City goes dark

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City goes dark: dark trading and adverse selection in *aggregate* markets

GBENGA IBIKUNLE*
University of Edinburgh, United Kingdom
European Capital Markets Cooperative Research Centre, Pescara, Italy
RoZetta Institute, Sydney, Australia

MATTEO AQUILINA†
Financial Conduct Authority, London, United Kingdom
Financial Stability Board, Basel, Switzerland

IVAN DIAZ-RAINEY‡
University of Otago, New Zealand

YUXIN SUN¶
London Stock Exchange Group, United Kingdom

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Abstract We investigate the impact of dark trading on adverse selection in an aggregate market for trading UK stocks. Dark trading is linked to lower adverse selection risk and improved informational efficiency and liquidity in the aggregate market, even as liquidity declines in the lit market with dark trading. However, there is a trading value-based threshold when dark trading starts to induce adverse selection. We estimate that this threshold varies from around 9% for the most liquid stocks to 25% for the least liquid stocks. The overall average threshold for the 288 FTSE 350 stocks in our sample is 14%.

JEL classification: G10, G14, G15

Keywords: dark pools, adverse selection, market liquidity, pricing noise, informational efficiency

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*Corresponding author: Gbenga Ibikunle, University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh EH8 9JS, United Kingdom; e-mail: Gbenga.Ibikunle@ed.ac.uk; phone: +441316515186.
†Financial Conduct Authority, 12 Endeavour Square, London E20 1JN, United Kingdom; matteo.aquilina@fca.org.uk; Matteo.Aquilina@fsb.org
‡Department of Accountancy & Finance, University of Otago, P.O. Box 56, Dunedin 9054, New Zealand; ivan.diaz-rainey@otago.ac.nz
¶ 10 Paternoster Square, London EC4M 7LS, United Kingdom; YSun3@lseg.com

1. Introduction

Over the course of the past decade, regulators in the US and the EU have increased their efforts to make global financial markets more transparent and fairer. The enactment of the 2005 Regulation NMS (RegNMS) in the US and the 2007 Markets in Financial Instruments Directive (MiFID) in the EU, coupled with technological advancements, led to the proliferation of new classes of trading venues. One of the most prominent is a class of venues known as 'dark pools'. Trades executed in dark pools have no pre-trade transparency: market participants, other than the submitter and the pool operator, are not aware of the presence of orders submitted prior to their execution.

The volume of trades executed in dark pools accounted for 9.1% of all on-exchange activity in European markets in April 2019. This is one of the largest monthly volumes recorded since the implementation of a provision in MiFID II directive, which imposes an 8% cap on dark trading stock-level volumes in European financial markets over any 12-month period.[1] In the US, during the same period, dark pools and other off-exchange trading venues executed 38.6% of all equity volume.[2] These volumes underscore a need to investigate the effects of dark trading on overall market quality. Such an investigation is also of critical importance to investors who already view dark pool activity with some suspicion. A survey conducted among market participants by the CFA Institute finds that 71% of respondents are of the view that dark pools constitute problems for price discovery in the markets (see Schacht et al., 2009). At first glance, the scepticism appears valid. A lack of pre-trade transparency suggests that dark pools impair price discovery, and this perception has led to efforts to increase disclosure and/or regulation of dark trading in the US, Canada and Australia and, most relevant to this

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[1] See https://www.thetradenews.com/dark-pool-trading-volumes-surge-pre-mifid-ii-levels/ and https://www.thetradenews.com/dark-trading-volumes-reach-highest-level-mifid-ii/

[2] See https://www.wsj.com/articles/dark-pools-draw-more-trading-amid-low-volatility-11556886916

paper, in Europe via MiFID/MiFIR. However, recent studies offer insights that are at odds with this view (see as examples, Zhu, 2014; Comerton-Forde and Putniņš, 2015; Farley et al., 2018).

While a few papers have empirically examined the impact of dark trading on various market quality characteristics, the evidence has been mixed. While Buti et al. (2011) find no evidence of dark trading harming market liquidity and Brugler (2015) shows that dark trading improves liquidity on the primary exchange, Nimalendran and Ray (2014), using trading data from one of the 32 US dark venues, find that dark trading is associated with increased price impact on quoting exchanges. Degryse et al. (2015), based on a Dutch sample of stocks, also show that dark trading has a detrimental effect on market liquidity.

This paper approaches the question of the effect of dark trading on market quality by investigating the effects of mid-point dark trading[3] in the aggregate market[4] on adverse selection risk.[5] Examining these effects is important, because the degree of adverse selection is identified as a driver of key market quality characteristics (liquidity and price discovery) in theoretical models (see as an example, Zhu, 2014) and in existing empirical studies (see as examples, Comerton-Forde and Putniņš, 2015; Foley and Putniņš, 2016; Nimalendran and Ray, 2014). The effects of dark trading on adverse selection risk holds implications for liquidity and price discovery; therefore, we also investigate how dark trading impacts them.

[3] A venue engaged in mid-point dark trading matches its trades to the mid-point of a lit trading venue (i.e. a venue that offers full transparency).

[4] The term 'aggregate (or overall) market' is used to refer to a hypothetical virtual market, with an order book containing all trading activity from all venues where an instrument is being traded simultaneously. The focus on the aggregate market is important from a regulatory perspective given the level of proliferation in financial markets across developed markets like the UK.

[5] Two recent working papers (Farley et al., 2018; Rindi and Werner, 2017) provide equivalent 'aggregate market' evidence for the US, at least for a select group of stocks. They both explore the 'trade-at' rule that was applied to selected stocks in 2016, and subsequently led to a reduction in dark trading for the affected stocks. The rule prevents a trading venue from executing a trade at the National Best Bid or Offer quote, unless the venue displays that quote, which by definition does not happen in dark pools. The venue must instead either offer a five-cent price improvement or route the order to the venue with the best quote. Farley et al. (2018) find that the associated decrease in dark trading resulting from the 'trade-at' rule has had no effect on trading costs, thus contradicting the belief that a reduction of dark trading would lower trading costs.

By focusing on the UK stock market, we elucidate the European context. Dark pools in Europe mainly operate as Multilateral Trading Facilities (MTFs); the three largest dark trading venues on the continent are MTFs, and they operate alongside lit order books. These are Chi-X Europe, BATS Europe, and Turquoise. These platforms are all based in London, UK; specifically, within the city's financial hub often called the 'City'. The City thus hosts four high volume trading venues (including the London Stock Exchange), making it the largest aggregate stock market in Europe and the world's largest market for mid-point dark trading.[6] Investigating the impact of dark trading on market quality characteristics in the London market may offer additional insights distinct from those obtained from studies based on other markets.

Although Degryse et al. (2015) also examine the impact of dark trading on liquidity in a European market, i.e. the Dutch market, a review from the Securities and Exchange Commission argues that Degryse et al.'s (2015) fifty-one stock sample covers a period when market fragmentation (including fragmentation due to trading on dark pools) had not set in within the Dutch mid and large stocks employed in the study.[7] Our data clearly include the years (2010 – 2015) when dark trading and market fragmentation are deemed to have become fully entrenched in the London market. Furthermore, according to Cboe Europe's data, the entire Dutch market regularly accounts for less than 7% of European trading activity in currency terms, while just the FTSE 350 index's stocks (288 of which make up this study's sample) alone consistently account for more than 25% of daily trading activity in Europe.[8] Therefore, the findings based on the more active and broader sample of UK stocks may offer additional insights to those already offered by Degryse et al. (2015).

[6] Often distinctions are made among types of dark trading approaches (see for example Foley and Putniņš, 2016). In this paper, our data and market structure information, available from the examined exchanges, indicate that we exclusively deal with 'mid-point dark trading' data.

[7] See Equity Market Structure Literature Review (Part I: Market Fragmentation) published by the US Securities and Exchange Commission on 7th October 2013: https://www.sec.gov/marketstructure/research/fragmentation-lit-review-100713.pdf.

[8] Trading activity reports can be downloaded from www.markets.cboe.com/Europe/equities/market_share/index/legacy/

We find that dark trading is linked with a statistically significant reduction in adverse selection risk and improvements in informational efficiency in the aggregate market. While liquidity improves with dark trading in the aggregate market, consistent with the literature (see as examples, Comerton-Forde and Putniņš, 2015; Foley and Putniņš, 2016), it deteriorates in the lit market. The decrease in adverse selection risk in the aggregate market does not necessarily imply a reduction in the number of informed traders in the market, rather it is similar to the impact of traditional upstairs broker-dealer venues. This effect is well-documented in the literature (see as an example Madhavan and Cheng, 1997). Specifically, dark trading venues, like upstairs markets that offer uninformed traders protection against adverse selection, increase the participation rate of uninformed/liquidity traders in the aggregate market, even as their participation rate declines in the lit market. The increased participation in dark venues dilutes the concentration of informed traders in the aggregate market.

However, we also find that the relationship between dark trading and adverse selection risk in the aggregate market is non-linear, such that there is a threshold of dark trading value relative to the aggregate market trading value, when dark trading starts to negatively affect market quality characteristics. Based on our analysis, we estimate that, overall, dark trading of up to 14% of total trading value reduces adverse selection risk in the aggregate market. However, the threshold is significantly lower for very liquid stocks (approximately 9%) and far higher for less liquid ones (at around 25%).

2. Theory and hypotheses

2.1. Hypotheses 1A, 1B and 1C

In Zhu's (2014) model, the addition of a dark pool attracts uninfomed traders to the dark pool and results in a concentration of infomed traders on the lit exchange. This concentration improves overall price discovery. Uninformed/liquidity traders tend to gravitate towards the dark pool because their risk of being adversely selected by an informed trader is lower in a dark venue. Thus traders *self-select* their trading venues based on how much information they hold, and this has implications for adverse selection risk and market quality characteristics in the aggregate market.

To expand, if all informed traders hold similar information sets (for example, fundamental information about the value of an instrument) as modelled by Zhu (2014), the self-selection induced by dark trading can lower adverse selection risk and improve the efficiency of the price discovery process. This is because a reduction in the number of informed trades due to fewer uninformed traders in the lit market (informed orders execute against uninformed orders as in Kyle, 1985; Glosten and Milgrom, 1985 and many others) results in a lowering of competition on the same private information set held by informed traders. This implies a lower risk of uninformed traders being adversely selected in the aggregate market, although there is no change in the amount of private information held in the aggregate market since all informed traders hold identical information. The exit of uninformed traders from the lit exchange leads to informed traders making up an increasing proportion of the lit exchange. Thus, adverse selection risk in the lit market will rise as dark trading volume rises.

However, given the ability of dark pools to shield uninformed traders from being adversely selected, there should be an increase in uninformed trading activity once a dark pool is added to the market. Specifically, as dark pools allow uninformed traders to trade more safely (as noted above, it lowers adverse selection risk for uninformed traders) and cheaply (no spread or price impact due to large order sizes, as in Nimalendran and Ray, 2014), orders that otherwise would not have been submitted would be submitted. This effect of dark pools is akin to that of the traditional upstairs market. Madhavan and Cheng (1997) show that upstairs markets[9] enable transactions that would otherwise not occur in the downstairs (the typical lit exchange) market. Thus, the existence of dark pools can improve liquidity in the aggregate market (even when it reduces it on lit exchanges) and lower adverse selection risk in the aggregate market (even when it concentrates it on the lit exchange as predicted by Zhu, 2014). Adverse selection risk falls as the proportion of informed traders to the rest of the (aggregate) market declines due to the increase in uninformed trading volume, which improves liquidity. Therefore, we test the following hypotheses:

Hypothesis 1A: Dark trading is related to a reduction in adverse selection in the aggregate market.

Hypothesis 1B: Dark trading is related to an improvement in liquidity in the aggregate market.

The exit of uninformed traders from the lit exchange also leads to a reduction of noise in the price discovery process in the lit market – noise in the price discovery process is usually due to uninformed trading activity. The reduction in noise inevitably enhances the market's capacity to incorporate information into prices and improves price discovery. In a regulatory environment that requires that dark pools use the lit market's prices as reference for pricing, such as that of the EU/UK environment, aggregate informational efficiency should be enhanced in line with the improvements observed in the lit market.[10] Hence, we test the following hypothesis:

Hypothesis 1C: Dark trading is related to an improvement in informational efficiency in the aggregate market.

2.2. Hypotheses 2A, 2B, 2C

[9] The main differences between the upstairs markets and the modern mid-point dark pools, which we study, is that execution prices in the latter are constrained within the downstairs market spread, and dark pools are not usually subject to trading intermediation as it conceptually affords complete opacity of trading intentions.

[10] Dark venues executing against lit exchanges' prices contrasts with the requirements in some regulatory regimes that mandate that dark venues offer price improvements (see Brolley, 2020; Comerton-Forde et al., 2018).

Although the theorised consequences of dark trading in the aggregate market are the reduction of adverse selection risk and the enhancement of liquidity and informational efficiency, there are indications in the empirical and theoretical literature that the effects of dark trading on market quality are non-linear.

Building on the discussion of Zhu's (2014) model, as informed trader concentration increases in the lit market, volatility widens the exchange spread and encourages more liquidity traders to migrate to the dark pool. As volatility in the exchange exceeds the maximum level needed for informed traders to avoid the dark pool and the cost of trading rises with widening spreads, informed traders start to migrate to the dark pool. Thus, liquidity constraints in the lit market can result in informed traders entering into quasi-dark/dark venues in order to reduce their transaction costs and increase their profits, as already reported by some empirical studies (see Hendershott and Mendelson, 2000; Nimalendran and Ray, 2014). This implies a higher adverse selection risk for the aggregate market, because competition among informed traders rises if they start spreading their trading activity across lit and dark venues. Hence, initially, informed traders' reducing level of competition as uninformed traders exit lit venues reduces adverse selection risk. Their incursion into dark pools then increases adverse selection risk in the aggregate market as they go in search of uninformed traders to adversely select. This will also increase the proportion of trades executed in the dark, at least temporarily. Temporarily because, in order to avoid being adversely selected, uninformed traders are predicted to exit dark pools when informed traders start to move in (see Zhu, 2014). This provides further intuitive reasoning for why eventually, at higher levels of dark pool activity, the initially beneficial effect of dark trading may be reversed, leading to a deterioration of liquidity and informational efficiency. [11]

[11] Consistent with Glosten and Milgrom (1985), information acquisition in future periods may also decline on account of a reduction in the market participation rates of uninformed traders, and this decline holds market quality implications for the aggregate market. Specifically, informational efficiency should decline in line with reductions in the amount of information being traded with.

An additional reason why the effects of dark trading on adverse selection risk could be non-linear is found in Eom et al. (2007). They argue that market quality is an increasing concave function of transparency. This implies that while low levels of dark trading may not negatively impact market quality, higher levels of dark trading may do so. Thus, our next set of hypotheses are as follows:

Hypothesis 2A: *High levels of dark trading is related to an increase in adverse selection in the aggregate market.*

Hypothesis 2B: High levels of dark trading is related to a decline in liquidity in the aggregate market.

Hypothesis 2C: High levels of dark trading is related to a decline in informational efficiency in the aggregate market.

3. Policy background to the study

Due to its competition-enhancing principles, MiFID, introduced by the European Union in 2007, led to the proliferation and growth of alternative high-tech 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 group in Europe by market share.[12] As at 30th March

[12] The order books are still operated separately, although they are 'integrated'. Also, before 20th May 2013, BATS Chi-X Europe only had a licence to operate MTFs; however, since being granted Recognised Investment Exchange (RIE) status, BATS Chi-X can now operate a listing exchange as well as MTFs. The data employed 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. We analyse individual one-year samples on either side of the paper merger,

2016 there were 151 MTFs listed on the MiFID database managed by the European Securities and Markets Authority (ESMA).[13]

While, under MiFID guidelines, 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 price impacts if published prior to their being 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 by MTFs to maintain dark pools of liquidity. MTFs may avoid abiding with 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 mid-points 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 based on 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, 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. The dark pools in our sample use the Reference Price Waiver.

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specifically 2012 and 2014. Our inferences remain unchanged irrespective of the years in question, although levels of statistical significance fall in some instances. Hence, we present results for the full five-year sample.
[13] ESMA builds rulebooks for financial markets within the EU jurisdiction.

4. Data and Descriptive Statistics

4.1. Data

In this paper, we conduct our investigations by using 288 of the constituents of the FTSE 350 index of stocks in relation to our research questions; the FTSE 350 includes the 350 largest firms listed on the LSE. These firms account for about 96.60% of the total market capitalisation of the FTSE All Share index as at 30th June 2015, the final date in our dataset. All FTSE 350 stocks trade on several trading venues and our data consists of trading data from the four main markets where these stocks trade – the LSE, BATS Europe, Chi-X Europe and Turquoise. The total trading volume from these four trading venues accounts for about 95% of the FTSE 350 lit and dark trading value.

We obtain intraday time and sales tick data from the Thomson Reuters Tick History (TRTH) version2 database. The dataset includes variables such as the Reuters Identification Code (RIC), qualifiers (identifying trade/order type/unique characteristics, such as whether a trade is executed in the dark or not), date, TRTH timestamp, Exchange timestamp, price, volume, bid price, ask price, bid volume, ask volume, and bid and ask quotes. The exchange timestamp is critical given that we are aggregating data across different venues. This timestamp is different from the TRTH timestamp and is provided as part of the TRTH version2 database. It allows us to observe the exact time each trading activity observation is recorded at each trading venue using the London local time; the local time is the same for all exchanges we use in this paper. All four exchanges are based in the same geographical location (London). 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; we also compile 10-level market depth quotes and corresponding sizes for each transaction. 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 sample data employed covers the period from 1st June 2010 to 30th 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 a high frequency analysis. Finally, we merge the order book level data for the four trading venues in order to create a single 'global' order book/venue for the London market. The final dataset contains 1.152 billion transactions valued at 4.95 trillion British Pounds Sterling executed in 288 stocks over the sample period.

4.2. Descriptive statistics

Panel A of Figure 1 shows a time series of trading value for the London market's total off-exchange and dark transactions values during the five-year period ending June 2015. All values are in billions of pounds. The cumulative growth in dark trades appears to be tracking the total trading value for the market throughout the time series; 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 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. Panel B 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 since increased by 350% to attain an average of 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%.

INSERT FIGURE 1 ABOUT HERE

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 US markets (see Chordia et al., 2011), there was a general fall in average trade sizes for both lit and dark trades. Early on in the plot, dark transactions were generally smaller in trade sizes than lit transactions; however, they became steadily comparable to 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 likely identity of some key actors in the dark pools – institutional traders.

INSERT FIGURE 2 ABOUT HERE

5. Methodology

5.1. Main variables

In order to examine the impact of dark trading on adverse selection risk, we identify two proxies for the concept. We use both the volume-synchronised probability of informed trading (VPIN) developed by Easley et al. (2011; 2012) and the predictability of short-horizon returns (see Chan and Fong, 2000; Chordia et al., 2005; Comerton-Forde and Putniņš, 2015; Rösch et al., 2016), as proxies for adverse selection risk. VPIN is considered to be more suited to a high frequency environment than its predecessor, the probability of informed trading (PIN) measure, as developed by Easley et al. (1996; 1997). This is because its development is aimed at matching the speed of information arrival in the market (see Easley et al., 2012). It also incorporates a broader definition of information and allows for sampling in volume time rather than clock time;[14] thus, it accounts for high frequency trading. Abad and Yagüe (2012) argue that VPIN is a broad measure for adverse selection, while Easley et al. (2011; 2012) view their

[14] Computing VPIN requires determining the number of buckets to be employed for volume classification and a buy/sell trade classification method. We use 50 buckets for volume classification; hence, the volume in each bucket is equal to one-fiftieth of the daily trading volume. Buy and sell volumes are computed using the BVC approach proposed by Easley et al. (2011).

PIN measure as one that captures market toxicity, described as the high frequency trading environment equivalent of adverse selection risk.

Since we hypothesise that the evolution of adverse selection risk in line with changes in dark trading volume is linked to liquidity, we also test the relationship between liquidity and dark trading. To this end, we proxy illiquidity using the Amihud (2002) illiquidity measure, which captures the price impact of trading activity. The Amihud ratio in our set-up equals daily absolute return divided by daily volume. We also employ a variant of this measure as used by Goyenko et al. (2009), the Amivest ratio, which is the inverse value of the Amihud ratio for non-zero-return days. Therefore, the Amivest ratio is a measure of liquidity.

If all informed traders hold an identical set of private information, as depicted by Zhu (2014), dark trading-induced self-selection can enhance price discovery/informational efficiency. This is because a reduction in the number of informed trades in the lit market brought about by fewer uninformed traders in the lit market leads to a decrease in the level of competition on the same private information set, although the amount of private information held in the aggregate by informed traders remains unchanged (see also Comerton-Forde and Putniņš, 2015). The enhancement of price discovery also implies a reduction in noise in the price discovery process. Therefore, we test whether there is a reduction in the pricing noise levels and whether informational efficiency improves in the aggregate market along with dark trading. Our inverse measure of pricing noise is called the 'Relative Noise Avoidance' (RNA). We estimate the RNA by extending Gonzalo and Granger's (1995) common factor share (CFS) computation approach. Consistent with Comerton-Forde and Putniņš (2015) and O'Hara and Ye (2011), we also use variance ratio as a proxy of informational efficiency. In an efficient market, stock prices follow a random walk, such that the variance of returns measured over longer horizons is equal to the sum of variances of shorter horizon returns. Therefore, values closer to one would imply higher levels of informational efficiency, while higher values will imply worsening efficiency levels. We expect informational efficiency to increase in line with reductions in pricing noise.

All variables are formally defined in Appendix A.

5.2. Multivariate analysis

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 run for all the 288 stocks using their 'global' values as calculated based on the individual exchange values from Chi-X Europe, LSE, BATS Europe and Turquoise. In order to obtain the global values, following Ibikunle et al. (2020), we combine the order book data from the four exchanges and create a single order book using time stamps provided in the TRTH data. For example, in computing the VPIN variable, we combine high frequency order book data for the four venues, and then compute VPIN based on the newly generated order book. The panel estimations are done using a two-stage least squares (2SLS) instrumental variables (IV) regression framework. Standard errors are double clustered by stock and by date in all the estimated regressions to account for dependencies within the panel data.[15] The IV estimations are employed to account for the likelihood of the endogeneity of dark and off-exchange trading values.[16]

The panel regression estimated is of the following form:

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

[15] For robustness, panel corrected standard errors are also computed; the estimates obtained are identical to those obtained from double clustering.

[16] Panel Least Squares estimations with stock and time fixed effects models are also estimated, and we observe that they are more likely to yield statistically significant results; however, the explanatory powers of the models are highly comparable. The identical nature of the results thus 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} corresponds to VPIN ($VPIN_{it}$), predictability of short-horizon returns ($\overline{R_{it}^2}$), Amihud illiquidity ratio ($Amihud_{it}$), Amivest liquidity measure ($Amivest_{it}$), RNA (RNA_{it}) or variance ratio (VR_{it}) for stock i on day t, $DARK_{it}$ is the proportion of stock i's total pound trading volume executed in the dark on day *t*, while $OFFEX_{it}$ is the percentage of stock *i*'s total pound volume of trades executed away from the four exchanges' order books, but not including dark transactions, on day *t*; off-exchange is an agglomeration of trading activity in the OTC market (including the LSE's broker-dealer market), BCNs and SIs.[17] 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 log of market capitalisation for stock *i* on day *t* ($MCap_{it}$), log of average trade size for stock *i* on day *t* ($TSize_{it}$), log of pound volume of lit trades for stock *i* on day *t* (Lit_{it}), and the stock-day average of effective spread ($ESpread_{it}$), which is defined as twice the absolute value of the difference between transaction price for stock *i* at time *t* and its prevailing mid-point. Given that dark orders are routinely executed at the midpoint of the lit exchanges' prevailing bid and ask orders (see Aquilina et al., 2016), aggregate effective spread is computed using only orders from the lit order books; thus all (dark and lit) trades' effective spread estimates are computed using the best prevailing lit bid and ask quotes in the London market at the time of each trade. The quadratic term $DARK_{it}^2$, inspired by Degryse et al. (2015), is added in order to test for the existence of a non-linear relationship between dark trading and market quality as discussed in Section 2. $P_{other\ stocks}$, which is the average of the dependent variable (i.e. one of $VPIN_{it}$, $\overline{R_{it}^2}$, $Amihud_{it}$, $Amivest_{it}$, RNA_{it} or VR_{it}) on the same day for all the other stocks in the same size quintile, is also included to account for commonality across stocks.[18] We winsorize the variables in

[17] 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.

[18] In the GMM IV estimations, a two-stage least squares (2SLS) weighting is used to weigh the various GMM moment conditions to be satisfied by the parameters of interest. The moment conditions are restricted to those that

order to limit the impact of extreme outliers; specifically, we set the extreme values on either tail of the variables to the 1st and 99th percentile across dates within each stock.

We face a challenge concerning identifying suitable instruments for $DARK_{it}$ and $OFFEX_{it}$. It would be preferable to exploit a natural event in developing an experiment that would allow us to account for endogeneity issues, but no such event presents itself for our sample period. Ideally, we would also instrument dark trading separately from market fragmentation. However, this is not possible without a specific exogenous shock relating to only dark trading. Thus, we focus our attention on developing instruments that meet the usual conditions for good instrument candidates: instruments must (1) be highly correlated with the variable to be instrumented, and (2) be largely uncorrelated with ε_{it} in Equation (1) above. We employ two sets of IVs.

The first set involves using an approach that has become increasingly popular in the recent literature; this is the one first proposed by Hasbrouck and Saar (2013) and thereafter used by several others such as Buti et al. (2011), Comerton-Forde and Putniņš (2015) 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 pounds sterling) 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 (2018). In his paper, Ibikunle (2018) 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-

could be written as an orthogonality condition between the residuals of Equation (1) and its right-hand side variables.

sectional stock averages and the other control variables. The residuals from this step are then employed as IVs in the GMM estimation. The IVs obtained should satisfy the two conditions stated above. According to Ibikunle (2018), the reason to expect a lack of correlation between the IVs and Equation (1)'s error term 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. We note that the estimates obtained from the application of both sets of IVs are highly consistent across all the regressions; therefore, for parsimony, we present results for only the regressions based on the second set of IVs. The second set of IVs-based results are also presented due to their slightly higher level of consistency across quintiles.

In the first stage regressions, we regress $DARK_{it}$ and $OFFEX_{it}$ on the set of instruments and control variables as described above, for each stock. The first-stage *F-statistics*, testing the null of weak instruments, show that our models do not suffer weak instruments issues, with only one test statistic (6.71) falling below the threshold of 10, which Stock et al. (2002) suggest is needed for 2SLS inferences to be reliable, when instrumenting for $DARK_{it}$. None falls below the suggested threshold for both sets of IVs when instrumenting for $OFFEX_{it}$. Furthermore, in all the regressions, Cragg-Donald (1993) and Kleibergen-Paap LM statistics reject the nulls of weak instruments and under-identification, based on the Stock and Yogo (2005) critical values, respectively. All the p-values of the Sargan χ^2 test obtained also indicate that we cannot reject the null that the over-identifying restrictions are valid.

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 the largest stocks generally have larger trading values across the board, except in the case of average trade sizes. Average trade sizes are shown to be larger in low volume stocks due to their 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 illiquidity and liquidity proxies, the Amihud PI and Amivest measures, are respectively negatively and positively correlated with both $DARK_{it}$ and $OFFEX_{it}$. Thus, it appears that dark trading serves a similar purpose in the UK, the US and Australia. The correlation coefficients are unsurprising since the aggregate market is still dominated by lit trading. However, in contrast to previous studies, $DARK_{it}$ is negatively correlated with HFT_{it}, the algorithmic trading proxy. This is also not surprising since there are fewer advantages to algorithmic trading in the dark than in the lit markets.

INSERT TABLE 1 AND TABLE 2 ABOUT HERE

6. Results and discussions

The purpose of this paper is to empirically investigate the effects of dark trading on adverse selection risk. However, the effects of dark trading on adverse selection risk manifests itself on several market quality variables; hence, we also test whether dark trading impacts market quality, with regards to its effects on market liquidity and noise in the price discovery process. Our findings are presented and discussed in this section.

6.1. Dark trading and adverse selection risk

Panel A of Table 3 presents the results for the IV regression results with $VPIN_{it}$ as a dependent variable; estimates are presented for the full sample of 288 stocks as well as for each quintile of stocks. All of the coefficients for the full sample are statistically significant at conventional levels. Most of the coefficient estimates for all of the quintile regressions are also statistically significant, especially when the estimates reflect the expected relationship of the relevant variables with $VPIN_{it}$. Most importantly, both the $DARK_{it}$ and $DARK_{it}^2$ coefficients for the full sample of stocks are highly statistically significant. The coefficient capturing relationship between $VPIN_{it}$ and $DARK_{it}$ is negative for the full sample, with an estimate of –0.619, and a t-statistic of –4.79. The estimates are also negative and statistically significant for all but one of the five quintiles. This trend implies that increasing levels of dark trading in the London equity market are linked with reductions in adverse selection risk. Thus, Hypothesis 1A holds (see Section 2). The results suggest that informed traders tend to concentrate in the lit market when dark trading is an option, thus increasing adverse selection risk in that section of the aggregate market. Furthermore, the proportion of informed trading will fall in the aggregate market due to an increased level of uninformed trading volume encouraged by dark trading, which induces an increase in the order submission rate of liquidity traders in dark pools. The opportunity to trade with a lower risk of being adversely selected encourages liquidity/uninformed traders to submit orders that otherwise would not have been submitted. This effect is similar to that of an upstairs market that offers a measure of protection against microstructure price impact of uninformed trades (see Madhavan and Cheng, 1997). An increase in the rate of order submission by liquidity traders implies an improvement in aggregate market liquidity, which we examine in the next section.

In addition, following on from Zhu (2014), since informed order flow executes against uninformed order flow, a reduction in the number of uninformed traders on the lit exchange will also lead to a lower number of informed trades being executed on the lit exchange, although the available private information set does not change. This implies a fall in adverse selection risk faced by uninformed traders in the aggregate. However, the reduction in the number of uninformed traders on the lit exchange will still imply that informed traders will make up an increasing proportion of the lit market relative to the volume of uninformed traders going to trade in the dark market. Thus, adverse selection risk in the lit market will rise as dark trading volume rises.[19]

INSERT TABLE 3 ABOUT HERE

The positive and highly statistically significant $DARK_{it}^{2}$ coefficient estimates for the full sample and two quintiles of stocks in Table 3 suggest that the relationship between adverse selection risk and dark trading is quadratic in nature, i.e. there is a level of dark trading in the market when it starts to induce an increase in adverse selection risk. Therefore, the estimates are in keeping with Hypothesis 2A (see Section 2). The reporting of a quadratic relationship between dark trading and a market quality proxy is not dissimilar to the previously reported relationship between trading fragmentation and market quality characteristics (see for example, Degryse et al., 2015; Ibikunle et al., 2020). 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.

The positive relationship between adverse selection risk and dark trading at high levels can be explained by theory. In Zhu's (2014) model, an increase in volatility in the lit market due to an increased concentration of informed traders widens the exchange spread and encourages more liquidity traders to migrate to the dark pool – this is the natural state of things when volatility is moderate. However, as volatility exceeds the maximum level needed for informed traders to avoid the dark pool, informed traders start to use both venues. The entry of informed traders into the dark pool introduces adverse selection risk into the dark pool, and leads to a reduction in the participation rate of liquidity traders there. This implies a higher

[19] For comparison, we examine the impact of dark trading on adverse selection risk in the lit market alone. The results presented in Appendix B show that adverse selection risk increases as the percentage of trading in dark venues increases.

adverse selection risk for the aggregate market, because competition among informed traders rises if they start spreading their trading activity across both the lit exchange and the dark pool. Furthermore, the increased entry of informed traders into the dark pool will lead to the exit of some uninformed traders from the market altogether due to the increased adverse selection risk from the informed traders entering the dark pools. Thus, dark trading could only be beneficial up to a point; beyond that threshold, its impact turns negative for market quality.

The predominantly negative and statistically significant estimates reported for the $OFFEX_{it}$ coefficients in Panel A of Table 3 also back up the potential of alternative venues offering execution opportunities for orders that otherwise would not have been executed.

There are other results of interest in Panel A. First, the effect of $TSize_{it}$ on $VPIN_{it}$ is negative and statistically significant in four of six regressions. This is consistent with the market microstructure literature. Many Microstructure studies argue that informed traders prefer to break their orders into smaller pieces in order to camouflage their trading intentions (see as examples, Admati and Pfleiderer, 1988; Barclay and Warner, 1993; Chakravarty, 2001). Thus, given the increasing levels of high frequency trading across platforms, stocks are more likely to have order flows large enough to act as camouflages for informed trades. The consistently negative and statistically significant relationship between $VPIN_{it}$ and the $ESpread_{it}$, as seen in Panel A, is surprising because it implies that as market toxicity/adverse selection increases, liquidity improves. However, if we further consider what $VPIN_{it}$ measures, and its unique relationship with liquidity, the result might not appear so surprising after all. Easley et al. (2011) argue that $VPIN_{it}$ captures the level of toxicity affecting the provision of liquidity. Thus, $VPIN_{it}$ is detrimental to liquidity provision only when it is at high levels. In cases where $VPIN_{it}$ estimates are at moderate levels, we would expect to find no adverse relationship with liquidity, as is the case in Panel A. For completeness, in the next section (6.2) we make the impact of dark trading on aggregate market liquidity the subject of our inquiry.

The $P_{other\ stocks}$ coefficient is also positive and statistically significant for the full and quintile-based regressions, indicating a high level of commonality across stocks in the full sample and within each quintile examined. In relation to the effects of high frequency trading, measured as the ratio of messages to executed trades, the impact is more nuanced. However, consistent with the recent literature (see as an example, Hendershott et al., 2011), there is sufficient evidence in the results to suggest that the overall impact of high frequency trading for large stocks is an improvement in price efficiency. This impact is due to HFTs speeding up the price discovery process by promptly conveying new information to the market through their high frequency trades (Brogaard et al., 2014; Chaboud et al., 2014).

For robustness, we replicate the regressions using a different proxy of adverse selection risk as the variable of interest; this is the predictability of short-horizon returns ($\overline{R_{it}^2}$). As an inverse measure of market efficiency, the proxy captures the extent to which short-horizon returns could be predicted from order imbalance; hence, it is a reflection of informed trading activity and adverse selection risk. The results for the full sample and quintiles of stocks are presented in Panel B of Table 3. The first key observation is the high level of statistical significance obtained for the regression estimations. All of the $Dark_{it}$ and $Dark_{it}^2$ coefficient estimates are negative and positive respectively, and all are statistically significant at the 0.01 level. Thus, the estimates are consistent with the findings in Panel A, suggesting the existence of a quadratic relationship between adverse selection risk in the aggregate market and dark trading; indeed, the results are stronger in Panel B. The negative and statistically significant off-exchange coefficient estimates also support the view that when alternative venues offer additional opportunities for order execution, they encourage the execution of orders that otherwise would not have been executed, which can dilute adverse selection risk.

Although the headline results in Panels A and B are consistent, there are a couple of differences. For example, the positive and statistically significant effective spread coefficients in Panel B are at odds with the negative ones in Panel A; however, the Panel B estimates are fully consistent with the expectations based on the literature. Chordia et al. (2008) show that the predictability of short-horizon returns increases with reducing liquidity; hence, our results showing the predictability of short-horizon returns increases with rising illiquidity are in line with the literature (see also Chung and Hrazdil, 2010). This is also linked to the negative and statistically significant $MCap_{it}$ coefficient estimates. Since trading activity and liquidity are closely related with stock size (see Barclay and Hendershott, 2003; Hedge and McDermott, 2003), we would expect that the predictability of short-horizon returns is lower for firms with larger market capitalisation.

Thus far, we have established the relationship between dark trading and adverse selection risk by relating $DARK_{it}$ and $DARK_{it}^2$ to two proxies of adverse selection risk, $VPIN_{it}$ and $\overline{R_{it}^2}$. Our analysis suggests that dark trading is inversely related to the level of adverse selection risk in the aggregate market. However, there is a threshold when dark trading's effect on adverse selection risk (and therefore market quality) is zero; beyond this point, further dark trading induces adverse selection and may impair market quality (again refer to Section 2). It is useful, not least to policymakers, to estimate this threshold. Therefore, in Figure 3, we plot estimates of the implied effect of dark trading on the inverse proxy for aggregate adverse selection risk. Specifically, we employ the $DARK_{it}$ and $DARK_{it}^2$ coefficient estimates computed in Panel B of Table 3 to plot the implied effects of adverse selection for every proportion of dark trading by market value. Panel B of Table 3's estimates are used because it is the only panel where all the dark trading coefficients are statistically significant across quintiles. This allows us to compute thresholds for varying levels of stock liquidity. We use the stock-day panel regressions coefficients' standard errors in estimating 95% confidence intervals for the curves.

Panel A of Figure 3, showing the plot for the full sample, suggests that the turning point of the positive effect of dark trading on adverse selection risk is when dark trading is at about 14% of the total trading value in the aggregate market. Thus, when dark trading is at about 14% in the market, its impact on adverse selection risk in the aggregate market is zero. However, this single threshold value can be misleading in a market with a large number of stocks with vastly different levels of trading activity; hence, we also plot estimated values for average daily pound/currency volume quintiles. As suspected, the threshold estimate varies across quintiles, from 9% for the highest trading stocks (Quintiles 5 and 4) to 25% (Quintile 2) and 23% (Quintile 1) for the lowest trading stocks. The estimate for stocks around the median (Quintile 3) is 14%. Therefore, the lower trading stocks have a higher threshold than the highest trading ones. Market structure may play a part in the threshold variation across quintiles. In the London market, lower trading stocks, such as those in the FTSE 250, have always traded mostly away from the downstairs (lit) market, with most of their trades by value taking place in the less transparent LSE operated (upstairs) broker-dealer market. In the LSE's broker-dealer market, publishing of orders is not mandatory and executed orders may go unreported for up to three minutes, with only order submitters and the attending broker-dealers aware of their existence until reported.[20] Thus, increasing levels of dark trading in such stocks are unlikely to immediately lead to higher levels of adverse selection, given that they already extensively exploit a similar trading mechanism. For example, Armitage and Ibikunle (2015) document that more than 62% of the executed orders by value in some FTSE 250 stocks are done in the LSE's broker-dealer market.

The estimated thresholds should be interpreted with caution for at least three reasons. Firstly, dark trading as a proportion of total trading in the London market as observed in our

[20] Note that new prices in the broker-dealer market can only be set for order quantities that exceed those available in the downstairs market. Please see Armitage and Ibikunle (2015) for a detailed explanation of the structure of the LSE's upstairs/broker-dealer market.

data is yet to consistently attain the estimated thresholds; hence, the estimates are based on regression coefficients computed using data with much lower levels of dark trading. Secondly, the estimated thresholds are dependent on the coefficient values and thus easily influenced by the estimation approach used. Thirdly, the estimated thresholds also vary significantly depending on the liquidity of the stocks investigated; hence, a single point estimate for a group of stocks could be misleading. However, irrespective of the regression estimation approach used, we find consistency in the nature of the relationship between market quality variables and dark trading across all stock liquidity quintiles.

6.2. Dark trading and aggregate market liquidity

We now turn to the previously raised question of the impact of dark trading on aggregate market liquidity. Table 4 (Panel A) presents the results for the IV regressions, estimating the impact of dark trading on market illiquidity; illiquidity is proxied using the Amihud price impact ratio, $Amihud_{it}$. The results presented are based on estimations employing the full sample of 288 stocks. In addition to the full sample results, quintile-based results are also presented. The $DARK_{it}$ coefficients are only statistically significant for the full and the largest quintile samples of stocks, and both are also negative. These estimates are therefore consistent with Hypothesis 1B (see Section 2). While increasing levels of dark trading might lead to worsening liquidity in the lit market, as predicted by Zhu (2014) and reported in Comerton-Forde and Putniņš (2015), in our sample, which aggregates trading lit and dark volume from the major trading platforms in London, the impact is exactly the opposite.

The negative and statistically significant $DARK_{it}$ coefficients in Panel A of Table 4 are linked to uninformed trading inducing effects of dark trading platforms that offer additional execution outlets for orders that otherwise would not have been submitted or executed in the existing lit venues, perhaps due to concerns of being adversely selected. Rising adverse selection, which increases price impact, should ensue in the lit market when uninformed traders migrate from the lit market to trade in the dark;[21] hence this explains the findings in the existing studies (see as an example, Comerton-Forde and Putniņš, 2015) that focus only on investigating the impact of dark trading on the lit market. However, this is not the case when the market is considered in its aggregate, since the opportunity to trade in dark pools encourages the submission of uninformed orders that would otherwise not have been submitted to the (aggregate) market (see Section 2).

INSERT TABLE 4 ABOUT HERE

$DARK_{it}^2$ coefficients for the full and the two highest quintiles of stocks are positive and statistically significant at conventional levels of statistical significance, implying a quadratic relationship between aggregate market liquidity and dark trading. These results are expected given that we also document a higher level of adverse selection risk at higher levels of dark trading. Uninformed traders in the dark and lit venues are unlikely to want to continue trading when the risk of adverse selection is high. They would reduce their order submission rates as more informed traders enter the market, eventually leading to a contraction in liquidity, even as informed traders assert themselves more aggressively in their search for liquidity in both lit and dark venues in order to increase their profits (Hendershott and Mendelson, 2000; Nimalendran and Ray, 2014; Suominen, 2001). The desperate search for liquidity by informed traders is expected when uninformed traders excessively migrate to the dark venues; high levels of dark trading will force informed traders to make incursions into dark pools (Nimalendran and Ray, 2014). Hence, Hypothesis 2B holds.

For robustness, we also employ a second measure, $Amivest_{it}$, as a direct measure of liquidity; the estimated coefficients are presented in Panel B of Table 4. The first observation

[21] We examine the impact of dark trading on market quality variables (including illiquidity/liquidity) in the lit market and find results consistent with Comerton-Forde and Putniņš (2015). The results, presented in Appendix B, show that liquidity deteriorates in the lit market in the presence of dark trading.

is that the results of the regressions based on $Amivest_{it}$ appear to be stronger than those for the $Amihud_{it}$. This is likely due to the fact that $Amivest_{it}$ is the inverse of $Amihud_{it}$ for non-zero return days, and therefore every observation holds non-negligible information. Nevertheless, the headline results are fully consistent with the results obtained when liquidity is proxied with $Amihud_{it}$.

6.3. Dark trading and pricing noise and informational efficiency

If all informed traders hold an identical set of private information as in Zhu's (2014) model, the self-selection engendered by dark trading can improve the efficiency of the price discovery process. This is because a reduction in the number of informed trades due to fewer uninformed traders in the lit market leads to a decrease in the level of competition on the same private information set (see Section 2). In addition, although there is no change in the amount of private information held by actors in the market, since all informed traders hold identical information, a higher proportion of informed traders in the lit market (due to uninformed traders migrating to dark pools) implies lower pricing noise and enhances the market's capacity to incorporate information into prices. In a regulatory regime where dark orders execute against the more informationally efficient lit venues' quotes, aggregate informational efficiency should increase.

Therefore, we test whether there is a reduction in the pricing noise levels and whether informational efficiency improves in the aggregate market in the presence of dark trading. Our (inverse) measure of pricing noise is RNA_{it}, while VR_{it} is used to estimate informational efficiency; we would expect to observe increasing informational efficiency as pricing noise decreases. We also anticipate that dark trading is positively related to RNA_{it}. A positive relationship means that in the aggregate market, increasing dark trade levels lead to declining pricing noise. Panels A and B of Table 5 present the results for the RNA_{it} and VR_{it} IV regressions testing the relationship between dark trading and the two market quality proxies; several control variables, as enumerated in Section 5, are included in the model.

In Panel A, generally, the quintile-based estimates are not statistically significant; however, the full sample regressions yield statistically significant coefficients for both $DARK_{it}$ and $DARK_{it}^2$. Consistent with Hypothesis 1C, and with the preceding analysis, $DARK_{it}$ coefficient estimates suggest reductions in noise levels in the presence of dark trading. The full sample $DARK_{it}$ value coefficient is 0.297 and is highly statistically significant. The result shows that aggregate market pricing noise falls about 29.7% with every unit rise in dark trading value in the London equity market. This result is also in line with what we should find if dark trading does enhance price discovery in the aggregate market as a result of traders self-selecting where they would trade based on their information stocks. Consistent with the results presented in the previous sections, the $DARK_{it}^2$ estimate (–1.457) takes the opposite sign to the $DARK_{it}$ coefficient estimate; both estimates are statically significant. This outcome suggests that Hypothesis 2C holds.

INSERT TABLE 5 ABOUT HERE

In Panel B, the $DARK_{it}$ and $DARK_{it}^2$ coefficient estimates relating VR_{it} with dark trading are generally statistically significant and also have opposite signs, with the $DARK_{it}$ coefficients consistently negative, and the $DARK_{it}^2$ estimates consistently positive. These negative $DARK_{it}$ coefficient estimates are in direct contradiction to the findings in Comerton-Forde and Putniņš (2015). 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 factor, which are intuitively similar to our approach. Their results suggest a deterioration in informational efficiency in the presence of dark trading, which is at odds with ours. This is surprising because the RNA_{it} as computed is unlikely to evolve over our sample period in a significantly different way if we had computed it using observations from lit-only venues, and also because Australian dark pools can only trade at the midpoint or on the same price grid as the lit market. One explanation for this difference in results could be that our analysis captures the positive effects of market fragmentation (see O'Hara and Ye, 2011; Degryse et al., 2015), which is inherent in our consolidated dataset. The dataset employed by Comerton-Forde and Putniņš (2015) is based on trading on a single exchange and its linked dark pool, Centre Point.

Another explanation is linked to the arguments of Comerton-Forde and Putniņš (2015), who reason that their results could be driven by high levels of dark trading exacerbating the inefficient price overreactions and reversals due to mid-quotes (see Anderson et al., 2013). This is line with what we observe with the coefficient estimates when VR_{it} is related with $DARK_{it}^2$ (consistently positive in Panel B), and the negative estimates when $DARK_{it}^2$ is related with RNA_{it}. It implies that at the lower levels of dark trading observed in our data, the effects of dark trading on informational efficiency is largely positive, while at higher levels of dark trading, informational efficiency reduces. Furthermore, overreactions and reversals are often due to decreases in liquidity, which is observed in the single lit exchange and single dark pool empirical framework of Comerton-Forde and Putniņš (2015). In our set-up, that appears not to have fully disentangled the positive effects of lit fragmentation on liquidity from the effects of dark trading on liquidity, we may inevitably be observing the underlying influence of fragmentation due to dark trading.

7. Conclusion

In this study, we test the impact of dark trading on adverse selection risk, liquidity and informational efficiency in the London market. Zhu (2014) develops a model where traders self-select trading venues based on whether they are informed or uninformed, and this in turn induces consequential changes in adverse selection and liquidity. Our results, based on a large

European sample of 288 of the largest UK stocks traded across the four main trading venues in London, suggest that the aggregate market benefits when dark trading occurs at moderate levels. We find that the impact of dark trading on adverse selection risk is related to the level of trading activity in stocks. Using data from mid-point dark order books and lit order books, we find that adverse selection risk falls, and liquidity is enhanced in the aggregate market as dark trading increases. This is because the option of trading in dark pools is more attractive to uninformed traders than to informed traders, thereby leading to the creation of a relatively safer haven for liquidity traders in dark pools, and this encourages the provision of liquidity that otherwise would not have occurred. The increased trading activity driven by dark trading thus dilutes the proportion of informed trading and adverse selection risk faced by uninformed traders in the aggregate market. The migration of uninformed trading volume to dark pools is also linked to a reduction in noise in the price discovery process and an improvement in informational efficiency in the aggregate market.

However, we also observe that the relationship between our proxies for adverse selection risk, informational efficiency and liquidity on the one hand, and dark trading on the other, is non-linear, which implies that at higher levels, dark trading could harm market quality. For adverse selection risk, we estimate that the impact of dark trading on market quality is about zero when the percentage value of dark trading in the aggregate market is roughly equal to 14%. This estimate, however, varies depending on the level of trading activity across stocks. Splitting the 288 stocks in our sample into quintiles, we estimate that the thresholds for the Quintile 5 and 4 (largest trading) stocks is about 9%, while the estimated thresholds for Quintiles 3, 2 and 1 are 14%, 25% and 23% respectively.

We urge caution regarding interpreting the estimated dark trading thresholds/ranges for three reasons. The first is that dark trading as a proportion of total trading in the London market is yet to consistently attain the estimated thresholds; secondly, since the thresholds are based on coefficient estimates, they could be affected by estimation approaches; and finally, trading activity is a strong factor in determining the thresholds, and hence single point estimates for stock groups could be misleading. Nevertheless, irrespective of the estimation approach used, the quadratic relationship between dark trading and adverse selection risk holds. In addition, we note that, consistent with classic information-based models (see for example, Glosten and Milgrom, 1985), under certain conditions, information acquisition in the future may decline as uninformed traders migrate to dark pools. Our empirical framework does not directly address this predictive element of the declining participation rate of uninformed traders in lit exchanges.

The EU's MiFID II/MiFIR emphasises investor protection and fairer/more efficient pricing in financial markets. We have shown in this study, based on UK data, 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 dark trading restrictions. By showing that certain levels of dark trading in the UK market is beneficial, this study is timely and could have significant policy implications as UK financial regulation starts to diverge from that of the EU post-Brexit.

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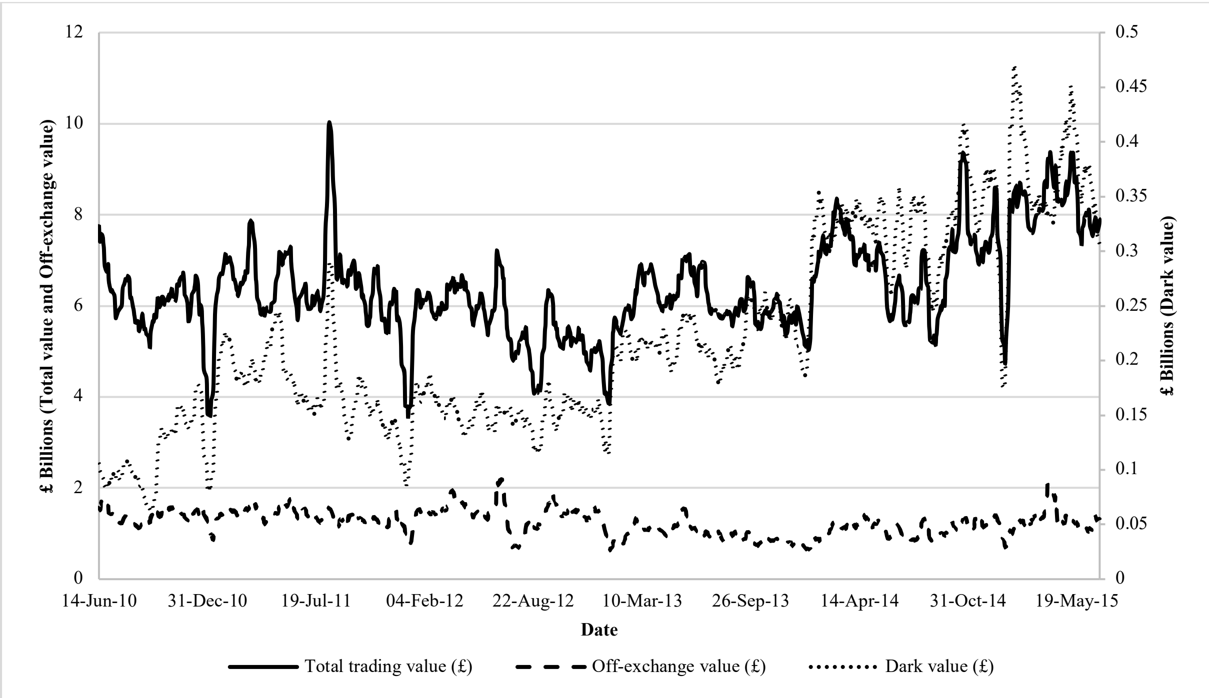
Figure 1: Trading values

Panel A 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 plots the pound values for dark and off-exchange trading as 10-day moving average percentages of total market value for the same sample and over the same period.

PANEL A



PANEL B

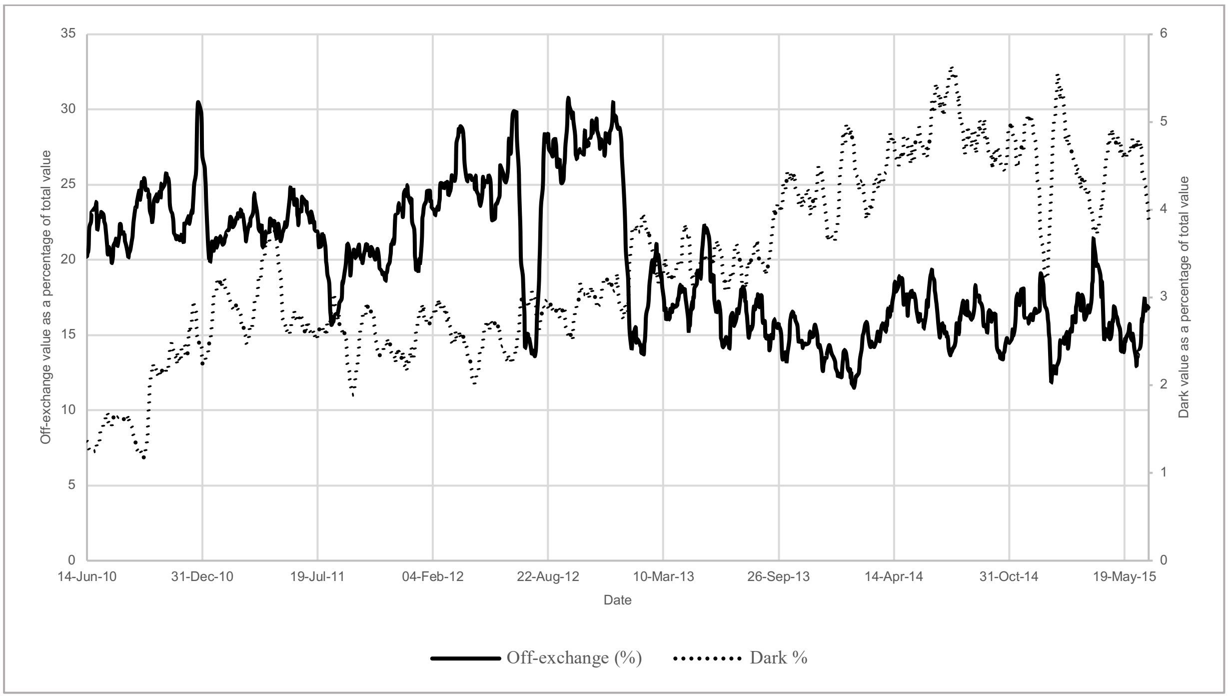


Figure 2: Average trade sizes

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.

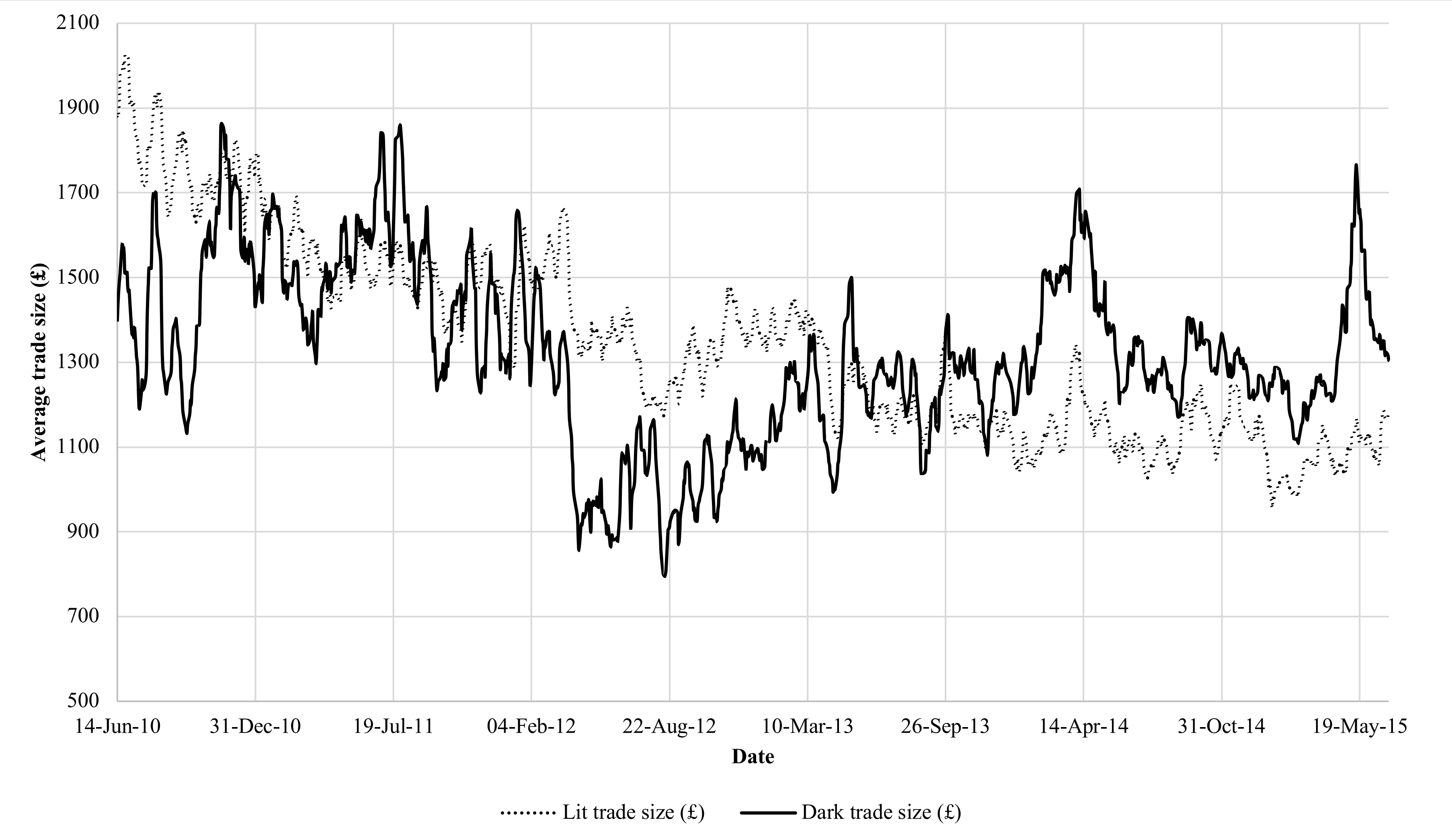
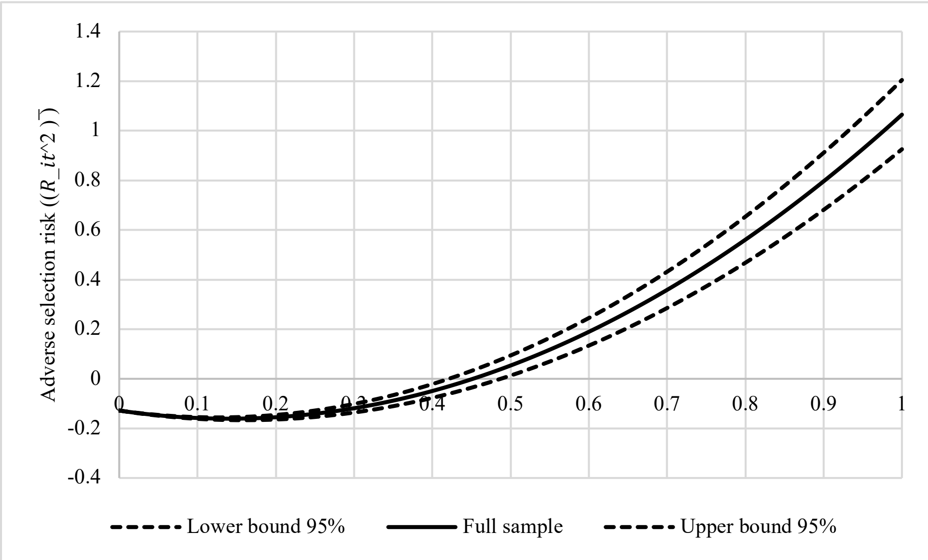


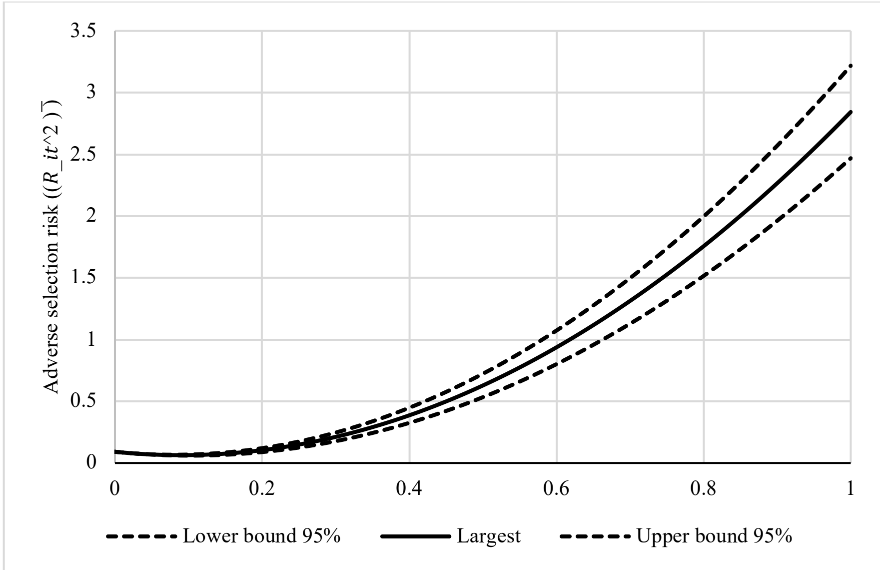
Figure 3: Effects of dark trading on adverse selection risk

The figure plots the implied/estimated effects of dark trading on market quality, with the predictability of short-horizon returns used as a proxy for adverse selection risk. Panels A – F show the full sample and five quintiles 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 solid line represents the implied effects while the square dot lines represent the upper and lower bounds of the 95% confidence intervals, computed using double-clustered 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.

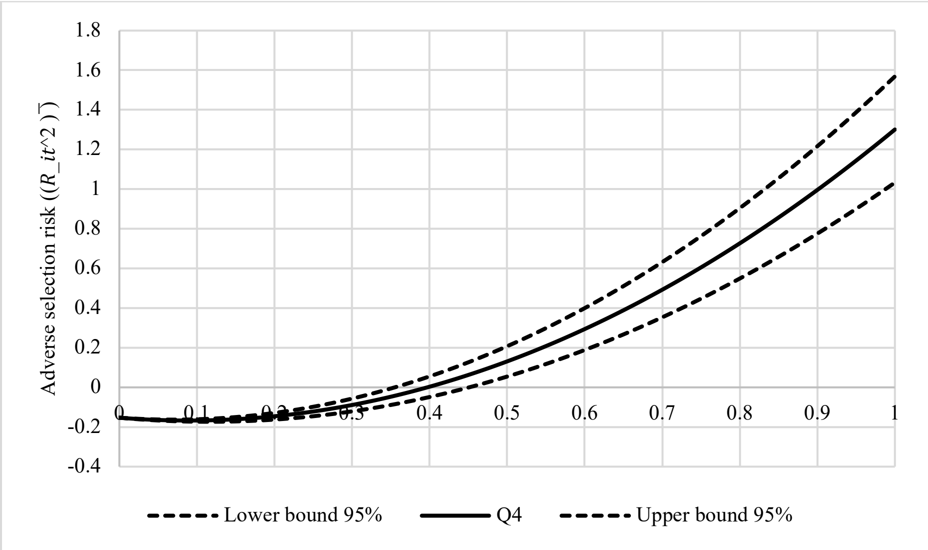
Panel A: Full sample of stocks



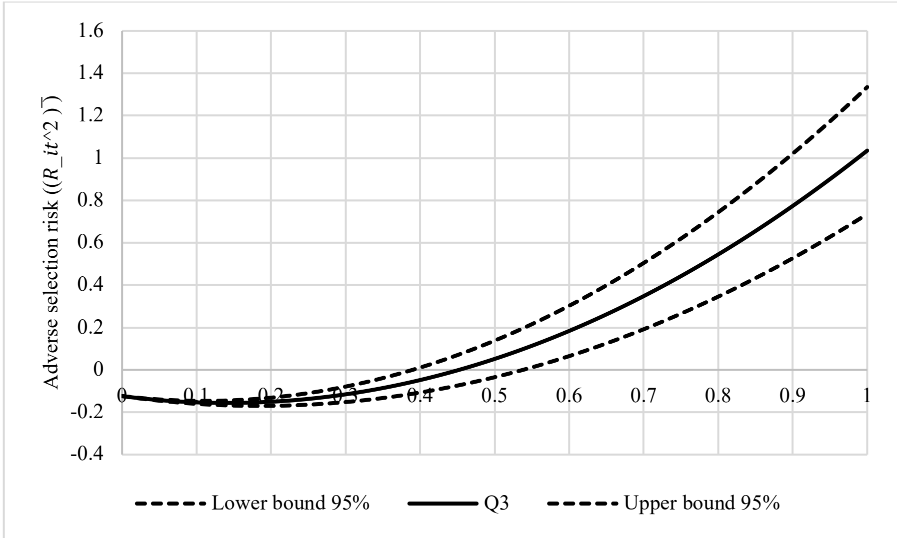
Panel B: Largest volume stocks



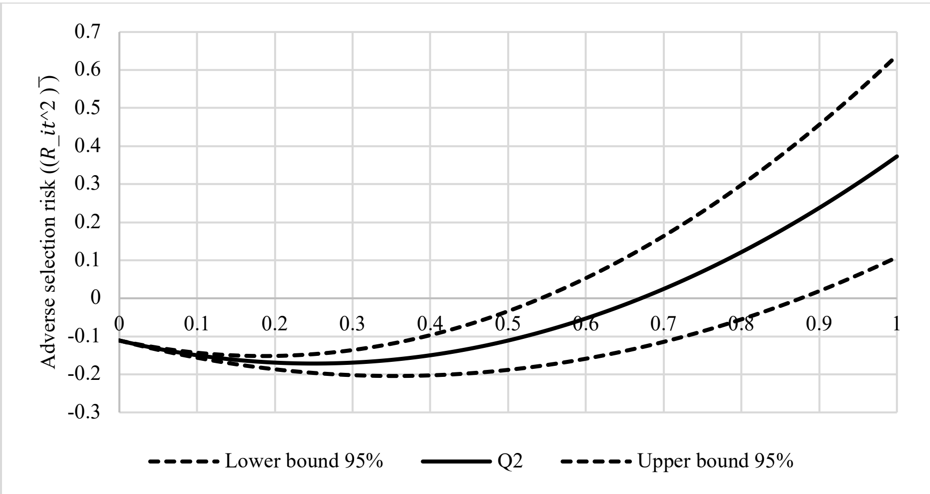
Panel C: Quintile 4 stocks



Panel D: Quintile 3 stocks



Panel E: Quintile 2 stocks



Panel F: Smallest volume stocks

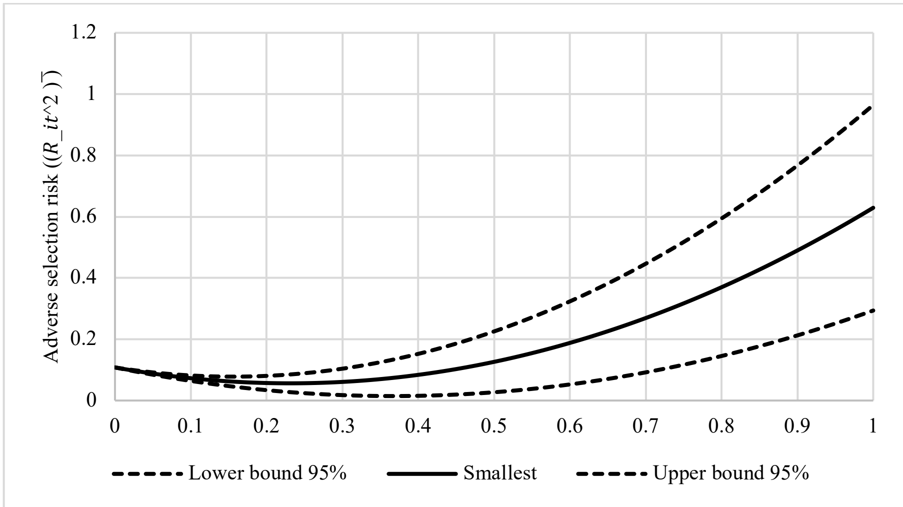


Table 1: Descriptive statistics

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 1st June 2010 to 30th June 2015. The quintiles are computed on the basis of daily pound volume across the sample period.

Variables	Definition	Full sample of stocks	Highest volume stocks	4	3	2	Lowest volume stocks
$NLit_{it}$	Number of lit trades for stock *i* on day *t*	3050.47 (1156.00)	9507.43 (6644.00)	3268.75 (2670.00)	1487.96 (1221.00)	592.82 (427.00)	148.88 (83.00)
$NDark_{it}$	Number of dark trades for stock *i* on day *t*	139.51 (35.00)	436.44 (276.00)	150.36 (100.00)	63.27 (35.00)	27.98 (12.00)	8.14 (1.00)
$£DARK_{it}$	Pound value of dark trading volume for stock *i* on day *t*	8.07×10^{5} (1.01×10^{5})	2.82×10^{6} (1.52×10^{6})	6.74×10^{5} (3.40×10^{5})	2.39×10^{5} (7.66×10^{4})	9.06×10^{4} (1.97×10^{4})	7.97×10^{4} (2.91×10^{3})
$£OFFEX_{it}$	Pound value of volume traded at alternative venues and reported to exchange for stock *i* on day *t*	4.52×10^{6} (9.92×10^{5})	1.53×10^{7} (7.92×10^{6})	3.05×10^{6} (1.76×10^{6})	1.44×10^{6} (6.80×10^{5})	1.14×10^{6} (5.10×10^{5})	9.21×10^{5} (2.81×10^{5})
$£TSize_{it}$	Average trade size for stock *i* on day *t*	4408.36 (3263.81)	6608.19 (6209.36)	3976.09 (3559.98)	3517.65 (2496.85)	3852.43 (2453.789)	3970.83 (2350.76)
$£MCap_{it}$	Market capitalisation for stock *i* on day *t*.	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})
$ESpread_{it}$	Stock-day average of effective spread in bps, which is defined as twice the absolute value of the difference between transaction price for stock *i* at time *t* and its prevailing mid-point.	1.14 (0.55)	0.35 (0.26)	0.58 (0.40)	1.11 (0.6)	1.59 (1.06)	2.15 (1.59)
$£Lit_{it}$	Pound value of orders executed on lit platforms for stock *i* on day *t*.	1.26×10^{7} (2.04×10^{6})	4.53×10^{8} (2.86×10^{7})	9.16×10^{6} (6.02×10^{6})	2.79×10^{6} (1.48×10^{6})	1.26×10^{6} (6.21×10^{6})	1.23×10^{6} (2.11×10^{6})
HFT_{it}	The ratio of messages to trades for stock *i* on day *t*.	536.55 (194.61)	840.29 (221.78)	727.29 (216.28)	502.07 (160.96)	330.06 (132.82)	201.83 (132.75)
$VPIN_{it}$	Volume-synchronised probability of informed trading	0.25 (0.22)	0.20 (0.17)	0.21 (0.17)	0.24 (0.21)	0.28 (0.24)	0.33 (0.30)

	for stock *i* on day *t*; it is a measure of order flow imbalance, as developed by Easley et al. (2011; 2012) (see Appendix A).						
RNA_{it}	Relative Noise Avoidance for stock *i* on day *t*; it is computed by extending Gonzalo and Granger's (1995) common factor share (CFS) computation approach. The CFS metric is computed using quote mid-point at 1-second intervals. (see Appendix A)	1.47 (1.41)	1.44 (1.38)	1.47 (1.41)	1.50 (1.43)	1.53 (1.45)	1.54 (1.44)
$\overline{R_{it}^2}$	The predictability of one-minute returns by lagged order imbalance for stock *i* on day *t*.	0.075 (0.066)	0.085 (0.077)	0.086 (0.077)	0.075 (0.065)	0.070 (0.056)	0.061 (0.05)
$Amihud_{it}$	The ratio of the absolute return to trading volume for stock *i* on day *t*.	1.21×10^{-8} (2.42×10^{-10})	6.30×10^{-10} (1.67×10^{-11})	1.08×10^{-9} (9.91×10^{-11})	1.11×10^{-8} (3.71×10^{-10})	1.14×10^{-8} (8.49×10^{-10})	3.76×10^{-8} (2.18×10^{-9})
$Amivest_{it}$	The inverse value of $Amihud_{it}$ for non-zero-return days.	7.41×10^{10} (7.63×10^{9})	2.59×10^{11} (7.87×10^{10})	4.47×10^{10} (1.55×10^{10})	1.99×10^{10} (5.27×10^{9})	1.32×10^{10} (2.87×10^{9})	1.06×10^{10} (1.24×10^{9})
VR_{it}	Variance ratio for stock *i* on day *t*.	0.71 (0.75)	0.59 (0.62)	0.70 (0.71)	0.75 (0.76)	0.77 (0.78)	0.77 (0.78)

Table 2: Correlation matrix

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. $DARK_{it}$ is the proportion of the stock-day's total pound volume executed in dark pools in the London market, while all other variables are as defined in Table 1. 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.

	$DARK_{it}$	$£OFFEX_{it}$	$£TSize_{it}$	$£MCap_{it}$	$ESpread_{it}$	$£Lit_{it}$	HFT_{it}
$DARK_{it}$	1.000	-0.039	0.080	0.014	-0.037	0.045	-0.130
$£OFFEX_{it}$	-0.039	1.000	0.623	0.597	-0.238	0.694	-0.116
$£TSize_{it}$	0.080	0.623	1.000	0.510	-0.216	0.584	-0.012
$£MCap_{it}$	0.014	0.597	0.510	1.000	-0.213	0.689	-0.087
$ESpread_{it}$	-0.037	-0.238	-0.216	-0.213	1.000	-0.283	0.405
$£Lit_{it}$	0.045	0.694	0.584	0.689	-0.283	1.000	-0.148
HFT_{it}	-0.130	-0.116	-0.012	-0.087	0.405	-0.148	1.000

Table 3: The impact of dark trading on adverse selection risk

The table reports the stock-day instrumental variable regression coefficient estimates using a stock-day panel, in which Q_{it} corresponds to the Easley et al. (2011) volume synchronised probability of an informed trade (VPIN) measure ($VPIN_{it}$) or the $\overline{R^2}$ obtained from regressing one-minute returns on lagged order imbalance ($\overline{R^2_{it}}$) for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues (London Stock Exchange, BATS, Chi-X and Turquoise); both dependent variables are defined in Appendix A. The estimated regression model is:

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

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 for stock *i* on day *t* ($MCap_{it}$), log of average trade size for stock *i* on day *t* ($TSize_{it}$), log of pound volume of lit trades for stock *i* on day *t* (Lit_{it}), and the stock-day average of effective spread ($ESpread_{it}$), which is defined as twice the absolute value of the difference between transaction price for stock *i* at time *t* and its prevailing mid-point, the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of Q_{it} on the same day for all the other stocks in the same sized quintile. $DARK_{it}$ and $OFFEX_{it}$ are instrumented 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 standard errors clustered by stock and date. *, ** 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.

Panel A

			$VPIN_{it}$			
Variables	Full sample	Largest stocks	4	3	2	Smallest stocks
$DARK_{it}$	-0.619*** (-4.79)	-0.076** (-2.38)	-0.096*** (-2.94)	-0.053** (-1.97)	-0.107*** (-3.73)	-0.040 (-1.036)
$DARK^2_{it}$	1.778** (2.06)	0.285 (1.24)	0.178 (0.83)	0.702*** (4.49)	0.171 (1.15)	0.373** (2.258)
$OFFEX_{it}$	-0.006*** (-5.86)	-0.007*** (-14.66)	-0.004*** (-8.32)	0.006*** (10.36)	0.004*** (4.82)	-0.002** (-2.192)

$TSize_{it}$	-0.001 (-0.21)	-0.005** (-2.10)	0.000 (0.11)	-0.004*** (-2.70)	-0.021*** (-10.75)	-0.008*** (-3.79)
$MCap_{it}$	0.019*** (18.99)	0.006** (4.11)	0.014*** (8.89)	0.031*** (16.24)	0.033*** (12.89)	0.007*** (3.07)
$Spread_{it}$	-0.002*** (-4.47)	-0.002 (-0.93)	-0.007*** (-6.00)	-0.012*** (-14.31)	-0.007*** (-12.97)	0.000 (0.525)
Lit_{it}	-0.003*** (-4.11)	-0.002* (-1.90)	-0.006*** (-4.97)	-0.011*** (-7.63)	-0.011*** (-6.54)	-0.001 (-1.107)
HFT_{it}	-0.003*** (-5.64)	0.006*** (5.43)	-0.006*** (-5.10)	-0.018*** (-14.17)	-0.010*** (-9.80)	0.004*** (4.105)
$P_{other\ stocks}$	0.967*** (48.09)	0.987*** (38.23)	0.962*** (43.72)	0.981*** (37.72)	0.985*** (36.32)	0.989*** (34.99)
$Intercept$	-0.229*** (-9.40)	0.089*** (2.62)	-0.102*** (-4.05)	-0.421*** (-14.52)	-0.241*** (-8.08)	0.002 (-0.064)
$\overline{R^2}$	0.11	0.11	0.11	0.05	0.03	0.05
N	309,342	64,367	62,302	63,731	60,136	58,806

Panel B

			$\overline{R_{it}^2}$			
Variables	Full sample	Largest stocks	4	3	2	Smallest stocks
$DARK_{it}$	-0.467***	-0.605***	-0.318***	-0.457***	-0.484***	-0.448***
	(-47.05)	(-36.55)	(-39.56)	(-19.64)	(-21.79)	(-12.77)
$DARK_{it}^2$	1.660***	3.357***	1.772***	1.616***	0.968***	0.969***
	(12.15)	(11.47)	(14.05)	(4.75)	(8.56)	(6.16)
$OFFEX_{it}$	-0.008***	-0.014***	-0.011***	-0.007***	-0.007***	-0.002
	(-28.21)	(-29.79)	(-32.46)	(-14.21)	(-11.44)	(-1.44)
$TSize_{it}$	0.010***	0.034***	0.022***	0.003**	-0.005***	-0.009***
	(16.40)	(21.18)	(6.91)	(2.45)	(-3.14)	(-3.72)
$MCap_{it}$	-0.011***	-0.005***	-0.012***	-0.018***	-0.018***	-0.000
	(20.60)	(-12.84)	(-5.67)	(-11.42)	(-9.15)	(-0.19)
$Spread_{it}$	0.002***	0.006***	0.007***	0.006***	0.001	0.002***
	(7.81)	(4.02)	(1.01)	(8.22)	(0.13)	(3.77)
Lit_{it}	-0.002**	-0.002**	-0.004***	-0.005***	-0.002	0.004***
	(-3.31)	(-2.97)	(-1.85)	(-3.81)	(-1.76)	(3.44)
HFT_{it}	-0.009***	-0.021***	-0.021***	-0.014***	-0.008***	-0.002***
	(-21.03)	(-27.08)	(-10.09)	(-12.84)	(-8.59)	(-2.48)
$P_{other\ stocks}$	0.949***	0.979***	0.899***	0.940***	0.954***	0.986***

	(46.53)	(51.31)	(35.81)	(36.94)	(32.26)	(29.31)
$Intercept$	-0.128***	0.091***	-0.153***	-0.124***	-0.111***	0.108***
	(-24.76)	(13.40)	(-3.09)	(-5.74)	(-5.56)	(3.71)
$\overline{R^2}$	0.34	0.57	0.54	0.61	0.58	0.59
N	309,342	64,367	62,302	63,731	60,136	58,806

Table 4: The impact of dark trading on market liquidity

The table reports the stock-day instrumental variable regression coefficient estimates using a stock-day panel, in which Q_{it} corresponds to $Amihud_{it}$, defined as the ratio of the absolute return to trading volume, or $Amivest_{it}$, defined as the inverse value of $Amihud_{it}$ for non-zero-return days, for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues (London Stock Exchange, BATS, Chi-X and Turquoise); both dependent variables are defined in Appendix A. The estimated regression model is:

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

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 for stock *i* on day *t* ($MCap_{it}$), log of average trade size for stock *i* on day *t* ($TSize_{it}$), log of pound volume of lit trades for stock *i* on day *t* (Lit_{it}), and the stock-day average of effective spread ($ESpread_{it}$), which is defined as twice the absolute value of the difference between transaction price for stock *i* at time *t* and its prevailing mid-point, the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of Q_{it} on the same day for all the other stocks in the same sized quintile. $DARK_{it}$ and $OFFEX_{it}$ are instrumented 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 standard errors clustered by stock and date. *, ** 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.

Panel A

	$Amihud_{it}$					
Variables	Full sample	Largest stocks	4	3	2	Smallest stocks
$DARK_{it}$	-0.094** (-2.10)	-0.146** (-2.03)	0.019 (1.17)	-0.032 (-0.11)	-1.550 (-1.47)	1.230 (0.51)
$DARK_{it}^2$	0.100** (2.50)	2.040*** (4.71)	0.263* (1.69)	-2.620 (-1.38)	1.950 (0.75)	-12.000 (-1.07)
$OFFEX_{it}$	-0.040*** (-2.69)	0.006** (2.46)	0.001 (1.07)	-0.034 (-0.72)	-0.102 (-1.46)	-0.312** (-2.56)
$TSize_{it}$	-0.007*** (-3.11)	-0.029** (-2.15)	-0.042 (-1.25)	-0.097 (-1.33)	0.106 (0.73)	-0.074 (-0.72)

$MCap_{it}$	-0.002 (-0.77)	0.007 (0.45)	0.003 (0.50)	-0.423 (-1.17)	-0.317* (-1.65)	-0.392*** (-5.34)
$Spread_{it}$	0.018*** (3.97)	0.054** (2.48)	0.039*** (2.64)	0.429** (2.30)	0.126*** (3.46)	0.232*** (2.95)
Lit_{it}	0.005 (1.38)	-0.014* (-1.93)	0.017 (1.56)	0.214 (1.27)	0.133 (1.39)	0.226* (1.87)
HFT_{it}	0.004 (1.89)*	0.004*** (2.95)	0.037 (1.47)	0.092** (2.00)	0.063*** (3.35)	0.106*** (4.51)
$P_{other\ stocks}$	0.998** (2.60)	0.998 (2.47)	0.998 (1.17)	0.998 (1.27)	0.998* (1.88)	0.998 (1.60)
$Intercept$	0.104*** (6.67)	0.398*** (3.05)	-0.052 (-0.54)	6.57 (1.43)	4.500*** (2.61)	9.760*** (6.73)
$\overline{R^2}$	0.16	0.21	0.20	0.20	0.17	0.37
N	309,342	64,367	62,302	63,731	60,136	58,806

Panel B

	$Amivest_{it}$					
Variables	Full sample	Largest stocks	4	3	2	Smallest stocks
$DARK_{it}$	8.150*** (14.00)	9.310*** (3.61)	1.620*** (3.20)	2.840*** (3.57)	2.360*** (5.09)	0.241 (0.95)
$DARK_{it}^2$	-34.100*** (-13.75)	-31.900*** (-2.68)	-12.000*** (-4.13)	-10.700*** (-4.26)	-9.190*** (-4.10)	-1.700 (-1.27)
$OFFEX_{it}$	0.309*** (12.60)	0.177*** (4.06)	0.086*** (3.91)	0.045*** (4.14)	0.058*** (3.23)	0.081*** (2.67)
$TSize_{it}$	0.129*** (3.69)	0.535** (2.15)	0.050 (0.79)	0.154 (1.50)	-0.009 (-0.18)	0.024 (0.85)
$MCap_{it}$	0.723*** (17.93)	0.816*** (5.91)	0.134** (2.02)	0.065*** (2.79)	0.062 (1.04)	0.036** (2.12)
$Spread_{it}$	-0.017 (-1.25)	-0.300*** (-6.05)	-0.034*** (-3.53)	-0.010 (-0.41)	-0.018*** (-2.79)	-0.022** (-2.27)
Lit_{it}	0.154*** (3.63)	0.101 (1.13)	-0.029 (-0.38)	0.017 (0.29)	-0.032 (-0.78)	-0.004 (-0.11)
HFT_{it}	-0.203*** (-11.31)	-0.138 (-1.40)	-0.126*** (-3.55)	-0.069 (-1.34)	-0.093*** (-4.03)	-0.004 (-1.03)
$P_{other\ stocks}$	0.963*** (4.14)	0.980*** (2.94)	0.980*** (2.74)	0.980 (1.10)	0.980 (1.39)	0.980 (1.43)
$Intercept$	16.245*** (-34.92)	-33.300*** (-8.79)	-4.18*** (-6.17)	-1.310*** (-5.46)	-1.130*** (-3.96)	-0.809*** (-5.19)
$\overline{R^2}$	0.23	0.47	0.34	0.26	0.35	0.50
N	309,342	64,367	62,302	63,731	60,136	58,806

Table 5: Dark trading, noise in the price discovery process and informational efficiency

The table reports the stock-day instrumental variable regression coefficient estimates using a stock-day panel, in which Q_{it} corresponds to RNA_{it}, an order imbalance measure based on the component factor share (CFS) of Gonzalo and Granger (1995), or VR_{it}, defined as the variance ratio, for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues (London Stock Exchange, BATS, Chi-X and Turquoise); both dependent variables are defined in Appendix A. The estimated regression model is:

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

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 for stock *i* on day *t* ($MCap_{it}$), log of average trade size for stock *i* on day *t* ($TSize_{it}$), log of pound volume of lit trades for stock *i* on day *t* (Lit_{it}), and the stock-day average of effective spread ($ESpread_{it}$), which is defined as twice the absolute value of the difference between transaction price for stock *i* at time *t* and its prevailing mid-point, the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of Q_{it} on the same day for all the other stocks in the same sized quintile. $DARK_{it}$ and $OFFEX_{it}$ are instrumented 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 standard errors clustered by stock and date. *, ** 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.

Panel A

			RNA_{it}			
Variables	Full sample	Largest stocks	4	3	2	Smallest stocks
$DARK_{it}$	0.297** (2.44)	0.059 (0.65)	0.591 (1.73)	0.076 (0.53)	0.318 (0.84)	1.062* (1.80)
$DARK_{it}^2$	-1.457** (-2.23)	-0.794 (-1.09)	-1.512 (-1.18)	-1.077 (-1.61)	0.199 (0.13)	-2.401 (-1.22)
$OFFEX_{it}$	0.004 (1.05)	0.003** (2.56)	0.036*** (2.72)	-0.008** (-2.47)	-0.021*** (-3.52)	-0.049*** (-2.73)
$TSize_{it}$	0.050** (2.11)	0.022** (3.71)	-0.073 (-0.86)	0.149*** (6.69)	-0.025 (-0.31)	-0.219 (-1.56)
$MCap_{it}$	0.472*** (7.15)	0.100*** (8.57)	0.704*** (3.50)	0.307*** (8.26)	0.085** (1.99)	0.070** (2.47)

$Spread_{it}$	0.523*** (6.41)	0.358*** (15.02)	1.089*** (2.78)	0.510*** (6.66)	0.187*** (3.81)	0.250*** (3.54)
Lit_{it}	0.003 (0.213)	-0.007 (-1.38)	-0.094*** (-6.44)	-0.042* (-1.89)	0.161 (1.35)	0.226 (2.11)
HFT_{it}	0.129*** (10.17)	0.065*** (13.77)	0.097*** (5.52)	0.067*** (3.47)	0.152*** (3.03)	0.119*** (2.81)
$P_{other\ stocks}$	0.781*** (3.21)	0.356*** (11.04)	0.631*** (4.70)	0.756*** (12.11)	0.919*** (24.21)	0.836*** (6.59)
$Intercept$	-12.570*** (-7.62)	-2.927*** (-10.47)	-14.584*** (-3.62)	-8.323*** (-7.12)	-5.106*** (-3.02)	-2.709*** (-2.73)
$\overline{R^2}$	0.30	0.35	0.38	0.32	0.55	0.29
N	309,342	64,367	62,302	63,731	60,136	58,806

Panel B

	VR_{it}					
Variables	Full sample	Largest stocks	4	3	2	Smallest stocks
$DARK_{it}$	-0.131***	-0.190***	-0.079***	-0.156***	-0.092***	-0.043***
	(-15.18)	(-8.33)	(-3.49)	(-11.71)	(-6.34)	(-2.74)
$DARK_{it}^2$	0.938***	0.609***	0.123	0.415***	0.725***	0.578***
	(23.58)	(5.16)	(0.98)	(6.65)	(10.07)	(8.84)
$OFFEX_{it}$	-0.034***	-0.049***	-0.024***	-0.018***	-0.016***	-0.023***
	(-70.29)	(-41.11)	(-56.82)	(-57.91)	(-13.36)	(-35.45)
$TSize_{it}$	0.042***	0.104***	0.053***	0.029***	0.033***	0.023***
	(59.92)	(37.14)	(32.66)	(42.01)	(12.42)	(23.82)
$MCap_{it}$	-0.041***	-0.033***	-0.030***	-0.025***	-0.023***	0.021***
	(-53.17)	(-12.90)	(-18.36)	(-24.55)	(-12.52)	(26.11)
$Spread_{it}$	0.008***	0.020***	0.007***	0.007***	0.007***	0.005***
	(28.43)	(8.67)	(10.85)	(22.69)	(26.64)	(21.84)
Lit_{it}	-0.010***	-0.024***	-0.005***	-0.007***	-0.012***	-0.005***
	(13.46)	(-11.22)	(5.94)	(-11.39)	(-6.63)	(-8.59)
HFT_{it}	-0.013***	-0.020***	-0.016***	-0.018***	-0.015***	-0.004***
	(-38.27)	(-4.58)	(-19.47)	(-35.45)	(-25.28)	(-12.68)
$P_{other\ stocks}$	0.702***	0.740***	0.825***	0.840***	-0.118	0.898***

	(23.57)	(20.41)	(34.48)	(34.82)	(-0.17)	(22.76)
$Intercept$	0.924*** (39.74)	1.094*** (29.22)	0.350*** (11.98)	0.381*** (17.16)	0.906* (1.73)	-0.188*** (-5.21)
$\overline{R^2}$	0.38	0.39	0.27	0.16	0.13	0.33
N	309,342	64,367	62,302	63,731	60,136	58,806

Appendix A. Definition of main variables

Volume-synchronised probability of informed trading (VPIN)

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 the 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:

$$VPIN = \frac{\sum_{\tau=1}^{n} |V_\tau^S - V_\tau^B|}{nV} \tag{A1}$$

where ${V_\tau}^S$ and ${V_\tau}^B$ 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, the 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), and 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 it is more appropriate for a high frequency trading environment; hence, we employ BVC when classifying buy and sell volumes. The fraction of buy volumes is computed as:

$$V_\tau^B = V_\tau \times Z\left(\frac{\Delta\rho_\tau}{\sigma_{\Delta\rho}}\right) \tag{A2}$$

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

$$V_\tau^S = V_\tau - V_\tau^B \tag{A3}$$

A 1-minute time bar is used to compute 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.

Predictability of short-horizon returns

We estimate the Chordia et al. (2005) short-term return predictability model at one-minute frequency for each day and each stock in our sample, and then collect the $\overline{R^2}$ estimates for each stock-day:

$$return_{it} = \alpha + \beta_1 OIB_{it-1} + \varepsilon_{it} \tag{A4}$$

The higher the $\overline{R^2}$ for a stock-day, the higher the probability of returns being predictable from the order flow for that stock-day. Therefore, we employ the measure as a proxy for adverse selection risk.

Illiquidity and liquidity measures: Amihud price impact ratio and Amivest ratio

In less liquid markets, any given level of trading volume will give rise to a greater price response than in liquid markets; the Amihud (2002) ratio is therefore defined as the ratio of the absolute return to trading volume, and is computed as follows:

$$Amihud_{it} = \frac{1}{H}\sum_{h=1}^{H}\left(\frac{|r_{ith}|}{vol_{ith}}\right) \tag{A5}$$

where $r_{i,t,h}$ is the mid-quote return for stock i during hour h on day t, and $vol_{i,t,h}$ is the volume in pounds for stock i during hour h on day t.

Amivest ratio is the inverse value of Amihud ratio for non-zero-return days.

Relative Noise Avoidance (RNA)

There are two well-established conventional approaches for measuring the price discovery contributions of different markets/venues; these are Hasbrouck's (1995) information share (IS) and 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 mainly measures 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[1] at one-second intervals, t:

$$\begin{aligned} \Delta P_t^v &= \alpha_0^v + \alpha_1^v\left(P_{t-1}^v - P_{t-1}^g\right) + \textstyle\sum_{i=1}^{P}\gamma_i \Delta P_{t-i}^v + \sum_{i=1}^{P}\vartheta_i \Delta P_{t-i}^g + \varepsilon_t^v, \\ \Delta P_t^g &= \alpha_0^g + \alpha_1^g\left(P_{t-1}^v - P_{t-1}^g\right) + \textstyle\sum_{i=1}^{P}\gamma_i \Delta P_{t-i}^g + \sum_{i=1}^{P}\vartheta_i \Delta P_{t-i}^v + \varepsilon_t^g. \end{aligned} \tag{A6}$$

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 constituted 'global' 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:

$$RNA^v = \left|\frac{CFS^v}{CFS^g}\right| \tag{A7}$$

[1] 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 mid-point of prevailing quotes from lit platforms rather than execution prices.

where the CFS^v and CFS^g 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.

Variance ratio

We follow O'Hara and Ye (2011) in constructing stock-day variance ratios as follows:

$$VR_{it} = |1 - \frac{\sigma^2_{kl;i,t}}{k\sigma^2_{l;i,t}}| \quad \text{(A8)}$$

where $\sigma^2_{l;i,t}$ and $\sigma^2_{kl;i,t}$ are the variances of k-second and kl-second mid-quote returns for a given stock-day. For robustness, we compute VR_{it} in two ways: we use a long and short return combination of 1-minute and 10-seconds (VR_{it} – 1min), as well as a 5-minute and 1-minute long and short return combination (VR_{it} – 5min). In an efficient market, stock price follows a random walk and the variance of returns is a linear function of the return measurement frequency. Furthermore, the variance of returns measured over longer horizons is equal to the sum of variances of shorter horizon returns, as long as the summation of the shorter horizons is equal to that of the longer horizon. Therefore, values closer to zero would imply higher levels of informational efficiency and lower adverse selection risk.

Appendix B. Dark trading and lit market quality

The table reports the stock-day instrumental variable regression coefficient estimates using a stock-day panel, in which Q_{it} corresponds to one of six market quality variables computed for 288 FTSE 350 stocks trading simultaneously on the four main London 'City' exchanges/trading venues (London Stock Exchange, BATS, Chi-X and Turquoise). $QSpread_{it}$ is the daily average of the minute-by-minute intraday relative quoted spread estimates for stock i on day t; relative quoted spread is computed as the ratio of the difference between the best ask and bid prices for a given minute and the midpoint for that minute; all other dependent variables are defined in Appendix A. The estimated regression model is:

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

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 for stock *i* on day *t* ($MCap_{it}$), log of average trade size for stock *i* on day *t* ($TSize_{it}$), log of pound volume of lit trades for stock *i* on day *t* (Lit_{it}), and the stock-day average of effective spread ($ESpread_{it}$), which is defined as twice the absolute value of the difference between transaction price for stock *i* at time *t* and its prevailing mid-point, the square of $DARK_{it}$ and $P_{other\ stocks}$. $P_{other\ stocks}$ is the average of Q_{it} on the same day for all the other stocks in the same sized quintile. $DARK_{it}$ and $OFFEX_{it}$ are instrumented 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 standard errors clustered by stock and date. *, ** 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.

	$VPIN_{it}$	RNA_{it}	$\overline{R_{it}^2}$	$QSpread_{it}$	$Amihud_{it}$	$Amivest_{it}$
$DARK_{it}$	0.056*** (3.02)	0.235*** (8.84)	0.118*** (13.24)	5.65*** (15.72)	0.537** (2.09)	-1.190*** (-10.05)
$DARK_{it}^2$	0.596*** (4.67)	0.957*** (8.50)	0.197*** (4.27)	34.05*** (19.01)	0.887** (1.98)	-5.000*** (-8.02)
$OFFEX_{it}$	-0.015*** (-6.78)	0.009*** (6.22)	-0.010*** (-52.23)	-0.455*** (-28.93)	0.038*** (-2.86)	0.065*** (6.00)
$TSize_{it}$	0.001 (0.55)	0.004** (2.07)	0.007*** (12.73)	0.290*** (15.40)	0.007 (0.61)	0.034*** (-3.26)
$MCap_{it}$	-0.014** (-4.04)	0.027*** (5.00)	-0.018*** (57.01)	-0.470*** (-21.95)	-0.009 (-0.60)	0.137*** (7.51)
$Spread_{it}$	-0.001 (-1.62)	0.002*** (4.45)	0.007*** (50.99)	–	0.013*** (3.63)	0.002 (0.55)

Lit_{it}	0.036*** (7.53)	0.067*** (9.33)	-0.009*** (-25.13)	-0.206*** (-7.66)	-0.002 (-0.11)	-0.028 (-1.33)
HFT_{it}	0.008*** (4.44)	-0.022*** (-15.04)	-0.013*** (-44.81)	1.033*** (53.32)	-0.008** (-2.06)	-0.024*** (-4.80)
$P_{other\ stocks}$	0.683*** (24.80)	0.629*** (25.37)	0.959*** (50.09)	0.632*** (12.41)	0.999* (1.88)	0.984** (2.11)
$Intercept$	-0.005*** (-28.76)	0.626*** (44.29)	-0.072*** (-21.72)	6.60*** (39.99)	0.936*** (6.45)	-3.180*** (-21.22)
$\overline{R^2}$	0.54	0.66	0.11	0.33	0.06	0.23
N	309,342	309,342	309,342	309,342	309,342	309,342