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The impact of multilateral trading facilities on price discovery

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Abstract

Our study aims to examine whether market segmentation and competition manifested in the proliferation of multilateral trading facilities (MTFs) improve market quality after the implementation of MiFID. To do this, we employ the Common Factor Weight and Weighted Price Contribution methods to study relative price discovery for three major MTFs—LSE, BATS, and Turquoise, using intra-day, five-minute transaction prices. The results suggest that the two trading venues, BATS and Turquoise, contribute more to impounding fundamental information, implying a shift in price dominance from traditional LSE to MTFs. In addition, the intra-day price contributions of MTFs are higher than those of LSE, especially during the first and last periods of the day. The estimated average daily price contributions are consistent with this result.

KEYWORDS

Common Factor Weight, Multilateral Trading Facilities, Post-MiFID, Price Discovery, Weighted Price Contribution

1 | INTRODUCTION

Previously, when an investor bought shares in Sainsbury's, a UK-based food and clothing retail company, they had to discover its price on the London Stock Exchange. In recent years, however, capital markets have changed dramatically and with the implementation of the Markets in Financial Instruments Directive (MiFID) in 2007—a European Law on financial services for the 31 member states of the European Economic Area—Sainsbury's shares are now listed on a pan-European basis, where an investor can access many prices over many alternative trading venues in addition to LSE. The centrepiece of MiFID was to abolish the way that shares were only traded on their national exchange—and this, in turn, paved the foundation for the growth of many multilateral trading facilities (MTFs).[1] Ultimately, the goal of MiFID is to encourage competition in share dealing in the European capital markets. Also, the emergence of MTFs could effectively reduce trading fees, making the costs of Europe's capital markets more conformable to the US.

TABLE 1 Market share of different trading systems in FTSE 100 stocks

Panel (a): Market Share of FTSE 100 Constituents Traded through Different Facilities[a]

	2009	2010	2011	2012	2013	2014	2015	2016
LIT	59.81%	55.15%	54.04%	38.71%	41.43%	46.50%	49.45%	47.68%
DARK	0.80%	2.07%	2.67%	2.48%	3.41%	4.82%	5.34%	5.99%
SI	2.68%	3.13%	3.38%	2.52%	1.65%	1.45%	1.44%	2.01%
OTC	36.71%	39.64%	39.91%	56.29%	53.50%	47.23%	43.77%	44.32%
Total:	100%	100%	100%	100%	100%	100%	100%	100%

Panel (b): Order Book of FTSE 100 Traded Through LIT[b]

	2009	2010	2011	2012	2013	2014	2015	2016
LSE	41.20%	32.09%	29.47%	22.82%	24.30%	28.56%	29.51%	27.36%
CHI-X	**11.57%**	**14.51%**	**15.59%**	**10.77%**	**9.93%**	**9.02%**	3.62%	3.83%
BATS	2.95%	5.23%	4.79%	2.40%	2.45%	2.49%	**9.74%**	**9.51%**
TURQUOISE	3.47%	2.57%	3.98%	2.60%	4.71%	6.33%	6.58%	6.97%

Panel (c): Size and Volume of Trade for FTSE 100 LIT Order Book[c]

Year	Average Size (£)	Number of Trades (Million)	Volume of Trade (Billion £)
2009	2344	102	240
2010	2302	91	211
2011	1865	97	182
2012	1718	91	156
2013	1566	85	133
2014	1359	105	143
2015	1527	128	159
2016	1593	145	172

Source: Fidessa Fragulator

[a]Notes: 1. FTSE shares are traded through LIT and OTCs each year. In contrast, the same trading via dark pools and SIs is at a small scale. 2. Trading through dark pools increases steadily through time (although it accounts for a small scale in the entire FTSE 100 shares trading). Nearly 50% European equities is settled in dark pools instead of open markets from 2008 to 2010, even when these orders could use the facilities of RMs, MTFs or OTCs (CFA 2011). This could be due to the proliferation of MTFs during these years, as when MTFs are exempted from pre-trade transparency via waiver, MTFs will be a Dark Pool.

[b]Notes: 1. Panel (b) shows how trading in FTSE 100 shares through LIT spreads among the four exchanges. 2. LSE, which used to be the largest MTF for this type of trading, now gradually gives its dominance to other co-locations, especially Chi-X (from 2009 to 2014), and BATS (in 2015, 2016).

[c]Notes: 1. The trading of FTSE 100 shares through LSE LITs declines as the average order size declines considerably during MiFID's post-launch period. This coincides with CESR's (2009) report and also verifies our findings in Panel (b): LSE used to be the largest MTF for this type of trading, and now gradually gives its dominance to other co-locations. 2. The trading volume of FTSE 100 though LSE LIT has declined dramatically throughout the years of MiFID, which could be a consequence of growth in OTCs and dark pools trading revealed in Table 1, Panel (a).

The UK equity market saw a proliferation in MTFs since the beginning of MiFID in 2007. Not surprisingly, the quasi-monopoly position led by the London Stock Exchange diminished as various exchanges started to serve as the venues to trade FTSE 100 constituents. These co-trading houses that form the recording of 100% order book of FTSE 100 constituents include: Chi-X (from late 2007); and Turquoise and BATS (from late 2008).[2] Table 1, Panel (b) takes the order book of FTSE 100 traded through LIT as an example of how trading activities spread among the four exchanges.[3] Clearly, LSE, which used to be the largest MTF for such a type of trading, gradually lost its dominance to other co-locations, especially Chi-X and BATS (in 2015, 2016). It is open to question whether market segmentation and competition manifested in the proliferation of MTFs can improve market quality. Indeed, academic literature for the evidence of whether a fragmented market enhances market quality is twofold. Many studies are in favour of consolidation—they hold the belief that concentration of liquidity can increase the chance of order execution, reduce trading costs and therefore, attract more liquidity.[4] Therefore, the direct consequence of MiFID, i.e. a propagation of MTFs, could typically have a negative impact on market liquidity and market quality. For example, Pagano (1989) argues that the trading equilibrium under a two-market system is naturally unstable as traders tend to spontaneously move to the market with greater liquidity. Madhavan (1995) suggests that as the level of fragmentation increases, price volatility also increases. Chowdhry and Nanda (1991) find that under a fragmented financial market, informed traders can selectively execute orders based on their privileged information, which creates the "cream skimming" effect which is harmful for market quality, and the adverse selection costs raised from asymmetric information are in line with the level of market fragmentation.

It is interesting to note, however, that there is a large number of literature which supports the view that fragmentation improves market quality.[5] In particular, Economides (1996) argues that the benefits from network externalities under consolidation may not offset the losses occurred from monopoly market makers, whereas competition and fragmentation tend to reduce trading costs and improve market efficiency. Hendershott and Mendelson (2000) argue that fragmentation and crossing networks may benefit traders with reduced adverse selection risks and low costs of inventory holdings.

Given that researchers have long sought to explain the quality of a fragmented market, and that they have done so with varying degrees of success, it is interesting to examine how fragmented the UK equity market remains after MiFID and whether such a multi-market system contributes greatly to the improvement of market quality. Table 1, Panel (a) shows the market share of different types of trading facilities for FTSE 100 constituents, from 2009 to 2016, when MiFID was implemented. More than 90% of trading in FTSE 100 constituents is settled through LIT order book and OTCs (over-the-counters) each year. In contrast, the same trading through dark pools and SIs (System Internalizers) is at a small scale. Despite LIT and OTCs still forming the primary means of trading in FTSE 100 constituents, however, we notice that the trading increases continuously through dark pools (from 0.8% in 2009 to 5.99% in 2016) while decreasing through SIs. One may argue that the dark pools trading accounts lightly for the entire FTSE 100 constituents, according to Fidessa's data. However, such growth is worth noticing because: (1) nearly 50% of the European equities is settled in dark pools instead of open markets from 2008 to 2010, even when these orders could use the facilities of RMs (Regulated Markets), MTFs or OTCs (CFA 2011); (2) MTFs may be exempted from pre-trade transparency via waiver, and such a case, MTFs will be a dark pool. The proliferation of MTFs may contribute to the growth of dark pools.

To look further, we report the average order size, number of trades and total trading volume of FTSE 100 shares through LSE LITs (see Table 1, Panel c). There is a decreasing trend in the average order size during MiFID's post-launch period. This coincides with the CESR (2009) report, which suggests that the size of trade for FTSE 100 LIT order book started to drift downwards, both before and after MiFID. This also verifies our general observations at the beginning of the paper (see Table 1, Panel b). This could be the result of several observed factors, including proliferation of algorithmic trading, fragmentation of the market and market volatility.[6] A similar declining trend in the size of trade can be found in dark pools, SI and OTC order books (see Figure 1).

In general, there is a declining trend in the average size of the order books settled through these trading vehicles. The evidence of the commonality of falling trends in sizes and volumes across different trading facilities leads us to believe in the rise of MTFs. In particular, in high frequency trading, those new trading venues focus greatly on developing through technology innovations to reduce trading latency and trading costs in the competition against conventional primary markets. These are of great importance: on one hand, it could cause traders to migrate from primary markets to MTFs and new trading houses, and eventually alter the price discovery relation across trading venues; on the other hand, with the migration and emergence of a new type of trading, the market complexity and structure may be greatly affected and even changed—particularly with more unknown factors, like trading dynamics and so on, in the dark pool. It is clear that either impact would be highly relevant for traders in their daily activities and profitability.

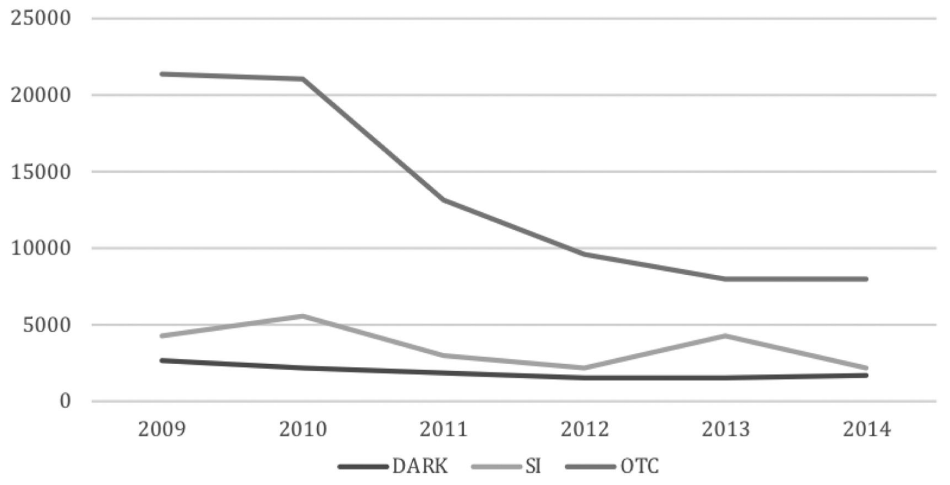

FIGURE 1 Average sizes of dark pools, SI and OTC order books
Source: BATS Chi-X Europe.
Notes: 1. In general, the average sizes of dark pools, SI and OTC order books decline through time. 2. The period of the sample relevant to the average size of SI order books is limited to 2014 due to data restrictions.

1.1 | The competitive pressure facing traditional regulated markets

Traditional RMs are facing tremendous competition and pressure from MTFs under MiFID because either those innovative ways of trading provided by MTFs are unavailable from RMs, or the scope, depth and diversity of trading that MTFs manage to handle are not achievable by RMs. Typical reasons include: 1) though there are some MTFs solely focusing on domestic markets like most RMs,[7] the majority of MTFs offer pan-European trading under the provision of the MiFID passport rule; 2) MTFs put heavy investments into fast information technology in order to attract order flows through algorithmic trading and statistical arbitrage; 3) most MTFs operate in dark pools in order to lower transaction costs and 4) MTFs usually operate a Smart Order Routing System (SORS) that optimizes order execution by navigating the orders out of traffic jam in one particular market queue to other possible external trading platforms. Some complicated SORS can also decide to split block orders smartly in order to achieve the most effective execution.

Lately, RMs have started to upgrade their trading platforms in order to increase trading speed and reduce transaction fees.[8] They also offer “sponsored access” that allows clients to have direct technical connection to regulated markets’ order books with restriction, so that the trading latency can be reduced. Further, most RMs have also established their own MTFs, such as dark pools, not only to diversify and expand their revenue sources, but also to compete with the main MTFs. One example is Turquoise (owned by London Stock Exchanges), which now has become one of the largest MTFs in Europe.

1.2 | Our proposed study

Our study aims to explore whether market segmentation and competition manifested in the rise of MTFs can improve market quality—in particular, the price discovery process, which is an important indicator of market quality that reflects timely dissemination and incorporation of information into market prices. Recent academic literature focuses on the informational role of MTFs in the financial market. For example, Aitken, Harris, and Sensenbrenner (2010, 2012), Gentile and Fioravanti (2011) and Riordan, Storkenmaier, and Wagener (2011) find evidence that supports the view that MTFs facilitate price discovery, and MTFs have since taken over the role of price discovery from traditional primary market. Conversely, Spankowski et al. (2012) argue that MTFs do not facilitate price discovery, and that they free-ride on the information emanating from the primary market. The uniqueness of this paper is the use of intra-day five-minute transaction prices of selected company's shares grouped under three major MTFs (LSE, BATS, and Turquoise), as well as Huang's (2002) price-weighted contribution measure as a validation to the common factor weight method commonly employed in this type of study.

In the paper, we first employ Gonzalo and Granger's (1995) common factor weight method to examine price discovery. In particular, we investigate which of those trading venues contribute more to impounding fundamental information, and how price leadership shifts among trading venues under certain competitive environments under MiFID. Price leadership refers to the ability where one trading venue adjusts trading prices on arriving information ahead of its competitors. We focus on ten FTSE 100 constituents[9] that are also actively traded on MTFs. The results suggest that trading venues are facing more intense competition than ever, and leadership in price discovery shifts from traditional LSE to MTFs, including BATS and Turquoise. We then apply Huang's (2002) weighted price contribution metric to estimate intra-day price contribution of the same assets. The results suggest that intra-day price contributions of MTFs are higher than those of LSE—especially during the first and last periods of the day. The estimated average daily price contributions are consistent with this result. The remainder of the paper is organized as follows: Section 2 critically reviews the existing literature, Section 3 discusses the research methodology and hypotheses formation, Section 4 describes the empirical data for this paper, Section 5 presents the estimated results and findings, and Section 6 concludes with this study.

2 | LITERATURE REVIEW

2.1 | Is market fragmentation beneficial for the improvement of market quality?

This literature review reveals two competing views about this topic. The first view holds that the trading costs are lower in concentrated markets when compared to fragmented ones, as it is easier to find trading parties in the former—which can create network externality, and the benefit of externality itself can bring in more liquidity to concentrated markets (see, for example, Pagano, 1989; Chowdhry & Nanda, 1991). Hence, the larger the market, the more investors will move in for greater opportunities of trade execution, which implies that liquidity begets liquidity and further improves price discovery. Mendelson (1987) examined market performance under four different exchange models—the consolidated, fragmented, monopoly and interdealer—and concludes that fragmentation may harm the quality of a market. Madhavan (1995), however, focused on the mechanism for information disclosure and finds that fragmentation may be beneficial for large traders who place multiple orders due to the lack of necessary information disclosure. But when trade information disclosure is not mandatory, liquidity will not necessarily be consolidated. The study also points out that high price volatility in conjunction with low price efficiency are possible in a fragmented market. Bennett and Wei (2006) also supported the view that fragmentation has a negative impact on liquidity and market efficiency, and order flow consolidation is crucial especially for equities with less liquidity. Gajewski and Gresse (2007) compared the trading costs on the hybrid order book of London Stock Exchange and the centralised order book of Euronext. The study suggested that price volatility was significantly higher in the hybrid order book and the transaction costs are lower in the centralised order book. In addition, the dealers outside the centralised order book are faced with higher execution and inventory costs, combined with higher adverse selection risks. The Securities and Exchange Commission (2001) reported the effective spread on the NYSE is lower than that of NASDAQ for a sample of matched stocks, where NYSE is a more consolidated market and NASDAQ has high level of fragmentation. Bennett and Wei (2006) also studied movement of order flows from NASDAQ to NYSE, where the overall execution costs were found to be lower in the more consolidated market.

While there is documented evidence supporting the view that consolidation is beneficial for the quality of a market, many other studies argued, however, that a fragmented market is much better for market quality. Economides (1996) focused on the network externalities and argued that although network externality may bring in more liquidity to a concentrated market, it cannot off-set the welfare losses under a market with monopoly providers. Harris (1993) also pointed out that although liquidity can attract liquidity, different traders require different market mechanisms to satisfy various trading needs, which can result in a fragmented market. Hendershott and Mendelson (2000) examined the dealer markets and alternative trading crossing networks in their study, and suggested that market participants who use crossing networks to execute orders can indeed benefit from fragmentation with reduced adverse selection risk[10] and lower costs of inventory holdings. Battalio (1997) studied the bid-ask spread for stocks listed on the NYSE and found that the quote-based spread narrowed after the introduction of a major third market dealer (Madoff Securities), and the trading costs did not increase. The study also indicated that the adverse selection risk associated with fragmentation was lower. In addition, the market efficiency improves even with the possible presence of adverse selection risk.

Boehmer and Boehmer (2003) found significant liquidity improvement after the entry of NYSE into AMEX listed ETF trading. The quoted, effective and realised spreads decreased significantly after the entry, and the quote-based depth documented high level of increase, which lay between 68% and 69%. Foucault and Menkveld (2008) tested the effects of fragmentation after the entry of EuroSETS into the Dutch equity market, where trade previously took place in the centralised market NSC. Their findings suggested that due to increased competition between the incumbent and new entrant markets, there was a reduction in the trading costs, the market depth for both markets saw an improvement, and the overall market quality became better. O'Hara and Ye (2011) compared the market quality at different levels of fragmentation in the U.S markets. They took trade reporting facilities (TRF) volume as a measure for the level of fragmentation for an individual stock. Their findings also supported the view that market fragmentation led to better market efficiency, despite the fact that it may induce short-term volatility. Moreover, a fragmented market is able to generate higher execution speed in conjunction with lower execution costs.

2.2 | What is the impact of MiFID and the contribution of MTFs to price discovery?

There are a number of empirical studies that analysed and explained whether the market segmentation and competition manifested in the proliferation of MTFs may improve market quality—in particular, the discovery of prices during different stages of MiFID. Riordan et al. (2011) employed the Hasbrouck information share method to investigate the contribution of several alternative trading facilities to price discovery in the UK equity market. The mean of the estimated upper and lower bounds of information share for each of the trading venues is used to indicate the percentage of contributions to price discovery from a respective trading venue. During the period of April and May 2010, Chi-X and LSE are found in the leading position, with Chi-X contributing 44.6% of the total price discovery, and LSE unexpectedly 10% lower than Chi-X with 34.6%, which contradicts the common view that a regulated market is in a dominant position relative to MTFs in the price discovery processes. More interestingly, Riordan et al. (2011) revealed that the prices from Chi-X move ahead of other markets, and thus Chi-X is the most efficient market. In addition, BATS contributes 12.9% to the total price discovery with 7.8% from Turquoise. Further, the prices from Turquoise contain stale information, and this can be exploited by arbitrageurs.

Aitken et al. (2010) compared the price formation process before and after the implementation of MiFID for four leading British equities listed on LSE and Chi-X. The study employed both the Hasbrouck (1995) information share and Gonzalo and Granger (1995) common factor weight to measure price discovery. Similar to Riordan et al. (2011), the study suggested that there was a significant shift of price discovery for the leading British stocks from LSE to MTFs. In this study, Chi-X again led price discovery. The shift was caused by changes in the fee schedules, rather than the implementation of MiFID or MiFID's new trading rules. In other words, the transition was due to the reduction in the trading execution fees and low latency services provided by Chi-X.

Gentile and Fioravanti (2011) also evaluated the impact of fragmented trading environment on price discovery. Their sample included 50 equities from the Stoxx Europe and 50 indices for the study period from September 2010 to February 2011. It is interesting to see that in some cases, traditional primary equity exchanges lost their leading position in the price discovery processes. In particular, in 32% of the chances Chi-X was the leading venue, and in 46% of the chances, primary exchanges took the lead. Also, 88% of the stock trading, where Chi-X took the lead, were stamped as highly fragmented, and 83% of the stock trading, where primary venues led, were classified as having low levels of fragmentation.

Aitken, Harris, and Di Marco (2012) examined the competition dynamics after the implementation of MiFID by using the CAC 40 constituents. The analysis was undertaken across the various trading venues—NYSE Euronext Paris, Chi-X and BATS. The results showed that the primary venue NYSE Euronext Paris dominated the market with more than 90% of permanent information impounding. Chi-X, however, was only responsible for about 10% of information flow, and BATS accounted for very little with respect to permanent information impounding. It was not possible to discern any effect for these MTFs during the study period in early 2010. However, the information share accounted for by Chi-X increased over 2009 and 2010, especially for those stocks within CAC 40 constituents, which had the largest market capitalisation. This suggests that the competition for order flows among the trading venues is concentrated on those largest stocks. Furthermore, traders in alternative trading venues were found to have high price discovery efficiency with the aid of their technologically advanced trading models, despite these participants being unlikely to be the first to impound information.

Spankowski et al. (2012) studied the intra-day patterns for 69 blue chip stocks from FTSE 100 constituents over the period of January and December 2009. These stocks were traded on LSE (primary market) and on Chi-X, BATS and Turquoise (alternative venues). The study revealed that trading was mostly concentrated in the primary market (LSE) during the opening and closing periods of the day, while the volumes of trade in alternative venues only surged during the second half of the day. This may suggest that traders are mostly dependent on the traditional market with regard to the price formation process, particularly avoiding high volatility/uncertainty involved in alternative trading venues during early periods of the day, but then shift back to alternative trading venues in the second half of the day.

Using Hasbrouck's (1995) information share and Gonzalo and Granger's (1995) common factor weight approach to assess price discovery across the primary and MTFs markets, Aitken et al. (2010)) argued that during the period from July 2007 to December 2008, when the MiFID was just launched and trading in MTFs was relatively less active, there was no evidence of shifting in price discovery from LSE to MTFs due to MiFID. They also believed that the cut in the MTFs trading fees effectively induced trade in MTFs. Riordan et al. (2011) found that Chi-X and LSE were the leading force in price discovery, ahead of BATS and Turquoise, on the basis of their analysis from April to May 2010. Spankowski et al. (2012) found that the volumes of trade shifted across primary and MTFs during intra-day; however, they tended to concentrate in LSE during the information-intensive period. O'Hara and Ye (2011) studied the US markets on the impact of MiFID on market quality. They argued that fragmentation and competition did not harm market quality. Our study employs more recent data to investigate the price discovery processes among primary and MTFs, in comparison to aforementioned studies which generally investigated the period during MiFID when changes due to the implementation of MiFID were still on the way to work through markets. During this specific target sample period, we find that trading venues faced intense competition than before, and the price discovery had migrated from traditional LSE to MTFs.

3 | TESTABLE FRAMEWORK

3.1 | The Gonzalo and Granger (1995) permanent-transitory model

While Hasbrouck's (1995) information share method uses the variance of the common factor innovations to measure price discovery, such that the contribution by each market to the variance is the information share, Gonzalo and Granger's (1995) common factor weight method concentrates on an error correction process which impounds permanent shocks to raise system disequilibrium, with the error correction coefficient as the contribution of each market to the common factor. Central to Gonzalo and Granger (1995) is a permanent-transitory decomposition process from which price discovery may be measured. Such a decomposition process closely follows the Stock and Watson (1988) common trend representation of P_t, which is:

$$P_t = \Gamma_1 f_t + G_t \tag{1}$$

where P_t is a vector of $I(1)$ time series of prices (for example, actual transaction prices; bid/offer quotes); Γ_1 is the loading matrix, f_t is the common factor, and G_t is the transitory component that has no permanent effect on P_t. Gonzalo and Granger (1995) further impose a linear restriction on P_t in order to identify f_t, that is:

$$f_t = \Phi_j P_t \tag{2}$$

where Φ_j is the coefficient vector which associates the prices with the common factor. Harris, McInish, and Wood (2002b) and Baillie, Booth, Tse, and Zabotina (2002) suggested that Φ_j can be normalized such that they pick up the weights of market j's contributions to the common factor. The higher the common factor weight Φ_j, the greater is the importance of market j's contributions to the long-term stochastic trend.[11]

Gonzalo and Granger (1995) proved that Φ_j is orthogonal to the error correction coefficient vector α in the Vector Error Correction representation of P_t, such that $\alpha_\perp = \Phi'$. Additionally, $\alpha_\perp$ can be found by estimating this Vector Error Correction representation of P_t via OLS, which is:

$$\Delta P_t = \alpha\beta' P_{t-1} + \sum_{j=1}^{k} A_j \Delta P_{t-j} + e_t \tag{3}$$

where α represents an error correction vector; β is the co-integrating vector; e_t represents a vector of serially uncorrelated innovations with zero-mean. The fundamental assumption is that when one security is traded in several markets, the prices of the security in different markets will not drift too much from each other, and the price differentials are captured by the error correction term.

Following Johansen (1988), the maximum likelihood estimator of $\alpha_\perp$ can be found by solving Eq. (4):[12]

$$\left| \lambda S_{00} - S_{01} S_{11}^{-1} S_{10} \right| = 0 \tag{4}$$

for the eigenvalues $\hat{\lambda} > \hat{\lambda}_2 \ldots \hat{\lambda}_n$ and eigenvectors $\hat{M}$ $(\hat{m}_1, \ldots, \hat{m}_n)$. Normalising the eigenvectors such that $\hat{M}' S_{00} \hat{M} = I$, the selection of $\hat{\alpha}_\perp$ is given by Eq. (5):

$$\hat{\alpha}_\perp = (\hat{m}_{r+1}, \ldots, \hat{m}_n) \tag{5}$$

It is important to note that the selection of $\hat{\alpha}_\perp$ is according to the last column of the eigenvector $\hat{M}$, and $\hat{\alpha}_\perp = \Phi'$.

Following the Gonzalo and Granger (1995) permanent-transitory model, our testable framework is explained as follows. We allow the long-run common stochastic factor shared by security prices on different markets to be expressed as a linear combination of these series where:

$$f_t = \Phi_1 PL + \Phi_2 PB + \Phi_3 PT \tag{6}$$

and f_t is the common factor, and PL, PB and PT are the price series with respect to LSE, BATS trading and Turquoise. Φ_j can be seen as the contributions from each trading venue to the common factor f_t.

3.2 | Huang's (2002) weighted price contribution method

The weighted price contribution method uses intra-day price change observation over multiple days to generate the intra-day breakdown of price discovery of the same financial asset. In finance, the method is often used to reveal price variation, for the same asset, taking place at different periods of the trading day. Huang (2002) takes the cross-sectional aspect of the method, which allows the revelation of price change for the same asset, taking place at different trading venues at different periods of a trading day. In particular, Huang (2002) calculates the relative contribution of the jth trading venue to the total price change at intra-day time periods for a given financial asset, and thereby the market (or price) leadership may be tested and compared. Central to Huang (2002) is the aggregated weighted price contribution at a given trading hour k, for the jth venue over multiple days m, that is:

$$WPC_{k,j} = \sum_{i-1}^{m} WPC_{k,i,j} \tag{7}$$

where:

$$WPC_{k,i,j} = \Delta P_{k,i,j}(\%) \times W_i$$

$$\Delta P_{k,i,j}(\%) = \frac{\Delta P_{k,i,j}}{\sum_{j=1}^{3}\sum_{t=1}^{k}\Delta P_{k,i,j}}$$

$$W_i = \frac{\left|\sum_{j=1}^{3}\sum_{t=1}^{k}\Delta P_{k,i,j}\right|}{\left|\sum_{j=1}^{3}\sum_{t=1}^{k}\Delta P_{k,i,j}\right|\Sigma_{i=1}^{m}}$$

$WPC_{k,i,j}$ is the weighted price contribution from jth trading venue during kth trading hour on ith day; $\Delta P_{k,i,j}$ is the price change of jth trading venue during kth trading hour on ith day, which is calculated as the price difference at two successive time intervals within ith day; $\Delta P_{k,i,j}(\%)$ is the percentage of the price change of the jth trading venue during kth trading hour on ith day where the denominator of $\Delta P_{k,i,j}(\%)$ shows the sum of total price changes on ith day across all three trading venues; W_i is the weighting factor of the price changes on ith day[13] where the denominator of W_i shows the aggregated absolute price changes at all three trading venues across the whole sample period m; $|\Delta P_i|$ is the absolute value of total price changes across a total of $j = 1, 2, 3$ venues and m is the number of days included in the calculation.

As the methodology stands, Eq. (7) allows us to generate intra-day breakdown of price variations at each of $j = 1, 2, 3$ trading venues. Another salient feature of Huang's (2002) weighted price contribution method is that we may use Eq. (8) to reveal daily average price variation at j's trading venue for a stock over multiple days m:

$$WPC_j = \sum_{i=1}^{m}\left(\frac{|\Delta P_i|}{\Sigma_{i=1}^{m}|\Delta P_i|}\right)\times\left(\frac{\left|\Delta P_{i,j}\right|}{\Sigma_{j=1}^{3}\left|\Delta P_{i,j}\right|}\right) \tag{8}$$

where:

$|\Delta P_i|$ is the absolute value of total price changes across a total of $j = 1, 2, 3$ venues and $\Delta P_{i,j}$ is the daily price change at jth trading venue on ith day.

The second term on the right-hand side of Eq. (8) is the relative contribution of jth trading venue to the total price change on ith day. The first term on the right-hand side of Eq. (5) is the weighting factor, which shows the contribution of total absolute price change during ith day to the aggregated absolute price change throughout the whole sample period m.

In our empirical analyses, the last transaction prices were used in the calculation. Each trading day was classified into 17 half-hour periods, starting from 8:00 until 16:30 London time. The intra-day weighted price contribution by each trading venue over the post-MiFID sample years is generated according to Eq. (7). The daily average weighted price contribution from each trading venue is calculated by Eq. (8).

4 | DATA

The data used in this study are intra-day five-minute transaction prices data, obtained from the Thomson Reuters Tick History Database. Despite the fact that the five-minute prices data show high levels of convergence, the price differences across those trading venues under our study, although small, are still observable and testable. The one-minute data obtained from the same data source show high levels of non-synchronized trade and high level of noises (i.e. more misrecorded and missing data in consecutive observation periods, and more significant outliers than those from the five-minute data), which requires intensive data filtering and filling techniques to process the data. Although these data processing techniques might cause the overall estimations and analyses to become complicated and introduce potential bias to the results, these improved better quality one-minute / higher frequency data are capable of generating enriched information and results.

Ten companies have been selected from the FTSE 100 constituents list that are also traded on BATS Europe and Turquoise. The ten companies are HSBC, BHP Billiton, Vodafone, Rio Tinto, Barclays, GlaxoSmithKline, AstraZeneca, Xstrata, Anglo American and TESCO. The sample period extends from January 2010 to October 2013. Thus, standing at the third year since the commencement of MiFID in 2007, most of the major changes are in place and incorporated into trading in different venues. Data from MTFs are now free of the problem of infrequent trade, which could have been the case during the first two years of MiFID.

Our selection of MTFs is limited by the availability of data. Both Chi-X and BATS are subsidiaries under BATS Chi-X Europe. Although Chi-X has highest market share over all MTFs in the UK market, and a number of studies did employ Chi-X data (rather than BATS), the Chi-X order book is unavailable in this study. This unavailability of data is mainly because MiFID does not force the introduce of central consolidated tap for all market data across different trading venues. Consequently, the data vendors may not have the full access to market data. Two MTFs stand out and remain usable data sources—BATS trading which was the second largest MTF, followed by Turquoise, at fourth place in terms of market share.[14]

The continuous trading hours for the London Stock Exchange start from 8:00 to 16:30 in London time, and the time remains the same for the BATS trading and Turquoise. In order to address the data problem during opening and closing time periods where high price volatility occurs, as well as to synchronize the data that were offset by the Thomson Reuters database with regards to the British summer time,[15] the first and last hours were censored and therefore only the data from 9:00 to 15:30 were adopted in our analysis. Also, the data that had been mistakenly recorded or missed were filtered and filled by previous valid data. The data were also split into a few subsets on a yearly basis, so it is more convenient to generate year-on-year changes and analyses. In addition, in order to avoid the possible correlations in overnight prices, only the lagged observations within the same day were used in our regression analyses. In doing so, a number of data points at the beginning of the day with regards to the lagged length were censored.

5 | EMPIRICAL RESULTS

5.1 | Common factor weight results

We use one of the companies under study, Anglo American, to explain how we estimate the Gonzalo and Granger (1995) common factor weight Φ_j. The Augmented Dickey-Fuller and Johansen and Juselius (1990) trace test results for *PL*, *PB* and *PT* are reported in Tables 2 and 3 (note that the two tables also provide the relevant test results for all other companies under study). The sample period is from 2010 to 2013. All series (*PL*, *PB* and *PT*) are found to be $I(1)$; there are two co-integrating vectors among the three series and hence there is one common stochastic trend shared by them. Note that the characteristics of sub-sample period data for 2010, 2011, 2012 and 2013 are highly consistent with the whole sample results shown in Tables 2 and 3—all prices at the three different venues are I(1) for each year; and there is one common stochastic trend shared by *PL*, *PB* and *PT* for each year. For simplicity, only the whole sample results are reported. These empirical results indicate that the prices formed by different trading venues for the same stock are co-integrated by a long-run underlying informational equilibrium. This shows that the proliferation of MTFs and the competition between trading venues do not harm the information contained in prices. The trading activities for a stock in different venues shows a convergence pattern, which is the result of arbitrage. It, in turn, suggests that MTFs are able to incorporate and disseminate price information to facilitate price discovery.

Then, we use the Akaike Information Criterion to determine the optimal lag length for an unrestricted VAR formed of *PL*, *PB* and *PT*. The optimal lag length is estimated as 2. Given this, the co-integrating structure for Anglo American represented by a VECM with 2 lags is estimated using the maximum likelihood estimation method (see Table 4). The matrix $\alpha_\perp$ assigned for the Gonzalo and Granger (1995) common factor weight Φ_j is selected from the last column of the eigenvector $\widehat{M}$, which is $\alpha_\perp(1.080, 1.029, 0.640)'$. The common factor comprising of Φ_j for each trading venue is identified as $f = 1.080PL{+}1.029PB{+}0.640PT$. These weights are indicative of the importance of respective venue's contribution to the common factor—the higher the weight, the greater the contribution for that

TABLE 2 Descriptive statistics and ADF results of ten companies' shares

Table 2 examines 10 selected companies that are listed under FTSE 100 constituent list during 2010 to 2013, and the data covers the period from January 2010 to October 2013. Our data sample contains intra-day five-minute transaction prices of these company's shares grouped under three trading venues, LSE, BATS, and turquoise from which the company's shares are actively traded

Anglo American	**LSE**	**BATS**	**Turquoise**	**AstraZeneca**	**LSE**	**BATS**	**Turquoise**
ADF (Log price)	−2.56	−2.57	−2.62	ADF (Log price)	−3.12	−3.20	−3.12
	(> 0.10)	(> 0.10)	(> 0.10)		(> 0.10)	(> 0.05)	(> 0.10)
ADF First Difference	−208.61	−201.30	−200.96	ADF First Difference	−175.91	−200.81	−201.33
	(< 0.0001)	(< 0.0001)	(< 0.0001)		(< 0.0001)	(< 0.0001)	(< 0.0001)
Mean	7.73	7.73	7.73	Mean	8.01	8.01	8.01
Variance	0.24	0.24	0.24	Variance	0.06	0.06	0.06
Skewness	−0.45	−0.44	−0.44	Skewness	0.08	0.08	0.08
Kurtosis	2.31	2.31	2.31	Kurtosis	2.68	2.68	2.68
Barclays	**LSE**	**BATS**	**Turquoise**	**BHP Billiton**	**LSE**	**BATS**	**Turquoise**
ADF (Log price)	−1.83	−1.86	−1.85	ADF (Log price)	−3.13	−3.16	−3.12
	(> 0.10)	(> 0.10)	(> 0.10)		(> 0.05)	(> 0.05)	(> 0.10)
ADF First Difference	214.04 (< 0.0001)	−200.71	−200.36	ADF First Difference	−209.39 (< 0.0001)	−283.13	−201.66
		(< 0.0001)	(< 0.0001)			(< 0.0001)	(< 0.0001)
Mean	5.54	5.54	5.54	Mean	7.62	7.62	7.62
Variance	0.23	0.23	0.23	Variance	0.11	0.11	0.12
Skewness	−0.73	−0.73	−0.74	Skewness	0.56	0.56	0.56
Kurtosis	2.49	2.49	2.49	Kurtosis	2.41	2.41	2.41
GlaxoSmithKline	**LSE**	**BATS**	**Turquoise**	**HSBC**	**LSE**	**BATS**	**Turquoise**
ADF (Log price)	−3.81	−3.81	−3.80	ADF (Log price)	−2.06782	−2.075974	−2.077427
	(> 0.01)	(> 0.01)	(> 0.01)		(> 0.10)	(> 0.10)	(> 0.10)
ADF First Difference	−224.17	−202.15	−202.65	ADF First Difference	−215.6367	−203.4252	−203.3129
	(< 0.0001)	(< 0.0001)	(< 0.0001)		(< 0.0001)	(< 0.0001)	(< 0.0001)
Mean	7.22	7.22	7.21	Mean	6.437152	6.437146	6.437155
Variance	0.11	0.11	0.11	Variance	0.117219	0.117198	0.117198
Skewness	0.361	0.361	0.36	Skewness	−0.582359	−0.581735	−0.5818
Kurtosis	2.48	2.48	2.48	Kurtosis	2.25	2.25	2.25

(Continues)

TABLE 2 Continued

Rio Tinto	LSE	BATS	Turquoise	TESCO	LSE	BATS	Turquoise
ADF (Log price)	−3.02	−3.00	−3.00	ADF (Log price)	−2.37	−2.36	−2.43
	(> 0.10)	(> 0.10)	(> 0.10)		(> 0.10)	(> 0.10)	(> 0.10)
ADF First Difference	−217.81	−202.13	−202.03	ADF First Difference	−212.15	−202.55	−282.41
	(< 0.0001)	(< 0.0001)	(< 0.0001)		(< 0.0001)	(< 0.0001)	(< 0.0001)
Mean	8.15	8.15	8.15	Mean	5.93	5.93	5.93
Variance	0.145	0.145	0.145	Variance	0.11	0.11	0.11
Skewness	0.38	0.38	0.38	Skewness	−0.36	−0.36	−0.36
Kurtosis	2.09	2.09	2.09	Kurtosis	1.93	1.93	1.93
Vodafone	**LSE**	**BATS**	**Turquoise**	**Xstrata**	**LSE**	**BATS**	**Turquoise**
ADF (Log price)	−2.98	−2.95	−2.95	ADF (Log price)	−2.54	−2.61	−2.61
	(> 0.10)	(> 0.10)	(> 0.10)		(> 0.10)	(> 0.10)	(> 0.10)
ADF First Difference	−220.25	−202.58	−202.95	ADF First Difference	−200.86	−188.39	−188.66
	(< 0.0001)	(< 0.0001)	(< 0.0001)		(< 0.0001)	(< 0.0001)	(< 0.0001)
Mean	5.13	5.13	5.13	Mean	7.02	7.02	7.02
Variance	0.10	0.10	0.10	Variance	0.17	0.17	0.17
Skewness	−0.23	−0.23	−0.23	Skewness	0.20	0.20	0.20
Kurtosis	3.24	3.25	3.25	Kurtosis	2.23	2.23	2.23

Notes: 1. We examine 10 selected companies that are listed under FTSE 100 constituent list, from 2010 to 2013. Our data sample contains intra-day five-minute transaction prices of these company's shares grouped under three trading venues, LSE, BATS, and Turquoise, from which the company's shares are actively traded. The data covers the period from January 2010 to October 2013. 2. Our empirical analyses involve the use of the permanent transitory decomposition method by Gonzalo and Granger (1995). The method is constructed on a vector error correction model (VECM), which requires non-stationarity of the price series. Thus, we performed the Augmented Dickey-Fuller (ADF) unit root tests on all 30 price series of equity indices, grouped under the three venues. The ADF unit root tests were carried out on levels and then on first differences of these time series. The results confirm that all series are integrated of order 1 across all classified markets.

TABLE 3 Johansen and Juselius (1990) trace test for co-integrating rank of the long-run π matrix
Table 3 consolidates the results of the Johansen and Juselius (1990) trace test after assessing the co-integrating rank of the long-run π matrix. The results confirm that the prices of the same company's equity traded under LSE, BATS, and turquoise are co-integrated with at least two co-integrating vectors, and hence there is one common stochastic trend shared by these price series

Anglo American			AstraZeneca		
Hypothesized No. of CE(s)	γ_{trace}	γ_{max}	**Hypothesized No. of CE(s)**	γ_{trace}	γ_{max}
r = 0	5177.51*	3031.20*	r = 0	8965.52*	5914.39*
r = 1	2146.31*	2139.59*	r = 1	3051.13*	3041.36*
r = 2	6.71	6.71	r = 2	9.77	9.77
Barclays			**BHP Billiton**		
Hypothesized No. of CE(s)	γ_{trace}	γ_{max}	**Hypothesized No. of CE(s)**	γ_{trace}	γ_{max}
r = 0	18374.81*	10747.24*	r = 0	11579.43*	7689.03*
r = 1	7627.57*	7624.13*	r = 1	3890.40*	3880.59*
r = 2	3.44	3.44	r = 2	9.81	9.81
GlaxoSmithKline			**HSBC**		
Hypothesized No. of CE(s)	γ_{trace}	γ_{max}	**Hypothesized No. of CE(s)**	γ_{trace}	γ_{max}
r = 0	14811.95*	8106.79*	r = 0	18766.80*	10903.26*
r = 1	6705.16*	6690.42*	r = 1	7863.54*	7858.52*
r = 2	14.74*	14.74*	r = 2	5.03	5.03
Rio Tinto			**TESCO**		
Hypothesized No. of CE(s)	γ_{trace}	γ_{max}	**Hypothesized No. of CE(s)**	γ_{trace}	γ_{max}
r = 0	17133.52*	9312.23*	r = 0	5629.97*	3993.23*
r = 1	7821.29*	7812.28*	r = 1	1636.74*	1630.96*
r = 2	9.01	9.01	r = 2	5.78	5.78
Vodafone			**Xstrata**		
Hypothesized No. of CE(s)	γ_{trace}	γ_{max}	**Hypothesized No. of CE(s)**	γ_{trace}	γ_{max}
r = 0	8888.89*	6677.65*	r = 0	13335.17*	8994.33*
r = 1	2211.24*	2202.36*	r = 1	4340.83*	4334.28*
r = 2	8.89	8.89	r = 2	6.55	6.55

Notes: 1. Statistical significance at the 95% level or greater is signified by *. 2. We perform the Johansen and Juselius (1990) Trace Test to assess the co-integrating rank of the long-run π matrix. The results confirm that the prices of the same company's equity traded under LSE, BATS, and Turquoise are co-integrated with at least two co-integrating vectors, and hence there is one common stochastic trend shared by these price series.

trading venue to the common factor, and the closer is the co-movement between that trading venue and the long-term common stochastic trend (Chu, Hsieh, & Tse, 1999). The venue with the highest weight is considered as the dominant market, which in turn is the common factor leading other markets in the price discovery processes. In order to make a more a sensible comparison of the price leadership, the estimated common factor weight may be interpreted in percentages (Booth et. al 1999). Thus, in the case of Anglo American in 2010, each of the weighting coefficients (1.080, 1.029, 0.640) may be divided by the sum of these coefficients, which is 2.749. The results are then transformed into percentages, which are 39%, 37% and 24%, implying that all three markets do contribute to price discovery, with LSE having the highest contribution to the common factor, followed by BATS and Turquoise, respectively.

In conjunction with the above example based on Anglo American for 2010, we now generate the relevant Gonzalo and Granger (1995) common factor weight for all other companies for all four years under our study (see Table 5). At

TABLE 4 The Estimated Gonzalo and Granger (1995) common factor weight
Table 4 reports the co-integrating structure for anglo American is estimated in the table below. The maximum likelihood estimation is applied on the VECM representation of the data with an optimum lag length of two, which is determined by the akaike information criterion, given a maximum of eight lags were selected and tested in the study

	Eigenvalues $\hat{\lambda}$		
	0.246	0.099	0.000
	Eigenvectors $\hat{v}$		
PL	7.110	6.866	−0.005
PB	−16.891	−0.730	0.029
PT	9.784	−6.135	0.052
	Eigenvectors $\hat{M}$		
PL	4.716	7.313	1.080
PB	−11.555	−0.982	1.029
PT	6.933	−6.618	0.640

Note: 1. The cointegrating structure for Anglo American is estimated as follows. The maximum likelihood estimation is applied on the VECM representation of the data with an optimum lag length of two, determined by the Akaike Information Criterion, given a maximum of eight lags were selected and tested in the study. 2. The matrix $\alpha_{\perp}$ assigned for the common factor weight Φ_j is selected from the last column of the eigenvector $\hat{M}$, which is $\alpha_{\perp}$=(1.080, 1.029, 0.640)′. The common factor comprising of Φ_j's for each trading venue is identified as $f = 1.080PL + 1.029PB + 0.640PT$. These weights are indicative of the importance of respective venue's contribution to the common factor, such that the higher the weight, the greater is the contribution of that trading venue to the common factor, and the closer is the co-movement between that trading venue and the long-term common stochastic trend (Chu et al., 1999).

first glance, all trading venues significantly contribute to the informational common long-term factor for the underlying asset values. In particular, the results indicate that the LSE lost its dominant position over the years after the implementation of the MiFID,[16] as there is no evidence in support of the view that the common factor weight for the LSE are significantly higher than the other two markets. In nearly all of the cases, the multilateral trading venues make significantly higher contributions to the common factor than the LSE for the entire post-MiFID periods under study. For instance, for Anglo American, the LSE contributes 7% and 16% to the common factor in 2011 and 2012, while the other two markets contribute 33% to 51% to the common factor. Additionally, for AstraZeneca, LSE contributes 3% while BATS contributes 73% in 2011, implying that the BATS trading becomes the dominant force in price discovery. There are more cases where MTFs are in the dominant position: Barclays and BHP Billiton in 2010, where BATS contributes 76% and 83%, respectively; GlaxoSmithKline in 2013, where BATS contributes 70% to the common factor weights; and, HSBC in 2013, where Turquoise contributes 68.3%.

It is interesting to note, however, that Riordan et al. (2011) revealed Chi-X as having the highest contribution to the price discovery, followed by LSE, with BATS and Turquoise having the lowest contributions. The prices from Turquoise lag behind other markets and are more likely to have contained stale information. Our study finds BATS and Turquoise all leading the price discovery over the LSE.[17] These new changes in market share revealed in our analyses indicate that MTFs have gained success over LSE, which may be relevant to the low latency and low costs trading that they offered. With the proliferation of algorithmic trade in recent years, the technology advantages and low latency trading system have become the driving forces for high frequency traders as well as informed traders. Although these questions have not been explored in detail in this study, a comparison on the impacts of both trading speed and trading costs on price discovery from post-MiFID MTFs may be explored by some future research.

5.2 | Weighted price contribution results

The results in Table 6 show that the estimated weighted price contributions from the multilateral trading venues are slightly higher than the LSE on a daily basis. The daily average price contributions from BATS and Turquoise are about 34% for each MTF in each post-MiFID year, while those from the LSE are about 32% in each year. In particular, BATS

TABLE 5 The estimated Gonzalo and Granger (1995) common factor weight for all 10 companies during the Post-MiFID period

Table 5 displays the estimated Gonzalo and Granger (1995) common factor weight in percentage terms to make a more sensible comparison of the price leadership (Booth, So & Tse, 1999)

Anglo American	2010	2011	2012	2013	AstraZeneca	2010	2011	2012	2013
LSE	39%	7%*	16%*	42%	LSE	26%	3%*	15%*	35%
BATS	37%	47%	51%	4%*	BATS	56%	73%	48%	35%
TURQ	24%*	46%	33%	54%	TURQ	18%*	24%	37%	30%*
Barclays	2010	2011	2012	2013	BHP Billiton	2010	2011	2012	2013
LSE	6%*	0.40%*	24%	3%*	LSE	8%*	12%*	11%*	3%*
BATS	76%	59%	14%*	30%	BATS	83%	51%	31%	31%
TURQ	18%	40.60%	62%	67%	TURQ	9%	37%	58%	66%
GlaxoSmithKline	2010	2011	2012	2013	HSBC	2010	2011	2012	2013
LSE	14%*	14%*	12%*	2%*	LSE	14%*	28%	7%*	0.70%*
BATS	66%	26%	47%	70%	BATS	66%	70%	47%	31%
TURQ	20%	60%	41%	28%	TURQ	19%	2%*	46%	68.30%
Rio Tinto	2010	2011	2012	2013	TESCO	2010	2011	2012	2013
LSE	17%*	2%*	4%*	11%*	LSE	26%	19%*	5%*	22%*
BATS	50%	44%	36%	29%	BATS	52%	27%	17%	34%
TURQ	33%	54%	60%	60%	TURQ	22%*	54%	78%	44%
Vodafone	2010	2011	2012	2013	Xstrata	2010	2011	2012	2013
LSE	8%*	4%*	3%*	0.30%*	LSE	4%*	0.50%*	9%*	37%
BATS	78%	67%	51%	50%	BATS	52%	10%	15%	26%*
TURQ	14%	29%	46%	49.70%	TURQ	44%	89.50%	76%	37%

Notes: 1. The estimated Gonzalo and Granger (1995) common factor weight were reported in percentage terms to make a more sensible comparison of the price leadership (Booth et al., 1999). 2. *signifies the case where the estimated common factor weight is the smallest among the three equivalent estimates in the same year. In the majority of the cases, the common factor weight for LSE were small relative to those for BATS or Turquoise, indicating that the relative importance of the trading venue LSE in the overall financial markets became minor after MiFID.

trading has the highest price contribution during 2010 and 2012, while Turquoise has the highest contribution in 2011 and 2013. These results indicate that the multilateral trading venues take a slight lead in terms of price discovery over the LSE, which is consistent with Aitken et al. (2010) and Riordan et al. (2011) as well as our findings from the common factor weight method (see Section 5.1).

The estimated average price contributions from each trading venue at intra-day levels shows a U-shape pattern similar to the findings of Blau, Van Ness, and Van Ness (2009) and Vanthuan and Chanwit (2009). In other words, the contribution to daily total price movement at each intra-day period is mostly high during the first half-hour of the day, and gradually declines through the day. However, it increases slightly in the afternoon from 14:30 to 15:00. In particular, the price contribution within the first half-hour ranges from 5% to 8% across years, and declines to about 2% in other trading intervals, with an exception during 14:30 to 15:00 where the price contributes about 3%–4% to daily price movement across years.

It is interesting to see that, with the exception of 2011, both BATS and Turquoise yield higher price contributions than LSE in 2010, 2012 and 2013, especially during the first half-hour of the day. In 2010, BATS has the highest contribution among the three venues, which is 5.82%, and LSE has the lowest contribution at 5.41%. During 2012, BATS and Turquoise both contribute 5.88% during the first period of the day, while the LSE contributes 5.56%. In 2013, BATS and Turquoise contribute 7.98% and 7.95% respectively, while the LSE contributes 7.81%. LSE gradually gained back price contribution over 2013.

TABLE 6 Intra-day & daily average weighted price contribution during the Post-MiFID period

Table 6 reports the weighted price contribution, calculated based on Huang's (2002) and Barclay and Hendershott's (2008) methods. These contributions are first calculated for each stock at each trading venue and then averaged monthly. The monthly weighted price contributions are then averaged for each stock to obtain annualised WPCs. Finally, the average of the annualised weighted price contribution across the stocks is determined

	2010			2011			2012			2013		
	LSE	BATS	Turquoise	LSE	BATS	Turquoise	LSE	BATS	Turquoise	LSE	BATS	Turquoise
8:00~8:30	5.41%*	5.82%	5.64%	5.65%	5.55%	5.50%*	5.56%*	5.88%	5.88%	7.81%*	7.98%	7.95%
8:30~9:00	3.27%	3.20%	3.10%	2.28%	2.27%	2.31%	2.99%	2.99%	2.98%	3.41%	3.62%	3.46%
9:00~9:30	2.26%	2.26%	2.33%	1.91%	2.02%	2.02%	2.97%	2.88%	2.92%	2.39%	2.30%	2.38%
9:30~10:00	1.87%	1.92%	1.88%	1.85%	1.75%	1.81%	1.43%	1.52%	1.52%	1.69%	1.64%	1.62%
10:00~10:30	1.84%	1.85%	1.85%	1.47%	1.45%	1.44%	1.10%	1.13%	1.12%	1.43%	1.38%	1.46%
10:30~11:00	2.22%	2.14%	2.17%	1.40%	1.45%	1.48%	2.15%	2.10%	2.11%	1.44%	1.46%	1.44%
11:00~11:30	1.14%	1.24%	1.24%	1.46%	1.42%	1.50%	1.20%	1.26%	1.25%	1.56%	1.61%	1.63%
11:30~12:00	0.69%	0.68%	0.71%	1.39%	1.51%	1.50%	1.90%	1.83%	1.82%	1.15%	1.03%	1.00%
12:00~12:30	1.39%	1.31%	1.36%	1.35%	1.19%	1.19%	0.78%	1.08%	1.12%	1.22%	1.37%	1.34%
12:30~13:00	0.78%	0.71%	0.65%	1.18%	1.13%	1.16%	0.78%	0.71%	0.67%	0.61%	0.61%	0.62%
13:00~13:30	1.77%	1.79%	1.82%	1.48%	1.55%	1.44%	1.20%	1.04%	1.05%	1.36%	1.34%	1.35%
13:30~14:00	0.73%	0.75%	0.77%	1.36%	1.33%	1.41%	1.64%	1.61%	1.61%	1.26%	1.47%	1.48%
14:00~14:30	1.32%	1.31%	1.26%	1.35%	1.36%	1.36%	0.77%	0.79%	0.78%	1.45%	1.33%	1.35%
14:30~15:00	3.38%	3.32%	3.36%	3.73%	3.69%	3.72%	3.49%	3.51%	3.50%	2.98%	2.82%	2.81%
15:00~15:30	2.18%	2.25%	2.22%	2.23%	2.20%	2.22%	2.33%	2.32%	2.32%	1.32%	1.37%	1.39%
15:30~16:00	2.17%	2.06%	2.05%	1.88%	1.97%	1.95%	1.63%	1.61%	1.63%	1.07%	1.15%	1.09%
16:00~16:30	0.31%*	1.39%	1.48%	0.14%*	1.95%	1.97%	0.20%*	1.71%	1.66%	0.05%*	1.44%	1.52%
Daily	32.37%*	33.91%	33.72%	32.29%*	33.79%	33.91%	32.51%*	33.79%	33.69%	32.57%*	33.68%	33.74%

Notes: 1. Following Huang's (2002) and Barclay and Hendershott's (2008) methods, these weighted price contributions are first calculated for each stock at each trading venue, and then averaged monthly. The monthly weighted price contributions are then averaged for each stock to determine annualised WPCs. Finally, the average of the annualised weighted price contribution across the stocks is taken. 2. The daily average weighted price contribution are reported at the bottom of the table. 3. * signifies the case where the estimated weighted price contribution is the smallest among the three equivalent estimates in the same year. The intra-day price contributions of MTFs (BATS and Turquoise) are higher than those of LSE—especially during the first and last periods of the day. The estimated daily price contributions are consistent with this result.

It is also worth noticing that in the last period of the day, the price contribution from LSE is generally very low in comparison with the two MTFs. From 2010 to 2013, price contributions from LSE are between 0.05% to 0.31%, while the price contributions from BATS and Turquoise are between 1.4% to 2%.

5.3 | The U-shape pattern of intra-day trading activities

The U-shape pattern observed from intra-day price variations is widely documented in the literature. Early studies such as Stoll and Whaley (1990) and Brock and Kleidon (1992) suggested that demand for transactions is higher in the opening period than in any other periods during a day. Market makers are therefore able to take advantage of the inelasticity of demand and post wider spread quotes for transactions at such a peak trading hour of the day. When informed traders execute orders on their privileged information during this time period of the day, price discovery is facilitated. Admati and Pfeiderer (1988) and Barclay and Warner (1993) also argued that the informed traders prefer opening period of the day for trade due to the concentration of trading volume, such that the informed traders could camouflage their information during this period. Stoll and Whaley (1990) suggested that the discovery process can be better facilitated by greater transparency, and this view is supported by Boehmer, Saar, and Yu (2005), who found evidence that greater pre-trade transparency can improve price efficiency and induce better price discovery. Huang (2002) and Theissen (2002) pointed out that the multilateral trading venues have the advantage of faster trading speed which could attract informed traders and facilitate price efficiency and improve transparency.

Such an argument may well explain higher price contributions of BATS and Turquoise (than LSE) at the opening period of the day as the multilateral trading venues are able to disseminate price information faster than LSE. In addition, the price contributions of the multilateral trading venues at the end of a trading day are also found to be much higher than those of LSE, which reinforces the view that MTFs lead price discovery. The trading stoppages hypothesis, which is supported by Cyree and Winters (2001), stated that the moving of prices away from the optimal position at the end of a day is the result of arriving overnight information, and the price movement at the end of a day is in need of initiation of opening trade for the following trading day. The greater price movements of BATS and Turquoise at the end of a day may be an indication of informed traders' preference of venues for price discovery.

6 | CONCLUSIONS

Back to year 2000 at the Financial Markets Conference of the Federal Reserve Bank of Atlanta, Chairman of the Board of Governors Alan Greenspan mentioned that "concern that this fragmentation (of order flow) will harm the price discovery process, investors' ability to obtain the best executions, and overall market liquidity are driving many policy questions." (see also Tse, Bandyopadhyay, & Shen, 2006.) Seven years later, however, a European Law on financial services which promotes multi-market trading of similar underlying assets has been passed. The Markets in Financial Instruments Directive (MiFID), the cornerstone of the pan-Europe regulatory framework, came into force on 1st November 2007. It aims to build a more harmonised European financial market through the removal of the "concentration rule'. Consequently, MiFID has caused a proliferation of Multilateral Trading Facilities (MTFs) and increased competition across different trading venues. Is the gain in the market share for MTFs beneficial for market quality? Our paper examines the questions as to whether the dominant position of traditional primary markets is challenged by the competition, and whether MTFs contribute to price discovery in financial markets. In particular, we analysed and explained whether MTFs are able to disseminate and incorporate price information, as well as whether the prices for the same security at different trading venues reflect the common information for the underlying asset value. Our research findings are summarised as follows:

1. In line with the CESR 2009 reports, the declining trend in the average order size is observed throughout the years after MiFID. It is also interesting to note that the number of trades is much higher in the post-MiFID period than the pre-MiFID period. This could be due to a combined effect from the proliferation of high frequency trading and the

transparency waiver with MiFID. More specifically, there is a large-in-scale waiver for pre- and post-trade transparency, and the large-in-scale threshold is determined by the average order size. Therefore, investors could have incentives to reduce order size and exploit the benefit from these transparency waivers.

2. The prices formed by different trading venues for the same stock are co-integrated with a long-run underlying informational equilibrium. This indicates that the proliferation of MTFs and the competition between trading venues do not harm the information contained in prices. The trading activities for a stock in different venues show a convergence pattern, which is the result of arbitrage. This, in turn, suggests that MTFs are able to incorporate and disseminate price information to facilitate price discovery.
3. The result based on the Gonzalo and Granger (1995) common factor weight approach suggests that all trading venues, especially BATS and Turquoise, significantly contribute to the informational common long-term factor for the underlying asset value.
4. Unlike Riordan et al. (2011), where Turquoise is found lagging behind other MTFs and is more likely to have contained stale information, our paper shows that Turquoise leads price discovery over LSE. These new changes in the market share revealed in our analyses indicate that MTFs have gained some success over LSE, which may be relevant to low latency and low-cost trading that they offer. However, due to data constraints, the relationship between low latency, low-cost trading and the preference of informed traders cannot be tested in this study.
5. The results based on Huang's (2002) weighted price contribution method suggests that intra-day price contributions of MTFs are higher than those of LSE, especially during the first and last periods of the day. The estimated average daily price contributions are consistent with this result.

ENDNOTES

[1] The Markets in Financial Instruments Directive (MiFID) replaced its predecessor, the Investment Services Directive (ISD) and came into force on the 1st of November in 2007. It aims to promote a harmonized European financial market through a pan-Europe regulatory framework for more efficient supervisions, as well as cultivating competition among trading venues to foster a fair game market.

[2] The first pan-European equities exchange Chi-X Europe was launched in 2007, followed by BATS Europe in the subsequent year. In February 2011, BATS Global Markets agreed on the purchase of Chi-X Europe for $300 million. The deal was referred to the Competition Commission by the Office of Fair Trading to investigate further whether substantial lessening of competition was possible resultant from the anticipated merger in June 2011. However, the Commission approved the transaction in late November 2011, which caused BATS to close the deal on 30th November 2011.

[3] The LIT order book refers to transparent limited order books that are operated by RMs (Regulated Markets) and MTFs, which is the opposite of the “Dark” order book.

[4] See, for example, Pagano (1989), Chowdhry and Nanda (1991), Madhavan (1995), Bennett and Wei (2006), and Gajewski and Gresse (2007).

[5] See, for example, Harris (1993), Economides (1996), Hendershott and Mendelson (2000), Boehmer and Boehmer (2003), Foucault and Menkveld (2008), and O'Hara and Ye (2011).

[6] It is also interesting to note that the trading volume for FTSE 100 declined dramatically from £240 billion in 2009 to £172 billion in 2016, which could be the consequence of growth in OTC and dark pools trading revealed in Table 1, Panel (a).

[7] An example of such MTFs that compete with the incumbent exchanges is the Nordic trading facility Burgundy.

[8] The actions available for traditional RMs to counter those competitive pressure include mergers and acquisitions to expand their business regimes.

[9] Due to data restrictions, our study uses ten FTSE 100 constituents that are also traded actively on MTFs.

[10] In contrast, Chowdry and Nanda (1991) suggested fragmentation could lead to an increase in adverse selection risk because of asymmetric information and a “cream skimming” effect.

[11] The empirical applications of the common factor weight method can be found in Booth, So, and Tse (1999), Chu, Hsieh, and Tse (1999), and Harris, McInish, and Wood (2002a).

[12] $S_{i,j} = T^{-1} \sum_{t=1}^{T} R_{it} R'_{jt}$, $i, j = 0, 1$. It captures the residuals R from regressing ΔP_t and on $(\Delta P_{t-1}, \ldots, \Delta P_{t-q+1})$, respectively.

[13] This weighting factor helps control any potential problems caused by heteroscedasticity, as addressed by Barclay and Hendershott (2008), Barclay and Warner (1993), and Vanthuan and Chanwit (2009).

[14] According to the records from BATS Chi-X Europe.

[15] For example—when it is actually 16:30 London time, but the database recorded the price with time stamp 15:30 after offsetting the British summer time. Therefore, the prices between 15:30 and 16:30 in the database are actually from closing auction and after market reports, rather than from continuous trading. Similar issues arise for the pre-opening sessions.

[16] This is similar to the findings in Aitken, Harris, and Sensenbrenner (2010)) and Riordan, Storkenmaier, and Wagener (2011).

[17] Data from Chi-X is unavailable in our study.

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