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EVIDENCE OF INTEGRATION OF THE EU SECURITIES MARKET INFRASTRUCTURE

Ensuring the free movement of capital is a crucial element of European integration, which has to rely on the political will of countries on the one hand, and their respective infrastructure – on the other. Reasoning of the assessment methods to evaluate the progress on integration of securities market infrastructure is one of the most pressing issues facing the European Commission today. The paper puts forward a hypothesis and finds evidence that the process of integration of securities market infrastructure in the EU countries enhances the convergence of average transactions size on the organised markets.

Keywords: *integration, infrastructure, securities market, stock exchange, transaction, methodology.*

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ДОКАЗ ІНТЕГРАЦІЇ ІНФРАСТРУКТУРИ РИНКУ ЦІННИХ ПАПЕРІВ ЄС

У статті доведено, що забезпечення вільного руху капіталу є одним з принципових елементів європейської інтеграції, що має спиратися, з одного боку, на політичну волю країн, а з іншого – на його забезпечення відповідною інфраструктурою. Обґрунтування методики оцінювання поступу щодо інтеграції інфраструктури ринку цінних паперів є одним з найактуальніших питань, що постали нині перед Європейською Комісією. Висунута та знайшла підтвердження гіпотеза про те, що в процесі розвитку інтеграції інфраструктури ринку цінних паперів країн ЄС відбувається зближення середнього розміру угод на організованих ринках.

Ключові слова: *інтеграція, інфраструктура, ринок цінних паперів, біржа, угода, методика.*
Форм. 17. Табл. 8. Рис. 4. Літ. 23.

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ДОКАЗАТЕЛЬСТВО ИНТЕГРАЦИИ ИНФРАСТРУКТУРЫ РЫНКА ЦЕННЫХ БУМАГ ЕС

В статье показано, что обеспечение свободного перемещения капитала является одним из принципиальных элементов европейской интеграции, которое должно опираться, с одной стороны, на политическую волю стран, а с другой – на его обеспечение соответствующей инфраструктурой. Обоснование методики оценки продвижения интеграции инфраструктуры рынка ценных бумаг является одним из актуальнейших

вопросов, которые рассматриваются сейчас Европейской Комиссией. Выдвинута и нашла подтверждение гипотеза о том, что в процессе интеграции инфраструктуры рынка ценных бумаг стран ЕС происходит сближение среднего размера сделок на организованных рынках.

Ключевые слова: *интеграция, инфраструктура, рынок ценных бумаг, биржа, сделка, методика.*

Problem setting. The advancement of European integration assigns the European Commission the task of measuring the progress in this direction. Unfortunately, the methods for estimating the results of integration efforts are not thoroughly developed, justified and unified. In particular, the securities market infrastructure (SMI), which lays down the main burden of ensuring the free capital movement within the EU, still lacks appropriate instruments.

Latest research and publications analysis. In 2006 the European Commission anticipated that the consolidation of the stock infrastructure within the EU would allow saving from 2 to 5 bln EUR, being spent on trading, clearing and payments, and the lower transaction costs due to stock exchanges mergers, in turn, would increase trading volumes (Nielsson, 2009). As a result of active capital consolidation process in European securities market infrastructure companies the total value of transactions in 2007–2008 ranged at 40 trln EUR per year and slightly less in the following 2–3 years. Hence, the total annual number of transactions has reached approximately 818–961 mln (Table A).

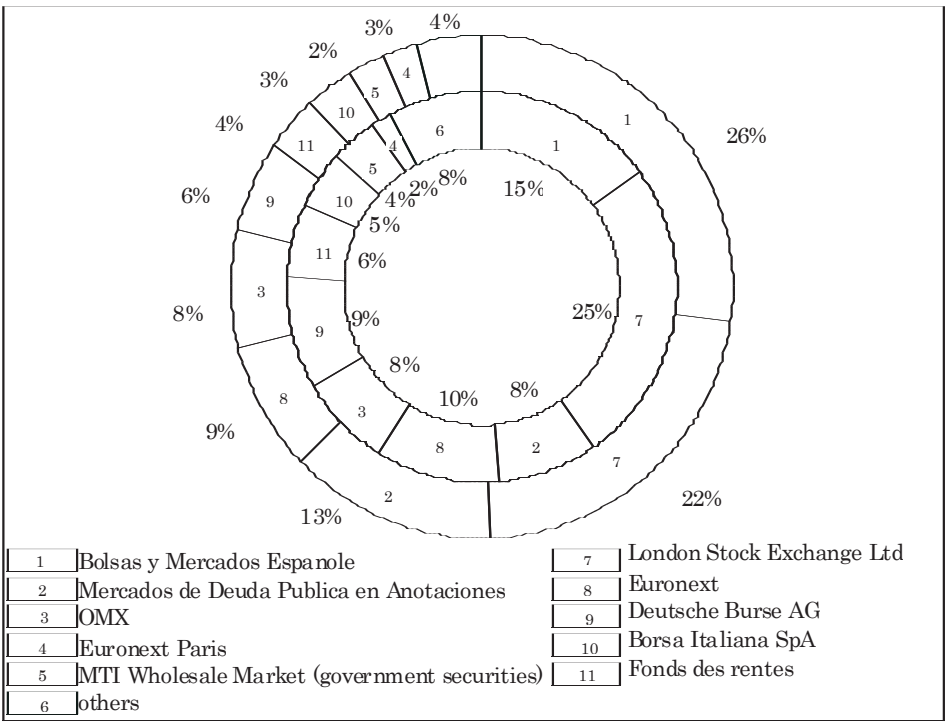
The literature on the subject offers a number of publications on various aspects of the EU SMI convergence, but however, they do not display the full picture. The research on convergence received wide support particularly after the following two works have been written by Mankiw, Romer, Weil (1995) and Barro, Sala-i-Martin (1991). These became the theoretical framework for all the subsequent studies on the convergence (divergence) phenomenon. Current research projects in this area are being conducted by Russian scholars, as represented by the works of A.A. Iodchyn (2007) and K.P. Glushchenko (2009), and Ukrainian scientists D.G. Lukianenko and V.I. Chuzhykov (2009), I. Khomaiko (2006). The econometric aspects are covered in Islam Nazur's paper (1995), applied issues of the probability theory are found in the works of V.I. Zhluktenko and S.I. Nakonechnyi (2000). The concepts of β- and σ-convergence are interrelated, being analysed in detail by D. Quah (1995). Analysis of convergence based on time series is represented by the following academic works (Giles and Feng, 2003; Nahar and Inder, 2002). On the other hand, P. Hoffmann (2010) offers the analysis of MiFID application outcomes. Internal issues in the key contractors and multilateral netting performance are discussed in the paper published by the ECB (2007). K. Pirrong developed a theoretical model anticipating that the economy of scale will contribute to consolidation of stock exchanges as long as the benefits of access to liquidity vanish (Pirrong, 1998). Various aspects of the securities market liquidity have been analysed by the following authors: H. Degryse, F. de Jong, V. van Kervel (2011), C. Fohlin, T. Gehrig, T. Brunner (2009), T. Chordia, R. Roll, A. Subrahmanyam (2008) and others.

In recent years, the activity on removing the bottlenecks in the EU SMI, hindering the free movement of capital has been extremely intensified.

The unresolved issues lie primarily in the fact that although the European Commission applies the system of indicators (MARKT/2006/14/G), there is still no single unified approach to evaluate the results of integration efforts within the securities market infrastructure. Since stock exchanges are seen as a crucial element in the securities market infrastructure, analysing their performance indicators would facilitate the identification of the state of SMI convergence. The mathematical apparatus for convergence analysis is used mainly with regard to the regional EU policy. We propose to implement it for the research of the EU SMI as well.

Thus, the **research objective** is to put forward and test the hypothesis about the possible convergence of the EU stock exchanges performance indicators with further argumentation and application of the respective economic and mathematical tools.

Key research findings. Over 80% of the total transactions value within the EU stock exchange accounts for only 6 major European stock exchanges: Bolsas y Mercados Espanole (26%), London Stock Exchange Ltd (22%), Mercados de Deuda Publica en Anotaciones (13%), Euronext (9%), OMX (8%) and the Deutsche Borse AG (6%) (Figure 1).



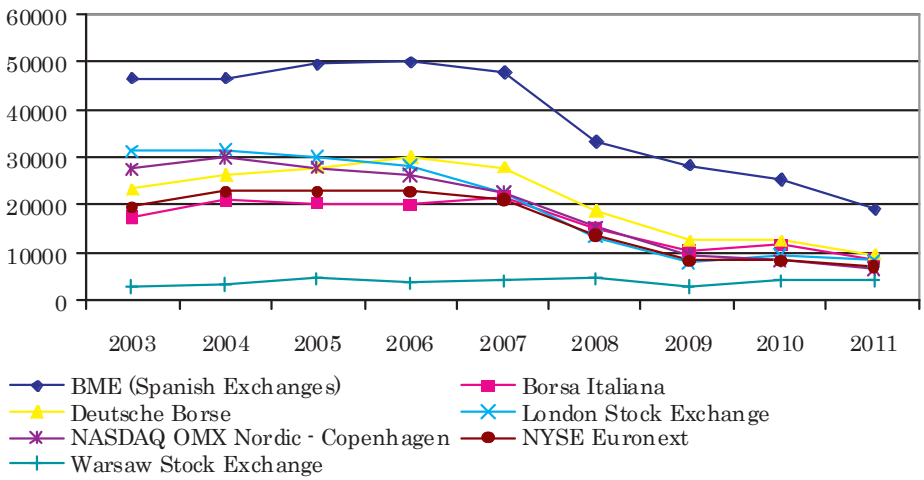
Source: developed by the author with reference to Federation of European Securities Exchanges and European Central Bank.

Figure 1. **Share of the EU stock exchanges in the total transaction value in 2007 (internal circle) and 2010 (outer circle),** *% of the grand total*

The average transactions volume in the EU stock market in 2010, according to the author's calculations, amounted to 40.9 thousand euros (Table A). However, the range of variation is very wide, since the average transaction volume on the 5 stock

exchanges exceeded 3 mln euros, though being still less against the previous years. This fact can be partially explained by different specialisation of stock exchanges. Thus, the above stock exchanges specialise in facilitating large wholesale operations and operations with government securities. The list also includes the stock exchanges of the new member states, as well as those that maintain retail securities transactions, which on the whole determines the overall low average across the EU.

Based on these data, ***a hypothesis*** has been put forward stipulating that the efforts towards the integration of the EU SMI should have certain effects. Prior analysis of the graphical display of the dynamics of the average transaction values change over the period from 2003 to 2011 at the 6 largest EU stock exchanges (see Fig. 2) allows to hypothesise that the factors related to both the integration process and the world financial globalisation lead to convergence, compliance of their performance indicators.



Developed by the authors with reference to Federation of European Securities Exchanges and European Central Bank.

Figure 2. **The dynamics of the average transaction values over the period from 2003 to 2011 at the 6 largest EU stock exchanges,** *EUR*

Methods argumentation. To test the above hypothesis, we first propose to use the approaches, applied in Ukrainian and Russian academic literature basically to analyse the regional income inequality within the economic growth theory framework, although in terms of application of the mathematical tools the given methods seem more effective against the works of Western scholars. The starting point in the studies on integration process is primarily driven by the concept of convergence. The process of convergence assumes the rapprochement in time of the development indicators of countries, regions or other business entities. The opposite process is called divergence.

The development indicators for different participants of international economic relations are selected up to a researcher's individual choice, since there is no clearly established framework those indicators must meet. Thus, the mathematical modelling tools applied for the regional inequality analysis, seem to be also appropriate to

use within the study on convergence across the EU SMI. The literature review (Islam Nazur, 1995: 3) enables to identify a variety of convergence aspects for further research, in particular the following key instrumental analysis areas:

- β- or σ-convergence;
- absolute or conditional convergence;
- determinated or stochastic convergence.

β-convergence is a negative dependence of a discrete index growth rate against its entry level. β-convergence is observed in samples when in the case of spatial regression, which demonstrates the dependence of indicators against their entry level, the regression parameter estimation is negative and statistically significant.

Apart from the above dependence, other types of regression models are also offered. In particular, the paper (Glushchenko, 2009) proposes the following econometric dependency types to be applied for the convergence analysis:

$$\ln y_{iT} = \beta_0 + \beta_1 \ln y_{io} + \varepsilon; \quad (1)$$

$$\ln \frac{y_{iT}}{y_{io}} = \beta_0 + \beta_1 \ln y_{io} + \varepsilon; \quad (2)$$

$$\frac{\ln \frac{y_{iT}}{y_{io}}}{T} = \beta_0 + \beta_1 \ln y_{io} + \varepsilon, \quad (3)$$

where y_{iT} and y_{io} are the values of the economic indicator at a final and entry time level respectively, T is the number of time periods. The parameters estimates for the given models (1–3) are obtained for $N(i = \overline{1,N})$ data elements of spatial sampling.

Using the first model (1) the hypothesis is being tested with $\beta_1 < 1$, for other models (2) and (3) the hypothesis is to be tested when $\beta_1 < 0$. In case the hypothesis is confirmed, the β-convergence occurrence could be stated.

Further classification identifies absolute and conditional convergence. An absolute β-convergence could be interpreted as a rapprochement of the average transactions at the EU stock exchanges over time without imposing additional conditions on the above process, i.e. the models regressors' structure (1–3) comprises only the entry level of the analysed indicator. When the econometric dependency includes additional regressors, this is the case of conditional convergence. Thus, the conditional β-convergence occurs when the regression (4), which includes additional factors, exhibits the estimated coefficient β_1 to be negative and statistically significant:

$$\ln \frac{y_{iT}}{y_{io}} = \beta_0 + \beta_1 \ln y_{io} + X_i \gamma + \varepsilon, \quad (4)$$

where X_i is a matrix for additional regressors; γ are the respective regressor coefficients. However, due to the lack of sufficient information to analyse the additional regressors matrix, the occurrence of conditional β-convergence has not been investigated within the given research.

The β-convergence concept is closely related to the notion of σ-convergence. The σ-convergence could be interpreted as the variation reduction over time (differentiation) of mid-sized transactions at the EU stock exchanges. In case of spread of values against the mean value of an economic indicator, the absolute σ-convergence

occurs. Statistical indicators used for the analysis of σ-convergence can be represented by variance, standard deviation, variation coefficient and its modifications etc.

According to the probability theory the variance and standard deviation constitute the indicators of differentiation that characterise scatter observations of a random variable against its average (Zhluktenko and Nakonechnyi, 2000). In the case of a discrete random variable X that takes the value $X = \{x_1, x_2, \ldots, x_N\}$ with probability $P = \{p_1, p_2, \ldots, p_N\}$ the variance is to be calculated by the following formula:

$$D(X) = \sum_{i=1}^{N} (x_i - M(X))^2 p_i, \quad (5)$$

where $M(X)$ is a mathematical expectation of a random variable X.

In the absence of data for the values $P = \{p_1, p_2, \ldots, p_N\}$ statistical estimates of the respective variables are applied. Statistical variance estimation is calculated by the formula:

$$\overline{D(X)} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{M(X)})^2, \quad (6)$$

where $\overline{M(X)}$ is a statistical estimate of the expectation of a random variable X (i.e., its average value).

Statistical estimation of standard deviation is given by:

$$\overline{\sigma(X)} = \sqrt{\overline{D(X)}}. \quad (7)$$

Application of statistical evaluation for standard deviation is more convenient, since the value has the same measurement units as the variable under consideration. On the other hand, statistical evaluation of the variation coefficient has no measurement units and is calculated as follows:

$$\overline{CV(X)} = \frac{\overline{\sigma(X)}}{\overline{M(X)}}. \quad (8)$$

In practice, the coefficient of variation (its statistical estimation) has a significant advantage over variance and standard deviation, both having a major drawback which limits their application for the differentiation analysis. This refers to their dimension and scale dependency which prevents from comparing the indicators having different measurement units. In this regard, it would be more convenient to use the variation coefficient. In addition, the coefficient of variation allows comparing different indicators. In case when separately according to variance and mathematical expectation indicators such a comparison is impossible to handle, then the relative variation coefficient enables making an unambiguous conclusion.

The above statistical estimates of the variance, standard deviation and variation coefficient are used to determine the occurrence of σ-convergence. In this regard, their changes over time have to be considered as well. In the case of the indicators value growth the sampling would exhibit divergence. If the value decreases over time, then the σ-convergence occurs.

The notions of β- and σ-convergence are interrelated, in other words, β-convergence is a necessary condition for σ-convergence (Quah, 1995). This conclusion, from a practical perspective, specifies that levelling medium-sized transactions on the EU stock exchanges in the short and the long term has not to be bounded by mere pace of their change, additional measures that might affect the differentiation reduction should also be undertaken in regard to the mid-sized transactions in the EU

stock exchanges. The final direction for the analysis refers to determinated and stochastic convergence. The former suggests that the difference between non-random elements of time series X_t and Y_t over time should become arbitrarily small (or be resolved to the constant α):

$$\lim_{t\to\infty}\|X_t - Y_t\| = \alpha, \quad (9)$$

where the character ‖...‖ describes the degree of the two time series convergence.

Since the economic indicators series (here, the average transactions size on the EU stock exchanges) reflect random processes, in that case stochastic convergence occurs, based on average data:

$$\lim_{t\to\infty} E\|X_t - Y_t\| = \alpha, \quad (10)$$

where the $E\|$ character expresses the mathematical expectation.

Thus, the difference between determinated and stochastic convergence lies in time series, subject to the object of analysis.

First, let us explore the possibility to use the approaches for determining the presence (absence) of β-convergence for mid-sized transactions on the EU stock exchanges within the integration process of the EU SMI in space and over time. Further, we shall consider in more detail each of the above three types of models (1–3). The ***type 1 model*** (1) can provide two cases. The first one refers to the situation when during the analysed period the average transaction size on the EU stock exchanges at the end of the period ($t = T$) is in a narrow range compared to a larger interval of corresponding values of the entry period ($t = 0$) across the entire data array. That is, at the start of the research period the average transaction size on the EU stock exchanges yields significant differences, while at the end of the period they are slightly different from each other, thus exhibiting convergence (β-convergence) (Figure 3). The line has a slope angle less than one ($\beta_1 < 1$).

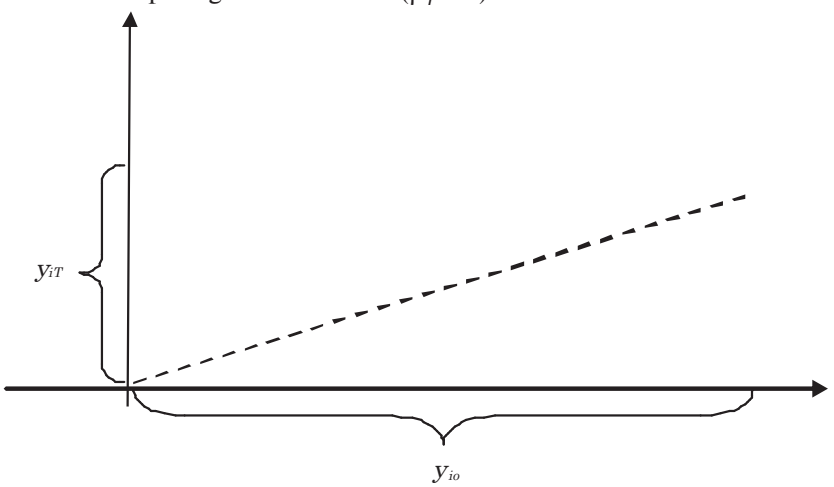


Figure 3. **Evidence for β-convergence presence for conditional data ($\beta_1 < 1$)**

In the second (opposite) case over the entire period the average transaction size on the EU stock exchanges at the end of the period ($t = T$) takes the values of a wider range, compared to a smaller interval of corresponding values of the entry period ($t =$

0) across the data array. Hence, if at the starting period the average transaction size on the EU stock exchanges yields significant differences, at the end of the period the values of the investigated variables exhibit even more differences among themselves and take greater range. This is the case of divergence, with no convergence present ($\beta_1 > 1$) (Figure 4).

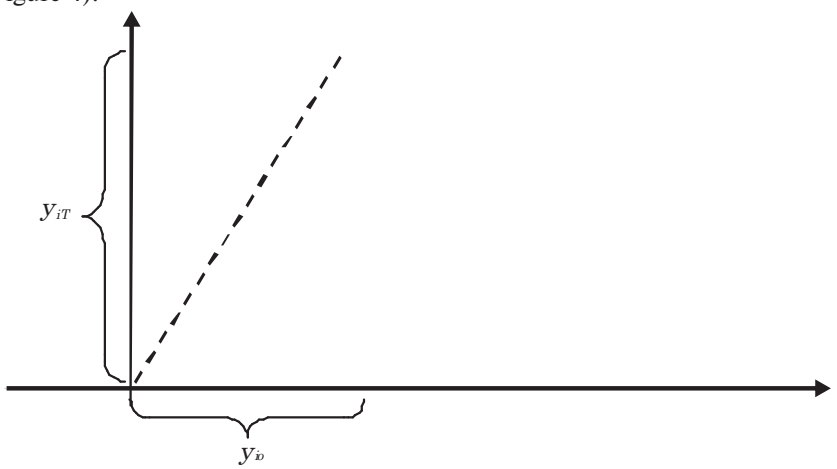


Figure 4. **Evidence of absence of β-convergence for conditional data ($\beta_1 > 1$)**

Let us proceed and explore the ***type 2 models*** (2). The value increase in the average transaction size at the EU stock exchanges $y_{io}(i=\overline{1,N})$ will reduce the variables ratio $\frac{y_{iT}}{y_{io}}(i=\overline{1,N})$, as the denominator increases. Thus, the value growth $y_{io}(i=\overline{1,N})$ will result in proportional reduction in $\frac{y_{iT}}{y_{io}}(i=\overline{1,N})$ values, which means that under the construction of an econometric model of type 2 (2) the coefficient β_1 will take the value less than zero. In this case we evidence convergence of the investigated processes (β-convergence). In the opposite case, when $\beta_1 > 0$ divergence is observed, with no convergence present. Similar arguments refer to the ***type 3 model*** (3). It differs from the previous one only by consideration of the number of years in the research period within the construction of econometric dependency. The analysis of the given models demonstrates that the described approach could be applied to study the convergence (divergence) presence in a variety of economic processes dynamics.

For the analysis of β- and σ-convergence on the EU SMI based on the stock exchanges performance indicators, we have applied a phase-by-phase research pattern with a traditional approach *in the first place* (used in most convergence studies) – i.e. a construction of spatial regressions, and *secondly* other approaches for the time series analysis. Thus, ***the analysis structure*** is given by:

- analysis of absolute β-convergence in all time slots with application of regression models of types 1–3 (1–3). The simulation framework is developed with application of spatial samplings;

- analysis of σ-convergence. To formulate the conclusions statistical fluctuations of midsize transactions on the stock exchanges are calculated and their dynamics is determined.

Method application. To evaluate the presence of β-convergence based on the stock exchanges performance, the mean value data for transaction size over the period from 2003 to 2011 were used (the data prior to 2003 are not available in public information sources) (Federation of European Securities Exchanges database and European Central Bank). The index values for 2003 are marked with $t = 0$, the data for 2011 are marked with $t = T$, the list of stock exchanges under analysis comprises 23 items ($i = 1,..., N; N = 23$) (Table B). Using the type 1 model (1) for data survey the following result was obtained (Table 1).

Table 1. **Estimates for a type 1 model parameters (1) and their statistical significance based on the EU 23 stock exchanges statistics for the period from 2003 to 2011**

Model parameters (1)	Parameters estimates	Standard deviations of the parameters estimates	Significance level of the estimated parameter
β_0	7.155141	0.694766	–
β_1	0.181899	0.074654	$\alpha = 0.05$

Thus, the model (1) is given by:

$$\ln y_{iT} = 7.15 + 0.18 \ln y_{io} + \varepsilon.$$

The value of $\beta_1 = 0.18 < 1$, the estimated parameter is statistically significant (the reliability level of $\gamma = 0.95$), thus, the hypothesis of the β-convergence of the type 1 model is also ***confirmed***.

Using the type 2 model (2) for the research data we obtain the following results (Table 2).

Table 2. **Estimates for a type 2 model parameters (2) and their statistical significance based on the EU 23 stock exchanges statistics for the period from 2003 to 2011**

Model parameters (2)	Parameters estimates	Standard deviations of the parameters estimates	Significance level of the estimated parameter
β_0	1.868759	0.086815	–
β_1	-0.09701	0.009328	$\alpha = 0.001$

Thus, the model (2) is given by:

$$\ln \frac{y_{iT}}{y_{io}} = 1{,}87 - 0{,}097 \ln y_{io} + \varepsilon.$$

The value of $\beta_1 = -0.097 < 0$, the estimated parameter is statistically significant (the reliability level of $\gamma = 0.999$), thus, the hypothesis of the β-convergence of the type 2 model is also ***confirmed***.

Using the type 3 model (3) for the research data we obtain the following results (Table 3).

Table 3. **The type 3 model estimated parameters (3) and their statistical significance based on the 23 EU stock exchanges statistics for the period 2003–2011**

Model parameters (3)	Parameters estimates	Standard deviations of the parameters estimates	Significance level of the estimated parameter
β_0	0.20764	0.009646	–
β_1	-0.01078	0.001036	$\alpha = 0.001$

Thus, the model (3) is given by:

$$\frac{\ln \frac{y_{iT}}{y_{io}}}{T} = 0.21 - 0.01 \ln y_{io} + \varepsilon.$$

The value of $\beta_1 = -0.01 < 0$, the estimated parameter is statistically significant (the reliability level of $\gamma = 0{,}999$), thus, the hypothesis of the β-convergence of the type 3 model is also ***confirmed***.

The estimates obtained for β_1 based on absolute convergence models 1–3 reflect the general tendency to reduce the divergence of the mid-size transactions at the EU stock exchanges. Since the values obtained are insignificant, a conclusion can be drawn that despite the ***evidence of convergence, the rapprochement rate is rather slow***.

The next stage of our study, after defining the β-convergence, is to test the presence of σ-convergence. Since there is evidence for absolute β-convergence as a necessary condition for the existence of σ-convergence, we can assume that σ-convergence will also occur.

Let us explore σ-convergence using the values of statistical estimates for standard deviation and variation coefficients. If the standard deviation of mean value logarithms related to the transaction size across the list of stock exchanges within the research period tends to decrease, i.e. $\sigma_{t+1} \langle \sigma_t,\ t = \overline{0,T},$ then the σ-convergence occurs, where σ_t is statistical evaluation of standard deviation, calculated by the formula:

$$\overline{\sigma_t} = \left[\frac{1}{N} \left(\sum_{i=1}^{N} (y_{it} - \frac{1}{N} \sum_{i=1}^{N} y_{it})^2 \right) \right]^{1/2}, \qquad (11)$$

where y_{it} is the average value of transactions occurred at the *i*-stock exchange in *t* year.

The calculations made with this formula (11) provide the following result (Table 4).

Table 4. **Values of statistical estimates of standard deviation and variation coefficients for mid-sized transactions on the 23 EU stock exchanges**

year	2003	2004	2005	2006	2007	2008	2009	2010	2011
$\overline{\sigma_t}$	13407	13161	14425	13617	12798	11577	5590	5246	4043
$\overline{CV_t}$	0.78	0.65	0.699	0.62	0.61	0.75	0.607	0.58	0.52

Over the entire research period the statistical estimates for standard deviations of σ_t are constantly decreasing. For statistical estimates of variation coefficients a similar pattern is observed, except for one value referring to 2008, although further on the tendency for the decrease in values remains, thus ***confirming the hypothesis of the existence of σ-convergence***.

Convergence of individual stock exchanges. As noted above, the research framework provides convergence simulation based on time series instruments. This seems logical, since convergence occurs in time and represents gradual rapprochement of time series. It is assumed that over time the indicators differentiation do not disappear completely but become stable at a certain level (Giles and Feng, 2003; Nahar and Inder, 2002).

Taking into account that the entry data for our research are presented by the time series, deeper analysis of relationships of their elements involves implications to use the appropriate instruments applied for the time series comparison. In this context the Theil index (Olenev, 2008) displayed by $E(Y_{rt}, Y_{st})$ seems reasonable to measure the divergence between the two time series Y_{rt} and Y_{st} within the time slot $i = 1,..., T$. The closer the index value is to zero, the higher level of approximation between the compared series will be obtained. However, for the ease of computation, instead of the Theil index the proximity coefficient $U(Y_{rt}, Y_{st}) = 1 - E(Y_{rt}, Y_{st})$ could be used. The higher value takes the above coefficient (the closer it is to 1), the closer are the series. The index is calculated by the formula:

$$\bigcup(Y_{rt}, Y_{st}) = 1 - \sqrt{\frac{\sum_{t=t_0}^{T}(y_{rt} - y_{st})^2}{\sum y_{rt}^{\ 2} + \sum y_{st}^{\ 2}}}. \qquad (12)$$

The disadvantage of using indicators for time series analysis is that this approach allows identifying the presence of convergence only for the two stock exchanges, therefore, for general sampling of N elements the estimating equation $C_N^2 = \frac{N!}{2(N-2)!}$ is required. For the case of 23 stock exchanges we have $C_N^2 = \frac{N!}{2(N-2)!} = \frac{23!}{2 \times 21!} =$ 253 pairs.

Since the estimation range is too big, we have focused on the most important ones and made calculations for the 6 stock exchanges $C_6^2 = \frac{6!}{2(6-2)!} = 15$, according to the priorities. Further, using the proximity coefficient, we verify the time series describing the changes in the transaction mean values at the 6 stock exchanges for pairwise correlations (Table 5).

Table 5. **Pairwise proximity coefficient value for transaction mean values at the six stock exchanges over the period 2003–2011**

	London Stock Exchange	NYSE Euronext	BME (Spanish Exchanges)	Borsa Italiana	Deutsche Borse	Warsaw Stock Exchange
London Stock Exchange	1	0.80	0.59	0.74	0.86	0.16
NYSE Euronext	0.80	1	0.48	0.91	0.83	0.22
BME (Spanish Exchanges)	0.59	0.48	1	0.46	0.61	0.09
Borsa Italiana	0.74	0.91	0.46	1	0.80	0.23
Deutsche Borse	0.86	0.83	0.61	0.80	1	0.17
Warsaw Stock Exchange	0.16	0.22	0.09	0.23	0.17	1

The analysis evidences that the highest integration level is demonstrated by the NYSE Euronext and Borsa Italiana, NYSE Euronext and the London Stock Exchange, Deutsche Borse and the London Stock Exchange, Deutsche Borse and Borsa Italiana. The major EU stock exchanges – the London Stock Exchange, NYSE Euronext and the Deutsche Borse – exhibited the highest degree of integration. Slightly lower is their integration with the stock exchanges in Spain and Italy, which achieved an average level of integration between them. The Warsaw Stock Exchange

from this sampling is the least integrated with both major and smaller stock exchanges.

Comparing time series with a single indicator is insufficient to give an unambiguous answer, i.e. to generalise reliable conclusions a set of proximity and similarity indicators is required. Therefore, we offer to use another approach from the publication (Glushchenko, 2009). The best approach is the one that allows avoiding application of linear dependencies. Convergence between the two processes r and s occurs when

$$\lim_{t\to\infty} E(y_{rt} - y_{st}) = 0, \tag{13}$$

where mathematical expectation is represented by $E(\ )$.

To test the time series for compliance with formula (13) the following model is used

$$y_{rst} = v_t, \tag{14}$$

where

$$y_{rst} = y_{rt} - y_{st}. \tag{15}$$

Taking into consideration that

$$v_t = \rho v_{t-1} + \varepsilon_t, \tag{16}$$

we get the standard equation to test time series for stationarity:

$$y_{rst} = \rho y_{rs,t-1} + \varepsilon_t. \tag{17}$$

A time series $\{y_{rst}\}_{t=0,\dots T}$ will be stationary, and therefore satisfy the relation (13) with $\rho < 1$, where ρ is convergence characteristics of time series. With this approach we verify the conclusions obtained by the proximity coefficient, which can be presented in Table 6.

Table 6. **Value of coefficient ρ for transaction mean values at the six stock exchanges over the period 2003–2011**

	London Stock Exchange	NYSE Euronext	BME (Spanish Exchanges)	Borsa Italiana	Deutsche Borse	Warsaw Stock Exchange
London Stock Exchange	–					
NYSE Euronext	0.34	–				
BME (Spanish Exchanges)	0.08	0.14	–			
Borsa Italiana	0.30	0.08	0.15	–		
Deutsche Borse	0.23	0.06	0.17	0.10	–	
Warsaw Stock Exchange	0.24	0.18	0.16	0.17	0.15	–

Consequently, the table entries take values indicating ***the presence of convergence of time series*** (for all entries we have $\rho < 1$).

Conclusions. Thus, subject to the calculations made, we can draw a general conclusion: all approaches to test the presence of convergence of stock exchanges by the average transaction size indicator confirm the occurrence of β- and σ-convergence. Pairwise comparisons of time series data demonstrate a significant level of similarity of the processes they describe.

In addition to market factors, the adoption of MiFID further contributes to convergence among the major EU stock exchanges (Degryse, de Jong and van Kervel, 2011). Analysis of policies and practices of MiFID enabled to resume that it actually allows (but does not oblige) market operators to meet customers' needs at those markets and through those platforms that offer the best prices (the so-called "trade-throughs" – i.e., trading across different platforms and different regulated markets) (Hoffmann, 2010). Such conditions contradict the norms defined in the US[1], and provide the relevant framework for improving the positions of major market operators. Market operators (market-makers) who position themselves as liquidity providers, due to uneven access of traders to trading platforms[2], have an opportunity to assign quotas on different markets and use the price variances in their own interests.

Furthermore, the existence of the developed CCC (Central Counterparty Clearings) considerably simplifies multilateral netting, which, according to the research findings, to a great extent enhances the risk reduction in relation to gross positions, sometimes up to 90% (ECB, 2007), which in turn increases liquidity and the market scale. Apart from the above, the economy of scale will facilitate the consolidation of stock exchanges as long as the benefits of joining the liquidity disappear (Pirrong, 1998). The global corporate rights market liquidity is increasing simultaneously with competition growth on the part of non-market securities traders, however, not all investors get the benefits of this, since the local liquidity decreases (Degryse, de Jong and van Kervel, 2011). Market liquidity is further enhanced by liquid markets attractiveness to uninformed traders, for integrated trade offers much lower spreads (the difference between the bid and ask prices) (Fohlin, Gehrig, Brunner, 2009). Liquidity promotes efficiency in the sense that market ability to allocate orders flow is greater in the periods when the market is more liquid (Chordia, Roll, Subrahmanyam, 2008).

Thus, there is strong evidence of stock exchanges convergence in the EU and it will probably continue to occur for quite a long time, since its rate is relatively slow.

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[1] Which anticipate shipment of orders to other market centres only in the case when they offer better prices.

[2] It is considered that the major trading platforms (regulated markets) are available to all market participants, but some specialised trading platforms (platforms with low costs) are accessible only to individual players due to certain restrictions.

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Стаття надійшла до редакції 20.06.2012.

Annexes:

Table A. **Basic performance indicators of the EU stock exchanges, 2007–2010**
(Federation of European Securities Exchanges and European Central Bank)

Name (Country)	Average transaction size, thousand EUR				Number of transactions, thousand				Transaction value, mlrd EUR			
	2007	2008	2009	2010	2007	2008	2009	2010	2007	2008	2009	2010
Fonds des rentes (Belgium)	8651.8	7452.8	7519.0	7729.4	77	80	87	103	666.2	596.2	654.2	796.1
Deutsche Borse AG (Germany)	21.6	23.5	17.8	16.4	179794	154095	111445	126400	3884.7	3624.2	1985.1	2066.9
Irish Stock Exchange Ltd (Ireland)	143.9	63.9	100.7	121.9	875	1275	1180	1115	125.9	81.5	118.9	135.9
Athens Exchange (Greece)	10.5	8.3	5.0	4.4	11693	9419	10151	7849	122.6	78.2	51.0	34.6
Bank of Greece	5618.8	5301.4	5263.9	3813.6	101	52	62	25	567.5	275.7	326.4	95.3
Mercados de Deuda Publica en Anotaciones (Spain)	15785.3	13022.5	13090.4	14674.9	220	190	201	321	3472.8	2474.3	2631.2	4710.6
Bolsas y Mercados Espanole (Spain)	179.6	165.7	223.9	231.1	35806	38382	32936	41577	6431.5	6358.5	7372.8	9610.0
Euronext Paris (France)	24.8	17.4	10.3	9.8	106914	133492	111759	125450	2656.7	2324.4	1148.9	1229.4
Borsa Italiana SpA (Italy)	23.9	16.7	13.7	15.1	81863	76566	73541	71054	1956.6	1277.4	1010.0	1069.5
MTI Wholesale Market (government securities) (Italy)	4940.5	4991.0	5520.1	5535.5	337	175	132	159	1664.9	873.4	728.6	880.1
MTI BONDVISION (Italy)	5382.1	3606.1	4225.1	4343.4	124	110	130	129	667.4	396.7	549.3	560.3
Cyprus Stock Exchange (Cyprus)	5.9	3.6	3.6	9.8	711	427	374	211	4.2	1.5	1.3	2.1
Societe de la Bourse de Luxembourg SA (Luxemburg)	38.4	54.4	18.1	18.3	17	26	15	12	0.7	1.4	0.3	0.2
Malta Stock Exchange (Malta)	30.5	34.9	39.5	25.8	15	14	14	20	0.5	0.5	0.6	0.5
Euronext Amsterdam NV (Netherlands)	36.1	18.2	10.2	10.7	39200	45642	44155	45309	1414.6	829.3	452.1	485.8
Wiener Burse AG (Austria)	17.0	11.7	7.4	7.9	5642	6258	5113	4843	95.9	73.2	37.6	38.2
Euronext Lisbon SA (Portugal)	26.9	9.9	6.2	7.0	4954	5623	5423	5960	133.5	55.5	33.7	41.6
Ljubljana Stock Exchange (Slovenia)	14.3	7.9	7.9	4.9	284	255	162	123	4.0	2.0	1.3	0.6
Bulgarian Stock Exchange (Bulgaria)	10.3	3.7	4.0	4.4	473	391	195	106	4.9	1.5	0.8	0.5
Prague Stock Exchange (Czech Rep.)	77.9	42.4	25.1	31.1	685	1408	1580	1170	53.4	59.7	39.7	36.3
Budapesti Ertektozsde Rt (Hungary)	21.7	11.7	5.7	7.6	1651	1948	3475	2791	35.8	22.8	19.8	21.1
Gielda Papierow Wartosciowych w Warszawie (Poland)	4.0	4.9	3.2	4.6	15271	9904	13336	13188	61.4	48.8	42.2	60.4
Bursa de Valori Bucuresti (Romania)	2.9	1.5	1.1	2.1	1531	1349	1317	902	4.4	2.0	1.5	1.9
Bratislava Stock Exchange (Slovakia)	1306.1	5937.3	2948.8	774.8	8	4	4	8	10.4	23.7	11.8	6.2
London Stock Exchange Ltd (UK)	66.4	57.4	45.4	51.2	161887	202898	167517	153611	10755.2	11643.0	7610.7	7858.1
Euronext (EU)	27.0	16.1	10.1	15.9	161838	199004	175132	189797	4365.9	3207.9	1761.3	3011.4
OMX	66.5	50.6	40.7	36.0	51214	58761	56863	73917	3405.1	2974.5	2314.6	2659.8
Total	48.7	38.9	35.4	40.9	875143	961018	818087	866191	42600.8	37372.3	28973.0	35414.1

Table B. **List of European stock exchanges for which the convergence analysis has been carried out**

1.	Athens Exchange
2.	BME (Spanish Exchanges) Madrid
3.	Borsa Italiana
4.	Bratislava Stock Exchange
5.	Bucharest Stock Exchange
6.	Bulgarian Stock Exchange
7.	CEESEG – Budapest
8.	CEESEG – Ljubljana
9.	CEESEG – Prague
10.	CEESEG – Vienna
11.	Cyprus Stock Exchange
12.	Deutsche Bırse
13.	Irish Stock Exchange
14.	Istanbul Stock Exchange
15.	London Stock Exchange
16.	Luxembourg Stock Exchange
17.	Malta Stock Exchange
18.	NASDAQ OMX Nordic
19.	NYSE Euronext
20.	NYSE Euronext Lisbon
21.	Oslo Bors
22.	SIX Swiss Exchange
23.	Warsaw Stock Exchange

КНИЖКОВИЙ СВІТ

Сучасні проблеми розвитку національної економіки і шляхи їх розв'язання: Колективна наукова монографія / За наук. ред. д.е.н., проф. М.М. Єрмошенка. – К.: Національна академія управління, 2008. – 452 с. Ціна без доставки – 50 грн.

У монографії розглядаються теоретичні і практичні проблеми розвитку економіки України, пропонуються шляхи їх розв'язання з метою зростання її конкурентоспроможності та ефективності.

Буде корисною для аспірантів, викладачів вищих навчальних закладів, практичних працівників.