Dark Trading and the Fundamental Information in Stock Prices

Jonathan Brogaard
David Eccles School of Business
University of Utah
brogaardj@eccles.utah.edu

Jing Pan
Cox School of Business
Southern Methodist University
jingp@smu.edu

March 2019

Abstract: Theory suggests dark pools may facilitate or discourage price informativeness. We find that more dark trading leads to greater firm-specific fundamentals in stock prices. To overcome endogeneity concerns we exploit the SEC's Tick-Size Pilot Program that resulted in a large exogenous shock to dark pool trading. The results remain. The results cannot be explained by lit market liquidity, high frequency trading, or price efficiency. In support of the information acquisition interpretation, we find a shift in the information acquisition through SEC EDGAR searches for the treatment firms. Overall, the evidence suggests dark trading improves the price informativeness of stock prices.

JEL classification: G14; G18
Keywords: dark pools, informed trades, earnings information, price informativeness

---

We are grateful to Hedi Benamar, Hank Bessembinder, Neil Bhattacharya, Ted Christensen, Michael Drake, Thierry Faucault, Rachel Hayes, Wayne Landsman, Joshua Mollner, Marlene Plumlee, Matthew Ringgenberg, Ernst Schaumberg, Steve Stubben, Jake Thornock, Ingrid Werner, Melissa Western, and workshop participants at the University of Utah, Brigham Young University, University of Arkansas, University of Texas at Austin, Southern Methodist University, National University of Singapore, Chinese University of Hong Kong, and Hong Kong Polytechnic University for valuable comments and suggestions. We appreciate the staff of the Division of Trading and Markets of the U.S. Securities and Exchange Commission for their assistance with dark trading data.

Among the more dramatic changes in financial markets in the last few decades is the rise of multiple trading venues. Of the varying characteristics of the competing exchanges one that stands out is that some venues are dark. Dark venues, often referred to as dark pools, are equity trading venues in which traders buy and sell stocks without publicly displaying their orders. The market share of dark pools in the United States has grown from 7.5% in 2008 to 16.6% in 2015 (Rosenblatt Securities, 2016). This rapid growth in dark trading has raised regulatory concerns about its impact on the informativeness of stock prices.[1] Unlike trades made on lit stock exchanges, which directly affect prices, trades on a typical dark pool free-ride on the price discovery function of exchanges, as they are passively executed at prices derived from exchanges (Zhu, 2014; Nimalendran and Ray, 2014). By giving investors an alternative to trading on an exchange, dark pools could affect information acquisition of stock prices with respect to firm-specific fundamental information. This paper examines whether dark trading facilitates or discourages the incorporation of firm-specific fundamentals into stock prices.

We are careful in constructing our research question of whether dark trading impacts price informativeness, the fundamental information in stock prices. We distinguish our focus from that of a focus on informational efficiency, also referred to as price efficiency. Brunnemeier (2005) provides a clear distinction between the two. Price informativeness captures the amount of public information generated. Whereas informational efficiency describes the ability for stock prices to

[1] In 2014, then U.S. Securities and Exchange Commission (SEC) Chair Mary Jo White remarked that "we must continue to examine whether dark trading volume is approaching a level that risks seriously undermining the quality of price discovery provided by lit venues." See https://www.sec.gov/news/speech/2014-spch060514mjw.

reflect the public information in to stock prices.[2] Another related term to these ideas is price discovery, which refers to impounding information into stock prices (O'Hara, 2003). It is often used to capture both processes, and is frequently used ambiguously. For instance, two common measure of price discovery, the permanent price impact from Hasbrouck (1991) and the Information Share (Hasbrouck, 1993) capture the impounding of public information into stock prices, but may not reflect price informativeness (Collin-Dufresne and Fos, 2015). While the question of price discovery / informational efficiency and dark pools has been studied by others (e.g. Comerton-Forde and Putniņš, 2015), to the best of our knowledge, we are the first to ask the broader question regarding dark pool activity and information acquisition.

Theoretical arguments suggest that dark pools may encourage or discourage information acquisition. Grossman and Stigliz (1980) show that in order for investors to acquire new information it must, in expectation, be profitable to do so. One of the primary motives of dark pools is to allow for transactions to occur at low cost. If investors who acquire information can access dark pools to enter and exit transactions at low cost, lower value information acquisition opportunities will be worthwhile, all else being equal. Alternatively, if the introduction of dark pools results in separating equilibrium whereby uninformed traders use dark pools and informed traders use lit markets, then the speed of price discovery may increase and the cost of trading may also rise (Zhu, 2014). As a result, investors may expend less resources to acquire and trade on idiosyncratic information, which decreases price informativeness (Grossman and Stiglitz, 1980;

[2] Specifically, price informativeness is "the reciprocal of the conditional variance $var[v|I_t^{Public}]$," where I_t^{Public} is the set of all public information. That is, price informativeness is about how much information is public. Informational efficiency is defined as "The reciprocal of the variance $var[E[v|I_t^{Pooled}]|I_t^{Public}]$ conditional on the public information, I_t^{Public}," where I_t^{Pooled} is the information set that pools public and private information (i.e. the stock price).

Diamond and Verrecchia, 1981; Verrecchia, 1982; Admati, 1985; Kyle, 1985; and Kyle, 1989). Knowing whether dark pools encourage or discourage information is fundamentally important to whether dark pools improve or distort one of the main roles of financial markets.

We use newly available weekly dark trading data provided by the Financial Industry Regulatory Authority (FINRA). In an effort to increase market transparency, starting the week of May 11, 2014, FINRA has required each dark pool to report its weekly trading volume information regarding Tier 1 NMS stocks (i.e., NMS stocks that are very actively traded, such as stocks in the S&P 500 Index), Tier 2 NMS stocks (i.e., all NMS stocks that are not in Tier 1), and OTC stocks. We construct a sample of 26,212 firm–quarter observations from September 2014 to December 2017. Similar to prior studies (e.g., Buti et al., 2011; Comerton-Forde and Putniņš, 2015; Foley and Putniņš, 2016), we compute the level of dark trading as the ratio of the trading volume executed on dark pools to the consolidated volume.

We use three measures of price informativeness. The first is the cumulative abnormal return (CAR) before a firm's earnings announcement. We focus on the one month prior, days -21, to -2 relative to the earnings announcement, $CAR_{i,t}^{-21,-2}$. Some investors acquire information about upcoming earnings news and trade before the information becomes widely available (Demski and Feltham, 1994; McNichols and Trueman, 1994). To the extent that the acquired information is partially revealed through information-motivated trades (Kyle, 1985; Glosten and Milgrom, 1985), stock prices should adjust in the direction of the acquired information before earnings are actually announced.

The second measure is the reciprocal of the pre-emptive returns. If more information is incorporated into prices prior to the earnings announcements, then the earnings should be less of a surprise and generate less of a CAR. Specifically the second measure is the CAR for days -1, 1 relative to the earnings announcement, $CAR^{-1,1}_{i,t}$. Earnings announcements should provide less new information, resulting in smaller price adjustments at the announcements (Kim and Verrecchia, 1991, 1997).

If dark trading promotes the acquisition of information prior to earnings announcements, stocks with a higher level of dark trading should have (1) larger associations between pre-announcement abnormal returns and the upcoming earnings surprises, and (2) smaller price reactions to earnings surprises.

The third measure of price informativeness is the future earnings response coefficient (FERC). The FERC is a longer horizon price informativeness measure. Prior research has found that sophisticated investors, such as institutional investors and short sellers, become well informed about future earnings by acquiring and processing information about firms' current economic actions that affect future earnings (e.g., long-term sales contracts and investment activities). If dark trading increases information acquisition, this should facilitate the incorporation of acquired information about future earnings into stock prices (i.e., "bring the future forward," Lundholm and Myers, 2002, p. 809).

Before dealing with reverse causality and possible omitted variables, we perform a traditional ordinary least squares analysis of the dark trading level on the three different measures of price informativeness. The results show that a high level of dark trading is associated with greater price informativeness (higher $CAR^{-21,-2}_{i,t}$ and FERC, and lower $CAR^{-1,1}_{i,t}$).

Dark trading is endogenous. To determine the causal effects of dark trading is complicated by endogeneity issues. Unobservable factors that affect investors' decisions to trade on exchanges or in dark pools could also affect the market's response to, and processing of, earnings news related to the stock being traded. In addition, it could be that the level of price informativeness drives the level of dark trading. To identify the causal effect of dark trading on price informativeness, we use the SEC's Tick Size Pilot Program, enacted in October 2016, as a plausible source of exogenous variation in firm-level dark trading. Others have studied this change (Albuquerque, Song, and Yao, 2018; Rindi and Werner, 2017; Lee and Watts, 2018; Li, Ye, and Zheng, 2018; and Farley, Kelley, and Puckett, 2017).

The stocks in the group 1 (G1) of the SEC's Tick Size Pilot Program must be quoted in 5 cent increments. In addition to the rules applying to G1 stocks, the stocks in SEC's group 2 (G2) are required to be traded in 5 cent increments. In addition to the requirements applying to G2 stocks, the stocks in SEC's group 3 (G3) are subject to the "trade-at" provision, which requires orders to be executed in lit venues unless dark venues can execute them at a meaningfully better price. By giving execution priority to lit venues, the "trade-at" provision shifts trades from dark to lit venues.

The difference-in-differences (DiD) analysis we conduct includes all G2 and G3 stocks of the Tick Size Pilot Program. A comparison of effects between G2 and G3 holds constant the quoting and trading increments and thereby isolates any dark trading effects. Thus, we use G3 stocks as the treatment stocks and G2 stocks as the control stocks in the analysis. We use a [-120, 120] day window around the effective dates of the pilot to conduct the DiD analysis. This controls the impact of unobserved variables, since unobserved variables are less likely to change significantly during such a short window.

We find that in the treatment group the average market share of dark pools drops by 30% (from 14.6% to 10.3%) from the twenty weeks before to the twenty weeks after the implementation dates of the pilot. Using a DiD analysis around the implementation, we observe a decrease in price informativeness for treated firms relative to control firms ($CAR_{i,t}^{-21,-2}$ and FERC decline, $CAR_{i,t}^{-1,1}$ rise). The results show that a decline in dark trading results in a decline in price informativeness.

While the DiD approach can help overcome endogeneity problems, the shock may have been associated with other changes as well. It is important to explore these channels. In our setting, we worry about three confounding factors: lit market liquidity, high frequency trading, and price efficiency. We find that none of these alternative stories can explain the results.

If dark pools encourage information acquisition, it will leave other patterns in the data. We focus on three of these patterns. The first pattern we study is investors' information acquisition. Following Drake, Roulstone, and Thornock (2015, 2016), we measure investors' information acquisition by analyzing the SEC EDGAR search database. The EDGAR search database contains the extent and timing of investors' acquisition of firm-level financial statements from EDGAR. From the raw data we construct firm-quarter measures of direct information acquisition. We evaluate the amount of information acquisition using our DiD analyses. If dark trading encourages information acquisition, we expect that the decrease in the level of dark trading resulting from the implementation of the pilot leads to less information acquisition, which is what we find.

The second pattern we study is the Probability of Informed Trading. The EDGAR measure is an attempt to observe investors directly acquiring information. An alternative approach is to try to observe how the market may respond when more information is being acquired. We rely on the Easley, Kiefer and O'Hara's (1996) Probability of Informed Trading (PIN) measure to proxy the likelihood of there being an informed trader. PIN takes higher values when the arrival rate of information-motivated trades is higher. We find that in our DiD framework PIN declines when dark trading is exogenously decreased. This is consistent with PIN increasing, as would be expected when there is more information being acquired, as dark trading increases.

The third pattern we examine is idiosyncratic news. We decompose earnings into systematic component and idiosyncratic component, and find that the exogenous decrease in the level of dark trading decreases the association between current returns and idiosyncratic component of future earnings. The evidence is consistent with dark trading increasing traders' incentives to acquire and trade on firm-specific information.

This study makes contributions to two streams of literature. First, it adds to the emerging literature on the consequences of dark trading. Much prior empirical research on dark trading has focused on price efficiency with mixed results (Buti et al., 2011; Fleming and Nguyen, 2013; Nimalendran and Ray, 2014; Comerton-Forde and Putniņš, 2015; Foley and Putniņš, 2016; Hatheway et al., 2017; Albuquerque el al., 2018). We add to the literature on dark trading by focusing on price informativeness and the acquisition of information.

Second, this paper contributes to the broad literature on studying the flow of earnings information to the markets. Prior research has examined forces such as information environments (e.g., Abarbanell and Bernard, 1992; Roulstone, 2003), trading by sophisticated investors (e.g., Utama and Cready, 1997; Jiambalvo et al., 2002; Ali et al., 2008), disclosure quality (e.g., Lee, 2012), reporting regimes (e.g., Landsman et al., 2012), algorithmic trading (Weller, 2017) and the acquisition of information by investors (e.g., Drake et al., 2015b). We add to the literature by focusing on the fact that the rise of dark pools has impacted the ability for investors to trade large quantities at a low price. We show that such fragmentation has implications for the flow of earnings information to stock prices.

1. Data and Measures of Price Informativeness

We obtain weekly trading volume on dark pools from FINRA's ATS Transparency Data. As part of FINRA's effort to increase market transparency, FINRA Rule 4552 has required each ATS, including dark pools and ECNs, to report its weekly volume information to FINRA on a stock-by-stock basis since the week of May 11, 2014. FINRA's ATS Transparency Data publishes the weekly volume information regarding Tier 1 NMS stocks (i.e., NMS stocks that are very actively traded, such as stocks in the S&P 500 Index), Tier 2 NMS stocks (i.e., all NMS stocks that are not in Tier 1), and OTC stocks. Since ECNs publicly display their quotations, they are generally considered lit markets. We exclude trades on ECNs, including Bloomberg Tradebook, Citigroup Lava Flow, and Credit Suisse Light Pool, from the sample.[3] Overall, dark pools account for a substantial fraction of the total trading volume on U.S. equity markets: about 14% of the consolidated trading volume is executed on dark pools each month.

We obtain dark trading volume for common stocks listed on the NYSE, NYSE MKT, and NASDAQ (Center for Research in Security Prices, or CRSP, share codes 10 and 11; exchange codes 1, 2, and 3) from FINRA from July 2014 to December 2017. To allow for a three-month measurement window for quarterly measures of dark trading, the sample period spans from September 2014 through December 2017. We combine the initial dark trading data with stock

[3] We are grateful to the Division of Trading and Markets of the SEC for providing the list of ECNs. More detailed information on ECNs is available at https://www.sec.gov/divisions/marketreg/mr-noaction.shtml#ecns.

returns, consolidated trading volume, stock prices, and total shares outstanding from CRSP, trade size from Trade and Quote (TAQ) consolidated trade data, financial statement data from Compustat, analyst coverage and consensus forecast data from I/B/E/S, and institutional holding data from the Thomson-Reuters Institutional Holdings (13F) database.[4] We exclude observations with missing values for the variables required in the regression analyses. The final sample consists of 40,192 firm–quarter observations. By requiring nonmissing values for the analysts' consensus forecast, we retain 31,611 firm–quarter observations for analyzing stock price reactions to earnings announcements.

First we discuss the preemption of earnings news measures. Some investors possess acquired pre-disclosure information regarding upcoming earnings news long before the earnings announcements (e.g., Ke and Petroni, 2004; Vega, 2006; Ke, Huddart, and Petroni, 2003; Christophe et al., 2010). When investors trade on their acquired information, the acquired information is partially revealed to market participants (see Kyle, 1985; Glosten and Milgrom, 1985), resulting in stock price adjustments in the direction of the acquired information prior to earnings announcements. Consequently, to the extent that the information content of earnings news has already been partially preempted, earnings announcements should provide less new information, resulting in smaller price adjustments at the announcements (See Kim and Verrecchia, 1991, 1997). If dark trading leads to a disproportionately high percentage of information-motivated trades on exchanges, the revelation of informed investors' acquired information prior to earnings

[4] The consolidated volume reported by the CRSP contains the trading volume executed on different market centers, including exchanges, ECNs, ATSs, and broker–dealers. See "The Consolidated Tape: Yes Dark Pool Trades Are in There," available at http://blogs.wsj.com/marketbeat/2009/11/19/the-consolidated-tape-yes-dark-pool-trades-are-in-there.

announcements will increase. Thus, a higher level of dark trading should be associated with stronger link between pre-announcement abnormal stock returns and upcoming earnings surprises and smaller stock price reactions to earnings surprises.

Figure 1 Panel A displays how we capture information acquisition that preempts earnings news.

INSERT FIGURE 1 ABOUT HERE

Next we discuss the long-horizon informational acquisition. Prior research investigates the effect of sophisticated market participants on the relation between current returns and future earnings. Certain economic actions taken by a firm in the current period (e.g., long-term sales contracts and investment activities) affect future earnings. By acquiring and processing information about such economic actions, various types of sophisticated investors, such as institutional investors (Ayers and Freeman, 2003), insiders (Crawford et al., 2011), and short sellers (Drake et al., 2015a), become informed about future earnings. If acquired, value-relevant information about future earnings is impounded into prices, current stock prices will reflect information about future earnings. If dark pools are relatively more attractive for non-information-motivated orders, then the exchanges will have a disproportionately high percentage of orders motivated by acquired information about future earnings. The proportion of information about future earnings reflected in current-period stock prices should thus increase with the level of dark trading.

Figure 1 Panel B lays out how we capture long-horizon information acquisition. Table 2 reports summary statistics for the sample.

INSERT TABLE 2 ABOUT HERE

The average stock has 15% of its total trading volume executed on dark pools. The mean (median) cumulative abnormal return over trading days [-21, -2], $CAR_{i,t}^{-21,-2}$, is -0.05% (-0.01%). The mean (median) cumulative abnormal return over a three-day window, $CAR_{i,t}^{-1,1}$, is 0.05% (0.1%). The average (median) firm has a market capitalization of \$6.96 billion (\$0.78 billion), suggesting the distribution of market capitalization in this sample is highly skewed to the right. On average, a sample firm has seven analysts following it and 62% institutional ownership.

2. The Relation between Dark Trading and Price Informativeness

We begin by examining whether dark trading increases the preemption of earnings news. Some investors acquire information about upcoming earnings news and trade before the information becomes widely available (Demski and Feltham, 1994; McNichols and Trueman, 1994). To the extent that the acquired information is partially revealed through information-motivated trades (Kyle, 1985; Glosten and Milgrom, 1985), stock prices should adjust in the direction of the acquired information before earnings are actually announced. As a consequence, earnings announcements should provide less new information, resulting in smaller price adjustments at the announcements (Kim and Verrecchia 1991, 1997). We expect that stocks with a higher level of dark trading should have (1) larger associations between pre-announcement abnormal returns and the upcoming earnings surprises, and (2) smaller price reactions to earnings surprises.

To test these hypothesis we estimate the following event-study models:

$$CAR_{i,t}^{-21,-2} = \alpha + \beta_1 Dark\ Ratio_{i,t} \times Unexpected\ Earnings_{i,t} + \beta_2 Dark\ Ratio_{i,t} + \beta_3 Unexpected\ Earnings_{i,t} + \gamma' X_{i,t} + \psi' Unexpected\ Earnings \times X_{i,t} + \theta_i + \theta_t + \varepsilon_{i,t}, \qquad (1)$$

$$CAR_{i,t}^{-1,1} = \alpha + \beta_1 Dark\ Ratio_{i,t} \times Unexpected\ Earnings_{i,t} + \beta_2 Dark\ Ratio_{i,t} + \beta_3 Unexpected\ Earnings_{i,t} + \gamma' X_{i,t} + \psi' Unexpected\ Earnings \times X_{i,t} + \theta_i + \theta_t + \varepsilon_{i,t}, \qquad (2)$$

where the subscripts *i* and *t* denote firm *i* and year-quarter *t*, respectively. The variable $CAR_{i,t}^{-21,-2}$ is the cumulative abnormal return over trading days [-21, -2] prior to earnings announcements, and $CAR_{i,t}^{-1,1}$ is the cumulative abnormal return over trading days [-1, 1] around earnings announcements. We compute daily abnormal return as the raw return less the buy-and-hold return to a benchmark portfolio of firms matched on size and the book-to-market ratio over the same period. The benchmark portfolios are constructed using Fama and French's (1992) method. For

June of year t, we classify all firms with CRSP share codes 10 and 11 into 25 portfolios by size at the end of June of year t and by the book-to-market ratio at the end of December of year t - 1.

The variable $DarkRatio_{i,t}$ is the ratio of the trading volume of firm i executed on dark pools divided by the consolidated volume during the pre-announcement period of quarter t. The pre-announcement period includes all weeks between the earnings announcement date of quarter t - 1 and 21 trading days before the announcement date of quarter t. In addition, if an earnings announcement for quarter t - 1 is released on a Friday, we exclude the week following the earnings announcement. The variable $Unexpected\ Earnings_{i,t}$ is unexpected earnings based on analyst forecasts scaled by price at the end of the fiscal quarter, calculated as $Unexpected\ Earnings_{i,t} = (EPS_{i,t} - Analyst\ Forecast_{i,t})/Price_{i,t}$, where $EPS_{i,t}$ is the actual earnings per share and $Analyst\ Forecast_{i,t}$ is median analyst forecasts. We use $Analyst\ Forecast_{i,t}$ as a proxy of the market's expectation for earnings prior to earnings announcements. Following Livnat and Mendenhall (2006), we obtain both $EPS_{i,t}$ and $Analyst\ Forecast_{i,t}$ from I/B/E/S. We predicts a positive coefficient on the interaction term $Unexpected\ Earnings_{i,t} \times DarkRatio_{i,t}$ (β_1) in Model (1), and a negative coefficient on the interaction term $Unexpected\ Earnings_{i,t} \times DarkRatio_{i,t}$ (β_1) in Model (2).

The vector $X_{i,t}$ is a set of control variables that prior research has found to be associated with price reactions to earnings news. Specifically, we include firm size, $Size_{i,t}$; the book-to-market ratio, $Book\ to\ Market_{i,t}$; and leverage, $Leverage_{i,t}$, to control for cross-sectional differences in the riskiness of firms (Fama and French, 1992). We include stock price, $log(Price)_{i,t}$, to control for trading costs at the individual stock level (Bhushan, 1994). We include idiosyncratic return volatility, $Idiosyncratic\ Volatility_{i,t}$, to control for firm-specific risk. We include analyst coverage, *log(#Analysts)*$_{i,t}$, and institutional ownership, *Institutional Ownership*$_{i,t}$, because these intermediaries have been shown to affect the dissemination of earning news (e.g., Utama and Cready, 1997; Ali et al., 2008). In addition, we include Corwin and Schultz (2012) Effective Spread measure, *Spread*$_{i,t}$ to control for liquidity on the lit market. We include an indicator variable for the fourth fiscal quarter, *Qtr4*$_{i,t}$, to control for differential market reactions to annual earnings announcements. The term *Unexpected Earnings*$_{i,t}$×*Controls*$_{i,t}$ is a set of interactions between *Unexpected Earnings*$_{i,t}$ and control variables. Finally, we include firm fixed effects, θ_i, and year-quarter fixed effects, θ_t, to control for unobserved heterogeneity over time and across firms. Following Hirshleifer, Lim, and Teoh (2009), we cluster standard errors by firm and earnings announcement date.

INSERT TABLE 2 ABOUT HERE

Table 2 provides the results from estimating Models (1) and (2). In columns (1) and (2), we present the results using $CAR_{i,t}^{-21,-2}$ as the dependent variable. In columns (3) and (4), we use $CAR_{i,t}^{-1,1}$ as the dependent variable. Columns (1) and (3) report results for the tests without year-quarter fixed effects and columns (2) and (4) show results after controlling for both firm and year-quarter fixed effects. While we include the interactions between the control variables and *Unexpected Earnings*$_{i,t}$ in all of the regressions, for parsimony, we do not tabulate their coefficients.

In columns (1) and (2), we find that the coefficient on the interaction term, *Unexpected Earnings*$_{i,t}$×*DarkRatio*$_{i,t}$, is significantly positive (β_1 = 1.834, t-statistic = 2.31 in column (1); β_1 = 1.849, t-statistic = 2.31 in column (2)). This result suggests that, when the level of dark trading is high, price reactions prior to earnings announcements reflect more of the information content of the upcoming earning news. In terms of economic significance, the association between pre-announcement abnormal returns and the upcoming earnings surprises increases by 114% [(1.849×0.03)/(-0.284+1.849×0.18)] if a firm's *DarkRatio* increases from a 75th percentile value of 0.18 to a 90th percentile value of 0.21.

In columns (3) and (4), the coefficients on the interaction term, *Unexpected Earnings*$_{i,t}$×*DarkRatio*$_{i,t}$, are significantly negative (β_1 = -0.827, t-statistic = -2.36 in column (3); β_1 = -0.835, t-statistic = -2.38 in column (4)). These results are consistent with dark trading increasing the preemption of information content of earnings announcements, leading to smaller price reactions to earnings news at the time of the announcements. The economic magnitude of the effect is also significant. The three-day price reactions to earnings surprises decrease by 235% [(–0.835×0.03)/(0.160 – 0.835×0.18)] if a firm's *DarkRatio* increases from a 75th percentile value of 0.18 to a 90th percentile value of 0.21. Overall, the results in Table 3 provide evidence consistent that a higher level of dark trading leads to greater preemption of upcoming earnings news.

Next, we test whether dark trading affects the informativeness of stock prices with respect to firm fundamentals over a longer horizon. Prior research has found that sophisticated investors, such as institutional investors and short sellers, become well informed about future earnings by acquiring and processing information about firms' current economic actions that affect future earnings (e.g., long-term sales contracts and investment activities). If dark trading increases the revelation of sophisticated investors' acquired information by increasing the proportion of informed to uninformed trades on exchanges, this should facilitate the incorporation of acquired information about future earnings into stock prices (i.e., "bring the future forward," Lundholm and

Myers, 2002, p. 809). We test this prediction using quarterly future earnings response coefficients (FERCs), which measure the mapping of future earnings to current returns.

We predict that dark trading improves the association between current returns and future earnings (*FERC*). To test this hypothesis, we follow prior FERC research (e.g., Lundholm and Myers, 2002; Ettredge et al., 2005) and estimate the following regression model using quarterly data:

$$Return_{i,t} = \alpha + \sum_{k=-1}^{1} \delta_k Earnings_{i,t+k} \times Dark\ Ratio\_Qtr_{i,t} + \sum_{m=-1}^{1} \beta_m Earnings_{i,t+m} + \beta_2 Dark\ Ratio\_Qtr_{i,t} + \gamma' X_{i,t} + \sum_{n=-1}^{1} \psi' Earnings_{i,t+n} \times X_{i,t} + \theta_i + \theta_t + \varepsilon_{i,t}, \quad (3)$$

where the subscripts *i* and *t* denote firm *i* and year-quarter *t*, respectively. The variable $Return_{i,t}$ is quarterly buy-and-hold return. The variable $Return_{i,t}$ is 3-month return from month t-2 to month *t*+1 relative to fiscal quarter end. The variable $DarkRatio\_Qtr_{i,t}$ is the ratio of trading volume of firm *i* executed on dark pools divided by the consolidated volume during the trading weeks over fiscal quarter *t*. The variable $Earnings_{i,t+k}$ is quarterly seasonally adjusted net income before extraordinary items scaled by the market value of equity at the beginning of quarter *t*. The variable $DarkRatio\_Qtr_{i,t}$ denotes the ratio of the trading volume executed on dark pools to the consolidated volume during fiscal quarter *t*. The coefficient β_1 is the *FERC*. It measures the extent to which current stock returns reflect future earnings. A positive coefficient on the interaction term $Earn_{i,t+1} \times DarkRatio\_Qtr_{i,t}$ (δ_1) indicates that an increase in $DarkRatio\_Qtr_{i,t}$ is accompanied by an increase in the association between contemporaneous returns and future earnings.

In addition, we include $Return_{i,t+1}$, $log(Size)_{i,t}$, $Book\ to\ Market_{i,t}$, $Leverage_{i,t}$, $Growth_{i,t}$, $Idiosyncratic\ Volatility_{i,t}$, $log(\#Analysts)_{i,t}$, $Institutional\ Ownership_{i,t}$, and $Loss_{i,t}$ to control for factors that prior research finds to be associated with *FERC* (Lundholm and Myers, 2002; Choi et al., 2011). Specifically, we include the buy-and-hold return in quarter t+1, $Ret_{i,t+1}$, to control for the potential measurement error induced by using actual future earnings as a proxy for expected value (Collins et al., 1994). Because high-growth firms tend to have larger *FERCs*, we include book-to-market ratio, $Book\ to\ Market_{i,t}$, and growth in assets, $Growth_{i,t}$. We include idiosyncratic return volatility, $Idiosyncratic\ Volatility_{i,t}$, to control for firm-specific uncertainty. We include firm size, $Size_{i,t}$, analyst coverage, $log(\#Analysts)_{i,t}$, and institutional ownership, $Institutional\ Ownership_{i,t}$, to control for cross-sectional differences in firms' information environments. Following Lundholm and Myers (2002), we include an indicator variable, $Loss_{i,t}$, because loss firms are expected to have lower *FERCs*. In addition, we include Corwin and Schultz (2012) Effective Spread measure, $Spread_{i,t}$. All of these variables are measured at the end of the fiscal quarter. Finally, we account for time-invariant firm heterogeneity and time effects by including firm and year-quarter fixed effects. We cluster standard errors by firm and year-quarter.

INSERT TABLE 3 ABOUT HERE

Table 3 presents the results from estimating Model (3). Columns (1) and (2) report results for the tests without interactions between Earnings and control variables. Columns (3) and (4) show results after controlling for those interactions. In all columns, we find that the coefficients on the interaction term $Earn_{i,t+1} \times DarkRatio\_Qtr_{i,t}$ are significantly positive (1.509, t-statistic = 5.10

in column (1); 1.338, t-statistic = 4.63 in column (2); 0.943, t-statistic = 2.35 in column (3); 0.977, t-statistic = 2.47 in column (4)). The results suggest that an increase in the level of dark trading leads to an increase in the association between contemporaneous returns and future earnings.

The effect of dark trading on the FERCs is also economic large. Specifically, the *FERC* is 0.085 [-0.91+0.977×0.18] for firms with a *DarkRatio_Qtr* of 75th percentile value of 0.18, and is 0.114 [-0.91+0.977×0.21] for firms with a 90th percentile value of *DarkRatio_Qtr* of 0.21. The *FERC* increase by 35% [(0.114-0.085)/0.085] if a firm's *DarkRatio* increases from a 75th percentile value to a 90th percentile value. Overall, the results show that a higher level of dark trading leads to an increase in the long-horizon informational acquisition of fundamental information.

3. The Causal Relation between Dark Trading and Price Informativeness

To identify the dark pools' effect on price informativeness we use the SEC's Tick Size Pilot Program to perform a DiD analysis. The 2012 Jumpstart Our Business Startups (JOBS) Act directed the SEC to assess how decimalization affects the liquidity and trading of smaller-capitalization companies. In response to this request, the Tick Size Pilot Program was launched on October 3, 2016, and implemented on a staggered basis over two years. The pilot consists of a control group of 1,400 randomly selected stocks and three treatment groups, each containing 400 randomly selected stocks.

Specifically, the stocks in the control group continue quoting and trading in 1 cent increments. The stocks in treatment group 1 (G1) must be quoted in 5 cent increments. In addition to the rules applying to G1 stocks, the stocks in treatment group 2 (G2) are required to be traded in 5 cent increments. In addition to the requirements applying to G2 stocks, the stocks in treatment group 3 (G3) are subject to the "trade-at" provision, which requires orders to be executed in lit venues unless dark venues can execute them at a meaningfully better price. By giving execution priority to lit venues, the "trade-at" provision should shift trades from dark to lit venues.

The DiD analysis includes all G2 and G3 stocks of the Tick Size Pilot Program. A comparison of effects between G2 and G3 holds constant the quoting and trading increments and thereby isolates any dark trading effects. Thus, we use G3 stocks as the treatment stocks and G2 stocks as the control stocks in the analysis. We use a [-120, 120] day window around the effective dates of the pilot to conduct the DiD analysis. This controls the impact of unobserved variables, since unobserved variables are less likely to change significantly changes during such a short window.

Before performing the DiD analysis, we document that the treatment stocks subjected to the "trade-at" provision experienced a decrease in dark trading volume. In Figure 2, we plot the ratio of the consolidated trading volume executed on dark pools (*DarkRatio*) by week for G2 stocks (control stocks) and G3 stocks (treatment stocks) over weeks t-20 to t+20 relative to the implementation of the SEC's Tick Size Pilot.

INSERT FIGURE 2 ABOUT HERE

We find that control stocks and treatment stocks have a similar level of dark trading prior to the pilot's implementation. Consistent with the idea that the "trade-at" provision should result in a transfer of trading volume from dark to lit venues, treatment stocks experience a decrease in the level of dark trading from the implementation week of the pilot. Specifically, we find that the average market share of dark pools drops by 30% (from 14.6% to 10.3%) from the twenty weeks before the implementation dates of the pilot to the twenty weeks after the implementation dates.

The validity of the DiD estimator depends on the parallel trend assumption, i.e., the underlying trend in the outcome variable is the same for both the treatment and control groups. To verify the validity of the assumption, following Fang et al. (2014), we perform a t-test on the differences in characteristics between the two groups prior to the implementation of the pilot. Panel A of Table 5 shows no statistically significant differences between the treatment group and the control group in firm characteristics that affect the incorporation of earnings information. Only *Price* (t - statistic = 2.46) violates the parallel trends assumption. Moreover, the two groups have a similar level of dark trading prior to the implementation of the pilot.

To allow the pilot to affect the level of dark trading and thus the incorporation of earnings information during the pre-announcement period, we exclude the earnings announcements made in the [-1, 1] trading day window around the effective dates of the pilot for the tests focusing on price reactions to earnings news. Similarly, we exclude the earnings announcements made in the [-21, -2] trading day window around the effective dates of the pilot for the tests focusing on the pre-announcement abnormal stock returns and the upcoming earnings news. Finally, for each firm in the sample, we exclude the fiscal quarter when the pilot is implemented for the tests focusing on *FERCs*. We conduct the DiD analysis on the first two measures of price informativeness by estimating the following models:

$$CAR_{i,t}^{-21,-2} = \alpha + \beta_1 Post_t \times Treatment_i \times Unexpected\ Earnings_{i,t} +$$
$$\beta_2 Treatment_i \times Unexpected\ Earnings_{i,t} + \beta_3 Post_t \times Unexpected\ Earnings_{i,t} +$$
$$\beta_4 Post_t \times Treatment_i + \beta_5 Unexpected\ Earnings_{i,t} + \gamma' X_{i,t} +$$
$$\psi' Unexpected\ Earnings \times X_{i,t} + \theta_j + \theta_t + \varepsilon_{i,t}, \qquad (4)$$

$$CAR_{i,t}^{-1,1} = \alpha + \beta_1 Post_t \times Treatment_i \times Unexpected\ Earnings_{i,t} +$$
$$\beta_2 Treatment_i \times Unexpected\ Earnings_{i,t} + \beta_3 Post_t \times Unexpected\ Earnings_{i,t} +$$
$$\beta_4 Post_t \times Treatment_i + \beta_5 Unexpected\ Earnings_{i,t} + \gamma' X_{i,t} +$$
$$\psi' Unexpected\ Earnings \times X_{i,t} + \theta_j + \theta_t + \varepsilon_{i,t}, \qquad (5)$$

where the subscripts *i, j,* and *t* refer to firm *i*, industry *j,* and year-quarter *t*, respectively. The variables $CAR_{i,t}^{-21,-2}$ and $CAR_{i,t}^{-1,1}$ are defined in Section 2. The indicator variable $Treatment_{i,t}$ equals 1 for treatment firms and 0 for control firms. The indicator variable $Post_{i,t}$ equals 1 for dates after the pilot is implemented.

The variable $Unexpected\ Earnings_{i,t}$ is defined in Section 2. In Model (4), the coefficient on the interaction term $Unexpected\ Earnings_{i,t} \times Post_{i,t} \times Treatment_{i,t}$ (β_1) captures the changes in the association between pre-announcement abnormal stock returns and upcoming earnings surprises for treatment firms relative to control firms. We expect the decrease in the level of dark trading resulting from the implementation of the pilot to be associated with a smaller preemption of upcoming earnings news—that is, a negative coefficient on β_1 in Model (4). In Model (5), β_1 captures the changes in stock price reactions to earnings surprises for treatment firms relative to control firms. Therefore, we expect a positive coefficient on β_1 in Model (5). The vector $X_{i,t}$ is the same set of control variables as that in Models (1) and (2). We account for time-invariant industry heterogeneity and time effects by including Fama French 48 industry fixed effects, θ_j, and earnings announcement date fixed effects, θ_t. We cluster standard errors by industry and earnings announcement date. The results are reported in Table 4.

INSERT TABLE 4 ABOUT HERE

In Panel B of Table 4, columns (1)-(2) present the results of DiD analyses based on Models (4) and (5). We observe a smaller preemption of upcoming earnings news for treated firms than for control firms: (1) a negative and significant coefficient on the interaction term *Unexpected Earnings*$_{i,t}$ × *Post*$_{i,t}$ × *Treatment*$_{i,t}$ (-0.163, t-statistic = -1.86 in column (1)) when the dependent variable is $CAR_{i,t}^{-21,-2}$; and (2) a positive and significant coefficient on the interaction term *Unexpected Earnings*$_{i,t}$ × *Post*$_{i,t}$ × *Treatment*$_{i,t}$ (2.906, t-statistic = 2.12 in column (2)) when the dependent variable is $CAR_{i,t}^{-1,1}$.

Next, we repeat the DiD analysis on our third measure of price informativeness, *FERC*. The regression specification is:

$$Return_{i,t} = \alpha + \sum_{k=-1}^{1} \delta_k Earnings_{i,t+k} \times Post_{i,t} \times Treatment_{i,t} +$$

$$\sum_{m=-1}^{1} \mu_m Earnings_{i,t+m} \times Post_{i,t} + \sum_{n=-1}^{1} \varphi_n Earnings_{i,t+k} \times Treatment_{i,t} +$$

$$\sum_{p=-1}^{1} \beta_k Earnings_{i,t+p} + \beta_2 Post_t \times Treatment_i + \gamma' X_{i,t} +$$

$$\sum_{n=-1}^{1} \psi' Earnings_{i,t+n} \times X_{i,t} + \theta_j + \theta_t + \varepsilon_{i,t}, \qquad (6)$$

where the subscripts i, j, and t refer to firm i, industry j, and year-quarter t, respectively. $Return_{i,t}$, are defined in Section 2. The indicator variable $Treatment_{i,t}$ equals 1 for treatment firms and 0 for control firms. The indicator variable $Post_{i,t}$ equals 1 for dates after the pilot is implemented. The vector $X_{i,t}$ is the same set of control variables as that in Model (3). The coefficient on the interaction term $Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$ (δ_1) captures the change in *FERC* for treatment firms relative to control firms. We expect the decrease in the level of dark trading resulting from the implementation of the pilot to be associated with smaller *FERC*. That is, we expect a negative coefficient on δ_1 for Model (6). Similar to Models (4) and (5), we include Fama French 48 industry fixed effects, θ_j, and year-quarter fixed effects, θ_t. Finally, we cluster standard errors by industry and year-quarter.

The results are reported in column (3), Panel B, Table 4. We find smaller *FERC* for treated compared to control firms, as evidenced by a negative and significant coefficient on the interaction term $Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$ (-1.854, t-statistic = -2.94 in column (3)). Overall, these results suggest that dark trading improves price informativeness with respect to firm fundamentals.

4. Alternative Stories

While we exploit the Tick Pilot Size Program to generate exogenous variation in the level of dark pool trading to argue that price informativeness improves because of dark trading, alternative stories may explain the findings. In particular, other explanations that may warrant further investigation are the role of lit market liquidity, high frequency trading, and information efficiency in driving the findings. In this section, we further test these possible alternative explanations.

4.1 Lit Market Liquidity

The first alternative explanation for the findings that we attribute to dark pool trading is that it is simply a reaction to liquidity on the lit market. We have already carried out a number of controls to rule out this possible alternative explanation. In particular, we include in all the analysis conducted so far the Corwin and Schultz (2012) Effective Spread measure. This measure absorbs any variation in information acquisition driven by liquidity changes on the lit market.

In addition, in unreported results, when we consider what happens to the liquidity of lit markets in our DiD framework, we find that when dark pool trading is exogenously reduced that liquidity in the lit market increases. This is consistent with Zhu (2014) and Comertone-Ford and Putnins (2014), who show that dark pool trading can result in less liquid lit markets. This result is in the opposite direction that would explain our results. Thus, liquidity in the lit market does not explain our findings.

4.2 High Frequency Trading

Another possible explanation of our findings is that they are driven by high frequency traders. Weller (2017) and Lee and Watts (2018) shows that the rise of algorithmic trading, which includes high frequency trading, has resulted in a decrease in information acquisition. If high frequency trading is negatively correlated with dark pool trading, then it is possible we are attributing the information acquisition change to dark pools when in fact it is being driven by high frequency traders.

To test the high frequency trading hypothesis, we rerun Models (4) to (6) but now include an additional control variable, *HFT*. As there is no formal publicly available HFT proxy, the literature has used a few lose proxies. We consider four measures of HFT that are used in prior studies: the Odd Lot Ratio, the Trade-to-Order Ratio, the Cancel-to-Trade Ratio, and the Average Trade Size.

We obtain the *HFT* proxies from the SEC's Market Information Data Analytics System (MIDAS) dataset. First, we calculate the Odd Lot Ratio ($Odd\ Lot\ Ratio_{i,t}$) as the volume of trades executed in odd-lot sizes divided by the total volume traded. The variable $Odd\ Lot\ Ratio_{i,t}$ is positively correlated with *HFT* (O'Hara et al., 2014). Second, the Trade-to-Order Ratio ($Trade\text{-}to\text{-}Order\ Ratio_{i,t}$) is the total volume traded divided by the total volume of orders placed, where greater $Trade\text{-}to\text{-}Order\ Ratio_{i,t}$ is associated with lower *HFT* because high frequency traders place and cancel high numbers of orders when executing trades (Hendershott et al., 2011). Third, we measure the cancellations-to-trades ratio ($Cancel\text{-}to\text{-}Trade\ Ratio_{i,t}$) as the number of orders cancelled divided by the number of trades executed. The variable $Cancel\text{-}to\text{-}Trade\ Ratio_{i,t}$ is positively correlated with *HFT*, because high frequency traders place and cancel large numbers of orders (Hasbrouck and Saar, 2013; Hendershott and Riordan, 2013). Our final proxy is trade size ($Average\ Trade\ Size_{i,t}$), calculated as the total volume traded divided by the number of trades. The level of *HFT* is expected to be negatively correlated with the *Average Trade Size*, as high frequency traders execute a greater number of small orders to trade a given volume (Brogaard et al., 2014; Menkveld, 2014; O'Hara, 2015).

INSERT TABLE 5 ABOUT HERE

Table 5 presents the results from the tests with each HTF proxy as an additional explanatory variable. Panel A reports the results from estimating Models (4) and (5), and Panel B shows results from estimating Model (6). First, across our three measures of price informativeness, our results are robust to HFT measures and there is no meaningful change in the economic size or statistical significance. Second, Panel A shows that for the two CAR measures none of the HFT proxies are statistically significantly different than zero. In Panel B, for the FERC measure, while the Odd Lot Ratio and the Average Trade size are statistically significantly different from zero (-0.158, t-statistic =-3.17 in column (1); 0.582, t-statistic =4.02 in column (4)), the coefficient on the interaction term $Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$ is still negative and significant (-1.625, t-statistic = -2.32 in column (1); -1.655, t-statistic = -2.49 in column (2); -1.998, t-statistic = -3.22 in column (3); -1.666, t-statistic = -2.44 in column (4)). Therefore, the hypothesis that HFT drive our results is not supported.

4.3 Informational Efficiency

The third alternative explanation worth exploring is that the SEC Tick Pilot Test Program is changing the informational efficiency of the market. Zhu (2014) and Ye (2012) have opposing theories on how dark pools can change the market's informational efficiency. A change in the market's informational efficiency may then lead to a change in price informativeness. Comertone-Forde and Putnins (2014) find that a rise in dark pools leads to an increase in price efficiency through a process predicted by Zhu (2014). Dark pools attract uninformed traders whereas informed traders tend towards the lit markets. This bifurcation leads to clearer supply and demand price signals, creating a more informationally efficient price process.

We consider two measure of informational (or price) efficiency: Variance Ratio and the Hou and Moskowitz (2005) Price Delay measure. The variance ratio is defined as the ratio of the variance of 2-day returns divided by two times the variance of 1-day returns. If the ratio is closer to one, the prices behave more like a random walk, and thus the stock price is more efficient. Hou and Moskowitz (2005) use stock price delay in reflecting market-wide information to measure price efficiency. The stock price delay is measured as one minus the ratio of a stock's weekly return variation explained by the concurrent weekly market return divided by a stock's weekly return variation explained by the concurrent and four past weekly market returns. If the measure is lower (approaching to zero), less stock return variation is captured by lagged weekly market returns, and thus the stock price is more efficient.

Instead of including the measures as an independent variable in regression models, we use the DiD structure around the SEC Tick Pilot Test Program to test directly whether informational efficiency changed. That is, we use the informational efficiency measures as dependent variables. The variable of interest is therefore the interaction term $Post_{i,t} \times Treatment_{i,t}$ in each specification.

INSERT TABLE 6 ABOUT HERE

The results are reported in Table 6. We fail to find any statistically significant effect of dark trading on informational efficiency. For both dependent variables the coefficient on the interaction term $Post_{i,t} \times Treatment_{i,t}$ is statically insignificant (0.066, t-statistic = 1.40 in column (1); -0.059, t-statistic = -1.37 in column (2)). There, we conclude that in our setting, the information acquisition results are not driven by changes in informational efficiency.

5. Further evidence of increased information acquisition

To provide further evidence that dark pools cause an increase in information acquisition, we directly test whether we can detect information acquisition changing, whether we can observe that the probability of informed trading changes, and whether we see a shift in the sensitivity to the systematic or idiosyncratic component of earnings. All three tests support the notion that dark pools encourage information acquisition.

5.1 Direct Evidence of Information Acquisition

The three measures of information acquisition we have been using are established in the literature and have strong economic reasoning for why they capture price informativeness. Nonetheless, perhaps the most convincing measure of information acquisition is one that tracks the actual acquisition of information. Following Drake et al. (2015, 2016), we generate such a measure using the SEC's EDGAR search data.

The EDGAR search data contains information extracted from the server log files that record and store user access statistics for the SEC's EDGAR database. The SEC's EDGAR database hosts all of the regulatory filings mandated by the SEC, including annual and quarterly reports (10K and 10Q), current report (8-K), equity ownership updates (Form 4), registration statements (S-1), and proxy statements (DEF 14A), among others. The EDGAR search data is used to examine the extent and the timing of investors' acquisition of firm-level financial statements (Drake et al., 2015, 2016).

We construct four measures of EDGAR search activities: the number of requests for 10-K filings (*#10K Reports*), for 10-Q filings (*#10Q Reports*), for firms' periodic accounting filings, including 10-Ks, and 10-Qs (*#Accounting Reports*), and for all other EDGAR filings (*#Other Reports*). In specific, for each type of filings, we compute the average number of requests made in quarter t, scaled by the total number of trading volumes in quarter *t*.

We use each of these four measures of EDGAR search activities as the dependent variables in DiD analyses. If dark trading does encourage information acquisition, we expect that the decrease in the level of dark trading resulting from the implementation of the pilot leads to lower level of EDGAR search activities—that is, a negative coefficient on the interaction term $Post_{i,t} \times Treatment_{i,t}$. The results on EDGAR search activities are presented in Table 7.

INSERT TABLE 7 ABOUT HERE

Across all measures of EDGAR search activities except for *#Other Reports*, the coefficients on the interaction term $Post_{i,t} \times Treatment_{i,t}$ are negative and statistically significant (-0.002, t-statistic = -2.26 in column (1); -0.001, t-statistic = -2.23 in column (2); -0.001, t-statistic = -2.14 in column (3)). The EDGAR search activity results are consistent with dark trading facilitating information acquisition.

5.2 Probability of Informed Trading

The test on EDGAR search activities is an attempt to directly examine the effect of dark trading on investors' information acquisition. An alternative approach is to try to observe how the market may respond when more information is being acquired. The Easley, Kiefer and O'Hara's (1996) Probability of Informed Trading (PIN) measure is the best existing measure of the likelihood of there being an informed trader. *PIN* is defined as the ratio of information-based trades to total trades and thus takes higher values when the arrival rate of information-motivated trades is higher. For each stock-quarter, we estimate a stock's quarterly *PIN* measure using the number of buy and sell trades across all trading days within the same quarter.

We repeat the DiD specification in Section 5.1 but use *PIN* as the dependent variable. If dark trading increases the arrival rate of informed trades, we expect the decrease in the level of dark trading resulting from the implementation of the pilot to be associated with a smaller *PIN*—that is, a negative coefficient on the interaction term $Post_{i,t} \times Treatment_{i,t}$. We report the results in Table 8.

INSERT TABLE 8 ABOUT HERE

We find that the coefficient on the interaction term $Post_{i,t} \times Treatment_{i,t}$ is negative and statistically significant (-0.034, t-statistic = -2.91 in column (1)), consistent with the probability of an informed trades in the market decreasing as the level of dark trading declines.

5.3. Firm specific versus Systematic information

To further ensure our interpretation of price informativeness increasing due to dark trading, we next evaluate different components of information. We decompose earnings into its systematic component and its idiosyncratic component. Lee, Israeli, and Sridharan (2018) show that firm specific information acquisition is more profitable than systematic information. Therefore, if dark trading is facilitating information acquisition we expect it to be more for firm specific news than for systematic news.

To decompose earnings into its systematic and idiosyncratic components, we perform the following steps. For each stock with earnings data in the past 20 quarters, we estimate the model $Earnings_{i,t} = a_0 + a_1\ Mkt\_Earnings_{i,t} + a_2\ Ind\_Earnings_{i,t} + e_{i,t}$, where $Earnings_{i,t}$ is quarterly seasonally adjusted net income before extraordinary items, scaled by the market value of equity at the beginning of quarter t. The variable $Mkt\_Earnings_{i,t}$ is the market cap-weighted average of $Earnings_{i,t}$ of all firms. The variable $Ind\_Earnings_{i,t}$ is the market cap-weighted average of $Earnings_{i,t}$ of firms in the same Fama-French 48 industry as firm i. $Sys\_Earnings_{i,t}$ is computed as the calculated as the fitted value from the quarterly regression; and $Idio\_Earnings_{i,t}$ is computed is the residuals of the model.

We take the decomposed earnings and include both in the Equation (6) model. Thereby replacing *Earnings* with the two distinct components of *Earnings*, systematic component ($Idio\_Earnings_{i,t+1}$) and idiosyncratic component ($Sys\_Earnings_{i,t+1}$). The model is:

$$Return_{i,t} = \alpha + \sum_{k=-1}^{1} \beta_k Sys\_Earnings_{i,t+k} \times Post_{i,t} \times Treatment_{i,t} + \sum_{k=-1}^{1} \delta_k Idio\_Earnings_{i,t+k} \times Post_{i,t} \times Treatment_{i,t} + \sum_{m=-1}^{1} \zeta_m Sys\_Earnings_{i,t+m} \times Post_{i,t} + \sum_{m=-1}^{1} \eta_m Idio\_Earnings_{i,t+m} \times Post_{i,t} + \sum_{n=-1}^{1} \kappa_n Sys\_Earnings_{i,t+k} \times Treatment_{i,t} + \sum_{n=-1}^{1} \lambda_n Idio\_Earnings_{i,t+k} \times Treatment_{i,t} + \sum_{p=-1}^{1} \mu_k Sys\_Earnings_{i,t+p} + \sum_{p=-1}^{1} \pi_k Idio\_Earnings_{i,t+p} + \beta_2 Post_t \times Treatment_i + \Upsilon' X_{i,t} + \sum_{n=-1}^{1} \Phi' Sys\_Earnings_{i,t+n} \times X_{i,t} + \sum_{n=-1}^{1} \psi' Idio\_Earnings_{i,t+n} \times X_{i,t} + \theta_j + \theta_t + \varepsilon_{i,t}, \quad (7)$$

where the subscripts i, j, and t refer to firm i, industry j, and year-quarter t, respectively. $Return_{i,t}$, are defined in Section 2. The indicator variable $Treatment_{i,t}$ equals 1 for treatment firms and 0 for control firms. The indicator variable $Post_{i,t}$ equals 1 for dates after the pilot is implemented. The vector $X_{i,t}$ is the same set of control variables as that in Model (3). The variable of interest is the interaction term $Idio\_Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$ (δ_1). If dark trading is facilitating information acquisition, we expect that the decrease in the level of dark trading resulting from the implementation of the pilot leads to a smaller association between current returns and future idiosyncratic component of earnings. That is, we expect a negative coefficient on δ_1 for Model (7).

Similar to Model (6), we include Fama French 48 industry fixed effects, θ_j, and year-quarter fixed effects, θ_t. Finally, we cluster standard errors by industry and year-quarter.

INSERT TABLE 9 ABOUT HERE

Table 9 presents the estimation results of Model (7). Column (1) reports results without interactions between $Sys\_Earnings_{i,t+1}$ /$Idio\_Earnings_{i,t+1}$ and each control variable and column (2) shows results after controlling for interactions between $Sys\_Earnings_{i,t+1}$ / $Idio\_Earnings_{i,t+1}$ and each control variable. In both specifications, the coefficient estimates on the interaction term $Idio\_Earnings_{i,t+1} \times \times Post_{i,t} \times Treatment_{i,t}$ are negative and statically significant (-2.486, t-statistic = -3.32 in column (1); -2.821, t-statistic = -3.63 in column (2)). In contrast, the coefficient estimate on the interaction term $Sys\_Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$ is negative and statistically significant in column (1) but becomes statically insignificant in column (2) where we control for all variables in Model (7). Collectively these results suggest that dark trading facilitates the incorporation of firm-specific earnings into stock prices but not systematic earnings, consistent with our hypothesis that dark trading facilitates information acquisition.

6. Conclusion

We examine the effect of dark trading on the incorporation of firm-specific fundamentals into stock prices. Given the dark pools' opacity and rapidly growing market share, regulatory authorities are increasingly concerned about the impact of dark trading on informativeness of stock prices. Our central conjecture is that dark trading influences the informational acquisition for a stock.

If dark trading improves price informativenss then stock prices will more accurately reflect investors' acquired information about fundamental values. Using newly available weekly dark trading data for a comprehensive sample of firms, we find that dark trading is associated with (1) greater preemption of earnings announcements, as evidenced by a stronger association between pre-announcement abnormal stock returns and upcoming earnings news and by smaller price reactions to earnings news, and (2) improvement in long horizon information acquisition of fundamental information, as evidenced by larger FERC. Using the differential treatment of the Tick Size Pilot Program as an exogenous shock to the level of dark trading we find that the positive relationship between dark pool trading and information acquisition is causal.

We show that alternative explanations do not invalidate or explain our findings. In addition, we show supporting evidence through dark trading increasing SEC EGDAR searches, the probability of informed trading, and the idiosyncratic part of stock returns. Overall, the evidence is consistent with dark trading improving the price informativeness of stock prices with respect to firm fundamentals.

References

Abarbanell, J. S., Bernard, V. L., 1992. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. Journal of Finance 47, 1181–1207.

Albuquerquey, R., Song, S., and Yao, C., 2018. The price effects of liquidity shocks: A study of SEC's Tick-Size Experiment. Working Paper.

Ali, A., Klasa, S., Li, O. Z., 2008. Institutional stakeholdings and better-informed traders at earnings announcements. Journal of Accounting and Economics 46, 47–61.

Ayers, B., Freeman, R., 2003. Evidence that analyst following and institutional ownership accelerate the pricing of future earnings. Review of Accounting Studies 8, 47–67.

Bakke, T. E., Whited, T. M., 2010. Which firms follow the market? An analysis of corporate investment decisions. Review of Financial Studies 23(5), 1941–1980.

Baruch, S., Panayides, M., and Venkataraman, K., 2017. Informed trading and price discovery before corporate events. Journal of Financial Economics 125, 561-588.

Balakrishnan, K., and Taori, P., 2017. Information asymmetry and trading in dark pools: Evidence from earnings announcement and analyst recommendation revisions. Working paper.

Bernard, V., Thomas, J., 1989. Post-earnings-announcement drift: Delayed price response or risk premium? Journal of Accounting Research 27, 1–48.

Bertomeu, J. and Beyer, A., and Taylor, D., 2016. From casual to causal inference in accounting research: The need for theoretical foundations. Foundations and Trends in Accounting 2016, 1-53.

Bessembinder, H., 2003. Selection biases and cross-market trading cost comparison. Unpublished Working paper.

Bhushan, R., 1994. An informational efficiency perspective on the post-earnings announcement drift. Journal of Accounting and Economics 18, 45–65.

Boehmer, E., and Wu, J., 2012. Short selling and the price discovery process. Review of Financial Studies 26: 287-322.

Boehmer, E., Jones, C. M., Zhang, X., 2008. Which shorts are informed? Journal of Finance 63, 491–527.

Bond, P., Edmans, A., Goldstein, I., 2012. The real effects of financial markets. Annual review of Financial Economics 4, 339–360.

Brown, S., Warner, J. B., 1980. Measuring security price performance. Journal of Financial Economics 8, 205–258.

Brown, S., Warner, J. B., 1985. Using daily stock returns: The case of event studies. Journal of Financial Economics 14, 3–31.

Brunnermeier, M., 2005. Information leakage and market efficiency. Review of Financial Studies 18, 417-457.

Brunnermeier, M. K., Pedersen, L. H., 2005. Predatory trading. Journal of Finance 60, 1825–63.

Bushman, R., Smith, A., Wittenberg-Moerman, R., 2010. Price discovery and dissemination of private information by loan syndicate participants. Journal of Accounting Research 48, 921–972.

Buti, S., Rindi, B., Werner, I. M., 2011. Diving into dark pools. Working paper, Fisher College of Business, Ohio State University.

Butler, G. 2007. Liquidity aggregation: what institutional investors need to know. Journal of Trading Spring: 108–114.

Butler, M., Kraft, A., Weiss, I., 2007. The effect of reporting frequency on the timeliness of earnings: The cases of voluntary and mandatory interim reports. Journal of Accounting and Economics 43, 181–217.

Carlin, B. I., Lobo, M. S., Viswanathan, S., 2007. Episodic liquidity crisis: Cooperative and predatory trading. Journal of Finance 62, 2235–2274.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Chen, Q., Goldstein, I., Jiang, W., 2007. Price informativeness and investment sensitivity to stock price. Review of Financial Studies 20(3), 619–650

Choi, J., Myers, L. A., Zang, Y., Ziebart, D. A., 2011. Do management EPS forecasts allow returns to reflect future earnings? Implications for the continuation of management's quarterly earnings guidance. Review of Accounting Studies 16, 143–182.

Chordia, T., Roll, R., Subrahmanyam, A., 2002. Order imbalance, liquidity, and market returns. Journal of Financial Economics 65, 111–130.

Christophe, S. E., Ferri, M. G., and Hsieh, J., 2010. Informed trading before analyst downgrades: Evidence from short sellers. Journal of Financial Economics 95, 85-106.

Comerton-Forde, C., Putniņš, T., 2015. Dark trading and price discovery. Journal of Financial Economic 118, 70–92.

Crawford, S., Park, D., Roulstone, D., 2011. Insider trading and the incorporation of future earnings news into stock prices. Working paper.

Demski, J. S., and Feltham, G. A., 1994. Market response to financial reports. Journal of Accounting and Economics 17, 3-40.

Diamond, D. W., Verrecchia, R. E., 1981, Information aggregation in noisy rational expectations model. Journal of Financial Economics 9, 221–235.

Diamond, D., Verrecchia, R. E., 1987. Constraints on short selling and asset price adjustment to private information. Journal of Financial Economics 18, 277-311.

Drake, M. S., Myers, J. N., Myers, L. A., Stuart, M. D., 2015a. Short sellers and the informativeness of stock prices with respect to future earnings. Review of Accounting Studies 20, 747–774.

Drake, M. S., Rees, L., Swanson, E., 2011. Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers. The Accounting Review 86, 101–130.

Drake, M. S., Roulstone, D., Thornock, J., 2015b. The determinants and consequences of information acquisition via EDGAR. Contemporary Accounting Research 32, 1128–1161.

Drake, M., Roulstone, D. T., and Thornock, J. R., 2016. The usefulness of historical accounting reports. Journal of Accounting and Economics 61, 448-464.

Drake, M. S., Thornock, J., Twedt B., 2017. The internet as an information intermediary. Review of Accounting Studies, Forthcoming.

Easley, D., O'Hara, M., 1992. Time and the process of security price adjustment. Journal of Finance 47, 577–605.

Engelberg, J. E., Reed, A. V., Ringgenberg, M. C., 2012. How are shorts informed? Journal of Financial Economics 105, 260–278.

Ettredge, M. L., Kwon, S. Y., Smith, D. B., Zarowin, P. A., 2005. The impact of SFAS No. 131 business segment data on the market's ability to anticipate future earnings. The Accounting Review 80, 773–804.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fleming, M., Nguyen, G., 2013. Order flow segmentation and the role of dark trading in the price discovery of U.S. Treasury securities. Technical Report 624, Staff Report, Federal Reserve Bank of New York.

Foley, S., Putniņš, T. J., 2016. Should we be afraid of the dark? Dark trading and market quality. Journal of Financial Economics 122, 456–481.

Gkougkousi, X., Landsman, W., 2017. Dark trading volume at earnings announcements. Working paper.

Glosten, L. R., Milgrom, P. R., 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. Journal of Financial Economics 14, 71–100.

Gresse, C., 2006. The effect of crossing-network trading on dealer market's bid-ask spreads. European Financial Management 12, 143–160.

Grossman, S., Stiglitz, J. E., 1980. On the impossibility of informationally efficient markets. American Economic Review 70, 393–408.

Harris, L., 2015. Trading and exchanges: Market microstructure for practitioners. The CFA Institute Research Foundation Publications 2015, 1-79.

Harris, M., Raviv, A., 1993. Differences in opinion make a horse race. Review of Financial Studies 6, 473–506.

Hatheway, F., Kwan, A., Zhen, H., 2017. An empirical analysis of market segmentation on U.S. equities markets. Journal of Financial and Quantitative Analysis (Forthcoming).

Hellwig, M. F., 1980. On the aggregation of information in competitive markets. Journal of Economic Theory 22, 477–498.

Hendershott, T., Mendelson, H., 2000. Crossing networks and dealer markets: Competition and performance. Journal of Finance 55, 2071–2115.

Hendershott, T., Livdan, D., Schürhoff, N., Are institutions informed about news? Journal of Financial Economics 117, 249-287.

Hirshleifer, D., Lim, S. S., Teoh, S. H., 2009. Driven to distraction: Extraneous events and underreaction to earnings news. Journal of Finance 64, 2289–2325.

Holden, C. W., Subrahmanyam, A., 1992. Long-lived private information and imperfect competition. The Journal of Finance 47, 247–270.

Ivkovic, Z., Weisbenner, S., 2005. Local does as local is: Information content of the geography of individual investors' common stock investments. Journal of Finance 60, 267–306.

Jiambalvo, J., Rajgopal, S., Venkatachalam, M., 2002. Institutional ownership and the extent to which stock prices reflect future earnings. Contemporary Accounting Research 19, 117–145.

Kandel, E., Pearson, N. D., 1995. Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103, 831–872.

Ke, B., Petroni, K., 2004. How informed are actively trading institutional investors? Evidence from their trading behavior before a break in a string of consecutive earnings increases. Journal of Accounting Research 42, 895–927.

Kim, O., Verrecchia, R. E., 1991. Market reaction to anticipated announcements. Journal of Financial Economics 30, 273–309.

Kim, O., Verrecchia, R. E., 1994. Market liquidity and volume around earnings announcements. Journal of Accounting and Economics 17, 41–67.

Kim, O., Verrecchia, R. E., 1997. Pre-announcement and event-period private information. Journal of Accounting and Economics 24, 395-419.

Kothari, S.P., 2001. Capital markets research in accounting. Journal of Accounting and Economics 31, 105–231.

Kraus, A., Stoll, H. R., 1972, Price impacts of block trading on the New York Stock Exchange. The Journal of Finance 27, 569–588.

Kyle, A., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

Kyle, A., 1989. Informed speculation with imperfect competition. The Review of Economic Studies 56, 317–355.

Landsman, W., Maydew, E. L., Thornock, J. R., 2012. The information content of annual earnings announcements and mandatory adoption of IFRS. Journal of Accounting and Economics 53, 34–54.

Lee, C., 2001. Market efficiency and accounting research. Journal of Accounting and Economics 31, 233–253.

Lee, C., and Watts, E., 2018. Tick size tolls: Can a trading slowdown improve price discovery? Working Paper.

Lee, C., Israeli, D., Sridharan, S., 2018. Is there a dark-side to exchange traded funds (ETFs)? An information perspective. Review of Accounting Studies 22, 1048-1083.

Lee, Y., 2012. The effect of quarterly report readability on information efficiency of stock prices. Contemporary Accounting Research 29, 1137–1170.

Livnat, J., Mendenhall, R., 2006. Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. Journal of Accounting Research 44, 177–205.

Lundholm, R., Myers, L., 2002. Bringing the future forward: the effect of disclosure on the returns-earnings relation. Journal of Accounting and Economics 40, 809–839.

McMullin, J. L., Miller, B. P., Twedt, B. J., 2015. Increased mandated disclosure frequency and price formation: Evidence from the 8-K expansion regulation. Working paper.

McNichols and Trueman, 1994. Public disclosure, private information collection, and short-term trading. Journal of Accounting and Economics 17, 69-94.

Menkveld, A., Yueshen B., Zhu, H., 2016. Shades of darkness: A pecking order of trading venues. Working paper.

Nimalendran, M., Ray, S., 2014. Informational linkages between dark and lit trading venues. Journal of Financial Markets 17(C), 230–261.

O'Hara, M., Ye, M., 2011. Is market fragmentation harming market quality? Journal of Financial Economics 100, 459–474.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Review of Financial Studies 22, 435–480.

Ready, M., 2010. Determinants of volume in dark pools. Working paper, University of Wisconsin.

Reed, A. V., Samadi, M., Sobobin, J., 2017. Where do shorts trade? Intermarket competition and information horizon. Working paper.

Rindi, B., and Werner, I., 2017. U.S. tick size pilot. Working paper.

Rosenblatt Securities, 2016. Let there be light.

Roulstone, D. T., 2003. Analyst following and market liquidity. Contemporary Accounting Research 20(3), 552–578.

Shorter, G., Miller, R., 2014. Dark pools in equity trading: Policy concerns and recent developments. Congressional Research Service 1, 5.

Staiger, D., Stock, J. H., 1997. Instrumental variables regression with weak instruments. Econometrica 65(3) 557-586.

Tabb Group, 2011. Liquidity matrix. Technical report.

Tetlock, P. C., 2011. All the news that's fit to reprint: Do investors react to stale information? Review of Financial Studies 24, 1481–1512.

Twedt, B., 2016. Spreading the word: Price discovery and newswire dissemination of management earnings guidance. The Accounting Review 91, 317–346.

Utama, S., Cready, W. M., 1997. Institutional ownership, differential predisclosure precision and trading volume at announcement dates. Journal of Accounting and Economics 24, 129–150.

Vega, C., 2006. Stock price reaction to public and private information. Journal of Financial Economics 82, 103–133.

Weller, B., 2018. Does algorithmic trading deter information acquisition? Working paper.

Wooldridge, J. 2015. Control Function Methods in Applied Econometrics. Journal of Human Resources 50: 420-445.

Ye, M., 2010. Non-execution and market share of crossing networks. Working paper.

Zhu, H., 2014. Do dark pools harm price discovery? Review of Financial Studies 27, 747–789.

Appendix 1. Background of dark pools.

1.1 History

Dark pools first appeared in the late 1960s (Shorter and Miller, 2014). According to the SEC, dark pools were created "to offer certain market participants, particularly institutional investors, the ability to minimize transaction costs when executing trades in large size by completing their trades without prematurely revealing the full extent of their trading interest to the broader market" (SEC Release No. 34-76474). The proliferation of dark pools in the United States is commonly attributed to two SEC regulations: Reg ATS and Reg NMS.

Implemented in 1998, Reg ATS was designed to encourage the development of innovative trading venues by placing a lighter regulatory burden on alternative trading systems (ATSs), and to ensure basic investor protections (SEC Release No. 34-39884). Under Reg ATS, ATSs, including both dark pools and electronic communications networks (ECNs), are registered as broker–dealers with the SEC, and are exempt from registering as exchanges. Reg ATS gives dark pools the option to restrict access to their trading platforms. This allows dark pools to provide customized services to customer segments—a significant competitive advantage over traditional exchanges.

Implemented in 2005, Reg NMS was intended to make markets more competitive and thus to promote more efficient trading services and the more efficient stock pricing (SEC Release No. 34-61358). Under Reg NMS, the Sub-Penny Rule (Rule 612) prohibits trading venues from quoting in increments of less than $0.01 (subpenny price increments) to the NBBO. Because dark pools are allowed to execute transactions at subpenny price increments to the NBBO, Rule 612 allows dark pools to attract order flow by offering better prices.[5]

The market share of dark pools has increased dramatically since the regulations were designed and adopted. In 2005, ATSs accounted only for roughly 4% of the equity trading volume.[6] According to an analysis by Rosenblatt Securities in 2016, the market share of dark pools in the United States grew from 7.51% in 2008 to 16.57% in 2015.

1.1. Overview

Dark pools are equity trading venues that operate without pre-trade transparency. The proliferation of dark pools is commonly attributed to Regulation Alternative Trading Systems (Reg ATS) and Regulation National Market System (Reg NMS), which were designed to encourage the development of innovative trading venues and competition between trading venues. We present a brief history of dark pools in Appendix 1.

Dark pools do not publicly display orders prior to order execution. After an order has been executed, dark pools are not required to disseminate as much information about that order as exchanges are. Specifically, orders filled in dark pools are reported to a trade-reporting facility and recorded to the national consolidated tape as over-the-counter transactions.[7] Market participants

[5] As broker-dealers, dark pools cannot accept an order that is explicitly priced at a subpenny increment, but are allowed to accept orders involving instructions or information to derive a price at subpenny increments, such as the midpoint of the NBBO and the volume-weighted average price. See "Division of Market Regulation: Responses to Frequently Asked Questions Concerning Rule 612 (Minimum Pricing Increment) of Regulation NMS," available at http://www.sec.gov/divisions/marketreg/subpenny612faq.htm.
[6] See https://www.sec.gov/news/statement/shedding-light-on-dark-pools.html.
[7] The SEC required that, as of March 5, 2007, all non-exchanges must report to a trade-reporting facility, which in turn would report trades to the consolidated tape.

do not know when the order was submitted, the original size of the order, any revisions to the order price, the order imbalance, or which dark pool executed the order.

Dark pools generally provide little or no price discovery. Most of them match buy and sell market orders at prices derived from the National Best Bid and Offer (NBBO) in lit markets (Zhu, 2014; Nimalendran and Ray, 2014), such as the midpoint of the NBBO or the volume-weighted average price. According to a study by Tabb Group in 2015, more than 70% of trades on prominent dark pools, such as Barclays DirectEx and BIDS Trading, are executed at the NBBO midpoint. In addition, since execution prices in dark pools are bound within the NBBO by Rule 611 of Reg NMS, they provide very limited or no improvement to exchange prices. Collectively, dark pools free-ride on the price discovery of exchanges.

1.2. Effect of dark trading on traders' order submission strategy

Because dark pools provide little or no direct contribution to price discovery, their impact on price informativeness likely derives from how they affect investors' strategic choice of trading venues and, thus, the way lit markets process information and determine asset prices. Three primary differences in market structure between dark pools and lit markets affect investors' choice of trading venue: transaction costs, execution probability, and access restrictions on information-motivated orders. While the dark pools' low transaction costs are generally attractive to all investors, the dark pools' high execution uncertainties and access restrictions direct more information-motivated than non-information-motivated orders into the exchanges. We will discuss each of these three factors in detail in the paragraphs to come.

First, compared with exchanges, dark pools save on transaction costs several ways: they charge lower execution fees, they save investors the bid-ask spread by executing orders within the NBBO (e.g., at the mid-point of the NBBO), and they reduce the price impact of large trades.[8] Regarding the latter cost differential, unlike large orders submitted to a dark pool, large orders submitted to exchanges adversely move the execution price away from the price of previous trade (Kraus and Stoll, 1972). The cost of this price impact is further magnified by predatory trading. For example, when an institutional investor needs to buy a large block of shares, predators could quickly purchase shares to increase the price and subsequently sell back those shares to the institution for a profit at the higher price (Brunnermeier and Pedersen, 2005; Carlin et al., 2007). Dark pools claim to protect traders from predatory traders by limiting predators' (e.g., high frequency traders) access to their trading platforms.

Second, the use of dark pools generally entails low execution probability (Gresse, 2006; Ready, 2010; Ye, 2010). A typical dark pool does not have market makers to absorb excess order flow and thus cannot guarantee execution. Traders place their orders anonymously, and order matching depends on the availability of counterparties. Moreover, dark pools are bound by Reg NMS Rule 611, which requires that orders be matched at or within the NBBO. Therefore, if there is no match within the NBBO, the trade will not take place. In contrast, exchanges can execute orders immediately, even if the resulting execution prices are outside the NBBO. Ye (2010) finds dark pool execution probabilities of 4.11% for New York Stock Exchange (NYSE) listings and 2.17% for NASDAQ listings, compared to exchange execution probabilities of 31.47% and

[8] Price impact is costly for large traders (e.g., institutional investors) because large position changes of institutions typically involve a number of separate trades that take place over a short period. When institutions place a sequence of buy (sell) orders, they generally pay an increasingly higher cost for each incremental purchase (sale).

26.48%. The execution uncertainty is further magnified by the pre-trade opacity of dark venues. In dark pools, traders cannot see orders waiting to be filled, so they have little information with which to determine outstanding buy and sell interest. The risk of losing an informational advantage due to poor execution may discourage investors from submitting information-motivated orders to these venues.

Third, under Reg ATS, dark pools are registered as broker–dealers. This means that, unlike exchanges, they are not subject to fair access requirements and thus can prohibit or limit certain investors' access to their services (see Reg ATS Rule 301(b)(5)). Dark pools take advantage of this, advertising trading environments that restrict relatively informed order flow. Hatheway et al. (2017, p. 3) state that the "practice of dark pools to restrict informed trading has been widely recognized in the industry." For example, Barclays LX restricts informationally motivated order flow by scoring the trading behavior of the participants in their dark pool. The participants of Barclays LX have the option of trading only with counterparties with high trading behavior scores, i.e., traders who trade passively.[9] Other dark pool operators, such as Credit Suisse and Deutsche Bank, claim to have similar practices.

Nonetheless, because dark pools are exempt from disclosing information on executed orders, market data, and execution procedures (see Reg ATS Rule 301(b)(6), SEC Rule 3a1-1, and SEC Concept Release 2010), few details are known about how they operate. The opacity of dark pools has led to concerns that some of them may mislead traders about their restrictions on informational motive order flow. For example, in 2014, the New York Attorney General alleged

---

[9] See "Shining More Light on Dark Pools" at http://www.institutionalinvestor.com/Article/3176017/ Shining-More-Light-on-Dark-Pools.html#.WSYQ8FXyu70.

that dark pools operated by UBS AG and Deutsche Bank AG allowed high-frequency traders to aggressively take advantage of uninformed traders through “toxic predatory trading” (Securities Exchange Act Release No. 74060, 79576). Concerns about dark pools’ insufficient or inaccurate disclosures about their operating mechanisms may prevent some investors from submitting orders to them.

1.3. Prior research on dark trading

Prior work in empirical microstructure has examined the link between dark trading, market quality, and price efficiency. Much of this work is measured by transaction costs, intraday volatility, the intraday price variance ratio, and market depth. The literature has produced different conclusions. Using data from 11 dark pools in the United States, Buti et al. (2011) find that dark trading improves market quality and price efficiency. But when Nimalendran and Ray (2014) and Hatheway et al. (2017) employ proprietary trade-by-trade data for a small set of firms in the U.S. market, they find the opposite. After the implementation of the Tick Size Pilot Program, Albuquerque el al. (2018) document that stocks subjected to the “trade-at” provision experience larger price errors and price delay than control stocks do, suggesting that dark trading improves intraday price efficiency. In addition to evidence on equity markets, Fleming and Nguyen (2013) conclude that dark trading improves the price efficiency of the U.S. Treasuries. A few recent studies add international evidence to this literature. Using dark trading data from the Australian Securities Exchange, Comerton-Forde and Putniņš (2015) find a positive impact of dark trading on price discovery. Exploiting minimum price improvement regulation in Canada and Australia as shocks to dark trading, Foley and Putniņš (2016) document that different types of dark pools have heterogeneous effects on market quality and price efficiency.

A few concurrent studies examine traders' choice of trading venues and provide mixed evidence. Rseed et al. (2017) document that information-motivated trades, as proxied by short sales, account for a greater proportion of exchange trading than of dark trading. Using a one-month panel of 117 NASDAQ-listed stocks, Menkveld et al. (2016) find that shocks to investors' urgency to trade, using the announcement of public news as a proxy, increase the market share of exchanges. This evidence is consistent with the idea that investors prefer venues with higher execution rates (i.e., exchanges) when their trading needs are urgent. In contrast, using a comprehensive sample of dark trading provided by FINRA, Balakrishnan and Taori (2017) and Gkougkousi and Landsman (2017) find that the market share of exchanges decreases during the week of and the week after earnings announcements. Since traders are likely to delay uninformed trades during the earnings announcement period, Balakrishnan and Taori (2017) and Gkougkousi and Landsman (2017) interpret an increase in the level of dark trading around the announcements as the evidence of more informed trading in dark pools.

In contrast to these studies, this study focuses on the causal impact of dark trading on information acquisition of fundamental information, as proxied by earnings news.

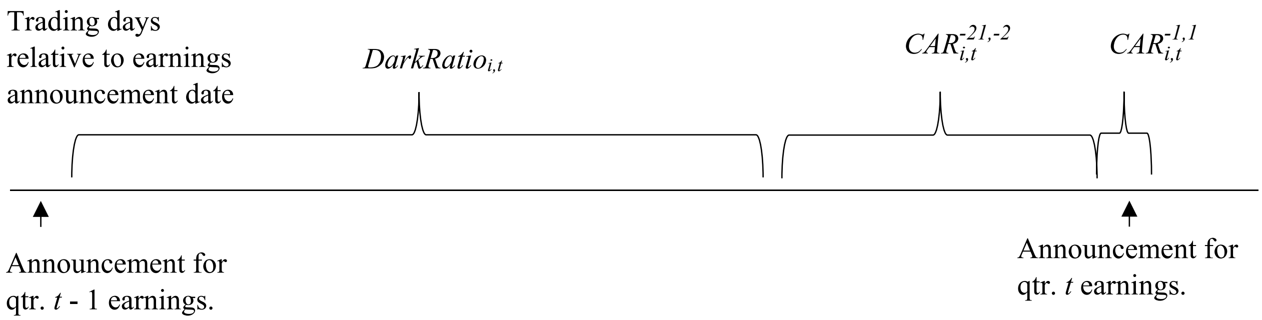
Appendix 2. Variable definitions.

Variable	Definition
Dark Trading Variables	
DarkRatio	Ratio of the trading volume executed on dark pools to the consolidated volume over the pre-announcement period. The pre-announcement period includes all weeks between the earnings announcement date of quarter *t* - 1 and 21 trading days before the announcement date of quarter *t*.
DarkRatio_Qtr	Ratio of the trading volume executed on dark pools to the consolidated volume in quarter *t*.
Other Variables	
$CAR_{i,t}^{-1,1}$	Cumulative abnormal return over trading days [-1, 1] around earnings announcements. Daily abnormal returns are computed as the raw return less the buy-and-hold return to a benchmark portfolio of firms matched on size and the book-to-market ratio. The benchmark portfolios are constructed using Fama and French's (1992) method. For June of year t, all firms with CRSP share codes 10 and 11 are classified into 25 portfolios by size at the end of June of year t and by the book-to-market ratio at the end of December of year t - 1.
$CAR_{i,t}^{-21,-2}$	Cumulative abnormal return over trading days [-21, -2] prior to earnings announcements. Daily abnormal returns are computed as the raw return less the buy-and-hold return to a benchmark portfolio of firms matched on size and the book-to-market ratio. The benchmark portfolios are constructed using Fama and French's (1992) method. For June of year t, all firms with CRSP share codes 10 and 11 are classified into 25 portfolios by size at the end of June of year t and by the book-to-market ratio at the end of December of year t - 1.
Unexpected Earnings	Unexpected earnings based on analyst forecasts scaled by price as of the end of the fiscal quarter, calculated as $Unexpected\ Earnings_{i,t} = (EPS_{i,t} - Aanalyst\ Forecast_{i,t})/Price_{i,t}$.
Return	The buy-and-hold quarterly return.
Earning	Seasonally adjusted net income before extraordinary items scaled by the market value of stock *i* at the beginning of the quarter.
Size	Market value of common shares.
Book to Market	Book value of common shares divided by the market value of equity.
Leverage	Total debt (Compustat data item DLTT plus data item DLC) divided by total assets (Compustat data item AT).
Growth	Growth in assets.
Price	Average stock price in quarter *t*.
Turn	Trading volume scaled by the number of shares outstanding in quarter *t*.
Idiosyncratic Volatility	The variance of the residual obtained by fitting the Carhart (1997) four-factor model to the time series of daily stock return.
#Analysts	Number of analysts following the firm.
InstOwn	Institutional ownership.
Loss	Indicator variable taking the value of one if income before extraordinary items (Compustat item IB) is negative and zero otherwise.
Qtr4	Indicator variable taking the value of one if the earnings announcement is the firm's fiscal year-end announcement and zero otherwise.

Trade Size	Average trade size in quarter *t*, calculated as the consolidated volume divided by the number of trades. The consolidated volume and the number of trades are available from TAQ.
Odd Lot Ratio	Volume of trades executed in odd-lot sizes divided by the total volume traded.
Trade-to-Order Ratio	Total volume traded divided by the total volume of orders placed.
Cancel-to-Trade Ratio	Number of orders cancelled divided by the number of trades executed
Average Trade Size	Total volume traded divided by the number of trades
Price Delay	One minus the ratio of a stock's weekly return variation explained by the concurrent weekly market return divided by a stock's weekly return variation explained by the concurrent and four past weekly market returns
Variance Ratio	The ratio of the variance of 2-day returns divided by two times the variance of 1-day returns
#Accounting Reports	Number of requests for a firm's periodic accounting reports, including 10-Ks, and 10-Qs, scaled by trading volume.
#10K Reports	Number of requests for 10-K filings, scaled by trading volume.
#10Q Reports	Number of requests for 10-Q filings, scaled by trading volume.
#Other Reports	Number of requests for all other EDGAR filings, scaled by trading volume.
PIN	Probability of informed trading.

Figure 1. Sample construction timeline

Panel A: Sample for event study



Panel B: Sample for FERC analysis

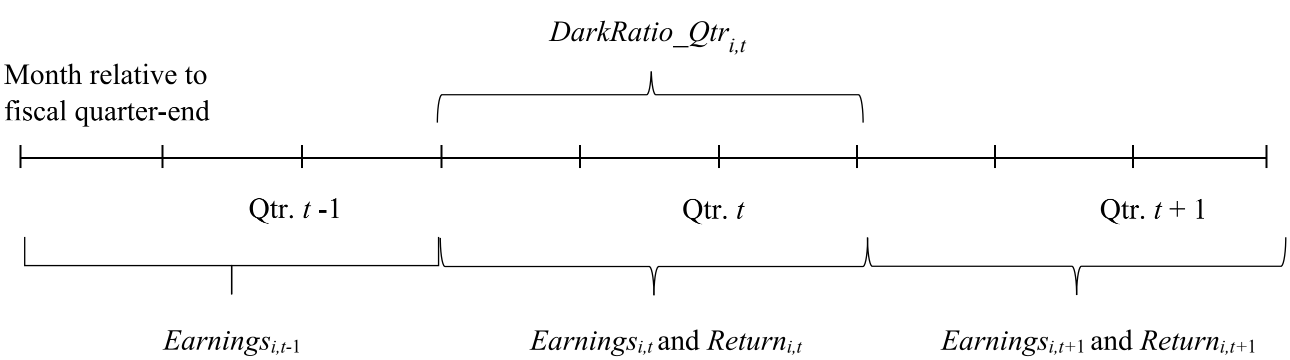


Figure 2. Differences in the ratio of the trading volume executed on dark pools for treatment and control stocks. This figure plots the ratio of the trading volume of common shares executed on dark pools (*DarkRatio*) by week over weeks t-20 to t+20 relative to the implementation of the SEC's "Tick Size Pilot".

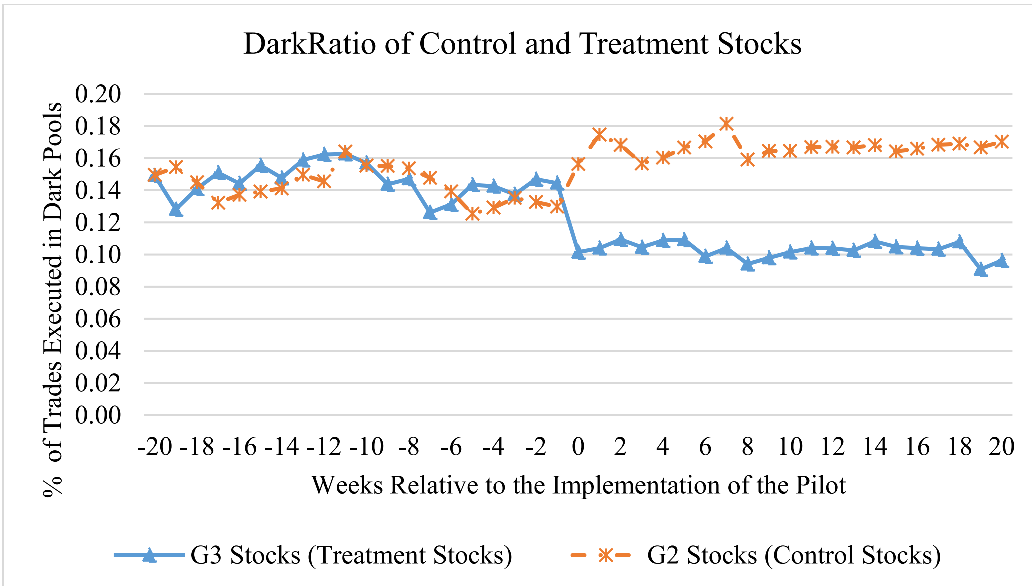


Table 1. Summary statistics. This table presents univariate statistics for key variables in the sample. Variable definitions are provided in Appendix 2.

	N	Mean	Std.	10%	25%	50%	75%	90%
				Dark Trading Variables				
$DarkRatio_{i,t}$	40,192	0.14	0.06	0.05	0.11	0.15	0.18	0.21
$DarkRatio\_Qtr_{i,t}$	40,192	0.14	0.06	0.06	0.11	0.15	0.18	0.21
				Other Variables				
$CAR_{i,t}^{-21,-2}$	40,192	0.00	0.10	-0.11	-0.05	0.00	0.05	0.11
$CAR_{i,t}^{-1,1}$	40,192	0.00	0.08	-0.10	-0.04	0.00	0.04	0.09
$Return_{i,t}$	40,192	0.02	0.21	-0.23	-0.09	0.02	0.12	0.24
$Earnings_{i,t}$	40,192	0.00	0.07	-0.03	-0.01	0.00	0.01	0.02
$Unexpected\ Earnings_{i,t}$	31,611	0.00	0.03	-0.01	0.00	0.00	0.00	0.01
$Size_{i,t}$ ($ billions)	40,192	6.96	28.95	0.05	0.17	0.79	3.30	12.29
$Book\ to\ Market_{i,t}$	40,192	0.58	0.51	0.12	0.25	0.47	0.78	1.12
$Levervage_{i,t}$	40,192	0.18	0.19	0.00	0.01	0.13	0.30	0.45
$Growth_{i,t}$	40,192	0.02	0.13	-0.08	-0.02	0.01	0.03	0.09
$Idiosyncratic\ Volatility_{i,t}$	40,192	0.02	0.02	0.01	0.01	0.02	0.03	0.04
$\#Analysts_{i,t}$	40,192	7.19	7.42	0.00	2.00	5.00	10.00	18.00
$Institutional\ Ownership_{i,t}$	40,192	0.62	0.33	0.07	0.34	0.71	0.89	0.98
$Loss_{i,t}$	40,192	0.33	0.47	0.00	0.00	0.00	1.00	1.00
$Price_{i,t}$	40,192	34.12	38.91	2.54	8.30	21.45	45.60	79.35
$Trade\ Size_{i,t}$	40,192	194.18	714.11	100.12	115.71	141.64	194.95	318.56
$Turn_{i,t}$	40,192	0.48	0.88	0.07	0.16	0.32	0.56	0.94
$Spread_{i,t}$	40,192	0.01	0.01	0.00	0.00	0.00	0.01	0.02
$Qtr4_{i,t}$	40,192	0.24	0.43	0.00	0.00	0.00	0.00	1.00

Table 2. Effect of dark trading on the process of price formation prior to earnings announcements. This table provides the estimation results of regressing pre-announcement abnormal returns ($CAR_{i,t}^{-21,-2}$) and price reactions at the announcements ($CAR_{i,t}^{-1,1}$) on dark trading ($DarkRatio_{i,t}$) from Models (1) and (2). $CAR_{i,t}^{-21,-2}$ is the cumulative abnormal returns over trading days [-20, -2] prior to earnings announcements and $CAR_{i,t}^{-1,1}$ is the cumulative abnormal returns over trading days [-1, 1] around earnings announcements. $DarkRatio_{i,t}$ is the ratio of the trading volume of firm *i* executed on dark pools, divided by the consolidated volume during the pre-announcement period of quarter *t*. The variable $Unexpected\ Earnings_{i,t}$ is unexpected earnings based on analyst forecasts scaled by price as of the end of the quarter *t*. For brevity, the intercept, the interactions between the control variables and $Unexpected\ Earnings_{i,t}$, firm fixed effects, and year-quarter fixed-effects are not reported. T-statistics based on standard errors clustered by firm and earnings announcement dates are shown in parentheses. See Appendix 2 for variable descriptions. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

	$CAR_{i,t}^{-21,-2}$		$CAR_{i,t}^{-1,1}$	
	(1)	(2)	(3)	(4)
$Unexpected\ Earnings_{i,t} \times DarkRatio_{i,t}$	1.834**	1.849**	-0.827**	-0.835**
	(2.31)	(2.31)	(-2.36)	(-2.38)
$Unexpected\ Earnings_{i,t}$	-0.274	-0.284	0.160*	0.160*
	(-1.30)	(-1.35)	(1.68)	(1.68)
$DarkRatio_{i,t}$	-0.000	0.010	-0.002	0.000
	(-0.02)	(0.57)	(-0.24)	(0.05)
$log(Size)_{i,t}$	-0.020***	-0.025***	-0.006***	-0.008***
	(-3.83)	(-4.78)	(-2.76)	(-3.21)
$Book\ to\ Market_{i,t}$	0.021***	0.018***	0.007***	0.007***
	(3.60)	(3.03)	(2.63)	(2.65)
$Leverage_{i,t}$	-0.021*	-0.034***	0.001	0.000
	(-1.85)	(-2.91)	(0.25)	(0.02)
$log(Price)_{i,t}$	-0.006	-0.002	-0.005**	-0.005**
	(-1.08)	(-0.46)	(-2.19)	(-2.04)
$Idiosyncratic\ Volatility_{i,t}$	0.175	0.141	0.130***	0.132***
	(1.48)	(1.17)	(3.03)	(3.04)
$log(\#Analysts)_{i,t}$	-0.008**	-0.006*	-0.000	0.001
	(-2.45)	(-1.90)	(-0.06)	(0.30)
$Institutional\ Ownership_{i,t}$	0.001	-0.008	-0.001	-0.001
	(0.21)	(-1.09)	(-0.27)	(-0.24)
$Spread_{i,t}$	0.889***	0.900***	-0.238*	-0.138
	(2.71)	(2.69)	(-1.71)	(-0.97)
$Qtr4_{i,t}$	0.002	0.021**	0.001	0.008
	(1.20)	(2.53)	(0.88)	(1.58)
Year-quarter FEs	No	Yes	No	Yes
Firm FEs	Yes	Yes	Yes	Yes
Unexpected Earnings × *Controls*	Yes	Yes	Yes	Yes
Observations	31,611	31,611	31,611	31,611
Adjusted R^2	0.046	0.056	0.038	0.040

Table 3. Effect of dark trading on FERCs. This table provides the estimation results of regressing current quarterly stock returns (*$Return_{i,t}$*) on future earnings (*$Earnings_{i,t+1}$*), the interaction between future earnings and dark trading (*$Earnings_{i,t+1} \times DarkRatio\_Qtr_{i,t}$*), control variables (*$Controls_{i,t}$*), and the interaction terms. The variable *$Return_{i,t}$* denotes quarterly buy-and-hold return of firm *i* for quarter *t*. The variable *$Earnings_{i,t}$* is quarterly seasonally adjusted net income before extraordinary items, scaled by the market value of equity at the beginning of quarter *t*. The variable *$DarkRatio\_Qtr_{i,t}$* denotes the ratio of the trading volume executed on dark pools to the consolidated volume during quarter *t*. In column (2), *$DarkRatio_{i,t}$* is continuous. For brevity, the intercept, the interaction terms *$Earnings_{i,t-1} \times Controls_{i,t}$*, *$Earnings_{i,t} \times Controls_{i,t}$*, and *$Earnings_{i,t+1} \times Controls_{i,t}$*, firm fixed effects, and year-quarter fixed effects are not reported. T-statistics based on standard errors clustered by firm and year-quarter are shown in parentheses. See Appendix 2 for variable descriptions. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	$Ret_{i,t}$			
	(1)	(2)	(3)	(4)
$Earnings_{i,t+1} \times DarkRatio\_Qtr_{i,t}$	1.509***	1.338***	0.943**	0.977**
	(5.10)	(4.63)	(2.35)	(2.47)
$Earnings_{i,t} \times DarkRatio\_Qtr_{i,t}$	0.345	0.104	0.952*	0.875*
	(1.01)	(0.30)	(1.90)	(1.67)
$Earnings_{i,t-1} \times DarkRatio\_Qtr_{i,t}$	-0.838*	-0.951**	0.202	0.114
	(-1.75)	(-2.01)	(0.31)	(0.17)
$Earnings_{i,t+1}$	-0.033	-0.046	-0.232*	-0.091
	(-0.79)	(-1.11)	(-1.78)	(-0.74)
$Earnings_{i,t}$	0.070	0.122**	0.320**	0.451***
	(1.42)	(2.50)	(2.26)	(3.21)
$Earnings_{i,t-1}$	0.111*	0.106*	0.636***	0.524***
	(1.77)	(1.74)	(3.81)	(3.18)
$Return_{i,t+1}$	-0.029***	-0.107***	-0.026***	-0.103***
	(-4.26)	(-14.64)	(-3.90)	(-14.06)
$DarkRatio\_Qtr_{i,t}$	-0.045**	-0.313***	-0.040*	-0.305***
	(-2.00)	(-9.53)	(-1.77)	(-9.42)
$Earnings_{i,t-1} \times Controls$	No	No	Yes	Yes
$Earnings_{i,t} \times Controls$	No	No	Yes	Yes
$Earnings_{i,t+1} \times Controls$	No	No	Yes	Yes
Year-quarter FEs	No	Yes	No	Yes
Firm FEs	Yes	Yes	Yes	Yes
Observations	40,192	40,192	40,192	40,192
Adjusted R^2	0.117	0.146	0.125	0.154

Table 4. Difference-in-differences analysis. Panel A reports variable averages for the treatment and control groups prior to the implementation of the pilot, the differences in means of each variable, and the corresponding t-statistics. See Appendix 2 for variable descriptions. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively. Panel B provides the estimation results of the DiD regression models in Equations (4) and (5). Variable definitions are listed in Appendix 2. Standard errors are clustered by firm and year-quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: Differences in variables prior to the implementation of the Trade Size Pilot

	Treatment	Control	Difference	t -statistic
	Dark Trading Variables			
$DarkRatio_{i,t}$	0.15	0.15	0.00	-0.87
$DarkRatio\_Qtr_{i,t}$	0.15	0.15	0.00	-0.16
	Other Variables			
$Return_{i,t}$	0.03	0.05	-0.02	-1.34
$Earnings_{i,t}$	0.00	0.00	0.00	0.18
$Unexpected\ Earnings_{i,t}$	0.00	0.00	0.00	0.96
$Size_{i,t}$ ($ billions)	0.74	0.68	0.06	1.36
$Book\ to\ Market_{i,t}$	0.63	0.67	-0.04	-1.29
$Leverage_{i,t}$	0.14	0.15	-0.01	-0.92
$Growth_{i,t}$	0.03	0.03	0.00	0.65
$Idiosyncratic\ Volatility_{i,t}$	0.02	0.02	0.00	-1.66
$\#Analysts_{i,t}$	3.99	4.03	-0.03	-0.15
$Institutional\ Ownership_{i,t}$	0.59	0.62	-0.03	-1.44
$Loss_{i,t}$	0.25	0.26	-0.01	-0.42
$Price_{i,t}$	26.76	23.03	3.73	2.46
$Trade\ Size_{i,t}$	149.15	147.36	1.79	0.44
$Turn_{i,t}$	0.33	0.33	0.00	-0.11
$Qtr4_{i,t}$	0.09	0.07	0.02	0.96

Table 4 Continued

Panel B: Estimation results of the difference-in-differences analysis.

	$CAR_{i,t}^{-21,-2}$	$CAR_{i,t}^{-1,1}$	$Return_{i,t}$
	(1)	(2)	(3)
$Unexpected\ Earnings_{i,t} \times Post_{i,t} \times Treatment_{i,t}$	-0.163*	2.906**	
	(-1.86)	(2.12)	
$Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$			-1.854***
			(-2.94)
$Unexpected\ Earnings_{i,t}$	-2.790	0.119	
	(-0.97)	(0.05)	
$Post_{i,t}$	0.031**	0.011	-0.008
	(2.23)	(0.97)	(-0.21)
$Post_{i,t} \times Treatment_{i,t}$	-0.027*	-0.001	-0.004
	(-1.92)	(-0.05)	(-0.17)
$Unexpected\ Earnings_{i,t} \times Treatment_{i,t}$	-0.101	-1.107	
	(-0.16)	(-1.47)	
$Unexpected\ Earnings_{i,t} \times Post_{i,t}$	-1.126	-2.576**	
	(-0.80)	(-2.38)	
$Earn_{i,t+1} \times Treatment_{i,t}$			0.342
			(0.95)
$Earn_{i,t+1} \times Post_{i,t}$			1.283**
			(2.34)
Controls	Yes	Yes	Yes
$Unexpected\ Earnings_{i,t} \times Controls$	Yes	Yes	N/A
$Earnings_{i,t-1} \times Controls$	N/A	N/A	Yes
$Earnings_{i,t} \times Controls$	N/A	N/A	Yes
$Earnings_{i,t+1} \times Controls$	N/A	N/A	Yes
Year-quarter FEs	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes
# Observations	628	805	1,459
Adjusted R^2	0.068	0.071	0.076

Table 5. Difference-in-differences analysis controlling high frequency trading. Panel A provides the estimation results of DiD regression models (4)-(5) controlling high frequency trading. Variable definitions are listed in Appendix 2. Standard errors are clustered by industry and earnings announcement dates. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Panel B provides the estimation results of DiD regression model (6) controlling high frequency trading. For brevity, the intercept, the interaction terms $Earnings_{i,t-1} \times Controls_{i,t}$, $Earnings_{i,t} \times Controls_{i,t}$, and $Earnings_{i,t+1} \times Controls_{i,t}$, industry fixed effects, and year-quarter fixed effects are not reported. T-statistics based on standard errors clustered by industry and year-quarter are shown in parentheses. See Appendix 2 for variable descriptions. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

Panel A. Estimation results of the difference-in-differences analysis of the effect of dark trading on the preemption of earnings news, controlling high frequency trading.

Dependent Variable =	$CAR_{i,t}^{-21,-2}$				$CAR_{i,t}^{-1,1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Unexpected\ Earnings_{i,t} \times Post_{i,t} \times Treat_{i,t}$	-0.463*	-0.491*	-0.686*	-0.049*	2.855**	2.793**	2.547*	2.904**
	(-1.82)	(-1.82)	(-1.70)	(-1.98)	(2.10)	(1.98)	(1.76)	(2.12)
$Unexpected\ Earnings_{i,t}$	-2.476	-3.876	-0.713	-2.794	0.297	-0.452	1.750	-0.426
	(-0.78)	(-1.12)	(-0.23)	(-0.76)	(0.14)	(-0.19)	(0.71)	(-0.14)
$Post_{i,t}$	0.035**	0.034**	0.032**	0.032**	0.011	0.012	0.011	0.011
	(2.52)	(2.43)	(2.26)	(2.26)	(0.95)	(1.01)	(0.94)	(0.95)
$Post_{i,t} \times Treat_{i,t}$	-0.028**	-0.027*	-0.027*	-0.027*	-0.001	-0.000	-0.000	-0.001
	(-2.00)	(-1.87)	(-1.90)	(-1.94)	(-0.08)	(-0.01)	(-0.04)	(-0.05)
$Unexpected\ Earnings_{i,t} \times Treat_{i,t}$	-0.620	-0.603	0.055	-0.098	-1.103	-1.078	-1.113	-1.093
	(-0.81)	(-0.75)	(0.08)	(-0.15)	(-1.47)	(-1.44)	(-1.51)	(-1.45)
$Unexpected\ Earnings_{i,t} \times Post_{i,t}$	-1.409	-1.485	-1.345	-1.120	-2.566**	-2.555**	-2.500**	-2.594**
	(-0.86)	(-0.85)	(-1.00)	(-0.79)	(-2.36)	(-2.38)	(-2.32)	(-2.40)
$Odd\ Lot\ Ratio_{i,t}$	0.039				-0.060			
	(0.52)				(-1.07)			
$Trade\text{-}to\text{-}Order\ Ratio_{i,t}$		-0.117				-0.149		
		(-0.44)				(-0.66)		
$Cancel\text{-}to\text{-}Trade\ Ratio_{i,t}$			0.000				0.000	
			(0.50)				(0.41)	
$Average\ Trade\ Size_{i,t}$				-0.060				0.019
				(-0.50)				(0.19)

Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unexpected Earnings$_{i,t}$ × *Controls*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Earnings$_{i,t-1}$ × *Controls*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Earnings$_{i,t}$ × *Controls*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Earnings$_{i,t+1}$ × *Controls*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	620	620	620	620	805	805	805	805
Adjusted R^2	0.073	0.067	0.071	0.065	0.070	0.069	0.071	0.069

Table 5 Continued

Panel B. Estimation results of the difference-in-differences analysis of effect of dark trading on FERCs, controlling high frequency trading.

	$Return_{i,t}$			
	(1)	(2)	(3)	(4)
$Earnings_{i,t+1}$ × $Post_{i,t}$ × $Treatment_{i,t}$	-1.625**	-1.655**	-1.998***	-1.666**
	(-2.32)	(-2.49)	(-3.22)	(-2.44)
$Post_{i,t}$	-0.005	-0.013	0.003	-0.006
	(-0.13)	(-0.34)	(0.07)	(-0.17)
$Post_{i,t}$ × $Treatment_{i,t}$	-0.006	-0.004	-0.006	-0.004
	(-0.28)	(-0.17)	(-0.25)	(-0.17)
$Earn_{i,t+1}$ × $Treatment_{i,t}$	0.246	0.085	0.217	0.240
	(0.94)	(0.30)	(0.75)	(0.78)
$Earn_{i,t+1}$ × $Post_{i,t}$	0.256	-0.163	0.046	0.142
	(0.57)	(-0.39)	(0.10)	(0.33)
Odd Lot $Ratio_{i,t}$	-0.158***			
	(-3.17)			
Trade-to-Order $Ratio_{i,t}$		0.691**		
		(2.38)		
Cancel-to-Trade $Ratio_{i,t}$			0.000	
			(0.94)	
Average Trade $Size_{i,t}$				0.582***
				(4.02)
Controls	Yes	Yes	Yes	Yes
Unexpected $Earnings_{i,t}$ × *Controls*	N/A	N/A	N/A	N/A
$Earnings_{i,t-1}$ × *Controls*	Yes	Yes	Yes	Yes
$Earnings_{i,t}$ × *Controls*	Yes	Yes	Yes	Yes
$Earnings_{i,t+1}$ × *Controls*	Yes	Yes	Yes	Yes
Year-quarter FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	1,459	1,459	1,459	1,459
Adjusted R^2	0.086	0.089	0.086	0.087

Table 6. Difference-in-differences analysis of price efficiency around the implementation of the Tick-Size Pilot. This table provides the estimation results of the following DiD regression model, $Price\ Delay_{i,t}$ $[Variance\ Ratio_{i,t}] = \alpha + \beta_1\, Post_{i,t} \times Treatment_{i,t} + \beta_2\, Post_{i,t} + \beta_3\, Treatment_{i,t} + \gamma' X_{i,t} + \theta_j + \theta_t + \varepsilon_{j,t}$. The variable $Treatment_{i,t}$ equals 1 for treatment stocks (G3 stocks of the Pilot) and 0 for control firms (G2 stocks of the Pilot). The indicator variable $Post_{i,t}$ equals 1 for dates after the pilot is implemented. Variable definitions are listed in Appendix 2. Standard errors are clustered by industry and year-quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	$Price\ Delay_{i,t}$	$Variance\ Ratio_{i,t}$
	(1)	(2)
$Post_{i,t} \times Treatment_{i,t}$	0.066	-0.040
	(1.40)	(-1.37)
$Post_{i,t}$	0.031	0.025
	(0.52)	(0.62)
$Treatment_{i,t}$	0.003	0.041***
	(0.10)	(2.98)
$log(Size)_{i,t}$	-0.201***	0.029***
	(-10.44)	(3.00)
$Book\ to\ Market_{i,t}$	-0.077**	0.004
	(-2.31)	(0.27)
$Leverage_{i,t}$	0.040	0.027
	(0.52)	(0.72)
$Idiosyncratic\ Volatility_{i,t}$	3.376***	0.822
	(3.59)	(1.28)
$log(\#Analysts)_{i,t}$	-0.053**	0.020
	(-2.15)	(1.49)
$Institutional\ Ownership_{i,t}$	-0.080	-0.043
	(-1.17)	(-1.44)
$Log(Turnover)_{i,t}$	-0.014	0.034***
	(-0.71)	(3.48)
Year-quarter FEs	Yes	Yes
Industry FEs	Yes	Yes
Observations	1,445	1,445
Adjusted R^2	0.351	0.153

Table 7. Difference-in-differences analysis of EDGAR Search Volume around the implementation of the Tick-Size Pilot. This table provides the estimation results of the following DiD regression model, $EDGAR\ Search\ Volume_{i,t} = \alpha + \beta_1\, Post_{i,t} \times Treatment_{i,t} + \beta_2\, Post_{i,t} + \beta_3\, Treatment_{i,t}\ + \gamma' X_{i,t} + \theta_j + \theta_t + \varepsilon_{j,t,}$ where $Price\ Delay_{i,t}$ is Hou and Moskowitz (2005) Price Delay measure, and $Variance\ Ratio_{i,t}$ is the ratio of the variance of 2-day returns divided by two times the variance of 1-day returns. The variable $Treatment_{i,t}$ equals 1 for treatment stocks (G3 stocks of the Pilot) and 0 for control firms (G2 stocks of the Pilot). The indicator variable $Post_{i,t}$ equals 1 for dates after the pilot is implemented. Variable definitions are listed in Appendix 2. Standard errors are clustered by industry and year-quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	$\#Accounting\ Reports_{i,t}$	$\#10K\ Reports_{i,t}$	$\#10Q\ Reports_{i,t}$	$\#Other\ Reports_{i,t}$
	(1)	(2)	(3)	(4)
$Post_{i,t} \times Treatment_{i,t}$	-0.002**	-0.001**	-0.001**	-0.055
	(-2.26)	(-2.23)	(-2.14)	(-1.37)
$Post_{i,t}$	0.004**	0.002**	0.002**	0.197*
	(2.20)	(2.11)	(2.16)	(1.81)
$Treatment_{i,t}$	0.002**	0.001**	0.001**	0.065
	(2.18)	(2.25)	(2.02)	(1.52)
$log(Size)_{i,t}$	0.002*	0.001*	0.001	0.048
	(1.68)	(1.74)	(1.61)	(1.44)
$Book\ to\ Market_{i,t}$	0.001**	0.001**	0.001*	0.024
	(2.21)	(2.33)	(1.88)	(1.44)
$Leverage_{i,t}$	0.001	0.001	0.001	0.103*
	(0.98)	(1.19)	(0.75)	(1.80)
$Idiosyncratic\ Volatility_{i,t}$	0.222	0.105	0.117	3.363**
	(1.47)	(1.45)	(1.49)	(2.01)
$log(\#Analysts)_{i,t}$	0.000	0.000	0.000	0.015
	(0.83)	(0.91)	(0.71)	(0.64)
$Institutional\ Ownership_{i,t}$	-0.001	-0.001	-0.000	-0.154
	(-0.58)	(-0.77)	(-0.36)	(-1.41)
$Log(Turnover)_{i,t}$	-0.005***	-0.002***	-0.002***	-0.158***
	(-2.94)	(-2.89)	(-2.96)	(-3.03)
Year-quarter FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Observations	1,232	1,232	1,232	1,232
Adjusted R^2	0.422	0.394	0.437	0.384

Table 8. Difference-in-differences analysis of probability of informed trading around the implementation of the Tick-Size Pilot. This table provides the estimation results of the following DiD regression model, $PIN_{i,t} = \alpha+\beta_1 Post_{i,t} \times Treatment_{i,t} + \beta_2 Post_{i,t} + \beta_3 Treatment_{i,t} + \gamma' X_{i,t}+\theta_j+\theta_t+\varepsilon_{j,t.}$ where $PIN_{i,t}$ is the probability of informed trading, calculating following Easley, Kiefer and O'Hara's (1996). The variable $Treatment_{i,t}$ equals 1 for treatment stocks (G3 stocks of the Pilot) and 0 for control firms (G2 stocks of the Pilot). The indicator variable $Post_{i,t}$ equals 1 for dates after the pilot is implemented. Variable definitions are listed in Appendix 2. Standard errors are clustered by industry and year-quarter. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	$PIN_{i,t}$
	(1)
$Post_{i,t} \times Treatment_{i,t}$	-0.034***
	(-2.91)
$Post_{i,t}$	0.018
	(1.03)
$log(Size)_{i,t}$	-0.026***
	(-4.68)
$Book\ to\ Market_{i,t}$	0.005
	(0.45)
$Leverage_{i,t}$	-0.009
	(-0.44)
$Idiosyncratic\ Volatility_{i,t}$	-0.609
	(-1.23)
$log(\#Analysts)_{i,t}$	-0.017*
	(-1.80)
$Institutional\ Ownership_{i,t}$	0.004
	(0.19)
$Log(Turnover)_{i,t}$	-0.007
	(-1.08)
Year-quarter FEs	Yes
Industry FEs	Yes
Observations	1,017
Adjusted R^2	0.243

Table 9. Estimation results of the difference-in-differences analysis of effect of dark trading on the relation between current return and components of future earnings. This table provides the estimation results of regressing current quarterly stock returns (*$Return_{i,t}$*) on the interaction terms (*$Sys\_Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$*, *$Idio\_Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$*), where systematic component of future earnings (*$Sys\_Earnings_{i,t+1}$*) is computed as the calculated as the fitted value from the quarterly regression; and idiosyncratic component of future earnings (*$Idio\_Earnings_{i,t+1}$*) is computed is the residuals of the model. T-statistics based on standard errors clustered by industry and year-quarter are shown in parentheses. See Appendix 2 for variable descriptions. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	$Return_{i,t}$	
	(1)	(2)
$Idio\_Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$	-2.486***	-2.821***
	(-3.32)	(-3.63)
$Sys\_Earnings_{i,t+1} \times Post_{i,t} \times Treatment_{i,t}$	-2.225**	-1.51
	(-2.43)	(-1.03)
$Post_{i,t}$	-0.003	0.002
	(-0.08)	-0.05
$Treatment_{i,t}$	-0.017	-0.014
	(-1.33)	(-1.02)
$Post_{i,t} \times Treatment_{i,t}$	-0.004	-0.003
	(-0.18)	(-0.11)
	(-0.78)	-1.02
Controls	Yes	Yes
$Sys\_Earnings_{i,t-1}$, $Idio\_Earnings_{i,t-1}$	Yes	Yes
$Sys\_Earnings_{i,t}$, $Idio\_Earnings_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t+1}$, $Idio\_Earnings_{i,t+1}$	Yes	Yes
$Sys\_Earnings_{i,t-1} \times Post_{i,t}$, $Idio\_Earnings_{i,t-1} \times Post_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t-1} \times Treatment_{i,t}$, $Idio\_Earnings_{i,t-1} \times Treatment_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t-1} \times Post_{i,t} \times Treatment_{i,t}$, $Idio\_Earnings_{i,t-1} \times Post_{i,t} \times Treatment_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t} \times Post_{i,t}$, $Idio\_Earnings_{i,t} \times Post_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t} \times Treatment_{i,t}$, $Idio\_Earnings_{i,t} \times Treatment_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t} \times Post_{i,t} \times Treatment_{i,t}$, $Idio\_Earnings_{i,t} \times Post_{i,t} \times Treatment_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t+1} \times Post_{i,t}$, $Idio\_Earnings_{i,t+1} \times Post_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t+1} \times Treatment_{i,t}$, $Idio\_Earnings_{i,t+1} \times Treatment_{i,t}$	Yes	Yes
$Sys\_Earnings_{i,t-1} \times Controls$, $Idio\_Earnings_{i,t-1} \times Controls$	No	Yes
$Sys\_Earnings_{i,t} \times Controls$, $Idio\_Earnings_{i,t} \times Controls$	No	Yes
$Sys\_Earnings_{i,t+1} \times Controls$, $Idio\_Earnings_{i,t+1} \times Controls$	No	Yes
Year-quarter FEs	Yes	Yes
Industry FEs	Yes	Yes
# Observations	1,448	1,448
Adjusted R^2	0.066	0.105