock splits into three pre-stock split price groups: pre-stock split price less than \$50, pre-stock split price between \$50 and \$100, and pre-stock split price greater than \$100. To the extent that higher pre-split price levels prohibit retail investors from trading the stock, we hypothesize that a higher pre-stock split price level will result in greater retail trading activity.

Table 7 provides the changes in retail trading around forward stock splits grouped by their pre-stock split price. Consistent our prediction that higher pre-stock split levels constrain retail trading, we find more retail trading following the stock split date for splits with a higher pre-stock split price. In columns (5) and (6), we find positive estimates for both Split_{t+1}, Split_{t+2}, and $\text{Split}_{t+3,,t+10}$. For example, we document a coefficient estimate of 0.0074 and 0.8044 for Split_{t+1} in columns (5) and (6). In columns (3) and (4), we show that only the coefficient estimate for Split_{t+1} is positive, indicating a higher retail trading. Further, the results in columns (1) through (4) indicate no change in retail trading in the event period following the effective stock split-date. In columns (1) and (2), we find that retail trading participation is lower than pre-stock split levels for forward splits with a lower pre-stock split price range. If stock splits reduce stock prices from prohibitively high pre-stock split price levels, resulting in an optimal price for retail trading, then our findings in Table 7 suggest that this is only true for stocks with higher pre-stock split price levels.

We next analyze retail trading around forward stock splits, grouped by their pre-stock split price levels. Consistent with our findings in Table 7, we expect greater retail buying following the stock split-date for forward stock splits with a higher pre-stock split price level. Table 8 provides the estimates from regressing retail trading imbalances around the stock split-date, sorted via the stock's pre-stock split price level. We find positive estimates for variables Split_{t+1} and Split_{t+2} across all forward stock splits. However, the coefficient estimate for $\text{Split}_{t+3,,t+10}$ is not significant for stock splits with pre-stock split price level less than \$30. In columns (3) through (6), we show a positive coefficient estimate for $\text{Split}_{t+3,,t+10}$, indicating that stock splits with a higher pre-stock split price level result in long-term participation. The results provided in Table 7 and 8 suggests that pre-stock split price levels affect the long-term participation of retail traders following the split. Our evidence demonstrates that stock splits, particularly those with higher pre-split levels, appear to align the stock price to favorable range, resulting in greater retail participation.

We next focus on the role of pre- and post-stock split price levels in affecting the relation between reverse splits and retail trading. Consistent with our earlier tests, we examine retail trading around reverse stock splits with a pre-split price around $1.00, but now investigate whether the pre-stock split price affects retail buying. In Table 3, we provided evidence consistent with hypothesis 1 that retail trading declined, although only for reverse stock splits with a pre-stock split price less than $1.00. In Table 9, we show that retail trading imbalances are negative around all reverse stock splits, regardless of the pre-stock split price. The decline in net retail trading imbalances following the reverse stock splits is consistent with our contention that reverse stock splits push prices away from the preferred, lower levels of retail investors, resulting in greater selling pressure from retail investors. We also observe in Table 9, that order imbalances computed via executed trades provide support for our prediction that reverse stock splits results in greater retail selling, while imbalances computed via executed trade volume does not yield similar findings.

Figure 5 provides graphical illustrations of how retail trading imbalances change around forward and reverse stock splits. In Panel A, we show that retail trading imbalances increases around the stock split-date. Consistent with hypothesis 3 that the effects of stock splits on retail trading is transitory, we find that the increase in retail trading imbalances subsides in the subsequent 5 days after the stock split. In Panel B, we show the decline in retail trading imbalances around reverse stock splits. In Panels C and D, we provide the changes in retail trading imbalance for reverse stock splits with a pre-stock split price below or above $1.00. The results in both panels indicate that retail trading imbalances are not affected by the pre-stock split price level. The visual depictions in Figure 5 indicate support for hypothesis 2 that retail traders are net buyers (sellers) following forward (reverse) stock splits. Further, the results confirm our expectation that the effects of stock splits on retail trading are transitory, at least for forward stock splits.

In Table 10, we explore the changes in retail trading imbalances around reverse stock splits, partitioning the sample of reverse stock splits based on their post-stock split price. Many of the reverse stock splits have a post-split price between $1 and $5, consistent with many firms using a reverse stock split to avoid delisting requirements. To better analyze if the post-stock split level affects retail trading around reverse splits, we create three categories formed via the stock's post-split price: post-stock split price less than $2, post-stock split price between $2 and $5, and post-stock split price greater than $5. The three post-stock split price categories are consistent with those used by Koski (2007). To the extent that higher post-stock split price levels prohibit retail investors from trading the stock, we hypothesize that a higher post-stock split price level will result in less retail trading activity. The results in Table 10 indicate support that a higher post-stock split price for reverse stock splits results in less retail trading. In column (4) and (6), we show that retail trading decreases following the stock split-date for reverse stock splits with a pre-stock split price between $2 and $5 and as well as stock splits with a pre-stock split price above $5. For reverse stock splits with a post-stock split price below $2, we find a decline in retail trading on stock split date but no significant change in retail trading in days following the stock split date. The finding provided in Table 10 suggest that changes in retail trading around reverse stock splits is conditional on post-stock split price levels.

Our last test analyzes the changes in retail trading imbalances around reverse stock splits, conditioning the post-stock split price level. We posit that a higher post-stock split price for reverse stock splits will result in greater retail selling following the stock split date. The results provided in Table 11 confirm more retail selling around reverse stock splits with a higher post-stock split price. In columns (3) and (4), we find that retail trading imbalances, scaled and standardized, are negative following the stock split-date. We find similar evidence in columns (5) and (6), indicating more retail selling for reverse stock splits with higher post-stock split prices. However, in columns (1) and (2), we find no significant change in retail trading imbalances around reverse stock splits with a lower post-stock split price. Overall, our results suggest that conditioning on pre-stock split price levels as well as post-stock split price levels affects the participation and buying behavior of retail investors around reverse stock splits. However, consistent across all our sample cuts, we find that retail trading participation as measured by the either market share or buy-sell imbalances is transitory.

V. CONCLUSION

In this study, we analyze the effects of stock splits on retail trading. Previous literature suggests that stock splits, both forward and reverse, provide an optimal price range for retail investors, resulting in long-term retail participation following the stock split. Minnick and Raman (2014) suggest that changes in direct retail ownership contributes to the decline in stock splits over the last several decades, citing that retail investors no longer use stock splits to diversify their holdings. We use Minnick and Raman’s assertion on retail investor diversification tendencies to analyze if stock splits still induce greater retail trading participation. Further, we examine if retail investors are active long-term in the stock following the stock split date. Our evidence indicates that retail trading increases (decreases) around forward (reverse) stock splits. However, we find that increases in both retail trading participation and retail trading imbalances are transitory around the stock split date, only lasting for several days following the effective stock split-date. We further test if our results are dependent on the pre- and post-stock split levels of the stock, finding evidence that retail trading increases more for stock splits with higher pre-stock split prices but not for lower post-stock split prices. We also provide similar findings after partitioning the sample of reverse stock splits via pre- and post-stock split price levels. Our results provide additional evidence to the declining relevance of stock splits in creating long-term retail trading participation, casting doubt on the optimal price range hypothesis of stock splits.

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APPENDIX

APPENDIX 1: SUMMARY STATISTICS

Table 1: Summary Statistics

This table reports the summary statistics on 694 stock splits of firms from 2007 and 2016. The split factor refers to the number of shares of stock an individual would own after the stock split for each pre-stock split share. For reverse stock splits, the split factor refers to the reciprocal of the split factor. The pre-stock split price range is derived on the average trade price for the stock for the period−40 to−1 days prior the stock split. The post-stock split price range is derived on the average trade price of the stock for the 40 days after the stock split. Frequency is the number of firms in the specified category. Panel A reports the frequency of stock splits, forward and reverse, by year. Panel A also reports the frequency of reverse stock splits by year, partitioned by the pre-stock split price level around $1.00. Panels B and C report the frequencies of forward and reverse stock splits by split factor, pre-stock split price range, and post-stock split price range.

Panel A. Number of Stock Splits, By Year

Year	Forward	Reverse	>$1.00	<$1.00
2007	95	19	6	13
2008	28	26	5	21
2009	8	30	14	16
2010	24	37	10	27
2011	42	32	9	23
2012	27	49	8	41
2013	25	42	12	30
2014	35	18	9	9
2015	21	49	8	41
2016	10	77	10	67
Total	315	379	91	288

Panel B. Forward Stock Splits

Split Factor	Freq	Pre-Stock Split Price Range	Freq	Post-Stock Split Price Range	Freq
2	283	$0 to $15	4	$0 to $15	25
3	20	$16 to $20	4	$16 to $20	23
4	7	$21 to $25	3	$21 to $25	26
5	3	$26 to $30	9	$26 to $30	42
>5	2	$30 plus	295	$30 plus	199

Panel C. Reverse Stock Splits

Split Factor	Freq	Pre-Stock Split Price Range	Freq	Post-Stock Split Price Range	Freq
2	11	< $1	292	< $1	5
3	21	$1 to $5	72	$1 to $5	171
4	42	$6 to $10	7	$6 to $10	87
5	48	$11 to $15	1	$11 to $15	35
6 – 10	176	$16 to $20	2	$16 to $20	24
11 – 20	61	$21 to $25	1	$21 to $25	11
21 – 30	11	$26 to $30	1	$26 to $30	6
31 – 50	6	$31 to $40	2	$31 to $40	14
51 – 100	2	$41 to $50	1	$41 to $50	8
>100	1	$50 plus	0	$50 plus	18

APPENDIX 2: EVENT WINDOW OF RETAIL TRADING AROUND FORWARD AND REVERSE STOCK SPLITS

Table 2: Event Window of Retail Trading Around Forward and Reverse Stock Splits

Table 2 presents results from a 21-day event study around the ex-stock split date. In Panel A, we provide the levels of retail trading for forward and reverse stock splits. In Panel B, we provide the levels of retail trading for reverse stock splits, grouped via the pre-stock split price. The t-tests tests whether the standardized retail trading measure is significantly different from zero. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

Panel A. Forward and Reverse Stock Splits								
	Forward Stock Splits				Reverse Stock Splits			
	RetailTrdRatio	*SRetailTrdRatio*	*RetailVolRatio*	*SRetailVolRatio*	*RetailTrdRatio*	*SRetailTrdRatio*	*RetailVolRatio*	*SRetailVolRatio*
-10, -6	0.0391	-0.0561**	0.0555	-0.1087***	0.1634	0.0652***	0.2237	0.1114***
-5	0.0425	-0.0204	0.0585	-0.1208**	0.1622	0.0858*	0.2272	0.1567***
-4	0.0405	-0.0264	0.0549	-0.1065*	0.1581	-0.0009	0.2155	0.0176
-3	0.0423	-0.0392	0.0556	-0.1291**	0.1698	0.1012**	0.2337	0.1615***
-2	0.0391	-0.0702	0.0532	-0.1620***	0.1686	0.0874*	0.2265	0.0565
-1	0.0380	-0.0805	0.0550	-0.1016*	0.1573	-0.0213	0.2045	-0.0590
Split Date	0.0407	-0.0523	0.0526	-0.1594***	0.1470	-0.1207**	0.2085	-0.0857
1	0.0458	0.4128***	0.0680	0.4517***	0.1564	0.0373	0.2060	-0.0848*
2	0.0437	0.1287**	0.0650	0.1868***	0.1548	0.0348	0.2049	-0.0897**
3	0.0416	0.1072**	0.0625	0.1730***	0.1531	-0.0153	0.2057	-0.0820*
4	0.0403	0.0110	0.0593	0.0970*	0.1574	-0.0140	0.2091	-0.0410
5	0.0398	0.1201**	0.0591	0.1392***	0.1512	-0.1229***	0.1983	-0.1784***
+6, +10	0.0375	-0.0443*	0.0570	0.0520**	0.1495	-0.0852***	0.2086	-0.0797***
Panel B. Reverse Stock Splits with Pre-Stock Split Price Above (Below) $1.00								
	Reverse Stock Splits, < $1.00				Reverse Stock Splits, > $1.00			
-10, -6	0.1931	0.0922***	0.2576	0.1196***	0.0714	-0.0040	0.1187	0.0859*
-5	0.1921	0.1131*	0.2619	0.1593***	0.0694	-0.0011	0.1193	0.1487
-4	0.1887	0.0067	0.2499	0.0285	0.0642	-0.0242	0.1097	-0.0158
-3	0.2020	0.1496***	0.2684	0.1837***	0.0663	-0.0532	0.1222	0.0907
-2	0.2012	0.1776***	0.2658	0.1372**	0.0630	-0.2045**	0.0991	-0.2044**
-1	0.1843	0.0279	0.2316	-0.0421	0.0695	-0.1808*	0.1165	-0.1137
Split Date	0.1714	-0.1604***	0.2402	-0.1170*	0.0696	0.0055	0.1081	0.0138
1	0.1814	-0.0291	0.2355	-0.1098**	0.0754	0.2524**	0.1103	-0.0038
2	0.1808	-0.0084	0.2343	-0.1392***	0.0646	0.1840*	0.1032	0.0814
3	0.1780	-0.0463	0.2360	-0.0855*	0.0686	0.0901	0.1026	-0.0701
4	0.1812	-0.0651	0.2375	-0.0962*	0.0761	0.1607	0.1121	0.1476
5	0.1750	-0.1479***	0.2249	-0.2108***	0.0744	-0.0420	0.1126	-0.0743
+6, +10	0.1752	-0.1054***	0.2404	-0.0749***	0.0667	-0.0202	0.1062	-0.0955**

APPENDIX 3: RETAIL TRADING AROUND FORWARD AND REVERSE STOCK SPLITS

Table 3: Retail Trading Around Forward and Reverse Stock Splits

This table reports the regression results from equation (2). Columns [1] and [2] provide the results for forward stock splits only. Columns [3] and [4] provide the results for reverse stock splits only. Columns [5] and [6] provide the results for reverse stock splits, grouped via the pre-stock split price. The dependent variable refers to our scaled measure of retail trading, where retail trading is measured via either executed trades or trade volume. All retail trading ratios are measured for stock i on day t across the event window where $Split_t$ is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the stock's split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels.

	Stock Splits				Reverse Stock Splits Only	
	Forward		Reverse		Pre-Stock Split Price <$1.00	Pre-Stock Split Price >$1.00
	RetailTrd(%)	*RetailVol(%)*	*RetailTrd(%)*	*RetailVol(%)*	*RetailTrd(%)*	*RetailTrd(%)*
	[1]	[2]	[3]	[4]	[5]	[6]
$Split_{t-2}$	0.0008	-0.0005	0.0070	-0.0002	0.0029	-0.0185**
	(0.43)	(0.21)	(1.52)	(0.03)	(0.34)	(2.47)
$Split_{t-1}$	-0.0025	-0.0005	-0.0058	-0.0191***	-0.0243***	-0.0078
	(1.33)	(0.18)	(1.54)	(3.26)	(3.48)	(0.94)
$Split_t$	0.0025	-0.0011	-0.0200***	-0.0217***	-0.0229**	-0.0087
	(1.27)	(0.46)	(3.53)	(2.92)	(2.41)	(0.80)
$Split_{t+1}$	0.0051***	0.0130***	-0.0180***	-0.0362***	-0.0304***	-0.0135
	(3.03)	(5.14)	(2.99)	(4.92)	(3.77)	(1.20)
$Split_{t+2}$	0.0000	0.0031	-0.0101**	-0.0256***	-0.0280***	-0.0067
	(0.02)	(1.09)	(2.02)	(3.88)	(3.51)	(0.69)
$Split_{t+3,,t+10}$	-0.0012	0.0020	-0.0091**	-0.0181***	-0.0261***	-0.0017
	(1.07)	(1.25)	(2.45)	(3.83)	(4.51)	(0.27)
Intercept	0.0027	0.0098	0.1476***	0.1296***	0.1706***	0.0983**
	(0.28)	(0.70)	(8.64)	(5.73)	(9.06)	(2.12)
Adjusted R²	35.06%	31.26%	20.07%	0.1854%	0.1210%	30.15%
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 4: RETAIL TRADING IMBALANCES AROUND FORWARD AND REVERSE STOCK SPLITS

Table 4: Retail Trading Imbalances Around Forward and Reverse Stock Splits

This table reports the regression results from equation (2). Columns [1] through [4] report the results for retail trading and standardized retail trading using both executed trades and trade volume around the stock split date of forward stock splits. Columns [5] through [8] report the results for retail trading and standardized retail trading using both executed trades and trade volume around the stock split date of reverse stock splits. All retail trading ratios are measured for stock i on day t across the event window where $Split_t$ is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the ex-stock split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Forward Stock Splits				Reverse Stock Splits			
	OIBTRD	*SOIBTRD*	*OIBVOL*	*SOIBVOL*	*OIBTRD*	*SOIBTRD*	*OIBVOL*	*SOIBVOL*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$Split_{t-2}$	-0.0568***	-0.1529**	-0.0497**	-0.1082*	0.0426*	0.1025	0.0138	0.0443
	(3.27)	(2.42)	(2.35)	(1.67)	(1.86)	(1.57)	(0.55)	(0.70)
$Split_{t-1}$	-0.0254	-0.0943	-0.0328*	-1.0777*	0.0291	0.0773	0.0186	0.0298
	(1.64)	(1.65)	(1.67)	(1.75)	(1.47)	(1.36)	(0.78)	(0.51)
$Split_t$	-0.0187	-0.0187	-0.0380*	-0.0584	-0.0210	-0.0579	0.0227	0.0557
	(1.15)	(0.30)	(1.90)	(0.93)	(1.14)	(1.08)	(1.05)	(1.05)
$Split_{t+1}$	0.1635***	0.7683***	0.1485***	0.6030***	-0.0812***	-0.2075***	-0.0170	-0.0057
	(11.24)	(12.56)	(8.76)	(10.36)	(4.06)	(3.73)	(0.76)	(0.11)
$Split_{t+2}$	0.0794***	0.3975***	0.0627***	0.2777***	-0.0810***	-0.1950***	-0.0071	-0.0090
	(5.10)	(6.25)	(3.67)	(4.77)	(4.05)	(3.53)	(0.32)	(0.17)
$Split_{t+3,,t+10}$	0.0292***	0.1381***	0.0277***	0.1020***	-0.0467***	-0.1301***	0.0074	0.0334
	(3.07)	(3.80)	(2.61)	(3.03)	(4.02)	(4.06)	(0.59)	(1.08)
Intercept	-0.1698***	-0.0703	0.0080**	-0.05881	-0.1362*	-0.0781	-0.2718***	-0.1287**
	(2.58)	(1.21)	(2.07)	(1.11)	(1.87)	(1.09)	(4.48)	(2.00)
Adjusted R^2	0.0654	0.0380	0.0369	0.0234	0.0247	0.0094	0.0114	0.0014
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 5: RETAIL TRADING AROUND STOCK SPLITS BY POST-STOCK SPLIT PRICE

Table 5: Retail Trading Around Stock Splits by Post-Stock Split Price

This table reports the regression results from equation (2). Columns [1] through [4] report the results for retail trading and standardized retail trading using both executed trades and trade volume around the split date of forward stock splits with a post-stock split price less than $30. Columns [5] through [8] report the results for retail trading and standardized retail trading using both executed trades and trade volume around the stock split date of forward stock splits with a post-split price greater than $30. All retail trading ratios are measured for stock i on day t across the event window where $Split_t$ is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the ex-stock split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Post-Stock Split Price <$30.00				Post-Stock Split Price >$30.00			
	RetailTrdRatio	*SRetailTrdRatio*	*RetailVolRatio*	*SRetailVolRatio*	*RetailTrdRatio*	*SRetailTrdRatio*	*RetailVolRatio*	*SRetailVolRatio*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$Split_{t-2}$	-0.0022	-0.1697*	-0.0062	-0.2116**	0.0005	0.0818	0.0001	0.0588
	(0.54)	(1.68)	(1.39)	(2.01)	(0.61)	(0.97)	(0.07)	(0.72)
$Split_{t-1}$	-0.0064*	0.0319	-0.0012	0.1009	-0.0002	-0.0701	0.0001	-0.0181
	(1.74)	(0.29)	(0.24)	(0.92)	(0.18)	(0.97)	(0.01)	(0.25)
$Split_t$	0.0027	-0.0293	-0.0053	-0.1640	0.009	0.0075	-0.0006	0.0256
	(0.60)	(0.29)	(0.94)	(1.65)	(0.69)	(0.09)	(0.32)	(0.33)
$Split_{t+1}$	0.0028	0.2557**	0.0138**	0.3431***	0.0058***	0.6154***	0.0120***	0.7548***
	(0.72)	(2.42)	(2.44)	(3.20)	(4.98)	(6.82)	(2.90)	(8.96)
$Split_{t+2}$	-0.0021	0.0519	0.0019	0.1283	0.0027*	0.2581***	0.0062***	0.3854***
	(0.75)	(0.47)	(0.35)	(1.19)	(1.86)	(2.85)	(2.90)	(4.67)
$Split_{t+3,,t+10}$	-0.0065***	-0.1843**	-0.0049	-0.0797	0.0018**	0.1987***	0.0059***	0.3618***
	(2.62)	(2.48)	(1.49)	(1.13)	(2.58)	(3.70)	(4.49)	(7.37)
Intercept	0.3156***	-0.0325	0.3967***	-0.1359	-0.0323	-0.2381**	-0.0429	-0.3756***
	(5.35)	(0.22)	(5.39)	(0.93)	(1.47)	(2.37)	(1.48)	(3.89)
Adjusted R^2	0.4692	0.0170	0.4610	0.0160	0.5065	0.0257	0.3931	0.0543
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 6: RETAIL TRADING IMBALANCES AROUND STOCK SPLITS BY POST-STOCK SPLIT PRICE

Table 6: Retail Trading Imbalances Around Stock Splits by Stock Split Price

This table reports the regression results from equation (2). Columns [1] through [4] report the results for retail trading and standardized retail trading imbalances using both executed trades and trade volume around the stock split date of forward stock splits with a post-stock split price less than $30. Columns [5] through [8] report the results for retail trading and standardized retail trading using both executed trades and trade volume around the stock split date of forward stock splits with a post-stock split price greater than $30. All retail trading imbalances are measured for stock i on day t across the event window where $Split_t$ is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the ex-stock split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively

	Post-Stock Split Price <$30.00				Post-Stock Split Price >$30.00			
	OIBTRD	*SOIBTRD*	*OIBVOL*	*SOIBVOL*	*OIBTRD*	*SOIBTRD*	*OIBVOL*	*SOIBVOL*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$Split_{t-2}$	-0.1125***	-0.3333***	-0.0973**	-0.2703**	-0.0261	-0.0499	-0.0230	-0.0160
	(3.49)	(3.21)	(2.38)	(2.43)	(1.30)	(0.63)	(0.96)	(0.20)
$Split_{t-1}$	-0.0522*	-0.1563	-0.0482	-0.1353	-0.0115	-0.0591	-0.0252	-0.0921
	(1.75)	(1.61)	(1.31)	(1.33)	(0.65)	(0.83)	(1.09)	(1.18)
$Split_{t}$	0.0372	-0.0208	-0.0889**	-0.1660*	-0.0084	-0.1809	-0.0081	0.0035
	(1.23)	(0.21)	(2.46)	(1.82)	(0.44)	(0.22)	(0.34)	(0.04)
$Split_{t+1}$	0.1634***	0.5805***	0.1272***	0.3945***	0.1629***	0.8703***	0.1604***	0.7171***
	(6.66)	(7.00)	(4.02)	(4.79)	(8.90)	(10.53)	(8.00)	(9.27)
$Split_{t+2}$	0.0560*	0.2157**	0.0291	0.1249	0.0953***	0.5041***	0.0836***	0.3685***
	(1.84)	(2.07)	(0.87)	(1.27)	(5.45)	(6.23)	(4.35)	(5.09)
$Split_{t+3,,t+10}$	0.0227	0.0911	0.0119	0.0272	0.0338***	0.1648***	0.0378***	0.1454***
	(1.28)	(1.53)	(0.59)	(0.48)	(3.04)	(3.56)	(3.10)	(3.45)
	0.0238	-0.0649	-0.0160	-0.0807	-0.1875**	-0.1105	-0.0153	-0.0255
Intercept	(0.20)	(0.56)	(0.11)	(0.82)	(2.55)	(1.41)	(0.20)	(0.34)
Adjusted R^2	0.0832	0.0280	0.0517	0.0116	0.0729	0.0471	0.0414	0.0311
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 7: RETAIL TRADING AROUND STOCK SPLITS BY PRE-STOCK SPLIT PRICE

Table 7: Retail Trading Around Stock Splits by Pre-Stock Split Price

This table reports the regression results from equation (2). Columns [1] through [2] report the results for retail trading and standardized retail trading ratios using executed trades around the stock split date of forward stock splits with a pre-stock split price less than $50. Columns [3] through [4] report the results for forward stock splits with a pre-stock split price greater than $50 and less than $100. Columns [5] through [6] report the results for forward stock splits with a pre-stock split price greater than $100. All retail trading imbalances are measured for stock i on day t across the event window where $Split_t$ is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the ex-stock split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Pre-Split Price < $50.00		$50.00 < Pre-Split Price < $100.00		Pre-Split Price > $100.00	
	RetailTrd(%)	*SRetailTrd(%)*	*RetailTrd(%)*	*SRetailTrd(%)*	*RetailTrd(%)*	*SRetailTrd(%)*
	[1]	[2]	[3]	[4]	[5]	[6]
$Split_{t-2}$	-0.0006	-0.1365	-0.0000	-0.0034	-0.0004	0.1041
	(0.09)	(1.03)	(0.02)	(0.04)	(0.32)	(0.80)
$Split_{t-1}$	-0.0060	0.0916	-0.0008	-0.0339	-0.0012	-0.1481
	(1.23)	(0.70)	(0.68)	(0.40)	(1.07)	(1.32)
$Split_t$	0.0031	-0.0741	0.0008	0.0129	0.0023	0.0172
	(0.49)	(0.52)	(0.44)	(0.15)	(0.80)	(0.14)
$Split_{t+1}$	-0.0003	0.0720	0.0052***	0.5095***	0.0074***	0.8044***
	(0.04)	(0.55)	(4.22)	(5.64)	(3.59)	(4.98)
$Split_{t+2}$	-0.0003	0.0689	0.0004	0.1479	0.0037**	0.3800**
	(0.07)	(0.47)	(0.22)	(1.64)	(2.23)	(2.30)
$Split_{t+3,,t+10}$	-0.0094**	-0.2590***	0.0002	0.1012*	0.0026*	0.2496**
	(2.17)	(2.71)	(0.30)	(1.81)	(1.92)	(2.51)
	0.1721**	-0.0546	0.0630**	-0.1791**	-0.0508	-0.4546**
Intercept	(2.15)	(0.16)	(2.27)	(2.22)	(1.47)	(2.21)
Adjusted R^2	0.5071	0.0266	0.3954	0.0161	0.6726	0.0466
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 8: RETAIL TRADING IMBALANCES AROUND STOCK SPLITS BY PRE-STOCK SPLIT PRICE

Table 8: Retail Trading Imbalances Around Stock Splits by Pre-Stock Split Price

This table reports the regression results from equation (2). Columns [1] through [2] report the results for retail trading and standardized retail trading imbalances using both executed trades and trade volume around the stock split date of forward stock splits with a pre-stock split price less than $50. Columns [3] through [4] report the results for forward stock splits with a pre-stock split price greater than $50 and less than $100. Columns [5] through [6] report the results for forward stock splits with a pre-stock split price greater than $100. All retail trading imbalances are measured for stock i on day t across the event window where Split_t is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the ex-stock split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Pre-Split Price < $50.00		$50.00 < Pre-Split Price < $100.00		Pre-Split Price > $100.00	
	OIBTRD	*SOIBTRD*	*OIBTRD*	*SOIBTRD*	*OIBTRD*	*SOIBTRD*
	[1]	[2]	[3]	[4]	[5]	[6]
Split_{t-2}	-0.1404***	-0.3862***	-0.0558**	-0.1696**	0.0179	0.1058
	(3.03)	(2.66)	(2.39)	(2.02)	(0.71)	(0.83)
Split_{t-1}	-0.0868**	-0.2701**	-0.0107	-0.0626	-0.0084	-0.0188
	(2.00)	(2.07)	(0.55)	(0.83)	(0.31)	(0.16)
Split_{t}	-0.0494	-0.0554	-0.0287	-0.1050	0.0426	0.2362*
	(1.26)	(0.46)	(1.27)	(1.19)	(1.63)	(1.85)
Split_{t+1}	0.1308***	0.4144***	0.1655***	0.7393***	0.1810***	1.1358***
	(3.46)	(3.44)	(8.64)	(9.90)	(6.44)	(7.55)
Split_{t+2}	0.0889**	0.3214**	0.0723***	0.3479***	0.0933***	0.5847***
	(2.06)	(2.33)	(3.40)	(4.04)	(4.13)	(4.33)
$\text{Split}_{t+3,,t+10}$	0.0154	0.0794	0.0318**	0.1207**	0.0388***	0.2367***
	(0.60)	(0.96)	(2.44)	(2.47)	(2.71)	(3.15)
Intercept	-0.0578	-0.1564	-0.1030	-0.0757	-0.2023	-0.3673**
	(1.04)	(1.05)	(0.89)	(1.22)	(1.08)	(2.34)
Adjusted R^2	0.1046	0.0297	0.0624	0.0357	0.1580	0.0722
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 9: RETAIL TRADING IMBALANCES AROUND REVERSE STOCK SPLITS BY PRE-STOCK SPLIT PRICE

Table 9: Retail Trading Imbalances Around Reverse Stock Splits by Pre-Stock Split Price

This table reports the regression results from equation (2). Columns [1] through [4] report the results for retail trading and standardized retail trading imbalances using both executed trades and trade volume around the split date of reverse stock splits with a pre-stock split price less than $1. Columns [5] through [8] report the results for retail trading and standardized retail trading using both executed trades and trade volume around the stock split date of reverse stock splits with a pre-stock split price greater than $1. All retail trading imbalances are measured for stock i on day t across the event window where $Split_t$ is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the ex-stock split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Pre-Stock Split Price <$1.00				Pre-Stock Split Price >$1.00			
	OIBTRD	*SOIBTRD*	*OIBVOL*	*SOIBVOL*	*OIBTRD*	*SOIBTRD*	*OIBVOL*	*SOIBVOL*
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$Split_{t-2}$	0.0579**	0.1380*	0.0127	0.0324	0.0011	0.0011	0.0173	0.0801
	(2.10)	(1.84)	(0.42)	(0.45)	(0.03)	(0.01)	(0.39)	(0.61)
$Split_{t-1}$	0.0344	0.0817	0.0301	0.0504	0.0115	0.0600	-0.0179	-0.0396
	(1.45)	(1.27)	(1.04)	(0.76)	(0.33)	(0.49)	(0.44)	(0.31)
$Split_t$	-0.0193	-0.0340	0.0316	0.0878	-0.0369	-0.1487	-0.0157	-0.0683
	(0.89)	(0.58)	(1.22)	(1.49)	(0.96)	(1.17)	(0.40)	(0.55)
$Split_{t+1}$	-0.0908***	-0.2016***	-0.0183	0.0325	-0.0546	-0.2331**	-0.0093	-0.1240
	(3.77)	(3.10)	(0.68)	(0.53)	(1.54)	(2.04)	(0.23)	(1.09)
$Split_{t+2}$	-0.0791***	-0.1704***	0.0115	0.0460	-0.0850**	-0.2853**	-0.0567	-0.1877
	(3.30)	(2.69)	(0.43)	(0.78)	(2.38)	(2.51)	(1.36)	(1.50)
$Split_{t+3,,t+10}$	-0.0443***	-0.1040***	0.0084	0.0436	-0.0544**	-0.2234***	0.0103	-0.0018
	(3.19)	(2.87)	(0.55)	(1.24)	(2.59)	(3.17)	(0.50)	(0.03)
Intercept	-0.2818***	-0.1959*	-0.3304***	-0.1766*	0.3052*	0.1531	0.0807	-0.0500
	(3.39)	(1.96)	(3.72)	(1.90)	(1.68)	(0.85)	(0.52)	(0.34)
Adjusted R^2	0.0273	0.0091	0.0129	0.0019	0.0913	0.0144	0.0499	0.0040
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 10: RETAIL TRADING AROUND REVERSE STOCK SPLITS BY POST-STOCK SPLIT PRICE

Table 10: Retail Trading Around Reverse Stock Splits Post by Stock Split Price

This table reports the regression results from equation (2). Columns [1] through [2] report the results for retail trading and standardized retail trading ratios using executed trades and trade volume around the stock split date of reverse stock splits with a post-stock split price less than $2. Columns [3] through [4] report the results for retail trading and standardized retail trading ratios using executed trades and trade volume around the stock split date of reverse stock splits with a post-stock split price greater than $2 less than $5. Columns [5] through [6] report the results for retail trading and standardized retail trading ratios using executed trades and trade volume around the stock split date of reverse stock splits with a post-stock split price greater than $5. All retail trading imbalances are measured for stock i on day t across the event window where $Split_t$ is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the ex-stock split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Reverse Stock Splits – Post-Stock Split Price					
	Post-Split Price < $2.00		$2.00 < Post-Split Price < $5.00		Post-Split Price > $5.00	
	RetailTrd(%)	*RetailVol(%)*	*RetailTrd(%)*	*RetailVol(%)*	*RetailTrd(%)*	*RetailVol(%)*
	[1]	[2]	[3]	[4]	[5]	[6]
$Split_{t-2}$	0.0097	0.0100	0.0045	0.0028	-0.0014	-0.0102
	(0.46)	(0.48)	(0.55)	(0.23)	(0.30)	(1.40)
$Split_{t-1}$	-0.0274	-0.0268	-0.0172***	-0.0339***	0.0053	-0.0036
	(1.56)	(1.52)	(2.83)	(3.59)	(0.97)	(0.52)
$Split_t$	-0.0599***	-0.0593***	-0.0217**	-0.0097	-0.0131*	-0.0182*
	(2.74)	(2.72)	(2.44)	(0.76)	(1.94)	(1.84)
$Split_{t+1}$	-0.0112	-0.0101	-0.0186**	-0.0301***	-0.0030	-0.0257***
	(0.53)	(0.48)	(2.55)	(2.85)	(0.42)	(2.57)
$Split_{t+2}$	-0.0098	-0.0085	-0.0124	-0.0295***	-0.0067	-0.0233***
	(0.44)	(0.39)	(1.60)	(2.99)	(1.13)	(2.78)
$Split_{t+3,,t+10}$	-0.0072	-0.0061	-0.0200***	-0.0252***	-0.0071	-0.0200***
	(0.47)	(0.40)	(3.39)	(3.44)	(1.46)	(3.32)
Intercept	0.2479***	0.2419***	0.1363***	0.1478***	0.0716***	0.1431***
	(3.47)	(3.37)	(10.10)	(7.18)	(2.91)	(4.02)
Adjusted R^2	15.31%	15.19%	13.63%	13.39%	27.95%	26.93%
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 11: RETAIL TRADING IMBALANCES AROUND REVERSE STOCK SPLITS BY POST-STOCK SPLIT PRICE

Table 11: Retail Trading Imbalances Around Reverse Stock Splits by Post-Stock Split Price

This table reports the regression results from equation (2). Columns [1] through [2] report the results for retail trading and standardized retail trading imbalances using executed trades around the stock split date of reverse stock splits with a post-stock split price less than $2. Columns [3] through [4] report the results for reverse stock splits with a post-stock split price greater than $2 less than $5. Columns [5] through [6] report the results for reverse stock splits with a post-stock split price greater than $5. All retail trading imbalances are measured for stock i on day t across the event window where $Split_t$ is equal to one if day t is the ex-stock split date. Five separate dummy variables are included to capture the five days around the ex-stock split date. Other independent variables include firm size, price volatility, share turnover, percentage bid-ask spread, and split factor. Both industry and year fixed-effects are included in the regression. Standard errors are clustered at the firm level. T-statistics are reported in parentheses. *, **, *** denotes significance at 0.10, 0.05, 0.01 levels, respectively.

	Post-Split Price < $2.00		$2.00 < Post-Split Price < $5.00		Post-Split Price > $5.00	
	OIBTRD	*SOIBTRD*	*OIBTRD*	*SOIBTRD*	*OIBTRD*	*SOIBTRD*
	[1]	[2]	[3]	[4]	[5]	[6]
$Split_{t-2}$	0.0615	0.1695	0.0921**	0.2161**	-0.0126	-0.0297
	(0.94)	(1.01)	(2.48)	(2.15)	(0.41)	(0.30)
$Split_{t-1}$	0.0555	0.1813	0.0305	0.0601	0.0163	0.0579
	(0.91)	(1.19)	(0.99)	(0.71)	(0.56)	(0.64)
$Split_t$	-0.0250	-0.0234	0.0214	0.0660	-0.0644**	-0.2020**
	(0.46)	(0.18)	(0.75)	(0.84)	(2.42)	(2.33)
$Split_{t+1}$	-0.0309	-0.0142	-0.0711**	-0.1658*	-0.1070***	-0.3235***
	(0.47)	(0.09)	(2.19)	(1.93)	(4.02)	(3.93)
$Split_{t+2}$	-0.0624	-0.0930	-0.0690**	-0.1456*	-0.0941***	-0.2832***
	(1.02)	(0.63)	(2.19)	(1.74)	(3.34)	(3.29)
$Split_{t+3,,t+10}$	-0.0586	-0.1135	-0.0325*	-0.0820*	-0.0532***	-0.1884***
	(1.51)	(1.10)	(1.80)	(1.69)	(3.30)	(3.78)
Intercept	-0.0574	-0.5593*	-0.2141*	-0.2373*	0.1874	0.1274
	(0.16)	(1.68)	(1.78)	(1.86)	(1.44)	(1.19)
Adjusted R^2	0.0671	0.0125	0.0349	0.0095	0.0625	0.0148
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

APPENDIX 12: STOCK SPLITS OF S&P 500 COMPANIES

Figure 1: Stock Splits of S&P 500 Companies

This figure shows the decline in number of stock splits by S&P 500 companies between 1990 and 2017. These figures were first reported by the Wall Street Journal in an article published on May 26th, 2017. The article is accessible at https://www.wsj.com/articles/amazons-brush-with-1-000-signals-the-death-of-the-stock-split-1495791009 .

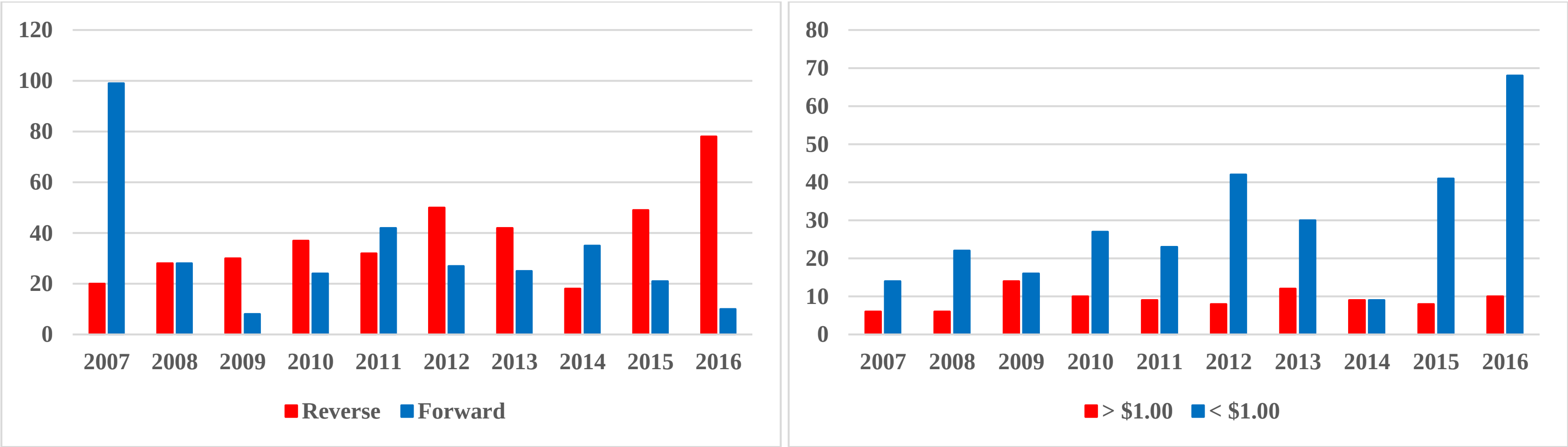
APPENDIX 13: FREQUENCY OF STOCK SPLITS

Figure 2: Frequency of Stock Splits

Figure 2 reports the frequency of stock splits between 2007 and 2016. Panel A reports the frequency between forward and reverse stock splits. Panels B reports all reverse splits, sorted via the pre-stock split price levels above (below) $1.00.

Panel A. Forward and Reverse Stock Splits

Panel B. Reverse Stock Splits, Split Price > (<) $1.00



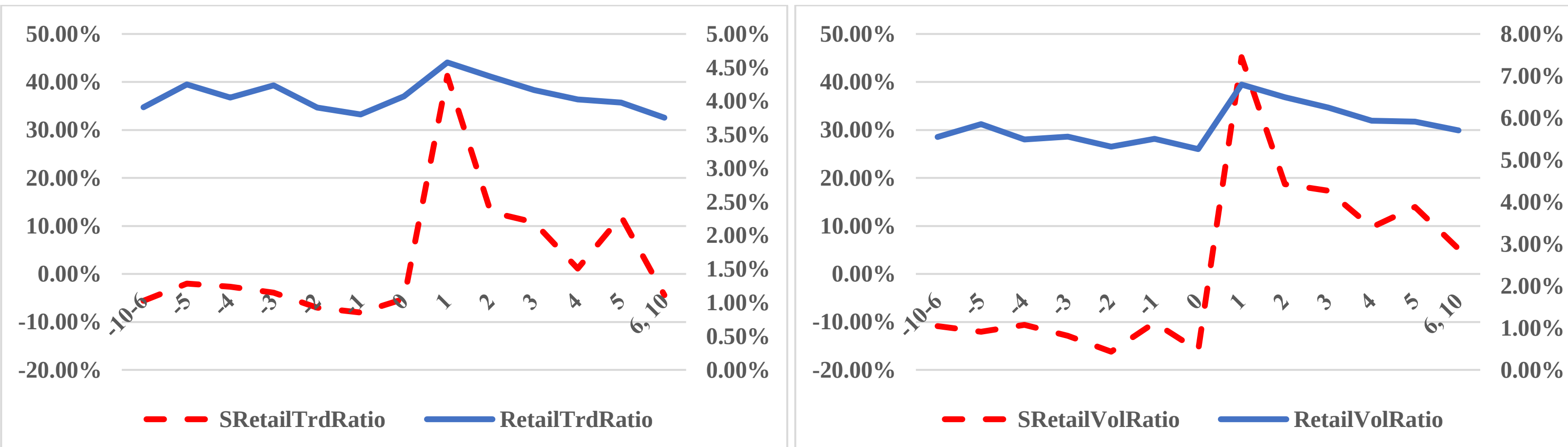
APPENDIX 14: RETAIL TRADING AROUND FORWARD STOCK SPLITS

Figure 3: Retail Trading Around Forward Stock Splits

Figure 3 reports retail trading activity around the ex-stock split date for forward stock splits across a 21-day event window. Panel A reports both the retail trading ratio and standardized retail trading ratio using executed trades for all forward stock splits. Panel B reports both the retail trading ratio and standardized retail trading ratio using executed trade volume for all forward stock splits.

Panel A. Retail Trading Ratio – Forward Stock Splits

Panel B. Retail Volume Ratio – Forward Stock Splits

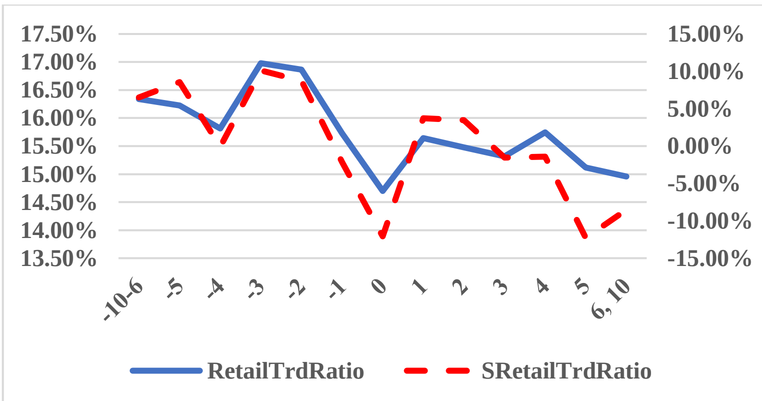


APPENDIX 15: RETAIL TRADING AROUND REVERSE STOCK SPLITS

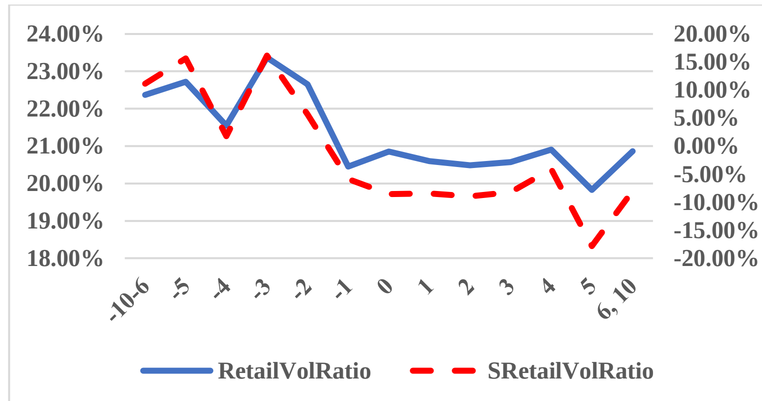
Figure 4: Retail Trading Around Reverse Stock Splits

Figure 4 reports retail trading activity around the ex-stock split date for reverse stock splits across a 20-day event window. Panel A reports both the retail trading ratio and standardized retail trading ratio using executed trades for all reverse stock splits. Panel B reports both the retail trading ratio and standardized retail trading ratio using executed trade volume for all reverse stock splits. Panels C (D) report both the retail trading ratio and standardized retail trading ratio using executed trades for reverse stock splits with a pre-stock split price below (above) $1.00.

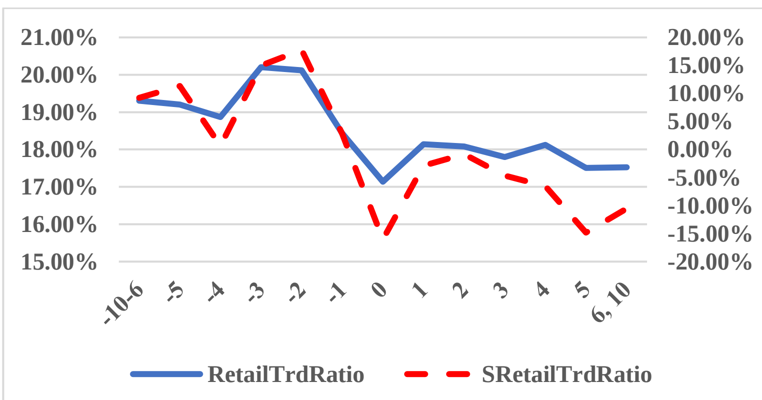
Panel A. Retail Trading Volume – Reverse Stock Splits



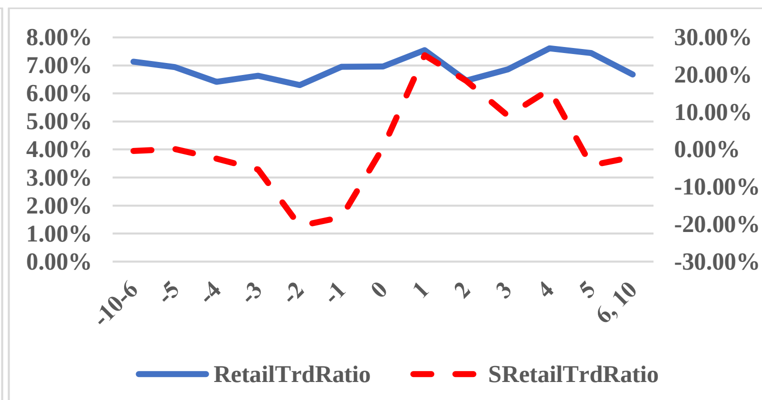
Panel B. Retail Volume Ratio – Reverse Stock Splits



Panel C. Pre-Stock Ssplit Price < $1.00



Panel D. Pre-Stock Split Price > $1.00

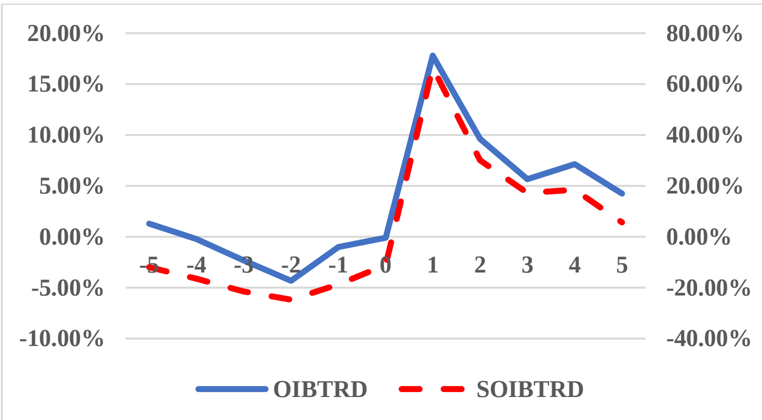


APPENDIX 16: RETAIL TRADING IMBALANCES AROUND FORWARD AND REVERSE STOCK SPLITS

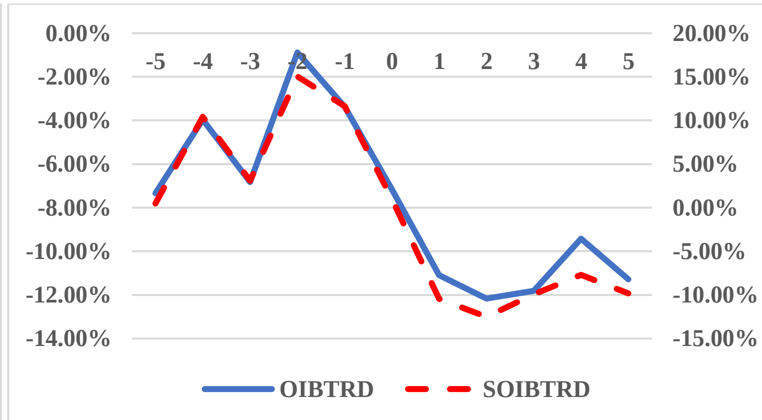
Figure 5: Retail Trading Imbalances Around Forward and Reverse Stock Splits

Figure 5 reports retail trading imbalances around the ex-stock split date for forward and reverse stock splits across an 11-day event window. Panel A reports both the retail trading ratio and standardized retail trading imbalances for all forward stock splits. Panel B reports both the retail trading ratio and standardized retail trading imbalances for all reverse stock splits. Panels C (D) report both the retail trading ratio and standardized retail trading imbalances for reverse stock splits with a pre-stock split price below (above) $1.00.

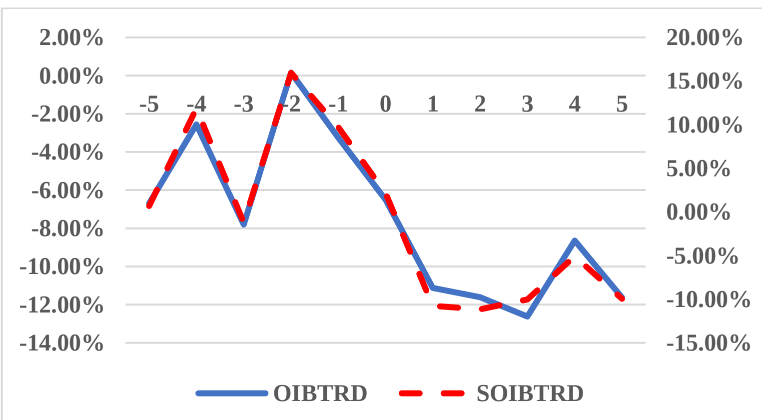
Panel A. Forward Stock Splits



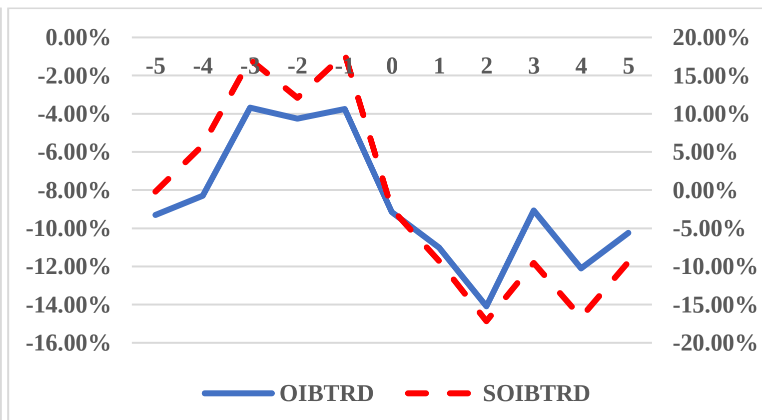
Panel B. Reverse Stock Splits



Panel C. Reverse Stock Splits, Pre-Split Price < $1.00



Panel D. Reverse Stock Splits, Pre-Split Price > $1.00



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EDUCATION

Ph.D., Business (Finance), University of Mississippi, Expected Graduation: May 2019
M.B.A., Business (Finance), Louisiana Tech University, August 2015
M.A., Sport and Fitness, University of Central Florida, August 2011
B.S.B.A, Finance, Coastal Carolina University, May 2007

WORK EXPERIENCE

Assistant Professor of Finance, Appalachian State University, August 2019-
Research Assistant & Instructor, University of Mississippi, August 2015-Present
Director of Football Operations, Louisiana Tech University, March 2013 – February 2014
Teacher, Lake Howell High School, Winter Park, FL August 2011- March 2013
Supply Chain Analyst, Pure Fishing Inc., Columbia, SC November 2008- July 2010

PUBLICATIONS

"When Elections Fail to Resolve Uncertainty: The Case of the 2016 U.S. Presidential Election", with T. Griffith, Conditional Acceptance, *Journal of Financial Research*

"Increasing the Tick: Examining the Impact of the Tick Size Change on Market Fee Venues" with B. Van Ness and R. Van Ness, Forthcoming, *The Financial Review.*

"Managerial Ability, Growth Opportunities, and Dual Class IPO Performance", *2017 (Sole Authored) Managerial Finance, Vol 43, Issue: 4, pp. 488-507.*

"Determining Whether an Activity is Engaged in For a Profit: An Empirical Assist", 2017 with T. Englebrecht, and W.B Dowis, *Journal of Applied Business Research, Vol 33, Issue: 4, pp. 775-790.*

WORKING PAPERS

"Pre-IPO Cash Volatility and Aftermarket Valuation", (Sole Authored), Under Review, *Quarterly Review of Economics and Finance*

"The Effects of Economic Policy Uncertainty on Market Liquidity and Price Stability: A Time-Series Analysis", with T. Griffith and I. Rhea

"Dark and Lit Fragmentation and Post-Earnings Announcements Drift", (Sole Authored),

"Trading Aggressiveness, Order Imbalances, and Individual Stock Returns" (Sole Authored)

WORK IN PROGRESS

"Tick Size Pilot Program and the Information Structure of the U.S. Stock Market", with B. Chakrabarty and J. Upson

"Settling Down: T+2 Settlement Cycle and Market Liquidity", with T. Griffith

"Price Clustering in Fragmented Markets", with R. Van Ness

"NASDAQ and the NYSE: A Trade Reporting Facility Comparison" (Sole Authored)

"Does What Happen in Vegas Stay in Vegas? Football Gambling and Stock Market Activity", with A. Schwartz and R. Van Ness

"IPO Costs and Innovation", with K. Fuller and Z. Lin

DISSERTATION

Essay #1: "Dark Side of IPOs: Examining Where and Who Trades in the IPO Secondary Market"

Essay #2: "Where Does Dividend Trading Occur? A Pecking Order of Trading Venues Explanation of Dividend Capture"

Essay #3: "Stock Splits and Retail Trading"

TEACHING EXPERIENCE

Course	Term	Average Evaluation
Business Finance I	Summer 2016	4.65 out of 5
Investments	Summer 2017	4.78 out of 5
Business Finance I	Fall 2017	4.38 out of 5
Investments	Fall 2017	4.52 out of 5
Business Finance I	Spring 2018	4.39 out of 5
Investments	Spring 2018	4.29 out of 5
Business Finance I	Fall 2018	4.28 out of 5
Business Finance I	Fall 2018	4.25 out of 5

ACADEMIC SERVICE

Referee for *Journal of Banking and Finance*, *Managerial Finance*
Discussant, Financial Management Association Annual Meeting, October 2017

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University of Mississippi Department of Finance Research Assistantship 2015-Present

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