Dealing in the Dark: Do Insiders Trade in Dark Pools?

Working Paper

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Abstract

We investigate the impact of legal insider trading on different types of dark and lit trading venues. We find that the market share of dark pools increases during weeks when insider transactions take place. This effect is more pronounced for internalization pools which provide the highest level of opacity for traders, and for stocks with large market capitalization. We further find strong evidence of strategic insider trading in dark pools ahead of stock buyback announcements, with trading patterns dependent upon the competition among insiders and their rank within the organisation.

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I. **Introduction**

Alternative Trading Systems (ATSs), in particular dark pools, have become important players in the securities trading landscape. In the U.S, dark venues execute approximately 14% of total trading volume (Buti et al., 2017). As their name suggests, dark pools are off-exchange trading venues that display little to no pre-trade information. As such, the contribution of these venues to price discovery is minuscule, since they cross orders at prices derived from lit venues, such as the midpoint of the National Best Bid and Offer (NBBO), or the volume-weighted average price (VWAP) (Zhu, 2014). As opposed to lit venues, dark pools can provide different advantages, such as the reduction of price impact costs, concealment of trading interest, and price improvement over lit trading venues[1]. These advantages, however, come at the cost of execution uncertainty, due to the absence of market makers in dark pools. The absence of market makers leads to unbalanced order books in dark pools, which lowers execution probability (Ye, 2011 and Zhu, 2014). As such, market participants face a trade-off between the potential price improvement of dark pools, and the execution certainty of lit venues.

The research on the impact of dark pools on price discovery has been a subject of discussion among academic researchers. The trading venue choice of informed traders, and the subsequent dissemination of private information lie at the heart of this discussion. For example, Ye (2011) argues that an informed trader is more likely to trade in dark pools, while Zhu (2014) argues that dark order flow is likely to be uninformed. Ye (2016) reconciles this conflicting evidence and argues that information precision has an influence on the role that dark pools play for price discovery. In particular, she argues that "when information precision is high (information risk is low), the majority of informed traders trade in the exchange hence adding a dark pool enhances price discovery, whereas when information precision is low (information risk is high), the majority of the informed traders trade in the dark pool hence adding a dark pool impairs price discovery" (Ye, 2016, p.1). Foley and Putniņš (2016) further argue that the market design of the dark pools matters. They differentiate between dark pools that restrict execution at the midpoint, and those

[1] Although unrelated to our paper, another advantage of ATSs is sub-penny trading. The SEC's minimum pricing increment rule (Rule 612 of Regulation NMS), which sets a minimum pricing increment of $0.01 per share for stocks that are priced above $1.00 per share, and a minimum pricing increment of $0.0001 per share for stocks that are priced below $1.00 does not apply to dark pools. Therefore, dark orders could potentially have quicker executions, without having to improve existing best prices.

that do not. Their findings suggest that non-midpoint dark pools are beneficial to informational efficiency. Ye and Zhu (2020) study the effect of informed trading in dark pools on price discovery depending on the value of private information. They find that price discovery decreases in the value of private information and dark trading volume.

In this paper, we further shed light into different cross-sectional and trader-specific factors which can play a role in the venue choice of informed traders and the impact on different trading venues, particularly dark trading. We specifically focus on the following key research questions. First, how does legal insider trading affect the market shares of different trading venues? Does legal insider trading increase market shares of public exchanges, or is there evidence that legal insider trading increases the market shares of trading venues with reduced levels of pre-trade transparency and price impact of trades, i.e. dark pools? Second, is there evidence of strategic insider trading in dark pools ahead of stock buyback announcements? Here, we attempt to determine whether corporate insiders strategically utilise dark pools to exploit their timely and privileged access to information relevant for firm valuation and performance. We employ stock buyback announcements as examples of corporate events generating such information. To address these questions, we use a sample of 7,852 insider transactions across 423 constituents of the S&P500 index from the years 2014 to 2019. We also disaggregate our sampled firms into size terciles, to explore the role of firm size.

We find that insider transactions are associated with a significant increase in the market share of dark pools. This increase is more pronounced for large firms, as compared to medium and small firms. In addition, disaggregating dark pools based on their opacity reveals that this increase is more pronounced for internalization pools, which are expected to provide the highest level of opacity for traders. Internalization pools match incoming orders strictly against that of the operator. Because of this, informed order flow never interacts with public order flow, thereby reducing the risk of information leakage. For this reason, we argue that order flow internalization is an attractive operational feature for an informed trader seeking to conceal trading interest. Overall, our findings on the impact of insider trading on different trading venues give support to the theoretical predictions of Ye (2011), that a monopolist informed trader is more likely to trade in dark pools, instead of lit venues.

Second, we investigate whether insiders trade strategically in dark pools ahead of stock buyback announcements. We choose announcements of stock buybacks since the market reaction to such news is relatively unambiguous; the market tends to react positively to such announcements (Dann 1981, Vermaelen 1981, and Lakonishok and Vermaelen, 1990). Because of the subsequent run-up in stock pries, Lee et al. (1992) find that insiders tend to purchase more shares of their own firms ahead of such announcements. We expect these purchasing transactions to take place in dark pools, instead of lit venues. Our results support this prediction; we find strong evidence of strategic insider trading in dark pools ahead of stock buyback announcements. This strategic trading behaviour depends on the competition among insiders and the rank of an insider. Strictly for firms with the lowest degree of insider competition, we find that the market share of dark pools increases significantly during weeks of insider purchases, ahead of stock buyback announcements. This is consistent with the theoretical predictions of Baruch et al. (2017), and the empirical findings of Reed et al. (2019) that informed traders become more patient and strategic when there is less competition among them. Our results also show that purchasing transactions of top managers ahead of buyback announcements are associated with a statistically significant and an economically large increase in the market share of dark pools. We find that this effect holds strictly for insiders in the top management group. This finding is consistent with the theoretical predictions of Ye (2011) and the empirical findings of Ye and Zhu (2020) that an informed trader has a greater incentive to conceal their trading interest when the quality of their private information is high.

To the best of our knowledge, our study is the first to investigate the impact of legal insider trading on different types of dark pools. This question is important, particularly in light of the conflicting theoretical predictions and empirical evidence with regards to the venue choice of informed traders (Ye, 2011, Zhu, 2014, Reed et al., 2019, and Ye and Zhu, 2020). Our paper contributes to the dark trading literature by attempting to reconcile this conflicting evidence. However, unlike previous papers that rely on theoretical assumptions (Ye, 2011, and Zhu, 2014) or those that investigate the venue choice of short sellers (Reed et al., 2019) and activist hedge funds (Ye and Zhu, 2020), we rely on insider transactions. To the extent that private information relates to firm valuation and future corporate events, insiders are expected to be the most informed. Research indeed documents that this is the case (Seyhun, 1986, Seyhun, 1990, John and Lang, 1991, Lee et al.,1992, Karpoff and Lee, 1991, and Seyhun and Bradley, 1997). Hence, our contribution is two-fold. First, we reveal new evidence that insider transactions are associated with a significant increase in the market share of dark pools, giving support to the predictions of Ye (2011). We also disaggregate dark pools based on their opacity and show that the venue choice of an informed trader depends not only on pre-trade transparency, but also on the opacity of a dark pool. This disaggregation reveals new evidence on the role of order flow internalization in altering the trading venue choice of an insider. Second, our study complements the empirical evidence in the insider trading literature that insiders tend to purchase more shares of their own firms ahead of buyback announcements (Lee et al., 1992). We show that these purchases are likely to take place in dark pools. We further provide new evidence that this strategic trading behaviour depends on insider competition and on an insider's rank.

Our paper is related to the dark trading literature in general, and informed trading in dark pools, in particular. The existing literature documents that the trading venue choice of informed traders depends on the degree of competition among informed traders (Ye, 2011, Zhu, 2014, Ye, 2016, Ye and Zhu, 2020, and Reed et al., 2019) and the quality of their private information (Ye, 2016 and Ye and Zhu, 2020). The theoretical framework of Zhu (2014) predicts that informed traders are more likely to trade in lit venues, whereas Ye (2011) predicts that an informed trader is more likely to use dark pools[2]. Ye and Zhu (2020) examine the venue choice of activist hedge funds and find that weeks with Schedule 13D trades are associated with a significant increase in the market share of dark pools. The authors argue that activist hedge funds possess unique private information. Because of this, they face a lower risk of non-execution, which drives them to dark pools, instead of lit venues. Reed et al. (2019) explore the venue choice of short sellers in the U.S equity market. They find that short selling volume, as a percentage of total volume, is significantly larger in lit venues, as compared to dark pools. This finding gives support to the theoretical predictions of

[2]These conflicting predictions are due to the different assumptions employed in these models. The theoretical framework of Ye (2011) is based on Kyle (1985), where an informed trader is assumed to be a monopolist; in the sense that they possess unique private information. In this setting, an informed trader has complete discretion in revealing their private information. Zhu (2014) and Ye (2016) are based on Glosten and Milgrom (1985), where multiple informed traders exist. Because of this, private information disseminates quickly, since informed traders trade on the same side of the market. This in turn subjects informed traders to a higher execution risk in dark pools, causing them to demand the execution immediacy of lit venues.

Zhu (2014), suggesting that informed traders rely on lit venues to capitalize on their information. A key finding in Reed et al. (2019) that is related to our analysis is that short sellers are more likely to use dark venues when there is less competition among them. Ye (2016) argues that informed traders with a higher quality of private information are more likely to trade in lit venues, whereas Ye and Zhu (2020) predict that such traders are more likely to use dark pools. These conflicting predictions are perhaps due to the assumed number of informed traders in each of these models. In Ye (2016), multiple informed traders exist, whereas in Ye and Zhu (2020) there exists a single monopolist informed trader. This difference is expected to have an important implication on the level of competition among informed traders.

Our paper also relates to the insider trading literature. The insider trading literature documents that insiders purchase (sell) more shares of their own firms ahead of positive (negative) unscheduled corporate events (Seyhun, 1990, John and Lang, 1991, Lee et al.,1992, Karpoff and Lee, 1991, and Seyhun and Bradley, 1997). These findings suggest that insiders possess timely and privileged access to private information, relating to future price-relevant events. In addition, insiders are likely to face less competition from informed outsiders (Cespa, 2008). Because of this, we expect the private information of insiders to be unique; allowing insiders to exploit such information strategically.

We combine the findings of the above two streams of literature, to formulate our hypotheses. We presume that corporate insiders, driven by their unique access to private information, act as a monopolist informed trader, as in Kyle (1985); disseminating their private information with caution, in order to avoid price impact and information leakage. This unique access to private information is expected to extend the lifespan of their private information; as insiders are likely to face less competition from informed outsiders (Cespa, 2008). We argue that these factors provide an additional incentive for insiders to conceal their trading interest, by trading in dark pools, instead of lit venues (Ye, 2011 and Ye and Zhu, 2020). We further motivate our hypotheses in the next section below.

II. Hypotheses

i. Effects of Insider Trading on Dark Trading

i.1 Venue Choice of Informed Traders

Evidence from the dark trading literature documents that informed traders are more likely to use dark pools when they have a unique monopolistic access to private information (Ye, 2011 and Ye and Zhu, 2020), face less competition from other informed traders (Reed et al., 2019), and trade based on highly accurate private signals (Ye and Zhu, 2020). We postulate that insiders satisfy these conditions, when trading shares of their own firms. Indeed, the strategic timing of insider trades (Seyhun, 1990, John and Lang, 1991, Lee et al., 1992, Karpoff and Lee, 1991, and Seyhun and Bradley, 1997) suggests that insiders possess unique and accurate private information relating to their firm's valuation and future corporate events. For this reason, we expect insiders to trade in dark pools, instead of lit venues, to minimize information leakage and capitalize on their private information.

i.2 Classification of Dark Venues

While dark pools share the common goal of suppressing pre-trade transparency, they can differ substantially in terms of operational design, to attract different clients (Mittal, 2008). The existing literature classifies dark pools based on execution mechanisms (Butler, 2007, Zhu, 2014 and Menkveld et al., 2017), order matching frequency (Carrie, 2007), and transparency of business model (Mittal, 2008). Based on these operational features, some dark pools can be more opaque than others (Mittal, 2008). The opacity of a trading venue has an important implication on our analysis; in the sense that it plays an important role in minimizing information leakage. Opaque trading venues tend to disclose little information about their business models, and tend to match incoming order flow strictly against that of the operator. We expect dark pools with a higher degree of opacity to better conceal trading interest, making them ideal trading venues for an insider with private information. Accordingly, we classify our sampled dark venues based on Mittal (2008), who identifies four distinct types of dark pools, based on ownership structure and business model transparency: exchange-based pools (light pools), public crossing networks, internalization pools, and ping destinations. Exchange-based pools operate like electronic communications networks (ECNs), displaying their limit order books publicly. Because of this, we treat these venues as lit venues (Brogaard and Pan, 2019). Public crossing networks do not display trading interest and match orders at specified price derived from the public market. While these venues hide trading interest, they also route orders to lit venues if an execution cannot take place in the network. For this reason, we expect crossing networks to subject an informed trader to a higher risk of information leakage, in the event that the order is routed to lit venues. In contrast, both internalization pools and ping destinations match incoming orders strictly against the operator's proprietary order flow. Because of this, we expect the risk of information leakage to be minimized in such venues; where only the operator knows the depth of liquidity that resides within the venue. If liquidity is not found within the pool, the order is not routed to a public exchange. Instead, it either resides within the pool to await execution, or it is cancelled, depending on the order type. By avoiding interaction with public order flow, this matching mechanism serves to conceal trading interest and suppress price impact. An important difference between internalization pools and ping destinations lies in order flow selectivity. Unlike internalization pools, ping destinations match orders selectively; they employ quantitative models that decide whether to accept or reject incoming orders. We provide a more detailed discussion of our venue classification, along with other venue classifications from the literature, in the Appendix.

In light of the above discussion, we argue that insiders, driven by their unique access to private information, can afford to sacrifice execution immediacy, in exchange for minimizing information leakage and price impact. Like Ye (2011), we expect the cost of information leakage to be higher than the cost of non-execution for a monopolist informed trader. Accordingly, our first hypothesis is as follows:

Hypothesis (1): *Insider transactions are associated with an increase in the market share of dark pools, where this increase is more pronounced for dark pools that internalize order flow.*

Because insider purchasing and selling transactions are expected to stem from different motives, they send different signals to investors. Insider purchases cause a run-up in stock prices, whereas insider sales cause a decline (Finnerty, 1976). Moreover, the results of Karpoff and Lee (1991) and Seyhun and Bradley (1997) suggest that insider sales precede negative corporate events. Because of this, we expect insiders to place a greater emphasis on concealing trading interest when selling shares of their own firms, in an effort to minimize the effect of the negative signals associated with such transactions. As such, we extend the hypothesis above, as follows:

Hypothesis (1A): *Insider selling transactions are associated with a larger increase in the market share of dark pools, as compared to insider purchases.*

We also expect firm size to play an important role in the venue choice of insiders, in light of the findings of Buti et al. (2011). They find that the number of active dark pools and dark trading volume are both substantially larger for large firms, as compared to medium and small firms. These findings have an important implication on our analysis; as the liquidity provided by uninformed traders is the primary channel through which a monopolist insider can exploit their private information (Kyle, 1985). Indeed, Ye and Zhu (2020) find that informed trading increases the market share of dark pools to a greater extent when the relative liquidity is larger in dark pools. As such, liquidity is an important determinant of dark volume, especially since execution probabilities are expected to be lower in dark pools, as compared to lit venues. For example, Ye (2010) finds that the execution probabilities in crossing networks are only 4.11% and 2.17%, compared to probabilities of 31.47% and 26.48% in lit venues, for NYSE and NASDAQ stocks, respectively. Therefore, based on the findings of Buti et al. (2011) and Ye and Zhu (2020), we hypothesize that insider transactions of large firms are associated with a larger increase in the market share of dark pools, as compared to those of medium and small firms. We extend Hypothesis (1) above, as follows:

Hypothesis (1B): *Insider transactions of large firms are associated with a larger increase in the market share of dark pools, as compared to those of medium and small firms.*

ii. Insider Trading Ahead of Buyback Announcements

Our second hypothesis relates to insider trading activity during periods of unscheduled corporate events. During such periods, we expect insiders to possess private information that is not yet incorporated in stock prices. Indeed, the findings of Seyhun (1990), John and Lang (1991), Lee et al. (1992), Karpoff and Lee (1991), Seyhun and Bradley (1997) show that insiders exploit their private information strategically ahead of unscheduled corporate events; buying more shares of their own firms ahead of positive news, and selling ahead of negative news. Importantly, Ye (2011) and Ye and Zhu (2020) predict that a monopolist informed trader has a greater incentive to conceal trading interest when the quality of their private information is high. Ye and Zhu (2020) confirm this prediction by documenting a larger increase in the market share of dark pools when the quality of private information is higher. Because of this, we expect insiders to trade strategically in dark pools ahead of unscheduled corporate events, to exploit their private information.

We use announcements of stock buybacks, as our primary unscheduled corporate event. We choose announcements of stock buybacks since there is evidence that suggests that the market reacts positively to such announcements (Dann 1981, Vermaelen 1981, and Lakonishok and Vermaelen, 1990). Announcements of stock buybacks often lead to an increase in stock prices; as they signal to outsiders that the firm is undervalued (Vermaelen, 1981, and Dann, 1981). Because of this subsequent run-up in stock prices, Lee et al. (1992) find that insiders tend to purchase more shares of their own firms ahead of such announcements. We expect such purchases to take place in dark pools, as opposed to lit venues, to minimize price impact and information leakage.

We investigate whether insiders trade strategically ahead of buyback announcements, by exploring two parallel hypotheses. We discuss these hypotheses below.

ii.1 Competition Among Insiders

We expect the strategic trading behaviour of insiders ahead of buyback announcements to depend on the level of competition among insiders, where competition refers to the extent to which insiders possess the same information. In that sense, insiders face a higher level of competition when they possess similar information, and vice versa. We argue that such competition plays an important role in the venue choice of insiders. For example, Holden and Subrahmanyam (1992), Baruch et al. (2017), and Reed et al. (2019) show that the trading behaviour of informed traders becomes more aggressive when multiple informed traders possess the same information. We expect insiders to possess similar private information ahead of unscheduled corporate events, leading to correlated private signals. In turn, these correlated private signals are expected to induce competition among insiders, as in Back et al. (2000). As such, we expect insider purchasing transactions in dark pools ahead of buyback announcements to be more pronounced in firms with a lower degree of competition among insiders, as compared to those with a higher level of competition. The lower degree of competition among insiders is expected to preserve an insider's informational edge, enabling them to behave like a monopolist informed trader, as in Kyle (1985). To proxy for the competition among insiders, we use the number of different insiders who initiated an open-market transaction in the same quarter of the buyback announcement. Our second hypothesis is as follows:

Hypothesis (2A): *Ahead of buyback announcements, firms with a lower degree of competition among insiders experience a larger increase in the market share of dark pools during weeks of insider purchasing, as compared to firms with a higher degree of competition among insiders.*

ii.2 The Rank of an Insider

We investigate a parallel hypothesis to the one stated above; focusing on the relationship between an insider's rank and their choice of trading venue. Previous studies provide evidence that top managers are likely to be better informed than lower ranking insiders (Seyhun and Bradley, 1997 and Agrawal and Cooper, 2015). Because of this, we expect an insider's quality of private information to be positively related to their rank. In turn, this higher quality of private information provides an insider with a greater incentive to hide their trading interest, as in Ye (2011) and Ye and Zhu (2020). As such, we expect top ranking insiders to trade more strategically in dark pools ahead of buyback announcements, as compared to lower ranking insiders. Based on Agrawal and Cooper (2015), we classify insiders into three groups, according to their rank: top management, financial officers, and directors. Top management includes the Chairman, Chief Executive Officer (CEO), Chief Operating Officer (COO), and President. Financial officers consist of the Chief Financial Officer (CFO), Controller, and Treasurer. Directors are members of the board of directors, excluding the Chairman. Under this classification, we expect top managers to possess a higher quality of private information, as compared to financial officers and directors. Accordingly, Hypothesis (2B) is as follows:

Hypothesis (2B): *Ahead of buyback announcements, purchasing transactions of top managers are associated with a larger increase in the market share of dark pools, as compared to those of financial officers and directors.*

III. Data and Institutional Details

i. U.S. Regulations of Legal Insider Trading

The U.S Securities and Exchange Commission (SEC) requires a firm's officers, directors, and shareholders that own more than 10% of a class of the firm's shares to file a statement of ownership with the SEC (Form 3). In addition, open-market transactions initiated by officers, directors, and shareholders that own more than 10% of a class of the firm's shares must be reported to the SEC within two business days (Form 4)[3]. These open-market transactions include share purchases, sales, and the exercise of stock options, all of which are stored on the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system.

ii. Dark Trading Regulation

Under the SEC's Regulation ATS (Reg ATS), dark pools and electronic communications networks (ECNs) are referred to as alternative trading systems (ATSs). Under Reg ATS, ATSs are registered with the SEC as broker-dealers, and are exempt from registering as national securities exchange (NSEs)[4]. This exemption allows operators of ATSs to exert more control over the access to their trading platforms, allowing them to restrict access to certain customers[5]. Moreover, because ATSs derive their execution prices from lit venues, they must comply with Rule 611 of Regulation NMS. This rule dictates that orders must be executed at or within the NBBO. This means that execution will not take place in dark pools unless the execution price is at or within the NBBO. Lit venues, however, allow the orders of those who improve the best NBBO to be executed immediately.

[3]Section 16 of the Securities Exchange Act of 1934. However, if these open-market transactions do not exceed $10,000 within a period of 6 months, they fall under different reporting requirements. To elaborate, smaller insider share purchases and sales are reported on Form 5, which has to be filed within 45 days after the end of the fiscal year. In this paper, we rely strictly on insider transactions reported on the SEC's Form 4.

[4]Section 242.301 of Reg ATS.

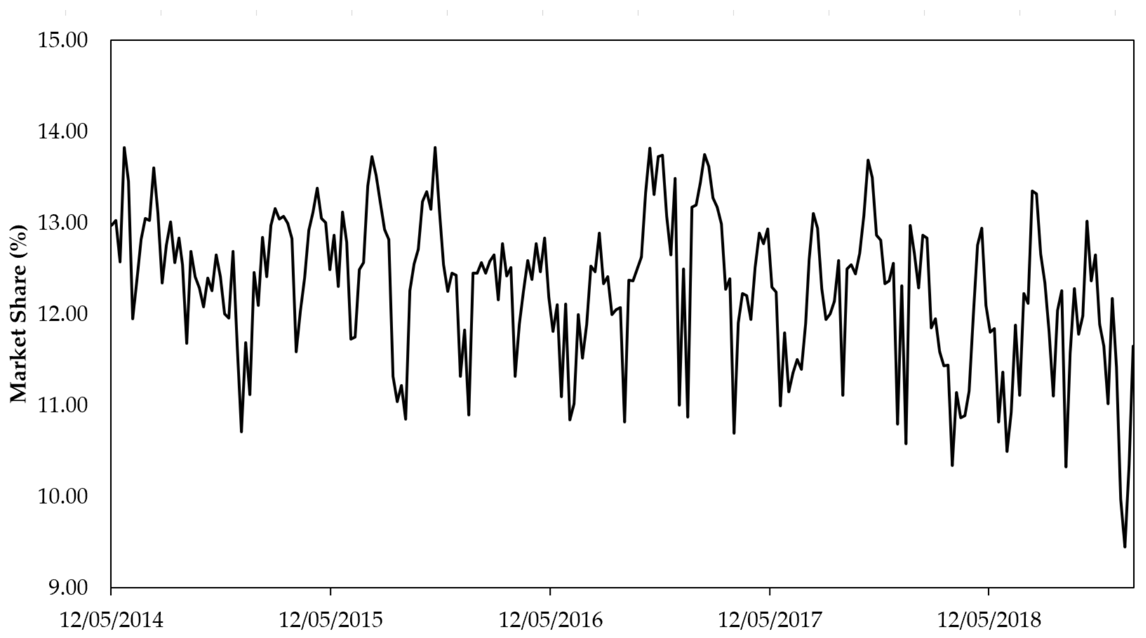
[5]Reg ATS Rule 301(b)(5).

iii. Dark Trading Data

We collect dark volume data from the Financial Industry Regulatory Authority (FINRA), from May 2014[6] to January 2019. The data includes weekly dark volume (in shares) as well as the weekly number of trades, for all National Market System (NMS) stocks. This data is reported separately for each ATS, allowing us to track trading volume across dark pool types. Figure (1) below plots the total market share of dark pools across our sample period, averaged across our sampled firms.

Figure 1: Time series of dark volume market share

This figure plots the market share of dark pools across our sample period, average across our sampled firms. In the figure below, we exclude ECNs from our calculation of dark volume market share; since these venues operate primarily as lit venues.



iv. Insider Trading Data

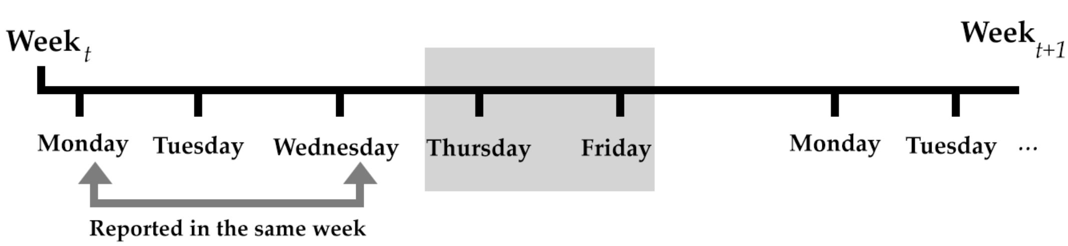
We collect all insider transactions from May 2014 to January 2019 for our sampled firms, using Form 4 filings reported on the SEC's EDGAR system. The data includes the number of shares traded per transaction, the price of the transaction, the rank of an insider, and the type of the

[6]FINRA began publishing dark volume data in May 2014.

transaction (purchasing, selling, and selling after an option exercise). We exclude transactions originating from those with a 10% ownership, and those with an indirect ownership in firms, for the following two reasons. First, we observe that those with 10% ownership trade infrequently with a large trade size, thereby creating outlier observations that distort the averages. Second, we are interested strictly in corporate insiders that are closely related to the day-to-day operations of the firm, thereby having privileged access to private information on firm valuation and future corporate events. This results in a total of 27,904 insider transactions, from May 2014 to January 2019. However, because the SEC dictates that open-market insider transactions must be reported within two business days, a weekly time series of insider transactions includes both the potential private information of insiders as well as the reporting effect of these transactions. The reporting effect is particularly evident in the empirical findings of Finnerty (1976) and Seyhun (1986) that show a significant market reaction to insider trades. To sidestep this issue, we exclude insider transactions that take place on Mondays, Tuesdays and Wednesdays, since these trades are reported in the same trading week. We also exclude the portion of trades that take place on a Thursday and are reported on the following day[7]. This ensures that the reporting effect of insider transactions is not triggered in the same trading week, allowing us to isolate the effect of insider transactions. This filtering procedure results in a final sample of 7,852 insider transactions. Figure (2) below shows the sampling procedure of insider transactions.

Figure 2: Removing the reporting effect of insider transactions

The timeline below shows our sampling procedure for insider transactions. Because the SEC dictates that open-market transactions initiated by insiders must be reported within two business days, we exclude trades that are reported in the same trading week, in order to remove the reporting effect of insider transactions. This task allows us to isolate the effects of insider transactions. The shaded area represents our sample of insider trades. We remove the portion of trades that take place on a Thursday and are reported on the following day.

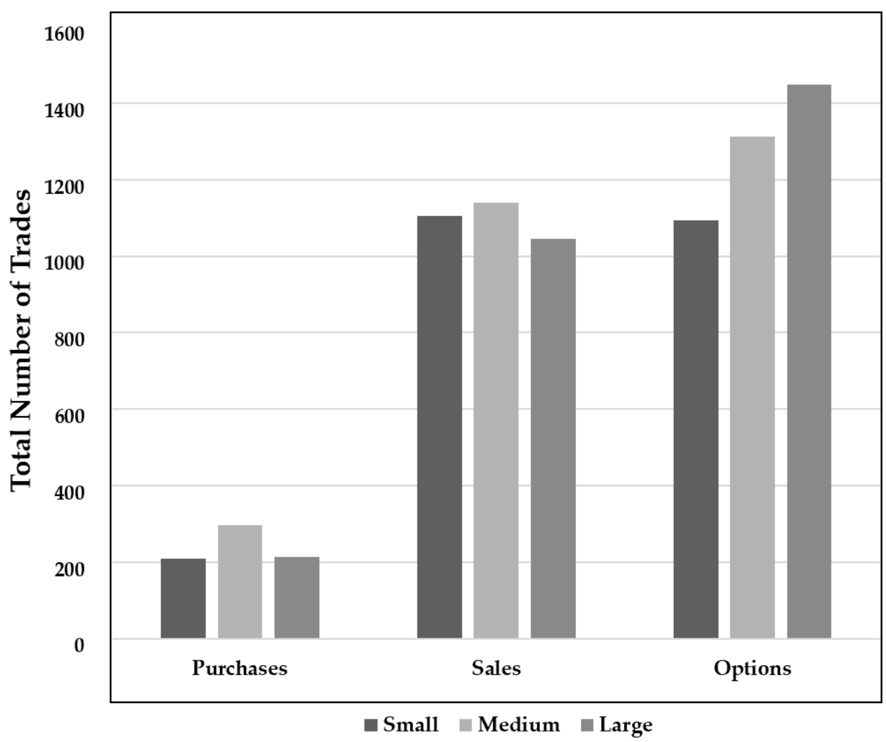


[7]In our dataset, we observe both the trading date as well as the reporting date. Hence, we are able to observe trades on a Thursday that were reported on the following day.

We also differentiate between pure selling transactions, and those that were initiated after an option exercise, because we expect the two transactions to stem from different motives. To elaborate, while the exercise of options can potentially be driven by private information, options can also be exercised based on liquidity needs, as Carpenter and Remmers (2001) show[8]. As such, we expect pure selling transactions to contain more information than those that were initiated after exercising an option. Figure (3) below shows the distribution of insider transactions across firm size terciles. Our data reveals that insider sales following an option exercise are the most dominant transaction type, and are positively related to firm size.

Figure 3: Distribution of insider trades

This figure plots the number of insider transactions across firm size terciles, based on insider transaction types. The vertical axis plots the number of trades. For each transaction type and firm size group, we aggregate the number of insider transactions across our sample period.



[8]However, the results of Carpenter and Remmers (2001) indicate that the returns of small firms are significantly negatively affected by insider option exercises, as compared to medium and large firms. As such, for small firms, options can be exercised to potentially exploit private information.

v. Firm-Level Data

We use the Center for Research in Security Prices (CRSP) to collect lit volume, stock prices, returns, number of shares outstanding, and bid-ask spreads for our sampled firms. Based on FINRA's data, we construct a sample of 423 firms, all of which are constituents of the S&P500 index. The S&P500 index is highly liquid and is representative of the entire market (Jaffe, 1989). We use S&P Capital IQ to collect announcements of scheduled and unscheduled corporate events. Because our data is weekly, it is difficult to isolate the effect of buyback announcements, due to confounding corporate events. To sidestep this issue, we collect all announcements of earnings, stock buybacks, mergers and acquisitions (M&As), seasoned equity offerings (SEOs), dividend initiations, and dividend terminations for our sampled firms, from May 2014 to January 2019. Our initial sample of corporate events includes 7,614 earnings announcements, 775 buyback announcements, 404 M&A announcements[9], 114 SEO announcements, and 7 dividend initiation announcements[10]. Next, we focus on earnings announcements that coincide with a buyback announcement, and those that do not include a buyback announcement in the same firm-quarter of the earnings announcement. This establishes the latter type of announcements to be a counterfactual to the former. We remove earnings announcements that coincide with announcements of acquisitions, SEOs, and dividend initiations in the same firm-quarter[11]. We also remove buyback announcements that coincide with any of the unscheduled corporate events highlighted above in the same firm-quarter, in order to isolate the effect of buyback announcements. This filtering procedure results in a final sample of 4,617 earnings announcements, 228 of which coincide precisely with announcements of stock buybacks.

vi. Descriptive Statistics

Table (1) below provides descriptive statistics for our full sample as well as for our firm size terciles. In Panel A, we report descriptive statistics of the market shares of trading venues, calculated based on the weekly trading volume, in number of shares. Across our sampled firms, approximately 12%

[9]These announcements relate primarily to acquisitions; we find only 2 merger announcements during our sample period. We collect all announcements of acquisitions (cash-based, stock-based, and both), with a disclosed transaction value equal to or greater than $1 million (Moeller et al., 2004).

[10]We find no announcements of dividend terminations for our sampled firms during the sample period.

[11]We do this since there is evidence of insider trading activity ahead of announcements of takeovers (Seyhun, 1990), issuance of common stock (Karpoff and Lee, 1991), and dividend initiations (John and Lang, 1991).

of total volume is executed in dark pools, on average. This figure is lower than the market shares reported in Ye and Zhu (2020) and Balakrishnan and Taori (2017), who report an average dark market share of 15% and 14%, respectively. This difference is perhaps due to the following reasons. First, we remove ECNs from our sample of dark pools, and add their market share to lit venues[12]. Second, our sample period is longer than that of Balakrishnan and Taori (2017). Third, firm sample selection in Ye and Zhu (2020) is based on Schedule 13D filings, whereas we use the SEC's Form 4 filings as our primary filtering criterion. This difference is expected to yield a different sample of firms. Like Balakrishnan and Taori (2017), we observe that the majority of our sampled dark pools fall under the category of internalization pools. Because of this, internalization pools handle the majority of dark trading volume, with an average market share of 10.61% across the sample period. In contrast, the average market share of crossing networks and ping destinations is 1.14%, and 0.14%, respectively.

In Panel B of Table (1), we report the descriptive statistics of the stock characteristics of our sampled firms. The average firm in our sample has a weekly turnover of 4.69%, a market capitalization of $41.48 billion, a stock price of $91.01, weekly absolute returns of 2.52%, and a weekly absolute bid-ask spread of $0.03[13]. In Panel C, we report the descriptive statistics of our sampled insider transactions, in number of shares. In calculating these statistics, we omit weeks with no insider transactions, in order to accurately reflect the trade size of insider transactions per firm-week. The average trade size of insider purchases, sales, and sales following an option exercise is 43.50, 42.84, and 52.81 thousands of shares, respectively. Our data also reveals that insider transactions of large firms are substantially larger in size, as compared to those of medium and small firms.

[12]The average market share of ECNs across our sample period is approximately 1%.

[13]For brevity, we omit the descriptive statistics of firm size terciles that relate to dark volume data and stock characteristics. We report these statistics in the Appendix.

Table 1: Descriptive statistics

This table reports descriptive statistics for our variables. In Panel A, we report the market share statistics of our sampled trading venues. These market share figures are based on weekly trading volume in number of shares. *Lit* and *Dark Share* refer to the weekly market shares of lit venues and dark pools, respectively, where the market share of dark pools excludes trading volume executed on electronic communications networks (ECNs), since these venues operate as lit venues. *CN*, *Int* and *Ping* refer to the weekly market shares of public crossing networks, internalization pools, and ping destinations, respectively. In Panel B, we report stock characteristics for our sampled firms. *Market Cap* is the product of a firm's weekly share price and number of shares outstanding, reported in billions of dollars. *Turnover* is total weekly volume divided by the number of shares of outstanding, reported in percentages. *Price* is the weekly share price. *Volatility* is the average weekly absolute return, reported in percentages. *Spread* is the average weekly absolute bid-ask spread. In Panel C, we report the statistics of our sampled insider transactions. In doing so, we exclude weeks with no insider transactions. *Purchase*, *Sale*, and *Option* refer to trading volume (in number of shares) of insider purchasing, selling, and selling after an option exercise transactions, respectively, reported in thousands of shares.

Panel A: Dark Volume Data (FINRA):

Variable	N	Mean	P25	P50	P75	Std. Dev.
Lit	103,212	87.84%	86.50%	88.06%	89.92%	3.26%
Dark Share	103,212	12.16%	10.08%	11.94%	13.95%	3.26%
CN	103,212	1.14%	0.74%	1.13%	1.71%	1.08%
Int	103,212	10.61%	8.96%	10.49%	12.11%	2.67%
Ping	103,212	0.14%	0.001%	0.02%	0.14%	0.33%

Panel B: Stock Characteristics (CRSP):

Variable	N	Mean	P25	P50	P75	Std. Dev.
Turnover	103,212	4.69%	2.59%	3.76%	5.61%	3.88%
Market Cap	103,212	$41.48	$11.00	$18.52	$38.82	$70.72
Price	103,212	$91.01	43.68	$67.71	$107.10	$93.89
Volatility	103,212	2.52%	0.84%	1.85%	3.39%	2.52%
Spread	103,212	$0.03	$0.01	$0.01	$0.02	$0.16

Panel C: Insider Transactions (EDGAR):

Variable	N	Mean	P25	P50	P75	Std. Dev.
Full Sample:						
Insider Purchases	103,212	43.50	0.78	3.00	12.00	228.13
Insider Sales	103,212	42.84	2.29	6.50	19.00	442.33
Insider Sales (Option Exercise)	103,212	52.81	5.83	17.42	48.84	191.98
Large Firms:						
Insider Purchases	34,404	65.04	1.00	4.34	20.00	258.80
Insider Sales	34,404	76.20	3.00	8.00	20.00	736.02
Insider Sales (Option Exercise)	34,404	64.32	7.28	20.00	58.44	130.06
Medium Firms:						
Insider Purchases	34,404	44.83	0.58	2.70	11.69	281.34
Insider Sales	34,404	25.66	2.01	6.00	17.82	188.32
Insider Sales (Option Exercise)	34,404	51.64	5.00	15.08	41.64	283.35
Small Firms:						
Insider Purchases	34,404	18.35	0.43	2.30	10.00	84.35
Insider Sales	34,404	29.17	2.00	5.85	17.92	192.22
Insider Sales (Option Exercise)	34,404	41.14	5.21	17.10	43.81	80.51

IV. **Methodology**

i. **The Venue Choice of Insiders**

We begin by examining the effect of total insider transactions on the aggregate market share of dark pools. We calculate the market share of dark pools as follows:

$$Dark\ Share_{i,t} = \left(\frac{Dark\ Volume_{i,t}}{Aggregate\ Trading\ Volume_{i,t}} \right) \times 100 \tag{1}$$

Then, we log transform the market share of dark pools, and estimate the following panel regression, to test our first hypothesis:

$$Dark\ Share_{j,i,t} = \alpha + \beta_1 Insider\ Transactions_{i,t} + \Sigma Controls_{i,t} + FE_i + \epsilon_{i,t} \tag{2}$$

In the equation above, $Insider\ Transactions_{i,t}$ is a dummy variable that takes the value of 1 if insider transaction takes place in week t for firm i, and zero otherwise. $Controls_{i,t}$ includes a list of control variables that are documented to affect the market share of dark pools (Buti et al., 2011, Ye and Zhu, 2020 and Balakrishnan and Taori, 2017). Buti et al. (2011) show that dark volume is positively related to firm size, share price, and liquidity, and negatively related to bid-ask spread and volatility. As such, we include the log of market capitalization, the log of stock price, the log of stock turnover, the log of the bid-ask spread, and absolute returns as controls. We also control for heterogeneity across firms by the term FE_i, which is a firm fixed-effects term. To control for cross-sectional dependence and contemporaneous heteroscedasticity, we cluster standard errors by week.

Next, we classify our sampled trading venues into four categories[14]: lit venues, crossing networks, internalization pools, and ping destinations. We designate venues that display their limit order books publicly as lit venues. As such, this category includes public exchanges as well as ECNs.

[14]We classify ATSs based on the information provided by these ATSs on the SEC's Form ATS-N.

Next, we turn to venues that do not display their order books publicly. We classify venues that do not internalize order flow as crossing networks, while those that do are classified as either internalization pools or ping destinations. Out of the venues that internalize order flow, we classify venues that operate based on IOIs and IOC orders as ping destinations. Our dependent variable then becomes the market share of trading venues, calculated as follows:

$$Venue\,Share_{j,i,t} = \left(\frac{Trading\,Volume_{j,i,t}}{Aggregate\,Trading\,Volume_{i,t}}\right) \times 100 \tag{3}$$

$Venue\,Share_{j,i,t}$ is the market share of venue j for firm i in week t. $Trading\,Volume_{j,i,t}$ is the weekly trading volume executed on venue j for firm i in week t. $Aggregate\,Trading\,Volume_{i,t}$ is the total consolidated trading volume for firm i in week t, across all trading venues. We log transform $Venue\,Share_{j,i,t}$ and estimate the following panel regression, to test our hypothesis that internalization is a key operational feature in reducing information leakage and price impact:

$$Venue\,Share_{j,i,t} = \alpha + \beta_1 Purchase_{i,t} + \beta_2 Sale_{i,t} + \beta_3 Option_{i,t} + \Sigma Controls_{i,t} + FE_i + \epsilon_{i,t} \tag{4}$$

In the equation above, $Purchase_{i,t}$, $Sale_{i,t}$, and $Option_{i,t}$ are dummy variables that take the value of 1 if insider purchases, sales, and sales following an option exercise take place in week t for firm i, and zero otherwise, respectively.

ii. Insider Trading Ahead of Buyback Announcements

We differentiate between two types of earnings announcements. The first type relates to earnings announcements that do not coincide with M&As, SEOs, dividend initiations, and dividend terminations in the same firm-quarter of the earnings announcement. We use this type of earnings announcements as our proxy for scheduled events. The second type relates to earnings announcements that coincide precisely with buyback announcements. We use this type of announcements as our proxy for unscheduled events.

ii.1 Competition Among Insiders

To ensure comparability among firms, we remove firms with no insider transactions ahead of buyback announcements. We then count the number of different insiders who initiated an open-market transaction in the same firm-quarter of the buyback announcement, and classify firms into three groups: high, medium, and low number of different insiders. This classification is based on the mean and median figures of the number of different insiders[15]. We calculate the mean and median figures of the number of different insiders across our subsample of firms, and classify firms as follows. Firms with a number of different insiders that is higher than the mean and median fall in the high category, firms with a number of different insiders that is equal to the mean and median fall in the medium category, while firms with a number of different insiders that is lower than the mean and median fall in the low category. The average number of different insiders for the high, medium, and low categories is 6, 3, and 1, respectively.

In investigating this hypothesis, we aggregate the market share of dark pools, excluding ECNs. We estimate the following panel regression for each earnings announcement type and each group of firms separately:

$$\begin{aligned} \mathit{Dark\ Share}_{i,t} = \alpha + \beta_1 \mathit{Earnings}_{i,t} + \beta_2(\mathit{Earnings}_{i,t} \times \mathit{Purchase}_{i,t}) + \beta_3(\mathit{Earnings}_{i,t} \times \mathit{Sale}_{i,t}) \\ + \beta_4(\mathit{Earnings}_{i,t} \times \mathit{Option}_{i,t}) + \Sigma \mathit{Controls}_{i,t} + \mathit{FE}_i + \epsilon_{i,t} \end{aligned} \tag{5}$$

Where $\mathit{Earnings}_{i,t}$ is a dummy variable that takes the value of 1 in the quarter of the announcement, excluding the announcement week, and zero otherwise. We remove the announcement week to exclude the market reaction to the release of such news when they become public. The interaction terms capture the incremental effect on the market share of dark pools that coincides with insider transactions ahead of earnings announcements.

[15] We find that the mean and median are approximately equal. The mean number of different insiders is 3.4, while the median is 3.

ii.2 The Rank of an Insider

Based on Agrawal and Cooper (2015), we classify insiders into three groups, according to their rank: top management, financial officers, and directors. Top management includes the Chairman, Chief Executive Officer (CEO), Chief Operating Officer (COO), and President. Financial officers consist of the Chief Financial Officer (CFO), Controller, and Treasurer. Directors are members of the board of directors, excluding the Chairman. Next, we estimate Equation (5) above for each group of insiders and each announcement type separately.

iii. Summary of Variables

In Table (2) below, we provide a summary of the variables that we employ in our regression models.

Table 2: A summary of variable definitions

This table provides a summary of the variables we employ in our regression models. Type X are exogenous variables, whereas type Y variables are endogenous. All variables are in weekly frequency.

Type	Variable	Definition
Y	$Dark\ Share_{i,t}$	The log of the market share of dark pools. The market share of dark pools does not include ECNs, since they operate as lit venues.
Y	$Lit_{i,t}$	The log of the market share of lit venues. Lit venues are comprised of public exchanges and ECNs.
Y	$CN_{i,t}$	The log of the market share of crossing networks. Crossing networks are defined as dark pools that neither display their limit order books publicly nor internalize order flow.
Y	$Int_{i,t}$	The log of the market share of internalization pools. Internalization pools are defined as dark pools that do not display their limit order books publicly and internalize order flow.
Y	$Ping_{i,t}$	The log of the market share of ping destinations. Ping destinations are defined as dark pools that do not display their limit order books publicly, internalize order flow, and operate based on IOIs and IOC orders.
X	$Insider\ Transcations_{i,t}$	A dummy variable that takes the value of 1 if an insider transaction takes place in week t, and zero otherwise.
X	$Purchase_{i,t}$	A dummy variable that takes the value of 1 if an insider purchasing transaction takes place in week t, and zero otherwise.
X	$Sale_{i,t}$	A dummy variable that takes the value of 1 if an insider selling transaction takes place in week t, and zero otherwise.
X	$Option_{i,t}$	A dummy variable that takes the value of 1 if an insider selling transaction following an option exercise takes place in week t, and zero otherwise.
X	$Earnings_{i,t}$	A dummy variable that takes the value of 1 in the quarter of an earnings announcement (excluding the week of the announcement), and zero otherwise.
Control	$Turnover_{i,t}$	The log of stock turnover. Turnover is calculated by dividing a stock's weekly total trading volume by its' number of shares outstanding.
Control	$Market\ Cap_{i,t}$	The log of market capitalization. Market capitalization is calculated as the product of a firm's number of shares outstanding and its' weekly share price.
Control	$Price_{i,t}$	The log of the stock price of firm i at the end of week t.
Control	$Volatility_{i,t}$	Weekly absolute returns, as a proxy for volatility.
Control	$Spread_{i,t}$	The log of the weekly bid-ask spread.

V. **Results**

i. **Effects of Insider Trading on Dark Trading**

As a first stage, we begin by exploring the effect of weeks with insider transactions on the market share of dark pools. We examine the effect of total insider transactions, regardless of type, on the aggregate market share of dark pools. In Table (3) below, we report the results of Equation (2), to investigate our first hypothesis. In Columns (1), (2), (3), and (4), we report the results of the full sample, large firms, medium firms, and small firms, respectively. Consistent with our prediction that a monopolist informed trader is more likely to rely on dark venues, we find that weeks of insider transactions are associated with a significant increase in the market share of dark pools. Weeks of insider transactions increase in the market share of dark pools by approximately 2%, as compared to weeks with no insider transactions. This effect is statistically significant at the 1% level. This finding is consistent with the theoretical predictions of Ye (2011) and Ye and Zhu (2020) that a monopolist informed trader with a unique access to private information is more likely to trade in dark pools, instead of lit venues.

Our analysis of firm size, as reported in Columns (2), (3), and (4) of Table (3) below, reveals a clear pattern. As hypothesized, we find that the increase in the market share of dark pools during weeks of insider transactions is positively related to firm size. Weeks of insider transactions increase in the market share of dark pools by approximately 3.5%, 1.4%, and 1.3%, for large, medium, and small firms, respectively.

Next, we disaggregate insider transactions based on their type, and classify dark venues based on their transparency, to investigate the specific venue choice of insiders. We report these results in Table (4) below, where Column (1) shows the results of the full sample. During weeks of insider purchases, the market share of internalization pools increases significantly, as compared to weeks without insider purchases. Economically, this represents an increase of approximately 2% in the market share of internalization pools. During weeks of insider pure selling transactions ($Sale_{i,t}$), the market share of internalization pools also increases significantly, by approximately 2%. During weeks of insider selling transactions following an option exercise, we observe the largest impact on the market share of dark pools. The market shares of crossing networks and internalization pools increase significantly, as compared to weeks without such transactions. The economic magnitude is an increase of approximately 5% and 2% in the market shares of crossing networks and internalization pools, respectively. Across all insider transaction types, we document an insignificant effect on the market share of ping destinations. We contend that this is due to the selectivity of ping destinations; as the black box of a ping destination decides whether to accept or reject an incoming order. We argue that such a mechanism is expected to reduce the execution probability of an incoming order, particularly if the black box can infer the level of informed trading.

Consistent with our prediction that internalization is an important factor in minimizing information leakage, all insider transaction types are associated with a significant increase in the market share of internalization pools. Particularly for insider purchasing and pure selling transactions, we document that the increase in the market share of dark pools takes place exclusively in internalization pools. However, for insider selling transactions following an option exercise, crossing networks experience the largest increase in market share. We attribute this to the signals associated with this type of insider transactions. While the exercise of options can potentially be driven by private information, insiders also exercise their options based on liquidity needs, as Carpenter and Remmers (2001) show. Because of this, insiders perhaps place less emphasis on concealing their trading interest when exercising options, by trading in both crossing networks[16] and internalization pools.

In terms of economic magnitude, we do not find support to our hypothesis that insider sales are associated with a larger increase in the market share of dark pools, as compared to insider purchases. However, our results do suggest that insiders place a greater emphasis on concealing trading interest when selling shares of their own firms, as weeks with insider pure selling transactions are associated with a significant increase in the market share of internalization pools only.

In Columns (2), (3), and (4) of Table (4) below, we report the results of firm size terciles, to

[16] We expect crossing networks to be a "lighter" shade of dark, since there is a possibility of interacting with public order flow.

explore the relationship between firm size and the venue choice of insiders. For large firms, weeks of insider purchases are associated with an increase of approximately 11% and 8% in the market shares of crossing networks and internalization pools, respectively. We document that this effect holds exclusively for large firms, as the effect is insignificant for medium and small firms. Weeks of pure selling transactions increase in the market share of internalization pools by approximately 3%, 1%, and 2%, for large, medium, and small firms, respectively, where the effect is statistically insignificant for medium firms. Weeks of insider selling transactions following an option exercise increase in the market share of internalization pools by approximately 2% for medium and small firms, and by 3% for large firms. However, for large firms in particular, the largest increase in market share during weeks of insider sales following an option exercise takes place in crossing networks. Economically, this translates to an increase of approximately 8% in the market share of crossing networks.

Taken together, our analysis of firm size reveals two key observations. First, strictly for large firms, we document higher dark trading activity in both crossing networks and internalization pools during weeks of insider transactions. In comparison, this trading activity is restricted to internalization pools only, for medium and small firms. We relate this finding to that of Buti et al. (2011), who find that the number of active dark pools is substantially larger for large firms, as compared to medium and small firms. Because of this, we expect execution probabilities in dark pools to be higher for large firms, as compared to medium and small firms. Second, our findings on the venue choice of insiders are in line with the insider trading literature. For large firms, the increase in the market share of crossing networks during weeks of insider purchases and sales following an option exercise suggests that insiders place less emphasis on concealing trading interest. This is due to the positive signals associated with insider purchases (Finnerty, 1976 and Seyhun, 1986), and the fact that an option exercise by an insider can be based on liquidity needs, rather than private information (Carpenter and Remmers, 2001). In contrast, our findings suggest that insiders place the greatest emphasis on concealing trading interest when selling shares of their own firms, by trading strictly in internalization pools. This is due to the negative market reaction to insider selling transactions (Finnerty, 1976), and the possibility of imminent negative corporate events, as the results of Karpoff and Lee (1991) and Seyhun and Bradley (1997) suggest.

Table 3: The effect of weeks with insider transactions on the market shares of dark pools

This table reports regression estimates, using a stock-week panel, where the dependent variable is the market share of dark pools. We estimate the following regression equation for the full sample and firm size terciles separately:

$$Dark\ Share_{i,t} = \alpha + \beta_1 Insider\ Transactions_{i,t} + \Sigma Controls_{i,t} + FE_i + \epsilon_{i,t}$$

In the above equation, $Dark\ Share_{i,t}$ is the log of the market share of dark pools. $Insider\ Transactions_{i,t}$ is a dummy variable that takes the value of 1 if an insider transaction takes place in week t for firm i, and zero otherwise. $Controls_{i,t}$ is a list of control variables. These variables are the log of stock turnover, the log of stock price, the log of market capitalization, absolute returns as a proxy for volatility, and the log of weekly bid-ask spread. FE_i is a firm fixed-effects term, included to absorb heterogeneity across our sampled firms. In each column, we report estimated coefficients and their t-statistics (in parentheses) calculated using standard errors clustered by week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) **Full Sample**	(2) **Large Firms**	(3) **Medium Firms**	(4) **Small Firms**
$Insider\ Transactions_{i,t}$	0.021***	0.034***	0.014***	0.013**
	(6.192)	(6.390)	(2.666)	(2.062)
$Turnover_{i,t}$	0.080***	-0.027	0.170***	0.097***
	(3.787)	(-0.897)	(9.184)	(4.661)
$Price_{i,t}$	0.078***	0.134***	0.095***	0.013
	(4.361)	(4.407)	(6.166)	(0.739)
$Market\ Cap_{i,t}$	-0.084***	-0.164***	-0.064***	-0.015
	(-6.676)	(-6.916)	(-4.430)	(-1.276)
$Volatility_{i,t}$	-0.032	0.024	-0.049	-0.068
	(-1.090)	(0.484)	(-1.030)	(-1.416)
$Spread_{i,t}$	-0.036***	-0.036***	-0.024***	-0.020**
	(-2.583)	(-2.646)	(-2.605)	(-2.298)
Adjusted R^2	31.22%	33.89%	30.88%	24.89%
Firm Fixed-Effects	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	103,212	34,392	34,400	34,387

Table 4: The effect of weeks with insider transactions on the market shares of trading venues

This table reports regression estimates, using a stock-week panel, where the dependent variable is the market share of trading venues. We estimate the following regression for each trading venue and firm size tercile separately:

$$Venue\ Share_{j,i,t} = \alpha + \beta_1 Purchase_{i,t} + \beta_2 Sale_{i,t} + \beta_3 Option_{i,t} + \Sigma Controls_{i,t} + FE_i + \epsilon_{i,t}$$

In the above equation, $Purchase_{i,t}$ is a dummy variable that takes the value of 1 if an insider purchasing transaction takes place in week t for firm i, and zero otherwise. $Sale_{i,t}$ is a dummy variable that takes the value of 1 if an insider selling transaction takes place in week t for firm i, and zero otherwise. $Option_{i,t}$ is a dummy variable that takes the value of 1 if an insider selling transaction following an option exercise takes place in week t for firm i, and zero otherwise. $Controls_{i,t}$ is a list of control variables. These variables are the log of stock turnover, the log of stock price, the log of market capitalization, absolute returns as a proxy for volatility, and the log of weekly bid-ask spread. FE_i is a firm fixed-effects term, included to absorb heterogeneity across our sampled firms. In each column, we report estimated coefficients and their t-statistics (in parentheses) calculated using standard errors clustered by week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Full Sample				**(2) Large Firms**			
	$Lit_{i,t}$	$CN_{i,t}$	$Int_{i,t}$	$Ping_{i,t}$	$Lit_{i,t}$	$CN_{i,t}$	$Int_{i,t}$	$Ping_{i,t}$
$Purchase_{i,t}$	-0.002	-0.026	0.023***	0.139	-0.009***	0.098***	0.075***	0.064
	(-1.239)	(-0.963)	(2.618)	(1.529)	(-3.957)	(2.448)	(4.816)	(0.658)
$Sale_{i,t}$	-0.002***	0.007	0.018***	-0.004	-0.003***	-0.007	0.027***	0.022
	(-2.927)	(0.614)	(3.488)	(-0.087)	(-2.645)	(-0.344)	(3.347)	(0.333)
$Option_{i,t}$	-0.003***	0.046***	0.024***	0.011	-0.004***	0.070***	0.029***	0.030
	(-4.905)	(3.314)	(5.745)	(0.254)	(-4.352)	(4.270)	(4.823)	(0.489)
$Turnover_{i,t}$	-0.019***	0.377***	0.044**	0.742***	-0.008***	0.243***	-0.061**	0.264
	(-7.259)	(8.122)	(2.207)	(5.578)	(-2.500)	(4.479)	(-2.121)	(1.545)
$Market\ Cap_{i,t}$	0.010***	0.058***	-0.084***	-0.534***	0.026***	0.094**	-0.179***	-1.524***
	(5.988)	(2.619)	(-7.215)	(-7.097)	(7.116)	(2.154)	(-7.910)	(-11.323)
$Price_{i,t}$	-0.008***	-0.210***	0.078***	2.022***	-0.020***	-0.358***	0.152***	3.213***
	(-3.755)	(-6.199)	(4.484)	(16.919)	(-4.993)	(-5.871)	(5.241)	(16.798)
$Volatility_{i,t}$	0.006	-0.131*	-0.014	0.059	-0.001	0.147	0.015	-0.012
	(1.594)	(-1.662)	(-0.514)	(0.218)	(-0.106)	(1.252)	(0.318)	(-0.029)
$Spread_{i,t}$	0.003***	-0.094***	-0.018**	-0.064	0.004***	-0.132***	-0.023**	-0.079
	(3.363)	(-4.480)	(-2.111)	(-0.506)	(3.177)	(-3.750)	(-2.289)	(-0.588)
Adjusted R^2	33.96%	14.13%	32.48%	8.55%	34.29%	18.70%	34.14%	10.96%
Firm Fixed-Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	103,212	103,179	103,179	78,459	34,404	34,392	34,392	30,953

	(3) Medium Firms				**(4) Small Firms**			
	$Lit_{i,t}$	$CN_{i,t}$	$Int_{i,t}$	$Ping_{i,t}$	$Lit_{i,t}$	$CN_{i,t}$	$Int_{i,t}$	$Ping_{i,t}$
$Purchase_{i,t}$	0.003	-0.089*	-0.008	0.120	0.002	-0.091**	0.000	0.236
	(1.227)	(-1.799)	(-0.606)	(0.751)	(0.927)	(-2.123)	(-0.016)	(1.346)
$Sale_{i,t}$	-0.002*	0.027	0.009	-0.006	-0.001	-0.002	0.017**	-0.045
	(-1.710)	(1.422)	(1.162)	(-0.077)	(-1.231)	(-0.085)	(2.211)	(-0.488)
$Option_{i,t}$	-0.003***	0.027	0.023***	0.015	-0.003**	0.039	0.020***	-0.018
	(-3.099)	(1.344)	(3.496)	(0.202)	(-2.190)	(1.438)	(2.440)	(-0.182)
$Turnover_{i,t}$	-0.027***	0.507***	0.127***	1.256***	-0.021***	0.399***	0.061***	0.802***
	(-10.611)	(10.891)	(7.530)	(7.796)	(-8.076)	(7.956)	(3.124)	(5.361)
$Market\ Cap_{i,t}$	0.009***	-0.068*	-0.069***	0.654***	0.000	0.097***	-0.029***	-0.301***
	(4.009)	(-1.757)	(-5.215)	(4.182)	(0.117)	(3.649)	(-2.590)	(-2.702)
$Price_{i,t}$	-0.012***	0.092**	0.080***	1.017***	0.001	-0.273***	0.030*	1.349***
	(-5.177)	(2.220)	(5.746)	(5.626)	(0.387)	(-7.231)	(1.801)	(9.014)
$Volatility_{i,t}$	0.007	-0.259*	-0.011	-0.475	0.011*	-0.220	-0.041	0.751
	(1.027)	(-1.943)	(-0.253)	(-0.884)	(1.614)	(-1.510)	(-0.898)	(1.241)
$Spread_{i,t}$	0.003***	-0.078***	-0.014*	-0.034	0.002***	-0.056***	-0.012*	-0.084
	(3.354)	(-5.679)	(-1.903)	(-0.273)	(3.354)	(-4.237)	(-1.752)	(-0.719)
Adjusted R^2	30.59%	14.45%	30.89%	7.12%	31.50%	11.07%	25.90%	6.25%
Firm Fixed-Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	34,404	34,400	34,400	26,137	34,404	34,387	34,387	21,369

ii. **Dark Trading Effects of Insider Trading Ahead of Buyback Announcements**

In this part of the paper, we report the effect of insider transactions on the market share of dark pools ahead of stock buyback announcements. We disaggregate firms based on the degree of insider competition and insider ranks. Next, we examine the role of insider competition and rank simultaneously[17].

ii.1 Competition Among Insiders

In Table (5) below, we report results of Equation (5), showing the effect of weeks with insider transactions on the market share of dark pools ahead of earnings announcements, based on the level of competition among insiders. In Columns (1) and (2), we report the results of earnings with and without buybacks, respectively. Our results suggest that competition among insiders plays an important role in their venue choice. We find that weeks of insider purchasing ahead of stock buyback announcements increases the market share of dark pools significantly. In contrast, we don't observe this effect ahead of earnings announcements that do not include a buyback announcement. Importantly, this effect holds exclusively for firms with a low number of different insiders trading in the 12 weeks preceding the event. This increase is both statistically and economically significant; the market share of dark pools increases by approximately 10%, in comparison to events with no insider purchasing.

The evidence above is consistent with the findings of Reed et al. (2019); suggesting that informed traders are more likely to use dark pools when there is less competition among them. Facing less competition from informed outsiders (Cespa, 2008) and having a low number of different insiders trading ahead of an unscheduled event, our results suggest that insiders of firms in the low category behave like a monopolist insider, as in Kyle (1985). Like Ye and Zhu (2020), our results suggest that a monopolist informed trader is more likely to exploit their private information strategically, by trading in dark pools, instead of lit venues.

[17] In unreported results, we examine the effect of insider transactions, regardless of competition and rank, on the market share of dark pools ahead of stock buyback announcements. We find that the market share of dark pools increases during weeks of insider purchases, albeit insignificantly. These results are available upon request.

Table 5: The effect of weeks with insider transactions on the market shares of trading venues ahead of earnings announcements

This table reports regression estimates, using a stock-week panel, where the dependent variable is the market share of dark pools. We differentiate between earnings announcements that do not include a buyback, acquisition, SEO, or dividend initiation announcements in the same firm-quarter of an earnings announcement, and those that coincide with a buyback announcement in the same firm-quarter of an earnings announcement. To ensure comparability, we remove firms with no insider transactions ahead of earnings announcement with a buyback. Next, we divide our sampled firms into three groups, based on the different number of insiders who initiated an open-market transaction in the 12 weeks preceding an announcement, to proxy for the level of competition among insiders. We estimate the following regression for each announcement type and each insider group separately:

$$Dark\ Share_{i,t} = \alpha + \beta_1 Earnings_{i,t} + \beta_2(Earnings_{i,t} \times Purchase_{i,t}) + \beta_3(Earnings_{i,t} \times Sale_{i,t}) + \beta_4(Earnings_{i,t} \times Option_{i,t}) + \Sigma Controls_{i,t} + FE_i + \epsilon_{i,t}$$

In the above equation, $Dark\ Share_{i,t}$ is the log of the market share of dark pools, excluding ECNs. $Earnings_{i,t}$ is a dummy variable that takes the value of 1 in the 12 weeks ahead of an earnings announcement, and zero otherwise. $Purchase_{i,t}$ is a dummy variable that takes the value of 1 if an insider purchasing transaction takes place in week t for firm i, and zero otherwise. $Sale_{i,t}$ is a dummy variable that takes the value of 1 if an insider selling transaction takes place in week t for firm i, and zero otherwise. $Option_{i,t}$ is a dummy variable that takes the value of 1 if an insider selling transaction following an option exercise takes place in week t for firm i, and zero otherwise. $Controls_{i,t}$ is a list of control variables. These variables are the log of stock turnover, the log of stock price, the log of market capitalization, absolute returns as a proxy for volatility, and the log of weekly bid-ask spread. FE_i is a firm fixed-effects term, included to absorb heterogeneity across our sampled firms. In each column, we report estimated coefficients and their t-statistics (in parentheses) calculated using standard errors clustered by week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) *Earnings With Buybacks*			**(2)** *Earnings Without Buybacks*		
No. of Insiders:	**High** *(6 Insiders)*	**Medium** *(3 Insiders)*	**Low** *(1 Insider)*	**High** *(6 Insiders)*	**Medium** *(3 Insiders)*	**Low** *(1 Insider)*
$Earnings_{i,t}$	0.016	0.001	0.009	-0.036***	-0.003	-0.050***
	(1.632)	(0.115)	(0.914)	(-5.484)	(-0.409)	(-6.089)
$(Earnings_{i,t} \times Purchase_{i,t})$	0.064	0.012	0.098**	-0.097	-0.056	0.006
	(0.497)	(0.640)	(2.359)	(-1.239)	(-0.822)	(0.157)
$(Earnings_{i,t} \times Sale_{i,t})$	0.018	0.061	0.008	0.007	-0.021	0.039
	(0.627)	(0.795)	(0.153)	(0.366)	(-0.628)	(1.455)
$(Earnings_{i,t} \times Option_{i,t})$	0.028	-0.028	0.173**	0.022	0.019	-0.012
	(0.640)	(-0.614)	(2.150)	(1.250)	(0.898)	(-0.405)
$Turnover_{i,t}$	0.018	-0.051	-0.026	0.008	-0.052	-0.073**
	(0.681)	(-1.288)	(-0.957)	(0.293)	(-1.320)	(-2.358)
$Price_{i,t}$	0.010	0.182***	0.061**	0.019	0.180***	0.290***
	(0.337)	(3.620)	(2.055)	(0.647)	(3.567)	(9.995)
$Market\ Cap_{i,t}$	-0.109***	-0.049	-0.061**	-0.113***	-0.047	-0.205***
	(-4.584)	(-1.175)	(-2.179)	(-4.684)	(-1.118)	(-7.381)
$Volatility_{i,t}$	-0.104	-0.104	0.169*	-0.098	-0.101	0.152
	(-1.190)	(-0.856)	(1.764)	(-1.117)	(-0.832)	(1.338)
$Spread_{i,t}$	-0.017**	-0.049***	-0.043**	-0.021***	-0.049***	-0.051*
	(-2.140)	(-2.869)	(-2.045)	(-2.679)	(-2.891)	(-1.806)
Adjusted R^2	26.10%	33.56%	35.67%	26.48%	33.56%	30.99%
Firm Fixed-Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	8,540	6,588	10,004	8,784	6,588	10,004

ii.2 The Rank of an Insider

In Table (6) below, we report the effect of weeks with insider transactions on the market share of dark pools ahead of earnings announcements, based on insiders' ranks. In Columns (1) and (2), we report the results of earnings with and without buybacks, respectively. We find that weeks of insider purchases initiated by top managers ahead of buyback announcements increase the market share of dark pools significantly. This effect holds exclusively for insiders in the top management group. Economically, this effect translates to an increase of approximately 11% in the market share of dark pools. In comparison, we don't find a similar effect ahead of earnings announcements that do not include a buyback.

The findings above give strong support to the theoretical predictions of Ye (2011) and the empirical findings of Ye and Zhu (2020). As predicted by Ye (2011) and Ye and Zhu (2020), an informed trader has a greater incentive to hide their trading interest when the quality of their private information is high. We attribute our findings to the higher quality of private information of top managers, as compared to lower ranking insiders. This higher quality of private information provides a top manager with a greater incentive to conceal trading interest, by trading in dark pools (Ye, 2011 and Ye and Zhu, 2020).

Table 6: The effect of weeks with insider transactions on the market shares of trading venues ahead of earnings announcements across insider ranks

This table reports regression estimates, using a stock-week panel, where the dependent variable is the market share of dark pools. We differentiate between earnings announcements that do not include a buyback, acquisition, SEO, or dividend initiation announcements in the same firm-quarter of an earnings announcement, and those that coincide with a buyback announcement in the same firm-quarter of an earnings announcement. Next, we identify three groups of insiders: top management, financial officers, and directors. Top management includes the Chairman, Chief Executive Officer (CEO), Chief Operating Officer (COO), and President. Financial officers consist of the Chief Financial Officer (CFO), Controller, and Treasurer. Directors are members of the board of directors, excluding the chairman. We estimate the following regression for each announcement type and each insider group separately:

$$\begin{aligned} Dark\ Share_{i,t} = \alpha + \beta_1 Earnings_{i,t} + \beta_2(Earnings_{i,t} \times Purchase_{i,t}) + \beta_3(Earnings_{i,t} \times Sale_{i,t}) + \\ \beta_4(Earnings_{i,t} \times Option_{i,t}) + \Sigma Controls_{i,t} + FE_i + \epsilon_{i,t} \end{aligned}$$

In the above equation, $Dark\ Share_{i,t}$ is the log of the market share of dark pools, excluding ECNs. $Earnings_{i,t}$ is a dummy variable that takes the value of 1 in the 12 weeks ahead of an earnings announcement, and zero otherwise. $Purchase_{i,t}$ is a dummy variable that takes the value of 1 if an insider purchasing transaction takes place in week t for firm i, and zero otherwise. $Sale_{i,t}$ is a dummy variable that takes the value of 1 if an insider selling transaction takes place in week t for firm i, and zero otherwise. $Option_{i,t}$ is a dummy variable that takes the value of 1 if an insider selling transaction following an option exercise takes place in week t for firm i, and zero otherwise. $Controls_{i,t}$ is a list of control variables. These variables are the log of stock turnover, the log of stock price, the log of market capitalization, absolute returns as a proxy for volatility, and the log of weekly bid-ask spread. FE_i is a firm fixed-effects term, included to absorb heterogeneity across our sampled firms. In each column, we report estimated coefficients and their t-statistics (in parentheses) calculated using standard errors clustered by week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) *Earnings With Buybacks*			(2) *Earnings Without Buybacks*		
	Top Mgmt	**Fin. Officers**	**Directors**	**Top Mgmt**	**Fin. Officers**	**Directors**
$Earnings_{i,t}$	0.017***	0.017***	0.018***	-0.026***	-0.026***	-0.026***
	(2.962)	(3.038)	(3.154)	(-5.474)	(-5.471)	(-5.436)
$(Earnings_{i,t} \times Purchase_{i,t})$	0.101**	–	-0.007	-0.089***	0.027	-0.010
	(1.982)	–	(-0.156)	(-2.579)	(0.855)	(-0.559)
$(Earnings_{i,t} \times Sale_{i,t})$	0.012	-0.029	-0.043	0.005	0.040**	0.001
	(0.389)	(-0.443)	(-0.870)	(0.384)	(2.037)	(0.055)
$(Earnings_{i,t} \times Option_{i,t})$	-0.016	0.022	-0.032	0.086***	0.012	0.000
	(-0.314)	(0.294)	(-0.509)	(3.070)	(0.728)	(0.033)
$Turnover_{i,t}$	0.082***	0.082***	0.082***	0.074***	0.074***	0.074***
	(3.855)	(3.855)	(3.855)	(3.518)	(3.515)	(3.519)
$Price_{i,t}$	0.080***	0.080***	0.080***	0.082***	0.082***	0.082***
	(4.447)	(4.446)	(4.446)	(4.524)	(4.529)	(4.530)
$Market\ Cap_{i,t}$	-0.084***	-0.084***	-0.084***	-0.085***	-0.085***	-0.085***
	(-6.669)	(-6.665)	(-6.665)	(-6.740)	(-6.746)	(-6.736)
$Volatility_{i,t}$	-0.032	-0.032	-0.032	-0.031	-0.031	-0.031
	(-1.095)	(-1.103)	(-1.105)	(-1.076)	(-1.079)	(-1.080)
$Spread_{i,t}$	-0.036***	-0.036***	-0.036***	-0.039***	-0.039***	-0.039***
	(-2.599)	(-2.599)	(-2.599)	(-2.825)	(-2.825)	(-2.825)
Adjusted R^2	31.20%	31.20%	31.20%	31.40%	31.39%	31.39%
Firm Fixed-Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	103,212	103,212	103,212	103,212	103,212	103,212

ii.3 The Rank of an Insider & Insider Competition

In Table (7) below, we combine Hypotheses (2A) and (2B), and estimate Equation (5) for each insider rank in each insider competition firm tercile. This allows us to investigate whether top ranking insiders, who are expected to possess the highest quality of private information, are more likely to trade strategically in dark pools ahead of buyback announcements when they face less competition from other insiders.

In Panels A, B, and C of Table (7) below, we report the results of firms in the high, medium, and low insider competition categories, respectively. Our results show strong evidence that top ranking insiders are more likely to purchase shares of their own firms in dark pools ahead of buyback announcements, when they face less competition from other insiders. Ahead of buyback announcements, weeks of insider purchases initiated by top managers increase the market share of dark pools significantly. Importantly, this effects holds strictly for firms with the lowest degree of insider competition, as reported in Panel C. This effect is both statistically and economically significant; the market share of dark pools increases by approximately 17%, where this effect is statistically significant at the 1% level. In addition, we find that a marginal increase in insider competition alters the venue choice of top ranking insiders. For example, for firms with a medium degree of insider competition, as reported in Panel B, we find that weeks of insider purchases initiated by top managers ahead of buyback announcements decrease the market share of dark pools significantly. This decrease translates to an increase of approximately 2% in the market share of lit venues.

Table 7: The effect of insider transactions on the market shares of trading venues ahead of earnings announcements across insider ranks and the level of competition among insiders

This table reports regression estimates, using a stock-week panel, where the dependent variable is the market share of dark pools. We differentiate between earnings announcements that do not include a buyback, acquisition, SEO, or dividend initiation announcements in the same firm-quarter of an earnings announcement, and those that coincide with a buyback announcement in the same firm-quarter of an earnings announcement. To ensure comparability, we remove firms with no insider transactions ahead of earnings announcement with a buyback. Next, we divide our sampled firms into three groups, based on the different number of insiders who initiated an open-market transaction in the 12 weeks preceding an announcement, to proxy for the level of competition among insiders. We also identify three groups of insiders: top management, financial officers, and directors. Top management includes the Chairman, Chief Executive Officer (CEO), Chief Operating Officer (COO), and President. Financial officers consist of the Chief Financial Officer (CFO), Controller, and Treasurer. Directors are members of the board of directors, excluding the chairman. We estimate the following regression for each announcement type, insider rank, and competition group separately:

$$Dark\ Share_{i,t} = \alpha + \beta_1 Earnings_{i,t} + \beta_2(Earnings_{i,t} \times Purchase_{i,t}) + \beta_3(Earnings_{i,t} \times Sale_{i,t}) + \beta_4(Earnings_{i,t} \times Option_{i,t}) + \Sigma Controls_{i,t} + FE_i + \epsilon_{i,t}$$

In the above equation, $Dark\ Share_{i,t}$ is the log of the market share of dark pools, excluding ECNs. $Earnings_{i,t}$ is a dummy variable that takes the value of 1 in the 12 weeks ahead of an earnings announcement, and zero otherwise. $Purchase_{i,t}$ is a dummy variable that takes the value of 1 if an insider purchasing transaction takes place in week t for firm i, and zero otherwise. $Sale_{i,t}$ is a dummy variable that takes the value of 1 if an insider selling transaction takes place in week t for firm i, and zero otherwise. $Option_{i,t}$ is a dummy variable that takes the value of 1 if an insider selling transaction following an option exercise takes place in week t for firm i, and zero otherwise. $Controls_{i,t}$ is a list of control variables. These variables are the log of stock turnover, the log of stock price, the log of market capitalization, absolute returns as a proxy for volatility, and the log of weekly bid-ask spread. FE_i is a firm fixed-effects term, included to absorb heterogeneity across our sampled firms. In each column, we report estimated coefficients and their t-statistics (in parentheses) calculated using standard errors clustered by week. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: High Competition Among Insiders:

	(1) *Earnings With Buybacks*			(2) *Earnings Without Buybacks*		
	Top Mgmt	**Fin. Officers**	**Directors**	**Top Mgmt**	**Fin. Officers**	**Directors**
$Earnings_{i,t}$	0.016	0.016	0.017*	-0.037***	-0.037***	-0.037***
	(1.634)	(1.605)	(1.759)	(-5.759)	(-5.735)	(-5.712)
$(Earnings_{i,t} \times Purchase_{i,t})$	-0.053	–	-0.169***	-0.001	0.080	-0.092
	(-0.544)	–	(-10.560)	(-0.015)	(1.254)	(-0.892)
$(Earnings_{i,t} \times Sale_{i,t})$	-0.001	0.000	-0.040	-0.017	0.025	0.044
	(-0.036)	(-0.010)	(-0.731)	(-0.358)	(0.330)	(1.513)
$(Earnings_{i,t} \times Option_{i,t})$	0.020	0.020	-0.015	0.045	-0.002	0.003
	(1.138)	(0.182)	(-0.154)	(0.802)	(-0.086)	(0.062)
$Turnover_{i,t}$	0.009	0.009	0.009	-0.002	0.030	-0.002
	(0.318)	(0.316)	(0.321)	(-0.078)	(1.003)	(-0.077)
$Price_{i,t}$	0.018	0.018	0.018	0.030	-0.122***	0.029
	(0.615)	(0.619)	(0.623)	(0.996)	(-4.933)	(0.978)
$Market\ Cap_{i,t}$	-0.115***	-0.115***	-0.116***	-0.122***	-0.100	-0.121***
	(-4.783)	(-4.783)	(-4.793)	(-4.919)	(-1.108)	(-4.918)
$Volatility_{i,t}$	-0.107	-0.106	-0.106	-0.100	-0.023***	-0.102
	(-1.182)	(-1.176)	(-1.178)	(-1.105)	(-2.798)	(-1.128)
$Spread_{i,t}$	-0.019**	-0.019**	-0.019**	-0.024***	0.000	-0.023***
	(-2.251)	(-2.253)	(-2.250)	(-2.803)	(0.000)	(-2.794)
Adjusted R^2	24.54%	24.17%	24.17%	24.59%	24.61%	24.61%
Firm Fixed-Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	8,540	8,540	8,540	8,540	8,540	8,540

Table 7 (Continued): The effect of insider transactions on the market shares of trading venues ahead of earnings announcements across insider ranks and the level of competition among insiders

Panel B: Medium Competition Among Insiders:

	(3) *Earnings With Buybacks*			(4) *Earnings Without Buybacks*		
	Top Mgmt	**Fin. Officers**	**Directors**	**Top Mgmt**	**Fin. Officers**	**Directors**
$Earnings_{i,t}$	0.001	0.000	0.002	-0.003	-0.003	-0.002
	(0.054)	(0.047)	(0.213)	(-0.460)	(-0.476)	(-0.311)
$(Earnings_{i,t} \times Purchase_{i,t})$	-0.163***	–	–	-0.064	0.113***	-0.172
	(-3.733)	–	–	(-0.670)	(5.591)	(-1.605)
$(Earnings_{i,t} \times Sale_{i,t})$	0.193***	0.025	-0.053	-0.037	0.026	-0.063
	(9.563)	(0.281)	(-0.570)	(-0.766)	(0.302)	(-0.913)
$(Earnings_{i,t} \times Option_{i,t})$	-0.163***	0.274***	-0.040	0.092*	0.080*	0.020
	(-3.733)	(5.161)	(-0.493)	(1.661)	(1.858)	(0.609)
$Turnover_{i,t}$	-0.052	-0.052	-0.052	-0.053	-0.053	-0.052
	(-1.304)	(-1.307)	(-1.296)	(-1.333)	(-1.327)	(-1.309)
$Price_{i,t}$	0.180***	0.180***	0.181***	0.180***	0.181***	0.178***
	(3.587)	(3.582)	(3.597))	(3.547)	(3.577)	(3.518
$Market\ Cap_{i,t}$	-0.046	-0.046	-0.047	-0.046	-0.047	-0.044
	(-1.122)	(-1.117)	(-1.127)	(-1.109)	(-1.130)	(-1.055)
$Volatility_{i,t}$	-0.104	-0.106	-0.106	-0.104	-0.106	-0.101
	(-0.866)	(-0.877)	(-0.875)	(-0.861)	(-0.878)	(-0.836)
$Spread_{i,t}$	-0.048***	-0.049***	-0.049***	-0.049***	-0.049***	-0.049***
	(-2.867)	(-2.867)	(-2.869)	(-2.889)	(-2.892)	(-2.891)
Adjusted R^2	33.57%	33.58%	33.56%	33.57%	33.56%	33.60%
Firm Fixed-Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	6,588	6,588	6,588	6,588	6,588	6,588

Panel C: Low Competition Among Insiders:

	(5) *Earnings With Buybacks*			(6) *Earnings Without Buybacks*		
	Top Mgmt	**Fin. Officers**	**Directors**	**Top Mgmt**	**Fin. Officers**	**Directors**
$Earnings_{i,t}$	0.011	0.012	0.012	-0.046***	-0.046***	-0.046***
	(1.111)	(1.238)	(1.241)	(-6.906)	(-6.984)	(-6.948)
$(Earnings_{i,t} \times Purchase_{i,t})$	0.160***	–	0.073	-0.106	–	-0.019
	(8.868)	–	(1.494)	(-1.201)	–	(-0.450)
$(Earnings_{i,t} \times Sale_{i,t})$	0.038**	0.057	-0.184*	0.032	0.076	0.014
	(2.277)	(0.986)	(-1.849)	(0.758)	(1.296)	(0.369)
$(Earnings_{i,t} \times Option_{i,t})$	0.191	0.031	0.003	0.049	0.048	0.012
	(1.544)	(0.507)	(0.023)	(0.522)	(0.792)	(0.143)
$Turnover_{i,t}$	-0.025	-0.026	-0.026	-0.044*	-0.044*	-0.044*
	(-0.927)	(-0.983)	(-0.989)	(-1.670)	(-1.670)	(-1.667)
$Price_{i,t}$	0.061**	0.062**	0.062**	0.055*	0.056*	0.055*
	(2.074)	(2.108)	(2.076)	(1.846)	(1.900)	(1.869)
$Market\ Cap_{i,t}$	-0.062**	-0.062**	-0.062**	-0.056**	-0.057**	-0.057**
	(-2.197)	(-2.215)	(-2.194)	(-1.989)	(-2.038)	(-2.012)
$Volatility_{i,t}$	0.165*	0.167*	0.166*	0.149	0.150	0.149
	(1.721)	(1.734)	(1.733)	(1.559)	(1.569)	(1.568)
$Spread_{i,t}$	-0.043**	-0.043***	-0.043**	-0.047**	-0.047**	-0.047**
	(-2.046)	(-2.045)	(-2.045)	(-2.261)	(-2.262)	(-2.261)
Adjusted R^2	35.67%	36.20%	35.64%	36.19%	36.20%	36.19%
Firm Fixed-Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of Observations	10,004	10,004	10,004	10,004	10,004	10,004

VI. **Conclusion**

In this paper, we investigate the venue choice of corporate insiders. We find that weeks of insider transactions are associated with a significant increase in the market share of dark pools. This finding is consistent with Ye (2011) and Ye and Zhu (2020), in the sense that insiders act as a monopolist informed trader, by trading in dark pools, as opposed to lit venues. Consistent with Buti et al. (2011), our analysis of firm size reveals that dark trading activity depends heavily on firm size. We find that the increase in the market share of dark pools during weeks of insider transactions is larger for large firms, as opposed to medium and small firms. Next, we disaggregate insider transactions based on their type, and dark venues based on their transparency. Our findings show that the increase in dark market share during weeks of insider transactions is more pronounced for internalization pools. These venues provide the highest level of opacity; allowing an informed trader to conceal trading interest to a larger extent. Importantly, we find that this increase in the market share of internalization pools is more pronounced during weeks of insider selling, as compared to purchasing transactions. This suggests that insiders are more likely to conceal trading interest when selling shares of their own firms. We attribute this finding to the negative signals associated with insider transactions, as they often cause a decline in stock prices (Finnerty, 1976), and to the possibility of imminent negative corporate events, as suggested by the results of Karpoff and Lee (1991) and Seyhun and Bradley (1997).

We also find strong evidence of strategic insider trading in dark pools ahead of stock buyback announcements. Importantly, our results show that this strategic trading behaviour depends on the competition among insiders and the rank of an insider. Strictly for firms with the lowest degree of insider competition, we find that the market share of dark pools increases significantly during weeks of insider purchases, ahead of stock buyback announcements. This is consistent with the theoretical predictions of Baruch et al. (2017), and the empirical findings of Reed et al. (2019) that informed traders become more patient and strategic when there is less competition among them. Our results also show that purchasing transactions of top managers ahead of buyback announcements are associated with a statistically significant and an economically large increase in the market share of dark pools. We find that this effect holds strictly for insiders in the top management group. This is in line with our prediction that the quality of private information of insiders is positively related to an insider's rank. This finding is also consistent with the theoretical predictions of Ye (2011) and the empirical findings of Ye and Zhu (2020) that an informed trader has a greater incentive to conceal their trading interest when the quality of their private information is high.

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Appendix

1. Classifications of Dark Venues

Dark venues can be classified based on different features, such as execution mechanisms, operational features, and transparency of business model. Butler (2007) provides a classification based on pricing mechanisms, type of order flow, and trade counterparties. Carrie (2007) identifies five types of dark pools based largely on execution mechanisms: scheduled, continuous, negotiated, event, and algorithm-cross dark pools. Scheduled dark pools are crossing networks that execute large volumes at fixed (usually non-overlapping) time intervals, usually at the midpoint of the NBBO. Continuous dark pools cross orders continuously at the midpoint of the NBBO. Negotiated dark pools prohibit the use of algorithms and restrict trading to humans only. Event dark pools operate based on Indications of Interest (IOI) and immediate or cancel (IOC) orders. Algorithm-cross dark pools cross orders on an algorithm-to-algorithm basis, thereby providing the opportunity to automate block-trading.

Mittal (2008) identifies five types of dark pools based on ownership structure and business model transparency: exchange-based pools (light pools), public crossing networks, internalization pools, ping destinations, and consortium-based pools. Exchange-based pools operate as ECNs that automatically match buyers and sellers outside public exchanges. ECNs register with the SEC as broker-dealers and are required by law to disseminate their orders publicly in real-time, and as such are often referred to as "light pools". Hence, as Mittal (2008) points out, these venues have a highly transparent business model. ECNs also share an important similarity with public exchanges; they contribute to price discovery, as pointed out by Huang (2002) and Baillie et al. (2002). Thus, ECNs are closer in their market design to lit venues than they are to dark pools. In matching buyers and sellers, ECNs give priority to internal liquidity within the ECN, and resort to public exchanges only when liquidity cannot be found internally (McAndrews and Stefanadis, 2000)[18]. The interaction with public order flow is expected to increase the risk of information leakage. Nonetheless, compared to lit venues, light pools still provide a lower risk of information leakage and price impact, as the order book is only available to the subscribers of the pool. Because trading interest is displayed to subscribers only, light pools are more opaque than lit venues.

[18] McAndrews and Stefanadis (2000) provide a comprehensive description of ECNs.

Public crossing networks match buyers and sellers at a specified price[19] derived from the public market, and route incoming orders to public exchanges if an execution cannot take place within the network. As such, these venues do not internalize order flow and exist primarily to generate commissions. While the business model of a crossing network is generally well understood by investors, they are more opaque than light pools in the sense that their order books are not publicly displayed. This means that they are often used by traders seeking to trade large sizes without inducing a price impact. Internalization pools are operated by broker-dealers seeking to reduce the costs of order routing. These venues match orders strictly against the operator's proprietary order flow, typically at the midpoint of the NBBO. If liquidity is not found within the pool, the order is not routed to a public exchange. Instead, it either resides within the pool to await execution, or it is cancelled, depending on the order type. This matching mechanism serves to conceal trading interest and suppress price impact. As order execution is confined within the pool, it ensures that only the operator of the pool knows the depth of liquidity that resides within the pool itself. As such, these venues are more opaque than both light pools and public crossing networks. Ping destinations operate primarily based on IOC orders. These venues not only internalize order flow, but they also employ quantitative models (known as "black boxes") that decide whether to accept or reject an incoming IOC order (Mittal, 2008). This black box feature of ping destinations effectively decides who gets to participate in the order flow. As a result, these trading venues are highly opaque and have the least transparent business model. Consortium-based pools are operated by partnering brokers, and combine the feautres of public crossing networks and internalization pools (Mittal, 2008).

Zhu (2014) employs a classification based on price discovery and execution price, differentiating between midpoint dark pools, continuous pools with nondisplayed limit order books, and electronic market makers. Midpoint dark pools derive execution prices from lit venues and hence do not contribute to price discovery (Zhu, 2014). Continuous pools with nondisplayed limit order books also cross their orders at the midpoint, but they can potentially provide a limited degree of price discovery, as Zhu (2014) points out. Electronic market makers decide immediately whether to accept or reject an incoming order, and they do not necessarily derive their execution prices from

[19]Some public crossing networks do so at the midpoint of the National Best Bid and Offer (NBBO), while others allow orders to be executed at prices away from the midpoint of the NBBO, such as the VWAP).

lit venues (Zhu, 2014). Menkveld et al. (2017) use a five-way classification of dark pools based on trading mechanism: midpoint, non-mipoint, retail, and print back dark pools[20]. Midpoint dark pools cross orders at the midpoint of the NBBO, while non-midpoint dark pools allow orders to be executed away from the midpoint. Retail dark pools refer to inernalization pools operated by broker-dealers, which often contain order flow from retail investors. Print back dark pools execute orders based on a volume-weighted average price plus a spread (Menkveld et al., 2017). Kwan et al. (2015) use a four-way classification of dark venues, based on operational features: dark ECNs, block crossing networks, ping destinations, and retail market makers. Unlike traditional ECNs, dark ECNs do not display their limit order books publicly. Operators of ECNs can act either as agents for their customers, or as market makers by providing liquidity. They can also limit access to the pool to certain market participants (Kwan et al., 2015). Block crossing networks, cross orders continuously, typically at the midpoint of the NBBO. These venues attract traders seeking to anonymously execute large orders while minimizing price impact (Kwan et al., 2015). Ping destinations operate primarily based on IOIs and IOC orders, as discussed earlier under the classification of Mittal (2008). Retail market makers are operated by broker-dealers and are characterized by the same features as internalization pools, discussed earlier under the classification of Mittal (2008).

Reed et al. (2019) devise a five-way classification, based on the information provided in the SEC's Form ATS-N[21]: block, scheduled, poolclub, non-display, and VWAP. Block refers to dark pools that allow block trading. Scheduled dark pools cross orders both continuously and periodically. Poolclub dark pools enable traders to choose to trade against specific order characteristics. Non-display dark pools do not disclose their limit order books publicly. VWAP refers to dark pools that cross orders at the VWAP.

In Table (A1) below, we provide a summary of the classifications discussed above.

[20]The fifth classification is "other" dark pools, which includes dark venues that do not fall in the other four categories, such as trades negotiated over the phone (Menkveld et al., 2017).

[21]Rule 304 of Regulation ATS requires ATSs to publicly disclose the ATS's manners of operations and the activities of its' operators, for all ATSs that trade National Market System (NMS) stocks.

Table A1: A summary of venue classifications

This table provides a summary of the classifications of dark venues highlighted above. We list the features that each classification is based on, along with the venues included in each classification. Bold, italic, and underlined text indicate venues that share the same features across different classifications.

Author(s)	Based on	Venue Classification
Butler (2007)	- Pricing mechanisms - Type of order flow - Trade counterparties	1. Pricing: Midpoint, non-midpoint, within spread, any 2. Order flow: Committed, uncommitted, pass-through, IOC, IOI 3. Counterparties: One-to-one, one-to-many, many-to-many, buy-side, sell-side, market makers
Carrie (2007)	- Execution mechanisms	1. Scheduled 2. Continuous 3. Negotiated 4. *Event* 5. Algorithm-cross
Mittal (2008)	- Ownership structure - Transparency of business model	1. Exchange-based pools (light pools) 2. **Public crossing networks** 3. Internalization pools 4. *Ping destinations* 5. Consortium-based pools
Zhu (2014)	- Price discovery - Execution price	1. Midpoint pools 2. Nondisplayed continuous pools 3. *Electronic market makers*
Menkveld et al. (2017)	- Trading mechanism	1. Midpoint pools 2. Non-midpoint pools 3. Retail pools 4. Print back pools 5. Other
Kwan et al. (2015)	- Operational features	1. Dark ECNs 2. **Block crossing networks** 3. *Ping destinations* 4. Retail market makers
Reed et al. (2019)	- Operational features	1. **Block** 2. Scheduled 3. Poolclub 4. Non-display 5. VWAP

Table A2: Descriptive statistics (continued)

This table reports descriptive statistics for our variables. In Panel A, we report the market share statistics of our sampled trading venues. These market share figures are based on weekly trading volume in number of shares. *Lit* and *Dark Share* refer to the weekly market shares of lit venues and dark pools, respectively, where the market share of dark pools excludes trading volume executed on electronic communications networks (ECNs), since these venues operate as lit venues. *CN*, *Int* and *Ping* refer to the weekly market shares of public crossing networks, internalization pools, and ping destinations, respectively. In Panel B, we report stock characteristics for our sampled firms. *Market Cap* is the product of a firm's weekly share price and number of shares outstanding, reported in billions of dollars. *Turnover* is total weekly volume divided by the number of shares of outstanding, reported in percentages. *Price* is the weekly share price. *Volatility* is the average weekly absolute return, reported in percentages. *Spread* is the average weekly absolute bid-ask spread.

Panel A: Dark Volume Data (FINRA):

Variable	N	Mean	P25	P50	P75	Std. Dev.
Large Firms:						
Lit	34,404	88.67%	87.07%	88.82%	90.53%	3.02%
Dark Share	34,404	11.42%	9.69%	11.26%	12.92%	2.50%
CN	34,404	1.29%	0.76%	1.10%	1.57%	0.88%
Int	34,404	9.92%	8.42%	9.84%	11.29%	2.48%
Ping	34,404	0.12%	0.01%	0.03%	0.13%	0.25%
Medium Firms						
Lit	34,404	87.55%	85.75%	87.77%	89.62%	3.16%
Dark Share	34,404	12.45%	10.38%	12.23%	14.25%	3.16%
CN	34,404	1.45%	0.76%	1.16%	1.78%	1.10%
Int	34,404	10.86%	9.23%	10.71%	12.35%	2.57%
Ping	34,404	0.15%	0.0004%	0.02%	0.16%	0.32%
Small Firms:						
Lit	34,404	87.31%	85.44%	87.49%	89.43%	3.42%
Dark Share	34,404	12.69%	10.57%	12.51%	14.56%	3.42%
CN	34,404	1.46 %	0.69%	1.13%	1.81%	1.23%
Int	34,404	11.07%	9.37%	10.99%	12.59%	2.80%
Ping	34,404	0.16%	0.00%	0.01%	0.15%	0.39%

Panel B: Stock Characteristics (CRSP):

Variable	N	Mean	P25	P50	P75	Std. Dev.
Large Firms:						
Turnover	34,404	3.34%	1.99%	2.78%	3.97%	2.31%
Market Cap	34,404	\$95.17	\$38.29	\$60.02	\$108.33	\$102.84
Price	34,404	\$110.99	\$51.66	\$82.10	\$128.59	\$121.95
Volatility	34,404	2.45%	0.84%	1.81%	3.30%	2.48%
Spread	34,404	\$0.02	\$0.01	\$0.01	\$0.02	\$0.04
Medium Firms:						
Turnover	34,404	4.93%	2.89%	4.05%	5.86%	3.54%
Market Cap	34,404	\$19.58	\$14.78	\$18.55	\$23.31	\$6.46
Price	34,404	\$88.00	\$43.40	\$64.58	\$97.13	\$87.26
Volatility	34,404	2.46%	0.81%	1.78%	3.27%	2.50%
Spread	34,404	\$0.04	\$0.01	\$0.01	\$0.02	\$0.28
Small Firms:						
Turnover	34,404	5.65%	3.22%	4.64%	6.78%	4.78%
Market Cap	34,404	\$9.67	\$7.46	\$9.38	\$11.54	\$3.17
Price	34,404	\$74.05	\$37.86	\$59.05	\$93.50	\$57.16
Volatility	34,404	3.62%	0.89%	1.96%	3.62%	1.96%
Spread	34,404	\$0.02	\$0.01	\$0.01	\$0.02	\$0.04