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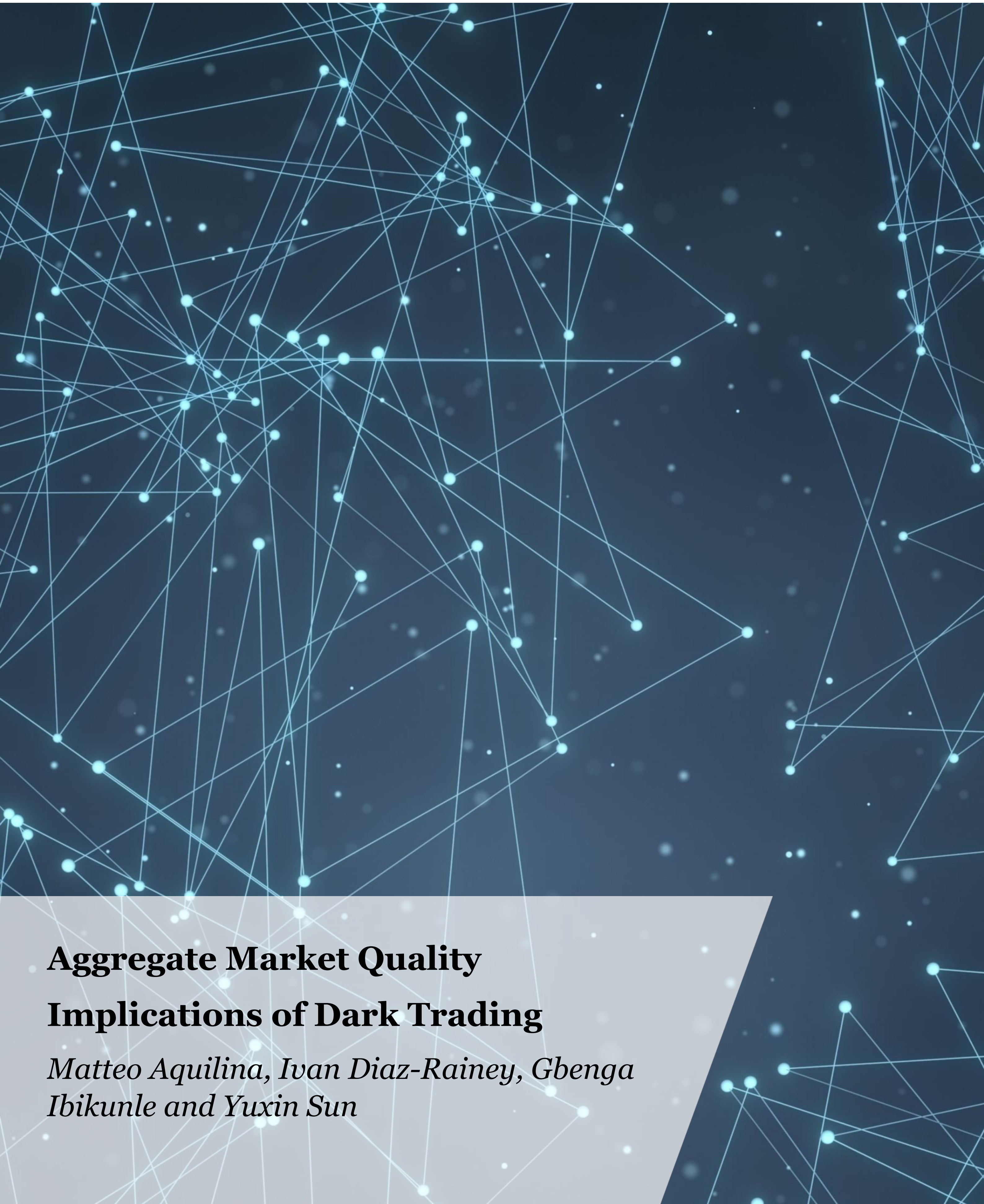

Aggregate Market Quality Implications of Dark Trading

Matteo Aquilina, Ivan Diaz-Rainey, Gbenga Ibikunle and Yuxin Sun

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Summary

Over the last decade, regulatory changes, coupled with technological advancements, led to the proliferation of new classes of trading venues. One of the most prominent new trading venue types is a class of venues known as 'dark pools'. Trades executed on dark pools have no pre-trade transparency. Other market participants apart from the submitter and the pool operator are not aware of orders submitted to a dark pool before their execution.

Many dark pools in Europe are operated as Multilateral Trading Facilities (MTFs). For example, the three largest dark trading venues on the continent are MTFs, which operate both dark and lit order books. These are Chi-X Europe, BATS Europe and Turquoise; all are based in London. As a proportion of European exchange volumes are now executed 'in the dark', it is vital to investigate how these volumes impact overall market quality. This investigation is of critical importance for investors, who already view dark pool activity with suspicion, and regulators, who are interested in having well-functioning financial markets.

This study contributes to the dark pools debate by presenting the first evidence on the impact of dark trading on aggregate market quality in Europe. The study is also the most comprehensive examination to date of dark trading in Europe, since we explore dark trading across all the major trading venues in the UK.

We use data for the whole universe of FTSE350 stocks and the period June 2010 to June 2015 to test competing theoretical predictions on the implications of dark trading on the quality of the aggregate market, comprising both the lit and dark sections. We find that, at current levels, dark trading does not appear to be harmful to market quality in the aggregate UK equity market. Our results imply that there is a threshold at which dark trading may start to negatively affect market quality. We estimate that threshold, for our full sample of stocks, to be when dark trading value is approximately between 11% and 17% of total trading by pound value, depending on the specific market quality attribute examined. We discuss caveats for these estimates in the paper.

1 Overview

Purpose

Dark pools are venues where orders with no pre-trade transparency are executed. Orders submitted to dark pools are called 'dark orders' and the trades arising because of such orders 'dark trades/transactions'. A significant proportion of trading in the UK now occurs in dark venues. For example, according to the Thomson Reuters Equity Market Share Reporter (March 2014), dark pool activity for all European equities accounted for more than €80.23 billion in March 2014, which was about 8.50% of all traded equities on the continent that month. For the 12-month period ending March 2014, the total value of dark trades stood at more than €898.22 billion, which represented more than 9.55% of all equity trades in Europe during that period. These developments raise questions about the quality of the price discovery process in the market in the presence of dark trading. This paper, therefore, investigates the market quality impact of dark trading on the aggregate UK equity market. Accordingly, we aggregate data from the UK's four main trading venues – the LSE, BATS Europe, Chi-X Europe and Turquoise.

The UK market and regulation of dark pools differ significantly from that of the US and other markets[1] but most of the analysis of dark pools has been carried out in other jurisdictions. This study uses high frequency data for 288 of the largest stocks in the London equity market. The stocks used are constituents of the FTSE 350, which consistently form part of the index over the five-year sample period (June 2010 – June 2015).

Key findings

Our main result is that the level of dark trading currently present in London, overall, does not appear to be detrimental to market quality.

For our full sample of stocks, we find no evidence of a negative effect of dark trading on market liquidity. This is until dark trading value as a proportion of total trading value exceeds 15%. The results also indicate that dark trading reduces adverse selection risk and noise in the price discovery process until it attains 16% and 11% of total trading value respectively. Results also indicate that, when we adjust our measure of adverse selection risk to account for increased trading volume in a high frequency trading environment, that threshold increases to 17%.

Once MiFID II becomes operational at the beginning of 2018, the overall value of dark trading will not be allowed to exceed 8% for each stock. In our sample, the daily level of dark trading in stocks exceeds the 8% threshold approximately 8.35% of the stock-day period under investigation, and we find no evidence that dark trading at this level of dark trading is detrimental to market quality. We also have approximately 1.7% of observations where dark trading exceeds 15%. So while it is difficult to estimate the effects at levels much higher than this, we also have a number of observations that exceed the turning points.

[1] See the FCA Thematic Review TR16/5: *UK equity market dark pools – Role, promotion and oversight in wholesale markets*, published in July 2016 and available at: https://www.fca.org.uk/publication/thematic-reviews/tr16-05.pdf

2 Research context

Policy background to the study

Due to its competition-enhancing principles, the Markets in Financial Instruments Directive (MiFID) introduced by the European Union in 2007 led to the proliferation and growth of alternative trading venues. MTFs are the most prominent of these alternative trading venues and are in direct competition with established national exchanges (or regulated markets – RMs) such as the London Stock Exchange (LSE). Other alternative venue types include broker crossing networks (BCNs) and systematic internalisers (SIs). The market share held by MTFs especially has grown sharply in recent years: BATS Chi-X Europe, a 'paper merger' of the Chi-X and BATS order books, is now the largest equity trading exchange in Europe by market share.[2] By 30 March 2016 there were 151 MTFs listed on the MiFID database managed by the European Securities and Markets Authority (ESMA).[3]

Although, under MiFID rules, MTFs are required to publish all current bid and ask prices as well as their corresponding bid and ask sizes, the regulations allow exemptions on four grounds. MTFs rely on these exemptions to operate dark pools. The first pre-trade transparency waiver applies to large orders, which could have large market impacts if published before they are executed; this is referred to as the Large-in-Scale (LIS) waiver. Qualification for a LIS requires that trades must be of a minimum size, which is based on the average daily turnover for each instrument. The minimum order size ranges from 50,000 for the least active stocks to 500,000 for the most active ones.

The second waiver is the Reference Price waiver; this is commonly used to maintain dark pools of liquidity. Venues may avoid the pre-trade transparency requirements if they passively match orders to a widely published reference price obtained from another market. For example, BATS, Chi-X and Turquoise dark pools passively match orders to LSE's posted midpoints in the case of FTSE stocks.

The third waiver applies to transactions negotiated bilaterally, away from the exchanges, by counterparties. These transactions are usually non-standard and need to be executed on the basis of prevailing volume weighted bid-ask spread or a reference price if the traded security is not traded continuously.

The fourth waiver is for the so-called 'iceberg orders', and is generally referred to as the Order Management Facility waiver. MTFs can waive pre-trade transparency for orders subject to order management until they are disclosed to the market. Usually only a fraction of a submitted iceberg order is displayed, and once that portion is fulfilled, it is refreshed from the non-displayed portion.

A brief review of the recent literature

The knowledge base needed to obtain a full understanding of the market microstructure impacts of dark pools is still being developed. This is largely due to the dearth of empirical academic literature on the dark pool phenomenon, which has three reasons. Firstly, modern dark pools are still comparatively new trading venues, hence the relatively small number of studies that are either published or in development. Secondly, it is difficult to obtain datasets that explicitly identify trades executed via dark pools. The latter of these two issues is being rapidly resolved, as new

[2] The order books are still operated separately, although they are 'integrated'. Also, before 20 May 2013, BATS Chi-X Europe only had a licence to operate MTFs; since being granted Recognised Investment Exchange (RIE) status, BATS Chi-X can now operate a listing exchange as well as MTFs. The data in this paper is for a period straddling the transition of BATS Chi-X to RIE status. The trading dynamics and rules of the BATS and Chi-X order books employed in this analysis remain essentially the same both before and after the transition. Enquiries made with BATS Chi-X Europe confirm that their current order books are still the same as when BATS Chi-X could only operate MTFs; thus those books are still classic MTFs. As at July 2016, BATS Trading Limited is still listed on the MiFID database as an MTF. However, BATS Europe Regulated Market is also now listed as a regulated market.

[3] ESMA builds rule books for financial markets within the EU jurisdiction.

datasets identifying dark trading activity are now emerging. A third reason is the endogenous determination of the relevant market quality metrics with dark trading.

Transparency, which should be enhanced by publicly displayed trading, is a vital ingredient in well-functioning financial markets, and aids efficient price discovery. Therefore, it implies that venues with no pre-trade transparency, like dark pools, are potentially harmful to financial markets' trading quality, and they might even have welfare consequences for the economy and society (see also Zhu, 2014). The total value of dark trades is economically significant; so it is unsurprising that there has been a lot of apprehension among market participants that dark pools could negatively impact trading quality. A survey of market participants by the CFA Institute finds that 71% of respondents believe that dark pools constitute problems for price discovery in the markets (see Schacht et al., 2009).

Despite the concerns of practitioners, academic theory suggests that the issue is much more complicated, and that dark pools could actually be beneficial to market quality. One of the main theoretical contributors to this emerging debate, Zhu (2014), holds that uninformed traders gravitate towards dark pools, while informed traders largely trade on the lit markets. This self-selection should result in reduced pricing errors/noise normally induced by uninformed traders when they submit their orders to lit markets, and therefore improve overall market price discovery. However, Ye (2011), employing a different framework of informed and uninformed traders, disagrees with Zhu's (2014) predictions. The difference in model predictions could be linked to differences in modelling approaches. While Zhu (2014) assumes that both informed and uninformed traders can freely select their trading venues, Ye's (2011) theoretical model gives only informed traders this selection ability.[4]

Over the past few years, several empirical papers examining different aspects of dark pool trading activity have been developed. For example, Buti et al. (2011), Preece and Rosov (2014), Ready (2014), Brugler (2015) and Foley and Putniņš (2016) investigate liquidity issues with regards to dark pools. Others, such as Comerton-Forde and Putniņš (2015) and Aquilina et al. (2016), examine price discovery-related functions of the market. Differences in regulatory environments, nature of data, and dates covered, make these papers distinct. Most of this literature uses US data, and where UK data is used, it is limited, as are the periods covered. By contrast, in this paper we provide the first large sample/aggregate market study of the impact of dark pools on market quality in the UK. Further, we do so in the context of the MiFID regulatory environment. Although there are similarities between the EU (MiFID) regulatory regime and several others around the world, there are also significant market microstructure differences. For example, the US (RegNMS) regime differs significantly from the EU (MiFID) regime in terms of the publishing/reporting of vital market variables such as bid and offer prices. The order protection rule, which mandates that venues re-route orders to where they could achieve better price execution, a cornerstone of the US regime, is not present under the MiFID regime.

Among the existing working papers on dark trading, only two, Brugler (2015) and Aquilina et al. (2016), employ UK data. However, the former study could not differentiate between dark and lit trades; it therefore excludes trades from venues operating both lit and dark order books. Nearly all of the UK's dark trading activity occurs on three venues operating both lit and dark order books; these are Chi-X, BATS and Turquoise. Furthermore, the sample period for the Brugler (2015) study is restricted to four months (September to December 2012). Therefore, the results are unlikely to be representative of dark trading either in the UK or in Europe as a whole. The latter study, Aquilina et al. (2016), focuses on liquidity provision and uses trades and orders for a random sample of five weeks over two years.

In this paper, the analysis is based on a five-year dataset spanning June 2010 to June 2015. Specifically, we investigate the impact of midpoint dark trading on quality (liquidity, adverse selection risk/market toxicity, levels of information asymmetry and pricing noise) in the aggregate market. Contrary to the findings of Foley and Putniņš (2016) in the Canadian lit market, we find that midpoint dark trading at moderate levels improves liquidity in the aggregate London market. It should be noted that Foley and Putniņš (2016) investigate current levels of dark trading, while we estimate dark trading impact beyond the current levels of trading.

We use four variables to proxy market quality attributes investigated. The first is the standard effective spread measure, used as a proxy for liquidity. The second is the number of times higher

[4] See Kyle (1985) for a discussion about the activities of informed and uninformed/noise traders.

than normal levels of order submission not justified by news are observed.[5] The third is the Easley et al. (1996; 1997) probability of informed trade (PIN) measure, and the fourth variable is an extension of the PIN measure, the Easley et al. (2011, 2012) volume-synchronised probability of informed trading (VPIN). Based on these variables, we present empirical evidence showing that moderate levels of mid-point dark pool activity improve aggregate market quality. In addition to these main indicators, we also investigate the impact of dark trading on the level of pricing noise in the market.

Dark pools, transparency and price discovery efficiency

Examining the impact of dark trading on market quality is complex (see also Comerton-Forde and Putniņš, 2015). This complexity is due to the different effects that dark trading could have on markets. Also of significance is the fact that a test for the impact of dark trading could effectively be a test for the impact of market fragmentation, thus making it difficult to distinguish the two effects.

There are competing theoretical arguments regarding the impact of dark trading on market quality. If dark transactions are less informative than lit transactions, on aggregate they contribute less to price discovery for the entire market. Therefore, larger proportions of dark trading could negatively affect the price discovery process. There are at least two reasons for this possibility. First, the lack of pre-trade transparency means that information contained in dark orders is not available to the wider market until after the orders are executed. Second, information contained in dark orders could be very low to begin with because uninformed traders select to trade in the dark because they are uninformed (see Zhu, 2014).

However, although dark orders may be less informative, the fact that these orders gravitate towards the dark pool should also make the price discovery process on the lit platforms less noisy. This may explain why Comerton-Forde and Putniņš's (2015) findings suggest that self-selection results in the reduction of noise in the pricing process. With noise in the lit venues now reduced and the price discovery process at those venues enhanced, if the dark pools use the more efficient price from a lit venue as reference for order execution, then dark trading improves overall market quality. Thus, if a network of lit venues exists alongside a system of dark pools, aggregate market quality could be improved if traders can self-select the venue they wish to trade in based on the information available to them. As explained earlier, dark pools in the UK use the Reference Price Waiver as a basis for their operation, that is, they execute their orders using prices published by lit venues (see also Aquilina et al., 2016 for further discussion of dark venue types and operations in the UK).

A hypothetical 'fully' transparent market is one where information is evenly distributed, therefore effectively eliminating traders with significantly superior levels of information. In this scenario, trades based on superior information are few, or arbitrage opportunities at any frequency are scarce. We argue that this market scenario is one possible consequence of traders choosing where they would trade as a result of their information sets. If only a small subset of traders on the lit venue holds the valuable information, they stand to profit by trading with a larger subset of (uninformed) traders. If nearly everyone is informed, the value of the information diminishes rapidly since opportunities for taking advantage of the information are reduced. The informed traders' orders are correlated with the underlying value of instruments traded in the market. Thus the larger their number, the more prevalent is the incidence of clustering of both buy and sell orders on one side of the market.

The empirical analysis by Foley and Putniņš (2016) supports the argument above as it fails to show any evidence of deteriorating liquidity in the presence of dark trading.

However, what happens when 'too many' uninformed traders migrate to the dark venues? Kyle (1985) and Glosten and Milgrom (1985) imply that the price discovery process is made possible by the ability of a section of the market (informed traders) to acquire information and incorporate it into prices. The informed players are compensated for their information-gathering activities when they gain while trading with uninformed traders. Thus, when information is costly, and uninformed

[5] This measure could also be viewed as a metric for potential quote stuffing. Quote stuffing involves rapidly submitting and cancelling large orders in order to flood the market with quotes requiring processing by competitors, and thus ensures that the competition loses its high frequency trading edge.

traders are few in the market, the price discovery process may breakdown, as traders have no incentive to acquire information.

In the same vein, when informed traders excessively migrate to the dark venues, the price discovery process becomes impaired in the lit and therefore aggregate markets. This is due to a reduced volume of potential uninformed counterparties that informed traders could trade with. When the opportunities of being compensated for gathering information are reduced, fewer potential informed traders find it advantageous to acquire information. This leads to less information being fed to the market in a timely manner. Theoretical and empirical links between price discovery and liquidity (see O'Hara, 2003) suggest that market liquidity deteriorates when price discovery is impaired. Deterioration of market liquidity implies a widening of the spread, which leads to larger adverse selection costs/risks. Thus, in our analysis, we expect to find a non-linear relationship between dark trading and the market quality variables we examine.

Based on the discussion above, we test two central hypotheses; the first is that dark trading enhances market quality in the aggregate market, as uninformed traders gravitate towards dark pools. The second is that there is a threshold of dark trading value relative to aggregate market value when dark trading impact negatively impacts market quality as the incentive to gather information and trade on the lit market is reduced.

3 Research design

Data

In our analysis of the aggregate market quality effects of dark trading, we examine the constituents of the FTSE 350 index of stocks, which includes the 350 largest firms listed on the LSE. These firms account for about 97% of the total market capitalisation of the FTSE All Share index as at 30 June 2015, the final date in our dataset. All FTSE 350 stocks are traded on several venues, and our data consists of trading data from the four main markets where these stocks are traded – the LSE, BATS Europe, Chi-X Europe and Turquoise. The total trading volume from these four venues accounts for more than 95% of the FTSE 350 lit trading value.

We obtain two sets of intraday tick data from the Thomson Reuters Tick History (TRTH) database. The first is the time and sales tick data, which includes variables such as the Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume and ask volume. We allocate each trade a pair of corresponding prevailing best bid and ask quotes based on the quotes submission information available in the TRTH database. Since we only focus on normal trading hours, we delete the opening auction (7:50hrs-8:00hrs) and closing auction (16:30hrs-16:35hrs) periods from the dataset – in any case, these auctions only run on the LSE.

The second set of TRTH data obtained is the 10-level market depth quotes and corresponding sizes for each transaction across the four venues. Our sample covers the period from 1 June 2010 to 30 June 2015. We retain only the stocks that consistently form part of the FTSE 350 index over the sample period and for which we are able to obtain sufficient intraday data for high frequency analysis. Finally, we merge the order book-level data for the four trading venues in order to create a single consolidated order book for the London market. The final dataset contains 1.152 billion transactions valued at £4.95 trillion executed in 288 stocks over the sample period.

In our sample, the daily level of dark trading in stocks exceeds the MIFID II-related 8% threshold, approximately 8.35% of the stock-day period under investigation. We also have approximately 1.7% of observations where dark trading exceeds 15%.

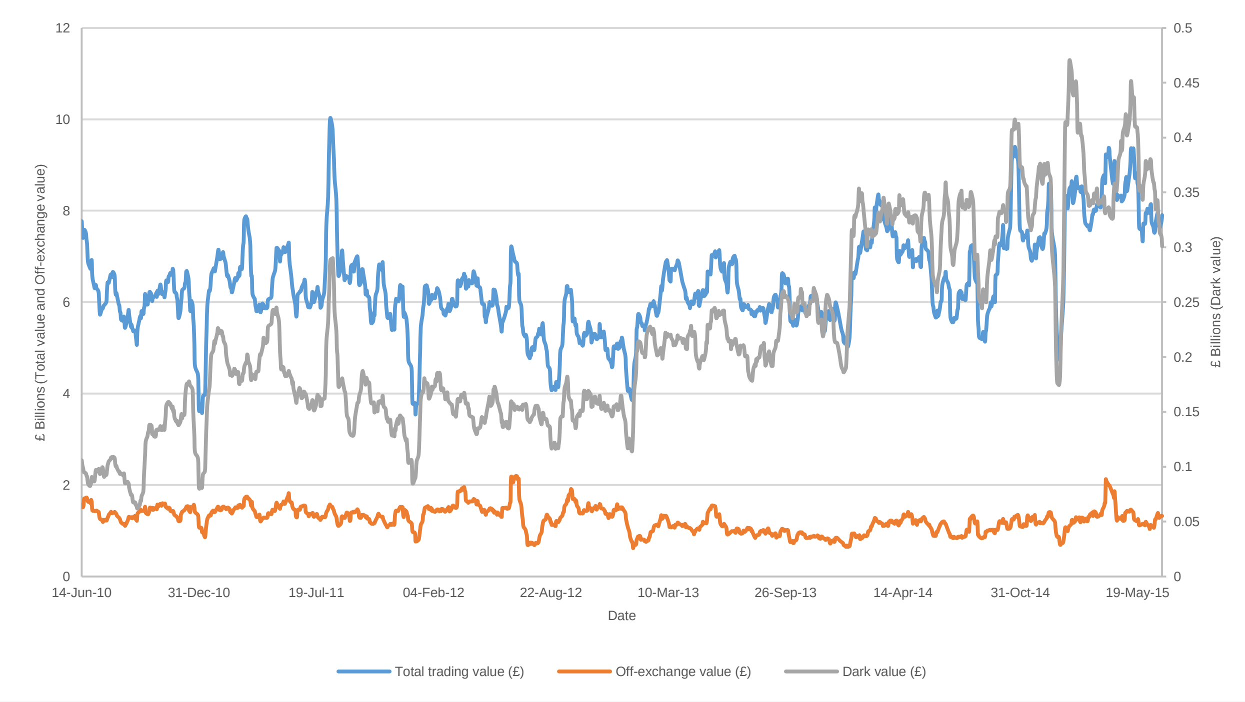
Descriptive statistics

Figure 1 presents the total, off-exchange and dark transactions values in our venues over the sample period.

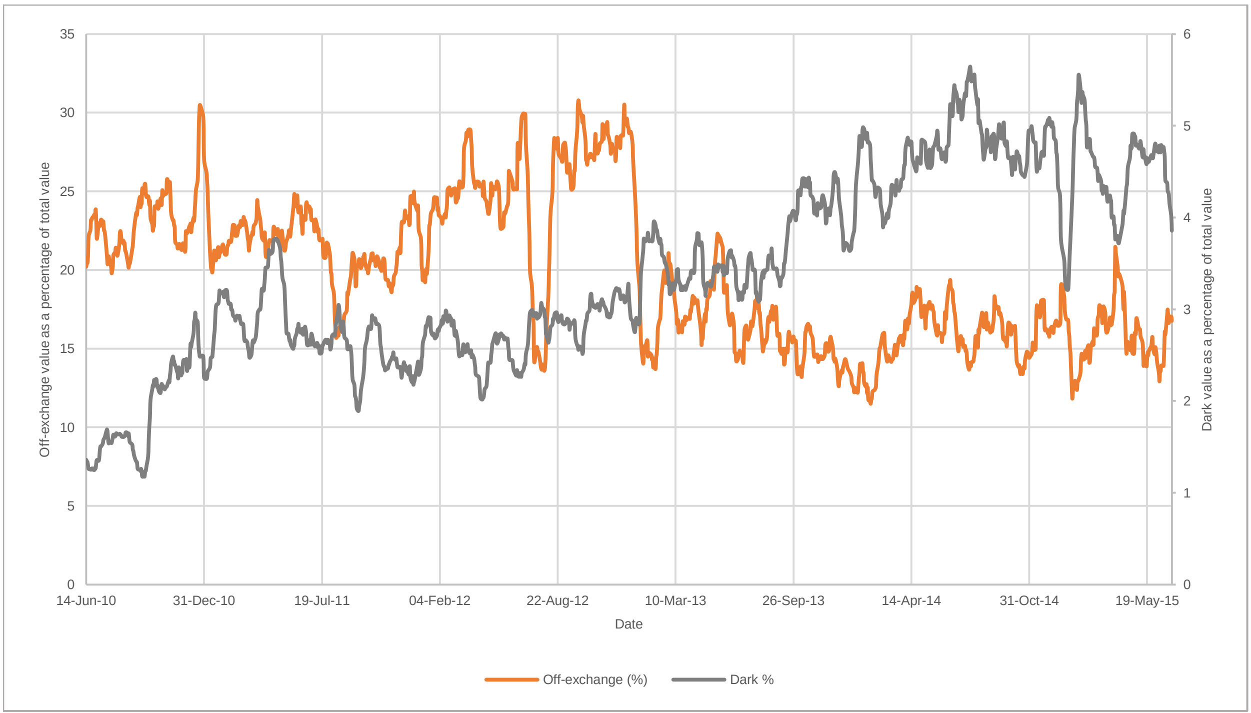
Panel A shows that dark trades appears to be tracking the total trading value for the market throughout the time series but with a higher rate of growth. Hence, the evidence here is that an increasing proportion of trades are now executed in the dark. Overall off-exchange values have also grown at a rate higher than the total market values; on aggregate, they are also much higher than dark values.

The dynamics are examined more closely in Panel B, which plots the dark and off-exchange values as percentages of the total market trading value. It shows that, when compared to dark values, there has been a fall in the proportion of trades executed off-exchange, while dark trade values continue to grow as a proportion of total market values. In June 2010, the average monthly proportion of dark trading value executed (for the stocks in our sample) in the market was 1.31%. This has more than trebled to 4.54% in the first six months of 2015. Over the same period, the proportion of trades executed off-exchange has fallen from 22.08% to 15.62%. Thus, it appears that the lost off-exchange trading value is mainly being shifted to the dark pools. This is important since most of the off-exchange executions are institutional and are viewed as largely liquidity-driven uninformed trades. It implies that dark trade is being driven by a search for institutional trading liquidity (see also Ibikunle, 2016). Overall, as shown in Panel C, changes in overall lit and dark values appear to be in lockstep throughout the five-year period.

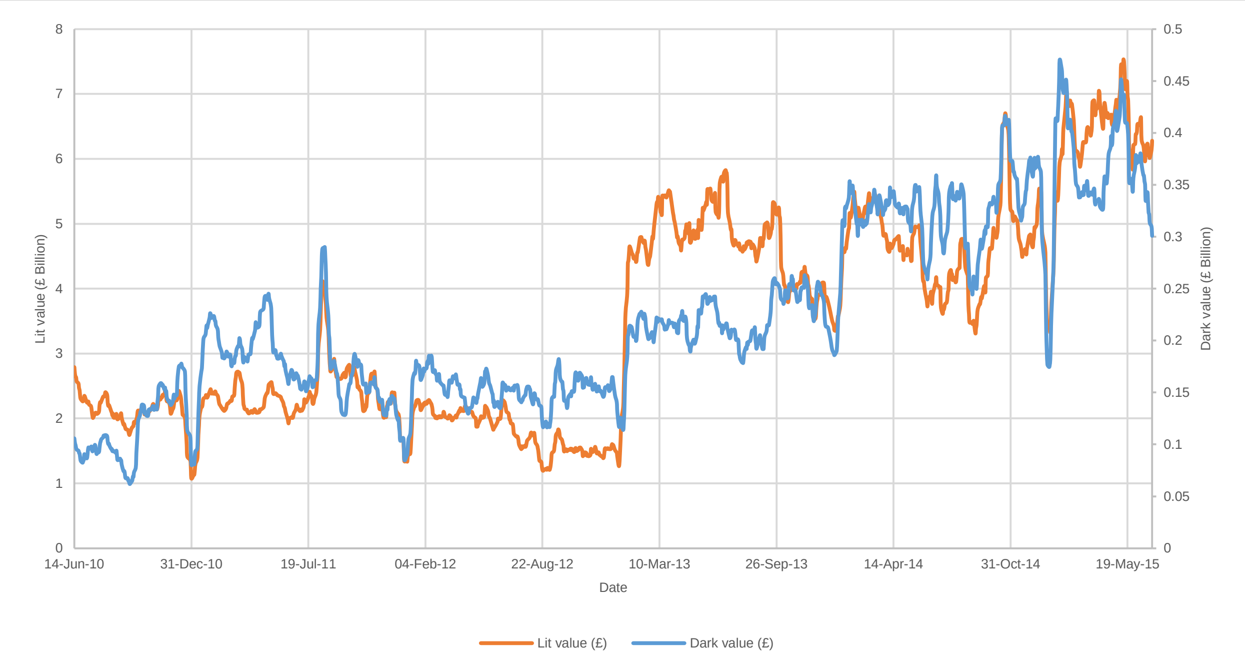
Figure 1: Trading values



Panel A: The figure plots the 10-day moving averages of total (dark, lit and off-exchange), off-exchange and dark pound trading values for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise between 1st June 2010 to 30th June 2015.



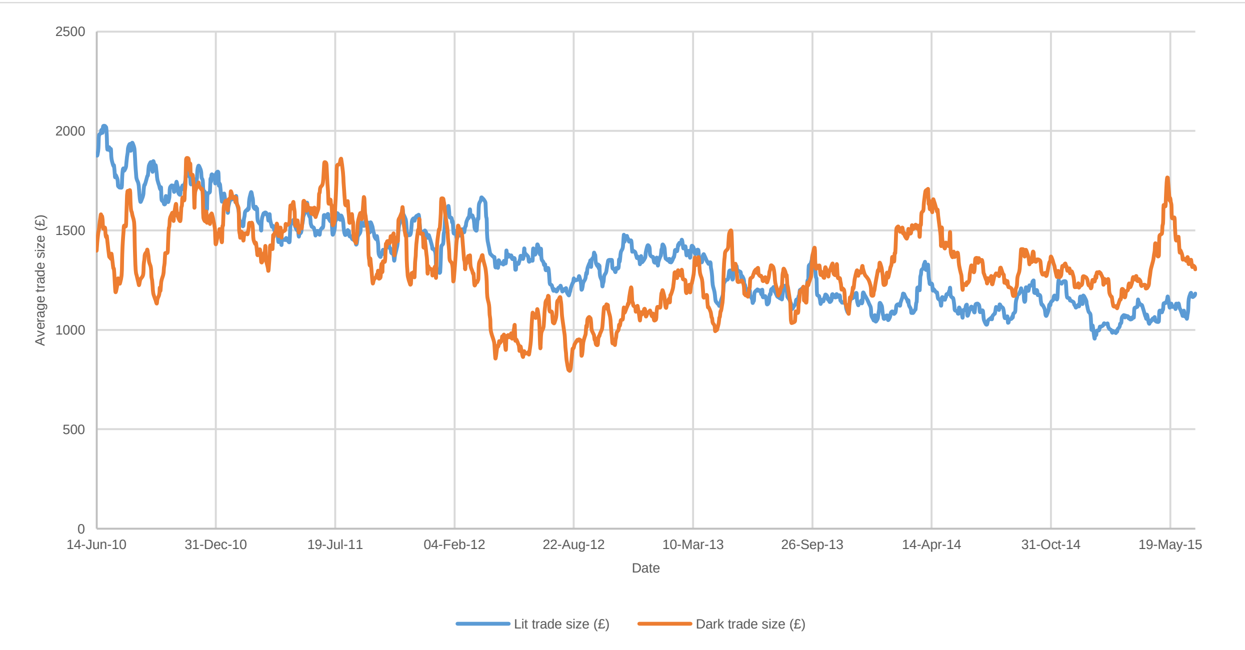
Panel B: The figure plots the pound values for dark and off-exchange trading as 10-day moving average percentages of total market value for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise between 1st June 2010 to 30th June 2015.



Panel C: The figure plots 10-day aggregate moving averages of dark and lit trading values for the same period, and for the same stocks and venues. The estimates are for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise between 1st June 2010 to 30th June 2015.

Figure 2 plots the average trade sizes of lit and dark transactions in the London market. The first point to note is that, consistent with the U.S. markets (see Chordia et al., 2011), there has been a general fall in average trade sizes for both lit and dark trades. Early on in the plot, dark transactions are generally smaller than lit transactions; however, they have since grown steadily larger over time, and become even larger than the lit ones in the last year of the period under review. The trend is, perhaps, connected with the growth in dark trades as well as the fact that institutional traders, who generally trade in larger than market average sizes, constitute a key group of actors in dark pools.

Figure 2: Trading values



Notes: The figure plots the 10-day moving average pound sizes per day of lit and dark trades for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise between 1 June 2010 to 30th June 2015.

Proxies for market quality

To examine the impact of dark trading on quality, we first identify proxies for two dimensions of market quality. Specifically, we aim to test the impact of dark trading on market liquidity and the level of adverse selection risk in the market.

We select the effective spread measure as a proxy for liquidity and the probability of informed trading (PIN) measure as developed by Easley et al. (1996; 1997) as a proxy for adverse selection risk. For robustness, we also compute the volume synchronised probability of informed trading (VPIN) (see Easley et al., 2011; Easley et al., 2012), and employ this measure as an additional proxy for adverse selection risk. The key difference between PIN and VPIN is that VPIN is seen as being more suited to a high frequency environment, since its development is aimed at matching the speed of information arrival in the market. It also incorporates a broader definition of information and allows for sampling in volume time rather than clock time, thus accounting for high frequency trading. Abad and Yagüe (2012) argue that VPIN is a broad measure for adverse selection. PIN and VPIN have been used in previous studies as suitable proxies for trading transparency and adverse selection/toxicity (see Vega, 2006; Easley et al., 2012; Abad and Yagüe, 2012).

We also develop a new proxy for transparency in the trading process. The measure, which we label 'quote stuffing incidences' (QSI), captures incidences of an abnormally large number of quote updates across the day. This could be intuitively interpreted as a measure of the number of times market participants attempt to 'muddy the trading waters' by posting many quotes in a small amount of time. Trading can be expected to be more transparent on days with fewer instances of QSIs. A drawback of this measure is that it might spike in quote stuffing events, but also in the presence of a higher level of algorithmic trading given that algorithmic traders generate many messages per trade. Thus, the measure might also incorporate the effects of heightened algorithmic trading.[6]

As a robustness check, we also compute a measure of the level of noise in each venue relative to the rest of the market and aggregate the estimates for each venue across the entire market. This is to investigate the impact of dark trading on the efficiency of the price discovery process. This measure is called Relative Noise Avoidance (RNA).

The details of our proxy measures are presented in Annex 2.

Our empirical approach

The empirical approach employed involves computing a series of stock-day panel estimations relating the market quality variables to dark trading activity and other control variables. Panel estimations are performed for all the 288 stocks. Following Sun et al. (2016), we combine the lit and dark order book data from the four exchanges and create a single order book using time stamps provided in the TRTH data. We use two approaches to estimate the relationship: (i) two-stage least squares (2SLS) instrumental variables (IV) regressions; and (ii) panel generalised method of moments (GMM). Panel corrected standard errors (PCSE) are computed to obtain heteroscedasticity and autocorrelation robust standard errors. The IV approach models are employed in order to account for the likelihood of the endogeneity of dark and off-exchange trading values.[7]

The panel regression estimated is of the following form:

$$Q_{it} = \alpha + \beta_{DARK} DARK_{it} + \beta_{OFFEX} OFFEX_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{6} \varphi_k C_{kit} + \varepsilon_{it} \qquad (1)$$

[6] However, it should be noted that the correlation between our measure of algorithmic/high frequency trading, that is, the ratio of quotes to trades and QSI is not excessively high, with a correlation coefficient of 0.606.

[7] Simple Panel Least Squares estimations with stock and time fixed effects are also employed for the IV estimations and are more likely to yield statistically significant results. The identical nature of the results hence imply that, just as reported by Comerton-Forde and Putniņš (2015), endogeneity appears not to significantly affect the one-stage least squares estimation results.

where Q_{it} is one of our quality proxies for stock *i* on day *t*, $DARK_{it}$ is the proportion of the stock-day's total pound trading volume executed in the dark,[8] while $OFFEX_{it}$ is the proportion of the stock-day's total pound volume of trades executed away from the four exchanges' lit venues for stock *i* on day *t*.[9] HFT_{it} serves as a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock *i* on day *t*. C_{kit} is a set of *k* control variables which includes (the log of) market capitalisation, average trade size, pound volume of lit trades, effective spread,[10] and the quadratic term $DARK^2_{it}$.

The quadratic term is added to capture the existence of a non-linear relationship between dark trading and market quality, as discussed above. It is also added due to a prediction of a trade-off in the positive and negative effects of fragmentation (see Degryse et al., 2015)[11] and dark trading in the US (see Preece and Rosov, 2014). $P_{other\ stocks}$, which is the average of the dependent variable (PIN, QSI or RNA) on the same day for all the other stocks in the same size quintile, is also included to account for commonality across stocks.

With regards to identifying suitable instruments for $DARK_{it}$ and $OFFEX_{it}$, the usual conditions on good instrument candidates apply:

- instruments must be highly correlated with the variable to be instrumented, and
- be largely uncorrelated with ε_{it} in Equation (1) above

We employ two sets of IVs. The first set uses an approach that has become increasingly popular in the recent literature; this approach was first proposed by Hasbrouck and Saar (2013) and used by several others such as Buti et al. (2011) and Degryse et al. (2015). Specifically, the variables are instrumented using the average level of dark and off-exchange trading in stocks of similar market capitalisation. In this paper, stocks in the same average daily trading value (in GBP) decile are used for instrumenting a stock's dark or off-exchange trading value.

The second set of IVs are computed based on an approach developed by Ibikunle (2016). In his paper, Ibikunle (2016) aims to maximise the potential for instrument-error term orthogonality by extending the Hasbrouck and Saar (2013) method. Firstly, the initial averages of the trading variables across stocks in the same decile are used in a panel least squares framework, which regresses each of the endogenous variables on their corresponding cross-sectional stock averages and the other control variables. Secondly, the residuals from this step are then employed as IVs in the GMM estimation. The IVs obtained satisfy the two conditions stated above to a very high degree. According to Ibikunle (2016), the reason for the lack of correlation between the IVs and Equation (1)'s residuals is that the common cross-sectional components in the stock averages have been 'exhausted' in explaining the changes in the endogenous variables, thus leaving only the stock-dependent factors not explained by the cross-sectional average.

Descriptive statistics for all the employed variables and a correlation matrix for the independent variables are reported in Table 1 and Table 2 respectively. Table 1 shows that large cap stocks generally have the larger trading values across the board, except in the case of average trade sizes. Average trade sizes are shown to be larger in low cap stocks due to being mainly executed off the main lit order books; Armitage and Ibikunle (2015) show that low volume stocks in the London market are usually executed via upstairs broker-dealer arrangements and then subsequently reported to the exchanges. Further, estimates show that about 3,051 lit trades and 140 dark trades are executed in an average stock each day during the sample period. As shown in Figure 1, dark value substantially lags lit and off-exchange values.

Table 2 shows the correlations between the independent variables used in the multivariate analysis. Consistent with Buti et al. (2011) and Comerton-Forde and Putniņš (2015), the effective spread is seen to be negatively correlated with dark value and off-exchange value. Thus, it appears that dark trading serves a similar purpose for market participants in the UK, the US and Australia, even when we focus on the aggregate market. The correlation coefficients are

[8] While the results presented in this paper are based on estimations computed with dark trading value as a proportion total trading value in pounds, we also conduct additional estimations using log values of dark trading value. The results, which are available on request, are consistent with the ones present in Section 4 and Annex 2 of this paper.

[9] We also use the log of pound volume of dark and off-exchange trades for stock *i* on day *t* as measures of dark and off-exchange trading respectively. The results obtained from this variation are qualitatively similar to the ones presented in the paper.

[10] Effective spread is excluded from the list of control variables when the dependent variable used in a regression estimation is the effective spread.

[11] Since migration to dark pools implies market fragmentation (a migration to new trading platforms), accounting for this possible trade-off is prudent.

unsurprising since the aggregate market is still dominated by lit trading. However, in contrast to previous studies, dark trading is negatively correlated with HFT, the algorithmic trading proxy.

Table 1: Descriptive statistics

Variables	Full sample	Highest volume stocks	4	3	2	Lowest volume stocks
Number of lit trades	3050.47 (1156.00)	9507.43 (6644.00)	3268.75 (2670.00)	1487.96 (1221.00)	592.82 (427.00)	148.88 (83.00)
Number of dark trades	139.51 (35.00)	436.44 (276.00)	150.36 (100.00)	63.27 (35.00)	27.98 (12.00)	8.14 (1.00)
Dark value (£)	8.07×10^{7} (1.01×10^{7})	2.82×10^{8} (1.52×10^{8})	6.74×10^{7} (3.4×10^{7})	2.39×10^{7} (7.66×10^{6})	9.06×10^{6} (1.97×10^{6})	7.97×10^{6} (2.91×10^{5})
Off-exchange value (£)	4.52×10^{8} (9.92×10^{7})	1.53×10^{9} (7.92×10^{8})	3.05×10^{8} (1.76×10^{8})	1.44×10^{8} (6.80×10^{7})	1.14×10^{8} (5.10×10^{7})	9.21×10^{7} (2.81×10^{7})
Trade size (£)	4408.36 (3263.81)	6608.19 (6209.36)	3976.09 (3559.98)	3517.65 (2496.85)	3852.43 (2453.789)	3970.83 (2350.76)
Market cap (£)	3.28×10^{10} (6.67×10^{9})	1.32×10^{11} (5.78×10^{10})	1.36×10^{10} (1.22×10^{10})	6.54×10^{9} (6.53×10^{9})	3.72×10^{9} (3.68×10^{9})	1.91×10^{9} (2.12×10^{9})
Effective spread (bps)	1.14 (0.55)	0.35 (0.26)	0.58 (0.40)	1.11 (0.67)	1.59 (1.06)	2.15 (1.58)
Lit value (£)	1.26×10^{9} (2.04×10^{8})	4.53×10^{10} (2.86×10^{9})	9.16×10^{8} (6.02×10^{8})	2.79×10^{8} (1.48×10^{8})	1.26×10^{8} (6.21×10^{8})	1.23×10^{8} (2.11×10^{8})
HFT (ratio)	536.55 (194.61)	840.29 (221.78)	727.29 (216.28)	502.07 (160.96)	330.06 (132.82)	201.83 (132.75)
PIN	0.25 (0.22)	0.20 (0.17)	0.21 (0.17)	0.24 (0.21)	0.28 (0.24)	0.33 (0.30)
QSI	4760.32 (1817)	8506.13 (3277.5)	5423.57 (2116.5)	4221.53 (1667.5)	3683.04 (1549.5)	3821.36 (1388)
Relative Noise Avoidance	1.47 (1.41)	1.44 (1.38)	1.47 (1.41)	1.50 (1.43)	1.53 (1.45)	1.54 (1.44)

Notes: This table reports daily mean values along with medians in parentheses per stock for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The sample period covers 1 June 2010 to 30 June 2015. The quintiles are computed based on daily pound volume across the sample period. HFT is a proxy for algorithmic trading and is measured as the ratio of messages to trades. QSI (quote stuffing incidences) is the number of times when per minute quotes update count in a stock is at least one standard deviation above the mean number of quote updates calculated for that minute using the surrounding period over days (–30, +30). Relative Noise Avoidance is based on the component factor share (CFS) of Gonzalo and Granger (1995) and is computed as the ratio of a stock venue's CFS to that of the other competing venues. The CFS metric is computed using quote mid-point at 1-second intervals. PIN is the Easley et al. (1996, 1997) probability of informed trading measure computed from the parameters yielded by maximising the following likelihood function:

$$L((B,S)\,|\,\theta) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!}$$
$$+\alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!},$$

where B and S respectively correspond to the total number of buy and sell orders for the day within each trading interval. $\theta = (\alpha, \delta, \mu, \varepsilon)$ is the parameter vector for the model. α corresponds to the probability of an information event, δ is the conditional probability of a low signal of an information event, μ is the arrival rate of informed orders, and ε is the arrival rate of uninformed orders. The probability that a trade is informed for each stock and within each interval is then computed as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}.$$

Table 2: Correlation matrix

Variables	Dark	Off-exchange value (£)	Trade size (£)	Market cap (£)	Effective spread (bps)	Lit value (£)	HFT
Dark	1.000	-0.039	0.080	0.014	-0.037	0.045	-0.130
Off-exchange value (£)	-0.039	1.000	0.623	0.597	-0.238	0.694	-0.116
Trade size (£)	0.080	0.623	1.000	0.510	-0.216	0.584	-0.012
Market cap (£)	0.014	0.597	0.510	1.000	-0.213	0.689	-0.087
Effective spread (bps)	-0.037	-0.238	-0.216	-0.213	1.000	-0.283	0.405
Lit value (£)	0.045	0.694	0.584	0.689	-0.283	1.000	-0.148
HFT	-0.130	-0.116	-0.012	-0.087	0.405	-0.148	1.000

Notes: The table reports correlations between independent variables calculated using trading data for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. Dark is the proportion of the stock-day's total pound volume executed in dark pools in the London market, and off-exchange value is the stock-day's total pound volume executed away from the downstairs of London's main four exchanges/trading venues. Lit value is the pound volume of all trades executed on the limit order books of the main four exchanges/trading venues in London. HFT is a proxy for algorithmic trading and is measured as the ratio of messages to trades, and effective spread is computed as twice the absolute value of the difference between transaction price and prevailing mid-point. Market cap, trade size, effective spread (bps) and lit value are in logs. The sample period covers 1 June 2010 to 30 June 2015. The quintiles are computed on the basis of average daily trading value in pounds sterling across the sample period.

4 Results

The main purpose of this paper is to test whether dark trading enhances aggregate market quality. This section presents the results of the analysis described in the previous section.

We discuss the results for each of the proxies we used separately, but the common message from all the estimates is that dark trading enhances market quality until it represents approximately 15% of overall trading.

Dark trading and market liquidity

Table 3 presents the results for both the 2SLS IV (Column A) and the GMM IV (Column B) regressions, estimating the impact of dark trading on market liquidity. The results presented are based on estimations employing the full sample of 288 stocks. In both sets of estimates, all of the *Dark* coefficients are negative and statistically significant. The results align with our expectations of the impact of dark trading on aggregate market liquidity. While increasing levels of dark trading might lead to widening spreads in the lit market, as shown in Comerton-Forde and Putnins (2015), in the aggregate London market, comprising of both lit and dark orders/trades, the impact is the opposite. The negative and statistically significant *Dark* coefficients across all estimations in Columns A and B of Table 3 show that spreads narrow (improving liquidity) in the aggregate market with increasing levels of dark trading.

However, $Dark^2$ coefficients in both Columns A and B are positive, implying a quadratic relationship between market liquidity and dark trading levels. These results are also consistent with our expectations that excessive migration of traders to the dark could lead to a breakdown in the price discovery process, and by extension lead to worsening liquidity in the market. If there are too few uninformed traders in the lit market, potential informed traders are not incentivised to expend resources in sourcing new information; hence, the breakdown in price discovery. This view is not dissimilar to the previously reported relationship between trading fragmentation and market quality characteristics (see for example, Degryse et al., 2015; Sun et al., 2016). The fragmentation studies are relevant because the migration of trades from lit venues to dark pools in the London market also implies a fragmentation of the trading process. Hence, our main result here is consistent with the existing literature on the effects of market fragmentation on market quality. In addition, this is backed up by the negative coefficient estimates reported for the off exchange value (OFFEX) coefficients across all estimations in both columns of Table 3.

In Figure 3, we plot the estimated impact of dark trading on effective spread based on full sample estimations. As can be observed, the turning point in the relationship occurs when dark trading volume in the market is around 15%. We use the stock-day panel regressions coefficients' standard errors in estimating 95% confidence intervals. The closeness of the confidence bands at the turning point, as seen in Figure 3, indicate a high level of statistical significance. Although, the confidence bands are constructed using standard errors of the coefficient estimates, at 0% dark trading, the constructed estimates' impact is zero, since the product of their values and dark trading at 0% will be zero. Hence, the confidence bands' values are the same as that of the implied curve estimate at 0% dark trading. The implied curve estimate at 0% dark trading equals the intercept/constant value in the regression. This means the *regressand* (effective spread) equals the value of the intercept/constant when the *regressors'* estimates (dark trading and its quadratic term) equal zero. As dark trading rises, we then observe the divergence of the confidence bands from the implied curve's estimates.

Table 3: The impact of dark trading on market liquidity

Variables	A	B
Dark	-3.83*** (-9.07)	-8.15*** (-7.37)
Dark^2	13.11*** (7.50)	21.49*** (4.61)
OFFEX	-0.16*** (-19.47)	-0.10*** (-11.08)
Trade size	0.35*** (20.25)	0.25*** (12.72)
Market cap	0.31*** (13.72)	0.44*** (32.04)
Lit value	-0.06*** (-8.01)	-0.13*** (-15.95)
HFT	0.34*** (37.41)	0.18*** (38.04)
$P_{other\ stocks}$	0.82*** (26.16)	0.27*** (19.51)
Intercept	-9.73*** (-29.06)	-9.84*** (-38.31)
R^2	0.77	0.65

Notes: The table reports regression coefficient estimates using a stock-day panel, in which the dependent variable is the effective spread (*EffectiveS*), which is defined as twice the absolute value of the difference between transaction price and prevailing mid-point, for 288 FTSE 350 stocks trading simultaneously on the four main London ‘exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The estimated regressions is:

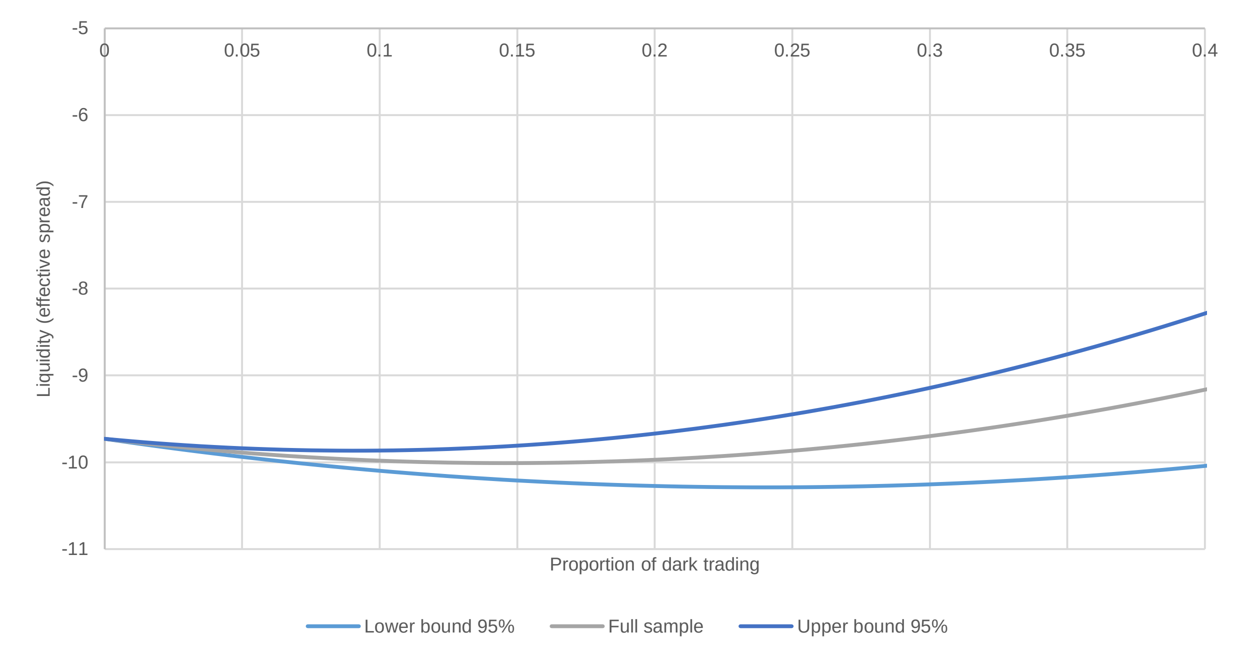
$$EffectiveS_{it} = \alpha + \beta_{DARK} DARK_{it} + \beta_{OFFEX} OFFEX_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{6} \varphi_k C_{kit} + \varepsilon_{it}$$

where $DARK_{it}$ is the proportion of the stock-day’s total pound trading volume executed in the dark, while $OFFEX_{it}$ is the log of the stock-day’s total pound volume of trades executed away from the four exchanges’ downstairs venues for stock *i* on day *t*. HFT_{it} is a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock *i* on day *t*. C_{kit} is a set of *k* control variables which includes log of market capitalisation, log of average trade size, log of pound volume of lit trades the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of Effective spread on the same day for all the other stocks in the same sized quintile. Column A and B report 2SLS and GMM estimations, respectively, using two different sets of instrumental variables (IVs). $DARK_{it}$ and $OFFEX_{it}$ are instrumented in the 2SLS estimation by using the average level of dark and off-exchange trading in stocks in the same market cap quintile respectively. In the GMM estimation IVs are obtained for $DARK_{it}$ and $OFFEX_{it}$ by first collecting the cross-sectional averages of the trading variables. $DARK_{it}$ and $OFFEX_{it}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as corresponding IVs for $DARK_{it}$ and $OFFEX_{it}$. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th June 2015.

A caveat is needed here. The turning point value is sensitive to coefficient values, which could vary significantly depending on the regression estimation methods used. For example, in this case, we plotted the implied effects by using the 2SLS estimation approach; if we were to use the GMM approach, we would obtain a turning point estimate of 18%. The 3% difference is economically significant, hence the need for caution. In the rest of the paper, we err on the side of caution by consistently reporting the lower turning points estimations. However, irrespective of the regression estimation approach used, we find consistency in the nature of the relationship between market liquidity variables and dark trading.

Results of a series of quintile-based analysis of the impact of dark trading on market liquidity are presented in Annex 2 of this paper.

Figure 3: Effects of dark trading on market liquidity (Turning point: 15%)



Notes: The figure plots the estimated effects of dark trading on market liquidity, with effective spread used as a proxy for market liquidity. The estimated effects are obtained by plotting the quadratic function of the coefficients obtained from stock-day panel regressions as described in Table 3. The grey line represents the implied effects while the dark and light blue lines represent the upper and lower bounds of the 95% confidence intervals, computed using standard errors obtained from the stock-day panel regressions. The sample consists of 288 FTSE 350 stocks trading simultaneously on the four main London 'exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise, between 1st June 2010 to 30th June 2015.

Dark trading and adverse selection risk

Table 4 presents the results for both the 2SLS IV (Column A) and the GMM IV (Column B) regressions. For the two sets of results, estimates are presented for the full sample of 288 stocks, with PIN employed as a proxy for adverse selection risk. In both columns, all of the coefficients are statistically significant, except in the case of the off-exchange value coefficient (0.1 level in Column A).

As predicted, in both sets of results the relationship between PIN and dark trading is negative while the quadratic term is positive. This implies, as in the case of our estimates on liquidity that increasing levels of dark trading are linked with improvements in market transparency and an elimination of adverse selection risk and information asymmetry (see Chung and Li, 2003; Brown et al., 2009) in the aggregate market. However, much higher levels of dark trading induce adverse selection risk and information asymmetry. Thus, based on the estimates in Table 3, we find a reason to support Zhu's (2014) prediction that the addition of a dark pool to a lit platform improves market quality for the aggregate market comprising of both the lit and dark platforms, due to self-trading venue selection of informed and uninformed traders.

The results are also consistent with the suggestion that the self-selection by traders results in declining trading noise in the market (see Comerton-Forde and Putniņš, 2015). As earlier stated, the inverse relationship between information asymmetry and dark trading is likely due to the increasing proportion of informed traders in the lit order books, as uninformed participants migrate to dark order books. This is a valid conclusion in the context of the dark pools we examine in this paper; the dark pools use the lit venues' prices as price reference points, specifically by matching trades to the lit venues' mid-points. This relationship implies, that most of the information released into the London market arises from the lit venues, and that dark trades by themselves, when not considered as part of the aggregate market, impair price discovery (see also Comerton-Forde and Putniņš, 2015).

Table 4: The impact of dark trading on adverse selection risk

Variables	A	B
Dark	-0.88*** (-7.25)	-0.48*** (-33.09)
Dark^2	3.49*** (4.30)	1.46*** (20.52)
OFFEX	-0.01*** (-7.61)	-0.02*** (-28.94)
Trade size	0.01*** (3.82)	0.03*** (34.80)
Market cap	-0.02*** (-26.28)	-0.02*** (-18.78)
Effective spread	0.01*** (19.41)	0.02*** (38.63)
Lit value	0.00*** (-6.17)	0.01*** (4.00)
HFT	0.00*** (-8.06)	0.01*** (6.89)
$P_{other\ stocks}$	0.75*** (31.40)	0.74*** (19.41)
Intercept	0.66*** (35.36)	0.27*** (27.11)
R^2	0.29	0.16

Notes: The table reports regression coefficient estimates using a stock-day panel, in which the dependent variable is the Easley et al. (1996, 1997) probability of an informed trade (PIN) measure computed as outlined in Table 1 for 288 FTSE 350 stocks trading simultaneously on the four main London exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The estimated regressions is:

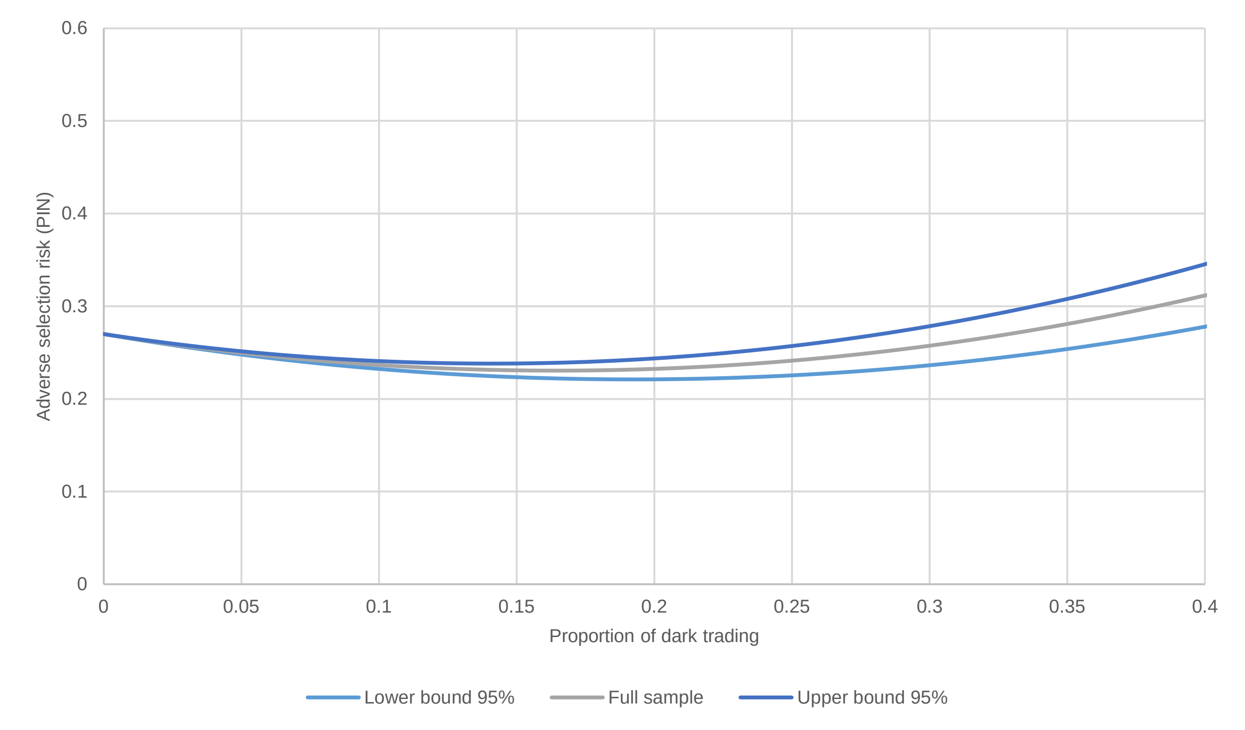
$$PIN_{it} = \alpha + \beta_{DARK} DARK_{it} + \beta_{OFFEX} OFFEX_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{6} \varphi_k C_{kit} + \varepsilon_{it}$$

where $DARK_{it}$ is the proportion of the stock-day's total pound trading volume executed in the dark, while $OFFEX_{it}$ is the log of the stock-day's total pound volume of trades executed away from the four exchanges' downstairs venues for stock *i* on day *t*. HFT_{it} is a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock *i* on day *t*. C_{kit} is a set of *k* control variables which includes log of market capitalisation, log of average trade size, log of pound volume of lit trades, effective spread, which is defined as twice the absolute value of the difference between transaction price and prevailing mid-point, the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of PIN on the same day for all the other stocks in the same sized quintile. Columns A and Panel B report 2SLS and GMM estimations, respectively, using two different sets of instrumental variables (IVs). $DARK_{it}$ and $OFFEX_{it}$ are instrumented in the 2SLS estimation by using the average level of dark and off-exchange trading in stocks in the same market cap quintile respectively. In the GMM estimation IVs are obtained for $DARK_{it}$ and $OFFEX_{it}$ by first collecting the within-quintile/full sample cross-sectional averages of the trading variables. $DARK_{it}$ and $OFFEX_{it}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as corresponding IVs for $DARK_{it}$ and $OFFEX_{it}$. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th June 2015. The quintiles are computed on the basis of average daily trading value in pounds sterling across the sample period.

However, the positive *Dark*^{2} estimates in both Columns A and B suggest that the negative relationship between PIN and dark trading is quadratic in nature. This implies that there is a level/range of dark trading in the market, which could lead to increasing information asymmetry/adverse selection for the aggregate market and thus hurt overall market quality. As stated above, this view fits in with the reported relationship between trading fragmentation and market quality characteristics (see for example, Degryse et al., 2015; Sun et al., 2016). In Figure 4, we plot estimates of the implied effect of dark trading on the inverse proxy for aggregate market transparency/adverse selection risk, PIN. The figure suggests that the turning point of the positive effect of dark trading on market quality is when dark trading is at about 16% of the total trading value in the market. The closeness of the upper and lower confidence bands at the turning point indicate a high level of statistical significance.

The results and plots arising from using VPIN as a proxy for adverse selection risk are consistent with the estimation results obtained using PIN as adverse selection risk proxy. The results are presented in Table A1 and Figure A1 in Annex 2 of this paper. Further results showing quintile sample analysis for PIN are also presented in the Annex 2.

Figure 4: Effects of dark trading on adverse selection risk (Turning point: 16%)



Notes: The figure plots the estimated effects of dark trading on adverse selection risk, with the probability of an informed trade (PIN) used as an inverse proxy for market transparency/adverse selection risk. The estimated effects are obtained by plotting the quadratic function of the coefficients obtained from stock-day panel regressions as described in Table 3. The grey line represents the implied effects while the dark and light blue lines represent the upper and lower bounds of the 95% confidence intervals, computed using standard errors obtained from the stock-day panel regressions. The sample consists of 288 FTSE 350 stocks trading simultaneously on the four main London ‘City’ exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise, between 1st June 2010 to 30th June 2015.

Dark trading and trading clarity

As an additional robustness check, we also proxy the clarity of trading in the market by computing the number of times abnormal levels of messages/quotes are observed for each stock across the four trading venues’ order books. We call this measure ‘quote stuffing incidences’ (QSI). The log of QSI is then employed as a dependent variable in the two sets of IV regressions as explained above. The results are presented in Column A and Column B of Table 5. The results for both columns are highly consistent; hence, the discussion of Table 5 focuses on one column. In Column A, the coefficient estimates and the directions of relationships with the QSI variable are as expected. *Dark* is found to be negatively related to QSI, and the relationship is statistically significant (–3.22, significant at 0.00 level). There is no advantage to stuffing quotes in a dark trading environment, since the state of the order book is not observable. Specifically, in order to devise and execute a quote stuffing strategy, usually aimed at eliminating the competitive edge of rival high frequency traders, one would need to possess information regarding the state of the target order book. This is less likely in dark markets than in lit markets. Therefore, as the proportion of dark trading in the aggregate market rises, one would expect a reduction in the incidences of quote stuffing. In addition, consistent with the PIN analysis, the $Dark^2$ estimate suggests that the relationship is quadratic. It is also important to note that while HFT is seen as enhancing price discovery by speedily eliminating order imbalances and arbitrage opportunities,[12] it is found here to be positively (and significantly) related with quote stuffing statistically. This is expected, given that quote stuffing is intuitively more likely in a high frequency trading environment.

[12] For example, in the literature, the overall impact of HFT is usually found to be positive for large cap stocks (see Chaboud et al., 2014; Hendershott et al., 2011).

Table 5: The impact of dark trading on quote stuffing incidences

Variables	A	B
Dark	-3.22*** (-18.84)	-2.40*** (-66.62)
$Dark^2$	8.37*** (4.47)	22.68*** (11.92)
OFFEX	0.15*** (5.76)	0.15*** (11.94)
Trade size	0.06 (0.98)	0.03*** (0.17)
Market cap	0.31*** (16.74)	0.32*** (6.81)
Effective spread	0.03*** (4.55)	0.03** (2.41)
Lit value	-0.03 (-1.35)	-0.02 (-0.16)
HFT	0.34*** (14.70)	0.33*** (5.54)
$P_{other\ stocks}$	0.28*** (14.25)	0.28*** (13.79)
Intercept	-6.82*** (-18.84)	-6.75*** (-17.21)
R^2	0.33	0.32

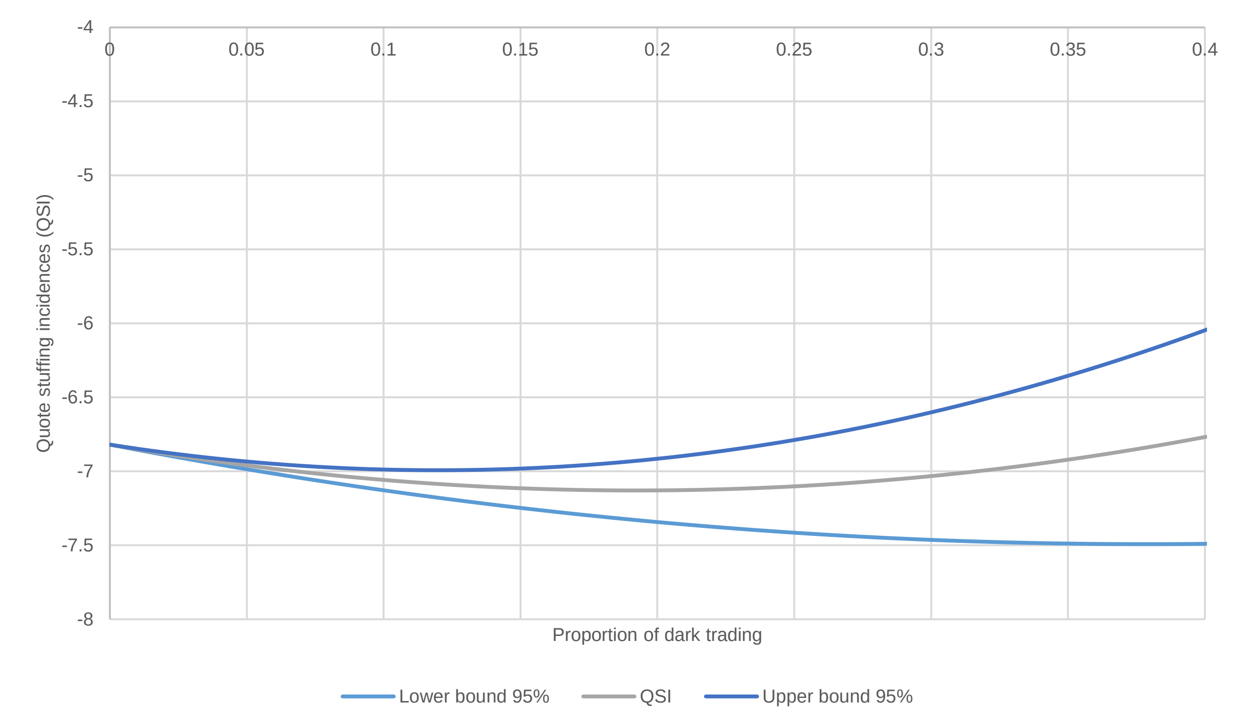
Notes: The table reports regression coefficient estimates using a stock-day panel, in which the dependent variable is QSI, defined as the number of times that per minute quotes update count in a stock is at least one standard deviation above the mean number of quote updates calculated for that minute using the surrounding period over days (–30, +30), for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The estimated regressions is:

$$\log(QSI)_{it} = \alpha + \beta_{DARK} DARK_{it} + \beta_{OFFEX} OFFEX_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{6} \varphi_k C_{kit} + \varepsilon_{it}$$

where $DARK_{it}$ is the proportion of the stock-day's total pound trading volume executed in the dark, while $OFFEX_{it}$ is the log of the stock-day's total pound volume of trades executed away from the four exchanges' downstairs venues for stock *i* on day *t*. HFT_{it} is a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock *i* on day *t*. C_{kit} is a set of *k* control variables which includes log of market capitalisation, log of average trade size, log of pound volume of lit trades, effective spread, which is defined as twice the absolute value of the difference between transaction price and prevailing mid-point, the square of $DARK_{it}$ and $P_{other\ stocks}$ is the log of the average of QSI on the same day for all the other stocks in the same sized quintile. Column A and Column B report 2SLS and GMM estimations using two different sets of instrumental variables (IVs). $DARK_{it}$ and $OFFEX_{it}$ are instrumented in the 2SLS estimation by using the average level of dark and off-exchange trading in stocks in the same market cap quintile respectively. In the GMM estimation IVs are obtained for $DARK_{it}$ and $OFFEX_{it}$ by first collecting the within-quintile/full sample cross-sectional averages of the trading variables. $DARK_{it}$ and $OFFEX_{it}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as corresponding IVs for $DARK_{it}$ and $OFFEX_{it}$. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th June 2015. The quintiles are computed on the basis of average daily trading value in pounds sterling across the sample period.

In Figure 5, we plot the estimated impact of dark trading on QSI. The turning point is at about 19%, and the closeness of the upper and lower confidence bands at the turning point indicate a high level of statistical significance.

Figure 5: Effects of dark trading on quote stuffing incidences (Turning point: 19%)



Notes: The figure plots the estimated effects of dark trading on quote stuffing incidences (QSI), defined as when a per minute quotes update count is at least one standard deviation above the mean number of quote updates calculated for that minute using the surrounding period over days (–30, +30). The estimated effects are obtained by plotting the quadratic function of the coefficients obtained from stock-day panel regressions as described in Table 3. The grey line represents the implied effects while the dark and light blue lines represent the upper and lower bounds of the 95% confidence intervals, computed using standard errors obtained from the stock-day panel regressions. The sample consists of 288 FTSE 350 stocks trading simultaneously on the four main London ‘exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise, between 1 June 2010 to 30 June 2015.

Dark trading and trading noise

Our final set of estimates deals with the amount of trading noise in the market. On balance, if dark trading enhances transparency in the overall London equity market, then we should also see a reduction in the overall noise levels in the market. Thus, we expect dark trading to be positively related to RNA, a measure of the extent of avoidance of trading noise in one venue relative to its competing venues. A positive relationship implies that, in the overall market, increasing dark trade levels lead to declining noise levels, since a rise in RNA values means a fall in market trading noise. Table 6 presents the results in the usual way. Consistent with our expectations, and with the PIN and QSI regressions, coefficient estimates for dark value suggest reduction in noise levels in the presence of dark trading. The dark value coefficients in Columns A and B of Table 6 are 0.41 (p-value of 21.10) and 0.30 (p-value of 2.35).

The result in Column A implies that overall trading noise falls by about 40% with every unit rise in dark trading value in the London market; the estimate is 30% when we consider the GMM estimation approach result in Column B. This result is also in line with what we should find if dark trading does really enhance quality in the overall market because of traders self-selecting, trading venue-wise.

Similar to this analysis, Comerton-Forde and Putniņš (2015) investigate the impact of dark trading on informational efficiency in the Australian market. The proxies they use include Autocorrelation and Variance Ratio, which are intuitively similar to our approach. Their results, focused on the impact of dark trading on just the lit market’s quality features, are consistent with ours, as is the insight that the relationship of informational efficiency with dark trading is conditioned on the level of dark trading.

Table 6: Dark trading and noise in the price discovery process

Variables	A	B
Dark value	0.41*** (21.10)	0.30** (2.35)
Dark^2	-0.92*** (-10.27)	-1.46** (-2.13)
Off-exchange value	0.00 (-0.38)	0.00 (0.99)
Trade size	0.10* (1.67)	0.05* (1.94)
Market cap	0.46*** (6.72)	0.47*** (6.74)
Effective spread	0.52*** (6.53)	0.52*** (6.49)
Lit value	0.00 (-0.06)	0.00 (0.14)
HFT	0.12*** (4.57)	0.13*** (8.27)
$P_{other\ stocks}$	0.78*** (3.22)	0.78*** (3.22)
Intercept	-12.60*** (-7.04)	-12.57*** (-7.07)
R^2	0.30	0.30

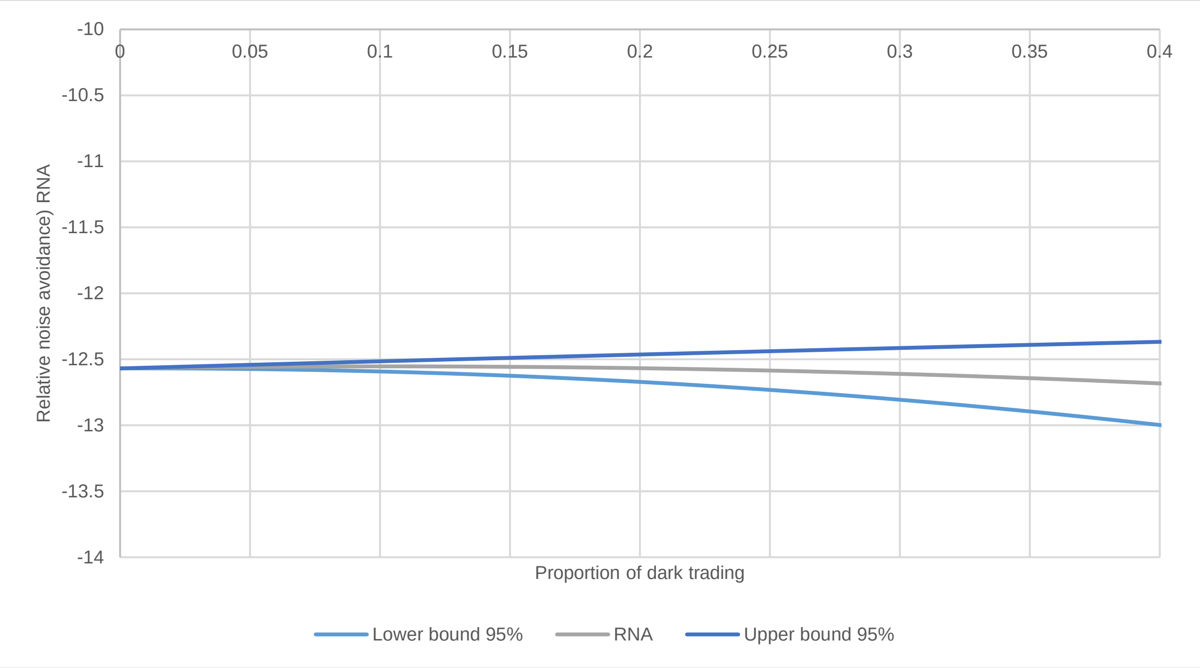
Notes: The table reports regression coefficient estimates using a stock-day panel, in which the dependent variable is Relative Noise Avoidance (RNA), a measure based on the component factor share (CFS) of Gonzalo and Granger (1995), and is computed as the ratio of a stock venue's CFS to that of the other competing venues, for 288 FTSE 350 stocks trading simultaneously on the four main London exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The estimated regressions is:

$$RNA_{it} = \alpha + \beta_{DARK} DARK_{it} + \beta_{OFFEX} OFFEX_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{6} \varphi_k C_{kit} + \varepsilon_{it}$$

where $DARK_{it}$ is the proportion of the stock-day's total pound trading volume executed in the dark, while $OFFEX_{it}$ is the log of the stock-day's total pound volume of trades executed away from the four exchanges' downstairs venues for stock *i* on day *t*. HFT_{it} is a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock *i* on day *t*. C_{kit} is a set of *k* control variables which includes log of market capitalisation, log of average trade size, log of pound volume of lit trades, effective spread, which is defined as twice the absolute value of the difference between transaction price and prevailing mid-point, the square of $DARK_{it}$ and. $P_{other\ stocks}$ is the average of RNA on the same day for all the other stocks in the same sized quintile Column A and Column B report 2SLS and GMM estimations using two different sets of instrumental variables (IVs). $DARK_{it}$ and $OFFEX_{it}$ are instrumented in the 2SLS estimation by using the average level of dark and off-exchange trading in stocks in the same market cap quintile respectively. In the GMM estimation IVs are obtained for $DARK_{it}$ and $OFFEX_{it}$ by first collecting the within-quintile/full sample cross-sectional averages of the trading variables. $DARK_{it}$ and $OFFEX_{it}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as corresponding IVs for $DARK_{it}$ and $OFFEX_{it}$. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th June 2015. The quintiles are computed on the basis of average daily trading value in pounds sterling across the sample period.

As with the results presented in the previous tables, the *Dark*^{2} estimates (–0.92 and –1.46) take opposite signs to the *Dark* coefficient estimate, and the estimates are statically significant. Comparing our results to Zhu's (2014) predictions, that operating a dark venue alongside a lit venue will, in equilibrium, enhance price discovery, we find ample evidence that the theoretical prediction holds. However, consistent with our findings for the other measures, our results suggest that at a certain point higher levels of dark trading start to harm market quality. Based on our measure of noise, we estimate that turning point to be at about 11%. The plot is presented in Figure 6 below. The confidence interval in this case, as plotted, is almost non-existent, indicating a very high level of statistical significance.

Figure 6: Effects of dark trading on noise in the pricing process (Turning point: 11%)



Notes: The figure plots the estimated effects of dark trading on market quality, with the Relative Noise Avoidance (RNA) measure as a proxy for noise in the pricing process. The estimated effects are obtained by plotting the quadratic function of the coefficients obtained from stock-day panel regressions as described in Table 3. The grey line represents the implied effects while the dark and light blue lines represent the upper and lower bounds of the 95% confidence intervals, computed using standard errors obtained from the stock-day panel regressions. The sample consists of 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise, between 1 June 2010 to 30 June 2015.

5 Conclusions

In this study, we test the central hypotheses arising from recent theoretical work on the impact of dark trading on market quality. Zhu (2014) argues that price discovery is enhanced by the addition of a dark pool to a lit exchange, because uninformed traders can choose to trade in the dark and thus reduce the level of noise in the lit market.

Our results, based on a very large sample of the 350 largest UK stocks traded across the four main trading venues in London, suggest that the current level of dark trading in the aggregate UK equity market does not appear to be detrimental to market quality. In addition, we find that the impact of dark trading is related to the level of trading activity in stocks. Based on analysis conducted using data from mid-point dark order books as well as lit order books, we find that the overall quality of the market improves at moderate levels of dark trading.

However, we also observe a non-linear relationship between our proxies of market quality and dark trading, which implies that at higher levels, dark trading could be harmful to market quality. For our full sample of stocks, the impact of dark trading on market quality starts to turn sour anywhere between 11% and 17%, depending on the market quality proxy being examined. This estimate, however, varies depending on the level of trading activity across stocks.

In line with academic theory, these results show that, when given an option to trade in the dark, uninformed traders are more likely to do so than informed traders. Hence, the availability of dark pools provides an opportunity of segmenting trader-types in the market. With the lit venues having a higher percentage of well-informed traders than in a scenario where dark pools do not exist, there arises a higher likelihood of timely incorporation of information into prices. In addition, since the trades executed in the dark are based on reference prices determined on the lit exchanges, the overall market's price discovery process is more efficient for each stock traded simultaneously in the dark and lit venues.

The estimated dark trading thresholds/ranges presented in this paper should be interpreted with caution for three reasons. Firstly, dark trading as a proportion of total trading in the London market is yet to consistently attain the estimated thresholds; hence, the estimates are based on regression coefficients computed using data with predominantly lower levels of dark trading. Secondly, the estimated thresholds are dependent on the coefficient values and thus easily influenced by the estimation approach used. In this paper, we consistently report the lower turning point estimates. Thirdly, the estimated thresholds also vary significantly depending on the liquidity of the stocks investigated; hence, an aggregate estimated threshold could be misleading.

One thing is clear irrespective of the estimation approach we employ; there is a consistent quadratic relationship between dark trading and market quality in the London market. This means that, although the current levels of dark trading are not negatively impacting market quality, much higher levels may be detrimental.

The UK and, indeed, European financial markets infrastructures are at a significant milestone with the imminent implementation of MiFID II/MiFIR, a package of regulations that partly aims to cap the volume of dark trading at 8%. This study, suggesting that moderate levels of dark trading do not harm market quality, is therefore timely and could have significant policy implications. This is even more so since a proportion of our stock-day sample (8.35%) evidences dark trading in excess of 8%. In Annex 2, we present a table showing the proportion of stock-days where dark trading is in excess of 8% for the full sample of stocks as well as for stock quintiles.

MiFID II/MiFIR emphasises investor protection and trading quality in financial markets. We have shown in this study that the latter aim is furthered by the existence of dark pools operating alongside lit exchanges. It is important that policy makers take care not to eliminate the market quality benefits of dark trading by arbitrarily imposing uniform dark trading restrictions for all stock sizes.

Annex 1: References

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Annex 2: Additional methodologies and results

Effective spread

The effective spread is defined as twice the absolute value of the difference between an execution price and the midpoint of the corresponding prevailing bid and ask quotes. Effective spread is computed for each time a trade occurs during the day in the aggregate market and then averaged across the day in order to obtain a daily measure used in the multivariate analysis described below.

PIN: an inverse proxy for market quality/adverse selection risk

Apart from being an inverse proxy for market quality, PIN could also serve as a proxy for adverse selection, especially since it is generally regarded as being strongly correlated with adverse selection risk and information asymmetry (see for example Chung and Li, 2003; Brown et al., 2009). PIN has also been employed as a proxy for priced information risk and information asymmetry in the wider financial economics literature (see for example Vega, 2006; Ellul and Pagano, 2006; Duarte et al., 2008; Chung and Li, 2003). Recently Lai et al. (2014) compute PIN measures for 30,095 firms across 47 countries over a 15-year period, and conclude that PIN is highly correlated with firm-level private information.

Therefore, we adopt PIN as an inverse proxy of the daily levels of market quality. The model is based on the expectation that trading between informed traders, liquidity traders and market makers occurs across the day. Trading commences with the informed traders acquiring a private signal regarding a stock's value. The probability of such a signal is α. Bad news based on the private signal will arrive with probability δ, and good news based on the private signal arrives with probability $(1 - \delta)$. The market makers generate their bid and ask prices with orders arriving from liquidity traders at the arrival rate ε. Should new private information become available, informed traders will join the trading process, with their orders arriving at the rate μ. It is expected that informed traders will execute a purchase trade if they have acquired a good news signal, and sell should the signal be bad news. We note that the allocation of different arrival rates for uninformed buy and sell orders does not qualitatively change estimations of the probability that an informed trade has been executed (see Easley et al., 2002).

The PIN model enables us to approximate the unobservable distribution of trades between informed and uninformed traders by modelling observable buy and sell orders.[13] Hence, the 'usual level' of sales and purchases executed within a stock on a given day over several trading cycles is interpreted as relatively uninformed aggregate trading activity by the model, and this information is employed to estimate ε. Unusual levels of purchase or sale transactions are interpreted as information-based transactions and used to estimate μ. In addition, the frequency of intervals during which 'abnormal' levels of purchases and sales are observed is used to estimate the values of α and δ. If we assume that the uninformed and informed trades arrive as a Poisson distribution, the likelihood function for the PIN model for each interval estimated can be expressed as:

[13] We infer purchase and sales through the running of Lee and Ready's (1991) trade classification algorithm.

$$L((B,S)\mid\theta) = (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu-\varepsilon_s)}\frac{(\mu-\varepsilon_s)^S}{S!} + \alpha(1-\delta)e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!}e^{-(\mu-\varepsilon_b)}\frac{(\mu-\varepsilon_b)^B}{B!} \qquad \text{(A1)}$$

where B and S respectively correspond to the total number of purchase and sale transactions for each one hour trading period within each trading day. θ = (α, δ, μ, ε) is the parameter vector for the structural model. Equation (A1) represents a system of distributions in which the possible trades are weighted by the probability of a one hour trading period with no news (1 – α), a one hour trading period with good news (α (1 – δ)), or a one hour trading period with bad news (αδ). Based on the assumption that this process occurs independently across the different trading periods, Easley et al. (1996; 1997) estimate the parameter vector using maximum likelihood estimation procedure. Thus, we follow their lead in obtaining the parameters for each trading day and for each stock in the sample. Consistent with Easley et al. (1996; 1997), PIN is then computed as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}$$

Quote Stuffing Incidences (QSI): a measure of trading clarity

The quote stuffing variable is simply a measure of the number of times an abnormal number of quotes updates is observed during a minute interval across the trading day, at all the venues included in our dataset. An abnormal level of quotes updates is defined as when a per minute quotes update count is at least one standard deviation above the mean number of quote updates calculated for that minute using the surrounding period over days (–30, +30).[14] This measure is linked to the level of clarity traders would have regarding the balance of buy and sell orders in the market; thus, it could be seen as an indication of how transparent the market is.

Relative Avoidance of Noise (RNA)

There are two well-established traditional approaches for measuring the price discovery contributions of different markets/venues; these are Hasbrouck's (1995) information share (IS) and the Gonzalo and Granger's (1995) common factor share (CFS). Essentially, both approaches arise from a vector error correction model (VECM) and aim to decompose price innovations into permanent and transitory components. Yan and Zivot (2010) and Putniņš (2013), however, contend that correctly allocating a market's share of price discovery contribution only holds for both measures if the competing venues have similar noise levels. When there are differences in the noise levels, IS and CFS measure to varying degrees a combination of speed of impounding information and relative avoidance of noise, rather than price discovery. According to Putniņš (2013), CFS measures mainly the relative avoidance of temporary shocks in the pricing process and thus allocates price discovery dominance to the venue with lower noise levels. We, therefore, extend the CFS measure to compute a new variable measuring the relative noisiness of the price discovery process in various venues; the individual stock-venue values for each day are then aggregated across all the venues in order to obtain a global value for the London equity market.

For each stock day we estimate the following VECM using mid-point of quotes[15] at one-second intervals, t:

[14] For robustness, (–15, +15) and (–60, +60) are also employed with very little variation in the results.

[15] Our decision to employ quotes here rather than trades is consistent with the literature on decomposing of pricing innovations (see as examples, Huang, 2002; Hupperets and Menkveld, 2002; Theissen, 2002). It is also a valid approach because dark trades are matched against the midpoint of prevailing quotes from lit platforms rather than execution prices.

$$\Delta P_t^v = \alpha_0^v + \alpha_1^v\left(P_{t-1}^v - P_{t-1}^g\right) + \sum_{i=1}^{p}\gamma_i \Delta P_{t-i}^v + \sum_{i=1}^{p}\vartheta_i \Delta P_{t-i}^g + \varepsilon_t^v,$$
$$\Delta P_t^g = \alpha_0^g + \alpha_1^g\left(P_{t-1}^v - P_{t-1}^g\right) + \sum_{i=1}^{p}\gamma_i \Delta P_{t-i}^g + \sum_{i=1}^{p}\vartheta_i \Delta P_{t-i}^v + \varepsilon_t^g. \tag{A2}$$

where P_t^v and P_t^g correspond, respectively, to the log of the mid-point of the last bid and ask prices from venue v's (LSE, Chi-X, BATS or Turquoise) order book and a consolidated order book made up of quotes from the three other venues. The CFS values for both price series are then computed following Baillie et al. (2002). For each venue the RNA measure for venue v on day t is given as:

$$RNA^v = \left|\frac{CFS^v}{CFS^g}\right| \tag{A3}$$

where the CFSv and CFSg are the component factor shares for venue v (LSE, Chi-X, BATS or Turquoise) and the combined other three venues respectively. The higher venue v's RNA value is on the day, the lower its noise levels on that day. A venue with a higher RNA has lower noise levels (and thus a higher level of pricing efficiency) than the competing venues.

Volume-synchronised probability of informed trading analysis

VPIN measures order flow imbalance in financial markets (see Easley et al., 2011; Easley et al., 2012). One of the most important properties of VPIN is that it distinguishes between buying and selling pressure on one hand and buyer and seller-initiated orders on the other. Specifically, the measure focuses on capturing buying and selling pressure, and it is given as:

$$VPIN = \frac{\sum_{\tau=1}^{n}\left|V_\tau^S - V_\tau^B\right|}{nV} \tag{A4}$$

where V_τ^S and V_τ^B are sell and buy volumes, respectively, V is the volume in every volume bucket and n is the number of buckets. Thus, computing the VPIN metric requires determining the number of buckets to be employed for volume classification, the volume in each bucket and a method of classifying trading volumes as buy and sell. The computation of VPIN is highly dependent on the method used for classifying the trading volume into buy and sell volumes. Generally, existing studies employ one of three methods; these are the tick rule, Lee and Ready (1991) algorithm and the bulk volume classification (BVC) method. The tick rule classifies a trade as buy (sell) trade if the trade price is above (below) the preceding trade price (Chakrabarty et al., 2012). Ellis et al. (2009) and Chakrabarty et al. (2007) report a 75% – 79% accuracy for this classification method. The Lee and Ready (1991) algorithm classifies a trade as a buy (sell) trade if it occurs above (below) the midpoint. Finucane (2009), Lee and Radhakrishna (2000), Ellis et al. (2009) Chakrabarty et al. (2012) all report a range of 79% – 93% accuracy for the method. BVC is a more recent approach proposed by Easley et al. (2011). They argue that this approach is more appropriate for a high frequency trading environment; hence, we employ the BVC classifying buy and sell volumes. The fraction of buy volumes is computed as:

$$V_\tau^B = V_\tau \times Z\left(\frac{\Delta\rho_\tau}{\sigma_{\Delta\rho}}\right) \tag{A5}$$

where V_τ^B is a buy volume, V_τ is a total trading volume, $Z(.)$ is a cumulative density function (CDF) of the standard normal distribution, Δp_τ is the price difference between the time bars τ and τ-1, $\sigma_{\Delta p}$ is the standard deviation of Δp_τ. The estimated sell volume is therefore given as:

$$V_\tau^S = V_\tau - V_\tau^B \tag{A6}$$

A 1-minute time bar is used in computing the change in price and the standard deviation of price changes.

The next step is volume bucketing, which implies implementing a volume-dependent sampling, where a given number of trades are selected into a bucket based on trading frequency. In order to determine the number of trades in each volume bucket (or bucket size), we first need to specify the number of buckets that we intend to use for our analysis. The traded volume in each bucket can then be determined by dividing the total trading volume by the number of buckets. If the last trade required to complete a bucket is of a size larger than needed, the excess volume is added to the next bucket (see Easley et al., 2011; Easley et al., 2012). Thus, a volume bucket is a group of trades with a total volume, *V*. Consistent with Easley et al. (2011), we use 50 buckets in order to compute daily VPIN; hence, the volume in each bucket is therefore equal to one-fiftieth of the daily trading volume. Next, we calculate the order imbalance, which is defined as the absolute difference between the buy volume and sell volume for each volume bucket. Order imbalance for time bars is different from order imbalance for volume buckets. In the final step, we compute VPIN by dividing the sum of order imbalances for all the buckets in the sample length by the product of volume bucket size multiplied by the sample length.

Following the computation of VPIN, we then substitute it for PIN in the multivariate panel regression analysis described in Section 3 (Research design). The resulting estimates are presented below in Table A1; corresponding plots of VPIN and proportion of dark trading are also shown below in Figure A1.

Table A1: The impact of dark trading on adverse selection risk (robustness analysis with VPIN)

Variables	A	B
Dark	-0.62*** (-4.74)	-4.82*** (-2.92)
Dark^2	1.78** (2.02)	26.10*** (2.86)
OFFEX	-0.01*** (-5.93)	0.00*** (-4.50)
Trade size	0.00 (-0.21)	-0.02*** (-4.11)
Market cap	0.02*** (20.51)	0.03*** (5.47)
Effective spread	0.00*** (-4.64)	0.00*** (-5.47)
Lit value	0.00*** (-4.16)	0.01* (1.83)
HFT	0.00*** (-5.92)	0.00*** (-4.44)
$P_{other\ stocks}$	0.97*** (58.91)	1.05*** (24.67)
Intercept	-0.23*** (-9.97)	-0.52*** (-3.78)
R^2	0.46	0.36

Notes: The table reports regression coefficient estimates using a stock-day panel, in which the dependent variable is the Easley et al. (2011) volume synchronised probability of an informed trade (VPIN) measure computed as outlined in Annex 2 above for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The estimated regressions is:

$$VPIN_{it} = \alpha + \beta_{DARK} DARK_{it} + \beta_{OFFEX} OFFEX_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{6} \varphi_k C_{kit} + \varepsilon_{it}$$

where $DARK_{it}$ is the proportion of the stock-day's total pound trading volume executed in the dark, while $OFFEX_{it}$ is the log of the stock-day's total pound volume of trades executed away from the four exchanges' downstairs venues for stock *i* on day *t*. HFT_{it} is a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock *i* on day *t*. C_{kit} is a set of *k* control variables which includes log of market capitalisation, log of average trade size, log of pound volume of lit trades, effective spread, which is defined as twice the absolute value of the difference between transaction price and prevailing mid-point, the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of VPIN on the same day for all the other stocks in the same sized quintile. Columns A and Panel B report 2SLS and GMM estimations, respectively, using two different sets of instrumental variables (IVs). $DARK_{it}$ and $OFFEX_{it}$ are instrumented in the 2SLS estimation by using the average level of dark and off-exchange trading in stocks in the same market cap quintile respectively. In the GMM estimation IVs are obtained for $DARK_{it}$ and $OFFEX_{it}$ by first collecting the within-quintile/full sample cross-sectional averages of the trading variables. $DARK_{it}$ and $OFFEX_{it}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as corresponding IVs for $DARK_{it}$ and $OFFEX_{it}$. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th June 2015. The quintiles are computed on the basis of average daily trading value in pounds sterling across the sample period.

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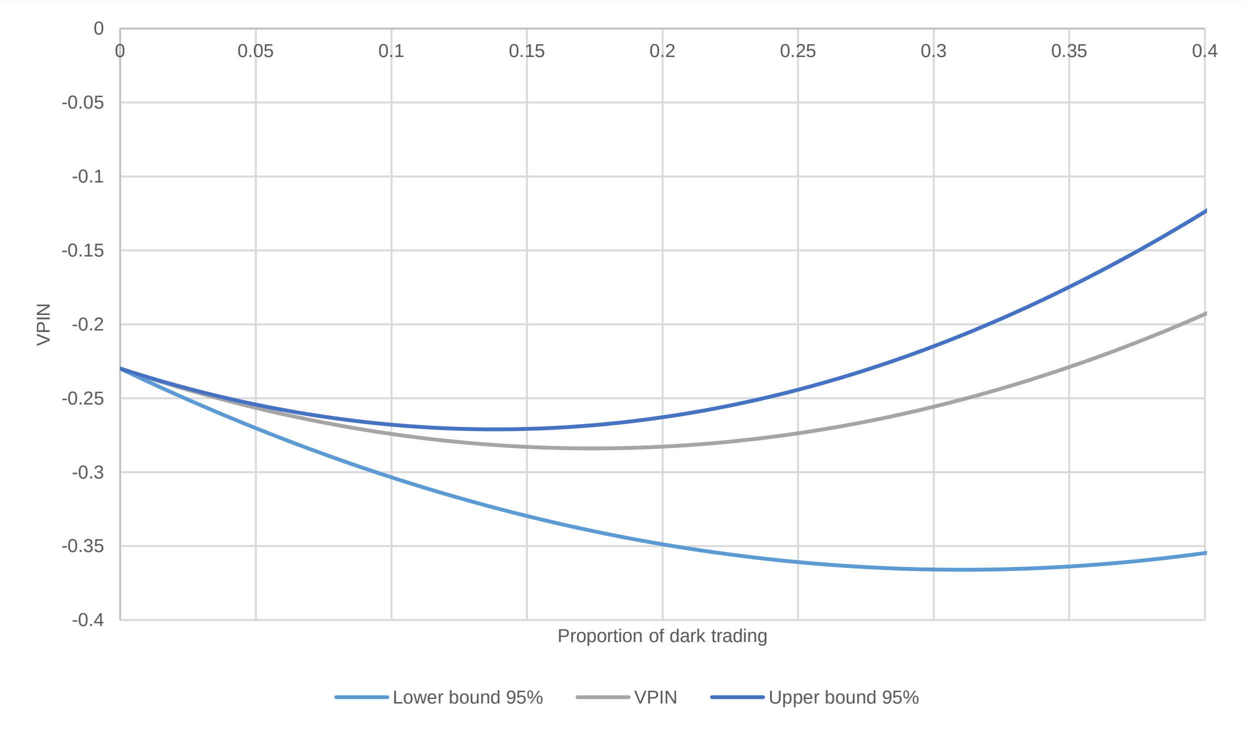
Figure A1: Effects of dark trading on adverse selection risk (robustness analysis with VPIN; Turning point: 17%)



Notes: The figure plots the estimated effects of dark trading on adverse selection risk, with the probability of an informed trade (PIN) used as an inverse proxy for market transparency/adverse selection risk. The estimated effects are obtained by plotting the quadratic function of the coefficients obtained from stock-day panel regressions as described in Table 3. The grey line represents the implied effects while the dark and light blue lines represent the upper and lower bounds of the 95% confidence intervals, computed using standard errors obtained from the stock-day panel regressions. The sample consists of 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise, between 1st June 2010 to 30th June 2015.

Quintile-based analysis using probability of informed trading

Below, we present regression estimation results for the PIN-based regressions by quintile.

Table A2: The impact of dark trading on adverse selection risk (PIN)

Panel A

Variables	Full sample	Highest volume stocks	Quintile 4	Quintile 3	Quintile 2	Lowest volume stocks
Dark	-0.88*** (-7.25)	-0.19 (-1.12)	-0.62*** (-3.74)	-0.46*** (-3.03)	-2.08*** (-3.22)	-1.25*** (-6.06)
$Dark^2$	3.49*** (4.30)	0.76 (0.49)	2.56** (2.09)	1.90** (2.37)	7.82** (2.53)	4.14*** (4.75)
OFFEX	-0.01*** (-7.61)	0.00** (1.98)	0.00 (-0.93)	-0.01*** (-6.55)	-0.05*** (-10.23)	-0.01*** (-8.28)
Trade size	0.01*** (3.82)	0.00 (0.40)	-0.01** (-2.05)	0.01*** (2.88)	0.05*** (4.53)	0.02*** (5.79)
Market cap	-0.02*** (-26.28)	0.00 (1.22)	-0.01*** (-3.76)	-0.02*** (-11.31)	-0.10*** (-12.30)	-0.05*** (-19.83)
Effective spread	0.01*** (19.41)	0.01*** (4.48)	0.03*** (19.80)	0.01*** (12.49)	0.02*** (9.09)	0.00*** (7.93)
Lit value	0.00*** (-6.17)	0.00 (-0.68)	0.01*** (5.19)	0.00 (-0.86)	0.02*** (4.45)	0.01*** (4.15)
HFT	0.00*** (-8.06)	-0.01*** (-7.23)	0.03*** (16.00)	0.00 (-0.95)	0.00 (0.13)	0.00*** (-4.32)
$P_{other\ stocks}$	0.75*** (31.40)	1.00*** (35.21)	1.00*** (30.60)	0.84*** (29.52)	3.04*** (30.14)	0.83*** (28.62)
Intercept	0.66*** (35.36)	-0.05 (-0.94)	-0.07** (-2.50)	0.53*** (13.31)	-0.46*** (-3.42)	0.99*** (21.22)
R^2	0.29	0.09	0.03	0.26	0.24	0.21

Panel B

Variables	Full sample	Highest volume stocks	Quintile 4	Quintile 3	Quintile 2	Lowest volume stocks
Dark	-0.48*** (-33.09)	-0.20*** (-5.54)	-0.34*** (-10.12)	-0.54*** (-18.10)	-0.39*** (-13.42)	-0.45*** (-14.29)
$Dark^2$	1.46*** (20.52)	0.96*** (3.51)	1.90*** (9.08)	2.10*** (13.06)	0.66*** (4.45)	0.67*** (4.80)
OFFEX	-0.02*** (-28.94)	0.00*** (5.32)	-0.01*** (-7.35)	-0.02*** (-23.34)	-0.03*** (-31.47)	-0.04*** (-34.60)
Trade size	0.03*** (34.80)	0.00 (-0.74)	0.00 (-0.12)	0.03*** (19.03)	0.08*** (36.94)	0.06*** (34.47)
Market cap	-0.02*** (-18.78)	0.00 (0.73)	-0.01*** (-4.84)	-0.03*** (-17.22)	-0.05*** (-17.88)	-0.02*** (-16.96)
Effective spread	0.02*** (38.63)	0.01*** (4.57)	0.03*** (20.79)	0.03*** (28.58)	0.02*** (25.58)	0.01*** (23.46)
Lit value	0.01*** (4.00)	0.00* (-1.89)	0.01*** (7.91)	0.02*** (10.38)	0.02*** (9.26)	0.00*** (2.60)
HFT	0.01*** (6.89)	-0.01*** (-7.78)	0.03*** (15.58)	0.03*** (19.16)	0.02*** (12.71)	-0.01*** (-18.79)
$P_{other\ stocks}$	0.74*** (19.41)	1.01*** (36.20)	0.97*** (30.22)	0.92*** (30.14)	0.86*** (25.36)	0.71*** (23.42)
Intercept	0.27*** (27.11)	0.02 (0.40)	-0.10*** (-3.75)	0.20*** (6.30)	0.29*** (9.78)	0.31*** (13.43)
R^2	0.16	0.09	0.04	0.07	0.02	0.14

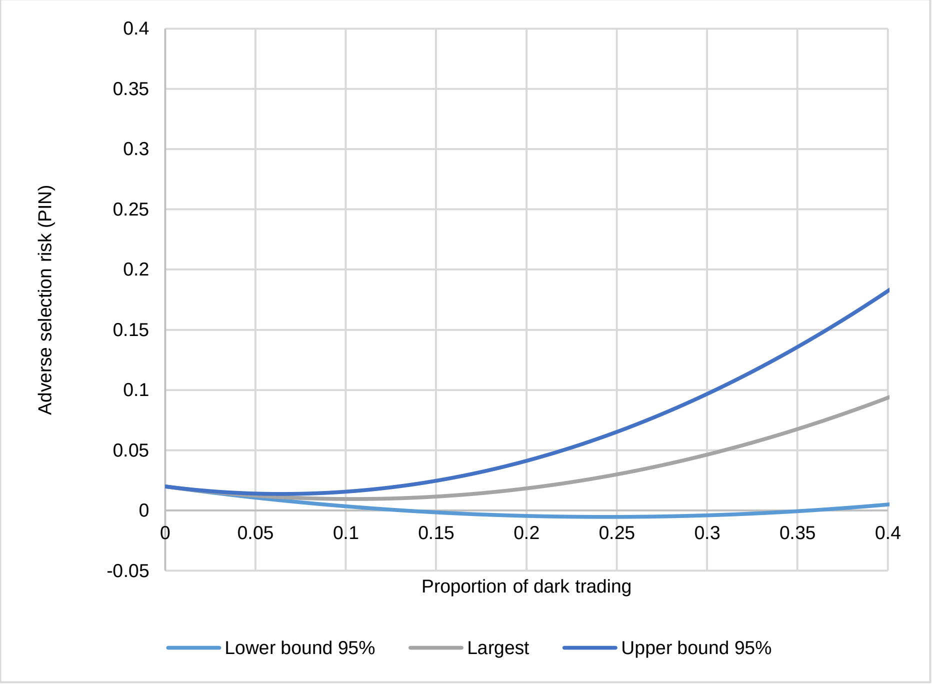
Notes: The table reports regression coefficient estimates using a stock-day panel, in which the dependent variable is the Easley et al. (1996, 1997) probability of an informed trade (PIN) measure computed as outlined in Table 1 for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The estimated regressions is:

$$PIN_{it} = \alpha + \beta_{DARK} DARK_{it} + \beta_{OFFEX} OFFEX_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{6} \varphi_k C_{kit} + \varepsilon_{it}$$

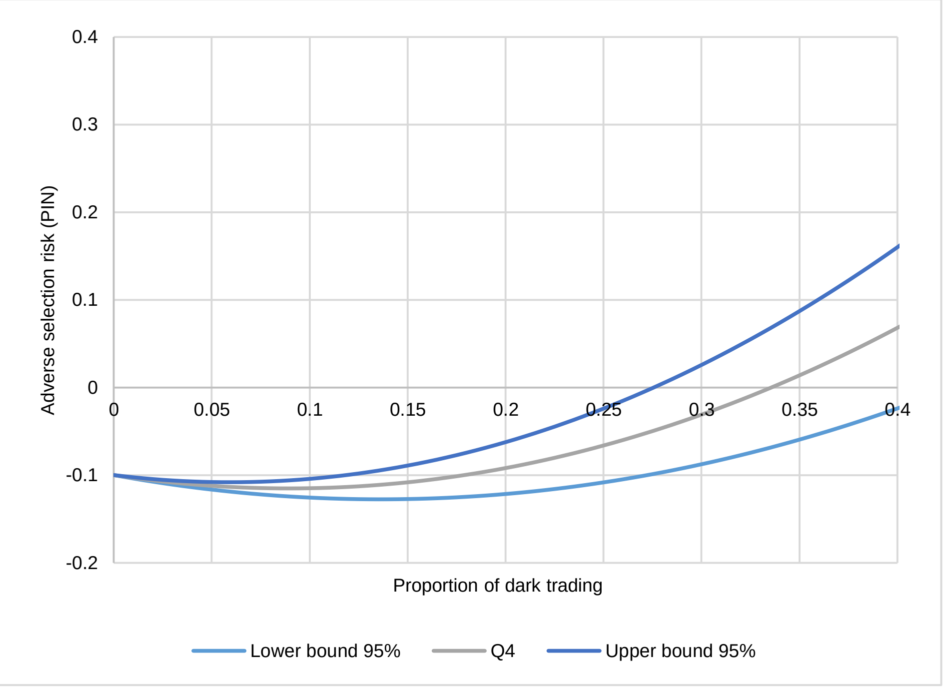
where $DARK_{it}$ is the proportion of the stock-day's total pound trading volume executed in the dark, while $OFFEX_{it}$ is the log of the stock-day's total pound volume of trades executed away from the four exchanges' downstairs venues for stock *i* on day *t*. HFT_{it} is a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock *i* on day *t*. C_{kit} is a set of *k* control variables which includes log of market capitalisation, log of average trade size, log of pound volume of lit trades, log of effective spread, which is defined as twice the absolute value of the difference between transaction price and prevailing mid-point, the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of PIN on the same day for all the other stocks in the same sized quintile. Panel A and Panel B report 2SLS and GMM estimations, respectively, using two different sets of instrumental variables (IVs). $DARK_{it}$ and $OFFEX_{it}$ are instrumented in the 2SLS estimation by using the average level of dark and off-exchange trading in stocks in the same market cap quintile respectively. In the GMM estimation IVs are obtained for $DARK_{it}$ and $OFFEX_{it}$ by first collecting the within-quintile/full sample cross-sectional averages of the trading variables. $DARK_{it}$ and $OFFEX_{it}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as corresponding IVs for $DARK_{it}$ and $OFFEX_{it}$. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th June 2015. The quintiles are computed on the basis of average daily trading value in pounds sterling across the sample period.

Figure A2: The impact of dark trading on adverse selection risk (PIN)

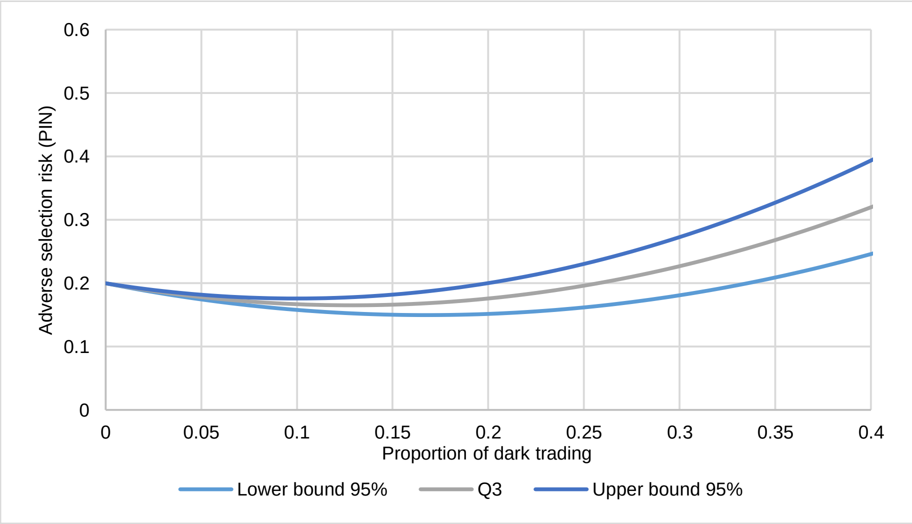
Panel A: Highest volume stocks (Turning point: 10%)



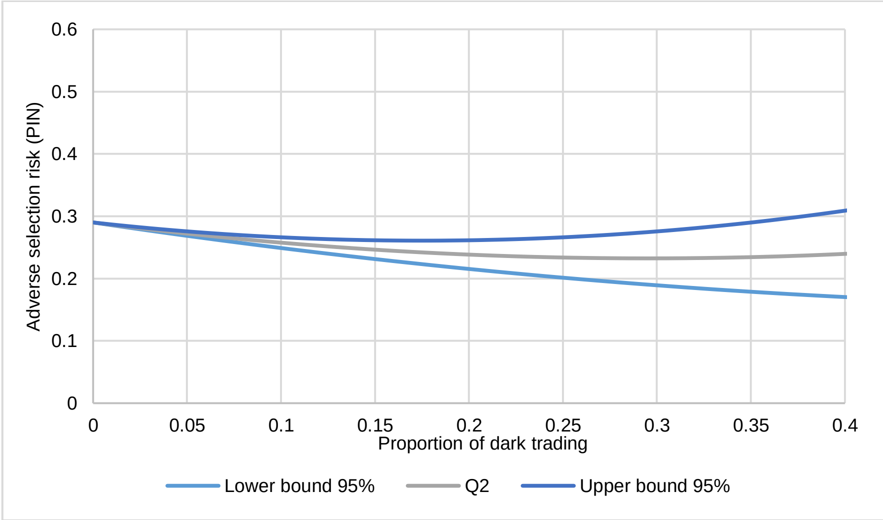
Panel B: Quintile 4 stocks (Turning point: 9%)



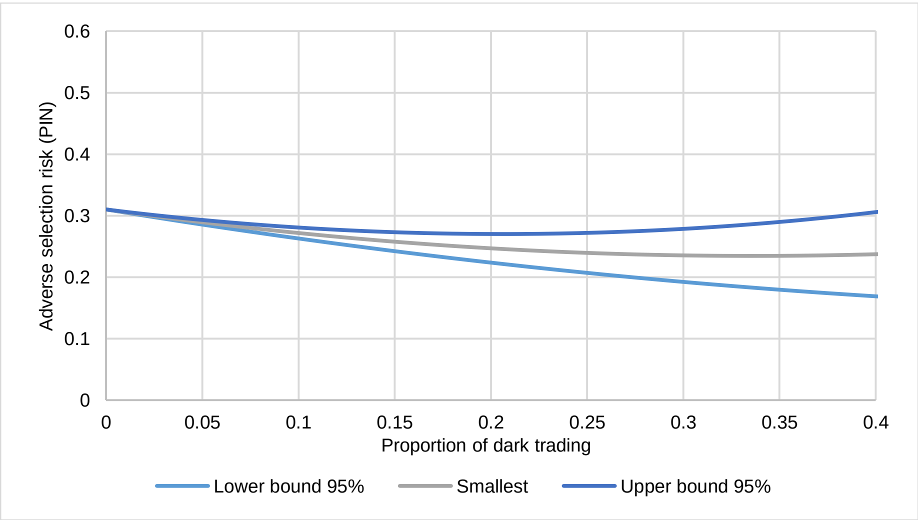
Panel C: Quintile 3 stocks (Turning point: 13%)



Panel D: Quintile 2 stocks (Turning point: 30%)



Panel E: Lowest volume stocks (Turning point: 35%)



Notes: The figure plots the implied/estimated effects of dark trading on market quality, with the probability of an informed trade (PIN) used as an inverse proxy for market transparency and adverse selection risk. Panels A – E show the full sample and five quintile of stocks, starting with the highest trading quintile to the least trading one. The estimated effects are obtained from stock-day panel regressions as outlined in Table 3. The grey line represents the implied effects while the dark and light blue lines represent the upper and lower bounds of the 95% confidence intervals, computed using standard errors obtained from the stock-day panel regressions. The sample consists of 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise, between 1st June 2010 to 30th June 2015.

Quintile-based analysis using effective spread

Below, we present regression estimation results for the Effective spread-based regressions by quintile.

Table A3: The impact of dark trading on liquidity (effective spread)

Panel A

Variables	Full sample	Highest volume stocks	Quintile 4	Quintile 3	Quintile 2	Lowest volume stocks
Dark	-8.15*** (-7.37)	-3.49*** (-3.86)	-3.58*** (-4.45)	-1.77** (-2.50)	-3.21*** (-3.80)	-8.15*** (-7.37)
$Dark^2$	21.49*** (4.61)	4.96*** (5.08)	4.00 (0.82)	3.89 (1.01)	8.06*** (2.11)	21.49*** (4.61)
OFFEX	-0.10*** (-11.08)	-0.06*** (-10.07)	-0.06*** (-11.94)	-0.04*** (-7.35)	-0.03*** (-4.94)	-0.10*** (-11.08)
Trade size	0.25*** (12.72)	0.23*** (13.83)	0.35*** (16.88)	0.20*** (10.84)	0.12*** (7.17)	0.25*** (12.72)
Market cap	0.44*** (32.04)	0.13*** (15.65)	-0.15*** (-12.69)	-0.07*** (-5.88)	0.28*** (22.20)	0.44*** (32.04)
Lit value	-0.13*** (-15.95)	0.00 (-0.12)	-0.09*** (-11.95)	-0.09*** (-9.93)	-0.03*** (-3.10)	-0.13*** (-15.95)
HFT	0.18*** (38.04)	0.15*** (40.24)	0.07*** (9.33)	0.14*** (21.05)	0.15*** (32.28)	0.18*** (38.04)
$P_{other\ stocks}$	0.27*** (19.51)	0.56*** (22.22)	0.48*** (14.25)	0.52*** (23.26)	0.46*** (27.81)	0.27*** (19.51)
Intercept	-9.84*** (-38.31)	-5.69*** (-29.33)	0.42* (1.78)	-0.29 (-1.23)	-8.14*** (-38.92)	-9.84*** (-38.31)
R^2	0.77	0.80	0.66	0.65	0.66	0.65

Panel B

Variables	Full sample	Highest volume stocks	Quintile 4	Quintile 3	Quintile 2	Lowest volume stocks
Dark	-3.83*** (-9.07)	-4.01*** (-12.18)	-0.91*** (-3.33)	-1.24*** (-5.12)	-1.35*** (-9.02)	-6.57*** (-9.77)
$Dark^2$	13.11*** (7.50)	14.60*** (9.52)	4.32** (2.11)	3.27*** (2.70)	2.34** (2.27)	10.90** (2.17)
OFFEX	-0.16*** (-19.47)	-0.02*** (-5.93)	-0.04*** (-10.72)	-0.10*** (-17.70)	-0.08*** (-12.66)	-0.05*** (-10.84)
Trade size	0.35*** (20.25)	0.29*** (25.85)	0.14*** (9.24)	0.26*** (14.75)	0.21*** (11.91)	0.38*** (23.99)
Market cap	0.31*** (13.72)	-0.09*** (-10.55)	-0.12*** (-7.49)	-0.33*** (-14.40)	0.12*** (5.66)	-0.08*** (-9.25)
Lit value	-0.06*** (-8.01)	-0.11*** (-17.73)	0.02*** (2.78)	0.08*** (5.62)	0.09*** (6.56)	-0.09*** (-12.31)
HFT	0.34*** (37.41)	0.01** (2.14)	0.16*** (15.37)	0.24*** (23.32)	0.28*** (30.22)	-0.02** (-2.49)
$P_{other\ stocks}$	0.82*** (26.16)	1.05*** (21.03)	0.67*** (22.45)	0.96*** (24.57)	0.93*** (29.36)	0.91*** (18.27)
Intercept	-9.73*** (-29.06)	-6.89*** (-20.63)	0.69** (1.98)	3.10*** (6.65)	-0.83*** (-3.87)	-1.90*** (-7.69)
R^2	0.65	0.82	0.45	0.50	0.45	0.47

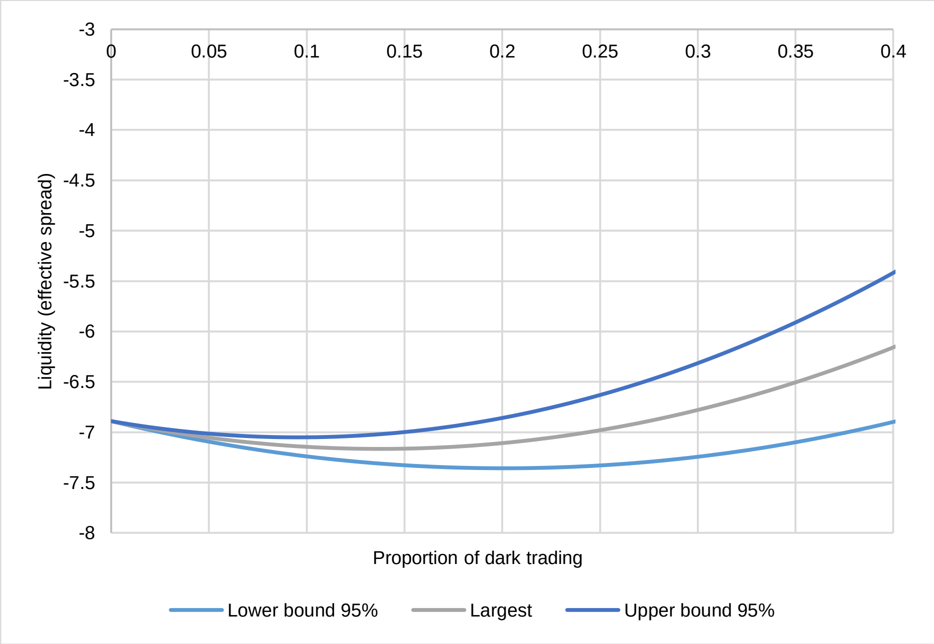
Notes: The table reports regression coefficient estimates using a stock-day panel, in which the dependent variable is the Effective spread (*EffectiveS*), which is defined as twice the absolute value of the difference between transaction price and prevailing mid-point, for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The estimated regressions is:

$$EffectiveS_{it} = \alpha + \beta_{DARK} DARK_{it} + \beta_{OFFEX} OFFEX_{it} + \beta_{HFT} HFT_{it} + \sum_{k=1}^{6} \varphi_k C_{kit} + \varepsilon_{it}$$

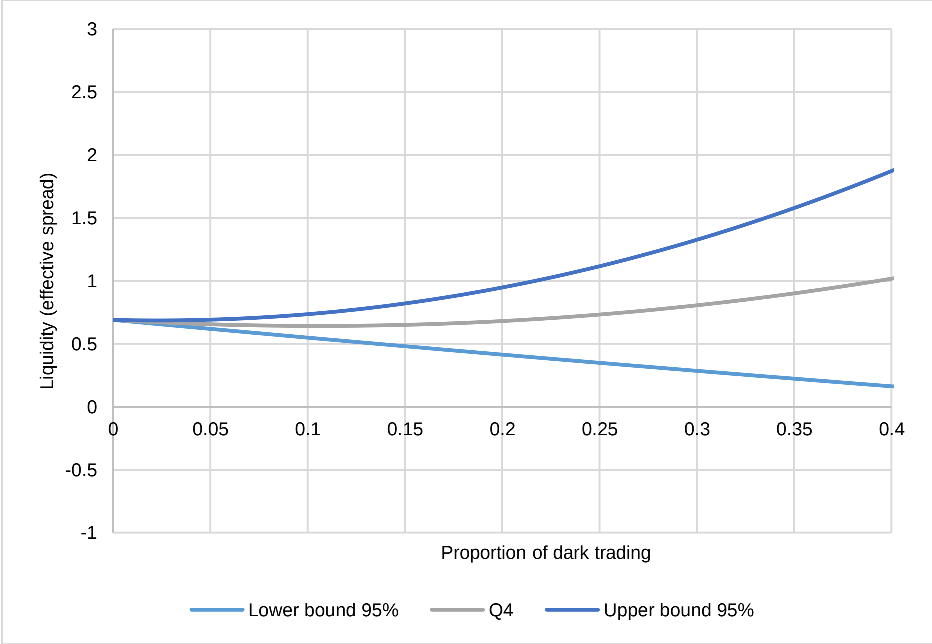
where $DARK_{it}$ is the proportion of the stock-day's total pound trading volume executed in the dark, while $OFFEX_{it}$ is the log of the stock-day's total pound volume of trades executed away from the four exchanges' downstairs venues for stock *i* on day *t*. HFT_{it} is a proxy for algorithmic trading and is measured as the ratio of messages to trades for stock *i* on day *t*. C_{kit} is a set of *k* control variables which includes log of market capitalisation, log of average trade size, log of pound volume of lit trades the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of Effective spread on the same day for all the other stocks in the same sized quintile. Panel A and Panel B report 2SLS and GMM estimations, respectively, using two different sets of instrumental variables (IVs). $DARK_{it}$ and $OFFEX_{it}$ are instrumented in the 2SLS estimation by using the average level of dark and off-exchange trading in stocks in the same market cap quintile respectively. In the GMM estimation IVs are obtained for $DARK_{it}$ and $OFFEX_{it}$ by first collecting the within-quintile/full sample cross-sectional averages of the trading variables. $DARK_{it}$ and $OFFEX_{it}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as corresponding IVs for $DARK_{it}$ and $OFFEX_{it}$. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th June 2015. The quintiles are computed on the basis of average daily trading value in pounds sterling across the sample period.

Figure A3: The impact of dark trading on liquidity (effective spread)

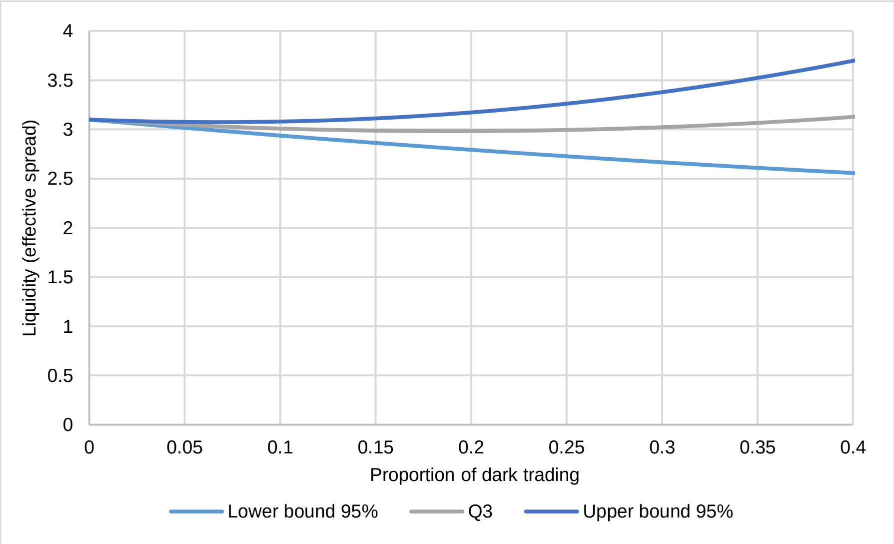
Panel A: Highest volume stocks (Turning point: 14%)



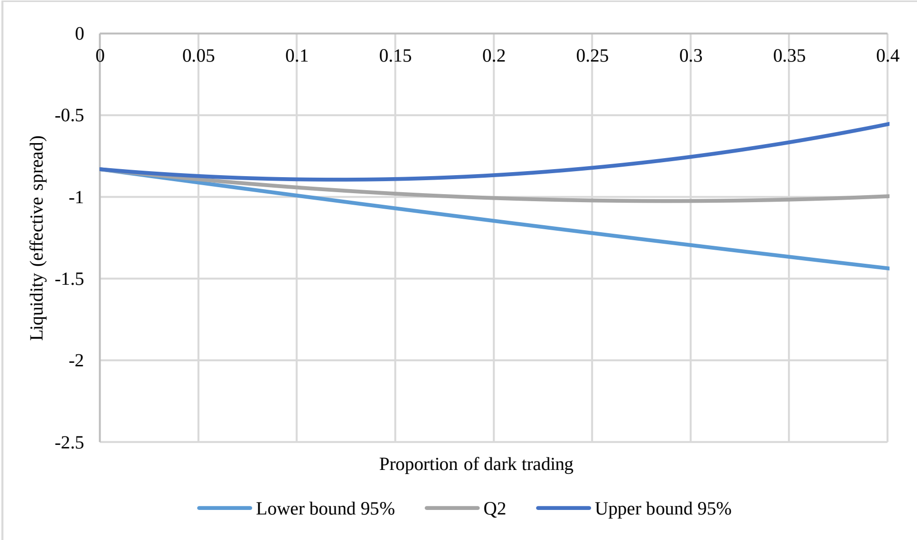
Panel B: Quintile 4 stocks (Turning point: 11%)



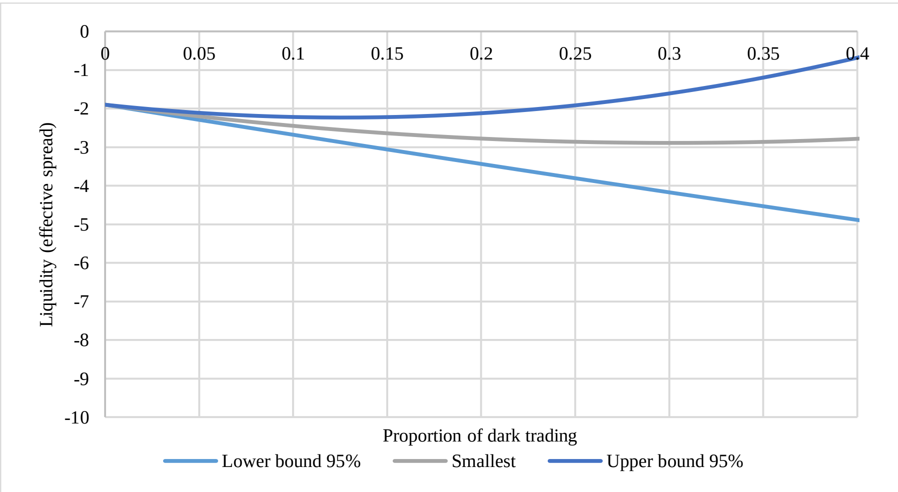
Panel C: Quintile 3 stocks (Turning point: 19%)



Panel D: Quintile 2 stocks (Turning point: 29%)



Panel E: Lowest volume stocks (Turning point: 31%)



Notes: The figure plots the implied/estimated effects of dark trading on market quality, with effective spread used as a proxy for liquidity. Panels A – E show the full sample and five quintile of stocks, starting with the highest trading quintile to the least trading one. The estimated effects are obtained from stock-day panel regressions as outlined in Table 3. The grey line represents the implied effects while the dark and light blue lines represent the upper and lower bounds of the 95% confidence intervals, computed using standard errors obtained from the stock-day panel regressions. The sample consists of 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise, between 1st June 2010 to 30th June 2015.

Observations with greater than 8% dark trading by value

Below, we present the number and percentages of stock-day observations where dark trading exceeds 8% in the sample of 288 FTSE 350 stocks.

Table A4: Stock-day observations with dark trading exceeding 8%

Variables	Count	As a percentage of total stock-day sample size
Full sample	25,843	8.35%
Highest volume stocks	2,620	4.07%
Quintile 4	5,776	9.27%
Quintile 3	7,301	11.46%
Quintile 2	5,359	8.91%
Lowest volume stocks	4,787	8.14%

Notes: The table reports the number of stock-day observations with dark trading values in excess of 8% of total trading value in that stock for each day. The stock-day occurrences as percentages of the corresponding total stock-day samples are also reported in the final column. The overall sample consists of 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise, between 1st June 2010 to 30th June 2015.

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