International Review of Economics and Finance 84 (2023) 756–769

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Does smile help detect the UK's price leadership change after MiFID?

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ARTICLE INFO

JEL classification:
G20
G14
C58

Keywords:
MiFID
Multilateral trading facility
Volatility smile
Weighted price contribution

ABSTRACT

We investigate intraday realised volatility, trading volume, and information transmission following a series of changes to the Markets in Financial Instruments Directive (MiFID) in the UK. We find that multilateral trading facilities attract order flows from the London Stock Exchange (LSE) and hence introduce new dynamics to market provisions, such as volatility and information transmission. In addition, the structure of the order books and market depth changed after the introduction of MiFID in the UK. However, our novel study conveying smile patterns of volatility and volume suggests that the LSE continues to lead the rest of the multilateral venues. This shows that although MiFID has led to market segmentation, there is still clear price discovery among multilateral trading facilities.

1. Introduction

The Markets in Financial Instruments Directive (MiFID)[1] is a European law on financial services introduced in 2007. The highlight of MiFID was to impose transparency obligations on trading venues to disclose all information on their current trades (for example, ask and bid prices and trading interests at those prices) on a continuous basis, which ensures efficiency and facilitates price discovery. Another key factor of MiFID legislation is to allow trading venues to take the unique form of systematic internalisers (bilateral trading venues, BTVs) and multilateral trading facilities (MTFs). In particular, BTVs, mostly operated by investment firms, can internalize order flows and match trades on their own account, whereas MTFs can use pre-settled terms and conditions to prioritise prices and time to match orders from multiple parties. By design, both transparency enhancement and new order flow management aims to attract order flows and promote orderly competition among new and existing trading venues. Subsequently, these regulatory interventions would affect the market structure and most likely introduce new dynamics to volatility and liquidity in regulated markets (Cumming & Johan, 2019). In this paper, we investigate whether MiFID changes have led to new price discovery dynamics and a lead-lag relationship among multiple trading venues. We examine both realised volatility and trading volume to determine whether they still have classic intraday U-shapes.

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[1] Markets in Financial Instruments Directive (MiFID) is a European Law on financial services for the 31 member states of the European Economic Area. Prior to the implementation of MiFID, all regulated markets across Europe enjoyed a dominant position with regard to executing trading orders. The main function of MiFID was to abolish the way that shares were only traded on regulated markets—and this, in turn, laid the foundation for the growth of many multilateral trading facilities (MTFs).

https://doi.org/10.1016/j.iref.2022.11.033
Received 13 February 2022; Received in revised form 2 May 2022; Accepted 25 November 2022
Available online 8 December 2022
1059-0560/

A few competing theories in the literature show that the observed U-shaped patterns in intraday volatility and volume are relevant for private information on future stock prices and trading stoppages. Admati and Pfleiderer (1988) documented an intraday U-shaped[2] pattern in volatility and suggested that informed traders trade private information. The rationale is that informed traders tend to trade infrequently, but in terms of private information, we can expect to find high volatility at that time, because new information is rapidly incorporated into prices through the concentrated trading activity of competing risk-neutral informed traders. Barclay and Warner (1993) further found that intraday trading volumes follow a similar U-shaped pattern. They suggested that this is because informed traders prefer to place large orders during the opening period because trading volume is greatly concentrated in this period, and subsequently place small orders to camouflage their information during periods of low trading volume.

Multiple markets strategically allow traders, which can lead trading to be concentrated not only over time, but also over *locations*. Chowdhry and Nanda (1991) noted that small liquidity traders tend to concentrate on markets with the largest amount of trading because they lack the flexibility to select trading locations. Such markets, in turn, attract more trading by informed and large liquidity traders. When a financial asset trades on several locations simultaneously, this 'winner takes most' feature will result in one of the markets appearing to be the dominant venue for that asset to change hands.[3] The impact of trade concentration on price discovery is for large liquidity traders who split their trades across multiple markets: the more significant the correlation of volumes in different markets, the weaker the informativeness of prices.[4] Moreover, with multiple markets, trading activities across markets could shift with time in a day because correlated markets could have different settings to attract traders. For example, Theissen (2002) and Huang (2002) found that alternative trading venues can attract informed traders because they offer lower trading latency while discouraging uninformed traders due to an increase in adverse selection costs.[5]

Now, with the significant changes in MiFID that result in a natural *multilateral* trading facility, it would be crucial to further expand on the literature and investigate how the 'concentration' of trading can affect both the capacity of MTFs trading and how traders execute orders. From this perspective, we make the following contributions: First, informed traders often act on their private information and trade in great volumes during concentrated periods in a day. Empirical work has uncovered some intriguing features of financial assets, such as smiles. For example, Tzang et al. (2016) showed that the relationship between beta and implied volatilities presents a beta smile. Szu et al. (2011) noted that settlement-price-determined implied volatility is a smile function. In this study, we complement the literature and identify that trading volumes across MTFs present smile patterns. This reveals the trading behaviour of the new market (e.g., seasonality at the opening and closing), and hence, the possible structural shifts of the order book and market depth to new locations resulting from MiFID. Second, there is no doubt that the smile pattern of implied volatility in the literature is a well-known feature of price series (Onan et al., 2014), however, tests using (average) implied volatility are improper and give a false signal (Ahmed & Swidler, 1998). In their empirical analyses, Ahmed and Swidler (1998) used the volatility implied by options on the Oslo Stock Exchange (OSE) and predicted the volatility of stock returns. They suggested that tests of average implied volatility give a false signal that implied volatilities from different options series are noisy observations of future volatility. In this study, we complement the literature on implied volatility by identifying the U-shape of realised volatility, especially when trading is conducted in fragmented markets, such as MTFs. Finally, our novel study on the trade concentration pattern over locations has led us to believe that the capacity of information revealing among multiple trading locations remains strong in the UK.

Our study uses a typical sample of 5-min transaction prices[6] and trading volumes of ten representative stocks cross-traded on the London Stock Exchange (LSE) and two MTFs markets—BATS Europe and Turquoise. We address three key questions: 1) Does the U-shaped pattern in realised volatility remain and what does it suggest for the price leadership shift between regulated and MTFs markets after MiFID? 2) Is there a shift in price formation between markets, reflected by the lead-lag relationship of their volatility? 3) Does the U-shaped pattern in trading volume remain and what does it infer about the liquidity change of an MTFs market after MiFID? We find that a lead-lag relationship exists that is connected to a shift in price formation from LSE to BATS and Turquoise. Overall, MiFID was effective in improving the market quality of MTFs.

This article is organised as follows: Section 2 examines the literature, Section 3 describes the data and methodology, Section 4 presents the empirical results and discussion, and Section 5 concludes the paper. Our study of the fundamental regulatory changes brought about by MiFID is summarised in the appendix.

2. Literature review

Empirical studies on intraday volatility and trading volumes have identified a common U-shaped pattern in these data. Two competing theories explain this pattern: private information about future security prices and trading stoppages. Admati and Pfleiderer (1988) suggested that diverse private information causes trading to cluster around that of privately informed traders because informed traders trade their private information. If informed traders' trading occurs once a day, the time of trading is always early in the morning, for example, at 8:45 a.m. Therefore, we expect to find high intraday rate changes at 8:45 a.m. (Cyree & Winters, 2001). High

[2] See Section 2 for a review of the competing theories explaining the U-shaped pattern in intraday financial data.

[3] Chowdhry and Nanda (1991) assume that traders have no discretion to move between markets.

[4] As there exists little opportunity to exploit private information through that avenue.

[5] Also, Boehmer et al. (2005) and Nguyen and Phengpis (2009) find evidence that the different levels of transparency among trading venues could result in price leadership shifts.

[6] This is because persistent volatility is quite common at the daily horizon and a study of intra-day realised volatility is a better presentation (Andersen et al., 2001).

volatility results in this period because new information is rapidly incorporated into prices through the concentrated trading activities of informed traders. Brock and Kleidon (1992) suggested that stoppages cause the need to trade at daily trading. Their findings show a relatively inelastic hedging demand adjacent to periods of market closure. Spindt and Hoffmeister (1988) showed that a higher intraday variance is captured at the close, as banks trade more aggressively at the end of the day to offset deviations from their end-of-the-day target reserve balance. Further, Hong and Wang (2000) and Slezak (1994) suggested that trading is clustered around opening and closing times in markets with private information *and* market closure/overnight trading stops.

Empirical studies on the concentrated pattern of financial data and its implications for information transmission tend to use the weighted price contribution (WPC) method of Barclay and Warner (1993) to measure price discovery in sequential periods. For example, Blau et al. (2009) applied the WPC method to examine the intraday trading activities of NYSE-listed stocks. Their results show that the intraday price changes caused by large traders exhibit a U-shaped pattern, whereas the price changes caused by smaller traders reflect a reversed U-shaped pattern. Lin (2014) also noted a U-shaped intraday pattern for large trades, and a reversed U-shaped pattern for smaller trades. Cao et al. (2000) found that the pre-opening period of the NASDAQ contributes significantly to revealing information. Furthermore, a small fraction of 200 NASDAQ market makers account for approximately 40% of price changes during crosses, and a ranking of market makers' contribution to price changes is produced, which is an indication of market leadership among market makers. Barclay and Hendershott (2008) employed the WPC method to study price discovery and information flows from trading and non-trading mechanisms. Their results indicate that price discovery shifts to the pre-open period as trading volume increases, and the opening price becomes more efficient and informative.

Huang (2002), however, extends the classical WPC method to allow cross-market comparisons of price leadership, with the calculated information share still measured over sequential time periods. The study focuses on electronic communication networks (ECNs) and traditional market makers in NASDAQ and finds that quotes from ECNs are more informative, and that ECNs can also post quotes that are more often at the inside spread. Such results support the view that alternative trading venues and market fragmentation improve, rather than harm, quote quality. Huang (2002) suggested that because the WPC is flexible in making cross-sectional analyses, the method is preferred over other traditional measures of price discovery, such as Hasbrouck's (1995) information share and Gonzalo and Granger's (1995) common factor weights, which were employed in Huang's study.

Theissen (2002) focused on the price discovery process in the German stock market. The study regresses the common factor weights against the relative market share in the form of volume. The results suggest that market leadership is positively correlated with relative trading volume. Additionally, floor-based and electronic exchanges contribute equally to price discovery when using transaction prices, whereas the electronic trading system takes the lead when using quote midpoints. Schlusche (2009) examined the price discovery process of exchange-traded funds in Germany. The results indicate that, although volatility is the driving factor of price discovery, no link is noted between trading volume and price discovery. Blau et al. (2009) examined the intraday trading activities of NYSE-listed stocks. This study regresses the estimated Barclay and Warner (1993) weighted price contributions and the average price change (in cents) per unit volume for stock in interval t for trade-size category j against a volume variable for the stock during interval t. Their results suggest that volume increases monotonically with trade size.

3. Data and methodology

Our empirical work is based on a high-frequency dataset comprising continuously recorded 5-min transaction prices and trading volumes of selected stocks cross-traded on the LSE and MTFs. The reason for using high-frequency 5-min data is that they contain enriched information about the market to extract as much volatility or volume information as possible. Moreover, at some ultrahigh frequencies, data may contain microstructure noise. Therefore, a 5-min interval was considered for this study so that the microstructure noise was not overwhelming (Andersen et al., 2001).

Our analyses of intraday data are based on selected stocks from the FTSE100 constituents that are actively traded on two MTFs: BATS Europe and Turquoise. We initially sought to consider Chi-X, which has the highest market share among all the MTFs in the UK market; however, transaction price data on a wide range of stocks from the Chi-X order book are unavailable. Therefore, we turn to BATS and Turquoise, the second and fourth largest MTFs, in terms of their market share, because they are the only two MTFs providing useable data.

Ten stocks were selected for our analyses: HSBC, BHP Billiton, Vodafone, Rio Tinto, Barclays, GlaxoSmithKline, AstraZeneca, Xstrata, Anglo-American, and TESCO. These stocks are actively traded on the LSE, BATS, and Turquoise. The reason why only ten stocks from FTSE100 are used lies with the fact that the implementation of MiFID did not lead to the introduction of a centrally consolidated tape for all market data across different trading venues, and data vendors may not have full access to market data. During our data collection process, we found missing data across a wide range of stocks, which makes it even more difficult to match the crucial variables for our analyses in order to obtain a coherent data series, especially when we would like the selected stocks to be actively traded on our selected MTFs for this study.

The sample period ranges from January 2010 to October 2013, and we use the time-stamped last transaction price and trading volume for each company across each trading venue for our analyses. Note that this dataset covers the period *after* market fragmentation because our research question is to explore whether the regulatory changes brought about by MiFID affect price discovery in the UK. More precisely, the sample period starts from the third year after the initial implementation of the MiFID in 2007, when the policy changes of MiFID would have taken effect.[7] In addition, the two competing MTFs included in this study (BATS Europe and Turquoise) were launched in late 2008, when the market was experiencing the effects of the 2008 financial crisis. Therefore, we focus our analyses on the period from 2010 after stability is restored following the crisis. Aligning the trading time of all three venues, our analysis covers continuous trading hours from 8:00 to 16:30 h in London.[8] Data were obtained from Thomson Reuters TickHistory.™

3.1. Methodology

In this section, we first explain our empirical construction of Andersen et al.'s (2001) realised volatility and Huang's (2002) weighted price contribution. We illustrate our regression model, as well as the time-varying relative volume by Theissen (2002) and Schlusche (2009).

Existing approaches to measuring return (or price) volatility have distinct weaknesses. Black-Scholes options pricing models suggest that the smiles and smirks in volatility for options written at different strikes imply misspecification of the underlying model. Similarly, GARCH by fitting parametric models suggests that at most one of the models may be correct; hence it is impossible to obtain a strictly correct one. Although these approaches try to fit parametric (and potentially misspecified) models to capture volatility that is inherently *unobservable*, in this study, we use the realised volatility approach by Andersen et al. (2001), which takes a more direct measure of volatility and treats volatility as observed,[9] thereby enabling researchers to directly examine its properties. The approach computes realised volatility by summing the intraday squared returns. By sampling intraday returns across a sufficiently large sample, realised volatility closely approaches the underlying integrated volatility, which is the integral of instantaneous volatility.

Defining X and Y as any two semi-martingales, the covariation of X and Y over h-period $[t-h, t]$ is given by the expected increment to the quadratic covariation:

$$\text{Cov}\ (X(t), Y(t)|\mathscr{F}_{t-h}) = E\big([X,Y]_t\big|\mathscr{F}_{t-h}\big) - [X,Y]_{t-h} \qquad \text{Eq. (1)}$$

where $\mathscr{F}_{t-h}$ is the σ-field reflecting the information at $t-h$.[10]

Further, pk denotes the logarithmic price process and h denotes the number of trading days over which the volatility measures are computed ($h \geq 1$). The h-period quadratic variation and covariation for $t = h, 2h, \dots, T$ are defined as follows:

$$\text{Qvar}_{k,h}\ (t) \equiv [p_k, p_k]_t - [p_k, p_k]_{t-h} \qquad \text{Eq. (2)}$$

$$Q\text{cov}_{kj,h}\ (t) \equiv \big[p_k, p_j\big]_t - \big[p_k, p_j\big]_{t-h} \qquad \text{Eq. (3)}$$

where $[p_k, p_k]$ is the quadratic variation process, and $[p_k, p_j]$ is the covariation process.

Eq. (1) implies that the h-period quadratic variation and covariation are related to the conditional return variance and covariance in the common econometrics literature:

$$\text{Var}\ (p_k(t)|\mathscr{F}_{t-h}) = E\big[Q\text{var}_{k,h}\ (t)\big|\mathscr{F}_{t-h}\big] \qquad \text{Eq. (4)}$$

$$\text{Cov}\ \big(p_k(t), p_j(t)\big|\mathscr{F}_{t-h}\big) = E\big[Q\text{cov}_{kj;h}\ (t)\big|\mathscr{F}_{t-h}\big] \qquad \text{Eq. (5)}$$

These conditional variance and covariance processes become distinct from the quadratic variation and covariation processes through an error term. Following Andersen et al. (2001), this is acceptable because the conditional variance and covariance are ex ante, whereas the quadratic variation and covariation are ex post. Hence, quadratic variation and covariation can be treated as unbiased measures of the conditional variance and covariance common in the econometrics literature, which is theoretical and unobservable. In a practical context, they facilitate volatility analysis.

Then, we cumulate the relevant intraday return products over the required time horizon. In other words, for the price series on financial asset k to be sampled m times per day, the time-t realised h-period volatility is:

$$var_{k,h}(t;m) = \Sigma_{i=I\dots,mh} r^2_{k,(m)}\left(t-h+\left(\frac{i}{m}\right)\right) \quad (t = h, 2h, \dots, T) \qquad \text{Eq. (6)}$$

where $r_{k,(m)}$ is the return on asset k over $[\mathrm{t}-1/\mathrm{m}, \mathrm{t}]$ which takes the form of:

$$r_{k,(m)}(t) \equiv p_k(t) - p_k(t-1/m), t = 1\big/m, 2\big/m, \dots, T \qquad \text{Eq. (7)}$$

and $\mathrm{m} > 1$ corresponds to high-frequency intraday returns, whereas $\mathrm{m} < 1$ suggests daily returns.

[7] Buckle et al. (2018) show that the trading of FTSE 100 shares through LSE LITs exhibits a decreasing trend as its yearly-average order size and volume decline especially after the year 2010 where the effect of MiFID has passed through.

[8] In our main result graphs, the plots go beyond 15:30pm so that we can demonstrate the close-bell trading in LSE even though the other two exchanges should have ceased the continuous trading of the day.

[9] In the case of direct measures of volatility, however, some of them (for example, the ex-post squared returns) are found contaminated by the error term.

[10] The quadratic variation and covariation processes [X, X] and [X, Y] are given by: $[\mathrm{X},\mathrm{X}] = \mathrm{X}^2 - 2\int \mathrm{X}_{-}\mathrm{dX}$ $[\mathrm{X},\mathrm{Y}] = \mathrm{XY} - \int \mathrm{X}_{-}\mathrm{dY} - \int \mathrm{Y}_{-}\mathrm{dX}$

For a sufficiently large m, the time-t realised h-period volatility characterised by Eq. (6) provides a good approximation of the quadratic variation because for all $t = h, 2h, \ldots, T$,

$$\text{plim}_{m->\infty}\ \text{var}_{k,h}\ (t;m) = \text{Qvar}_{k,h}\ (t) \quad \text{Eq. (8)}$$

Our empirical construction of the realised volatility of Andersen et al. (2001),[11] is based on Eq. (6), where the realised volatility of an asset traded during the kth period on the ith day at the jth venue is calculated as:

$$Vola_{k,i,j} = \sum_{n=1}^{6} \Delta P_{j,n}^2 \quad \text{Eq. (9)}$$

where ΔP_j is the price change from the jth trading venue at a 5-min frequency, such that $\Delta P_j = P_j - P_{j-1}$. To observe the volatility across all three markets, considering there might be some natural lead-lag, we choose to look at the volatility measures every half an hour. This means that with a 5-min frequency, $n = 6$ in Eq. (9).

The intraday weighted price contribution is estimated based on the findings of Huang (2002), who calculated the relative contribution of one trading venue to the total price change at intraday periods for a given asset; therefore, the market (or price) leadership may be tested and compared. Central to Huang's findings (2002) is the intraday breakdown of price variations at each of $j = 1, 2$, and 3 trading venues, where the price contribution from the jth trading venue during the kth trading hour on the ith day, denoted by $WPC_{k,i,j}$, is defined as follows:

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

$$\Delta P_{k,i,j}(\%) = \frac{\Delta P_{k,i,j}}{\sum_{j=1}^{3} \Sigma_{t=1}^{k} \Delta P_{k,i,j}} \quad \text{Eq. (10)}$$

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

$\Delta P_{k,i,j}$ is the price change at the jth venue during the kth trading interval on the ith day and W_i is the weighting factor of the price changes on the ith day. For our empirical analyses, the intraday weighted price contribution of each trading venue over the post-MiFID sample years is generated according to Eq. (10) above. Each trading day contains 17 half-hour periods, starting from 8:00 h until 16:30 h in London.

The regression is performed on each of the ten stocks traded at LSE, BATS, and Turquoise:

$$WPC_{k,i,j} = \beta_0 + \beta_1 Vola_{k,i,j} + \beta_2 RVol_{k,i,j} + \varepsilon_{k,i,j} \quad \text{Eq. (11)}$$

where $WPC_{k,i,j}$ is the weighted price contribution of an asset traded at the jth trading venue to the total price change of the same asset traded across the three trading venues during the kth period on the ith day; $Vola_{k,i,j}$ is the realised volatility of an asset traded during the kth period on the ith day at the jth venue; and $RVol_{k,i,j}$ is the relative trading volume of an asset at the jth venue to its total trading volume across all three exchanges during the kth period on the ith day. We follow Theissen's method (2002) to calculate the intraday relative trading volume $RVol_{k,i,j}$ as:

$$RVol_{k,i,j} = \frac{Volume_{k,i,j}}{\sum_{j=1}^{3} Volume_{k,i,j}} \quad \text{Eq.(12)}$$

where $Volume_{k,i,j}$ is the trading volume of asset during the kth period on the ith day at the jth venue.

4. Results

4.1. Modelling intraday realised volatility and information share

Fig. 1 shows the average realised volatilities of the ten stocks for each exchange. In general, these realised volatilities are U-shaped or near-U-shaped, consistent with many studies that detect a similar smile pattern of volatility. In the mornings, all venues see high levels of volatility at the opening hours, which subsequently decreases. The volatility level at the LSE consistently exceeds the other

[11] This is an unrestricted measure of realised volatility, which is widely employed in the literature.

two patterns, although they follow one another closely, which may suggest that BATS and Turquoise tend to attract order flows from the LSE after MiFID, and MiFID may have introduced new dynamics to volatility in the UK market *because the concentrated trading activities of competing risk-neutral informed traders start to appear in the two MTFs in the opening*. Furthermore, all volatilities increase prominently during closing hours. For example, the LSE exhibits a sharp volatility increase during 15:30–16:00. The same trend was observed in BATS and Turquoise during 14:00–14:30. If one considers an hourly time difference between London and Europe, the volatility surge due to close-bell trading is almost synchronous across the LSE and the two MTFs, producing a U-shaped pattern of realised volatilities. However, if we observe the pattern strictly according to the closing time, the two MTFs' end-of-day volatility hikes arrive earlier and die down more quickly, which we do not observe in the LSE. This may indirectly reflect that both BATS and Turquoise, when compared to LSE, are relatively young exchanges; therefore, trading may not be as active as LSE, and the volatility changes may be well dominated by the occurrences in LSE.

Overall, all three volatility patterns remain approximately U-shaped, although LSE demonstrates a noisier pattern compared with BATS and Turquoise. However, we found some interesting intraday seasonality phenomena. From 12:30 to 2:00 p.m., volatility in LSE sharply rises. Then, it quickly collapsed back to its original level at approximately 2:30 p.m. This reflects that the market speculations on the exchange's afternoon announcement (usually at 2:00 p.m. if there is some significant news around the market). Once the announcement status is clear, the London market corrects itself. Looking at BATS and Turquoise, we observe that volatilities start to rise at approximately the same time as they also speculate on the potential LSE market announcement. We see that this increase also declines later, but neither reaches the same high level nor continues to increase as long as the LSE. This shows that both MTFs are dominated by the LSE's trading and news announcements.

Table 1 reports the weighted price contributions of the ten stocks traded over the three stock exchanges. We find that *both BATS and Turquoise yield marginally higher intraday price contributions than LSE, which generally appears during the first and last half-hour of the day*. For example, in 2012, BATS and Turquoise both contributed 5.88% to the overall price changes during the first period of the day, whereas LSE contributed 5.56% only.[12] The estimated daily price contributions (presented at the bottom of Table 1) show that the price contributions of these three exchanges are close, which may explain why the volatility smiles of the two MTFs coincide closely with the LSE. However, the important point is that the WPC results clearly suggest that MiFID introduced fragmentation into the market.

The regression results for the relationship between the intraday weighted price contribution of a stock, its realised volatility, and relative trading volume are presented in Table 2. We find significant and positive coefficients on realised volatility for all stocks across all venues. This means *when volatility of an individual stock is high at one market, its intraday price contribution to the overall price formation in these three trading platforms also increases.* This finding is aligned with that of Theissen (2002) and Schlusche (2009), who noted that volatility is a significant determinant of an asset's information share.

It is important to note that the average values of the coefficients of realised volatility (Vola) estimated for BATS and Turquoise appear notably higher and almost double the same coefficient for LSE,[13] thereby suggesting that these stocks respond to information shocks much more significantly in the MFTs than in LSE. Therefore, the information transmission into their underlying price process would be greater than that into LSE price formation. This may explain why we see the weighted price contributions in BATS and Turquoise are slightly higher than LSE in Table 1. Therefore, we expect the LSE to be dominant in price discovery because its price responses to information shocks are more stable than those of the two new venues. If a lead-lag relationship exists, we could see that LSE leads to major price shifts, whereas BATS and Turquoise might follow despite their own active responses to short-term and spontaneous information shocks.

4.2. Observations on trading volume

Fig. 2 shows the annualised intraday relative trading volumes of the ten stocks in these three exchanges. Although they all exhibit roughly smile patterns, the LSE clearly shows dominance in trading activities reflected by trading volumes. First, the LSE volumes are anywhere higher throughout the trading day relative to the two MTFs. One explanation offered in the literature is that small liquidity traders, who are inflexible in their selection of trading locations, tend to focus on the market with the most significant amount of trading (Chowdhry & Nanda, 1991). Second, if one observes the scale of fluctuations in the volume, the LSE tends to show a noisier pattern with a prominent concentration of trading at the opening and closing hours. However, during the closing hours for BATS and Turquoise (15:00–15:30), their trading volumes either go static or only gently rise. Both MTFs responded with sharp increases in their volumes between 14:30–15:00. In contrast, we did not observe any volume surges in BATS and/or Turquoise before LSE. These findings can lead us to believe that the LSE leads price discovery in the sense that price seasonality, such as opening and closing effects, can be better distinguished, whereas the price seasonality of the two MTFs does not always coincide with these trading timings, but rather with the LSE's volume changes. The fact that Turquoise sees a gentle rise in volume after 15:00 provides the possible assumption that some orders may flow through the LSE.

Interestingly, the volumes of the two MTFs fluctuate (primarily increase) much more during the second half of the day and are higher at closing than at opening. This has implications for the order book structure and market depth. Traders can place their trades on alternative trading venues during the remainder of the day, as they are concerned about high volatility and uncertainty in the

[12] At the closing period, we see LSE contributes only 0.20% whereas the two MTFs contribute 1.71% and 1.66% price variations. However, this might not be comparable because the two MFTs should have officially finished trading of the day.

[13] There are occasional cases that the volatility coefficients of a stock on Turquoise exceed its coefficient on LSE.

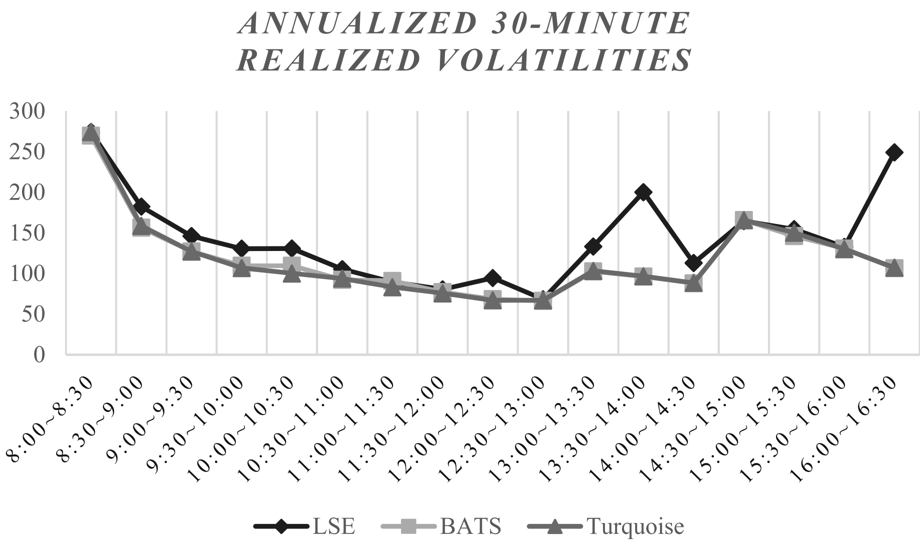

Fig. 1. Annualised Realised Volatilities Across the Ten Chosen Stocks
The annualised 30-min realised volatilities are calculated following Andersen et al. (2001). We first construct the volatilities every 30 min, according to Eq. (9), for each stock at each trading venue. The total of these 30-min realised volatilities is averaged daily. The calculated daily volatilities are averaged to determine annualised realised volatility for each stock at each trading venue. Finally, the average of the annualised realised volatility across the stocks is taken.
Notes: 1. In general, these realised volatilities are U-shaped or near U-shaped. 2. The volatility level at LSE exceeds the other two patterns though they follow one another closely, which may suggest BATS and Turquoise attract order flows from LSE after MiFID. 3. All volatilities increase prominently at the closing. For example, LSE exhibits a sharp volatility increase during 15:30–16:00. The same trend is captured in BATS and Turquoise during 14:00–14:30. If we observe the pattern according to the closing time, the two MTFs' end-of-day volatility hikes arrive earlier and die down more quickly, which we do not observe in LSE. 4. The data also brings interesting intra-day seasonality phenomena. After 12:30 until 2pm, the volatility in LSE sharply arises before it quickly collapses back to its original level at around 2:30pm. This could reflect that the market speculates on LSE's afternoon announcement. 5. For BATS and Turquoise, their volatilities start to rise at about the similar time as they also speculate on the LSE market announcement. Such an increase also declines later on but it never reaches the same high level as LSE.

primary market (LSE) in the morning. This indicates that MiFID imposes market segmentation. In addition, opening the US market may lead to an increase in the trading volume of an MTFs during the second half of the day.

In Table 2, RVol is the coefficient that indicates the relationship between the weighted price contribution of a stock and its relative trading volume. We observe that this coefficient tends to be positive across boards. This suggests that when trading of a stock is active at one market, the intraday price contribution to the overall price formation in all three trading platforms also increases. The average RVol coefficients of the two MTFs are similar, with 9.45E-6 for BATS and 9.23E-6 for Turquoise. However, the regulated market LSE has witnessed a much more positive coefficient of 1.12E-5, implying that the exchange's trading volumes affect the weighted price contributions more. This validates our previous discussion of volatility and price discovery, where the MTFs volatility pattern does not overpower that of the LSE (Fig. 1), nor are their WPCs more statistically significant than the LSE's WPC (Table 1). This result is also supported by the trading volume patterns in Fig. 2, where the price leadership of the LSE is retained.

Table 3 reports additional statistics of the trading volumes for the ten cross-traded stocks. In all cases, the average volumes at LSE are about 7–10 times higher than BATS and Turquoise. This may suggest that although informed traders can benefit from faster price discovery and more effortless exploitation of informational advantages offered by the MTFs, these benefits for informed traders may result in adverse selection costs for other traders, including uninformed traders, who are quite substantial.

5. Conclusion

This study examines how market fragmentation and competition affect trading across multiple venues. To do this, we investigate the intraday realised volatility, trading volume, and information transmission, following the introduction of MiFID in the UK. We find that the multilateral trading structure has resulted in interesting trading patterns across different exchanges: the intraday realised volatility retains the smile shape in all venues, despite fluctuations in the afternoons. Trading volume patterns also generally take a U-shape within a trading day. However, the LSE clearly dominates the BATS and Turquoise. First, both the levels of volatility and volume are much higher in the LSE than in the other two venues. Second, despite BATS and Turquoise trading 1 h ahead of LSE, we never observe any spikes in the volatility or trading volumes that occurred in BATS and/or Turquoise before appearing in LSE. Observing the scale of fluctuations in these two indicators, LSE tends to show much noisier patterns. Therefore, we conclude that price movements in the LSE lead to the rest of the multilateral venues. This shows that MiFID has imposed market segmentation, and there is clear price discovery among MiFID markets.

The limitations of this study mostly arise from the unavailability of data characterising some critical variables, which would have

Table 1

Intraday & Daily Average Weighted Price Contribution During Post-MiFID Period

*Table 1 reports the calculated weighted price contributions of the ten stocks traded over the three exchanges. The daily average weighted price contribution is reported at the bottom of the table. * signifies the case where the estimated weighted price contribution is the smallest among the three equivalent estimates of the same year.*

	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. BATS and Turquoise yield marginally higher intraday price contributions than LSE, which generally appears during the first and last half-hour of the day. For example, in 2012, BATS and Turquoise both contribute 5.88% towards the overall price changes during the first period of the day, while LSE contributes 5.56%. 2. The daily price contributions show that the price contributions of these three exchanges are close, which may explain why the volatility smiles of the two MTFs coincide with LSE tightly. But the important point is that the WPC results clearly suggest that MiFID has introduced market fragmentation.

Table 2

Regression Analysis of Weighted Price Contributions on Realised Volatility and Relative Trading Volume

This table provides the OLS regression results on Eq. (11), performed for all ten selected stocks traded separately at three trading venues: LSE, BATS Europe, and Turquoise. The dependent variable is the price leadership measurement $WPC_{k,i,j}$, and the independent variables are the realized volatility $Vola_{k,i,j}$ and relative trading volume $RVol_{k,i,j}$. The asterisks signify coefficient significance at 1% level. The last column of the table captures each market's average response of price contribution to a unit change in volatility and volume.

	AAL	AZN	BARC	BLT	GSK	HSBC	RIO	TESCO	VOD	XTA	Average
LSE											
Vola	1.25E-6***	2.26E-7***	1.46E-5***	7.15E-7***	1.19E-6***	1.57E-6***	4.92E-8***	3.40E-5***	7.33E-5***	1.81E-7***	1.27E-5***
RVol	4.55E-6***	1.71E-5***	1.14E-5***	5.96E-6***	1.54E-5***	1.45E-5***	9.14E-6***	1.21E-5***	6.76E-6***	1.52E-5***	1.12E-5***
R-squared	0.02715	0.02316	0.01082	0.00950	0.00337	0.00346	0.00776	0.04174	0.10142	0.00213	0.02305
BATS											
Vola	9.45E-7***	1.80E-6***	5.17E-5***	1.03E-6***	6.40E-6***	3.50E-5***	2.48E-7***	3.80E-5***	0.000116***	1.92E-6***	2.53E-5***
RVol	1.06E-5***	1.43E-5***	9.17E-6***	6.17E-6***	4.62E-6***	7.02E-6***	7.06E-6***	1.56E-5***	7.91E-6***	1.20E-5***	9.45E-6***
R-squared	0.02511	0.02116	0.09229	0.03791	0.03829	0.09295	0.06967	0.24809	0.12798	0.15914	0.09126
Turquoise											
Vola	1.31E-6***	1.78E-6***	5.50E-5***	9.89E-7***	6.35E-6***	3.38E-5***	2.54E-7***	3.74E-5***	0.000117***	1.93E-6***	2.56E-05***
RVol	6.31E-6***	1.50E-5***	9.02E-6***	6.52E-6***	4.64E-6***	7.76E-6***	6.88E-6***	1.58E-5***	7.95E-6***	1.24E-5***	9.23E-06***
R-squared	0.03235	0.02229	0.10315	0.03599	0.03587	0.09156	0.06819	0.24521	0.12918	0.15992	0.09237

Notes: 1. We find significant and positive coefficients on realised volatility for all stocks across all venues. This means when volatility of an individual stock is high at one market, its intraday price contribution to the overall price formation in these three trading platforms also increases. 2. The average values of the coefficients on realised volatility (Vola) estimated for BATS and Turquoise appear almost doubled the same coefficient for LSE. This suggests that these stocks respond to information shocks much more significantly in the MFTs than in LSE. Thus, we expect the LSE to be dominant in price discovery as its price responses to information shocks are more stable. 3. The coefficient on relative trading volume (RVol) remains positive across the board. This suggests that when trading of a stock is active at one market, the intraday price contribution to the overall price formation in all three trading platforms also increases. 4. The average RVol coefficients of the two MTFs are similar, with 9.45E-6 for BATS and 9.23E-6 for Turquoise. LSE, however, has witnessed a much more positive coefficient 1.12E-5, implying that the exchange's trading volumes affect the weighted price contributions more.

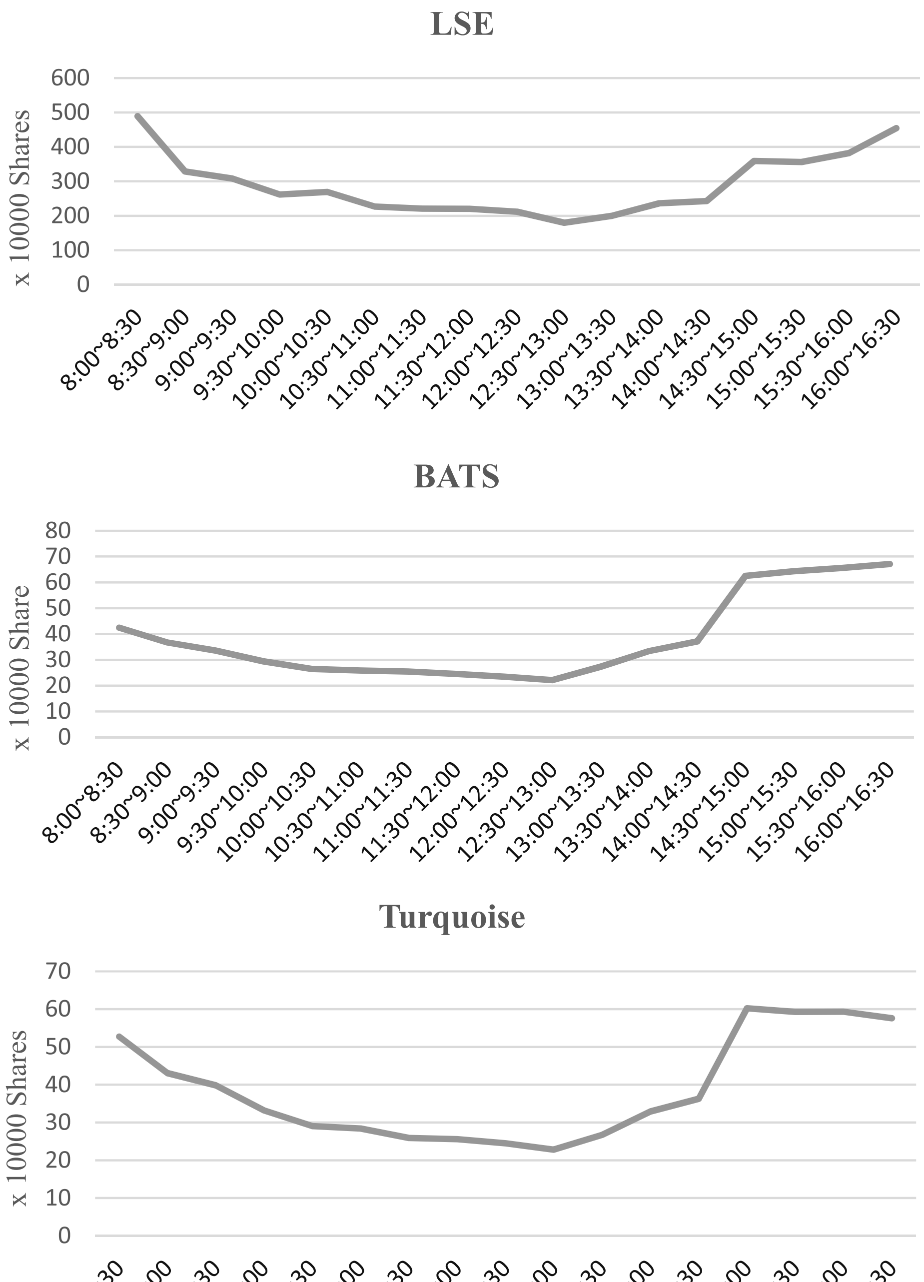

Fig. 2. Annualised Relative Trading Volumes Across the Ten Chosen Stocks

The annualised 30-min relative trading volumes are calculated as follows. We first construct the relative trading volumes every 30 min, according to Eq. (12), for each stock at each trading venue. The total of these 30-min relative trading volumes is averaged daily. The calculated daily volumes are averaged to determine annualised relative trading volumes for each stock at each trading venue. Finally, the average of the annualised relative trading volumes across the stocks is taken.

Notes: 1. The intraday relative trading volumes all exhibit roughly smile patterns, however, with LSE showing dominance in trading activities. 2. LSE's volumes are anywhere higher throughout a trading day relative to the two MTFs. They also show a nosier pattern with prominent concentration of trading at the opening and closing hours. 3. During the closing hours for BATS and Turquoise (15:00-15:30), their trading volumes either go static or gently arise. Both MTFs respond with sharp rises in their volumes between 14:30-15:00. These volume surges never come before LSE. 4. Intraday trading volumes at BATS Europe and Turquoise fluctuate (primarily increase) much more during the second half of the day and are higher at the closing than the opening. This shows that the structure of the order book and market depth has changed after MiFID in the UK.

Table 3
Descriptive statistics of the trading volume.

	AAL	AZN	BARC	BLT	GSK	HSBC	RIO	TSCO	VOD	XTA
LSE										
Mean	31,917.69	21,762.40	411,695.40	56,110.23	63,530.98	202,875.70	41,790.62	146,961.50	917,838.20	82,313.40
Median	20,153.50	11,846	268,703	36,062	34,781	112,545.50	27,049	79,505	542,830.50	48,398
Maximum	2,317,444	2,743,302	1.02E+08	4,753,146	8,485,758	27,585,383	2,562,375	30,195,277	85,538,933	14,016,766
Std. Dev.	52,095.21	58,150.18	879,466.40	97,487.23	159,568.90	502,544.90	63,465.70	440,264.60	2,053,248	147,754.90
BATS										
Mean	4987.14	3535.15	53,245.20	9540.09	11,924.48	30,410.26	5620.116	17,345.11	158,250.60	13,078.04
Median	3447	2261.50	35,340	6086.50	7232	19,034	3899	10,176	104,644	7752
Maximum	113,573	170,650	1,081,006	187,386	719,418	620,279	102,180	871,171	1,626,964	353,950
Std. Dev.	5352.14	4292.37	58,097.82	11,113.28	15,850.85	35,834.60	5917.10	25,555.31	170,534.70	16,640.72
Turquoise										
Mean	3863.32	2529.47	47,303.31	8323.07	9118.88	18,667.59	5004.65	19,559.29	56,507.57	11,238.86
Median	2433	1537	30,513	5531	5755	12,118	3429.50	11,375	37,302.50	6662
Maximum	118,758	89,109	998,991	157,909	452,120	760,854	145,177	1,468,032	1,439,201	306,604
Std. Dev.	4761.61	3239.02	55,495.25	9191.62	11,495.12	22,760.38	5505.86	33,141.55	69,080.21	14,170.18

Notes: Table 3 reports the descriptive statistics of the trading volumes for the ten cross-traded stocks. In all cases, the average volumes at LSE are about 7 to 10 times higher than BATS and Turquoise. This might suggest that although informed traders can benefit from informational advantages of the MTFs, these benefits may result in adverse selection costs for other traders including uninformed traders, which are substantial.

shed more light on the processes under investigation. The WPC method was initially introduced to test which trade size moves the prices. If the data for trading size and identity of market makers are available, the WPC method could be applied to them to better understand the price discovery process. This study relies on the transaction prices. If quote data were to be used, it would be possible to measure effective spread, market depth, and price efficiency. Consequently, this study provides a more detailed understanding of the price-discovery process.

Author statement

Mike Buckle: Conceptualization Supervision, Jing Chen: Conceptualization, Supervision, Investigation, Validation, Qian Guo: Writing- Reviewing and Editing, Investigation, Validation, Xiaoxi Li.: Data curation, Methodology, Software, Writing- Original draft preparation.

Declarations of competing interest

None.

Appendix

Institutional Details of MiFID and Key Regulatory Changes after MiFID

The Markets in Financial Instruments Directive (MiFID) is European law on financial services that came into force on 1st November 2007.[14] MiFID has its origins in its predecessor, the 1993 Investment Services Directive (ISD), which aimed to build a harmonised European financial market and provide principles for law-making in national security markets so that regulations can be mutually recognised across EU countries. ISD focuses on equity markets in the first instance. One of the critical legislations of ISD, known as the passport rule, allowed investment firms authorised and supervised domestically to provide investment services in other EU countries. However, it did not take long for the EU to realise that the ISD required serious revision. With the proliferation of alternative trading systems (ATSs) and electronic communication networks (ECNs) due to advancements in information technology and financial innovation, the division between regulated markets and investment firms became increasingly blurred—new regulations had to be flexible enough to accommodate and foster future innovations in trading. Moreover, the regulatory compliance required by investment firms conducting cross-border business may be interpreted differently by member states, which does not facilitate the implementation of passport rule.

Another key legislation of ISD, known as the concentration rule,[15] allowed government authorities to stipulate that retail investor orders should be executed only in a regulated market. Although the legislation has been defined, its implementation in EU member states differs significantly. According to Davies et al. (2006, pp. 163–197), Spain, Italy, and France were significantly influenced by the concentration rule, which forced all investors to execute their orders up to a specific size within the domestically regulated market. Gomber and Gsell (2006) pointed out that although Germany did not implement the concentration rule, the country followed a default rule, which requires transactions to be executed in a regulated market unless the investor chooses to trade outside exchanges on a per-order basis. In some extreme cases, such as in the UK and some Nordic countries, there was neither a concentration rule nor a default rule, thereby indicating that these nations either executed orders outside a regulated market or internalised them. However, there were always tax requirements or other regulatory enforcements to ensure that these trades occurring outside exchanges were relatively expensive, which put alternative trading venues at a disadvantage in a competitive environment and gave domestically-regulated markets a quasi-monopoly position.

Overall, MiFID replaces its predecessor, the 1993 Investment Services Directive (ISD), and focuses mainly on new order routing and trade transparency for prudential supervision to provide a better regulatory environment, ensuring investor protection and remaining flexible enough to allow for new markets and financial services.

New Order Routing

Under MiFID, trading venues take the unique form of regulated markets (RMs), multilateral trading facilities (MTFs) (multilateral trading venues),[16] or systematic internalisers (SIs) (bilateral trading venues).[17] MiFID aims to closely align the former two categories of trading venues to provide the same level of supervision, subject to similar operational costs, and thus create a level playing field for

[14] MiFID constitutes a major part of the Financial Services Action Plan (FSAP), which was set out by the European Commission in May 1999. The centerpiece of FSAP is the 42 measures to foster applicable legislative tools and build administrative structures with the aims of 1) constructing a single market for wholesale financial services across Europe, 2) opening up and securing the retail markets, and 3) creating stronger rules to provide prudential supervision.

[15] This corresponds to Article 14(3) of the 1993 Investment Services Directive (ISD).

[16] Multilateral trading venues use the pre-settled terms and conditions to set up prices and time priority to match orders from multiple parties under the non-discretionary principle.

[17] The bilateral venues are mostly operated by investment firms. They internalize order flows and match trades on their own account.

these trading venues. Under Article 4(1)(14), regulated markets are defined as 'a multilateral system operated and/or managed by a market operator, which brings together or facilitates the bringing together of multiple third-party buying and selling interests in financial instruments—in the system and in accordance with its non-discretionary rules—in a way that results in a contract, in respect of the financial instruments admitted to trading under its rules and/or systems, and which is authorized and functions regularly and in accordance with the provisions of Title III.' In Article 4(1)(15), MTFs are defined as 'a multilateral system, operated by an investment firm or a market operator, which brings together multiple third-party buying and selling interests in financial instruments—in the system and in accordance with non-discretionary rules—in a way that results in a contract in accordance with the provisions of Title II.' Titles III and II refer to the regulatory authorisation and operating conditions set by MiFID, with regard to the two trading venues, respectively. They generally give the RMs and MTFs similar functionalities and operational requirements, with an aim to closely align the regulatory frameworks for the RMs and MTFs and provide the same level of supervision. Unlike the multilateral system provided by RMs and MTFs, the systematic internalizer (SI) is a bilateral trading facility that deals with order flows and matches trades on its own account.[18]

Transparency Issues for Prudential Supervision

The MiFID imposes trade transparency obligations on trading venues to disclose all information on their current trade on a continuous basis. Such information may include the ask and bid prices and the volume of trading interests at those prices, thereby effectively reflecting the market depth. Although transparency obligations for trading venues are enforced, competent authorities have the right to waive the obligations of trading venues to make pre-trade information public.

To conclude, before the implementation of MiFID, all regulated markets across Europe enjoyed a dominant position in executing trading orders. The dominance of traditional regulated markets, enshrined by ISD, was considered an obstacle to reducing transaction costs. The introduction of MiFID provides a classification for regulated markets and multilateral trading facilities, thereby allowing for greater competition between them to reduce trading costs. It also creates a regulated level playing field along with more trading transparency for market efficiency and investor protection.

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[18] Article 4(1)(7) defines the Systematic Internalizer (SI) as 'an investment firm which, on an organized, frequent and systematic basis, deals on own account by executing client orders outside a regulated market or an MTF.'

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