Title: **The relevance of dark trading for information acquisition in European markets**

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1. Introduction

The rapid growth of dark pools in recent decades has impacted the operation of financial markets and the way in which information is reflected in asset prices. Concerned with the potential negative impact on market quality, particularly for retail investors, global regulators have introduced several restrictions on dark pool trading. One example is the 2018 introduction of a double volume cap (DVC) mechanism that limits the proportion of dark pool trading in European markets. We investigate the role that dark pool trading plays in *information acquisition* ahead of quarterly earnings announcements and use the implementation of the DVC mechanism as a natural experiment to understand how restrictions on dark trading affect the price discovery process.

A key role of financial markets is to aggregate information from different traders and use this to determine asset values. A trader's choice of trading venue can influence the price formation process, and market fragmentation can lead to traders re-evaluating their choice of venue. If the majority of traders migrate to different venues, such as dark pools, this could lead to a change in the way information is impounded into prices, thus affecting the price discovery process.

The price discovery process can be decomposed into two parts: *informational efficiency* and *information acquisition* (Brunnermeier, 2005; Weller, 2018; Brogaard and Pan, 2022). Informational efficiency refers to the incorporation of existing information into asset prices, while information acquisition refers to the means by which that information is obtained. The common belief is that prices become more informative as traders acquire more information (e.g., Grossman, 1976; Grossman and Stiglitz, 1980). This is because uninformed traders can observe prices and infer information since prices tend to rise (fall) in good (bad) economic states. Weller (2018) argues that mechanisms that "improve price efficiency with respect to *existing* information will deter information acquisition and diminish price efficiency with respect to *acquirable* information." However, Barlevy and Veronesi (2000) show this may not be the case if prices change for other reasons and so multiple equilibria form as traders have incentives to acquire additional information. Changes in the information environment can then be amplified by aggressive trading and information acquisition (Goldstein and Yang, 2015).

Our study focuses on information acquisition and contributes to the relatively scarce literature relating to the effects of dark pool trading on this aspect of the price discovery process.

We focus on information acquisition prior to quarterly earnings announcements because they are important firm-specific events that are closely followed by traders. If a higher proportion of traders acquire information ahead of earnings announcements, then asset prices become more informative. One way in which dark pools may encourage information acquisition is in providing a venue for informed traders to disguise their trading intentions thus lowering trading costs (Boulatov and George, 2013), and there is evidence that dark pools are used in this manner (Reed et al., 2020). However, there is a counterargument that dark pools are less attractive to informed traders if they do not offer trading immediacy (Zhu, 2014).

The relationship between dark pools and informational efficiency has been extensively studied in the literature. Comerton-Forde and Putniņš (2015) find low levels of dark trading will improve price discovery and decrease bid-ask spreads but once the dark volume traded exceeds 10% informational efficiency will fall. Similarly, dark limit order markets are shown to be beneficial to market quality and result in narrower spreads, greater depth, higher informational efficiency (Buti et al., 2011; Foley and Putniņš, 2016) and price improvements (Garvey et al., 2016). Fleming and Nguyen (2013) finds that an increased use of dark pools in Treasury securities is associated with higher market depth, lower bid-ask spreads, and higher trading intensity. They also report that dark liquidity is used more often during volatile times, but the information role becomes relatively less important.

Conversely, there is evidence that dark pool trading may have a negative impact on market quality, indicated by wider spreads, higher transaction costs, and larger price impacts (Foley et al., 2012; Weaver, 2014; Zhu, 2014; Hatheway et al., 2017). Nimalendran and Ray (2014) suggest that the price impact on lit markets is greater following dark pool transactions, indicating that the information flow is adversely affected.

The literature on the effects of dark pool trading on information acquisition is more limited. Brogaard and Pan (2022) use the SEC's Tick Size Pilot program as an exogenous event to measure the effects of dark pools on information acquisition. The Pilot Program was used to evaluate the impact of tick size on trading, liquidity, and market quality. This Program led to a large decrease in dark pool trading, and provides evidence that dark pools aid information acquisition. We follow a similar methodology to that adopted by Brogaard and Pan (2022), but we argue that the DVC mechanism provides a superior exogenous event as it imposes a direct ban on dark pool trading.

The emergence of dark pools has also led to increased market fragmentation, and the literature has yet to reach a conclusive agreement as to whether fragmentation is detrimental to market quality. To some extent this depends on the specific venue considered, since it is possible for fragmentation to improve overall lit market liquidity while 'traditional' market liquidity declines (Degryse et al., 2015). The choice of venue, in both lit and dark markets, depends on the urgency required to trade (Menkveld et al., 2017), while O'Hara and Ye (2011) suggest that market fragmentation may not harm market quality because it increases competition between market participants.

Our study is motivated by two factors: the significant growth in dark pools and associated market fragmentation, and the implementation of the DVC mechanism. Petrescu and Wedow (2017) show that, in the period 2009 to 2016, the market share of dark pools grew from 1% to 8% of total European share trading. In Germany, dark pool volume and the number of trading venues tripled in the decade to 2018.

In January 2018, the European Securities and Markets Authority (ESMA) implemented the updated markets in financial instrument directive (MiFID II). A key goal of this directive was to strengthen investor protection by improving market transparency and efficiency. The unbundling of research from transactions is one aspect of this directive already covered in the literature. There is evidence that the number of analysts covering each European firm has dropped, but the forecast error and informativeness has increased as a result since it is inaccurate analysts that are more likely to withdraw (Fang et al., 2020; Kammann et al., 2020; Guo and Mota, 2021).

Our analysis focuses on another aspect of this directive, which is also aimed at improving efficiency, namely the mandatory disclosure of dark pool transactions as they occur and, via the DVC mechanism, limits on the amount of dark trading that can occur. Guagliano et al. (2020) demonstrate that there was a sharp drop in dark trading for firms incurring a suspension under the DVC mechanism. The imposition of this directive therefore provides an exogenous event that allows us to understand the information acquisition role of dark trading.

We use this setting to find answers to two related research questions. First, does dark trading support or hinder information acquisition prior to earnings announcements? Some traders acquire information about company earnings announcements prior to the event (Demski and Feltham, 1994; McNichols and Trueman, 1994). These informed traders will trade on this information and in the process will reveal a part of this information to other market participants (Kyle, 1985). If informed traders trade in the dark markets, then information acquisition will increase in the lit markets. This is because informed traders face lower trading costs when trading in dark markets, and so pursue additional opportunities. Conversely, if informed traders use lit markets, and liquidity traders use dark markets, information acquisition will decline (even if information efficiency increases). Second, we focus on the specific effect of the DVC mechanism and asked whether this aided or reduced information acquisition during our sample period.

To address these questions, we measure pre-announcement information acquisition using the price jump ratio measure of Weller (2018). This ratio quantifies how much information is reflected in prices prior to the announcement relative to how much is *potentially acquirable*. A low (high) price jump ratio indicates that more (less) information is discovered before the earnings announcement.

Our empirical results show that dark trading is important for information acquisition ahead of earnings announcements. Dark trading has a significant negative relationship with the jump ratio. Hence, more (less) dark trading is associated with a lower (higher) jump ratio and higher (lower) pre-announcement information acquisition. This relationship is concentrated in trading ahead of negative earnings news, and for firms that are hard to value (small firms and value stocks). The relationship is also stronger when there is higher uncertainty about earnings, as indicated by lower analyst coverage and greater analyst disagreement. We then consider the effect of the DVC mechanism in the first year of implementation. The introduction of the DVC mechanism, associated with less dark trading in the control group, reduces pre-announcement information acquisition, and so amplifies the market response to earnings news.

There are several papers that study the effect that regulatory changes have on the contribution of dark pools to the price discovery process in Europe. First, Brandes and Domowitz (2010) find that an increase in dark trading following the 2007 MiFID I directive improved market quality. We focus on information acquisition rather than market quality, and the DVC mechanism which was introduced only in MiFID II. Second, Anagnostidis et al. (2019), Johann et al. (2019), and Guagliano et al. (2020) consider the implementation of the DVC mechanism but focus how it impacts market quality rather than information acquisition prior to earnings announcements that we use here. In addition, Brogaard and Pan (2022) attempt to tackle a similar question in relation to US stocks and the Tick Size Piot Program, which indirectly influences the level of dark trading. Our results are consistent with those of Brogaard and Pan (2022) and support generalizability of those results across countries and in relation to exogenous shocks of different types.

This paper proceeds as follows. Section 2 offers information on the institutional setting, including the DVC mechanism, and describes the data used in our analysis. Section 3 provides our empirical analysis relating to the importance of dark trading in respect to information acquisition and the effect of introducing the DVC mechanism. Section 4 concludes.

2. Institutional Setting and Data Description

This section starts with a brief overview of our institutional setting that describes the double volume cap (DVC) mechanism, and then proceeds to outline the data used within our empirical analysis.

2.1 DVC Mechanism

The possibility that some traders could have an unfair advantage over other market participants when using dark pools is a cause of concern for some policy makers. The DVC mechanism was implemented to limit the dark pool trading in Europe. Traders are allowed to deviate from lit market trading regulations and participate in dark markets under different waivers: 1) the reference price (*RP*)[1], 2) the negotiated price (*NP*)[2], and 3) the large-in-scale (*LIS*)[3] waivers. The DVC mechanism imposes a cap on the amount of dark trading conducted under the RP and NP waivers, but not LIS waivers. This is because the ESMA recognised that allowing dark trading of large orders may reduce price impact and improve market quality.

The DVC mechanism utilises two types of trading suspensions: a venue suspension or a market-wide suspension. A venue suspension is placed on a single trading venue (exchange) for a single stock if dark volume accounts for 4% or more of total (dark plus lit) trading volume for that stock in a 12-month rolling window. A market-wide suspension is given if dark volume accounts for 8% or more of total trading volume across the European Union. If a stock is suspended[4], then traders will be unable to use the RP or NP waiver to trade on dark markets for a period of six months.

Since over 99% of suspensions during our sample period are a result of the market-wide restriction we focus on this type of suspension. Our sample consists of two groups, the treatment group of firms that were subjected to a DVC market-wide suspension during the first year of the regulation (which commenced on 12 March 2018) and the control group of stocks that did not receive a suspension.

A sample timeline is shown in Figure 1. The *"Suspended Period"* represents the 6-month period during which the stocks in the treatment group are unable to be traded in dark pools across Europe under the reference and negotiated price waivers. We also consider six months pre- and post-

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[1] Reference Price waivers are available in dark markets that determine trade price by reference to prices in other markets. The reference price must be widely published and regarded as reliable. Under MiFID II the reference price is the midpoint price.

[2] Negotiated Trade waiver is available to dark markets that formalise negotiated transactions if the transaction takes place at or within the current volume-weighted spread or is subject to conditions other than the current market price of the share.

[3] Large-in-Scale waivers apply when an order is larger than normal market size, with the threshold determined by the stock's average daily turnover.

[4] The list of suspended stocks is published on the ESMA website each month. See: https://www.esma.europa.eu/sections/mifid-ii-transparency-calculations-and-dvc

suspension to capture the effects of the regulatory change. We create a dummy variable, *SUSPENDED*, to indicate whether the stock is banned (1) or not (0) at time *t*.

<Insert Figure 1>

2.2 Sample Selection

We focus on German stocks as they attract the highest proportion of dark volume trading on mainland Europe during our sample period. We apply a set of filters to the universe of German stocks. First, we focus on firms that have their major stock listing on the Frankfurt Stock Exchange (Frankfurter Wertpapierbörse) and so are traded via the Xetra[5] and Börse Frankfurt venues. Second, we remove firms for which we are unable to acquire the accounting and quarterly earnings data required for our study. Finally, we restrict our sample to those firms for which we are able to obtain the necessary dark market data. For this we use the Fidessa Fragmentation Index[6] which provides a weekly measure of the proportion of trading in dark markets and has previously been used in the literature (e.g., Brogaard and Pan, 2022; Johann et al., 2019). We manually search this database by ISIN and firms that are missing from the database, or have 0% dark volume for every period, are discarded from the sample. This leaves a final sample of 52 stocks in the treatment group and 195 in the control group.

2.3 Dark Ratio and Information Acquisition

The dark ratio, $DARK_{i,t}$, is the proportion of total trading volume for each stock, *i*, that takes place on dark markets during each quarter, *t*. As indicated earlier, this data is obtained from the Fidessa Fragmentation database[7].

The jump ratio, $JUMP_{i,t}$, is our proxy for information acquisition. We follow the literature (e.g., Weller, 2018; Brogaard and Pan, 2022) in defining this as the ratio of cumulative abnormal return over

[5] More than 90% of German stock trading takes place via Xetra. See: https://www.xetra.com/xetra-en/trading/market-quality/reference-market

[6] See: https://fragmentation.fidessa.com/

[7] One limitation in using this database is that it is not possible to differentiate between the three types of price waivers (RP, NT, LIS). This is relevant because Anagnostidis et al. (2019) show that average dark pool trade size increases following implementation of the DVC mechanism as more traders seek to use the LIS waiver to continue to trade in dark markets.

trading days [-1, 1] around earnings announcements to the cumulative abnormal returns over trading days [-21, 1]. In other words, the jump ratio is the surprise (news) component of the earnings announcement to the surprise (news) component plus earnings-related information acquired prior to the announcement. We calculate abnormal returns using the market model approach with DAX designated as the benchmark index.

$$JUMP_{i,t} = \frac{CAR_{i,t}^{-1,1}}{CAR_{i,t}^{-21,1}} \qquad (1)$$

The jump ratio provides a measure of information acquisition that occurs prior to earnings announcements, and so captures the pre-emption of earnings news. A smaller jump ratio indicates that more information is acquired, and reflected in the stock price, prior to announcements. Brogaard and Pan (2022) explain that this is because stock prices adjust as investors trade on their acquired information and therefore less new information is revealed during announcements.

In addition, we use a set of control variables to control for other factors that may affect information acquisition. This includes book-to-market ($BM_{i,t}$), size ($SIZE_{i,t}$ = $\text{LnMarketCap}_{i,t}$), and the Amihud (2002) illiquidity measure ($ILLIQ_{i,t}$). We also include the earnings surprise ($EPS\_SURP_{i,t}$ = $\text{Actual\_EPS}_{i,t}$ – $\text{Median\_Analyst\_Forecast}_{i,t}$) and the number of analysts providing EPS estimates ($ANALYST_{i,t}$) since this impacts the dissemination of earnings information (e.g., Utama and Cready, 1997; Ali et al., 2008). Data is accessed from Refinitiv Eikon and DataStream.

Summary statistics, disaggregated into control and treatment groups, are reported in Table 1. Both groups have a positive jump ratio on average, and this is (insignificantly) higher for firms in the treatment group. The statistical similarity of our outcome variable (*JUMP*) between the treatment and control groups is important for the validity of the difference-in-difference (DiD) estimator that we use in later analysis. Firms that receive a DVC suspension (Treatment group) tend to be smaller, growth oriented, more illiquid, and exhibit smaller positive earnings surprises. The dark ratio is significantly higher for those firms who received a DVC suspension (5.6%) than for those in the control group (3.3%). Figure 2 shows that this difference is primarily related to the period prior to the DVC mechanism – while the average dark ratio remains stable for the control group, it falls considerably for the treatment group. This is consistent with the findings of Guagliano et al. (2020) who note that DVC suspensions lead to substantial falls in dark trading.

<Insert Table 1>

<Insert Figure 2>

3. Empirical Analysis

3.1 Dark Trading and Information Acquisition

Our empirical approach proceeds in two stages. First, we clarify whether there is a relationship between dark pool trading and information acquisition prior to earnings announcements using the following panel model:

$$JUMP_{i,t} = \alpha + \beta_D DARK_{i,t} + \gamma_X X_{i,t} + \varepsilon_t \qquad (2)$$

Where $JUMP_{i,t}$ is the jump ratio for firm *i* at time *t*, $DARK_{i,t}$ is the dark ratio, $X_{i,t}$ is the set of control variables that includes *ANALYST*, *BM*, *EPS_SURP*, *ILLIQ*, and *SIZE*, and ε_t is the White standard error. If dark pool trading increases (decreases) the amount of information acquisition, then $DARK_{i,t}$ will be negative (positive) in our estimation, this is because a relatively smaller (larger) jump on the day of the earnings announcement implies information is already (not) impounded into prices.

Table 3 reports the estimated coefficients for equation 2. The first two columns provide estimates for the whole sample. The *DARK* coefficient is significant and negative, demonstrating that information acquisition before earnings announcements increases as the proportion of dark pool trading increases. This result is consistent with Brogaard and Pan (2022) and is economically significant since a 10% increase in dark pool trading is associated with a 3.53% decline in the jump ratio. One possible explanation is that informed traders tend to trade in dark markets ahead of earnings announcements and so more dark trading leads to prices reflecting a greater amount of information prior to the announcement.

The estimated coefficients for the control variables are statistically insignificant but the direction would suggest that larger, value stocks experience greater information acquisition ahead of the earnings announcement, while a larger earnings surprise results in a greater *JUMP*.

The final two columns of Table 2 provide estimates where the sample is disaggregated according to whether the EPS surprise was negative or positive. In both cases, the *DARK* coefficient is negative, but this is only statistically significant for negative surprises. This suggests that information acquired in dark markets is greatest ahead of negative earnings news. This result is somewhat surprising given that prior literature (e.g., Park and Lee, 2014) shows that stock prices tend to increase prior to positive earnings news but do not decline prior to negative earnings news.

<Insert Table 2>

The summary statistics presented in Table 1 illustrate that the firm characteristics of firms receiving a DVC suspension differ from firms that did not (e.g., they are significantly smaller). We investigate whether the firm characteristics affect the influence of dark trading on information acquisition by sorting our sample by size (according to market capitalisation) and value (according to book-to-market). We choose these characteristics because of the significant difference highlighted in Table 1 and because they are related to factors that are shown to explain a significant portion of expected stock returns (Fama and French, 1992).

Table 3 presents the estimated results for information acquisition by firm characteristic. The *DARK* coefficient is only negative, indicating that more dark trading leads to greater information acquisition ahead of earnings announcements, and statistically significant for *SMALL* firms and *VALUE* firms. This is interesting because Table 1 receiving a DVC suspension are typically smaller, so this indicates that dark trading is higher in those stocks (outside of suspension periods), resulting in additional information acquisition. The significant relationship for small and value stocks is consistent with those stocks that are hard to value (Yan and Zhao, 2011) which is partially resolved by informed traders dark trading.

<Insert Table 3>

Since we have some evidence that information acquisition from dark trading is more important for some stocks, we investigate whether other aspects of the information environment have a similar influence on our results. We consider whether information uncertainty around the EPS announcement itself influences our results, with our expectation that information acquisition is more useful when uncertainty is greater. We postulate that lower analyst coverage is consistent with less public information about forthcoming EPS announcements, and that a higher coefficient of variation in EPS estimates is consistent with greater disagreement among analysts - both are factors that contribute to information uncertainty.

We repeat our earlier analysis, disaggregating the sample into firms that have few (*LO*) or many (*HI*) analysts and low or high variation (*CVAR*) in EPS estimates according to whether the respective measure is above or below the median in quarter *t*. Table 4 shows that the estimated *DARK* coefficient is negative and statistically significant in the case of firms with few analysts and high variation in EPS estimates. The *DARK* coefficient is insignificant for firms with many analysts and low disagreement in EPS estimates. In other words, we have evidence in support of our proposition that dark trading has a significant impact on information acquisition when the information environment is more uncertain.

<Insert Table 4>

3.2 Effect of DVC Mechanism

In the second stage of our empirical analysis, we examine whether the dark trading – information acquisition relationship is affected by the imposition of the DVC mechanism which act as an exogenous shock. We use do this using two methods. First, we follow Brogaard and Pan (2022) in adopting a difference-in-difference (DiD) approach by estimating the following regression:

$$JUMP_{i,t} = \alpha + \beta_1 Post_{i,t} \times Treatment_{i,t} + \beta_2 Post_{i,t} + \gamma_X X_{i,t} + \varepsilon_t \qquad (3)$$

Where $JUMP_{i,t}$ is the jump ratio for firm *i* at time *t*, $Treatment_{i,t}$ is a dummy variable that equals one for treatment firms and zero for control firms, $Post_{i,t}$ is a dummy variable that equals one for dates after the implementation of the DVC regulation and zero otherwise. $X_{i,t}$ is the set of control variables that includes *ANALYST*, *BM*, *EPS_SURP*, *ILLIQ*, and *SIZE*, and ε_t is the White standard error.

Second, we repeat our earlier we repeat our earlier analysis separating our sample into the treatment group of stocks who receive a DVC suspension and the control group who do not.

Table 5 reports the estimated results, with column 1 reporting the results using the DiD approach. The interaction term *POST×TREATMENT* captures the change in information acquisition taking place in the EPS preannouncement period for treatment firms relative to control firms. The significant positive sign indicates that the decrease in dark pool trading resulting from DVC suspension results in a smaller pre-emption of upcoming EPS news (lower information acquisition). Columns 2 and 3 show that preannouncement information acquisition disappears for firms in the Treatment group but remains significant for the Control group. Together, this provides evidence that the implementation of DVC regulations, and subsequent suspensions, results in a lower amount of information acquisition prior to earnings news and points to greater market volatility (jumps) on EPS news.

<Insert Table 5>

4. Conclusion

Information acquisition, the method by which new information is obtained, is an important part of the price discovery process. The greater use of dark pool trading in recent years has the potential to reduce transparency and adversely impact price efficiency. In an attempt to address these perceived negative externalities, in 2018, ESMA introduced the DVC mechanism as part of MiFID II.

We consider the importance of dark pool trading for information acquisition prior to quarterly earnings announcements for German stocks. The imposition of the DVC mechanism then provides a natural experiment which allows us to demonstrate robustness of our initial results. Using the price jump ratio to measure pre-announcement information acquisition, we demonstrate that dark pool trading plays an important role. The proportion of dark trading is positively associated with pre-announcement information acquisition, particularly when there is more uncertainty about earnings, when earnings news is negative, and for both small firms and value stocks.

As intended, the introduction of the DVC mechanism significantly reduces the proportion of dark pool trading in stocks that trigger suspensions. In turn, this reduces pre-announcement information acquisition and leads to larger price jumps in response to earnings news. On the one hand, this may be interpreted to show that information leakage is reduced (this may be a goal for regulators). On the other hand, this indicates that prices may not incorporate all available information (i.e., prices are less efficient) ahead of earnings announcements, and market volatility is then higher upon the release of earnings news.

One concern is that traders may have found ways to circumvent the DVC mechanism. There is evidence that the use of LIS waivers (not subject to the DVC mechanism) and trading in quasi-dark markets has increased since the inception of MiFID II. Should more granular information become available, future research could consider the importance of those two factors, in addition to extending the analysis to other European countries to understand the importance of country specific characteristics.

References

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

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets*, 5, 31-56

Anagnostidis, P., G. Papachristou, and C. Varsakelis, 2019, Market quality and dark trading in the post MiFID II era: What have we learned so far? *Economics Letters*, 184, 108630

Barlevy, G., and P. Veronesi, 2000, Information acquisition in financial markets, *Review of Economic Studies*, 67, 79-90

Boulatov, A., and T.J. George, 2013, Hidden and displayed liquidity in securities markets with informed liquidity providers, *Review of Financial Studies*, 26, 2096-2137

Brandes, Y., and I. Domowitz, 2010, Alternative trading systems in Europe: Trading performance by European venues Post-MiFID, *Journal of Trading*, 5, 17-30

Brogaard, J., and J. Pan, 2022, Dark trading and information acquisition, *Review of Financial Studies*, 35, 2625-2666

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

Buti, S., B. Rindi, and I.M. Werner, 2011, Diving into dark pools, *Charles A. Dice Center Working Paper* (2010-10)

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

Degryse, H., F. De Jong, and V. Van Kervel, 2015, The impact of dark and visible fragmentation on market quality, *Review of Finance*, 19, 1587-1622

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

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

Fang, B., O.K. Hope, Z. Huang, and R. Moldovan, 2020, The effects of MiFID II on sell-side analysts, buy-side analysts, and firms, *Review of Accounting Studies*, 25, 855-902

Fleming, M., and G. Nguyen, 2013, Order flow segmentation and the role of dark trading in the price discovery of US treasury securities, *FRBNY Staff Report*, No. 624, 1-56

Foley, S., K. Malinova, and A. Park, 2012, Dark trading on public exchanges, *Working Paper*, Available at SSRN 2182839

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

Garvey, R., T. Huang, and F. Wu, 2016, Why do traders choose dark markets? *Journal of Banking & Finance*, 68, 12-28

Goldstein, I., and L. Yang, 2015, Information diversity and complementarities in trading and information acquisition, *Journal of Finance*, 70, 1723-1765

Grossman, S., 1976, On the efficiency of competitive stock markets where trades have diverse information, *Journal of Finance*, 31, 573-585

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

Guagliano, C., C. Guillaumie, P. Reiche, A. Spolaore, and A. Zanon, 2020, Double Volume Cap mechanism: The impact on EU equity markets, *European Securities and Markets Authority*, 43

Guo, Y., and L. Mota, 2021, Should information be sold separately? Evidence from MiFID II, *Journal of Financial Economics*, 142, 97-126

Hatheway, F., A. Kwan, and H. Zheng, 2017, An empirical analysis of market segmentation on US equity markets, *Journal of Financial and Quantitative Analysis*, 52, 2399-2427

Johann, T., T.J. Putniņš, S. Sagade, and C. Westheide, 2019, Quasi-dark trading: The effects of banning dark pools in a world of many alternatives, *Working Paper*, Available at SSRN 3365994

Kammann, B., J. Prokop, and M. Walting, 2020, Informational effects of MiFID: The case of equity analysts, *European Journal of Finance*, 26, 711-727

Kyle, A.S., 1985, Continuous auctions and insider trading, *Econometrica*, 53, 1315-1335

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

Menkveld, A.J., B.Z. Yueshen, and H. Zhu, 2017, Shades of darkness: A pecking order of trading venues, *Journal of Financial Economics*, 124, 503-534

Nimalendran, M., and S. Ray, 2014, Informational linkages between dark and lit trading venues, *Journal of Financial Markets*, 17, 230-261

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

Park, T.-J., and Y. Lee, 2014, Informed trading before positive vs. negative earnings surprises, *Journal of Banking & Finance*, 49, 228-241

Petrescu, M., and M. Wedow, 2017, Dark pools in European equity markets: emergence, competition and implications, *ECB Occasional Paper*, No. 193

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

Weaver, D.G., 2014, The trade-at rule, internalization, and market quality, *Internalization, and Market Quality* (April 17, 2014)

Weller, B.M., 2018, Does algorithmic trading reduce information acquisition? *Review of Financial Studies*, 31, 2184-2226

Yan, Z., and Y. Zhao, 2011, When two anomalies meet: The post–earnings announcement drift and the value–glamour anomaly, *Financial Analysts Journal*, 67, 46-60

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

Figure 1 - Sample Timeline

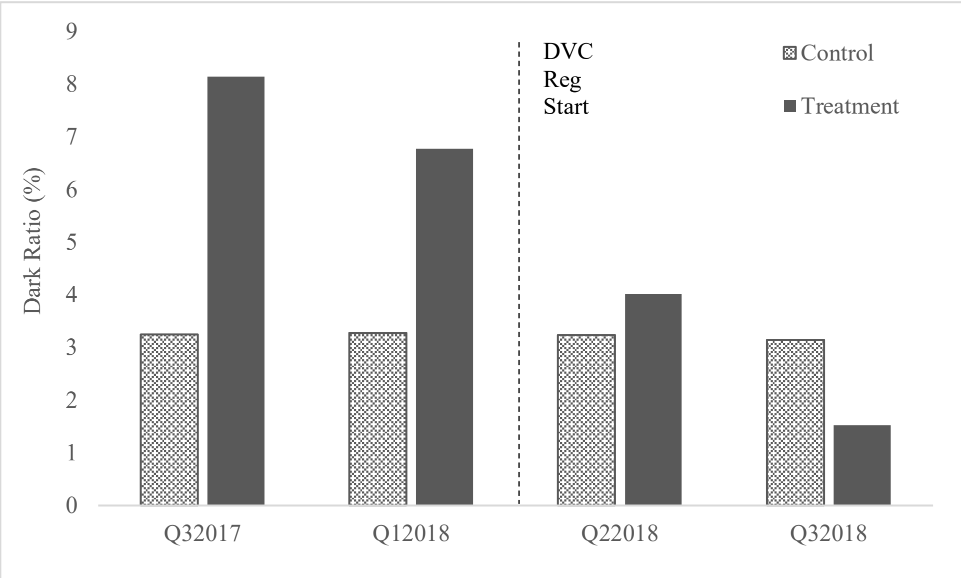

Figure 2 – Average Dark Ratio Pre-/Post-DVC Regulation (Q2 2018)

Table 1: Summary Statistics

This table presents the summary statistics for all the variable used in the regressions. This table disaggregates the sample into the (suspended) treatment group and the (not-suspended) control group. All the variables have quarterly frequency and *t*-tests are used to determine significance of difference in means.

	ALL			TREATMENT		CONTROL			
	N	Mean	Std. Dev.	N	Mean	N	Mean	Diff (*t*-test)	
JUMP	1402	0.26	3.19	309	0.49	1093	0.20	-0.326	
DARK	1402	0.04	3.61	309	0.06	1093	0.03	-10.441	***
EPS_SURP	1402	0.24	5.15	309	0.04	1093	0.30	0.801	
SIZE	1402	6552.36	15529.75	309	5476.67	1093	6838.54	1.374	
BM	1402	0.57	0.45	309	0.49	1093	0.59	3.554	***
ANALYST	1402	10.20	8.60	309	14.70	1093	9.38	-7.557	***
ILLIQ	1402	0.28	0.57	309	0.29	1093	0.25	1.172	

Table 2: Dark Pool Trading and Earnings Announcement Information Acquisition

This table presents the panel regression results that tests information acquisition prior to earnings announcements (Eq(2)). The dependent variable is the jump ratio (*JUMP*), while the key explanatory variable is the dark ratio (*DARK*) which is the proportion of total volume traded in dark markets during quarter *t*. Control variables include EPS surprise (*EPS_SURP*), log of market capitalisation (*SIZE*), the book-to-market ratio (*BM*), the Amihud illiquidity ratio (*ILLIQ*), and the number of analysts monitoring the firm (*ANALYST*). Columns 1 and 2 show estimated coefficients for the whole sample. Columns 3 and 4 disaggregate the sample according to whether the EPS surprises was negative (*NEG*) or positive (*POS*) in quarter *t*. White standard errors are shown in parentheses. *p<0.10, **p<0.05, ***p<0.01

Dependent Variable: $\boldsymbol{JUMP_{i,t}}$	ALL (1)	ALL (2)	NEG EPS SURP (3)	POS EPS SURP (4)
$DARK_{i,t}$	-0.495***	-0.353**	-0.719***	-0.263
	(0.171)	(0.171)	(0.249)	(0.211)
$\lvert EPS\_SURP_{i,t} \rvert$		0.148	0.668	-0.203
		(0.245)	(0.102)	(0.616)
$log(SIZE)_{i,t}$		0.524	1.349	1.517
		(0.545)	(1.538)	(2.264)
$BM_{i,t}$		-0.235	-3.689	-4.483
		(0.238)	(3.390)	(7.097)
$ANALYST_{i,t}$		0.327	0.656	-0.859
		(0.406)	(0.547)	(0.963)
$ILLIQ_{i,t}$		0.784	0.287	0.088
		(1.125)	(0.486)	(4.569)
Constant	0.182	-3.974	-1.619	-9.098
	(0.640)	(3.738)	(1.689)	(14.293)
Firm Fixed Effects	YES	YES	YES	YES
Adjusted R^2	0.016	0.026	0.039	0.003
Observations	1402	1402	648	370

Table 3: Information Acquisition by Firm Characteristic

This table presents the panel regression results that tests information acquisition prior to earnings announcements (Eq(2)). The dependent variable is the jump ratio (*JUMP*), while the key explanatory variable is the dark ratio (*DARK*) which is the proportion of total volume traded in dark markets during quarter *t*. Control variables include EPS surprise (*EPS_SURP*), log of market capitalisation (*SIZE*), the book-to-market ratio (*BM*), the Amihud illiquidity ratio (*ILLIQ*), and the number of analysts monitoring the firm (*ANALYST*). Columns 1 and 2 disaggregate the sample according to firm size (*SMALL, LARGE*). Columns 3 and 4 disaggregate the sample according to whether the firm's book-to-market ratio is in the highest 50% (VALUE) or smallest 50% (GROWTH) in quarter *t*. White standard errors are shown in parentheses. *p<0.10, **p<0.05, ***p<0.01

Dependent Variable: $\boldsymbol{JUMP_{i,t}}$	SMALL (1)	LARGE (2)	VALUE (3)	GROWTH (4)
$DARK_{i,t}$	-0.691**	-0.089	-0.802**	-0.036
	(0.308)	(0.134)	(0.330)	(0.074)
Constant	-4.314	-1.971	-1.469	-5.036
	(5.715)	(2.345)	(1.750)	(7.637)
Controls	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES
Adjusted R^2	0.054	0.016	0.041	0.031
Observations	658	744	689	713

Table 4: Information Acquisition by EPS Estimate Uncertainty

This table presents the panel regression results that tests information acquisition prior to earnings announcements (Eq(2)). The dependent variable is the jump ratio (*JUMP*), while the key explanatory variable is the dark ratio (*DARK*) which is the proportion of total volume traded in dark markets during quarter *t*. Control variables include EPS surprise (*EPS_SURP*), log of market capitalisation (*SIZE*), the book-to-market ratio (*BM*), the Amihud illiquidity ratio (*ILLIQ*), and the number of analysts monitoring the firm (*ANALYST*). Columns 1 and 2 disaggregate the sample according to the number of analysts providing EPS estimates (*LO, HI*). Columns 3 and 4 disaggregate the sample according to whether the coefficient of variation of analyst forecasts (*CVAR*) is below (*LO*) or above (*HI*) the median value in quarter *t*. White standard errors are shown in parentheses. *p<0.10, **p<0.05, ***p<0.01

Dependent Variable: $\boldsymbol{JUMP_{i,t}}$	LO ANALYST (1)	HI ANALYST (2)	LO CVAR (3)	HI CVAR (4)
$DARK_{i,t}$	-0.871**	-0.143	0.016	-0.803**
	(0.338)	(0.164)	(0.088)	(0.384)
Constant	-4.778	-1.928	-1.573	-5.684
	(6.441)	(2.752)	(2.016)	(7.468)
Controls	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES
Adjusted R^2	0.044	0.010	0.017	0.042
Observations	479	498	501	713

Table 5: The Effect of DVC Suspension on Information Acquisition

This table presents the panel regression results that tests information acquisition prior to earnings announcements (Eq(3)). The dependent variable is the jump ratio (*JUMP*), while the key explanatory variables are the dark ratio (*DARK*), which is the proportion of total volume traded in dark markets during quarter *t*, and a dummy variable (*BAN*) indicating whether the stock received a DVC suspension (1) or not (0) during quarter *t*. Control variables include EPS surprise (*EPS_SURP*), log of market capitalisation (*SIZE*), the book-to-market ratio (*BM*), the Amihud illiquidity ratio (*ILLIQ*), and the number of analysts monitoring the firm (*ANALYST*). Column 1 examines the impact of the DVC regulation using a DiD approach, while columns 2 and 3 disaggregate the sample according to Treatment or Control group. White standard errors are shown in parentheses. *p<0.10, **p<0.05, ***p<0.01

Dependent Variable:	ALL	TREATMENT	CONTROL
$\boldsymbol{JUMP_{i,t}}$	(1)	(2)	(3)
$DARK_{i,t}$		0.014	-0.518**
		(0.078)	(0.234)
$POST_t \times TREATMENT_{i,t}$	0.381**		
	(0.174)		
$POST_t$	0.188		
	(2.666)		
Constant	-2.528	-1.683	-4.555
	(2.345)	(1.981)	(4.290)
Controls	YES	YES	YES
Firm Fixed Effects	YES	YES	YES
Adjusted R^2	0.012	-0.028	0.019
Observations	1402	309	1093