Does Dark Trading Alter Liquidity? Evidence from European Regulation

by

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Abstract "Dark" (non pre-trade transparent) trading has been increasingly popular in Europe since 2007 and has raised concerns from regulators about its impact on equity markets' liquidity. MiFID II's Double-Volume-Cap mechanism stipulates than no more than 8% of volumes in any stock can be "dark", at risk of being banned from dark markets for 6 months. With a sample of stocks around that threshold, I use the regulation to identify the causal effect of dark trading on the bid-ask spread. My results show that banning stocks from trading in the dark has narrowed their spread by 10%. I also develop a model of spread determination in a market where a dark venue operates alongside a regular exchange and test empirically its predictions. Finally, I argue that despite a liquidity improvement, the regulation has made the European equity market structure even more fragmented.

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I would be happy to hear any comment or suggestion: please feel free to contact me at my email address: victor.saintjean@sciencespo.fr. All errors are mine.

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Introduction

Until the mid 2000s, most of equity trading in Europe occurred on large, national stock exchanges. Technological and regulatory changes have come to challenge the quasi-monopolistic structure of the industry. Today, stock trading is fragmented in two dimensions: between stock exchanges and other trading venues, and between lit and dark trading venues. Trading in a firm's share now takes place on several venues at the same time, in addition to the stock exchange where the shares are actually listed. Most important among those 'off-exchange' venues are Multilateral-Trading-Facilities (MTFs), self-regulated trading venues which have become very popular in Europe since 2007.

The fragmentation of public markets has coincided with a rise in dark trading. The difference between dark and lit trading lies in the availability of pre-trade information (post-trade disclosure is required for all trading venues in Europe). Dark trading has long been associated with the need for investors to limit their price impact, and to protect themselves from High-Frequency-Traders[1].

Dark pools are MTFs with external price reference: they match buyers and sellers at a price effective on another venue, rather than based on their own order book. On lit venues, the bid (highest price at which one can sell immediately) and ask (lowest price at which one can buy immediately) prices are set such that markets clear despite order imbalances. The difference between the two (the spread) is the cost for immediacy and a common measure of market liquidity. In dark pools, as prices cannot adjust to internal order book, some orders might remain unmatched: as long as there are more buyers than sellers, all buy orders will not be executed. Dark pools offer, in compensation, a price improvement: they generally match buyers and sellers at the mid-point of the reference venue's bid-ask spread[2]. Dark trading represented in December 2017 slightly less than 10% of all trading in Europe[3].

The rapid development of dark trading has raised concerns from regulators around the world (the US Securities and Exchange Commission as well as the European Central Bank have expressed their concern regarding the impact of dark trading

[1] HFTs benefit from higher execution speed to identify senders of large orders, buy the asset before them and sell it immediately at a slightly higher price

[2] ECB, 2017

[3] CBOE Markets data

on price discovery and liquidity, for instance). More specifically, if the absence of pre-trade transparency was supposed to protect investors sending large orders, it does not seem that orders sent to dark pools are significantly larger than orders sent to other MTFs or stock exchanges[4]. In order to investigate the impact of dark trading on liquidity, I develop a model of spread determination in a market where a mid-point dark pool operates alongside a regular stock exchange. Traders with private information about the future value of an asset are more likely to pay the spread on the lit exchange to benefit quickly from their informational advantage, while uninformed traders are more likely to trade in the dark to benefit from price improvement, even if they might have to wait before their order is matched. I show that having relatively more informed orders sent to the lit exchange widens the spread. However, testing empirically that prediction is limited by an endogeneity problem: dark trading can impact liquidity, but bad liquidity also induces a higher share of dark trading (wide spreads mean better price improvement in the dark). Proper identification of the impact of dark trading on liquidity requires to find an exogenous shock to dark trading or a valid instrument.
The introduction of the Double-Volume-Cap mechanism in Europe, as part of MiFID II, offers an ideal natural experiment. The mechanism bans, every month, from trading in dark pools any stock for which the share of dark trading in the last twelve months was higher than 8%. The first wave of bans occurred on the 12th of March 2018, banned 736 stocks, and saw the average level of dark trading in Europe fall by almost one third, literally overnight. The present paper compares the evolution of liquidity, as measured by the quoted bid-ask spread at the close, of stocks around the 8% threshold. Focusing on stocks with dark volumes between 6.5 and 9.5% before and after the implementation of the regulation allows, I argue, for a clean identification of the effect of dark trading on market liquidity. I show that banning stocks from trading in dark pools has narrowed their spread by around 10%. Those results are robust across several specifications and time periods, and are very close to that of Comerton-Forde and Putniņš (2015).

I begin by reviewing the related literature on the bid ask spread as well as on the impact of dark tarding on market quality. Section 2 provides a general background on equity trading regulations in Europe and more particularly on MiFID II. I develop my model in Section 3. Section 4 presents the data I use and my methodology. I present my results in Section 5 as well as a discussion on the evolution of the European equity markets' structure. Section 6 concludes.

[4]OECD, 2016

1.1 Related Literature

1.1.1 The Components of the Bid-Ask Spread

The bid-ask spread is an important indicator of market liquidity, in the sense that it is the price for immediacy of trading. As reviewed in De Jong and Rindi (2009), the market microstructure literature generally divides the spread in two components: inventory costs of the market-dealer and information asymmetry between market participants.
The spread incorporates the operational costs of the trading venue, which must be compensated for its expenses, and also covers the market makers' inventory costs: as they must satisfy the trading needs of both buyers and sellers, they must maintain inventories of risky instruments. Garman (1976) developed the first model addressing the problem of inventory imbalance. In his model, a monopolist market maker sets a bid and a ask prices such that all orders can be filled, bankruptcy is avoided and profits are maximized. Arrivals of buy and sell orders are assumed to follow a Poisson process, but it assumes that the bid and ask prices are set before trading and cannot be adjusted to changing market conditions. Amihud and Mendelson (1980) reformulate the Garman's model such that the bid and ask prices reflect the market maker's inventory. In their model, the bid-ask spread widens as the inventory deviates from its preferred size. Stoll (1978)'s model was the first to introduce risk-aversion, in which the market maker modifies her original portfolio to satisfy orders and introduces the spread to compensate risks. Glosten and Harris (1988) combine both inventory and operational costs in a transitory component, unrelated to the security's intrinsic value. Such models are based on the Walrasian paradigm of market equilibrium, according to which demand is inversely related to prices.

The main implication of the models discussed above is that transaction costs, in the end, determine the bid-ask spread. The origin of information-based models is generally credited to Bagehot (1971), and highlight the role of information asymmetry in the determination of the spread. Such models assume the presence of traders with superior information about the future price of the asset: they buy when the price is too low and sell when it is too high. Therefore, the market-maker always looses when she trades with informed traders. In order to remain solvent, she must be able to offset losses by making gains from uninformed traders. Those gains arise from the spread. The first attempt to formalize that concept is found in Copeland and Galai (1983), in which is developped a one-period model of a market maker's pricing problem given that some traders have superior information. They show that information itself is sufficient to induce market spreads. It is important to note that in that setting, the Walrasian paradigm described above is violated: when the price of a security increases, it signals an interest from other market participants and thus a higher expected future value of the asset. Another difference with models of inventory costs is that market makers are generally assumed to be in perfect competition (they just have to break even) and risk neutral. Glosten and Milgrom (1985) show that the spread increases linearly with the number of informed traders because of adverse selection. In their dynamic model, the clustering of informed traders on one side of the market leads the market maker to eventually learn the information, and the asset's price converges to its expected value given the information. However, a major prediction of the model is that returns are uncorrelated, which certainly contradicts empirical observations. Further developments of the model include Easley and O'hara (1987), in which traders are free to choose the size of their trade, and informed traders face a trade-off between benefiting from their information by sending large orders and trying not to reveal it by sending only small orders. My model developed in Section 3 relies on that second trend of literature.

1.1.2 Competition Between Lit and Dark trading Venues

My study falls into the scope of evaluating the introduction of competition between trading venues on market quality, and more precisely between a regular exchange and a dark pool. Theoretical arguments exist both in favor and against an increased competition.

Hendershott and Mendelson (2000) study the introduction of a Crossing Network functioning like a Dark pool alongside a dealer market such as in Glosten and Milgrom (1985). They show that the impact on liquidity depends on whether there are relatively more informed traders using the Crossing Network (in which case the spread narrows because adverse selection decreases). Similarly, Degryse et al. (2009) show that under certain conditions, the introduction is detrimental to overall traders' welfare. Ye (2011) shows that adding a Dark Pool alongside a dealer market improves the price discovery process. However, the model is based on Kyle (1985), in which the batched auction setup makes the bid-ask spread is irrelevant.
Zhu (2014) develops a two-period model of venue selection, where a dealer market competes with a mid-point Dark pool. The market maker competitively sets the bid-ask spread such that it breaks even in expectation. Zhu shows that informed traders will favor the immediacy of execution in order to benefit from their informational advantage and will cluster on one side of the market on the lit exchange. As predicted by information-based models, the spread widens and uninformed traders will prefer using the dark pool, where they can flee from informed traders and benefit from large price improvement. Ye (2016) extends Zhu's model by introducing a noisy signal about the asset's fundamental value and show that traders mitigate risks by trading in dark pools. The model argues that the quality of information determines the impact of dark pools on market quality. Buti et al. (2017) model a Dark pool alongside a Limit-Order-Book, that is, a venue where traders can choose to be liquidity takers or providers. They find that under most specifications, spreads widen following the introduction of a dark trading venue.

Menkveld et al. (2017) empirically test Zhu's prediction that informed traders favor lit exchanges. They find that, right after a shock to information (earnings announcement, macroeconomic news), the share of dark trading falls in favor of lit exchanges. They also find a significant improvement in spreads due to the fall of dark trading for small stocks. However, Gresse et al. (2011) finds that the proliferation of Dark trading venues in Europe following MiFID did not alter the liquidity on regular markets. Similarly, Hengelbrock and Theissen (2009) study the launch of Turquoise (a trading venue operated by nine major investment banks) in 14 countries simultaneously with an integrated Dark pool, and find no detrimental effect on spreads. Boneva et al. (2016) evaluate the impact of market fragmentation on market quality in the United Kingdom, and find that dark trading does not influence spreads, but does increase the volatility of volatility. Degryse et al. (2015) instrument the level of Dark trading for a stock with the average level of Dark trading in a basket of shares of the same size group, minus the stock of interest. They argue that a change in the liquidity of a share should not be impacted by the overall liquidity of the size group. Comerton-Forde and Putniņš (2015) use a similar instrument and find that Zhu's prediction that dark orders are relatively less informed holds, and that dark trading increases spreads. They find that an increase in dark trading from zero to 10% of total trading volume increases the spread by 11%.

Using a regulation as an exogenous shock to study the impact of Dark trading is not new. Kwan et al. (2015) exploit a difference in regulatory treatment between trading venues in the United States to assess the impact of dark pools on regular exchanges' competitiveness. They document the fact that dark venues become more attractive to traders when the bid-ask spread on lit exchanges worsens. Foley and Putniņš (2016) study the introduction of a new regulation forcing Dark Pools to guarantee a minimum price improvement of one tick size relative to the National Best Bid-Offer (NBBO) in Canada and Australia in 2012 and 2013 respectively, and which led the average level of Dark trading to fall by almost 30%, literally overnight. They use the regulation as an instrument and run a 2SLS regression, while controlling for confounding effects with a set of US stocks. They find a strongly and significant negative relationship between Dark trading and exchange spreads, meaning that Dark Pools benefit market quality. They find that an increase in dark trading of 5% of total dollar volume decreases spreads by around 2%. Finally, Comerton-Forde et al. (2018) study the same rule change and find that reducing the fragmentation of venues improves liquidity.

2

Institutional Setting

2.1 The Fragmentation of Public Equity Markets

Until the mid 2000s, most of equity trading in Europe occurred on large, national stock exchanges. Technological and regulatory changes have come to challenge the quasi-monopolistic structure of the industry. Today, stock trading is fragmented in two dimensions: between stock exchanges and other trading venues, and between lit and dark trading venues. The *Markets in Financial Instruments Directive* (MiFID) came into force in 2007 and introduced a market structure framework which facilitated the emergence of dark pools. Its goal was to increase the competitiveness of European financial markets and to harmonise pre and post trade requirements for equity trades. MiFID liberalised the market for trading and led to the creation of many new venues. Before MiFID, the *Investment Services Directive* allowed for a "concentration rule", where all equity trading had to occur on national exchanges. MiFID introduced new categories of trading venues, with different levels of regulation and rights. More specifically, it established rules under which Multilateral Trading Facilities, self-regulated trading venues, could be registered and operate. With the removal of barriers to competition, the market for equity trading became significantly more fragmented: the share of equities trading on MTFs in Europe increased from 0% in 2008 to almost 20% by 2011 (Fioravanti and Gentile (2011)). While most MTFs are lit trading venues, dark pools also emerged after MiFID.

Further regulatory changes strengthened the demand for for dark venues. MiFID made it mandatory for trading venues to display bid and offer prices and depth of the order book (volumes available for trading at different prices) on a continuous basis. Such pre-trade transparency disclosure increased the probability for senders of large orders to be detected by predatory traders. In order to protect investors from 'front-running', MiFID provided exemptions from pre-trade transparency in four cases, including for senders of very large orders. It also provided venue-wide exemptions for venues that do not match trades based on their own order books, but instead match orders at a price "determined in accordance with a reference price generated by another system, where that reference price is widely published"[1]. Most dark pools in Europe rely on this exemption in order to allow their clients to trade without pre-trade transparency, and match volumes using the displayed best bid-ask prices from one or more regulated markets. Dark pools also offer price improvements over market orders on lit venues because the execution price is usually the mid-point of the current bid-ask spread on an external venue (Petrescu and Wedow (2017)). Consequently, there is no market impact cost, as the price is unrelated to volumes traded. This mechanism insures a price improvement over lit exchanges as no trading counterparty has to pay the full spread. Ready (2014) documents that dark pools attract a lower share of trades in stock with lower spreads, as the gains from trading at the midpoint might not be as high. However, dark pools do not have as much liquidity as lit venues and thus once an order is sent, the time for a matching order to arrive is longer, leading to slower execution speeds (Vaananen (2014)). The aggregate impact of dark pools on market functioning is the subject of a debate among regulatory authorities. Fragmentation between dark and lit venues results in changes to market structure and dynamics. The International Organization of Securities Commissions identified two channels through which dark trading could be detrimental to market quality: liquidity and price formation. The trade-off between speed of execution and price improvement makes dark pools more attractive to uninformed traders, and the clustering of informed orders on lit market, more likely to be on the same side, could alter liquidity. By attracting volumes away from lit to dark markets, where trades do not contribute to price formation, could also alter the proper pricing of equity instruments. Those fears have fueled the work of European legislators over MiFID II.

2.2 From MiFID to MiFID II

MiFID II, which replaces MiFID, was adopted by the European Council in May 2014 and put into application since January 2018, aimed at "taking into account the exceptional technical challenges faced by regulators and market participants"[2]. MiFID had defined four types of exemptions, for which trading does not require pre-trade transparency:
- Large in Scale transaction (large orders),
- Transactions based on a reference price generated by another system,
- Negotiated transactions,
- Orders held in an order management facility of the trading venue.

MiFID II maintains those exemptions but introduces certain restrictions. More specifically, the "Double-Volume-Cap" mechanism[3] limits the use of the reference-price exemption. It states that, based on a 12-month rolling calculation:
1) the dark volume for a particular instrument should not exceed 8% of the total

[1] Commission Regulation No 1287/2006, Article 18
[2] European Commission, 2016
[3] Article 5, *Markets in Financial Instruments Regulation* (MiFIR)

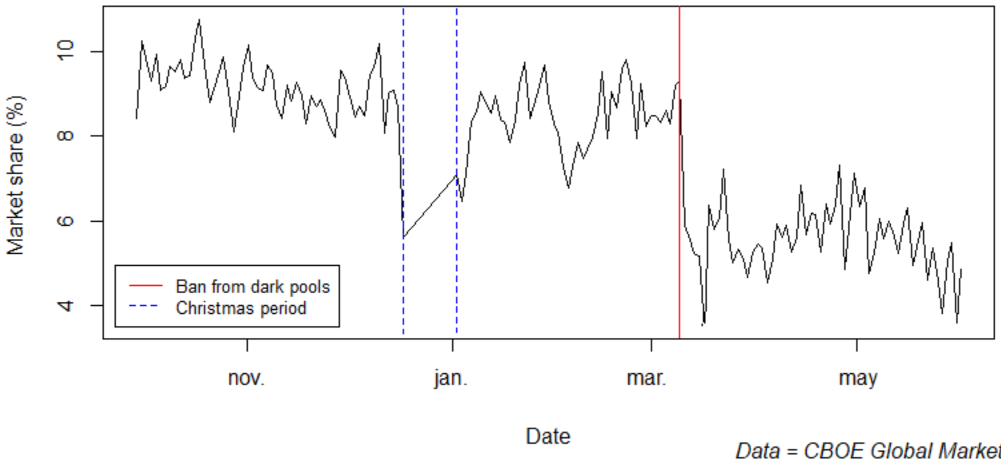

Figure 2.1: The Evolution of Dark Pools' Market Share in Europe Between September 2017 and May 2018

The figure displays the daily market share of dark pools in Europe, measured as the percentage of total notional volume traded across Europe that has been traded in dark pools. The red line shows the first wave of bans from dark pools (12th of March), and the blue dotted lines delimits the winter holidays period (from the 22nd of December 2017 to the 2nd of January 2018). The period covered spans from the 1st of October 2017 to the 1st of June 2018.

trading volume in the European Union, and
2) the share of trading in one dark venue for a particular instrument should not exceed 4% of all trading in the EU.
If MiFID II, as a whole, was implemented on the 3rd of January 2018, the implementation of the DVC mechanism was delayed because the regulator lacked the proper data[4]. From the 12th of March 2018, every month, the dark volume over the last 12 months of every share traded in the EU is calculated, and if more than 4% of total volume for a stock has been in one dark pool, the share cannot be traded in that dark pool for six months; and if more than 8% of total volume for a stock has been in all dark pools combined, it is banned from all dark venues for 6 months.
From the 26,037 securities under the ESMA's jurisdiction, 1349 have been suspended as of October 2018 (5% of all securities), 736 of which on the 12th of March 2018.
The impact of MiFID II on Dark Pools has been substantial. Figure 2.1 shows the market share of Dark Pools in Europe from the 12th of January 2018 to the 12th of May 2018. The data was downloaded from the *Chicago Board of Options Exchange* (CBOE). The average daily market share of Dark Pools in European markets fell from 8.45% before the first wave of bans to 5.7% after the ban. Dark Pools have lost about one third of their market share, literally overnight.

[4]ESMA press release: "ESMA delays publication of Double-Volume-Cap data", 9th of January 2018

3

A Model of Spread Determination With a Dark Pool

Why can one expect dark trading to impact liquidity? Here, I develop a model based on Zhu (2014). The latter model relies on less strong assumptions and allows for the analysis of price discovery, but lacks clarity when it comes to determining how liquidity on a lit exchange can be altered by the introduction of a mid-point dark pool.

3.1 Assumptions

There is one trading period. At the end of the period, an asset pays an uncertain dividend equally likely to be σ or $-\sigma$, and is publicly revealed at the end of the trading period.

Two trading venues operate simultaneously: a lit exchange and a dark pool. On the exchange, a risk-neutral market-maker sets a bid-ask spread such that she breaks even on average. Sell orders are executed at the bid and buy orders are executed at the ask. The spread is symmetric around zero: the ask price is S and the bid price is $-S$. The dark pool matches buyers and sellers at the mid-point of the lit exchange's bid-ask. Such dark pool falls into the scope of dark trading activities regulated under MiFID II's Double-Volume-Cap mechanism studied in this paper (the so-called *reference price exemption*). An order submitted to the dark pool contains no price information, and is invisible to anyone but the sender. Orders on the heavier side of the market are randomly matched with orders on the lighter side of the market. That is, when there are more buyers than sellers, buyers are not guaranteed to see their order executed, while sellers are sure to trade.

There are two types of traders: informed and non-informed (*liquidity*) traders. Informed traders benefit from preferential information about the value of the dividend and know for sure whether it is going to be σ or $-\sigma$. In case of the realization of σ, all informed traders are buyers (and sellers in case of $-\sigma$). Informed traders constitute a fraction α of the total mass of traders (the total mass of traders is normalized to one). Liquidity traders (fraction $1 - \alpha$) assign equal probability to

the two possible outcomes of the dividend. Liquidity buyers and liquidity sellers represent each half of the mass of liquidity traders.
Liquidity traders act as brokers: they trade on behalf of a client and receive a fee c_iS if they trade on the exchange[1]. c_i is expressed as a fraction (which can be greater than 1) of the spread, S, and is randomly distributed following a Cumulative Distribution Function $G : [0, \Gamma] \to [0, 1]$, with $\Gamma \in]0, \infty)$. The fee is positively related to the spread as one can suppose that a low spread means that a stock is more often/easily traded. If, however, liquidity traders decide to trade (successfully) in the dark pool, they can pocket the spread[2].
Traders arrive separately, can trade only one unit of the asset and must choose to which venue to send their order. Both exchanges do not require any trading fee, and no type of traders is incurred any delay cost if they fail to trade.

3.2 Equilibrium

We define β as the share of informed traders who choose to trade in the dark, and γ as the share of liquidity traders who choose to trade in the dark.

3.2.1 Equilibrium Spread Without a Dark Pool

I first derive the spread when both β and γ are equal to 0, that is, the no-dark pool equilibrium. The lit exchange's market-maker must break even on average, and thus will choose the spread, S_{NoDark}, such that

$$0 = -\alpha(\sigma - S_{NoDark}) + (1 - \alpha)S_{NoDark}$$

The equilibrium value of S_{NoDark} is

$$S_{NoDark} = \alpha\sigma. \tag{3.1}$$

The spread is equal to the market maker's expected loss: the dividend times the number of informed trader. Indeed, the market-maker, in expectations, looses only money to informed traders. In the case where all traders are uninformed, there would be no spread[3].

3.2.2 Equilibrium With a Dark Pool

In the case where a dark pool is operating, alongside the lit exchange, the risk-neutral market-marker sets the spread, S, such that

$$0 = -\alpha(1 - \beta)(\sigma - S) + (1 - \alpha)(1 - \gamma)S,$$

[1] The value of c_i is pinned-down later on.
[2] One interpretation here is to say that if they successfully buy an asset in a dark pool, liquidity traders can be tempted to act as market makers and sell the asset with the spread
[3] Consistently with information-based models of the bid-ask spread. See Section 1

rearranging,

$$S = \frac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)(1-\gamma)}\sigma < \sigma. \tag{3.2}$$

Which is similar to Zhu (2014).

I now turn to the dark pool. From now on and for simplicity, I assume that the realization of the dividend is σ (one can show that all equations are symmetric in the case $-\sigma$ is realized). Informed traders face a crossing probability in the dark

$$r^- = \frac{\frac{1}{2}(1-\alpha)\gamma}{\frac{1}{2}(1-\alpha)\gamma + \alpha\beta}. \tag{3.3}$$

r^- is indeed the ratio of sellers in the dark (half of the liquidity traders in the dark) and buyers (half of the liquidity traders in the dark and the informed buyers in the dark). Liquidity traders, on the other hand, don't know on which side of the market they are. In case they are in a different side of the market than informed traders, their probability of crossing is 1 ($r^+ = 1$). As they assign an equal probability to both events, I define

$$\bar{r} = \frac{1+r^-}{2} \tag{3.4}$$

as a liquidity trader's expected probability of trading in the dark.

I now turn to the equilibrium trading strategies. Informed traders have the following expected payoffs:

$$E^I[\pi]_{Exchange} = \sigma - S,$$

and

$$E^I[\pi]_{Dark} = r^-\sigma.$$

Liquidity traders have the following expected payoffs:

$$E^L[\pi]_{Exchange} = c_i S,$$

and

$$E^L[\pi]_{Dark} = \bar{r}S$$

Thus, γ is the proportion of liquidity traders with a fee c_i too low (or a crossing probability too high) to be incentivized to trade on the exchange,

$$\gamma = G(\bar{r}).$$

In equilibrium, β must be such that informed traders are indifferent between the two venues, that is

$$\sigma - S = r^-\sigma,$$

and the equation can be rewritten as

$$1-\frac{S}{\sigma}=r^{-}. \tag{3.5}$$

Replacing S and r^{-} by their equilibrium value, and solving for β as a function of γ gives us

$$\beta=\frac{\gamma}{2-\gamma}. \tag{3.6}$$

Proof: see Appendix A.0.2

Outside investor's objective function and the determination of c_i:
Liquidity traders trade on behalf of a client, who pays them a fee c_iS is the trade occurs on the lit exchange, and S if it occurs in the dark [4]. Liquidity traders choose c_iS so as to make the outside investor indifferent between the two venues. If they don't hold the asset at the end of the period, they have to incur a cost η_i depending on each investor's characteristics (with $\eta_i>0$). Thus her indifference condition is

$$-S-c_iS=\frac{1}{2}(-\sigma-S)+\frac{1}{2}(r^{-}\sigma-r^{-}S-(1-r^{-})\eta_i),$$

rearranging,

$$c_iS=\frac{(1-r^{-})(\sigma-S+\eta_i)}{2} \tag{3.7}$$

Thus, c_iS depends positively on the probability of not crossing, the value of the asset (opportunity cost of trading in the dark) and each investor's specific delay cost. One can easily see that the expression ensures a positive c_i, as $\eta_i>S-\sigma$ is always true.
In equilibrium, the trader indifferent between the two venues will be the one working for the outside investor with a delay cost

$$\eta_i=\frac{2S}{1-r^{-}}-\sigma.$$

Replacing with r^{-}'s equilibrium value:

$$\eta_i=\sigma.$$

Equilibrium: There exists a unique equilibrium (proof in the Appendix A.0.1) such that $\beta>0$ and $\gamma>0$ and S satisfies

$$S=\frac{\alpha\left(1-\frac{G(1-\frac{S}{2\sigma})}{2-G(1-\frac{S}{2\sigma})}\right)}{\alpha\left(1-\frac{G(1-\frac{S}{2\sigma})}{2-G(1-\frac{S}{2\sigma})}\right)+(1-\alpha)(1-G(1-\frac{S}{2\sigma}))}\sigma,$$

[4] We assume perfect competition between liquidity traders, see footnote 2 on page 16

simplifying,

$$S = \frac{2\alpha\sigma}{2\alpha + (1-\alpha)(2 - G(1 - \frac{S}{2\sigma}))}. \tag{3.8}$$

Then we can define

$$r^{-} = 1 - \frac{S}{\sigma}, \tag{3.9}$$

$$\bar{r} = 1 - \frac{S}{2\sigma}, \tag{3.10}$$

$$\gamma = G(1 - \frac{S}{2\sigma}), \tag{3.11}$$

$$\beta = \frac{\gamma}{2-\gamma}. \tag{3.12}$$

3.3 The Impact of Dark Pools on the Bid-Ask Spread

We now turn to the question: does adding a dark pool increase necessarily the bid-ask spread? One caveat of Zhu (2014) was that answering that question required to make strong assumptions about the curvature of the cost function of liquidity traders.
Here, as shown earlier, we have that

$$\beta < \gamma,$$

for all values of the parameters σ, α.
It is easy to show (proof: A.0.3) that it is enough to ensure that

$$S > \alpha\sigma = S_{NoDark}.$$

That is, adding a dark pool strictly increases the exchange spread. The mechanism can be described as follows: the dark pool attracts more liquidity traders, because they do not care about delays and want to maximize their profits and their expected crossing probability in the dark is higher than that of informed traders. On the other hand, informed traders want to benefit from their preferential information about the future value of the dividend and wish to make sure to trade before the end of the period. Moreover, they know that they are on the heavier side of the market and that their expected crossing probability is low in the dark. Thus, the market-maker is forced to deal with relatively more informed traders than in the case with no dark pool, and is forced to increase her spread to break even. I derive the main prediction of the model:

> **Prediction:** *Banning stocks from trading in dark pools narrows their bid-ask spread.*

If we ban the asset from being traded in the dark pool, its spread narrows by

$$\sigma \frac{G(1-\frac{S}{2\sigma})\alpha(1-\alpha)}{2-G(1-\frac{S}{2\sigma})+G(1-\frac{S}{2\sigma})\alpha}, \tag{3.13}$$

which is increasing in $G(.)$, that is, increasing in γ and β. The relationship between the difference in spread and the asset's volatility is hard to predict, but can be expected to be positive, as in Zhu (2014).

Some papers provide an empirical justification to the mechanism highlighted in the model, by showing that orders sent to lit venues are relatively more informed than orders sent to dark venues. By studying the impact of dark trading on price discovery, Comerton-Forde and Putniņš (2015) document that as more orders for a stock are sent to dark venues, their contribution to price discovery increases at a slower rate than their volume share, indicating that dark trades on average contain less private information than lit trades. Menkveld et al. (2017) study the changes in market share between different types of trading venues right after macroeconomic news, unexpected company announcement and spikes in volatility, and show that these factors, that can be regarded as shock to information, make the share of lit trading jump, at the expense of dark venues.

4

Data and Empirical Approach

4.1 Sample

My sample comprises 309 shares, 173 banned from dark pools on the 12th of March 2018, and 136 not banned from dark trading until at least June 2018. I delete observations with extreme values of spreads (2.5% trimming). My sample period extends from September the 29th, 2017 to June the 1st, 2018. I withdraw observations for the period spanning from the 18th of December 2017 to the 2nd of January 2018 (period of Winter holidays), as well as the 1st of May 2018 (holiday in several European countries), marked by abnormally low volumes. I am left with data from 158 trading days for 309 securities.
I obtained daily data from Reuters Datastream on shares' daily closing, daily high and low prices, as well as their closing bid and ask prices, their market capitalization and turnover by volume. The use of daily data is a limitation to my measure of market liquidity (as explained further below), but allows to ignore many financial markets empiricists' challenges when it comes to use order-level data, such as the identification of trade types, their inaccuracies and differences in reporting, as the European Union does not have a centralized and standardized platform of data reporting[1].

4.1.1 Calculation of the Spread

In practice, academics and financial markets professional rely on a variety of measures of a market's liquidity. Those include the order book's depth or the price impact of trades, which require access to order-book level data. Since I do not have access to such data, I follow Boneva et al. (2016), who also use daily data at the close of the London Stock Exchange, in calculating the bid ask spread as follows, for a stock i at the date t:

$$Spread_{i,t} = \frac{Ask_{i,t} - Bid_{i,t}}{\frac{1}{2}(Ask_{i,t} + Bid_{i,t})} \tag{4.1}$$

[1]MiFIR, EMIR and other European regulations aim at standardizing and harmonizing data reporting rule in the Union. For a discussion on the subject, see Petrenko (2016)

Where the denominator is the midpoint, and will be expressed in basis points. Mizen (2010) argues that trends in quoted bid-ask spreads calculated this way are similar to trends in effective bid-ask spreads (spreads actually paid by traders during the trading day).

4.1.2 Calculation of Volatility

Roll (1984) describes a relationship between the bid ask spread and intraday covariance of stock prices, in which volatility arises from the alternation of trades at the bid and ask prices. Thus, using the intraday movements of prices as a measure of volatility can suffer from a reverse causality issue when regressing the spread on volatility. Using the price range allows to ignore the effect of the bid ask spread on volatility: I compute each stock's daily volatility by using daily high and low prices, as in Hendershott et al. (2011). Parkinson (1980) was the first to propose the following measure of volatility, referred to as the *price range*:

$$\frac{P_{i,t}^{high} - P_{i,t}^{low}}{P_{i,t}^{close}} \tag{4.2}$$

Where $P_{i,t}^{high}$ and $P_{i,t}^{low}$ are respectively the highest price at which a trade for stock i occurred during the trading day t, and the lowest price at which a trade occurred for the same security. $P_{i,t}^{close}$ is the closing price of stock i on trading day t.
It has been shown that this estimator is robust to microstructure noise (Alizadeh et al. (2002)).

4.1.3 Choice of Controls

I use two sets of controls. First, I follow Boneva et al. (2016), Bessembinder (2003), Madhavan (2000) and Stoll (2000) by creating a set of controls comprised of Eurostoxx 50's return Index, Eurostoxx 50's volatility Index (options-based) and the log of each firm's market capitalization. In a second set of controls, as in Hendershott et al. (2011), I use the above measure of volatility, the inverse of the share price and the Turnover by Volume (measured by the number of shares traded on a single day). Finally, I will in some specifications control for firms' country of origin (country where the instrument was issued) and industry. Controlling for the volume might encounter an endogeneity issue and bias the estimate downwards, as low spreads can induce traders to send larger orders to benefit from advantageous liquidity. I use it in order to grasp the general relationship between the two, and find a very low coefficient, which suggests that the endogeneity is not too big a problem. I use a fixed measure of market capitalization as of the 29th of September 2017, because otherwise it would be perfectly correlated with the stock price, as the latter is adjusted for the number of shares by Datastream.

Table 4.1: Summary Statistics: Main Variables and Controls

Statistic	Mean	S.D.	Min	Pctl(25)	Pctl(75)	Max
Market cap (mln €)	8,716	17,448	10	1,317	8,601	193,012
Spread (bps)	21.6	21.9	0.1	6.6	29.2	143
Volume in Dark (%)	7.92	0.89	6.5	7.15	8.69	9.49
Price range (%)	2.11	1.54	0.001	1.21	2.58	76.76
Volume (shares traded, thousands)	2,172	9,145	0.1	67.4	1,115	331,223
Share price (€)	334.7	1,054	0.546	14.14	86.3	9,115

The table reports summary sample statistics for the sample data downloaded from Reuters Datastream, which covers stocks' characteristics over the period from September 29th 2017 to 1st of June 2018. $Marketcap$ is the market capitalization in millions of euros as of the 29th of September 2017, *Spread* is the daily quoted bid-ask spread at the close measured in basis points, *Volume in Dark* is the share of dark volume from February 2017 to March 2018, measured in percentage of total volume (notional), *Price range* is the daily difference between the highest and lowest prices of the trading session for a given stock, measured as a percentage of the closing price, $Volume$ is the daily number of shares traded during the trading session and *Shareprice* is, in euros, the daily price at the close. Details for the calculation for the *Spread* and *Price range* are given in the main text.

Table 4.2: Summary Statistics by Group

	Before Regulation		*After Regulation*	
Variable (mean)	Banned	Not Banned	Banned	Not Banned
Market cap (mln€)	10,147	6,966	10,147	6,966
log(Market cap)	22.12	21.61	22.12	21.61
Spread (bps)	16.83	27.6	16.5	28.3
Volume (number of shares)	2,917	1,012	3,223	1,076

The table reports a comparison between my two groups: the stocks banned from dark pools after the 12th of March and stocks not banned. I report the mean of each variable by group and by period: before the 12th of March 2018 and after. *Market cap* is in millions of euros and is as of the 29th of September 2017, and *log(Market cap)* is the log of the market capitalization. *Spread* is the quoted spread at the close, and is expressed in basis points. *Volume* is the daily number of shares traded.

4.2 Descriptive Statistics

My sample covers securities from 16 European countries and 10 industries. Some professionals[2] had highlighted the fact that the Double-Volume-Cap mechanism would hit more severely Northern-European countries, where Dark Pools are more popular, but my two groups appear relatively balanced across countries and industries (see Table B.1 and Table B.2). Among the 309 shares, 173 have been banned from trading on the 12th of March, 2018 and 136 have not been banned from dark

[2] See, for example, Bank of America Merrill Lynch Global Research, 2018

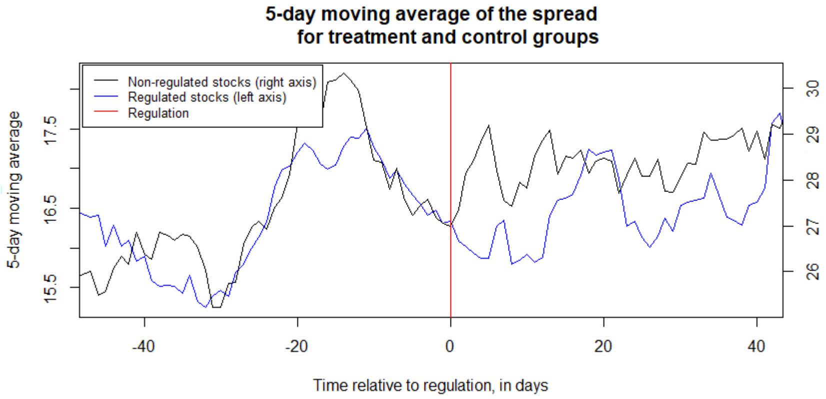

Figure 4.1: 5-Day Moving Average of the Spread for my Control and Treatment Groups
The figure displays a 5-day moving average of the quoted spread at the close for the group of stocks banned from dark dark after the 12th of March 2018 (in blue) and for the stocks not banned during the entire period (black), from the 3rd of January 2018 to the 1st of June 2018.

pools during the whole sample period. Figure 4.1 shows the evolution the spread for the two groups, before and after the regulation. It is a 5-day backward-looking moving average around the 12th of March. The first thing we notice is the difference in average spread between the two groups (16.83 bps and 27.6 bps), which can be explained by the higher market capitalization of stocks banned from dark pools relative to the others (10 billion euros and 7 billion euros, respectively) as well as higher average trading volume before the ban (2,917 shares per day and 1,012 shares per day respectively). However, while their trends look similar before the regulation, an irregularity appears on the 12th of March. Table 4.2 reports summary statistics by group (banned or not banned) before and after the regulation. It shows a decrease in average spread between the two periods for stocks banned from dark pools (by around 2%) and an increase for stocks not banned from dark pools (by more than 4%). Figure 4.2 shows a comparison between their change in spread before and after the regulation, with a kernel density estimation of their distribution. The median change for the stocks banned from dark pool has been a decrease in 4% in average spread between the two periods, while the median change in spread for the control group is an increase of 0.6%. Those statistics, altogether with Figures 4.1 and 4.2 point at a positive impact on spreads of the ban.

4.3 Identification Strategy

When studying the impact of dark trading on liquidity, an obvious challenge is endogeneity: bad market liquidity can induce traders to send their orders to a dark pool, where they might find alternative liquidity and a price improvement, especially when the exchange's spread is high (Ready (2014)). With the Double-Volume-Cap mechanism, the threshold of 8% offers a sharp non-linearity in the treatment of dark trading, and by selecting a sample with a level of dark trading

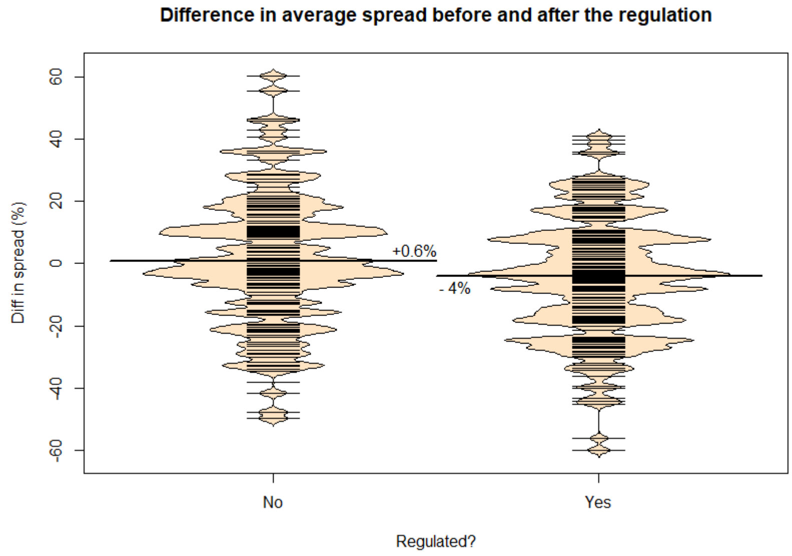

Figure 4.2: The Change in Average Spread Before and After the Ban

The figure displays the distribution of stocks by their change in average spread before and after the regulation and by group. The figure displays a kernel estimation (using an Epanechnikov function) of the probability density function of the change by group. The figure highlights the median change in each group. The period before the ban spans from the 29th of September 2017 to the 11th of March 2018, and the period after the ban spans from the 12th of March 2018 to the 1st of June 2018.

around that threshold allows for a fair comparison between the two groups. I argue that, for a stock, having a dark share of 7.9% or 8.1% is largely random, for at least two reasons. First of all, it is not in any trader's interest to change her trading strategy in order to limit/increase the share of dark trading for a stock. Secondly, it would also imply that traders have a good estimation of the dark volume for a stock. However, having a fair estimation of such volume is very complex, given the fragmentation of the market and the blurry definition of dark trading. One can imagine that only a regulatory authority with access to data from all trading venues can fairly estimate a stock's dark trading volume[3]. Moreover, the treatment is a very clean shock to dark trading. Former studies of dark pool regulation required a two-stage estimation, with a first stage estimating the impact of a regulation on dark trading. Here, banning stocks from trading in all dark pools, overnight, allows us to directly estimate the impact of dark trading on liquidity. Finally, the delay in the implementation of the DVC mechanism compared to other measures implied by MiFID II allows to get rid of confounding effects due to other new rules. Limits to the identification strategy are discussed in Section 5.

[3]Even the ESMA had to delay the ban because it lacked the proper data

4.4 Main Specification

I use an unbalanced panel data to regress the spread of each stock on a dummy equal to one for stocks banned from dark pools after the 12th of March, and equal to 0 for all other observations. I use firm and time (day) fixed effects. I cluster the standard errors at the firm level, consistently with most empirical studies (Boneva et al. (2016), Hendershott et al. (2011)), and estimate

$$Spread_{i,t} = \alpha_i + \delta_t + \beta(Dark > 8\% * Post\_Ban)_{i,t} + \gamma x'_{i,t} + \epsilon_{i,t}. \tag{4.3}$$

For each stock i and each day t for the entire period. $Dark > 8\%$ is a dummy equal to one if the share of dark trading for the stock was higher than 8% (that is, subject to the ban) and $Post\_Ban$ is equal to one after the 12th of March 2018 (that is, the period of ban from dark pools). α_i is the individual (firm) effect, δ_t is the time (day) effect, and $x'_{i,t}$ is a vector of controls (inverse of share price, volume, volatility), variable across time. This model allows to eliminate bias from unobservable factors that change over time but are constant over entities and it controls for factors that differ across entities but are constant over time. The use of firm fixed effect allows me to take into account the differences between the two groups and to correctly estimate the impact of the ban on quoted spreads. β is the coefficient of interest, and we expect it to be negative. The clustering of standard errors allows to take into account potential heteroskedasdicity and correlation between the error term across time.

4.5 Alternative Specification

A panel data analysis using fixed effects seems to be the best approach here. However, it does not allow to estimate the relationship between the bid-ask spread and some firm-specific characteristics (fixed across time) and markets conditions (day-specific). However, I argue that this approach is valid as I focus on stocks with similar level of dark trading, even if it requires the addition of controls to identify correctly the effect of the ban. If the estimate will be less precise than a regression with fixed effects, using a difference-in-differences framework allows to estimate the importance of the controls described above.

I first run the following difference-in-differences regression:

$$\begin{split} Spread_{i,t} = \theta + \mu Dark > 8\%_i + \eta Post\_Ban_t + \\ \beta(Dark > 8\%_i * Post\_Ban)_{i,t} + x'_{i,t}\Gamma + \epsilon_{i,t} \end{split} \tag{4.4}$$

Where θ is the intercept, μ measures the differences between the two groups, η measures the differences between the two time periods and β evaluates the impact of dark trading on liquidity. $Dark > 8\%_i$ is a dummy equal to one if the stock had a share of dark trading greater than 8% as of the 12th of March (that is, subject to the ban) and $Post\_Ban_t$ is a dummy equal to one after the 12th of March and 0

before.
I then run the same regression with two sets of controls, in vector form $x'_{i,t}$: first as in Boneva et al. (2016) to account for general market conditions (Stoxx 50 return index, Stoxx 50 volatility index) and the log of each firm's market capitalization. I then add the same controls as in the previous specification: the inverse of the share price, volume and volatility. Those specifications will shed a light on the impact of general market conditions on stocks' liquidity.
The results are presented in the next section.

5

Results

5.1 The Impact of Dark Trading on Liquidity

Table 5.1 reports the impact of banning stocks from trading in dark pools on their quoted bid-ask spread. Regression (1) reports the estimates for the simple panel data analysis, equation 4.3. Consistent with the prediction from Section 3 and the notion that a larger share of uninformed trades will execute in the dark, my results indicate that the spread becomes narrower as a stock is forced to be traded away from dark venues. The impact of dark trading on spreads in the lit market is negative across all my specifications and statistically significant across most of my regression specifications. The magnitude of the increase in quoted spreads is also economically significant. I report a decrease in spreads of 1.637 basis points for stocks banned from dark pool. Another way to understand that number is to say that the results imply, given my assumptions, that a fall in dark trading from 8.5% to zero narrows the quoted bid-ask spread by 10%. This figure is consistent with Comerton-Forde and Putniņš (2015) who find that increasing dark trading from zero to 10% of dollar volume is expected to increase quoted spreads by 11% after controlling for other factors. It contrasts, however, with Foley and Putniņš (2016), who find that an increase in 5% of dark volume narrows the spread by around 2%.

5.2 Robustness Checks

Different Time Periods

I run alternatively the above regression for three time periods:
- The whole period, from September 2017 to June 2018,
- From the 3rd of January to June 2018,
- From the 2nd of March to the 22nd of March 2018.

Comparing the coefficients between the three regressions allows to identify the potential differences between long-term and short-term effect of the regulation. The results are robust, both in sign and magnitudes, across all time periods (see Table 5.2). They range from -1.158 bps to -1.637 bps, which in percentage terms means a narrowing of quoted spread by between 7% and 10%. The fact that the coefficient

Table 5.1: Panel Data Estimates

	Dependent variable:	
	Spread	
	(1)	(2)
Dark>8%*Post_Ban	-1.637^{***}	-1.534^{***}
	(0.252)	(0.252)
Volatility		39.863^{***}
		(4.621)
Volume		-0.0001^{***}
		(0.00001)
ISP		8.863^{**}
		(3.857)
Firm Fixed effect	Yes	Yes
Day Fixed Effect	Yes	Yes
Observations	46,769	46,259
R^2	0.001	0.003
Adjusted R^2	−0.009	−0.007
F Statistic	42.363^{***} (df = 1; 46302)	31.819^{***} (df = 4; 45789)
Note:		*p<0.1; **p<0.05; ***p<0.01

This table reports regression estimates using a stock-day panel in which the dependent variable is the quoted spread at the close. The key independent variable is a dummy equal to 1 for stocks banned from dark pools. Controls: $Volatility$ is measured by the price range as a percentage of closing price, $Volume$ is the daily turnover by volume measured by the number of shares traded; ISP is the inverse of the closing share price. R^2 excludes the variance explained by the fixed effects. Standard errors are clustered by stocks and standard errors are reported in parentheses. The period considered spans from the 29th of September 2017 to the 1st of June 2018.

Table 5.2: Panel Data Estimates by Time Period: Summary

	Dependent variable:		
	Spread		
	All period	2018 only	20-day period
Dark>8%*Post_Ban	-1.637^{***}	-1.247^{***}	-1.158^{*}
	(0.252)	(0.294)	(0.600)
Firm Fixed effect	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes
Observations	46,769	30,523	6,834
R^2	0.001	0.001	0.001
Adjusted R^2	-0.009	-0.013	-0.050
F Statistic	42.363^{***}	18.024^{***}	3.716^{*}
	(df = 1; 46302)	(df = 1; 30111)	(df = 1; 6504)

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports regression estimates using a stock-day panel in which the dependent variable is the quoted spread at the close. The key independent variable is a dummy equal to 1 for stocks banned from dark pools. R^2 excludes the variance explained by the fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. Periods are defined in the main text.

is higher in absolute value when I consider the entire period might imply that there have been medium-term effects not captured by the 20-day period regression.

Addition of Controls

I follow Hendershott et al. (2011) by adding as controls the inverse of the share price, the volatility computed as in Parkinson (1980) and the turnover by volume. Those controls take into account the impact of firm-specific changes over time. The controls suggest that the spread increases in volatility (as predicted by Zhu (2014)), decreases in traded volume and with the share price. The impact of volatility is substantial: an increase in 1% in the price range (representing half of the average price range) increases, on average, the spread by 39 bps (the spread more than doubles). Intuitively, we can think of volatility as a measure of risk, and higher risk makes the market maker more reluctant to hold the asset, and asks for a higher reward in order to be willing to enter transactions (McInish and Wood (1992)). The positive coefficient for the Inverse of the Share Price implies that spreads narrow as the stock price increases, or, conversely, liquidity worsens when the stock price falls. Gennotte and Leland (1990) show that during crashes, market makers revise down their expectations and are less willing to absorb the demand for liquidity. The coefficient on volume, although statistically significant, is small: it implies that an increase by 10% in volume (an increase by 200 shares on average) will translate into a spread narrowing of 0.1%. Those coefficients are robust, both in sign and magnitude, across the three time periods I consider. The standard errors are cluster-robust at the firm level.

Do Large Stocks Respond Less to Dark Trading?

Several empirical studies (Menkveld et al. (2017) for instance) have highlighted the difference in responses from small and large capitalizations to dark trading. I sort stocks into quartiles based on market capitalization (Q1 contain the 25% smallest stocks and Q4 the 25% largest) and run regression 4.3 on each group. Estimates are reported in Table 5.4. The second and fourth quartiles do not exhibit major differences, with a spread response to the ban of, respectively, 3 and 2.6 basis points, representing a narrowing in spread of 13% and 20%. My results tend, indeed, to point at a larger response from large market capitalizations. In contradiction with previous findings, the smallest market capitalizations do not respond more than large market capitalizations to dark trading, with an average response to the ban of -1.86 bps, or -5.4%. Finally, stocks in the third quartile exhibit an increase in spread following the regulation, of more than 4%.
A possible explanation is the larger size of my sample compared to other studies: Comerton-Forde and Putniņš (2015) study a sample with an average market capitalization of around 1 billion dollars (890 million euros), Degryse et al. (2015) have an average of 8 million euros, while mine has an average of 8.7 billion euros. I may not have enough small very small stocks to derive conclusions about the impact of a stock's size on its response to dark trading.

As a whole, my results show that, consistently with my model's prediction, banning stocks from trading in dark pools has narrowed their spread. On average, a decrease in dark trading, measured as percentage of total notional trading volume, from 8.5% to zero has improved the spread by between 7 and 10%, a result very close to that of Comerton-Forde and Putniņš (2015). However, I do not find a significant evidence that stocks with a large market capitalization are less impacted by dark trading. Finally, I find that the bid-ask spread increases in the stock's volatility, and decreases in market capitalization and share price.

5.3 Alternative Specification: the Role of General Market Conditions

The results of the difference-in-differences regressions are reported in Table 5.4. Regression (3) allows me to evaluate the impact of general market conditions on stocks' bid-ask spread. It appears that volatility significantly increases the spread, which is consistent with Boneva et al. (2016), Comerton-Forde and Putniņš (2015), McInish and Wood (1992) and Zhu (2014)'s predictions. The estimates (between 0.09 and 0.1) indicate that an increase in market-wide volatility of 6% translates into an increase in spread of 0.4%. The stock-specific volatility has a substantially larger

Table 5.3: Panel Data Estimates by Market Capitalization

	Dependent variable:			
	Spread			
	Q1 (smallest)	Q2	Q3	Q4 (largest)
Dark>8%*Post_Ban	-1.859^{**}	-3.061^{***}	0.7618^{**}	-2.591^{***}
	(0.007)	(0.005)	(0.004)	(0.003)
Firm Fixed effect	Yes	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes
Observations	11,615	11,559	11,638	11,649
R^2	0.001	0.003	0.0003	0.006
Adjusted R^2	-0.020	-0.017	-0.020	-0.015
F Statistic	6.320^{**}	36.277^{***}	3.971^{**}	65.243^{***}
df	(1; 11377)	(1; 11325)	(1; 11405)	(1; 11415)

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports regression estimates using a stock-day panel in which the dependent variable is the quoted spread at the close. I report four regressions results, one by each quartile of my sample, defined by the stocks' market capitalization. The key independent variable is a dummy equal to 1 for stocks banned from dark pools and equal to 0 for stocks not banned and for all stocks before the regulation. R^2 excludes the variance explained by the fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. The period considered spans from the 29th of September 2017 to the 1st of June 2018.

effect: an increase of the price range of 50% increases the spread by almost five times. The market capitalization is a key determinant of a stock's bid-ask spread, a finding shared by most empirical studies. This can be due to the relatively lower volatility of large capitalization stocks, as well as their higher trading volume. Finally, my results indicate a positive relationship (although not significant) between the spread and the Stoxx 50 returns, inconsistently with the aforementioned studies and with Gennotte and Leland (1990)'s intuition.

Table 5.4: Difference-in-Differences Estimates

	Dependent variable:		
	Spread		
	(1)	(2)	(3)
Dark>8%*Post_Ban	−1.058**	−1.093***	−1.376***
	(0.413)	(0.390)	(0.316)
log(Mkt_cap)		−4.865***	−5.258***
		(0.064)	(0.064)
Volatility			117.541***
			(5.197)
Inverse of Share Price			0.899
			(0.633)
Volume			−0.00002**
			(0.00001)
Stoxx_return		0.001	0.002
		(0.004)	(0.003)
Stoxx_vol		0.101*	0.092**
		(0.052)	(0.042)
Constant	27.595***	130.503***	131.867***
	(0.184)	(6.580)	(5.482)
Dark vol > 8% (Dummy)	Yes	Yes	Yes
Post March 12th (Dummy)	Yes	Yes	Yes
Country of origin	No	No	Yes
Industry	No	No	Yes
Observations	46,769	46,769	46,259
R^2	0.064	0.168	0.443
Adjusted R^2	0.064	0.168	0.443
Residual Std. Error	21.216 (df = 46765)	19.999 (df = 46762)	16.113 (df = 46225)
F Statistic	1,063.671*** (df = 3; 46765)	1,576.452*** (df = 6; 46762)	1,114.989*** (df = 33; 46225)
Note:			*p<0.1; **p<0.05; ***p<0.01

5.4 Where Have the Dark Volumes Gone?

Regulatory changes are generally regarded by the market as being pro-exchange in their effects. In particular, the limits on dark trading were expected to drive volumes back into the lit markets (typically, the exchanges). However, significant concerns raised concerning the competition between exchanges and Systematic Internalisers after MiFID II. A Systematic Internaliser (SI) is a MiFID I construct, which was likely to be more important in MiFID II. It is a bank-owned platform which provides trading against proprietary capital. SIs provide pre and post trade transparency. In the middle of 2017 there was a significant concern about SIs usurping the main trading venues. The argument was that SIs would probably end up connecting to each other, building an alternative pool of liquidity to the traditional lit market. A key part of this was that SIs, unlike regulated exchanges, were not subject to the tick size regime, and could offer to execute at a fraction of a percent better price than exchanges, and be preferred by algorithms looking for the best price available. The ESMA launched a consultation aimed at clarifying the SI regime and claimed that:

> *It is doubtful that such an outcome would go hand in hand with real benefits for end clients. While it would result in marginally better prices, it would at the same time undermine the overall quality of the liquidity available, the efficient valuation of equity instruments as well as the efficient pricing of instruments traded*[1].

They also clarified that SIs would be subject to the same tick size regime as regular exchanges. That argument, combined with the development of auctions by lit platforms (which resembles dark trading) made the outcome of MiFID II on the market structure very unclear.

I investigate the dynamics of the equity market structure in response to regulatory changes and market conditions: I naively regress the market share of different trading venue categories on a dummy for MiFID II (equal to 1 after the 3rd of January and 0 before) and a dummy for the implementation of the ban from dark pools (equal to 1 after the 12th of March and 0 before) and a set of controls (Stoxx 50 volatility and return indices). Estimates must be interpreted carefully, as the use of certain types of trading venues might increase the volatility of European markets overall. The results are just shown as an estimation of the relationship between the equity market structure, regulatory changes and general market conditions. Consistently with findings from Menkveld et al. (2017), I find a significant increase in lit exchanges' market share when volatility is higher. It is the only significant impact of volatility across types of trading venues. I find a decrease in Auctions' market share when the returns increase. The rationale behind is straightforward: when the price of a stock falls too much during a specific trading day, trading in that stock is paused and buy and sell orders are cleared in an auction process[2].

[1] Amendments to Commission Delegated Regulation (EU) 2017/2018 (RTS 1) ESMA 70-156-275

[2] There is no harmonized threshold to trigger a trading halt, see ESMA's *Guidelines on the calibration of circuit breakers and the publication and reporting of trading halts under MiFID II*

Table 5.5: The Relationship Between the Market Share by Trading Venue Categories and the Regulation (Selected Categories)

	Dependent variable:		
	Market share (%)		
	SIs	Dark	Lit
DVC	2.830***	−1.693***	−2.012
	(0.944)	(0.189)	(1.280)
MiFID	26.034***	−1.194***	−10.591***
	(1.093)	(0.219)	(1.481)
Stoxx_return	−0.018	0.002	0.0004
	(0.018)	(0.004)	(0.024)
Stoxx_vol	−0.377	0.048	0.556*
	(0.230)	(0.046)	(0.312)
Constant	33.162	2.570	46.744
	(26.935)	(5.389)	(36.499)
Observations	148	148	148
R^2	0.881	0.631	0.396
Adjusted R^2	0.877	0.621	0.379
Residual Std. Error (df = 143)	4.606	0.921	6.241
F Statistic (df = 4; 143)	263.511***	61.132***	23.401***
Note:			*p<0.1; **p<0.05; ***p<0.01

This table reports OLS regression estimates using a panel in which the dependent variable is the market share, measured by notional amount. I report three regressions results, one for each trading venue category that I am interest in. The key independent variables are: *MiFID*, a dummy equal to 1 after the 3rd of January 2018 and 0 before; *DVC* a dummy equal to 1 after the 12th of March 2018 and 0 before; *Stoxx return*, the Stoxx 50 return index; *Stoxx vol* the Stoxx 50 volatility index. Standard errors are clustered at the firm level and are reported in parentheses. The period considered spans from the 1st of November 2017 to the 1st of June 2018.

Table 5.5 reports the impact of MiFID II and the Double-Volume-Cap mechanism on the fragmentation of the European equity markets. The DVC mechanism has hit dark pools, but, interestingly, lit exchanges as well. Figure 5.1 shows the evolution of the market share by trading venue category. In its 2018 Markets and Risks Outlook, the French Financial Markets Authority (*Autorité des Marchés Financiers*, AMF) criticized MiFID II and the DVC mechanism for, as feared before

from 2017

their implementation, the rapid rise in market share of SIs, which was almost nonexistent in November 2017 and accounted for almost 30% of total trading volume (in notional) in January 2018. My naive regression results estimate at 26% the rise in their market share due to the implementation of MiFID II, volume coming notably from Lit exchanges (loss in 11%) and other forms of OTC trading (-12%, see Table B.9 in Appendix B). Those coefficients are statistically significant at the 1% level. The DVC mechanism, implemented with a delay, has had no significant effect on exchanges' market share, but, as expected, hit dark pools (-1.7%). Auctions (+1.2%) and SIs (+2.8%) are the main beneficiaries. The impact that Systematic Internalisers might have on the bid-ask spread is hard to predict. Their specificity is that they do not rely on trading fees, but make money out of the spread. If they are tempted to offer a slight price improvement to attract algorithmic traders, it is hard to believe that their inventory depth can allow them to sustain better prices than a whole exchange. The mechanism behind their rise remains to be explored. By facilitating the development of SIs, MiFID II and the DVC mechanism failed at making the equity market structure more exchange-based and less fragmented.

5.5 Limits and Possible Extensions

My empirical analysis requires to make some assumptions. First of all, I need to assume that the effect that I have been trying to seize is due to the ban from dark pools, and not due to changes in market fragmentation, and in particular the rise in Systematic Internalisers. In a broad sense, SIs belong to the off-exchange trading, but is still considered lit. Their impact on liquidity is yet to be determined, and could thus bias my estimates (either upwards or downwards). Moreover, my measure of dark trading is an average over twelve months and does not tell anything about the trend. It does not allow me to infer the *actual* level of dark trading at the time of the ban from dark pools. In order to make my results relevant, I need to assume that the level of dark trading at the time of the regulation was similar to their twelve-month average. Considering the fall in dark trading due to the implementation of MiFID II on the 3rd of January, one could argue that there has been an anticipation effect due to the implementation of all other measures. I argue, here, that given the trend of dark pool's market share between the beginning of 2018 and the 12th of March (relatively constant and almost back to its original level after one week, see Figure 5.1), it is reasonable to assume that the dark share for my sample has remained constant. Moreover, it would only bias my estimates downward, and make my results more conservative.
A second limit of my analysis lies in the quality of the data used: contrarily to the United States, there is no unified framework for aggregating financial markets data in Europe. Moreover, the data used is at the day level: other measures of the bid-ask spread require order-level data and might yield different empirical results.
Finally, and more generally, my study focuses on only one measure of market quality. My findings do not say anything about the price discovery process, and not allow

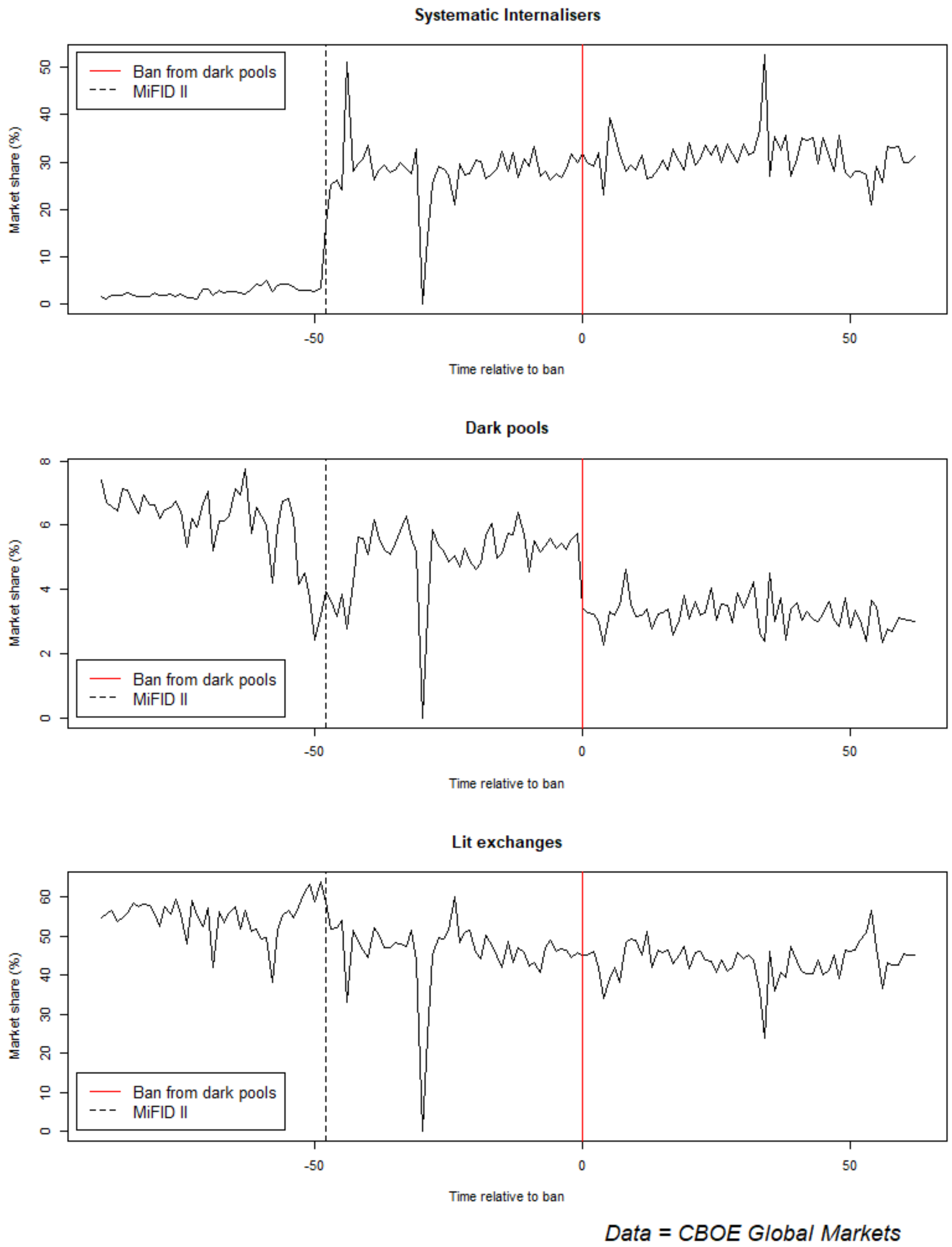

Figure 5.1: The Evolution of the Equity Trading's Landscape: Market Share by Trading Venue Category

The figure shows the daily market share, measured as a percentage of total notional volume of trading in Europe, of different trading venue categories, from the 1st of November 2017 to the 1st of June 2018. The red line corresponds to the first wave of bans from dark pools as part of the Double-Volume-Cap mechanism (12th of March 2018), and the dotted black line corresponds to the implementation of MiFID II (3rd of January 2018).

me to infer conclusions about overall investors' welfare.

6

Conclusion

Technological advances and regulatory changes have permitted the development of Multilateral-Trading-Facilities in Europe. Among them, dark pools have attracted a special attention: by removing pre-trade transparency and offering potential price improvement, they are more likely to attract uninformed investors and widen the spread of the reference lit exchange. A simple model of spread determination in a market where a dark pool operates alongside a regular stock exchange run by a risk-neutral market maker allows me to highlight that mechanism.
However, trying to evaluate the impact of dark trading on liquidity is limited by endogeneity issues. By banning a large amount of stocks from dark trading when their share of trading in the dark is greater than 8%, MiFID II's Double-Volume-Cap mechanism provides an ideal framework to identify the effect of dark pool on equity markets' liquidity. My results show that banning stocks from trading in the dark has narrowed their bid-ask spread by around 10%, and are robust across several specifications. In contradiction with previous literature, I do not find evidence that small capitalizations are more effected by dark trading. I also document the fact that Systematic Internalisers, rather than regular stock exchanges, have benefited from the regulation. Their impact on market quality, both on a theoretical and empirical point of view, remains largely unexplored.
Future research could focus on different measures of liquidity as well as other dimensions of market quality, and on the impact of the rapid expansion of SIs. On the theoretical side, developing a dynamic model of spread determination in a market where a dark pool and a regular exchange operate alongside could reach different conclusions, as informed traders might not want to reveal their private information by trading on the lit exchange.

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Appendix A

Appendix: Model

A.0.1 Existence and Uniqueness of the Equilibrium

We have:

$$S = \frac{2\alpha\sigma}{2\alpha + (1-\alpha)(2 - G(1 - \frac{S}{2\sigma}))}$$

Solving for $G(.)$ gives us:

$$G(1 - \frac{S}{2\sigma}) = \frac{2(S - \alpha\sigma)}{S(1-\alpha)}$$

Does that equality have a solution, and if yes, is it unique? By definition, $G'(.) > 0$ and $1 - \frac{S}{2\sigma}$ is decreasing in S, thus $G(.)$ is strictly decreasing in S.
What about $\frac{2(S-\alpha\sigma)}{S(1-\alpha)}$?

$$\frac{d\frac{2(S-\alpha\sigma)}{S(1-\alpha)}}{dS} = \frac{2S - 2(S - \alpha\sigma)}{S^2(1-\alpha)}$$

Which simplifies to $\frac{\alpha\sigma)}{S^2(1-\alpha)} > 0$.
Now we are sure that if both functions cross at some point, it will be at a unique point. We have to make sure that they cross on S' support, $[0, \sigma]$:

$$\lim_{S\to 0} G(1) > 0 > \lim_{S\to 0} \frac{2(S - \alpha\sigma)}{S(1-\alpha)} = -\infty$$

And

$$\lim_{S\to \sigma} G(0) = 0 < \lim_{S\to \sigma} \frac{2(S - \alpha\sigma)}{S(1-\alpha)} = 2$$

Which demonstrates existence and uniqueness of the equilibrium.

A.0.2 Proof That $\beta = \frac{\gamma}{2-\gamma}$

In equilibrium, β must be such that informed traders are indifferent between the two venues:

$$\sigma - S = r^{-}\sigma$$

The equation can be rewritten as:

$$1 - \frac{S}{\sigma} = r^-$$

Replacing with their true expressions:

$$\frac{(1-\alpha)(1-\gamma)}{\alpha(1-\beta) + (1-\alpha)(1-\gamma)} = \frac{\frac{1}{2}(1-\alpha)\gamma}{\frac{1}{2}(1-\alpha)\gamma + \alpha\beta}$$

As both denominators are strictly greater than 0:

$$\frac{\alpha(1-\beta) + (1-\alpha)(1-\gamma)}{(1-\alpha)(1-\gamma)} = \frac{\frac{1}{2}(1-\alpha)\gamma + \alpha\beta}{\frac{1}{2}(1-\alpha)\gamma}$$

Developing:

$$\frac{(1-\beta)\alpha}{(1-\alpha)(1-\gamma)} + 1 = 1 + \frac{\beta\alpha}{\frac{1}{2}(1-\alpha)\gamma}$$

Dividing both sides by α:

$$\frac{1}{(1-\alpha)(1-\gamma)} - \frac{\beta}{(1-\alpha)(1-\gamma)} = \frac{\beta}{\frac{1}{2}(1-\alpha)\gamma}$$

Rearranging:

$$\frac{1}{(1-\alpha)(1-\gamma)} = \beta(\frac{1}{(1-\alpha)(1-\gamma)} + \frac{1}{\frac{1}{2}(1-\alpha)\gamma})$$

Multiplying both sides by $(1-\alpha)(1-\gamma)$:

$$1 = \beta(\frac{\frac{1}{2}(1-\alpha)\gamma + (1-\alpha)(1-\gamma)}{\frac{1}{2}(1-\alpha)\gamma})$$

Isolating β and expressing the right-hand-side in terms of γ:

$$\beta = \gamma(\frac{\frac{1}{2}(1-\alpha)}{\frac{1}{2}(1-\alpha)\gamma + (1-\alpha)(1-\gamma)})$$

Getting rid of the $(1-\alpha)$:

$$\beta = \gamma(\frac{\frac{1}{2}}{\frac{1}{2}\gamma + (1-\gamma)})$$

Which gives:

$$\beta = \frac{\gamma}{2-\gamma}$$

And, as $\gamma < 1$:

$$\beta < \gamma$$

A.0.3 Proof of Sufficiency of $\beta < \gamma$

For the spread to always increase with a dark pool, we need to prove that:

$$\alpha\sigma < \frac{\alpha(1-\beta)}{\alpha(1-\beta)+(1-\alpha)(1-\gamma)}\sigma$$

Dividing both sides by $\sigma\alpha$:

$$1 - \frac{(1-\beta)}{\alpha(1-\beta)+(1-\alpha)(1-\gamma)} < 0$$

Developing:

$$\frac{\alpha(1-\beta)+(1-\alpha)(1-\gamma)-(1-\beta)}{\alpha(1-\beta)+(1-\alpha)(1-\gamma)} < 0$$

As the denominator is always positive, after simplification, we are left with:

$$(1-\gamma)(1-\alpha) < (1-\alpha)(1-\beta)$$

Which is equivalent to:

$$\beta < \gamma$$

Which is always true.

Appendix B

Appendix: Empirics

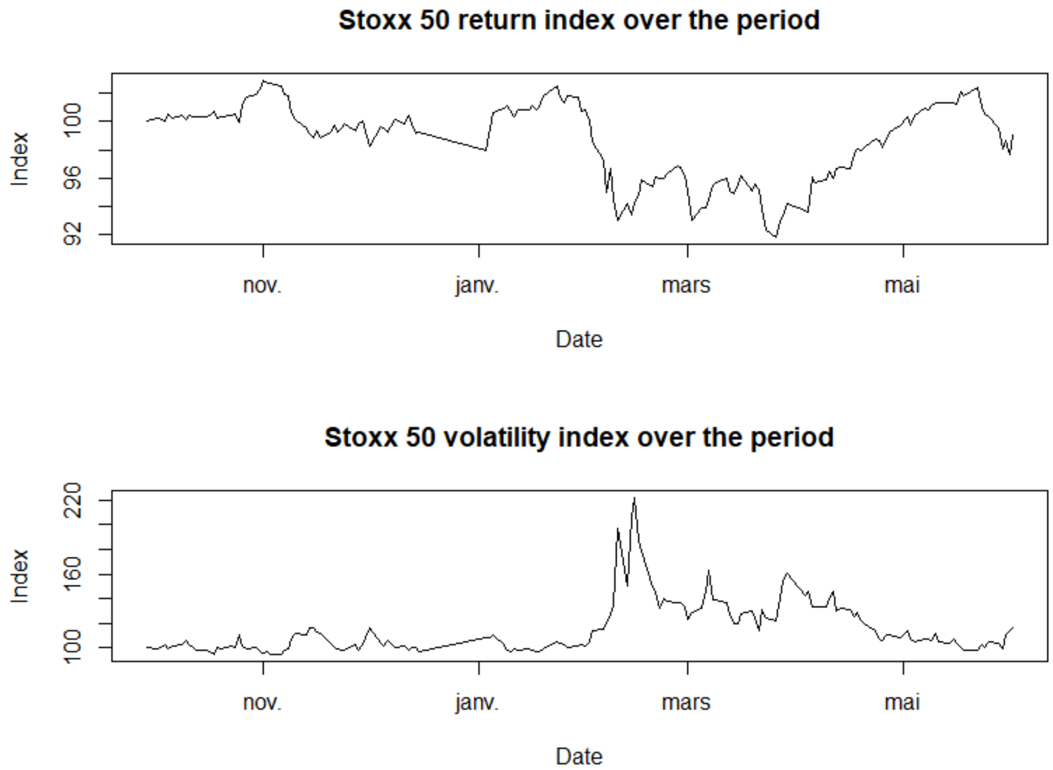


Figure B.1: Stoxx 50 Return and Volatility Indices Over the Period (Basis 100 on the 29th of September, 2017)

Table B.1: Summary Statistics: Country of Origin

Country	Stocks	Of which: treated
Austria	5	3
Belgium	8	5
Denmark	5	2
Finland	12	8
France	39	14
Germany	47	21
Ireland	6	5
Italy	39	23
Luxembourg	2	1
Netherlands	17	9
Norway	9	4
Portugal	4	3
Spain	9	6
Sweden	43	28
Switzerland	15	6
United Kingdom	49	35
Total	*309*	*173*

Table B.2: Summary Statistics: Industries

Industry	Stocks	Of which: treated
Basic Materials	23	16
Consumer Goods	39	23
Consumer Services	42	24
Financials	63	36
Healthcare	16	8
Industrials	75	42
Oil and Gas	9	4
Technology	19	3
Telecoms	8	7
Utilities	15	10
Total	*309*	*173*

Table B.3: Panel Data Estimates (All Period)

	Dependent variable:	
	Spread	
	(1)	(2)
Dark>8%*Post_Ban	-1.637^{***}	-1.534^{***}
	(0.252)	(0.252)
Volatility		39.863^{***}
		(4.621)
Volume		-0.0001^{***}
		(0.00001)
ISP		8.863^{**}
		(3.857)
Firm Fixed effect	Yes	Yes
Day Fixed Effect	Yes	Yes
Observations	46,769	46,259
R^2	0.001	0.003
Adjusted R^2	-0.009	-0.007
F Statistic	42.363^{***} (df = 1; 46302)	31.819^{***} (df = 4; 45789)
Note:		*p<0.1; **p<0.05; ***p<0.01

This table reports regression estimates using a stock-day panel in which the dependent variable is the quoted spread at the close. The key independent variable is a dummy equal to 1 for stocks banned from dark pools and equal to 0 for stocks not banned, and all stocks before the regulation. Controls: $Volatility$ is measured by the price range as a percentage of closing price, $Volume$ is the daily turnover by volume measured by the number of shares traded; ISP is the inverse of the closing share price. R^2 excludes the variance explained by the fixed effects. Standard errors are clustered by stocks and are reported in parentheses. The period considered spans from the 29th of September 2017 to the 1st of June 2018.

Table B.4: Panel Data Estimates (2018 Only)

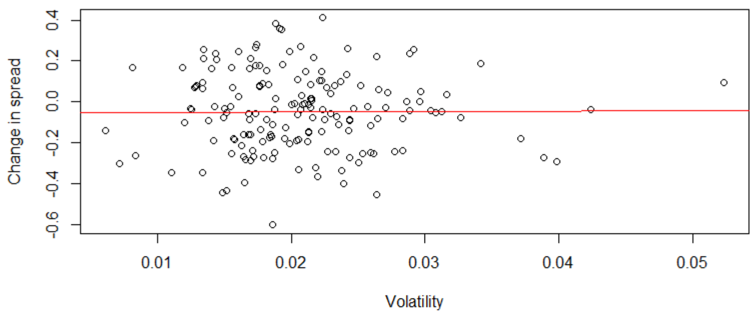
	Dependent variable:	
	Spread	
	(1)	(2)
Dark>8%*Post_Ban	-1.247^{***}	-1.221^{***}
	(0.294)	(0.294)
Volatility		35.655^{***}
		(5.607)
Volume		-0.00004^{**}
		(0.00002)
ISP		7.313
		(5.829)
Firm Fixed effect	Yes	Yes
Day Fixed Effect	Yes	Yes
Observations	30,523	30,179
R^2	0.001	0.002
Adjusted R^2	-0.013	-0.012
F Statistic	18.024^{***} (df = 1; 30111)	15.610^{***} (df = 4; 29764)
Note:		*p<0.1; **p<0.05; ***p<0.01

This table reports regression estimates using a stock-day panel in which the dependent variable is the quoted spread at the close. The key independent variable is a dummy equal to 1 for stocks banned from dark pools and equal to 0 for stocks not banned, and all stocks before the regulation. Controls: $Volatility$ is measured by the price range as a percentage of closing price, $Volume$ is the daily turnover by volume measured by the number of shares traded; ISP is the inverse of the closing share price. R^2 excludes the variance explained by the fixed effects. Standard errors are clustered by stocks and are reported in parentheses. The period considered spans from the 3rd of January 2018 to the 1st of June 2018.

Table B.5: Panel Data Estimates (20-Day Period)

	Dependent variable:	
	Spread	
	(1)	(2)
Dark>8%*Post_Ban	-1.158^{*}	-1.118^{*}
	(0.600)	(0.605)
Volatility		17.429
		(13.096)
Volume		-0.00003
		(0.00005)
ISP		-38.170
		(24.260)
Firm Fixed effect	Yes	Yes
Day Fixed Effect	Yes	Yes
Observations	6,834	6,768
R^2	0.001	0.001
Adjusted R^2	-0.050	-0.050
F Statistic	3.716^{*} (df = 1; 6504)	1.825 (df = 4; 6435)
Note:		*p<0.1; **p<0.05; ***p<0.01

This table reports regression estimates using a stock-day panel in which the dependent variable is the quoted spread at the close. The key independent variable is a dummy equal to 1 for stocks banned from dark pools and equal to 0 for stocks not banned, and all stocks before the regulation. Controls: $Volatility$ is measured by the price range as a percentage of closing price, $Volume$ is the daily turnover by volume measured by the number of shares traded; ISP is the inverse of the closing share price. R^2 excludes the variance explained by the fixed effects. Standard errors are clustered by stocks and are reported in parentheses. The period considered spans from the 2nd of March 2018 to the 22nd of March 2018.



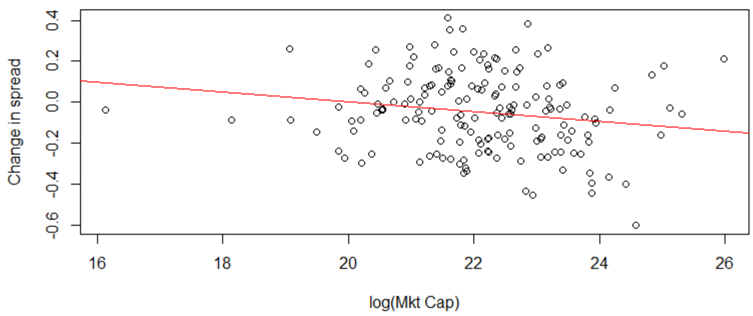


Figure B.2: Change in Spread by log(Market Cap) and Volatility in (%)

The figures above show the change in average spread before and after the regulation as a function of volatility (price range as a percentage of closing price, details are in the main text) and the log of the market capitalization (in millions euros, as of the 29th of September 2017). The red line is the prediction of a naive regression of the change in spread on the characteristic.

Table B.6: Diff-in-diff Estimates (All Period)

	Dependent variable:		
	Spread2		
	(1)	(2)	(3)
Dark>8%*Post_Ban	−1.058**	−1.093***	−0.900**
	(0.413)	(0.390)	(0.385)
Stoxx_return		0.001	0.004
		(0.004)	(0.004)
Stoxx_vol		0.101*	0.105**
		(0.052)	(0.051)
log(Mkt_cap)		−4.865***	−4.525***
		(0.064)	(0.068)
ISP			−3.619***
			(0.663)
Volume			−0.0001***
			(0.00001)
Volatility			99.036***
			(6.167)
Constant	27.595***	130.503***	115.703***
	(0.184)	(6.580)	(6.566)
Dark vol > 8% (Dummy)	Yes	Yes	Yes
Post March 12th (Dummy)	Yes	Yes	Yes
Country of origin	No	No	Yes
Industry	No	No	Yes
Observations	46,769	46,769	46,259
R^2	0.064	0.168	0.443
Adjusted R^2	0.064	0.168	0.443
Residual Std. Error	21.216 (df = 46765)	19.999 (df = 46762)	16.113 (df = 46225)
F Statistic	1,063.671*** (df = 3; 46765)	1,576.452*** (df = 6; 46762)	1,114.989*** (df = 33; 46225)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table B.7: Diff-in-diff Estimates (2018 Only)

	Dependent variable:		
	Spread2		
	(1)	(2)	(3)
Dark>8%*Post_Ban	−0.727	−0.777*	−0.683
	(0.492)	(0.464)	(0.457)
Stoxx_return		−0.0002	0.004
		(0.004)	(0.004)
Stoxx_vol		0.164***	0.183***
		(0.057)	(0.056)
log(Mkt_cap)		−4.831***	−4.530***
		(0.079)	(0.084)
ISP			−5.167***
			(0.828)
Volume			−0.0001***
			(0.00001)
Volatility			97.750***
			(7.555)
Constant	27.476***	129.287***	114.447***
	(0.271)	(7.039)	(7.046)
Dark vol > 8% (Dummy)	Yes	Yes	Yes
Post March 12th (Dummy)	Yes	Yes	Yes
Country of origin	No	No	Yes
Industry	No	No	Yes
Observations	30,523	30,523	30,179
R^2	0.067	0.170	0.440
Adjusted R^2	0.067	0.170	0.440
Residual Std. Error	21.257 (df = 30519)	20.056 (df = 30516)	16.182 (df = 30145)
F Statistic	735.961*** (df = 3; 30519)	1,041.314*** (df = 6; 30516)	719.184*** (df = 33; 30145)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.8: Diff-in-diff Estimates (20-Day Period)

	Dependent variable:		
	Spread2		
	(1)	(2)	(3)
Dark>8%*Post_Ban	−1.702	−1.607	−1.657*
	(1.035)	(0.982)	(0.964)
Stoxx_return		−0.0005	0.009
		(0.014)	(0.014)
Stoxx_vol		0.163	0.145
		(0.228)	(0.224)
log(Mkt_cap)		−4.639***	−4.213***
		(0.167)	(0.180)
ISP			−3.014*
			(1.805)
Volume			−0.0001***
			(0.00003)
Volatility			115.191***
			(17.303)
Constant	27.427***	125.323***	101.552***
	(0.539)	(18.902)	(18.962)
Dark vol > 8% (Dummy)	Yes	Yes	Yes
Post March 12th (Dummy)	Yes	Yes	Yes
Country of origin	No	No	Yes
Industry	No	No	Yes
Observations	6,834	6,834	6,768
R^2	0.070	0.164	0.434
Adjusted R^2	0.069	0.163	0.431
Residual Std. Error	21.219 (df = 6830)	20.121 (df = 6827)	16.271 (df = 6734)
F Statistic	170.983*** (df = 3; 6830)	223.168*** (df = 6; 6827)	156.502*** (df = 33; 6734)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.9: The Relationship Between the Market Share by Trading Venue Categories and the Regulation (All Categories)

	Dependent variable:					
	Market share (%, notional amount)					
	SIs	Dark	Lit	Auctions	OTC (no SI)	Request for Quotes
DVC	2.830***	−1.693***	−2.012	1.208*	−0.401	0.068***
	(0.944)	(0.189)	(1.280)	(0.721)	(1.778)	(0.021)
MiFID	26.034***	−1.194***	−10.591***	−1.864**	−12.415***	
	(1.093)	(0.219)	(1.481)	(0.834)	(2.057)	
Stoxx_return	−0.018	0.002	0.0004	−0.030**	0.045	0.001*
	(0.018)	(0.004)	(0.024)	(0.013)	(0.033)	(0.0004)
Stoxx_vol	−0.377	0.048	0.556*	−0.284	0.052	0.006
	(0.230)	(0.046)	(0.312)	(0.176)	(0.433)	(0.005)
Constant	33.162	2.570	46.744	57.665***	−39.089	−1.164*
	(26.935)	(5.389)	(36.499)	(20.561)	(50.712)	(0.640)
Observations	148	148	148	148	148	105
R^2	0.881	0.631	0.396	0.087	0.358	0.120
Adjusted R^2	0.877	0.621	0.379	0.061	0.340	0.093
Residual Std. Error	4.606 (df = 143)	0.921 (df = 143)	6.241 (df = 143)	3.516 (df = 143)	8.671 (df = 143)	0.101 (df = 101)
F Statistic	263.511***	61.132***	23.401***	3.388**	19.901***	4.571***
df	4; 143	4; 143	4; 143	4; 143	4; 143	4; 143

Note: *p<0.1; **p<0.05; ***p<0.01