Bulletin of Taras Shevchenko National University of Kyiv. Economics, 2023; 1(222): 56-62
УДК 339.9
JEL classification: E32; F02; F44
DOI: https://doi.org/10.17721/1728-2667.2023/222-1/7

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BUSINESS CYCLE TRENDS WITHIN THE EUROPEAN CORE AND PERIPHERY: IMPLICATIONS FOR UKRAINE

Economic theory suggests that economic integration can promote business cycle co-movement, which in turn facilitates the institution of common counter-cyclical policies. However, evidence from empirical studies on co-movement within the EU and Europe as a whole is mixed, particularly concerning a so-called group of peripheral countries. This article argues that the existence of large international shocks and their heterogeneous impact on national economies changes the interpretation of co-movement. A decomposition of business cycles into common and country-specific components via a flexible Bayesian dynamic factor model with time-varying parameters and stochastic volatility reveals that the patterns of co-movement among the EU core and periphery are similar after common shocks – such as the Great Recession and the COVID-19 pandemic – and the upward bias introduced by the use of the Pearson correlation coefficient is accounted for. However, it is found that there is another important distinction between the EU core and periphery; that is, during the period of the Great Re-moderation that followed the Great Recession, the business cycles of the core EU countries converged to a lower level of volatility than those of the periphery. Moreover, it is shown that various standard measures of business cycle co-movement can conflate co-movement and volatility convergence, which alters their interpretation. Importantly, this article relates the experience of the EU core and periphery to that of Ukraine. In particular, it is found that the business cycle of Ukraine is similar to those of the EU periphery in terms of the level of its volatility and co-movement vis-à-vis the core EU countries, which has important implications for further development of Ukraine's European integration policy.

Keywords: European integration; business cycles; co-movement; stochastic volatility; dynamic factor models.

INTRODUCTION. Following the European debt crisis and the emergence of an apparent divide between so-called groups of *core* and *peripheral* EU countries, the link between economic integration and business cycle co-movement has come once again to the forefront of the academic debate on European integration. Theoretically, the *endogeneity hypothesis* of Frankel and Rose suggests that economic integration fosters business cycle co-movement, which, in turn, is conductive to the institution of common economic policies [1]. However, the emergence of new approaches to measuring business cycles and their co-movement has brought to light new empirical evidence that disputes this hypothesis.

The purpose of this study was therefore to investigate the patterns of business cycle co-movement between the group of core EU countries – which is generally seen as a bench mark for successful economic integration – and peripheral EU countries using the latest advancements in econometrics. Additionally, we consider whether accounting for the changing volatility of business cycles and large international shocks such as the Great Recession (2007–2009) and the COVID-19 pandemic (2020–2022) might alter the interpretation of co-movement.

Using a Bayesian dynamic factor model to decompose business cycles into common and country-specific components, we found that the core and periphery exhibited similarly high levels of intra- and inter-group co-movement of the common components of their business cycles, but little co-movement of the country-specific components. However, we also found that there was another important facet of the core *vs.* periphery divide; namely, extraction of a time-varying measure of business cycle volatility from the dynamic factor model revealed that the business cycles of the group of the core EU countries have converged to a lower level of volatility than those of the periphery. Moreover, it is shown that a commonly used measure of business cycle co-movement – the negative absolute difference – tends to be more reflective of this convergence of volatility rather than co-movement.

As reported by the government of Ukraine, 72 % of the provisions of the EU-Ukraine Association Agreement have been implemented as of 2022 [2]. In this regard, the development of further integration policy that is grounded in data is becoming increasingly relevant. It is argued in this study that Ukraine is in a position similar to the EU periphery in terms of the level of its business cycle volatility and co-movement vis-à-vis the core EU countries; as such it would be useful, in practical terms, to draw upon the experience of the former group of countries in policy development.

The rest of this article is organized as follows. The literature review section provides a brief overview of the rich body of literature on business cycle co-movement and expands on the novelty of the present research in relation to other recent studies. The methodology section introduces and provides definitions for the key concepts used in this article, elaborates on the empirical strategy used, and describes the data source. The main results and discussion section presents our key findings and contextualizes them concerning our main hypothesis. In the conclusions, a summary of our findings is presented followed by a consideration of their practical implications and avenues for further research.

LITERATURE REVIEW. The modern analysis of business cycle co-movement can largely be traced back to the groundbreaking study by Frankel and Rose (1998), which introduced an effective empirical methodology for the evaluation of co-movement and the various factors that affect it [1]. While the initial studies in this field were frequently contextualized within the framework of the optimum currency area theory and concerned with the feasibility of the Eurozone, recent studies have shifted focus to investigating the evolution of the patterns of co-movement in economically turbulent times.

Following the Great Recession (2007–2009), one branch of literature has focused on the effects of financial contagion and common international shocks on co-movement. In a study of the link between financial integration and co-movement, Kalemli-Ozcan et al. (2013) show that accounting for common shocks through fixed time effects can meaningfully alter findings based on panel data. In particular, they find that banking integration leads to a decoupling of business cycles after common shocks are removed from the data, which is in contrast to previous empirical studies [3, p. 1195]. Cesa-Bianchi et al. (2019) developed this notion further by considering common shocks with heterogeneous impact across countries and proposed an alternative explanation that the results presented in Kalemli-Ozcan et al. (2013) were a consequence of asymmetric national responses to common shocks [4].

As pointed out by Mazurenko (2018) [5, p. 54-55], another emerging body of literature is concerned with the processes of economic disintegration in the EU. Within the context of the European debt crisis, of particular note is the growing core *vs.* periphery divide. Belke et al. (2017) found that the EU periphery, conventionally defined as to include Southern European countries and Ireland, had experienced declining co-movement both within itself and vis-à-vis the core EU countries during the period that followed the Great Recession [6]. Moreover, Ahlborn and Wortmann (2017) suggested that the use of predefined groups could be inadequate to reflect core *vs.* periphery patterns in the EU used a data-driven fuzzy clustering approach to show that the composition of the core and periphery could change over time [7].

In this study, we build upon both of these approaches to highlight that explicitly modeling the volatility of business cycles introduces further complexity to the interpretation of these phenomena. In particular, it was found that business cycles tend to converge toward a low level of volatility in normal times, which affects the interpretation of commonly used measures of co-movement. To our knowledge, the convergence of the volatility of business cycles remains a relatively infrequently-studied phenomenon, with Del Negro and Otrok (2008) remaining one of the most influential studies in this area [8]. In this respect, it is shown here that their findings are also applicable to the period between the Great Recession and the COVID-19 pandemic. Unique to this study is the extension of the core *vs.* periphery discussion to include Ukraine.

METHODOLOGY. Since business cycles are not directly observable or empirically measurable, the first and key methodological choice is the overall concept and the data processing method by which they are approximated. Thus, the *growth cycle* approach, which is favored by the OECD and implies a decomposition of macroeconomic data into a long-term trend and cyclical fluctuations, is adopted in this study.

As is standard in business cycle literature, real GDP time series is employed as an indicator of aggregate economic activity. Following recent advancements in econometrics, the cyclical components of real GDP are extracted using the machine-learning-boosted version of the Hodrick-Prescott filter introduced by Phillips and Shi (2020) [9]. In addition to being robust to user-specified parameters, Mei et al. (2022) showed that the boosted Hodrick-Prescott filter performed well in a variety of empirical settings [10], which makes it well suited for application to a heterogeneous set of countries.

The first measure of business cycle co-movement to be considered is the Pearson correlation coefficient (*PCC*). Its main advantage is that it has an intuitive interpretation concerning co-movement, e.g., values closer to 1 indicate a greater similarity of the shapes of the business cycles under consideration. However, *PCC* has the drawback of being calculated over the entire sample period and thus does not track time-variation in co-movement.

To overcome this limitation, some alternative measures have been proposed, such as the period-by-period correlation index of Cerqueira and Martins (2009) and the instantaneous quasi-correlation index proposed by Abiad et al. (2013) [11, 12]. However, in lieu of the *PCC* and its derivatives, measures of similarity based on Euclidean distance have gained traction in recent empirical studies, i.e., Prokopenko et al. (2021) [13, p. 11]. In this study, the negative absolute difference of cyclical components was employed, which was calculated as follows:

$$S_{i,j,t} = -|c_{i,t} - c_{j,t}|, \tag{1}$$

where $c_{i,t}$ and $c_{j,t}$ are the cyclical components of real GDP in countries *i* and *j* at time *t*. As discussed by Cesa-Bianchi et al. (2019), *S* has a different interpretation with respect to co-movement compared to *PCC* [4]. In particular, *S* can assume values close to 0 – which implies a high degree of co-movement – even in the case of completely uncorrelated business cycles, as long as the Euclidean distance between them is small. As will be shown later, *S* can be interpreted as a measure of convergence of business cycle volatility rather than co-movement.

Furthermore, it was relevant to investigate whether the existence of common international shocks with heterogeneous impact across countries can meaningfully alter the interpretation of *PCC* and *S*. Therefore, the cyclical components of real GDP were decomposed using a flexible Bayesian dynamic factor model with time-varying factor loadings using eq. 2:

$$c_{i,t} = B_{i,t}F_t + e_{i,t}, \tag{2}$$

where F_t is a factor that is common to all countries in the sample, $B_{i,t}$ are the factor loadings that quantify the sensitivity of the countries to this factor, and $e_{i,t}$ are the residual terms. According to the study of Del Negro and Otrok (2008), the product of $B_{i,t}$ and F_t is interpreted as the *common components* of business cycles that are driven by international shocks and $e_{i,t}$ – as *country-specific components* that are driven by domestic shocks [8, p. 22–23]. The model was run for 350,000 iterations, of which the first 50,000 were discarded as a burn-in period. The inefficiency factor for the slowest-mixing parameter in the model is close to 600, which results in an effective sample size of approximately 500 for inference. The median estimates of the parameters from the dynamic factor model were then used to construct the corresponding measures of co-movement for common and country-specific components. In the main results section, the superscripts *F* and *e* are used to explicitly denote when a measure of co-movement is calculated for common or country-specific components, respectively.

Lastly, to investigate the link between co-movement and business cycle volatility, the dynamic factor model was augmented with stochastic volatility of shocks to F_t and $e_{i,t}$. Following Prüser (2021) volatility was modeled as a random walk using the *horseshoe estimator* of Carvalho et al. (2010), which allows for both gradual evolution of volatility and abrupt structural breaks or extreme one-time events [14, p. 3-4; 15].

The data set used in this study comprises real GDP series for 35 countries that are participants of the extended European single market: Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Malta, the Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, and the United Kingdom. The data are quarterly and cover the period of 2001Q1–2021Q4. The source for the data is the World Bank's Global Economic

Monitor database [16]. All data were converted to natural logarithms before the application of the boosted Hodrick-Prescott filter. Moreover, the cyclical components extracted via the boosted Hodrick-Prescott filter were demeaned and standardized to have a variance of 1 before entering the dynamic factor model. Thus, the factor loading and volatility estimates reported in the results section correspond to the demeaned and standardized data, while the data used in the measures of co-movement were scaled back to the original but demeaned units.

To get a balanced view of common shocks in Europe, the entire sample was used to estimate the dynamic factor model. Moreover, since the first 22 quarters of observations were used as a training sample to set the lags and calibrate the priors used in the model, only the period of 2006Q3–2021Q4 was used for the final analysis.

Since the purpose of this study was to provide an overview of the patterns of business cycle co-movement and volatility in the EU core and periphery rather than rigorously define which countries should be included in these groups *per se*, the group compositions provided by Bartlett and Prica (2017) were used. In particular, the group of core EU countries comprises Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Latvia, Lithuania, Netherlands, Poland, Slovakia, Sweden, and the United Kingdom, and the group of peripheral EU countries – Bulgaria, Croatia, Cyprus, Greece, Hungary, Ireland, Italy, Malta, Portugal, Romania, Slovenia and Spain [17, p. 131–132]. Additionally, we include Malta in the peripheral group. We find that these group compositions are consistent with those used in the broader core *vs.* periphery literature. For comparison, cross-sectional means of the measure of co-movement for the group of non-EU countries in their relation to the core EU countries were also provided.

RESULTS. A summary of the sub-group and sub-period means of *PCC* and *S* is presented in Table 1. Note that in the *Core vs. Periphery* sub-group, the measures of co-movement are calculated only for country pairs that include one core country and one peripheral country; analogously, the first country in a pair is always Ukraine in the *Ukraine-Core* sub-group and a non-EU country – including Bosnia and Herzegovina, Iceland, North Macedonia, Norway, Serbia, Switzerland, and Turkey – in the *Other-Core* sub-group.

Table 1. **Co-movement of Business Cycles and their Components**

Sub-group	Overall cycles		Common components		Country-specific components	
2006Q3-2021Q4						
	PCC	*S*	PCC^F	S^F	PCC^e	S^e
All	0.704	-0.013	0.968	-0.003	0.014	-0.011
Core	0.785	-0.010	0.962	-0.003	0.066	-0.008
Periphery	0.712	-0.014	0.993	-0.003	0.035	-0.013
Core *vs.* Periphery	0.726	-0.012	0.975	-0.003	-0.006	-0.011
Ukraine-Core	0.575	-0.017	0.804	-0.007	-0.035	-0.014
Other-Core	0.694	-0.012	0.980	-0.003	0.006	-0.012
2006Q3-2014Q1						
	PCC	*S*	PCC^F	S^F	PCC^e	S^e
All	0.601	-0.013	0.998	-0.003	0.002	-0.012
Core	0.778	-0.010	0.999	-0.002	0.095	-0.009
Periphery	0.510	-0.012	0.999	-0.002	-0.032	-0.012
Core *vs.* Periphery	0.628	-0.011	0.999	-0.002	-0.031	-0.011
Ukraine-Core	0.725	-0.019	0.989	-0.010	-0.044	-0.014
Other-Core	0.566	-0.013	0.999	-0.002	0.009	-0.013
2014Q2-2021Q4						
	PCC	*S*	PCC^F	S^F	PCC^e	S^e
All	0.805	-0.013	1.000	-0.004	0.011	-0.011
Core	0.895	-0.009	0.999	-0.003	-0.010	-0.007
Periphery	0.791	-0.015	1.000	-0.004	0.096	-0.014
Core *vs.* Periphery	0.837	-0.013	1.000	-0.004	0.013	-0.011
Ukraine-Core	0.504	-0.016	0.997	-0.003	-0.027	-0.014
Other-Core	0.815	-0.011	1.000	-0.003	-0.005	-0.010

Source: compiled by the authors on the basis of [16].

First, the properties of *PCC* as a measure of co-movement were considered. The most striking observation from the data in Table 1 is that the co-movement of business cycles across all countries in the sample appears to be largely driven by the correlation of their common components, as reflected in the values of PCC^F. One possible explanation of this result is that common shocks have high explanatory power concerning the variance of business cycles in the sample. This conjecture was evaluated by performing a variance decomposition. The results indicate that the mean contribution of common shocks to the variance of business cycles across all countries in the sample is 38.234 %. This suggests that while domestic shocks play a major part in the evolution of business cycles in the sample, most of the co-movement, as defined by *PCC*, occurs at the level of responses to common shocks. As discussed later, this has important policy implications.

This issue is further complicated by the fact that the volatility of common shocks in the sample is not constant; e. g., volatility during the Great Recession and the beginning of the COVID-19 pandemic was substantially higher than during the inter-crisis period. As shown by Forbes and Rigobon (2002) and Corsetti et al. (2005), measures of co-movement based on *PCC* can be meaningfully biased upwards in the presence of cross-country spillovers of large shocks, even if they are rare relative to the length of the sample [18, 19]. We show that this result still holds when one considers a model where cross-country co-movement is partially driven by exposure to common shocks of varying magnitude. In particular, the mean cross-country *PCC* between the business cycles of all countries in the sample is noticeably higher in the second half of the sample despite the underlying common shock transmission mechanism that is embedded in the factor loadings remaining stable. Fig. 1 presents the evolution of the cross-sectional mean of the median estimates of $B_{i,t}$ across all countries in the sample as a solid line, with the 16th–84th percentile Bayesian credible intervals being represented by shaded areas.

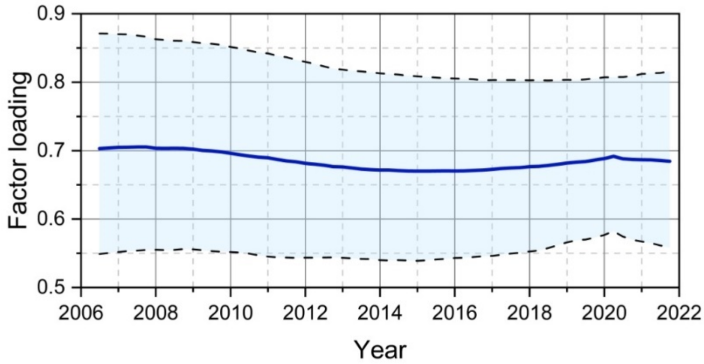

Fig. 1. Cross-sectional mean of factor loadings across all countries in the sample

Source: compiled by the authors.

Conversely, it was found that *PCC* also biased co-movement downwards in cases where an individual country in the sample experienced a similarly large but idiosyncratic shock; a particularly notable example of this in the sample was the sharp contraction of Ukraine's economy in 2014. However, the results reported in Table 1 suggest that the patterns of co-movement of Ukraine vis-à-vis the core EU countries are similar to those observed for the Core *vs.* Periphery sub-group after accounting for the biases described above via a decomposition of business cycles into common and country-specific components. In particular, the notion of a high cross-country correlation between the common components of business cycles and little correlation between the country-specific components still holds. Thus, it is concluded that caution should be exercised when making inferences for the entire sample period based on *PCC* alone.

In the next stage, the properties of *S* as a measure of co-movement were considered. Similarly to *PCC*, the values of *S* reported in Table 1 show that the co-movement of business cycles is greater within the group of core EU countries than other sub-groups in the sample. However, in contrast to *PCC*, a decomposition of business cycles into common and country-specific components did not smooth out the differences in *S* across the sub-groups. Moreover, these differences in *S* are largely driven by a dispersion of the country-specific components of business cycles, as reflected in the values of S^e. In view of this, we next focused on the interpretation of S^e. We also note that values of S^e for the group of non-EU countries in their relation to the core EU countries are similar to those reported for the Core *vs.* Periphery sub-group, which suggests that the business cycles of the group of core EU countries are different from all other European countries rather than just the EU periphery *per se*.

As discussed in the methodology section, the interpretation of *S* and its derivative measures concerning co-movement is elusive, as their relationship with *PCC* is ambiguous. We, therefore, attempt to shed some light on the mechanisms underlying S^e by plotting its evolution against the volatility of shocks to the country-specific components of business cycles. Fig. 2 presents the evolution of S^e and the cross-sectional mean and standard deviation of the median estimates of country-specific volatility across all countries in the sample. Note that in Fig. 2, S^e is scaled by 100 for the sake of visual clarity.

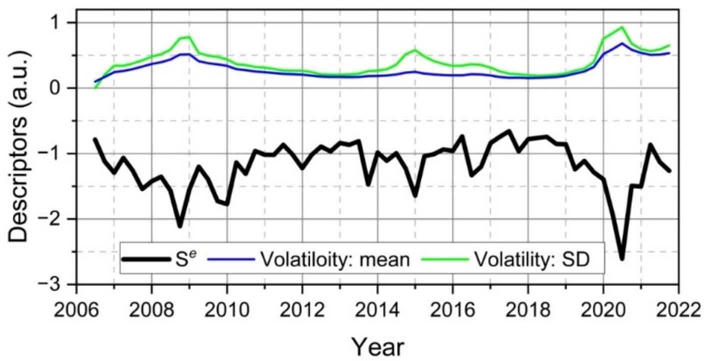

Fig. 2. Cross-sectional mean and standard deviation of country-specific volatility and cross-sectional mean of S^e across all countries in the sample

Source: compiled by the authors.

Data shown in Fig. 2 reveals that the cross-sectional mean and standard deviation of volatility are positively correlated with each other and negatively correlated with S^e. Thus, the volatility of the country-specific components of business cycles converges in normal times but diverges in turbulent times. This is an important observation, as it is theoretically possible for convergence to also occur in turbulent times. The fact that this is not the case in the sample indicates that country-specific business cycle volatility in Europe tends to be similarly low in normal times but disparately high in turbulent times. Quantitatively, *PCC* of 0.929 between the mean and standard deviation of volatility lends statistical credence to this observation.

Secondly, *PCC* of –0.784 between the cross-sectional mean of S^e and the cross-sectional standard deviation of volatility suggests that S^e can be interpreted as a bilateral measure of convergence of country-specific business cycle volatility. Thus, the core *vs.* periphery differences in the values of S^e – in conjunction with low values of PCC^e – provide first evidence consistent with our hypothesis that the difference between the EU core and periphery lies in the level of volatility of the country-specific components of their business cycles rather than the patterns of their co-movement. In practical terms, this means that, if one is to treat the group of core EU countries as a benchmark for successful economic integration, achieving a convergence of business cycle volatility may be more important than co-movement.

Conversely, the values of PCC^F and S^F are closely similar across both the core and the periphery, with the former being close to unity. This observation once again is of practical significance, as one of the main costs of deep economic integration is thought to be the partial or complete loss of policy independence in various domains. The fact that the responses of the core and the periphery to common shocks are similar in both magnitude and direction means that the European Central Bank (ECB) – and other EU institutions – are free to conduct a one-size-fits-all counter-cyclical policy in times of major international crises, such as the Great Recession and the COVID-19 pandemic.

Lastly, we consider the implications of our interpretation of S^e for Ukraine in its relation to the core EU countries. The values of S^e reported in Table 1 suggest that Ukraine is in a position similar to the EU periphery in terms of country-specific business cycle volatility vis-à-vis the core EU countries. Since Ukraine has experienced several severe domestic shocks, it is informative to also consider the evolution of S^e for the Ukraine-Core sub-group, which is presented in Fig. 3.

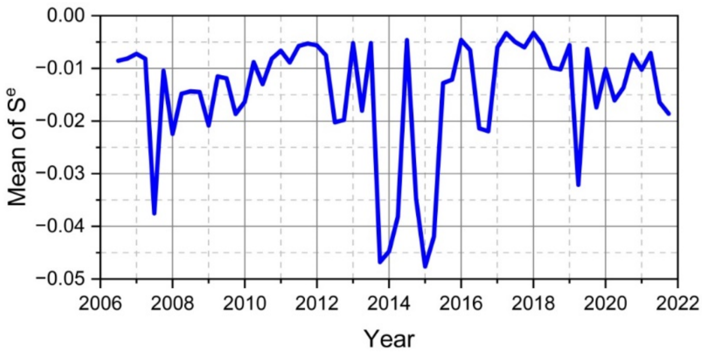

Fig. 3. The cross-sectional mean of S^e for the Ukraine-Core sub-group

Source: compiled by the authors.

The results of the data analysis presented in Fig. 3 reveal that the volatility of the country-specific component of the business cycle of Ukraine converged toward the core EU countries in the period between the Great Recession and the COVID-19 pandemic, albeit briefly interrupted in 2014–2015. Of particular note is the fact that if one excludes the years 2014 and 2015 from the sample, the mean value of S^e for the Ukraine-Core sub-group becomes –0.012, which is close to being on par with the value that is observed for the Core *vs.* Periphery sub-group over the entire sample period. Thus, one can conclude that Ukraine has, at various points in time, achieved greater similarity of business cycles with the EU than the traditional *PCC* would suggest.

CONCLUSIONS. Traditional economic theory suggests that various aspects of economic integration – such as increased trade or financial linkages – can promote business cycle co-movement, which, in turn, is of practical significance for the institution of common economic policies However, the emergence of a core *vs.* periphery divide in the EU, along with recent studies providing mixed evidence on co-movement within the EU, has called this commonly-held view into question.

Using a flexible Bayesian dynamic factor model, we show that the main distinction between the EU core and periphery lies along the lines of business cycle volatility rather than co-movement. In particular, the business cycles of the core EU countries have converged to a lower level of volatility than those of the periphery in the period between the Great Recession and COVID-19. Moreover, we find that both the core and the periphery tend to exhibit similarly high levels of business cycle co-movement in response to large international shocks, which suggests that the ECB – and other EU institutions – are free to conduct a one-size-fits-all counter-cyclical policy in turbulent times.

One can thus argue that insofar as one treats the group of core European countries as a benchmark for successful monetary integration, achieving a convergence of national business cycles toward a low level of volatility may be of greater importance than co-movement.

We find that after accounting for the biases that arise when calculating *PCC*, the patterns of co-movement of the business cycle of Ukraine vis-à-vis the core EU countries are closely similar to both the intra- and inter-group co-movement patterns in the core and periphery. Because of this, achieving convergence of the volatility of Ukraine's business cycle with those of the core EU countries may thus be of greater practical significance for Ukraine's European integration policy than further promoting co-movement.

Lastly, we highlight the fact that the negative absolute difference has ambiguous properties as a measure of co-movement. In particular, we show that it may be more reflective of the convergence of business cycle volatility than co-movement. Since this study is mostly concerned with empirical regularities, we thus emphasize that fundamental theoretical research is needed for a better understanding of the negative absolute difference and its properties, as well as further empirical research to establish whether the link between co-movement and business cycle volatility holds for a larger sample of countries.

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Received: 01/03/2023
1st Revision: 10/03/2023
Accepted: 30/04/2023

Author's declaration on the sources of funding of research presented in the scientific article or of the preparation of the scientific article: budget of university's scientific project.

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ОСОБЛИВОСТІ ДІЛОВИХ ЦИКЛІВ У КРАЇНАХ ЦЕНТРУ ТА ПЕРИФЕРІЇ ЄС: ДОСВІД ДЛЯ УКРАЇНИ

Однією з гіпотез сучасної теорії економічної інтеграції є те, що поглиблення міжнародних торговельних і фінансових зв'язків може мати своїм наслідком синхронізацію ділових циклів, що сприяє розробці спільної контрциклічної політики. Усупереч цьому, останні емпіричні дослідження тенденцій центру і периферії в ЄС засвідчують, що відбулася десинхронізація ділових циклів між цими двома групами країн. У дослідженні на основі байєсівської динамічної факторної моделі продемонстровано, що головна різниця між діловими циклами центру і периферії ЄС полягає не в рівні синхронності, а в рівні волатильності. Доведено, що діловий цикл України подібний до циклів периферійних країн ЄС.

Ключові слова: Європейська інтеграція, ділові цикли, синхронізація, стохастична волатильність, динамічні факторні моделі.

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