Bright Light, Dark Room: Where do Corporate Insiders Trade?

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Abstract

In the fragmented equity market landscape, corporate insiders may conceal high-quality information or engage in illegal activities by trading on dark markets. While existing literature extensively covers the timing and methods of insider trading, little attention is given to the specific venues utilized by corporate insiders. We analyze where corporate insiders trade and evaluate the impact of their venue choice on abnormal returns. We find that insiders are more likely to trade on dark markets when engaging in illegal activities, but less inclined to do so when they are informed. Given insiders' endogenous venue selection, trading on dark markets negatively impacts abnormal returns.

Keywords: Insider trading, market fragmentation, venue choice, abnormal return

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1. Introduction

Venue choice matters. Stocks trade on various platforms, each with its distinct traits.[1] Trading on exchanges offers high immediacy and transparency, while trading on dark markets is slow and opaque.[2] Informed traders weigh these factors carefully. They prefer trading on exchanges to profit from the information before it becomes known, yet they also favor the opaqueness of trading on dark markets to hide their information from others. Traders who illegally obtain or use information face a similar dilemma but typically prioritize opaqueness over immediacy due to higher legal risks and the lower likelihood of the information becoming public knowledge.

Corporate insiders, henceforth referred to as insiders, often possess confidential information regarding their firm's valuation (e.g., Seyhun, 1986; Seyhun, 1990). Trading on insider information is prohibited, and insiders must promptly disclose all of their trades. Additionally, they face restrictions on trading during specific periods known as "blackout periods". While insiders may be tempted to flout these regulations for potentially higher returns, the consequences of getting caught are severe. Therefore, the decision between trading on exchanges or dark markets is crucial for insiders, as it hinges on their assessment of the balance between immediacy and transparency, influenced by their level of information and adherence to trading restrictions.

[1] Previously, most countries had rules mandating that trades should be executed on each national exchange. However, in Europe, the Markets in Financial Instruments Directive (MiFID) introduction in 2007 removed such rules to promote competition for order flow with transparency (pre-and post) requirements for trading venues' quotes and related depth, exempting some venues from pre-trade transparency. Similar events in the US transpired with the introduction of the Regulation National Market System (Reg NMS) in 2007.

[2] We define dark markets as mechanisms that operate without or with limited pre-trade transparency, such as dark pools, systematic internalisers, and over-the-counter. Conversely, by exchanges, we mean mechanisms with full pre-trade transparency.

We conduct a two-stage analysis of the factors influencing insiders' choice of stock-trading venue and the impact of that choice on abnormal returns. In the first stage, we examine how insiders' venue choices are related to whether they are informed and whether they violate trading restrictions. We hypothesize that informed insiders are less likely to trade on dark markets, while those violating restrictions are more inclined to do so. Trading on exchanges provides immediacy and transparency, whereas trading on dark markets offers opacity but sacrifices certain execution. Informed insiders typically want to trade quickly, as the cost of waiting increases with the value of the information (e.g., Kaniel and Liu, 2006) and the uncertainty about when the price of a stock will reflect that information (e.g., Chau and Vayanos, 2008). In contrast, insiders who violate trading restrictions aim to conceal their trading, and their desire to trade is less urgent (Kacperczyk and Pagnotta, 2024).

In the second stage, we examine how venue choice affects insiders' abnormal returns. Venue choice is endogenous to insiders' possession of information and their adherence to trading restrictions, which influences their venue choice and subsequent return. For example, Ye (2024) suggests that informed traders prefer to trade on exchanges when they are confident of profiting from the information, as the urge for immediacy exceeds the desire to hide by trading on dark markets. Baruch, Panayides, and Venkataraman (2017) argue that the cost of non-execution outweighs the higher price impact when the value of information is high. Shkilko (2019) finds that insiders trade with haste when possessing high-value information.

Given their endogenous venue choice, we hypothesize that insiders receive lower abnormal returns when trading on dark markets. This hypothesis is driven by the notion that informed insiders prioritize immediacy on exchanges over the lower price impact on dark markets, leading to lower returns when they attempt to conceal their actions.[3]

We analyze a sample of insider trades in Swedish stocks from 2016 to 2023. The data, obtained from the Swedish supervisory authority, consist of self-reported insider trades. A key element of our analysis is the requirement for insiders to disclose the venues where they trade. Our empirical approach defines insiders as informed when they display opportunistic behavior – such as not trading in a routine manner, following Cohen, Malloy, and Pomorski (2012), or when engaging in large-volume trades, as per Bettis et al. (1997). Additionally, we identify insiders who violate trading restrictions when they fail to disclose trades promptly or trade during blackout periods.

We find that insiders are less likely to trade on dark markets when they are informed and more likely to do so when they violate trading restrictions. The factors influencing insiders' venue choice have significant economic implications. During our sample period, 18% of insider trading volume occurred on dark markets. Engaging in opportunistic trading or trading large volumes reduces the likelihood of insiders trading on dark markets by 5%. Conversely, trading during blackout periods or delaying trade disclosures increases the likelihood of on a dark market trading by 11% and 19%, respectively.

[3] Zhu (2014) argues that the risk of non-execution inherent in trading on dark markets motivates informed traders to trade on exchanges, where immediacy allows them to leverage their information advantage. In contrast, Ye and Zhu (2020) argue that exchange trading by informed traders decreases returns due to higher price impact from information leakage. Although insiders typically trade with low price impact (Lakonishok and Lee, 2001), disclosure of their trades prompts outsiders to mimic them, which increases the price impact (Bettis, Vickrey, and Vickrey, 1997; Brochet, 2010). Moreover, insiders often trade on short-lived information (Huddart, Ke, and Shi, 2007; Alldredge and Cicero, 2015) and face trading competition (Massa, Qian, Xu, and Zhang, 2015). Consequently, slow execution increases the risk of information leakage, as each trade triggers disclosure requirements and the risk of missing large returns.

Trading on dark markets is associated with a 5% decrease in insiders' abnormal returns. This finding is economically significant, given that insiders' average unconditional abnormal return is -1%. Our findings align with Zhu's (2014) prediction that informed insiders prefer immediacy on exchanges over the lower price impact on dark markets, resulting in lower returns when attempting to conceal their actions. Insiders violating trading restrictions opt for dark markets trading to conceal their activities, consistent with the findings of Kacperczyk and Pagnotta (2024). Consequently, our results support the notion that venue selection is endogenous to abnormal returns, as informed insiders tend to choose exchange trading, leading to a negative correlation between trading on dark markets and returns.

We make three contributions. Firstly, we contribute to the literature on corporate insiders. Existing research delineates *when* insiders trade. Huddart et al. (2007) highlight the clustering of insider trades due to trading restrictions, while Alldredge and Cicero (2015) note increased insider trading upon the public release of private information. Moreover, we also know *how* insiders trade from previous research. Klein, Maug, and Schneider (2017) and Shkilko (2019) demonstrate that informed insiders trade swiftly in competitive environments. Conversely, Kacperczyk and Pagnotta (2024) find that insiders trade less urgently when engaging in illegal activities. However, a gap persists in our knowledge of *where* insiders trade. We bridge this gap by furnishing direct evidence of insiders' choice of trading venues.[4]

[4] Some studies provide indirect evidence on where insiders trade by examining changes in market shares for venues when insiders trade. Alfarhoud, Bowe, and Zhang (2021) show that market shares for trading on dark markets increase when insiders trade. More generally, Ye and Zhu (2020) find increasing market shares for trading on dark markets when activist hedge funds trade on high-quality information. Alfarhoud et al. (2021) focus on market shares for internalization pools and ping destinations, while Ye and Zhu (2020) focus on market shares for alternative trading systems relative to exchanges.

Secondly, we contribute to the literature on informed traders' venue choice. Ye and Zhu (2020) propose that the price impact represents the cost of trading on exchanges for informed traders. Conversely, trading on dark markets may result in non-execution, thereby posing the risk of missed trading opportunities. When multiple informed traders are involved, Zhu (2014) suggests that the cost of missed trading opportunities outweighs the price impact on exchanges, incentivizing informed traders to opt for exchange trading. Although evidence from Ye and Zhu (2020) and Alfarhoud et al. (2021) indicates that informed traders choose to trade on dark markets, Reed, Samadi, and Sokobin (2020) demonstrate that short sellers exploit their informational advantage on exchanges. We enhance this literature by directly examining where informed insiders trade.

Thirdly, we contributes to the literature on performance for informed traders in general. Informed traders engage in trading only when it is feasible to achieve abnormal returns. Ye and Zhu (2020) suggest that trading on dark markets aids in minimizing information leakage, thereby potentially resulting in higher returns. Conversely, Zhu (2014) suggests that the risk of non-execution associated with trading on dark markets leads to missed trading opportunities and, consequently, to lower returns. Therefore, deciding where to trade is inherently linked to achieving higher returns. We enhance this literature by examining how venue choice influences insiders' abnormal returns while accounting for endogeneity.

Regulators have expressed concerns about the potential overuse of venues that offer concealment, as this could impede price discovery. Recently, regulatory discussions have focused on implementing rules to shift trading volume from opaque venues to more transparent ones.[5] According to ESMA (2020), nearly half of all stock trading volume occurs on dark markets. Our findings suggest that large volumes on dark markets are unlikely to impede price discovery, as informed traders tend to trade on exchanges to avoid missing profitable opportunities. However, there is a risk to market integrity, as insiders are more likely to use dark markets to conceal illegal activities. The opacity of dark markets makes it easier for them to evade detection and accountability, potentially undermining fairness and trust in the market. This risk highlights the importance of regulations aimed at safeguarding market integrity by preventing the misuse of dark markets.

2. Previous research and hypotheses

In this section, we review prior research examining how market fragmentation influences participants' venue choice and the informational content of their order flow, focusing on understanding insiders' venue preferences and their impact on abnormal returns. Finally, we formulate hypotheses.

2.1 Fragmentation

Competition among trading venues contributes to market fragmentation. Trading venues compete by influencing traders' choices. A crucial factor in venue choice is the liquidity cost, which refers to the cost of immediately executing an order of a given size without impacting the market price. A trading venue can attract more traders by reducing transaction fees (Colliard and Foucault, 2012) or incentivizing liquidity providers to narrow the bid-ask spread (Werner,

[5] MiFID II enhances equity market transparency by mandating pre-trade and post-trade transparency across trading venues. This regulation ensures that all market participants access essential trading information, promoting fairness and efficiency (Norton Rose Fulbright, 2020; Deutsche Börse Group, 2020).

Rindi, and Buti, 2017). As a result, competition between trading venues reduces liquidity costs for traders in the equity market (e.g., O'Hara and Ye, 2011).

In addition to implementing measures that reduce trading costs, a trading venue can attract order flow by providing limited or no pre-trade transparency. Institutions seeking to trade large blocks of shares may face disadvantages when routing their orders to transparent exchanges compared to trading on dark markets, which could lead to front running (Brunnermeier and Pedersen, 2005). However, trading on dark markets could result in delayed order execution, as opaque venues often involve negotiations or a lack of liquidity providers willing to fully absorb the orders.

Menkveld, Yueshen, and Zhu (2017) propose a pecking order in which traders rank trading venues based on a tradeoff between liquidity cost and immediacy of order execution. Traders initially consider venues with low liquidity costs and low immediacy. As trading urgency escalates, venues offering high immediacy at the cost of higher liquidity costs become more appealing. Trading on dark markets offers lower liquidity costs since orders execute within the bid-ask spread, albeit at a slower pace. In contrast, on-exchange trading provides fast execution but at a higher liquidity cost. Menkveld et al. (2017) offer empirical evidence supporting this pecking order. During periods of high volatility, indicating increased trading urgency, market shares for exchanges increase.

If a consolidated market is deemed optimal in the aggregate, it is unlikely to suit all traders. Harris (1993) underscores that traders vary in terms of their sophistication, trading objectives, order sizes, and patience. A key distinction among traders is their motivation for trading; are they informed or uninformed? The distinction is significant because the interaction between informed and uninformed traders influences market prices and liquidity costs. Informed traders possess valuable, price-relevant information and trade when prices do not reflect that information, potentially at the cost of liquidity providers. Informed trades adjust prices toward their intrinsic values, often prompting gradual execution to mitigate rapid price adjustments. Conversely, uninformed trades are unrelated to intrinsic value and contribute to the profit of liquidity providers by paying the bid-ask spread.

With a single exchange operating a visible order book, Kyle (1985) argues that an informed trader's order execution strategy hinges on how well he can camouflage his orders among others, as orders are batched and thus indistinguishable. Competition for order flow complicates an informed trader's order execution strategy as orders get less batched at a given venue. For example, trading over the counter (OTC) requires the trader to reveal his identity to a dealer. If the trader effectively signals that he is uninformed, the dealer may offer a discount on the liquidity cost (Battalio and Holden, 2001). Consequently, uninformed traders are more likely to trade OTC due to dealers' ability to provide better prices. The segmentation of informed trading on exchanges and uninformed trading on dark markets makes it more challenging for informed traders to conceal their orders on exchanges (Comerton-Forde and Putniņš, 2015; Lee and Wang, 2021).

Ye and Zhu (2020) expand upon Kyle's (1985) model by allowing a monopolistic informed trader to strategically decide between trading on and off the exchange. Each order the informed trader executes on the exchange results in price impact. Trading off the exchange does not affect the price, but the risk of non-execution increases with the order size. The tradeoff between the price impact on the exchange and the non-execution risk off the exchange encourages the informed trader to trade less aggressively on the exchange. Despite the risk of non-execution, Ye and Zhu predict that the informed trader will opt for trading on dark markets to minimize price impact and preserve the value of the information. Hence, the information is gradually incorporated into the exchange prices.

Zhu (2014) theoretically investigates the strategic venue choice among multiple informed traders who can trade on and off an exchange. Informed traders may send orders off the exchange to incur lower liquidity costs, albeit with slower execution, as suggested by the pecking order in Menkveld et al. (2017). However, given the presence of multiple informed traders, competition heightens the risk of non-execution, as fewer counterparties may be willing to trade with each informed order. Consequently, Zhu suggests that informed traders will trade on the exchange, resulting in a higher price impact.

Ye (2024) examines a theoretical model akin to Zhu's (2014). In Ye's model, the informed trader's venue choice is contingent on the information precision. Consequently, the informed trader will opt to trade on the exchange when information precision is high, as immediacy outweighs the reduced liquidity cost off the exchange. Lower information precision renders trading off the exchange more attractive. In such instances, paying lower liquidity costs compensates for the high uncertainty regarding the ability to profit from the information. Therefore, Ye suggests that an informed trader's venue choice is contingent on information precision.

2.2 Corporate Insiders

Corporate insiders are employees who have access to insider information. Due to their position, they may receive stock grants, for example, as additional compensation to their salary. Thus, insiders may trade for liquidity reasons. Cohen et al. (2012) propose a framework for detecting the informativeness of insider trades. Predictable insider trades, those with a historically consistent and predictable trading pattern, are classified as routine, while unpredictable, so-called "opportunistic" insider trades are classified as informed. Cohen et al. find that only opportunistic insider trades earn abnormal returns, and that many insiders whom the SEC charges for illegal insider trading classify as opportunistic.

Order size correlates with traders' informational motives. An informed trader who wants to trade will prefer to execute large trades at any given price (Easley and O'Hara, 1987). Bettis, Vickrey, and Vickrey (1997) construct portfolios following large trades by insiders and demonstrate that such portfolios are associated with abnormal returns. Fidrmuc, Goergen, and Renneboog (2006) show similar results: abnormal returns increase with the size of insiders' trades.

Corporate insiders are subject to restrictions. They are prohibited from trading before earnings announcements and must report their trades within a few days. These restrictions aim to minimize the likelihood that insiders trade on privileged information. Consequently, Bettis, Coles, and Lemmon (2000) demonstrate that insider trades are highly concentrated. Holden and Subrahmanyam (1992) suggest that a concentration of insider trades compels informed insiders to trade aggressively. Indeed, Klein, Maug, and Schneider (2017) find that informed insiders trade more aggressively when faced with competition. Since insiders are required to disclose their trades, informed insiders face an opportunity cost if their orders are not fully executed before disclosure. Huddart, Hughes, and Levine (2001) argue that incorporating a disclosure policy for the informed trader in Kyle's (1985) model would accelerate the incorporation of information into prices. Lakonishok and Lee (2001) show minimal market reaction in terms of abnormal returns when insiders report their trades. In contrast, Brochet (2010) demonstrates that insider trades elicit economically significant market reactions, and Klein et al. (2017) find that informed insiders trade more aggressively when confronted with shorter disclosure deadlines.

Kyle (1985) suggests that an informed insider will trade gradually to minimize price impact but become more aggressive as the publication of the information approaches. Holden and Subrahmanyam (1992) suggest that an informed insider will trade aggressively as other insiders may trade on the same price-relevant information. Huddart, Ke, and Shi (2007) demonstrate that insiders trade heavily after earnings announcements and avoid trading periods that could suggest trading on insider information. Additionally, Alldredge and Cicero (2015) show that insiders trade more profitably by paying closer attention to public information than outsiders.

Shkilko (2019) examines how insiders trade and finds that they trade aggressively by submitting large orders quickly and disregarding liquidity costs when they are informed. Trade aggressiveness escalates when other insiders are trading, when the value of price-relevant information is high, and when uncertainty exists regarding when the price will fully reflect the price-relevant information. Additionally, Inci, Lu, and Seyhun (2010) demonstrate that insider information is rapidly incorporated into the price when insiders are trading, and others quickly follow suit and mimic the insider trades.

Insiders can become informed through a breach of fiduciary duty, thereby facing detection and legal risks if they trade based on such information. Kacperczyk and Pagnotta (2024) propose a tradeoff in which illegal insider trading balances between legal risk and the price impact of the insider’s trades. Without legal risk, the insider will trade as Kyle (1985) suggests. Increasing legal risk reduces the insider’s trading aggressiveness. In support of their model, Kacperczyk and

Pagnotta (2024) empirically demonstrate that prosecuted illegal insiders trade less aggressively and that less information is incorporated into prices when legal risk increases.

Kacperczyk and Pagnotta (2019) show that prosecuted insiders time their trades when liquidity is better. Betzer, Gider, and Theissen (2015) argue that insiders who delay reporting their trades are more likely to trade on inside information. Cline and Houston (2018) find that insiders who delay their reporting beyond the deadline earn higher abnormal returns than other insiders. Klein et al. (2017) and Baruch et al. (2017) argue that insiders are informed if they trade a few weeks before an earnings announcement.

2.3 Empirical Analysis of Venue Choice

Ye and Zhu (2020) analyze venue choice by activist hedge funds. They use Schedule 13D filings, which contain the reported equity trading transactions by hedge fund activists who own at least a 5% stake in a company. Since the filings lack information on the specific venues chosen by the activists, Ye and Zhu (2020) use changes in market shares across trading venues and compare weeks with and without activist trading. They find that: 1) trading on dark markets increases when activists trade; 2) the increase is more pronounced the more valuable the activists' private information is; and 3) prices on the exchanges incorporate less information as the value of activists' private information and trading on dark markets increases. Alfarhoud, Bowe, and Zhang (2021) obtain similar results when using corporate insider transactions as a proxy for informed trading. Like Ye and Zhu (2020), they cannot observe the actual venue choices of insiders.

An issue with inferring venue choice from changes in market shares is the possibility that trading volume on dark markets is correlated with liquidity on exchanges. Buti, Rindi, and Werner

(2022) demonstrate that volumes on dark markets increase more for large-cap stocks with high liquidity than for small-cap stocks. Collin-Dufresne and Fos (2015) find that activists time their trading based on liquidity. Additionally, Alfarhoud et al. (2021) show that their results are more pronounced for large-cap stocks. Thus, the liquidity timing of informed traders may coincide with increasing market shares on dark markets.

Reed, Samadi, and Sokobin (2020) examine where short sellers trade. Short sellers are recognized as well-informed traders (e.g., Diether, Lee, and Werner, 2009; Christophe, Ferri, and Hsieh, 2010). Reed et al. use a sample containing the level of short selling for each exchange. They find that short selling occurs both on exchanges and dark markets, with most short selling occurring on exchanges. Additionally, short selling on exchanges produces more informative signals about future prices than short selling on dark markets, suggesting that short sellers primarily exploit their information advantage on exchanges.

2.4 Hypotheses

Based on the theoretical predictions regarding informed traders' venue choice and empirical evidence on the timing and methods of corporate insiders' trades, we form three hypotheses regarding insiders' venue choice and abnormal returns. The difference between Zhu's (2014) and Ye and Zhu's (2020) predictions stems from the number of informed traders that trade simultaneously. The need for immediacy intensifies with competition, prompting an informed trader to execute trades on an exchange. Insiders are subject to various restrictions and often trade on time-sensitive information. Therefore, we hypothesize:

H1. Informed insiders are less inclined to trade on dark markets than uninformed insiders.

In contrast, insiders involved in illegal trading should actively seek to conceal their trading intentions. Kacperczyk and Pagnotta (2024) suggest that due to legal risks, insiders engaging in illegal trades should trade less aggressively and have a greater incentive to conceal their activities. Disclosing trades late or trading during blackout periods provides more flexibility for insiders to execute trades, as there is less pressure to act urgently. Therefore, we hypothesize:

H2. Illegal insiders are more inclined to trade on dark markets than legal insiders.

The intuition of Zhu's (2014) and Ye and Zhu's (2020) models is that informed traders are better off managing the venue choice correctly. Informed traders achieve higher returns than expected (abnormal returns) if, for example, they trade on exchanges when those are the best places to exploit their information advantage. Zhu (2014) suggests that informed traders trade on exchanges and achieve higher abnormal returns since the cost of being slow (or non-execution) on dark markets is higher than the cost of immediacy on exchanges. In contrast, Ye and Zhu (2020) suggest that informed traders trading on dark markets achieve higher abnormal returns since they minimize their information leakage risk and, thus, price impact. However, it is not when insiders trade that leads to a price impact (Lakonishok and Lee, 2001); instead, it is the disclosure of their trades (Brochet, 2010). If insiders trade slowly, the risk of others imitating their trades before all orders are executed increases, as each insider trade triggers disclosure requirements. Additionally, insiders often act on public information that requires immediate action to capitalize on higher returns (Huddart et al., 2007; Alldredge and Cicero, 2015). The slow execution associated with trading on dark markets leads to missed opportunities, resulting in insiders earning lower abnormal returns when trading on this information. Therefore, we hypothesize:

H3. Insiders trading on dark markets achieve lower abnormal returns than insiders trading on exchanges.

3. Methodology

We propose a framework for analyzing the factors influencing corporate insiders' venue choice and its impact on abnormal returns. We outline a two-stage regression framework, where the first stage involves determining the venue choice, and the second stage models the abnormal return, given the venue choice. In the second stage, we employ an instrumental variable (IV) approach to address the potential endogeneity of insiders' venue choices. In the following, we present our measures of abnormal return and other key variables and describe the two-stage regression model used to test our hypotheses formally.

3.1 Insider abnormal return and trading performance

In three steps, we derive cumulative abnormal returns (CARs) following insider transactions. First, we measure daily returns using stock prices estimated as the volume-weighted average prices (VWAPs) on the days in question. We use VWAPs to compute stock returns because insiders must report their trades in this format. Second, we compute abnormal returns using the market model. Third, we calculate CARs over a 30-day period subsequent to each insider transaction.

Suppose that the insider transaction j occurs in stock i on day t.[6] To calculate the cumulative stock return over, for instance, k days, we first determine the daily return for each day s, where $s = t + 1, t + 2, \dots t + k$, as follows:

[6] To simplify the notation, we omit the index for stock i in Eq. (1) and onwards.

$$R_{j,s} = Q_j(P_s + DIV_{j,s} - P_{s-1})/P_{s-1}. \tag{1}$$

Here, P_s represents the stock price (VWAP) on day s, $DIV_{j,s}$ denotes any cash dividend paid on day s, and Q_j is an indicator variable equal to 1 if insider transaction j is a purchase and -1 if it is a sale. Therefore, a positive stock return for a purchase indicates that $P_s + DIV_{j,s}$ is greater than P_{s-1}, while for a sale, it signifies that $P_s + DIV_{j,s}$ is less than P_{s-1}.

Then, we define the abnormal stock return as:

$$AR_{j,s} = R_{j,s} - (\hat{\alpha} + \hat{\beta} R_{m,s}), \tag{2}$$

where $R_{m,s}$ represents the market return on day s, and $\hat{\alpha}$ and $\hat{\beta}$ are estimated parameters from the market model with a 260 day estimation window, 32 days before the insider transaction date t. We estimate the market model parameters with the following regression model:

$$R_{j,s} = \alpha + \beta R_{m,s} + \varepsilon_{j,s}, \tag{3}$$

where $s = t - 291, t - 290, \dots t - 32$ and $\varepsilon_{j,s}$ is a residual.

Finally, the CAR following insider transaction j over k days is given by:

$$CAR_{j,t+1,t+k} = \sum_{s=t+1}^{t+k} AR_{j,s}. \tag{4}$$

3.3 Regression analysis

Insider venue choice

To model insiders' conditional venue choice, we create a dummy variable $X_{j,t}$ equal to one if the insider transaction j on day t to some extent occurs on dark markets and zero if 100% of the transaction volume occurs on exchanges. In the first stage, we model the likelihood of insiders trading on dark markets with the following regression:

$$
\begin{gathered}
X_{j,t} = \gamma_1 X_{j,t}^{Depth} + \gamma_2 MiFID_{j,t} \times X_{j,t}^{Depth} + \gamma_3 Sell_{j,t} + \gamma_4 Opp_{j,t} + \gamma_5 Large_{j,t} \\
+\gamma_6 Blackout_{j,t} + \gamma_7 Late_{j,t} + \gamma_8 Rel_{j,t} + \gamma_9 Vol_{j,t} + \gamma_{10} PCAR_{j,t} + \gamma_{11} Pos_{j,t} \\
+\gamma_0 + \varepsilon_{j,t}^{I},
\end{gathered}
\tag{5}
$$

Where $X_{j,t}^{Depth}$ is the average limit order book depth for the best bid and ask during day t, for the stock that the transaction j is trading, $MiFID_{j,t}$ is a dummy variable that equals 1 for insider transactions occurring after the implementation of MiFID 2, from January 3, 2018, and zero otherwise, $Sell_{j,t}$ is a dummy variable equal to one if the insider transaction j on day t is a sale and zero if it is a purchase, $Opp_{j,t}$ is a dummy variable equal to one if the insider transaction j on day t is characterized as opportunistic according to Cohen et al. (2012) and zero if it is characterized as routine, $Large_{j,t}$ is a dummy variable equal to one if the insider transaction j on day t has a volume larger than the sample median and zero otherwise according to Bettis et al. (1997), $Blackout_{j,t}$ is a dummy variable equal to one if the insider transaction j occurs on day t during a blackout period and zero if its timing is legal, $Late_{j,t}$ is a dummy variable equal to one if the insider transaction j on day t is reported late and zero if it is reported on time, $Rel_{j,t}$ is a dummy variable equal to one if the transaction j on day t is carried out by a relative to an insider and zero otherwise, $Vol_{j,t}$ is the time-weighted mean intraday stock volatility on day t, $PCAR_{j,t}$ is the cumulative abnormal return 30 days before day t, $Pos_{j,t}$ is a dummy variable equal to one if the insider has an executive position and zero otherwise, γ_0 is a constant term, and $\varepsilon^{I}_{j,t}$ is a first-stage residual.

To proxy for insider informativeness, we use two variables from the literature. The first proxy, the dummy variable $Large_{j,t}$, follows the approach of Bettis et al. (1997) and is based on the theoretical prediction that larger trades convey more information than smaller ones (e.g., Kyle, 1985).

Secondly, we follow the framework proposed by Cohen et al. (2012), which relies on an insider's past transaction history. An insider trade is considered informed or opportunistic, $Opp_{j,t}$, if it is not considered routine. An insider trade is classified as routine if it occurs during the same month for at least three consecutive years.[7] Cohen et al. advocate for a static approach where past routine classification extends to all subsequent trades afterward for that insider. However, we use a trade-level approach to induce variation; each insider trade is evaluated regardless of the insider's past classification. For example, an insider with a history of routine trades may deviate from this pattern by trading in a different month. While Cohen et al. recommend evaluating only insiders with three consecutive years of trading, we diverge from this recommendation by classifying trades as opportunistic if they deviate from past patterns, even if the insider has not traded for three consecutive years. The rationale behind Cohen et al.'s framework is grounded in its ability to predict insider trades based on past transaction records. Our findings indicate that, with these adjustments, we obtain outcomes similar to those of Cohen et al.'s baseline tests.

[7] For robustness, we also classify an insider trade as routine if it occurs during the same month for at least two consecutive years. See Appendix for the corresponding regression results.

We use two variables to proxy for illegal insider trading. Firstly, the variable $Blackout_{j,t}$ indicates whether an insider transaction occurs during a blackout period, and secondly, the variable $Late_{j,t}$ indicates whether a transaction is reported late.

In the regression model in Eq. (5), the hypothesis that informed insiders are less likely to trade on dark markets than uninformed boils down to if one, or both, of the coefficients γ_4 and γ_5 is negative. Moreover, the notion that illegal insiders are more inclined to trade on dark markets than legal insiders corresponds to the situation when one, or both, of the coefficients γ_6 and γ_7 is positive.

To instrument for insider venue selection in the second stage regressions, we use the quoted depth on exchanges, i.e., the liquidity available at the best bid and ask prices. We compute the depth as the daily time-weighted average of the average *size* at the best bid and ask in millions of SEK ($X_{j,t}^{Depth}$) and use it as an explanatory variable in the first stage regression according to Eq. (6). The variable meets the requirements of an appropriate instrument because the depth in the same stock correlates with insider venue choice. If insiders prefer using limit orders, large depth on exchanges increases their incentive to trade in dark markets to bypass the long queues in the limit order book (Werner et al., 2017). In contrast, if the insiders prefer market orders, large depth on exchanges decreases the incentive to trade in dark markets since the large depth suggests less price impact (e.g., Collin-Dufresne and Fos, 2016). Also, depth is unlikely to be driven by insiders' information.

Our second instrumental variable is the interaction term, $MiFID_{j,t} \times X_{j,t}^{Depth}$, between depth and the dummy variable indicating the implementation of MiFID 2. MiFID 2 affected the European equity trading landscape by promoting trading on exchanges and limiting trading on dark markets by the double volume trading caps in dark pools. Accordingly, the interaction term enables different impacts on venue selection before and after the implementation of MiFID 2 in the first stage regression.

Abnormal returns

In the second stage regressions, we employ the following model to investigate if insiders' venue choice affects abnormal returns:

$$\begin{aligned} CAR_{j,t} = \delta_1 X_{j,t} + \delta_2 Sell_{j,t} + \delta_3 Opp_{j,t} + \delta_4 Large_{j,t} + \delta_5 Blackout_{j,t} + \delta_6 Late_{j,t} \\ + \delta_7 Rel_{j,t} + \delta_8 Vol_{j,t} + \delta_9 PCAR_{j,t} + \delta_{10} Pos_{j,t} + \delta_0 + \varepsilon_{j,t}^{II}, \end{aligned} \tag{6}$$

where $CAR_{j,t}$ corresponds to $CAR_{j,t,t+k}$ from Eq. (4) for insider transaction j on day t, δ_0 is a constant term, and $\varepsilon_{j,t}^{II}$ is a second-stage residual.

The hypothesis that insiders trading on dark markets achieve lower abnormal returns than insiders trading on exchanges boils down to the hypothesis that the coefficient δ_1 is negative. Note that we employ the IV procedure to estimate δ_1 to address endogeneity, acknowledging that insider traders condition their venue choice on the quality of information and the tradeoff between information risk and legal risk.

Moreover, in the regression model in Eq. (6), the hypothesis that informed insiders have higher abnormal returns than uninformed insiders, conditional on venue selection, is equivalent to the hypothesis that one or both coefficients δ_3 and δ_4 are positive. The corresponding conditional hypothesis that illegal insiders have higher abnormal returns than legal insiders is equivalent to the hypothesis that one or both of the coefficients δ_5 or δ_6 are positive.

4. Institutional setting and data

4.1 Regulatory framework

In Europe, insider trading regulation is overseen by local financial authoritiesunder the EU's harmonized legislation, known as the Market Abuse Regulation (MAR). Insiders are defined as employees or their relatives who have access to inside information, meaning non-public, price-relevant information. Similarly, in the US, Rule 10b-5 classifies employees, stockholders with a 10% stake in the firm, or anyone with access to inside information as an insider. The purpose of insider trading laws is to prevent trading based on inside information. Insider trading is generally prohibited, and while both MAR and Rule 10b-5 aim to minimize it, they differ in their specific definitions and restrictions.

Rule 10b-5 defines insider trading as trading based on information that violates a duty of trust or confidence. For example, in the 2014 Newman case, two hedge fund managers were charged with insider trading based on tips from insiders. To be convicted, the insider providing the tip must have a fiduciary duty and must breach that duty by disclosing inside information for personal gain. Additionally, the recipient of the tip must be aware of this breach when trading. The fund managers were found not guilty of insider trading because the inside information had passed through several intermediaries, distancing the managers from the original insider, and there was no evidence of compensation for the tips (Berman, Conceicao, Gatti, and O'Neil, 2015). In contrast, under MAR, a violation of trust or confidence is not required for a conviction. A person who trades on inside information, with full awareness of its nature, can be found guilty of insider trading regardless of how they acquired the information.

MAR and Rule 10b-5 both impose restrictions on insider trading, but they differ in their approach. In the EU, insiders are prohibited from trading during the 30 days preceeding an earnings announcement—a blackout period. The rationale behind the blackout period is to reduce the risk of insiders trading when they are likely to possess non-public information about the upcoming earnings announcement as the date approaches. However, relatives to insiders are exempt from this blackout period. In contrast, Rule 10b-5 does not mandate a blackout period; instead, it is left to US companies to decide whether to impose such restrictions on insiders. Bettis et al. (2000) document that over 92% of US companies have policies that prohibit insiders from trading during specific periods. Additionally, Rule 10b-5 mandates that insiders return (to the SEC) any profits from buying and selling company stock within six months.

Insiders are required to disclose any trades they make. In Europe, insiders must report their transactions to the local financial authority within three business days, while in the US, insiders must report their transactions within two business days. Both EU and US insider reports provide details such as the financial instrument involved, the type of transaction, the average daily transaction price, the transaction date, the reporting date, and the employee status.[8] Additionally, MAR requires EU insiders to report their choice of trading venue. This venue feature allows us to analyze insiders' venue choices in detail.

4.2 Data

We analyze insiders' trading in Swedish stocks from July 4, 2016, to July 4, 2023. Sweden's financial supervisory authority, Finansinspektionen (FI), oversees the jurisdiction for Swedish stocks, safeguarding the integrity and stability of Sweden's financial markets, such as companies listed on the Stockholm Stock Exchange (Nasdaq Stockholm). The Swedish financial market regulation integrates EU directives and regulations into the national legislation.

[8] MAR Article 19 and SEC Rule 16a-3(g)).

We focus on the fifty largest stocks according to their market capitalization as of June 2016, and we collect data from three sources: FI, LSEG Tick History (TH), and LSEG Eikon (E).

We obtain publicly available self-reported insider data from FI. Each report contains the data stipulated by MAR. We exclude insider trades executed on behalf of a company or as part of an option program. We also exclude trades that are reported without a price and/or trading volume and those reported with an unreasonable stock price, defined as being outside the range of the lowest and the highest traded market prices on the reporting day (from TH).

Our second data source is TH, which includes tick-by-tick quotes and transaction prices across all available trading venues, enabling us to calculate, for example, the volume-weighted average traded price on a stock-day basis. TH features a 14-character string forming qualifier based on the Market Model Typology. We use these qualifiers to categorize the type of trading venue where an order was executed, distinguishing between transactions on exchanges and dark markets. Transactions exempted from pre-trade transparency are categorized as transactions on dark markets, while those complying with pre-trade transparency regulations are classified as transactions on exchanges.

We use our third data source, E, to collect stock-day market capitalization values and identify earnings announcement days. This information enables us to categorize whether insiders violate blackout periods.

4.3 Description of the market for Swedish stocks

Table 1 presents descriptive statistics for stock characteristics during the sample period. The sample contains stocks of various company sizes. The average market capitalization is 117,891 MSEK, with a standard deviation of 122,016 MSEK. The stock trading volume is highly fragmented, with an average of 40.80% of the daily trading volume occurring on dark markets. In contrast, Alfarhoud et al. (2021), Ye and Zhu (2020), and Reed et al. (2020) report averages of 12.16%, 15.34%, and 13.10%, respectively, for daily trading volume occurring on dark markets. Therefore, in our sample, the higher trading volume on dark markets may facilitate insiders' concealment of trades. Additionally, compared to Ye and Zhu (2020), we observe higher stock liquidity, with an average quoted spread of 15.30 basis points (bps), while Ye and Zhu (2020) report a corresponding average quoted spread of 103 bps. The relatively high fragmentation and liquidity in our sample result from selecting the fifty largest stocks rather than using a larger sample that includes small stocks, as the studies above do.

Insert Table 1 here

4.4 Insiders' trade characteristics

Table 2 presents descriptive statistics for insiders' trade characteristics during the sample period. On average, there are 1.27 insider trades for each stock and day when insiders trade, suggesting that insiders typically execute their daily trading volume in a single trade. 81.63% of all insider trades are purchases. The average number of insiders trading in a stock on the same day is 1.73, suggesting that insiders are unlikely to face competition from other insiders when trading.

Most insiders trade on exchanges, with 81.70% of insiders' trading volume occurring on exchanges. Moreover, 98.10% of insiders' trading volume is classified as opportunistic, and 95.3%

is classified as legal.[9] Only 3.23% of insiders' trading volume is reported late, 1.28% is executed during blackout periods, and 0.18% is reported late and executed during blackout periods.

Insert Table 2 here

5. Regression results

This section presents our regression results. First, we show the results from the first-stage regression analyses of insiders' venue choice. Then, we turn to the results from the second-stage regressions of cumulative abnormal return, in which we treat the venue choice as endogenous.

5.1 Insiders' venue choice

Table 3 presents the results from the first-stage regression model according to Eq. (5). The column labeled "Probit" contains results from a probit estimation of the regression model. Each coefficient for the variables representing informed trading—opportunistic and large transactions—is significantly negative at the 1% level. Accordingly, opportunistic insiders are 7.91% less likely to trade on dark markets than insiders who trade routinely. Likewise, insiders who engage in large trades are 4.05% less likely to trade on dark markets than those trading small sizes. These effects carry economic significance, given that, on average, 18.3% of insiders' volume occurs on dark markets.

The Wald test rejects the hypothesis that the coefficients for the variables representing information proxies are jointly zero at the 1% significance level. Hence, we find support for hypothesis H1, indicating that informed insiders are less inclined to trade on dark markets than

[9] When we, for robustness, classify an insider trade as routine if it occurs during the same month for at least two consecutive years, 99.0% of insiders' trading volume is classified as opportunistic.

uninformed insiders. This result suggests that insiders prefer to exploit their information on exchanges, aligning with the findings of Shkilko (2019) and Reed et al. (2020). Accordingly, informed insiders may prioritize trading with urgency and hence value the immediacy of exchanges over the lower liquidity cost and the potential anonymity on dark markets. This finding is also in line with the theoretical predictions of Zhu (2014) but contradicts those of Ye and Zhu (2020).

Insert Table 3 here

The results in Table 3 indicate that each variable representing illegal insider trades—trading during blackout periods and reporting trades late—has a significantly positive coefficient at the 1% level. Insiders trading during blackout periods are 10.24% more likely to trade on dark markets than those who legally time their trades. Moreover, insiders reporting their trades later than required are 19.54% more likely to trade on dark markets than those reporting trades on time. Besides their statistical significance, we contend that these coefficients are sufficiently large to hold economic significance.

The Wald test rejects the hypothesis that the two coefficients associated with variables representing illegal insider trades are jointly zero at the 1% significance level. Therefore, we find support for hypothesis H2, indicating that illegal insiders are more inclined to trade on dark markets than legal insiders. This result aligns with the proposition by Kacperczyk and Pagnotta (2024) that illegal insiders trade less aggressively than legal insiders to conceal their activities.

The likelihood of insiders trading on dark markets is significantly positively correlated with depth and significantly negatively correlated with the interaction term between depth and the MiFID 2 dummy variable, both at the 1% level. The likelihood ratio test rejects the joint hypothesis that these two variables have coefficients equal to zero at the 1% significance level, indicating that the variables are valid instruments. Regarding the control variables, we observe that volatility is associated with a significantly negative coefficient at the 1% level. This finding implies that the likelihood of insiders trading on dark markets decreases with volatility, consistent with the notion in Menkveld et al. (2017) that insiders' urgency to trade is higher, and, thus, their inclination to trade on exchanges is higher, during periods of high volatility.

The column labeled "OLS" in Table 3 also presents the results from a regression model estimated with ordinary least squares (OLS). The results from the OLS regression closely resemble those from the probit regression. Therefore, we opt to use the OLS regression as the first stage in the two-stage regression estimation for cumulative abnormal returns.

5.2 Cumulative abnormal returns

Table 4 presents the results from the second-stage regression of CARs according to Eq. (6). The column labeled "2SLS" contains the results from the two-stage least squares estimation of the regression, wherein we use the OLS estimation of insider venue choice from Table 3 as the first stage. Therefore, the variable measuring transactions on dark markets, $X_{j,t}$, is the predicted value from the first-stage OLS regression according to Eq. (5). The coefficient for this variable is significantly negative at the 1% level. The endogenous decision by insiders to trade on dark markets decreases their CAR by 5.30%, which holds economic significance given that the unconditional average CAR is negative at 1.07%. This result supports our hypothesis H3, suggesting that insiders trading on dark markets achieve lower abnormal returns than those trading on exchanges.

Insert Table 4 here

The 2SLS regression results also reveal that CAR is significantly positively associated with variables representing information, even after controlling for insiders' endogenous venue selection. Opportunistic transactions exhibit a 0.80% higher CAR than routine transactions at the 10% level, and large size transactions show a 1.06% higher CAR than small size transactions at the 1% level. These findings align with those in the literature, indicating that insiders classified as informed achieve higher abnormal returns than those not classified as informed (Cohen et al., 2012; Bettis et al., 1997; Fidrmuc et al., 2006). However, proxies for illegal insider trades—trading during blackout periods and reporting late—do not significantly affect CAR in the 2SLS regression.

The key results from our two-stage analysis are that insiders' information and illegal behavior influence their venue choice in the first stage and the CAR in the second stage. The effects in the second stage are both direct, through each variable itself, and indirect, through venue selection. We use the regression results from Tables 3 and 4 to illustrate these effects and assess their relative importance. To do so, we consider a benchmark case featuring an "average" insider who is buying ($Sell_{j,t} = 0$) with a routine transaction ($Opp_{j,t} = 0$) of small size ($Large_{j,t} = 0$), which is legal ($Blackout_{j,t} = Late_{j,t} = 0$), not a relative ($Rel_{j,t} = 0$), and not holding a managerial position ($Pos_{j,t} = 0$). Additionally, we assume the market conditions to be "average", where the depth equals the average in Table 2 ($X_{j,t}^{Depth} = 0.40$), the transaction occurs before MiFID 2 ($MiFID\ 2 = 0$), stock volatility equals the average in Table 2 ($Vol_{j,t} = 4.07$), and the past cumulative abnormal return equals its average value ($PCAR_{j,t} =$ -0.02). Given these input values for the variables, our two-stage regression model predicts a likelihood of trading on dark markets equal to 26.22% and a CAR equal to -1.61% for the benchmark insider.

Table 5 presents a sensitivity analysis of changing each insider characteristic reflecting information and illegal behavior relative to the benchmark case. Firstly, we consider allowing the insider to be opportunistic rather than routine. From Table 3, we observe that the coefficient for the variable $Opp_{j,t}$ predicts a ceteris paribus decrease in the likelihood of trading on dark markets equal to 7.65%. Hence, if our benchmark insider is opportunistic rather than routine, the first-stage model predicts a likelihood of trading on dark markets equal to 18.57% instead of 26.22%. Our second-stage model predicts a CAR of -0.40% rather than -1.61% (in the benchmark case), corresponding to a ceteris paribus difference of 1.21%. This difference arises from a direct effect from the variable $Opp_{j,t}$ of 0.80% (the coefficient for $Opp_{j,t}$ in Table 4) and an indirect effect from the variable $X_{j,t}$ of 0.41%. Hence, the ceteris paribus effect on insider CAR from being opportunistic rather than routine is 66% (0.80/1.21) direct effect and 34% (0.41/1.21) indirect effect.

Secondly, we consider allowing the insider to trade a large transaction rather than a small one. Table 5 shows that the likelihood of trading on dark markets decreases when moving from small to large transactions, with the coefficient for the variable $Size_{j,t}$ indicating a decrease of 3.51%. Hence, when our benchmark insider is trading a large transaction rather than a small one, the first-stage model predicts a reduced likelihood of trading on dark markets from 26.22% to 22.71%. Moreover, the insider's predicted CAR improves to -0.36%, corresponding to a ceteris paribus increase of 1.25%. This increase constitutes a direct effect from the size of the transaction itself of 1.06% (or 85% of the increase) and an indirect effect through the venue choice of 0.19% (15%).

Thirdly, we consider the impact of trading during a blackout period. Table 5 indicates that insiders trading during such periods are more likely to trade on dark markets, with the coefficient for the variable $Blackout_{j,t}$ showing an increase of 11.93%. Thus, for our benchmark insider, the first-stage model predicts an increased likelihood of trading on dark markets from 26.22% to 38.15% when the insider trades during blackout periods rather than outside of them. Additionally, the second-stage model predicts a decrease in CAR to -1.34%, which is a difference of 0.27% relative to the benchmark case. This difference arises from a direct positive effect of 0.90% and an indirect negative effect of -0.63%.

Fourthly, we assess the effects of late-reported transactions in Table 5. If our benchmark insider reports a transaction late rather than on time, the first-stage model predicts a 18.43% higher likelihood of trading on dark markets, up from 26.22% in the benchmark case to 44.65%. The second-stage model shows a ceteris paribus decrease of 1.54% in CAR. This decrease results from the sum of the direct effect of late reporting (-0.56%) and the indirect effect through venue choice (-0.98%).

6. Concluding remarks

We show that venue choice matters. We sample insiders' trades in Swedish stocks, including their venue choice. Our benchmark insider, who neither is informed nor violates trading restrictions, has a 26.22% likelihood of trading on dark markets. This likelihood increases when insiders violate trading restrictions. Trading during blackout periods increases the likelihood of trading on dark markets to 38.15%, while reporting late increases it to 44.65%. In contrast, insiders prefer to trade on exchanges when they are informed. When insiders trade large volumes or engage in opportunistic trading, their likelihood of trading on dark markets decreases to 22.71% and 18.57%, respectively.

The variation in the likelihood of insiders trading on dark markets based on informational or illegal activities is consistent with predictions from Kacperczyk and Pagnotta (2024) and Zhu (2014). Insiders violating trading restrictions could internalize legal risks by trading on dark markets, and when informed, they prefer the immediacy of exchanges. Additionally, most informed insider trades occur on exchanges, suggesting that insiders exploit their informational advantage there.

Insiders' venue choice affects the subsequent abnormal return. Compared to our benchmark insider, violating trading restrictions worsens the abnormal return. Trading during blackout periods or reporting late decreases the subsequent abnormal return by 0.27% and 1.54%, respectively. The negative effect on subsequent abnormal return is primarily driven by the higher likelihood of trading on dark markets. In contrast, information is positively related to abnormal return. Relative to our benchmark insider, insiders who trade large volumes or engage in opportunistic trading have higher a subsequent abnormal return by 1.25% and 1.21%, respectively, with the lower likelihood of trading on dark markets contributing to 15% and 34% of the higher abnormal return, respectively.

Our results are consistent with Zhu's prediction (2014) that informed traders exploit their information advantage on exchanges, while trading on dark markets worsens the abnormal return. Thus, despite regulators' concerns, increasing volumes on dark markets are unlikely to hinder price discovery. However, insiders who often trade on dark markets might signal illegal activities.

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Table 1: Stock characteristics

	Mean	St. Dev.	25%	Median	75%
Market Capitalization (MSEK)	117,891	122,016	39,706	69,024	171,381
Trading Volume (MSEK)	459.89	1,155.02	55.07	211.03	588.36
Exchanges Volume Share (%)	59.20	19.90	45.96	56.88	69.69
Dark markets Volume Share (%)	40.80	19.90	30.31	43.12	54.04
Daily Turnover (%)	0.01	0.01	0.00	0.00	0.01
Quoted Spread (bps)	15.30	40.85	5.21	7.61	11.93
Effective Spread (bps)	15.15	733.16	4.38	6.34	10.26
Depth at BBO (MSEK)	0.40	2.69	0.11	0.21	0.39
VWAP (SEK)	161.85	118.95	91.91	135.60	200.12
Volatility (sq. bps)	4.07	18.63	2.22	2.87	4.10

This table presents the characteristics of the sample stocks from July 4, 2016, to July 4, 2023. All stocks have their primary listing on Nasdaq Stockholm. Market capitalization is the average of the market capitalization across (expressed in millions of Swedish kronor, MSEK). Other statistics are obtained across sample stock-days. Trading volume is in MSEK and is obtained across all trading venues. On exchange volume share is the percentage share of trading volume on exchanges (e.g., Nasdaq Stockholm). Dark markets volume share is the percentage share of trading volume on dark markets (e.g., OTC). The spread and depth measures use the consolidated limit order book data from Refinitiv (xbo). Quoted Spread is the time-weighted average of the bid-ask spread divided by its midpoint, expressed in basis points (bps). Effective Spread is twice the trade value-weighted average absolute difference between the trade price and the bid-ask midpoint. Depth at BBO is the time-weighted average of the trade volume in MSEK required to change the stock price, averaged across the sides of the order book. VWAP (Volume Weighted Average Price) denominated in SEK represents the average volume-weighted price at which the stocks trade over the sample period. Adjustments are made for stock splits. Volatility is daily the mean squared bps return over a 10-second interval, derived from the midpoint between bid and ask prices.

Table 2: Insiders' trade characteristics

	Mean	St. Dev.	25%	Median	75%
Number of insider trades	1.269	2.693	1	1	1
Share of purchases (%)	81.629	38.143	100	100	100
Share of sales (%)	18.371	38.143	0	0	0
Number of insiders	1.730	2.151	1	1	1
Insider volume (TSEK)	2,703.470	23,540.418	52.439	204.300	707.293
Distribution (%) of insider volume across types of trading venues					
Exchanges Volume Share (%)	81.693	35.027	91.656	100	100
Dark markets Volume Share (%)	18.307	35.027	0	0	8.344
Distribution (%) of insider volume with respect to information					
Opportunistic	98.098	9.815	100	100	100
Routinely	1.902	9.815	0	0	0
Distribution (%) of insider volume with respect to legality					
Legal	95.315	17.183	100	100	100
Reported late	3.233	14.472	0	0	0
During blackout periods	1.277	8.269	0	0	0
Reported late and during blackout periods	0.175	3.484	0	0	0

This table presents the characteristics of insiders' trade in our sample. All statistics are obtained across sample insider-days. We exclude the following insider trades (1) done on behalf of a company, (2) whose transaction price is too high (low) such that it is above (below) the day's highest (lowest) stock price, (3) that are part of an option program, and (4) whose price or volume is not reported. The number of insider trades is the number of trades an insider makes when trading, where the share of purchase (sales) indicates how much of those trades are of the acquiring (disposal) type relative to the insider's total trades for that day. Number of insiders is the number of insiders that trade in the same stock on the same day. Insider volume is in TSEK and is obtained across all trading venues. Exchanges volume share is the percentage share of insider volume on exchanges (e.g., Nasdaq Stockholm). Dark markets volume share is the percentage share of insider volume on dark markets (e.g., OTC). Opportunistic volume share is the percentage share of insider volume classified as informed according to the Cohen et al. (2012) framework; the same applies to routine volume share. Insider volume with respect to legality is the percentage share of insider volume that (i) neither reports late nor occurs during the blackout period, (ii) reports late, (iii) occurs during the blackout period, and (iv) reports late and occurs during the blackout period.

Table 3: Regression results for insider venue choice

	Probit	OLS
Depth at BBO ($X_{j,t}^{Depth}$)	6.11***	6.61***
	(1.23)	(1.47)
$X_{j,t}^{Depth} \times MiFID_{j,t}$	-4.1***	-5.79***
	(1.25)	(1.47)
Sale ($Sell_{j,t}$)	-3.37*	-2.62
	(1.8)	(1.61)
Opportunistic transaction ($Opp_{j,t}$)	-7.91***	-7.65***
	(2.33)	(2.32)
Large size transaction ($Large_{j,t}$)	-4.05***	-3.51**
	(1.53)	(1.42)
Illegal transaction during blackout period ($Blackout_{j,t}$)	10.24***	11.93***
	(2.86)	(3)
Illegal late reported transaction ($Late_{j,t}$)	19.54***	18.43***
	(4.07)	(3.93)
Transaction by relative ($Rel_{j,t}$)	-3.31	-3.33
	(2.8)	(2.39)
Volatility ($Vol_{j,t}$)	-2.43***	-1.64***
	(0.44)	(0.22)
Past Cumulative Abnormal Returns ($PCAR_{j,t}$)	-1.05	2.61
	(7.44)	(5.68)
Executive position ($Pos_{j,t}$)	0.76	0.9
	(1.36)	(1.29)
Constant		30.29***
		(2.33)
F-test (Likelihood-ratio test for probit) on the instruments' coefficients = 0	101.96***	59.298***
Adjusted R^2 (McFadden's for probit)	0.0804	0.0747
Wald-test on coefficients for $Opp_{j,t}$ and $Large_{j,t} = 0$	26.6***	25.6***
Wald-test on coefficients for $Blackout_{j,t}$ and $Late_{j,t} = 0$	44.7***	55.9***

This table presents results from regressions for insiders' venue choice according to Eq. (6) expressed in percent. The dependent variable in each regression is the dummy variable $X_{j,t}$ that is equal to one if an insider transaction j on day t to some degree occurs on dark markets and zero otherwise. The explanatory variables are: $X_{j,t}^{Depth}$, daily time-weighted average of the average size at the best bid and ask in millions of SEK, $MiFID_{j,t}$, a dummy variable that takes the value one for insider transactions occurring after the implementation of MiFID 2, from January 3, 2018, and onwards, and zero otherwise, $Sell_{j,t}$, a dummy variable that is equal to one if the insider transaction j on day t is a sale and zero otherwise, $Opp_{j,t}$, a dummy variable that is equal to one if the insider transaction j on day t is characterized as opportunistic according to Cohen et al., (2012) and zero otherwise, $Large_{j,t}$, a dummy variable that is equal to one if the insider transaction j on day t has a volume larger than the sample median and zero otherwise, $Blackout_{j,t}$, a dummy variable that is equal to one if the insider transaction j illegally occurs on day t during a blackout period and zero otherwise, $Late_{j,t}$, a dummy variable that is equal to one if the insider transaction j on day t is illegally late reported and zero otherwise, $Rel_{j,t}$, a dummy variable that is equal to one if the transaction j on day t is carried out by a relative to an insider and zero otherwise , $Vol_{j,t}$, is the time-weighted mean intraday stock volatility on day t, $PCAR_{j,t}$, is the cumulative abnormal return 30 days before day t, $Pos_{j,t}$ is a dummy variable equal to one if the insider has an executive position and zero otherwise. For the probit regression, the table reports marginal effects and standard errors in parentheses (and significance levels) for the regression coefficients. For the OLS regression, the table reports regression coefficients and associated standard errors in parentheses (and significance levels). Standard errors are adjusted for heteroscedasticity according to White (1980). *, **, and *** denote significance at the 10%, 5%, and 1% level. The F-test of the hypothesis that the instruments have zero coefficients refers to a Wald test of the joint exclusion of the variables $X_{j,t}^{Depth}$ and $MiFID_{j,t} \times X_{j,t}^{Depth}$ from each regression.

Table 4: Regression results for cumulative abnormal return (CAR)

	OLS	2SLS
Transaction on dark markets ($X_{j,t}$)	-0.63*	-5.30***
	(0.37)	(1.5)
Sale ($Sell_{j,t}$)	4.12***	4.11***
	(0.75)	(0.75)
Opportunistic transaction ($Opp_{j,t}$)	1.07***	0.80*
	(0.40)	(0.41)
Large size transaction ($Large_{j,t}$)	1.22***	1.06***
	(0.38)	(0.39)
Illegal transaction during blackout period ($Blackout_{j,t}$)	0.35	0.90
	(0.53)	(0.58)
Illegal late reported transaction ($Late_{j,t}$)	-1.38	-0.56
	(0.78)	(0.87)
Transaction by relative ($Rel_{j,t}$)	-0.76	-0.93
	(0.73)	(0.76)
Volatility $(Vol_{j,t})$	0.37***	0.26*
	(0.12)	(0.14)
Past Cumulative Abnormal Returns $(PCAR_{j,t})$	2.39	2.21
	(2.56)	(2.60)
Executive position $(Pos_{j,t})$	0.02	0.07
	(0.39)	(0.40)
Constant	-2.74***	-1.23
	(0.53)	(0.75)

This table presents results from regressions for the dependent variable cumulative abnormal return ($CAR_{j,t}$), expressed in percent, according to Eq. (7). The column labeled OLS contains results from an ordinary least squares regression. The column labeled 2SLS contains results from a two-stage least squares regression, where the variable $X_{j,t}$ is instrumented by $X_{j,t}^{Depth}$ and its interaction term from the first-stage OLS regression in Table 3. The remaining variables are described in Table 3. The table reports regression coefficients and associated standard errors in parentheses (and significance levels) for the regressions. Standard errors are adjusted for heteroscedasticity, according to White (1980). *, **, and *** denote significance at the 10%, 5%, and 1% level.

Table 5: Sensitivity analysis

	First stage		Second stage			
	Likelihood of trading on dark markets	Difference relative benchmark insider	Cumulative Abnormal Return	Difference relative benchmark insider	Direct effect	Indirect effect
Benchmark insider	26.22%	0.00%	-1.61%	0.00%	0.00%	0.00%
Opportunistic transaction ($Opp_{j,t}$)	18.57%	-7.65%	-0.40%	1.21%	0.80%	0.41%
Large size transaction ($Large_{j,t}$)	22.71%	-3.51%	-0.36%	1.25%	1.06%	0.19%
Transaction during blackout period ($Blackout_{j,t}$)	38.15%	11.93%	-1.34%	0.27%	0.90%	-0.63%
Late reported transaction ($Late_{j,t}$)	44.65%	18.43%	-3.15%	-1.54%	-0.56%	-0.98%

This table presents a sensitivity analysis based on the results from the regressions in Table 3 (first stage) and Table 4 (second stage). The variables are described in Table 3. The first row labelled Benchmark insider contains the predicted likelihood of trading on dark markets from the first stage OLS regression in Table 3, and the predicted CAR from the second stage regression in Table 4, with all dummy variables equal to zero and each continuous variable equal to its respective mean value. Each other row contains effects from a change in the corresponding dummy variable from zero to one on the likelihood to trade on a dark market and on the CAR, relative the benchmark case. In the second stage, the difference in CAR relative the benchmark case is decomposed into a direct effect from the variable's coefficient in the second stage regression, and an indirect effect from the likelihood of trading on dark markets.

Appendix

Table A3: Regression results for insider venue choice

	Probit	OLS
Depth at BBO ($X_{j,t}^{Depth}$)	5.59***	6.12***
	(1.22)	(1.46)
$X_{j,t}^{Depth} \times MiFID\ 2$	-3.57***	-5.30***
	(1.24)	(1.46)
Sale ($Sell_{j,t}$)	-3.69**	-2.87*
	(1.79)	(1.61)
Opportunistic transaction ($Opp_{j,t}$)	-5.41**	-5.38**
	(2.61)	(2.72)
Large size transaction ($Large_{j,t}$)	-4.59***	-4.07***
	(1.51)	(1.41)
Illegal transaction during blackout period ($Blackout_{j,t}$)	11.22***	12.88***
	(2.85)	(2.94)
Illegal late reported transaction ($Late_{j,t}$)	18.77***	17.94***
	(4.03)	(3.92)
Transaction by relative ($Rel_{j,t}$)	-3.80	-3.78
	(2.75)	(2.38)
Volatility $(Vol_{j,t})$	-2.52***	-1.71***
	(0.44)	(0.23)
Past Cumulative Abnormal Returns $(PCAR_{j,t})$	0.07	3.51
	(7.42)	(5.68)
Position $(Pos_{j,t})$	0.74	0.91
	(1.36)	(1.29)
Constant		29.29***
		(2.73)
F-test (Likelihood-ratio test for probit) on the instruments' coefficients = 0	98.30***	57.28***
Adjusted R^2 (McFadden's for probit)	0.077	0.072
Wald-test on coefficients for $Opp_{j,t}$ and $Large_{j,t} = 0$	16.7***	15.8***
Wald-test on coefficients for $Blackout_{j,t}$ and $Late_{j,t} = 0$	45.5***	58.0***

This table presents results from regressions for insiders' venue choice according to Eq. (6) expressed in percent. All variables are the same as in Table 3 except for the variable $Opp_{j,t}$. Here, we classify an insider trade as routine if it occurs during the same month for at least two (rather than three as in Table 3 results) consecutive years.

Table A4: Regression results for cumulative abnormal return (CAR)

	OLS	2SLS
	(1)	(2)
Transaction on dark markets ($X_{j,t}$)	-0.66**	-4.91***
	(0.37)	(1.48)
Sale ($Sell_{j,t}$)	4.17***	4.14***
	(0.75)	(0.74)
Opportunistic transaction ($Opp_{j,t}$)	0.57	0.41
	(0.48)	(0.49)
Large size transaction ($Large_{j,t}$)	1.32***	1.15***
	(0.38)	(0.38)
Illegal transaction during blackout period ($Blackout_{j,t}$)	0.17	0.70
	(0.52)	(0.58)
Illegal late reported transaction ($Late_{j,t}$)	-1.29	-0.57
	(0.78)	(0.86)
Transaction by relative ($Rel_{j,t}$)	-0.68	-0.85
	(0.73)	(0.76)
Volatility ($Vol_{j,t}$)	0.38***	0.28**
	(0.12)	(0.14)
Past Cumulative Abnormal Returns ($PCAR_{j,t}$)	2.26	2.12
	(2.56)	(2.59)
Position ($Pos_{j,t}$)	0.03	0.07
	(0.39)	(0.40)
Constant	-2.41***	-1.09
	(0.59)	(0.78)

This table presents results from regressions for the dependent variable cumulative abnormal return ($CAR_{j,t}$), expressed in percent, according to Eq. (7). All variables are the same as in Table 4 except for the variable $Opp_{j,t}$. Here, we classify an insider trade as routine if it occurs during the same month for at least two (rather than three as in Table 4 results) consecutive years.