**Spillover effects between lit and dark stock markets: Evidence from a panel of London Stock Exchange transactions**

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A characteristic of today’s equity markets is the fraction of trading that occurs in the dark (i.e., outside of regular and visible order books). This study extends investigation of the relationship between transactions that occurred in visible stock markets and those that occurred in dark stock markets. In particular, the study evaluates the quantitative impact of dark trading on the lit London stock market between January 2001 and December 2013. We find that dark trading has a substantial effect on both prices and liquidity in the lit market, counselling for regulation that protects ordinary investors participating in lit stock markets.

*Keywords*: Dark and lit stock markets; Panel firm data; London stock market

*JEL Classification*: G12; G28

**1. Introduction**

In recent years, there have been significant structural and behavioural changes in international financial markets. Advances in technology have made it easier to trade away from exchange markets and have facilitated a proliferation of dark trading venues known as ‘crossing systems,’ ‘crossing networks,’ and ‘dark pools.’ Such advances in technology have also fundamentally changed the way orders are generated and executed by all users of the market. Orders are now generated and executed by computer programs running decision and execution algorithms.

Dark liquidity refers to orders that are not known to the rest of the market before the orders are matched as executed trades. Such trades, known as dark trades, can occur in venues other than official (or lit) exchange markets. In particular, rather than routing an order to a market, a market participant may choose to fill the order from its own inventory or to ‘cross’ it with other client orders. The market has outlined the public benefits of dark liquidity, including minimizing the market impact of large orders and enabling some trading to occur that otherwise may not have occurred. Dark liquidity provides a number of private benefits. For example, it can protect clients from other traders getting an insight into their trading intentions and offers the possibility of better pricing or faster execution. There are also risks to market quality—specifically, potential negative effects on price discovery mostly arising from the excessive use of dark liquidity.

Prices are most efficient when there is optimal interaction between supply and demand. There is the risk that as more order flows from fundamental investors are directed away from exchange markets, the quality of prices on the exchange markets deteriorate, i.e., result in wider bid–offer spreads and possibly less volume at each price. Wider spreads can result in larger price fluctuations, yielding a more difficult and potentially more costly process for listed companies to raise capital. Wider spreads can also reduce investors’ confidence because they pay a higher price to access liquidity. At the end of the day, dark pools leave the collective informational content of the order flow impaired. Liquidity creation is impaired; thus, it is more difficult for willing counterparties to find one another.

Dark liquidity has been the subject of significant public commentary: there are concerns about the changing nature of dark liquidity and its impact on optimal price formation. There are also questions about the fairness of dark venues for investors—specifically, concerns that they are not regulated as markets and ‘free ride’ on the pricing and information set on exchange markets. Fundamental investors are contributing less to prices. Transactions of this type are expected to have negative implications for a number of parts in capital markets: a) they affect investors who may make uninformed decisions, b) it is harder to locate liquidity, and c) listed companies are unaware of where their securities are trading. O’Hara and Ye (2011) provide evidence of lower transaction costs due to fragmentation phenomena without explicitly considering the potential presence of any differential effects of fragmentation on liquidity coming either from lit or dark transactions.

Our paper concerns previous studies’ theories regarding the role of the trading strategies of informed and liquidity traders through crossing networks and how such networks affect price discovery in exchange markets (Buti et al., 2010; Ye, 2011; Zhu, 2011). The studies’ basic hypothesis is that it is highly likely that informed traders exploit the presence of such networks to limit their transaction expenses and, thus, to maximize profits. Research that links liquidity in lit markets and liquidity in dark markets is scant, unfortunately, and the majority of studies have provided only a theoretical framework for attempting to explain the potential mechanisms that link lit and dark markets. Such potential channels have not been empirically investigated. Analysis of the relationship between dark and lit markets is an extremely interesting and still relatively unexplored topic of research. It is interesting because the proportion of dark trading is growing in all financial markets around the world. It is still relatively unexplored as data from dark venues are not yet publicly available.

The goal of this study is to empirically identify and analyse specific trading attributes associated with dark liquidity outside of the U.S. equity context for which there has been empirical work. In particular, the empirical analysis makes use of a proprietary data set of prices and liquidity for a number of firms listed on the London Stock Exchange to explore the impact of both dark liquidity and dark prices on liquidity and prices on these firms. The two main questions to be addressed are whether transactions in the dark market can affect price discovery in the lit market and whether liquidity volumes in the dark market can sterilize counterpart liquidity in the lit market.

The closest studies to ours are those of Naes and Odegaard (2006) and Nimalendran and Ray (2014). The primary contribution of our paper to the literature is that we quantify the results through panel regressions of the price and liquidity effects of dark trading for one of the largest equity markets, the U.K. equity market, a task that has not been performed thus far in the (limited) empirical studies except for the case of the United States. We make use of a dataset that includes private and high frequency (i.e., daily) data on dark market liquidity and prices through the end of 2013. Dark liquidity and high-frequency trading have both generated a great deal of media attention and concern among investors.

The empirical findings show that dark market activities tend to reduce liquidity and increase stock prices in the lit market. These results survive a number of robustness tests. Therefore, in spite of the criticism that dark markets suffer from hidden information, the results highlight the presence of price discovery. As it concerns concurrent trading in both markets, this study is expected to provide valuable information to investors who trade in dark pools, help them to better understand the issues, and assist them in making well-informed and confident investment decisions. The empirical results may also validate theoretical predictions in asset pricing models regarding the impact of less informed transactions on equilibrium asset prices.

**2. Literature review**

In the theoretical strand of the literature, Boehmer et al. (2005) and Biais et al. (2010) document a negative effect of dark trading related to pre-trade transparency, as visible markets are more efficient because of faster and cheaper access to information. Degryse et al. (2009) make use of a dynamic model dealing with dark pool markets and show how various transparency requirements affect a number of market quality measures. Ye (2011) provides a theoretical framework in which transactions in dark venues lead to reduced price discovery and lower volatility, while Boulatov and George (2013) show that the quality of the market in a dark regime is better than in a transparent regime. The reason for this result is that better-informed agents are drawn into providing liquidity and trade more aggressively as liquidity providers than as liquidity demanders. Finally, Zhu (2013) offers a theoretical model through which he argues that informed traders have relatively low execution probabilities in the dark pool because they typically trade on the same side of the order book. In this manner, informed trading diverts to the traditional market, which adversely affects liquidity in that market.

In the empirical strand of the literature, Fong et al. (2004) find no evidence of any increases in adverse selection at the Australian Stock Exchange due to the presence of dark markets, while Gresse (2006) finds no negative effects of dark markets on visible markets (at the adverse selection stage) for the case of the London Stock Exchange. Buti et al. (2010) find that transactions in dark markets are positively associated with liquidity issues. Their empirical findings, however, display low statistical significance levels for the coefficients relating dark pool activity to liquidity. Weaver (2011) finds that in the case of the U.S. market, internalization of order flows is associated with an increase in bid–offer spreads and an increase in the price impact and volatility of trades on the lit exchange markets. According to his estimations, on average, a security listed on the New York Stock Exchange (NYSE) with 40% of its volume reported as dark equity (of all sizes) has an average spread that is $0.0128 wider than a similar security with no dark liquidity. This gap results in investors paying $3.9 million more per security per year. Comerton-Forde and Putnins (2012) examine the extent to which price discovery is coming from the dark or lit markets. Their findings suggest that the migration of order flows into the dark removes valuable information from the price formation process and leads to increased adverse selection and larger bid-offer spreads. Ang et al. (2013) exploit different market conditions to test theories of cross-sectional return premiums. Their findings indicate that, compared with premiums in listed markets, the Over-The-Counter (OTC) illiquidity premium is several times higher, the size, value, and volatility premiums are similar, and the momentum premium is three times lower. Such OTC illiquidity, size, value, and volatility premiums are largest among stocks held predominantly by retail investors and those not disclosing financial information. Finally, Nimalendran and Ray (2014) examine the linkages between dark and lit markets and find that trading in such venues leads to higher spreads and greater price discovery, although less information is transmitted to lit markets.

**3. Data, methodology and empirical results**

3.1 Data

Our dataset covers a number of common stocks listed on the London Stock Exchange that also trade in the dark pool. These stocks are not closed-end funds, REITs, or carrying dual class common stock. Our data span the period from January 2001 to December 2013. The data sample on trade and quote data are reported daily. We match the days when both transactions occur for the firms showing transactions in both markets on the same day. Given that the market is open from 08:00 am to 16:30 pm, we allow for a 30 second delay from the opening time of 08:00 to ensure that our sample is not affected by the opening call auction.

While data on lit markets are obtained from Compustat, data on the dark market come from a proprietary dataset, with data combined from rival platforms operated by large investment banks, such as Barclays, Morgan Stanley, Credit Suisse, and UBS, as well as by the London Stock Exchange itself through its own affiliated corporation, Turquoise.

We make use of the quoted spreads for the case of the lit market. Our dataset for dark trades provides information on broker-dealer crossing networks, internalized and Over-The- Counter (including trades executed over telephone). For the case of the dark market, crossing networks typically execute trades against the midpoint of the primary market (i.e., the midpoint of the best bid-offer of the lit market). We also exclude securities that had stock splits. The final sample covers stocks with market capitalization values in the London Stock Exchange ranging from 780 million to 30 billion GB pounds.

To further ensure adequate data quality, we restrict our sample to firms meeting the following requirements: Non-missing data on stock prices, market capitalization, and returns; at least one non-zero daily return; and positive trading volume. In addition, in the lit market, we delete quotes where the ask price or bid price is missing or equal to zero, crossed quotes, and quotes with a bid-ask spread greater than GBP 2.00. Any trade in the lit market resulting from an option exercise, a stock swap, or the cancellation of a previous trade is deleted. The resulting sample is downsized to 459 firms. We have information regarding prices and volumes of transactions.

Table 1 shows a snapshot of the descriptive statistics. The average market capitalization for our sample stocks is 19.57 billion GB pounds. Comparing between lit and dark venues, the daily trading volume and the number of trades are significantly greater for lit venues. Furthermore, the average dark market share, based on trading volume, is 2.02% in the London market. Moreover, the number of shares traded is also larger in lit venues than in dark venues.

**[Insert Table 1 about here]**

3.2 Methodology

As far as the liquidity measure is concerned, there are numerous indicators developed in the literature that attempt to measure stock market liquidity. The high frequency liquidity measures require data on bid/ask quotes, order flows, volume of trades, etc. For the case of the lit market, we use the liquidity measure of the relative spread (RS). According to Goyenko and Ukhov (2009) and Goyenko et. al. (2009), this liquidity measure is capable of capturing the spread cost. A market participant who wishes to fill his order immediately must be willing to pay the ask price for a buy order and collect the bid price for a sell order. The difference between the two prices is the bid-ask spread, which reflects the cost of immediacy. In the present study, we estimate a market-wide proportional spread measure, the relative bid/ask spread. It is estimated as the ratio of the quoted spread, i.e., the difference between the best-ask and the best-bid quote:



where PASKi, s and PBIDi, s are the ask and bid prices, respectively, for stock I, and DS is the number of observations within a time window S. This provides a relative measure of trading costs and proxies for a percentage two-way transaction cost, i.e., what fraction of the price needs to be paid to ‘cross’ from the bid to the ask price, or vice versa. The RS is an illiquidity measure, as a high spread indicates an illiquid market where the implicit cost of trading is large.

By contrast, for the case of the dark market and given the absence of bid and ask prices, the relative spread cannot be determined. Thus, liquidity is measured by the total value of the number of shares traded during a day, i.e., the volume of transactions, measured as the following:

n

Σ pi qi, where p is the average price of the stock i traded in the dark market, q is its

i=1

corresponding quantity, and n is the number of stocks.

Next, to carry out the empirical analysis and avoid potential endogeneity problems, as it is well known that dark liquidity is jointly determined with lit liquidity, we study the interaction between dark and lit market trading using the General Method of Moments (GMM) methodology, introduced by Arellano and Bover (1995), where we include only statistically significant lags in the estimation. To this end, the following GMM model is employed:

q

∆litlit = φ1 ∆litli(t-1) + ∑ β1j ∆darkli(t-j) + β2 CR + εit (1)

j=0

q

∆litpit = φ2 ∆litpi(t-1) + ∑β3j ∆darkpi(t-j) + β4 CR + ηit (2)

j=0

where i = 1, …, N for each stock in the panel, and t = 1, …, T refers to the time period. εit and ηit represent the residuals factors, darkp is stock prices in the dark market, litp is stock prices in the lit market, litl is the liquidity measure in the lit market, and darkl is the liquidity measure in the dark market. CR is a dummy variable that captures the recent financial crisis and takes a value of zero until September 2008, at which point it takes a value of one. Equation (2) resembles the modelling approach followed by Hasbrouck (1995) in which a security (i.e., a stock) is traded in two separate markets (i.e., lit and dark markets) and the two prices carry their own informational components, which can be transmitted from one to the other. It also resembles the approach followed by Comerton-Forbe and Putnins (2013) and by Hatheway et al. (2013), who show that dark markets tend to hamper price discovery only when trading occurs at high levels.

3.3 Panel unit root tests

We begin by examining the order of integration for each variable using several panel unit root tests: Levin and Lin (2002), Harris and Tzavalis (1999), Maddala and Wu (1999), Breitung (2000) and Hadri (2000). The tests by Leven and Lin (2002), Harris and Tzavalis (1999), Maddala and Wu (1999), and Breitung (2000) examine the null hypothesis of a unit root, while the test by Hadri (2000) has a null hypothesis of no unit root. The results in Table 2 show that the levels of all the variables under study contain a unit root at the 1% significant level. The findings remain robust across all unit root tests. By contrast, when these tests are applied on the first differences of those variables, the reported results show that all of the variables are stationary.

**[Insert Table 2 about here]**

Table 3 reports the results of the estimations for both equations (1) and (2). The Sargan test indicates valid instruments in both cases. In more diagnostics terms, the findings document that we reject the null hypothesis of no first-order autocorrelations in the residuals, but we cannot reject the null hypothesis of no second-order autocorrelations in the residuals.

In terms of equation (1), the findings show that both the contemporaneous and the lagged-one coefficients of dark liquidity are positive and statistically significant at the 1% level, indicating that increases in liquidity in the dark market increase illiquidity in the lit market. In other words, these findings indicate that the liquidity in the lit market decreases because of dark liquidity. More specifically, an overall change of dark liquidity leads to 0.37 percent lower liquidity in the lit market by (i.e., 0.302 percent contemporaneously and 0.064 percent after one day). In terms of equation (2), both the contemporaneous and the lagged-one coefficients of dark prices are positive and statistically significant, indicating that increases in prices in the dark market lead to increases in prices in the lit market. The empirical findings support the claim that a one percent increase in dark prices leads to 0.24 percent increase in lit prices within the same day and a 0.052 percent increase after one day (i.e., an overall effect of 0.19 percent).

Our results confirm the arguments made by Buti et al. (2010) and De Jong et al. (2011), both of whom argue that trading in dark pools tends to determine and, furthermore, discourage liquidity at the visible markets. In that sense, the findings highlight the presence of liquidity migration (from the lit to the dark markets). Our results also confirm the theoretical arguments by Zhu (2013) that, although dark markets improve price discovery, better price discovery conditions do not necessarily coincide with better liquidity conditions. Finally, the crisis dummy (CR) is shown to exert a positive impact on the illiquidity in the lit market and a negative effect on lit prices, indicating the deleterious impact of the recent financial crisis on the stability of financial markets.

**[Insert Table 3 about here]**

Our evidence has substantial implications for the dynamics of liquidity creation. In particular, liquidity begets liquidity, while illiquidity begets illiquidity. In other words, liquidity in the dark markets tends to attract both additional buyers and additional sellers, thus discouraging traders from going to the lit market. These findings are in line with Mittal (2008), who argues that transactions in a dark pool contain information that strategic traders and smart order routers are able to exploit.

The above findings suggest that dark trading leads to more adverse selection on the visible markets, implying consistency with the theoretical work of Hendershott and Mendelson (2000), Weaver (2011) and Zhu (2013) claiming that dark markets are more attractive to uninformed traders, leaving the informed traders to the visible markets. The intuition is that informed traders typically face relatively low execution probabilities in the dark pool or crossing network. As a result, the dark market ‘cream-skims’ uninformed order flow, worsening liquidity and adverse selection costs in the visible market.

3.4 Robustness checks: Alternative definitions of liquidity in the lit market

This part of the paper tests the robustness of the above results under alternative liquidity measures. In particular, we alternatively measure liquidity in the lit market through the Turnover (TUR) indicator. TUR is a common measure of activity and is calculated as the total number of shares traded during a time interval relative to the number of outstanding shares in the security. The TUR is a liquidity measure, as opposed to the RS, which is an illiquidity measure.

The new liquidity results are reported in Table 4. These robustness tests provide evidence that dark liquidity diminishes liquidity in the lit market, while the crisis dummy exerts a negative role on lit liquidity. The diagnostics also indicate the validity of the instruments employed, the ability to reject the null hypothesis of no first-order autocorrelations in the residuals, and the inability to reject the null hypothesis of no second-order autocorrelation in the residuals.

**[Insert Table 4 about here]**

3.5 Robustness checks: The role of depth of liquidity

The depth of a market is defined as the quantity of orders on the sell side and the buy side of the market, i.e., above and below the market price. In the narrow sense, depth is the largest volume of orders that still will not move the market price (Csávás–Erhart, 2005). Turnover is a common proxy for the depth of the market. While the previous empirical section of the analysis was implemented with respect to the concept of the tightness, i.e., the bid-ask spread of stock transactions, this part will consider the alternative measure of liquidity related to the size of the transactions required to change the price of the stock. Muranaga and Shimizu (1999) investigate the dynamics of market depth by constructing simulated markets by studying the role of depth in a financial market through the examination of high-frequency data on transactions involving individual stocks listed on the Tokyo Stock Exchange.

However, most of the conventional indicators characterizing the depth of a market, i.e., the trade volume or the trade value, cannot capture the fact that prices change in response to the net disequilibrium in buys and sells, not to total trading volume (Engle and Lange, 1997). These liquidity ratios can seldom distinguish the sources of price changes. Grossman and Miller (1988) note that such liquidity ratios fail to answer the critical question of how a sudden arrival of a larger-than-average order would affect price movements. Thus, market depth conditions should be measured by the market’s ability to absorb order imbalances without large price changes. Brockman and Chung (2001) find strong commonality in spreads and depth across all sizes of firms they examine. Finally, Chordia et al. (2002) outline two reasons why order imbalances should be more important to stock prices and liquidity than trading volume: they signal private information and a large order imbalance exacerbates the inventory risk faced by market-makers, which can worsen liquidity conditions.

To the end of the empirical analysis, we measure the depth dimension of liquidity according to Wong and Fung (2000), as the net buying/selling pressure indicator (BSI), measured as the net position of the order book, which is derived by subtracting the total selling orders at each 30-second tick from the total buying orders across all the firms in our sample. The new robustness findings are presented in Table 5. Once again, they confirm that both the contemporaneous and the lagged-one coefficients of dark liquidity exert a negative and statistically significant (at the one percent level) impact on liquidity in the lit market. The new diagnostics indicate the validity of the instruments employed, the ability to reject the null hypothesis of no first-order autocorrelations in the residuals, and the inability to reject the null hypothesis of no second-order autocorrelation in the residuals.

**[Insert Table 5 about here]**

3.6 Robustness checks: An alternative methodological approach

Given that the standard GMM estimator has been found to suffer from substantial finite sample biases, especially when the autoregressive parameter is close to the unit circle (Alonso-Borrego and Arellano, 1999), this set of robustness tests makes use of the Four Period Long Differencing (LPLD) methodological approach recommended by Hahn et al. (2007). They define a class of estimators based on linear combinations of asymptotically relevant moment conditions and show that a bias minimal estimator within this class can approximately be based on taking long differences of the dynamic panel model. According to them, the usual first-order asymptotic advice of using the full set of moment conditions does not provide proper guidance in the dynamic panel data model when the autoregressive parameter is close to one. Therefore, they show that a long differencing estimator, which alleviates the problem of weak instruments and relies on a set smaller than the full set of moment conditions, is much less biased than the GMM estimators. We report the results in Table 6 using differencing lengths of 4, 8, 18, and 28 days. The new empirical findings indicate that in both equations the signs remain consistently robust. In terms of the magnitude of the coefficients and depending on the differencing length, the estimated impact of overall liquidity in the dark market on liquidity of the lit market varies from 0.31% to 0.39%. In terms of stock prices, the impact of stock prices in the dark market on stock prices in the lit market varies from 0.23% to 0.32%. Comparing these results to the results reported in Table 3, these more consistent estimates imply that the GMM estimations were, somehow, underestimating the true impact of dark market activities on those in the lit market, mostly over the long run.

**[Insert Table 5 about here]**

**4. Concluding remarks**

Given that dark markets are a remarkable component of the equity markets’ structure, this paper used high frequency (i.e., millisecond) data spanning the period from January 2001 to December 2013 to study the quantitative influence of dark orders on prices and liquidity for equities traded on the London Stock Exchange.

GMM regression methodologies found that the introduction of dark orders affects liquidity spreads and prices in the lit market, suggesting that dark trading caused an increase in trading costs. In particular, we found that dark trading led to lower liquidity in the lit market and provided an extra boost to prices in the same market. The empirical findings note that the negative effect of dark trading is consistent with a ‘cream-skimming’ effect, whereby the dark markets attract mostly uninformed order flows, which in turn increases adverse selection costs on the visible markets.

Our results are relevant to concerns regarding fair markets and investor protection. Investors without access to all visible and dark markets—typically, retail investors—are worse off. As trade volumes associated with dark liquidity continue to rise, regulatory scrutiny can also be expected to become more stringent. Successful control of such transactions should help to maintain equilibrium, and as that occurs, financial clients will gravitate to institutions that are able to execute complex trades with speed and precision. Similarly, financial firms will select dark pools that deliver the breed of liquidity and, more importantly, efficiency that best allows firms to remain competitive.

Overall, our results are expected to be highly important from a regulator’s point of view, in the sense that the dissemination of information from dark to lit markets is expected to reduce concerns associated with impediments to gathering information related to liquidity measures and price discovery issues. Opaque and fragmented trading in dark pools seems to be encouraged by the lighter regulation of dark markets. Many market stakeholders have requested better oversight of dark pools, while the financial regulatory authorities have appealed for the better communication of their trading rules and practices. It seems that this reform will benefit not only ‘lit’ market investors but also investors in dark markets, as this reform will also protect dark market investors from possible manipulations in ‘lit’ markets that will disrupt both orders and prices in the off-exchange venues.

Potential avenues for future research involve the investigation of volatility spillovers across the two markets and the inclusion of more dark transactions from other stock markets. Finally, an interesting research project would be to explore whether the association between the two markets is regime non-neutral (i.e., how business cycle effects could affect the interactions across the two markets).

**Table 1** Descriptive statistics

This table presents a number of descriptive statistics relevant to the lit and dark markets, such as market capitalization, trading volume, the effective spread, the number of trades and market share. Market cap is stock market capitalization in billions. Trading (consolidated) volume is the number of shares traded in millions. No. of trades is the average number of transactions in thousands. Market share is the venue’s volume of shares traded divided by the total volume of shares traded, expressed as a percentage. The effective spread is measured in basis points.

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Lit Dark

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Market Cap. (bil.) 19.57 \_\_\_

Trading Volume 2,471 112.95

Effective Spread 15.24 \_\_\_

No. of Trades 12.43 0.62

Market Share 40.37 2.02

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**Table 2** Panel unit root tests

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**Variables LL Had (hom) Had (het) F-ADF F-PP HT Breit**

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litp -1.14 33.45\* 32.41\* 12.57 13.71 -1.36 -1.24

Δlitp -5.52\* 1.36 1.26 52.81\* 54.46\* -5.38\* -4.52\*

darkp -1.26 35.72\* 39.07\* 14.29 13.03 -1.37 -1.48

Δdarkp -5.81\* 1.29 1.35 50.28\* 48.80\* -5.46\* -4.36\*

litl -0.94 40.51\* 35.49\* 13.94 14.63 -1.28 -1.43

Δlitl -5.36\* 1.42 1.29 52.03\* 48.45\* -5.46\* -5.25\*

darkl -1.24 36.48\* 39.04\* 13.46 15.39 -1.48 -1.37

Δdarkl -5.82\* 1.35 1.42 55.81\* 51.10\* -5.52\* -5.29\*

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*Notes*: LL denotes the Levin and Lin test, Had denotes the Hadri test, F-ADF and F-PP denotes the Maddala and Wu test, respectively, HT denotes the Harris and Tzavalis test, and Breit denotes the Breitung test. Δ denotes first differences. \* accepts the null hypothesis of stationarity at the 1 percent level.

**Table 3** GMM estimations (liquidity in the lit market is proxied by the relative spread (RS), while the dark market is proxied by the turnover measure (TUR))

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**Equation (1)**

∆litlit = 0.573 ∆litli(t-1) + 0.302 ∆darklit + 0.064 ∆darkli(t-1) + 0.235 CR

(4.53)\* (5.29)\* (6.35)\* (6.11)\*

Adj. R2 = 0.52 Sargan test = 16.95 AR(1) = - 7.49 AR(2) = - 0.21

[0.37] [0.00] [0.84]

**Equation (2)**

∆litpit = 0.483 ∆litpi(t-1) + 0.235 ∆darkpit + 0.052 ∆darkpi(t-1) - 0.248 CR

(4.04)\* (6.10)\* (5.73)\* (-5.48)\*

Adj. R2 = 0.57 Sargan test = 13.49 AR(1) = - 7.35 AR(2) = - 0.16

[0.33] [0.00] [0.87]

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*Notes*: Sargan is the test for over-identifying restrictions, i.e., testing the null hypothesis that the instruments are valid. AR(1) and AR(2) are the Arellano-Bond (1991) tests for the null hypothesis of no first-order autocorrelation in the residual and the null hypothesis of no second-order correlation, respectively. Figures in parentheses denote t-statistics, while those in brackets denote p-values. \* denotes statistical significance at 1%.

**Table 4** GMM estimations (liquidity in both markets is proxied by the turnover measure (TUR))

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**Equation (1)**

∆litlit = 0.617 ∆litli(t-1) - 0.328 ∆darklit - 0.171 ∆darkli(t-1) - 0.326 CR

(6.15)\* (-6.25)\* (-6.15)\* (-5.36)\*

Adj. R2 = 0.53 Sargan test = 18.56 AR(1) = - 9.37 AR(2) = - 0.16

[0.31] [0.00] [0.89]

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*Notes*: Sargan is the test for over-identifying restrictions, i.e., testing the null hypothesis that the instruments are valid. AR(1) and AR(2) are the Arellano-Bond (1991) tests for the null hypothesis of no first-order autocorrelation in the residual and the null hypothesis of no second-order correlation, respectively. Figures in parentheses denote t-statistics, while those in brackets denote p-values. \* denotes statistical significance at 1%.

**Table 5** GMM estimations (liquidity in both markets is proxied by the net buying/selling pressure indicator (BSI))

**\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_**

**Equation (1)**

∆litlit = 0.579 ∆litli(t-1) - 0.326 ∆darklit - 0.167 ∆darkli(t-1) - 0.314 CR

(5.61)\* (-5.84)\* (-5.58)\* (-5.42)\*

Adj. R2 = 0.50 Sargan test = 20.17 AR(1) = - 10.63 AR(2) = - 0.19

[0.27] [0.00] [0.83]

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*Notes*: Sargan is the test for over-identifying restrictions, i.e., testing the null hypothesis that the instruments are valid. AR(1) and AR(2) are the Arellano-Bond (1991) tests for the null hypothesis of no first-order autocorrelation in the residual and the null hypothesis of no second-order correlation, respectively. Figures in parentheses denote t-statistics, while those in brackets denote p-values. \* denotes statistical significance at 1%.

**Table 6** Long-differencing estimations (both lit and dark liquidity are proxied by the TUR)

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**Equation (1)**

**Differencing = 4**

∆litlit = 0.506 ∆litli(t-5) - 0.258 ∆darklit - 0.049 ∆darkli(t-5) - 0.218 CR

(5.36)\* (-5.72)\* (-5.81)\* (-7.29)\*

Adj. R2 = 0.45

**Differencing = 8**

∆litlit = 0.528 ∆litli(t-9) - 0.277 ∆darklit - 0.056 ∆darkli(t-9) - 0.225 CR

(5.71)\* (-5.92)\* (-5.60)\* (-7.11)\*

Adj. R2 = 0.48

**Differencing = 18**

∆litlit = 0.569 ∆litli(t-19) - 0.304 ∆darklit - 0.068 ∆darkli(t-19) - 0.246 CR

(5.48)\* (-6.21)\* (-5.84)\* (-6.73)\*

Adj. R2 = 0.51

**Differencing = 28**

∆litlit = 0.571 ∆litli(t-29) - 0.317 ∆darklit - 0.073 ∆darkli(t-29) - 0.262 CR

(5.95)\* (-6.10)\* (-5.83)\* (-7.49)\*

Adj. R2 = 0.52

**Equation (2)**

**Differencing = 4**

∆litpit = 0.427 ∆litpi(t-5) + 0.189 ∆darkpit + 0.036 ∆darkpi(t-5) - 0.226 CR

(4.38)\* (5.74)\* (5.36)\* (-5.19)\*

Adj. R2 = 0.47

**Differencing = 8**

∆litpit = 0.459 ∆litpi(t-9) + 0.226 ∆darkpit + 0.043 ∆darkpi(t-9) - 0.250 CR

(4.62)\* (5.48)\* (5.55)\* (-5.38)\*

Adj. R2 = 0.48

**Table 6 continued**

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**Differencing = 18**

∆litpit = 0.481 ∆litpi(t-19) + 0.216 ∆darkpit + 0.048 ∆darkpi(t-19) - 0.274 CR

(4.58)\* (5.29)\* (5.58)\* (-5.36)\*

Adj. R2 = 0.52

**Differencing = 28**

∆litpit = 0.514 ∆litpi(t-29) + 0.246 ∆darkpit + 0.070 ∆darkpi(t-29) - 0.262 CR

(4.57)\* (5.61)\* (6.62)\* (-5.47)\*

Adj. R2 = 0.55

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*Notes*: Figures in parentheses denote t-statistics. The t-statistics use heteroscedastic consistent standard errors adjusted further for correlation across observations of a given firm (White, 1980; Rogers, 1993). \* denotes statistical significance at 1%.

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