The International Journal of Business Management and Technology, Volume 3 Issue 5 September–October 2019
ISSN: 2581-3889

Research Article Open Access

Determinants of the Trading Fragmentation

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Abstract: In November 2007 the elimination of the concentration of trading on the Regulated Markets has generatedthe phenomenon of fragmentation of trades across multiple venues. The objective of the analysis is double. The first scope is to search empirical results *circa* the fragmentation impact on the liquidity of the transaction with Difference in Difference estimator (or Double Difference). This technique estimates the effect of treatment (MiFID) by comparing the changes in outcomes over time between a subgroup of shares of the FTSE 100 (highly index fragmented) and FTSE MIB (the control group). The second objective is the identification of the variables that have influenced the fragmentation of trading across multiple trading venues. The empirical analysis is estimated through a fixed effect regression. For a better result interpretation, the diagnostic test of Hausmanis performed as well. The results of both analyses show that fragmentation did not have negative effects on the market quality of European stock markets.

Keywords: Difference in Difference, Fixed Effects, Fragmentation, Liquidity, Market efficiency, MiFID

JEL Classification

C1, D40, G10, G14

I. Introduction

The Markets in Financial Instruments Directive (MiFID), in force since November 2007, has represented the core pillar in EU financial markets up until January 2018. The aim was to promote the integration, competitiveness, and efficiency of the financial markets of the European Union. In practical terms, it abolished the obligation of concentration of trading on regulated markets. This through by the competition of the trading venues such as multilateral trading facilities (MTF) [1] and brokers who negotiate over the counter. In the last decade, the number of MTF operating in Europe boomed. Conversely, the exchanges made on regulated markets have suffered a strong reduction, partially because of the ability of some very successful MTF to capture trading activity. All this with the belief that greater competition in Europe has produced positive effects for the investors and for the efficiency of the markets through a reduction in trading costs. However, for one school of the literature, the increase in trading venues has led to a reduction of the liquidity and lower efficiency in the price discovery process and consequently affected the efficiency of markets as a whole. Many papers that analyse the fragmentation have as a reference to the US market. This is because the competition between trading venues is not a new phenomenon in the US. Bennett and Wei [2] affirm that the order flow consolidation is a dominant factor in determining how well markets form prices and provide liquidity that arranges capital efficiently. Hamilton [3] affirms that the competitive effects tend to reduce both the New York Stock Exchange (NYSE) specialist spread and the daily stock variances, more than they do increase with the effect of fragmentation. Pagano [4] [5] concludes that the fragmentation is counterproductive in the two-market case, no classification is possible if it involves off-exchange search. In contrast with this affirmation, there are the positive effects of the fragmentation of trade. Chowdhry and Nanda [6] indicate that in the absence of government regulation, competitive economic forces might facilitate the transmission of information between market locations. Biais [7] compares centralized and fragmented markets. He affirms that the average bid-ask spread is equal in the two markets, but the spread is more volatile in centralized than in fragmented markets other things equal. Battalio [8] compares the bid-ask spread of the securities listed in NYSE before and after the entry of a new competitor. The results suggest that the quoted bid-ask spread does not increase or better still tightens. Huang [9] affirms that the proliferation of alternative trading venues might promote quote quality rather than fragmentation markets. Boehmer and Boehmer [10] study the impact of a new entrant in the NYSE on market quality. The authors show that market entry leads to an improvement in the liquidity that they attribute to the elimination of market marker rents. Nguyen et al. [11] show that the competition effect exceeds the fragmentation effect over a long horizon and that market fragmentation leads to a decrease in trading costs. The authors do not find that more venues harm price efficiency or increase price volatility. O'Hara and Ye [12] find that the effects of the fragmentation regard all stocks; more fragmented stocks have lower transactions costs and faster execution speeds. The results show that fragmentation does not affect to harm market quality. Based on these results, it is clear that the effects of fragmentation on the quality of the market are not unique. It seems to prevail the idea that the benefits of fragmentation are greater of the disadvantages; even if it must be emphasized that most of the studies on the topic are prior to the implementation of the Directive. DeB&DiMarco [13] carried out a survey regarding the papers on the European market quality pre- and post-MiFID going to identify different metrics used in the literature to study the efficiency and integrity of the market. Few studies carried out ex-post, and four empirical studies are considered essential for our analysis because they focused on the effects of the fragmentation of trade of the European equities. Gresse [14] finds that the price quality of large UK and Euronext equities bettered after MiFID, but the mid-caps of the Euronext were adversely affected. Degryse et al. [15] show that visible fragmentation improves the consolidated liquidity, but is bad to the liquidity of the primary exchange. Boneva et al.[16] affirm that visible fragmentation has a positive effect on the variability of volatility, in particular, it decreases. Bastidon [17] analyses the effects of stock markets fragmentation on two types of investors optimization problems: "intermediary" and "final" investors. Tapia [18] focuses on the consequences of the fragmentation on the market liquidity of the Spanish Stock Exchange. The results show that fragmentation has a double effect: it is good for liquidity, but after beyond a certain level it is worse for the liquidity of the regulated market. da Silva [19] studies the proliferation of alternative trading venues in Europe. The empirical results show that fragmentation did not cause a lower price precision, but it suggests that fragmentation correlates positively with volatility.

Within this context, we find the following work, positioning itself in the literature of the microstructure of the post-MiFID markets.

The objectives of our work are dual:

1. To analyse the impact of the fragmentation of trade on the liquidity;
2. To identify the micro and macroeconomic factors, which could create fragmentation of trading across multiple trading venues.

In order, to analyse the impact of fragmentation of exchanges on the liquidity, the method of difference in difference is applied [19] [20]. This provides for the identification of two groups of securities (fragmented and not fragmented) and two periods (before and after the fragmentation process). The control sample is composed of the shares that comprise the FTSE MIB Index, whereas the group of fragmented stocks is composed of the first 40 shares for capitalization that constitute the FTSE100 Index. The different dynamics of liquidity of the stocks are analyzed by comparing 2006 (the year in which even the stocks of the FTSE100 could be considered as less fragmented) to 2014. The choice of the second objective is focused on the factors that have influenced the fragmentation of trade on multiple trading venues, also the strong development of the multilateral trading facilities.

II. Data and Indicators

This section explains the fragmentation index and liquidity indices used in the empirical analysis. The Fragmentation Index (FI) indicates how different shares are traded between primary markets and other trading venues. It shows the average number of venues that would like to visit in order to get the best possible execution at the time of the execution of the order. An index equal to one indicates that the stock is traded on a single trading venue. Its increase indicates fragmentation of trading across multiple locations, and as such, an investor who wishes to negotiate effectively their orders must be able to operate across multiple venues. Once the index exceeds the value of two, the liquidity is so fragmented that it "no longer belongs" to its place of origin. As aforementioned, the index is expressed mathematically through the inverse of the Herfindahl Index, which is for the generic stock:

$$\frac{FI_i = 1}{\sum_{j=1}^{N} \; q^2{}_{i,j}} \qquad (1)$$

where$q_{i,j}$ is the share of trading volume on exchange platform j for the stock i. The index is calculated by referring to regulated markets and multilateral trading venues with visible order books. The main advantage of FI in relation to other measures is that it gives more weight to the seats with larger market shares. The liquidity indicators applied in the analysis, are standard measures used in the literature of market microstructure [21].

Another indicator is the Relative Quoted Spread (RQS), which is based on the difference between the bid and the ask for the stock i at time t. It is a representation of the round trip transaction costs, i.e., the sequence of a transaction of buying and selling a stock. RQS is expressed mathematically by the following structure:

$$RQS_{i,t} = \left[\left(ask_{i,t} - bid_{i,t}\right)/\left(ask_{i,t} + bid_{i,t}\right)/2\right] * 100 \qquad (2)$$

where:

- PX_ASK that is the lowest price, at which a dealer agrees to sell a stock. When closing the market, the price will be the last ask of the last day on which the market is open and, in case there is no ask in the market, the provider provides the data "n/a";
- PX_BID that is the highest price, at which the investor is willing to buy a stock (same PX_ASK survey when the market is closed).

The third indicator is represented by Price Impact (PI) proposed by Amihud [22], which is based on the ratio between return and trading volume of the stock i at day t

$$\frac{PI_{i.t} = |r_{i,t}|}{Turnoverscambi\quad_{i,t}} \qquad (3)$$

where

$$r_{i,t} = log_e \frac{(P_{i,t}}{P_{i,t-1})} \qquad (4)$$

The logic of this indicator is that, if the level of liquidity is high, large trading orders should not lead to significant price changes.

Other variables used in the analysis are:

- $LogMarketCap$represents the logarithm applied to stock market capitalization. This variable was included as a proxy for firm size.
- $Logvolume$ represents the logarithm applied to volumes of individual stocks traded on regulated markets;
- $Logprice_i$ represents the logarithm of the price of individual stocks;
- $Volatility_{i,t}$represents the price change undergoing title. Volatility as a measure of exposure to fluctuations in prices for every stock is calculated as a standard deviation of the log daily variations prices;
- ESIrepresents the Economic Sentiment Index. The definition of the index is "It is a composite indicator made up of five sectoral confidence indicators with different weights: Industrial confidence indicator, Services confidence indicator, Consumer confidence indicator, Construction confidence indicator, and Retail trade confidence indicator." It is used as a proxy of the economic conditions of Europe (Table 1).
- $InvPrice$Represents the inverse of the price of individual stocks.

Table 1: Economic Sentiment Index composition

	Surveys
INDU	Industrial confidence indicator (40%)
SERV	Services confidence indicator (30 %)
CONS	Consumer confidence indicator (20%)
RETA	Retail trade confidence indicator (5%)
BUIL	Construction confidence indicator (5%)
ESI	The Economic sentiment indicator is a composite measure (average = 100)

Source: Eurostat

The data used in the analysis were provided respectively:

- from Bloomberg for the data necessary for the calculation of Relative Quoted Spread (RQS), for the Price Impact (PI), the market capitalization, volumes, price, and volatility;

- from the Fidessa Group for the trading volume of trade on the exchange platforms (only lit values are considered) and the timeframe was defined based on the time series provided. Using the data, the fragmentation indices were built of the securities making up the Stoxx Europe 50 (Fidessa do not provide the Fragmentation Index of the Stoxx Europe 50);
- from the website of the Stoxx for the identification of the sector in which the company operates, and the localization of the regulated market for each stock;
- from the website of Eurostat for Economic Sentiment Index (ESI).

Before the presentation of econometric models, we show a descriptive analysis by making a distinction among stocks based on the fragmentation level of the title that constitutes the Stoxx Europe 50. We compute the quartiles of the distribution of the Fragmentation Index: the first quartile corresponds to a "low" level of fragmentation; the second quartile corresponds to a "medium-low" level of fragmentation; the third level corresponds to a "medium-high" level of fragmentation, and the fourth quartile represents a high level of fragmentation (Table 2 and Figure 1).

Table 2: Composition and Fragmentation Index of Stoxx Europe 50

	Stoxx Europe 50	REGULATE MARKET	SECTOR	FRAGMENTATIO N INDEX
1	ENI	Milan	Oil & Gas	1.787382648
1	BANCO SANTANDER	Madrid	Banks	1.873199732
1	BBV ARGENTARIA	Madrid	Banks	1.900687967
1	TELEFONICA	Madrid	Telecommunications	1.927089773
1	AIR LIQUIDE	Paris	Chemicals	1.939603842
1	UBS GROUP	Swiss Exchange	Banks	1.986800844
1	TOTAL	Paris	Oil & Gas	1.993427544
1	AXA	Paris	Insurance	2.006093417
1	ING GROEP	Amsterdam	Banks	2.011741121
1	ZURICH INSURANCE	Swiss Exchange	Insurance	2.026241789
1	BNP PARIBAS	Paris	Banks	2.051697829
1	SCHENEIDER ELECTRIC	Paris	Industrial Good & Services	2.09967776
1	LVMH	Paris	Personal & Household Goods	2.104544048
2	NESTLE	Swiss Exchange	Food & Beverage	2.110518232
2	SANOFI	Paris	Healthcare	2.111442221
2	UNILEVER CERTS	Amsterdam	Personal & Household Goods	2.124578009
2	NOVARTIS	Swiss Exchange	Healthcare	2.144893585
2	CREDIT SUISSE GROUP	Swiss Exchange	Banks	2.148402234
2	ROCHE HOLDING	Swiss Exchange	Healthcare	2.284528435
2	ANHEUSER BUSCH INBEV	Brussels	Food &Bevarages	2.290247626
2	BASF	Deutsche Börse	Chemicals	2.32406229
2	SIEMENS	Deutsche Börse	Industrial Good & Services	2.477939928
2	DAIMLER	Deutsche Börse	Automobiles & Parts	2.483656324
2	GLENCORE	LSE	Basic Resources	2.540066005

	ALLIANZ	Deutsche Börse	Insurance	2.589853906
3	RICHEMONT	Swiss Exchange	Personal & Household Goods	2.604313917
	BARCLAYS	LSE	Banks	2.620435763
	BRITISH AMERICAN TOBACCO	LSE	Personal & Household Goods	2.621905355
	BAYER	Deutsche Börse	Chemicals	2.632970984
	LLOYDS	LSE	Banks	2.648238343
	BG	LSE	Oil & Gas	2.65335905
	BP	LSE	Oil & Gas	2.657750179
	UNILEVER	LSE	Personal & Household Goods	2.680113952
	RECKITT BENCKISER GROUP	LSE	Personal & Household Goods	2.692443731
	BHP BILLITON	LSE	Basic Resources	2.714907693
	DEUTSCHE TELEKOM	Deutsche Börse	Telecommunications	2.719248611
	RIO TINTO	LSE	Basic Resources	2.725676722
4	SAP	Deutsche Börse	Technology	2.727629332
	GLAXOSMITHKLINE	LSE	Healthcare	2.754088666
	VODAFONE	LSE	Telecommunications	2.773452647
	NATIONAL GRID	LSE	Utilities	2.808440923
	DIAGEO	LSE	Food &Bevarages	2.839820193
	BT GROUP	LSE	Telecommunications	2.864101951
	DEUTSCHE BANK	Deutsche Börse	Banks	2.896720494
	PRUDENTIAL	LSE	Insurance	3.134084142
	ABB LTD	Swiss Exchange	Industrial Good & Services	3.184118133
	STANDARD CHAPTERED	LSE	Banks	3.28746286
	ASTRAZENECA	LSE	Healthcare	3.434327266
	HSBC HDG	LSE	Banks	3.548801234
	ROYAL DUTCH SHELLA	LSE	Oil & Gas	3.767967388

Source: Elaborations data from www.stoxx.com

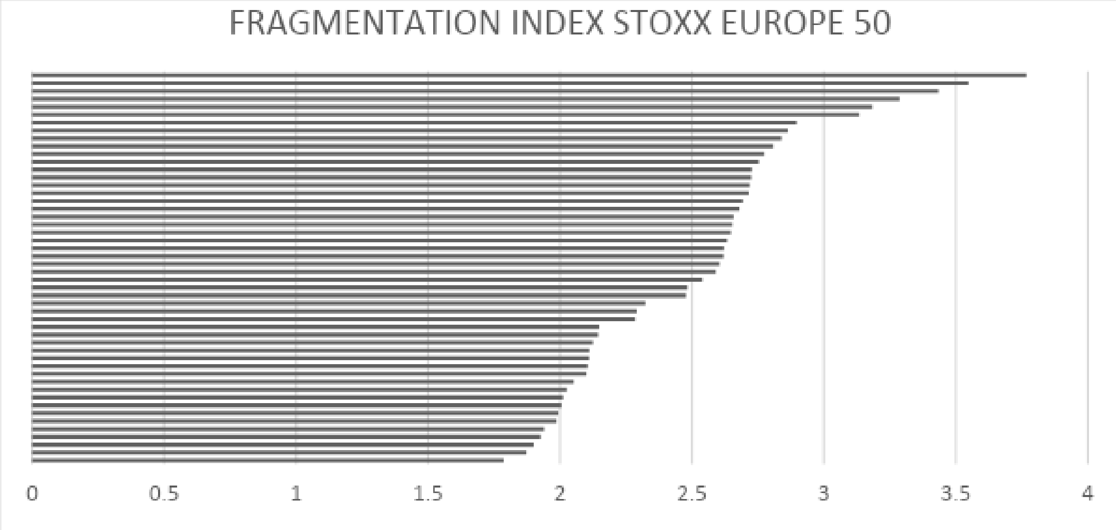

Figure 1: Fragmentation Index Stoxx Europe 50. Source: Elaboration data from Fidessa Group

III. ECONOMETRIC MODELS

3.1 Model 1: The fragmentation impact on the trade of liquidity

The empirical analysis of the impact of fragmentation on liquidity was conducted by taking into account any shocks that have affected the financial post-MiFID system (bankruptcy of Lehman Brothers and the sovereign debt crisis) through the use of control stocks that have not been the subject of the phenomenon. It was decided to apply a statistical methodology that allows you to measure the effect of fragmentation implicitly and to take into account the differences in other characteristics of stocks such as capitalization, trading volume, price, and volatility. This methodology is defined as "Difference in Difference" [19] [23]. The approach is one where the results are observed for two groups for two time periods. One of the groups is exposed to an event in the second period but not in the first period. The control group is not exposed to the treatment during either period. The estimator is defined as the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the control group before and after the event. This removes biases in second-period comparisons between the event and control group that could be the result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends.

The reasons that led to the identification as a sample of the analysis the FTSE MIB index, and the first 40 shares for capitalization that make up the FTSE 100 index are two:

- With regard to the choice of the control sample, that is the stocks are not fragmented, it is compared the trend of the Fragmentation Index IBEX35, used by Fioravanti et al. [23], with the trend of FTSE MIB in the period from June 2012 through May 2015. We found that even if the IBEX35 started with an index equal to 1 (consolidated), it has quickly shifted to higher values touching a peak of 1.75 (Figure 2), whilst the FTSE MIB has maintained a more stable performance and has never exceeded its quota of 1.70, thus shifting the choice on it (Figure 3).

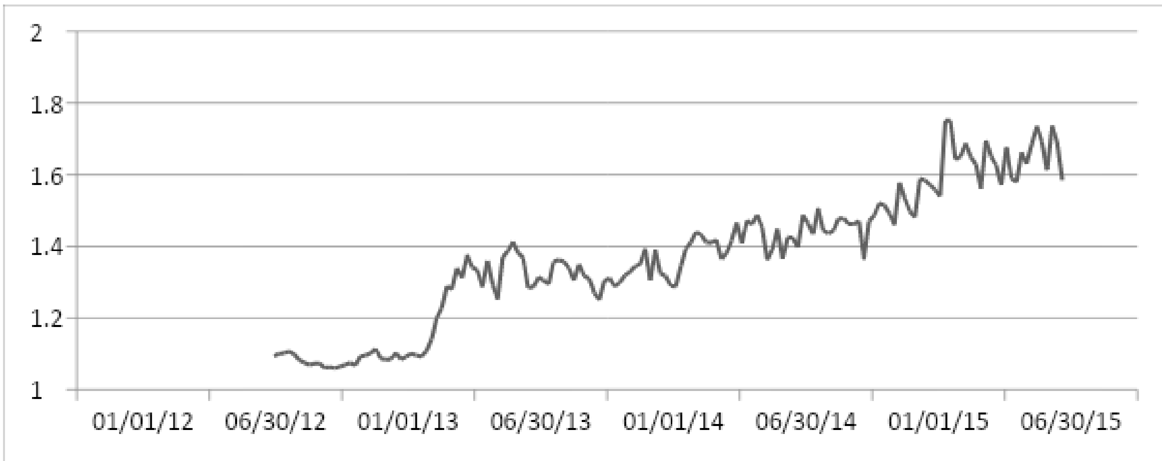

Figure 2: Fragmentation Index of IBEX35. Source: Elaboration data from Fidessa Group

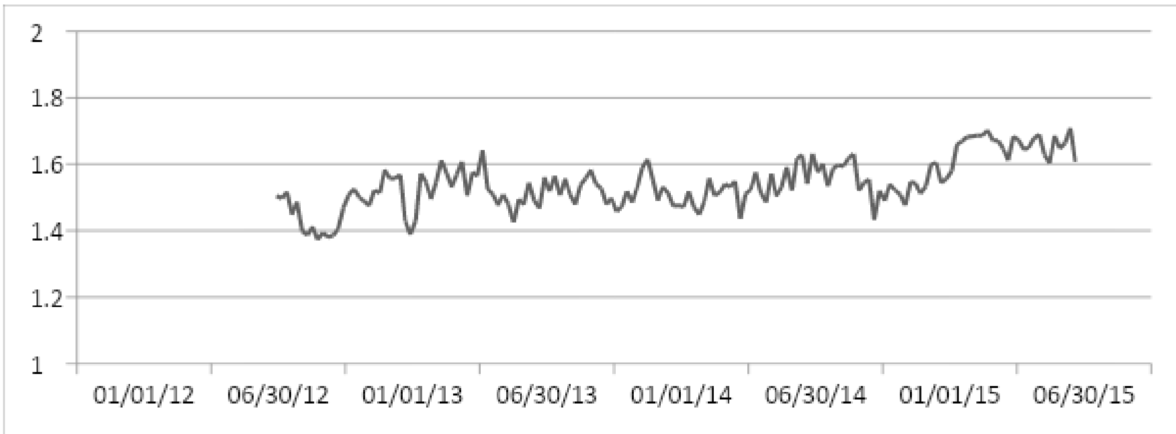

Figure 3: Fragmentation of FTSE MIB. Source: Elaboration data from Fidessa Group

Whereas the FTSE 100 has been chosen because it is the fragmentation index *par excellence* used by Gresse [24] and Fioravanti& Gentile [23].

The first econometric model is composed as follows:

$$RQS_{i,a}^{MR} = a_1 + b_1 DummyFrag_{i,a} + c_1 DummyMiFID_{i,a} + d_1 DummyFrag_{i,a} * DummyMiFID_{i,a} + e_1 LogMarketCap_{i,a} + f_1 Logvolume_{i,a} + g_1 InvPrice_{i,a} + h_1 Volatility_{i,a} + \varepsilon_{1,i,a} \quad (5)$$

where$RQS_{i,a}^{MR}$ is the Relative Quoted Spread. For the description of the other variables, see table 3.

Table 3: Description of variables of the "Difference and Difference" model

VARIABLES	DESCRIPTION
$RQS_{i,a}^{MR}$ is the Relative Quoted Spread	calculation of the RQS, historical series of the following variables were downloaded: PX_ASK that is the lowest price, at which a dealer agrees to sell a stock. When closing the market, the price will be the last ask of the last day on which the market is open and, in case there is no ask in the market, the provider provides the data "n/a"; and PX_BID that is the highest price, at which the

	investor is willing to buy a stock (same PX_ASK survey when the market is closed).
a	It is equal to 2006 or 2014
$DummyFrag_{i,a}$	It is a dummy variable that assumes the value equal to 0 in the case that the stock has not been subject to a process of fragmentation of trade and 1 otherwise
$DummyMiFID_{i,a}$	It is another dummy variable which is equal to 0 for the year 2006 and 1 for the year 2014
$DummyFrag_{i,a} * DummyMiFID_{i,a}$	It is the variable, which shows an interaction between MiFID and fragmentation and therefore assumes anything other than 0 only fragmented stocks of FTSE100 in 2014
$LogMarketCap_{i,a}$	It represents the logarithm applied to stock market capitalization*
$Logvolume_{i,a}$	It represents the logarithm applied to volumes of individual stocks traded on regulated markets
$InvPrice_{i,a}$	It represents the inverse of the price of individual stocks**
$Volatility_{i,a}$	It represents the price change undergoing title***

* Total market cap calculated as follows: Market capitalization + Preferred shares + Short and long term debts + Other long-term liabilities + Minority interest (consolidated balance sheet item representing the share capital of minority shareholders of a subsidiary or associate) - Cash and cash equivalents. This variable was included as a proxy for firm size.
** The price level is generally included in the liquidity models as it constitutes a proxy for the size of the company and the frequency of the trades (Harris, 1994).
*** Volatility as a measure of exposure to fluctuations in prices for every stock was calculated as a standard deviation of the log daily variations prices.

The specified regression model (5) powered by control variables, allows estimating the statistical significance of different effects simultaneously. "b_1" estimates the difference between the sample of the FTSE100 (benchmark) and the FTSE MIB (sample of control) in *pre* and *post*-MiFID (error matching. It can be interpreted as different initial conditions estimation of fragmented stocks compared with a sample of control so before the application of MiFID and is not subject to the process of fragmentation. " c_1" estimates the difference between *pre* and *post*-MiFID common both titles of the FTSE100 and FTSE MIB (shocks). It can be interpreted as the intervention of exogenous shocks, which may have influenced the evolution of the level of liquidity in the period following the implementation of the directive; and "d_1" estimates the differential impact of MiFID on titles covered by the directive, i.e., it represents the change in the level of liquidity of the FTSE100 than FTSE MIB less other effects related to the initial situation and diversity of stocks in terms of market capitalization, volumes, and volatility. Davies and Kim [20] recommend the use of price and market capitalization when employing matching methodology to measure the impact of involvements on liquidity.

Table 4 shows the results of averages of variables related to the two groups of stocks, fragmented against consolidated, in reference to 2006 and 2014, to which the PI was added to have an index that would indicate improvement or worsening of liquidity.

Table 4: Average of the variables with reference to FTSE MIB & FTSE100

2006	RQS	PI	Log Market Cap	Log volume	InvPrice	Volatility
FTSE MIB	0.097777788	0.4821013	3.950700814	6.49384237	0.125474	21.73999264
FTSE100	0.07451094	4.1807634	4.464437544	6.943263492	0.001635	21.59781292
2014						
FTSE MIB	0.09730192	0.2873842	3.817743633	6.636524677	0.23959	32.15116571
FTSE100	0.07411069	4.1302842	4.461062351	6.944604809	0.001671	21.54653675

For the calculation of Price Impact the historical series of variables were downloaded: MID_PRICE (the average bid price and ask price); and PX_VOLUME (the total number of stocks traded on day t on the regulated markets). The PI was multiplied by 10^6 (Hasbrouch 2006).

The RQS has higher values for the sample of control of FTSE MIB, which are characterized by a level of capitalization and trading volumes lower than the shares of the FTSE100 and also both decrease in 2014. This is the symptom of lower liquidity of securities belonging to FTSE MIB (sample control) compared to those in the FTSE100 (fragmented titles). Furthermore, the level of liquidity seems to improve in the aftermath of the MiFID as in both groups of securities the PI decrease through control titles from 0.48 to 0.29 whilst fragmented securities pass from 4.18 to 4.13. This is because, in fact, the PI is a measure of illiquidity, meaning that higher values of the same ones correspond to less liquidity of the title analyzed. Volumes negotiated on average also increased after the introduction of the directive for both samples demonstrating that the liquidity increases with increasing equity trading volumes. Moreover, the stocks included in the control sample are characterized by higher volatility.

Table 5 shows the results of the regression model (5) estimated via the OLS method with a robust estimator of the variance and covariance matrix, i.e., by taking into account the autocorrelation and the heteroscedasticity of residuals of the model.

Table 5: Difference in Difference estimates in a panel data setting - Model (1)

RelativeQuotedSpread	**Coef.**	**Robust Std. Err.**	**P>|t|**
DummyFrag	0.0427404	0.008394	0.000***
DummyMiFID	0.0060556	0.011365	0.595
DummyFrag*DummyMiFID	-0.0645462	0.009581	0.000***
LogMarketCap	-0.0398864	0.009124	0.000***
Logvolume	-0.010448	0.010928	0.341
InvPrice	0.0195901	0.014576	0.181
Volatility	8.90E-06	0.000332	0.979
_cons	0.3113437	0.073496	0.000***
R-squared			0.4853
*corresponds to 10% significance level ** corresponds to 5% significance level *** corresponds to 1% significance level			

The model's results show that the coefficient of interaction "DummyFrag*DummyMiFID" is significant at the 1% and shows a negative relation with Relative Quoted Spread then certainly the fragmentation has not affected the liquidity negatively; on the contrary, the round trip transaction costs have diminished by increasing the efficiency and thereby enhancing the liquidity. Moreover, the variable LogMarketCap is statistically significant at 1% with a relationship negative; thus the level liquidity increases with the capitalization. LogVolume, Volatility, and InvPrice are not statistically significant. The effects of the explanatory variables are in line with the economic theory. The explanatory power of the model stands at 48.5%.

The empirical results show that the elimination of concentration rule introduced by MiFID did not produce adverse effects on liquidity but the opposite, leading to a round trip transaction costs (that change in efficiency) and therefore greater liquidity.

3.2 Model 2: Determinants Fragmentation Index (FI)

The empirical analysis is conducted on 50 stocks that constitute the Stoxx Europe50. The sample is taken between July 13, 2012, and July 3, 2015, on a weekly basis. Table 2 shows for every stock of the Stoxx Europe 50, the sector and regulated market membership. Moreover, the stocks are divided by quartiles based on the calculated Fragmentation Index.

Table 2 shows clearly that the fragmentation level is very different within European equity markets, being smaller in countries like Italy and Spain appear in the top quartile thereby between the securities with low fragmentation; and otherwise is definitely high on the London Stock Exchange. Indeed, as many as 77% of stocks belonging to the fourth quartile, so highly fragmented securities are quoted on the LSE. With regard to the Eurostat's database and for the variable "Economic Sentiment Index", there are monthly averages for every single European country and its composition is shown in table 1. The indicator is calculated as an index with a mean of 100 and a standard deviation of 10 for a standardized and fixed period of time.

As a starting point for the analysis, descriptive statistics are included of all the variables that will be used within the regression model.

Table 6: Descriptive statistics of the variable

Variable		Mean	Std. Dev.	Min	Max
Frag Index	overall	2.104653	0.30163	1.043998	3.070632
	between		0.250544	1.395687	2.444074
	within		0.174057	1.415521	2.928008
RQS	overall	0.074859	0.261101	-16.44992	3.186825
	between		0.122305	-0.776849	0.5942541
	within		0.231328	-16.29738	2.674406
Price Impact	overall	9.96E-07	3.25E-06	0	0.0000949
	between		2.46E-06	4.91E-10	0.0000152
	within		2.16E-06	-0.0000141	0.0000806
LogMarketCap	overall	2422.907	16975.06	4.229011	141285.6
	between		17098.77	4.432655	120911.4
	within		1262.98	-21535.28	22797.16
LogVolume	overall	7.432847	0.562096	5.69787	9.344914
	between		0.54304	6.31708	8.81602
	within		0.163778	6.619428	8.268192
LogPrice	overall	2.137567	0.796547	0.623766	3.786432
	between		0.802073	0.7993234	3.668059
	within		0.062863	1.798773	2.369603
Volatility	overall	23.43346	7.835991	11.052	67.291
	between		5.706381	13.54424	35.36192
	within		5.430206	11.61817	57.69361
ESI	overall	101.8676	8.895918	80.6	119.7
	between		5.30326	94.04903	107.8168
	within		7.181346	85.25079	114.4592

Table 6 highlights the degree of fragmentation of the stocks making up the Stoxx Europe 50. Indeed, Fragmentation Index (FI), the dependent variable of our analysis, has an average of 2.10 within a range consisting of a minimum of 1.04 (concentrated) to a maximum of 3.07 (heavily fragmented title) and the standard deviation (in reference to the whole sample) is equal to a value of 0.30. In addition, as one would expect, descriptive statistics underline the high variability of market capitalization.

After listing in detail the databases and their respective data obtained with the corresponding descriptive statistics, the regression that will achieve the objective of the analysis is demonstrated: identify the variables that can influence the process of fragmentation of trading across multiple trading venues.

$$FI_{i,t} = \beta_0 + \beta_1 PI_{i,t} + \beta_2 LogMarketCap + \beta_3 Logvolume_{i,t} + \beta_4 LogPrice_{i,t} + \beta_5 Volatility_{i,t} + \beta_6 ESI_t + \in_{i,t} \quad (6)$$

In particular, one wants like to see if the several variables have influenced the degree of fragmentation of individual stocks that make up the Stoxx Europe 50 and in what way. It should be emphasized that in order to make the homogeneous variables, the logarithms are applied to market capitalization, trading volume, and prices.

The model was estimated through a fixed-effect regression and for a better result interpretation the diagnostic test of Hausman was also performed, which leads us to accept the null hypothesis [0.0020], as shown in table 7. Therefore, we prefer the fixed effects model to random effects.

Table 7: Fixed Effect regression with Hausman's Test

FragIndex	**Coef.**	**Std. Err.**	**P>|t|**
PriceImpact	-82.2927	900.7058	0.927
LogMarketCap	-2.44E-06	1.54E-06	0.113
Logvolume	-0.17414	0.012263	0.000***
LogPrice	0.281693	0.037206	0.000***
Volatiliy	-0.00086	0.000437	0.049**
EconomicSentimentIndicator	0.001352	0.00034	0.000***
_cons	2.679258	0.123753	0.000***
R-sq. Within	0.0521		
R-sq. Between	0.4370		
R-sq. Overall	0.3070		
Hausman test	0.0020		
** corresponds to 5% significance level			
*** corresponds to 1% significance level			

Table 7 shows the statistically significant variables that influence the process of fragmentation of trade; these are the volume, the price, volatility, and the Economic Sentiment Index. Instead, the variables of Price Impact, the logarithm of the market capitalization are not significant; therefore, they do not affect the fragmentation process of trade. Going into more detail, the volume is highly significant [-0.1741 ***] and it has a negative relationship with the Fragmentation Index. This means that if the volume of securities trading on regulated markets increase, the fragmentation decrease because there is a concentration of trade on a smaller number of trading venues. The variable of the logarithm of the price results statistically significant by finding a positive relationship with the Fragmentation Index; therefore, the higher the price of securities the higher the average Fragmentation Index (increase by 0.28). The last statistically significant variable is the Economic Sentiment Index (ESI), which refers to the perception of the general economic climate and identifies a positive relationship with the Fragmentation Index. This means that in a positive economic climate, investors are driven to trade the securities across multiple trading venues with the increase consequent of the Fragmentation Index (FI) of each security. This result may also be derived from the inverse relationship between volatility and fragmentation. Indeed, an economic climate with greater uncertainty generates greater price volatility and concentration of trade. The explanatory power of the model as a whole is equal to 30.70%, but if we consider R-square Between, it increases by over ten percentage points (R-sq. equal to 43.70%)

IV. Conclusions

The phenomenon of fragmentation of securities trading on multiple trading venues has assumed increasing importance, not only as a phenomenon studied in the literature but also by the legislators. It has been seen that the literature is not univocal in identifying if there have been positive effects or not. There are two distinct branches of the literature: one that affirms the positive effects of the consolidation and the other that, instead, asserts the positive effects of the fragmentation of trade. This paper has a double aim: the first is to analyse if the MiFID has an impact on the liquidity, and the second is to identify the determinants that have been able to generate fragmentation over multiple trading venues. For this reason, it is very different from previous works. The first econometric model analysis the impact of fragmentation on the liquidity through the methodology of "Difference in Difference". The results show that the fragmentation "DummyFrag", the variable of interaction "DummyFragDummyMiFID", and the market capitalization are statistically significant. This means that fragmentation did not have a negative effect on the liquidity, indeed it may have increased it. These results are in line with economic theory.

The second regression model has the Fragmentation Index of the stocks constitution the Stoxx Europe 50. It includes market variables and a proxy for the economic conditions of Europe. The results show that the variables that have influenced the willingness of investors to operate on multiple trading venues are: the volume and the volatility with a negative relationship, while the price and the Economic Sentiment Index with a positive relationship. If trading volume and volatility increases, the investor tends to concentrate his exchanges in a single market. Whereas, if the prices rise and there is a positive economic condition, the investor moves towards different trading venues. This study could be helpful to European legislators and intermediaries to understand what levers influence the volume of the transactions in certain markets. It would be interesting to verify if the new directive (MiFID 2) has modified the market conditions and whether they have improved or not.

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