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Regional integration and the economic geography of Belarus

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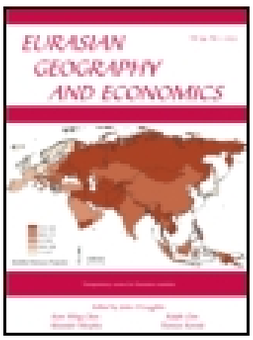

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Regional integration and the economic geography of Belarus

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ABSTRACT

This study presents novel research on the economic geography of Belarus. The 118 regions of Belarus are examined in relation to the Eurasian Customs Union (EACU) through the period 2005–2014. Our estimation methods specifically take spatial and dynamic processes into account. We observe that EACU membership has corresponded to a slowdown in the process of regional economic convergence in Belarus, and intensified economic competition with a geographical dimension among regions. Furthermore, we find some evidence that urban and industrial regions, and regional clusters of private business activity have benefited more from the EACU relative to less urbanized areas. Additionally, spatial clusters and outliers are identified and compared across the periods prior and after the establishment of the EACU. Our preferred estimation model results suggest half-lives of convergence of about 9.4 and 31.5 years for the pre-EACU and EACU periods, respectively.

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Eurasian Customs Union; Belarus; convergence; spatial analysis; regional integration; dynamic panels

Introduction

When several countries in Central and Eastern Europe joined the European Union (EU), many people in those countries expected that the integration would allow their nations to leap the development gap and catch-up with their western neighbors. This expectation lead to a prevailing question: does regional integration reduce economic disparities? The answer to this question is complex. For instance, the evidence found by Armstrong (1995) suggested that there was convergence in the EU, albeit a slow one. On the other hand, numerous studies have shown that the process of convergence varies by a considerable degree within the EU. Whereas convergence occurred primarily in Western Europe, other regions have experienced divergence (Dunford and Smith 2000; Giannetti 2002). A study by Puga (2002) finds that although income differences across countries have decreased, disparities across regions

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persist. Even further complexity was earlier introduced by Quah (1996) who observed that the evolution of the distribution of income in the EU differs also across time.

Most of the existing studies, however, use countries – or regions from multiple countries pooled together – as their units of analysis. As a result, these studies inform us only about the *between effect* of regional integration. But a policymaker from a national government may be interested in the *within effect* induced by integration as well. To illustrate, results from the previous analyses can tell a government official in Poland whether further integration would allow the country (or individual regions within Poland) to catch-up with Germany (or regions in Germany), but the official still would not know how much further integration may affect income disparities within Poland. This study addresses this knowledge gap and examines the distributional impacts of the Eurasian Customs Union (EACU) on regional disparities within Belarus.

After the dissolution of the Soviet Union in 1991, the economic power of Russia and former Soviet countries have declined. To reverse the trend, numerous attempts were made to reintegrate the region: the Ruble zone currency union, the Commonwealth of Independent States (CIS) and the Eurasian Economic Community (Libman and Vinokurov 2012). In common, these attempts tried to limit disintegration by strengthening regional trade within the Eurasian region. The Eurasian Customs Union (EACU), launched in 2010, is one of the recent examples of the Eurasian reintegration attempts. The EACU aims to eliminate nontariff barriers among the three member states: Belarus, Kazakhstan and Russia. It essentially adopted a common external tariff toward nonmember economies. The EACU was succeeded by the formation of the Common Economic Space in 2012, enabling the free movement of services, capital, labor and a greater variety of goods, due to the removal of nontariff barriers. The next step of the Eurasian integration was the creation of the Eurasian Economic Union (EEU) and the joining of Armenia and Kyrgyzstan to the EACU in 2015.

Regional integration through a customs union is a highly significant socioeconomic and political subject in relation to the Eurasian socioeconomic landscape. However, the economic outcomes of the EACU for Belarus are not yet clearly documented (Tochitskaya and Kirschner 2014). This may be partly attributable to the confounding caused by the pre-existing high level of economic integration between Belarus and Russia (Tochitskaya and De Souza 2009; De Souza 2011). As tariff-free trade already existed to some extent among member countries, the main influence of the EACU on the Eurasian economic landscape has been through the diversion of trade resulting from the introduction of common external tariffs, rather than an improvement of market access within the Union (Tarr 2016). Furthermore, the introduction of the common external trade tariffs, which lie in the core of the EACU agreement, has unevenly resulted in favor of Russia (Tarr 2016). In the face of such

complexities which obstruct the assessment of the economic consequences of the EACU, policymakers have been seeking to predict the prospective benefits of the Union against the backdrop of a long-standing ambiguity regarding its functionality (Tochitskaya 2010). In the early days of the EACU, De Souza (2011) implied further complexities by predicting that the integration would reduce the GDP's of the member countries as a result of trade creation effects being surpassed by trade diversion effects. Tarr and Jensen (2012) on the other hand, draw attention to another duality by highlighting that the tariff adjustments as part of EACU membership initially resulted in a decrease in real income in Kazakhstan, while estimating that the gains from the reduction of nontariff trade barriers may greatly outweigh this loss in the forthcoming years. In accordance with this argument, Mogilevskii (2012) notes that the EACU's overall effects on the economy of Kazakhstan are dubious because losses in welfare resulting from trade diversion go along with a counterbalancing increase in government revenue.

Our study is the first in specifically documenting the effects of EACU on economic convergence in Belarus. Research on the realized economic impacts – as opposed to predicted effects – of the EACU is scant and, if exists, is confined to the effect of the EACU on trade diversion (Isakova, Koczan, and Plekhanov 2016; Tarr 2016), competitiveness (Falkowski 2017; Hartwell 2016), economic stability (Vinokurov et al. 2017), and on welfare (Gnutzmann and Arevik 2016; De Souza 2011), aside of the literature on the potential political consequences for the region (Alimbekov, Madumarov, and Pech 2017; Cadier 2014; Kaczmarski 2017; Kirkham 2016; Roberts 2017). However, there is no information on the impacts of the Eurasian integration project on regional disparities within Belarus. That being so, our study presents a novel examination of the distributional effect of the EACU on the regional economies of Belarus, and a unique inspection of the regional economic geography of the country through the use of spatial and dynamic panel analysis methods.[1]

Regarding empirical approaches in particular, existing regional integration literature on convergence tends to concentrate on the between country variation – either in the national or regional level. In contrast, we focus on the within-country effect of regional integration, and thus provide groundwork for distinct policy implications. Furthermore, differing from most studies which only look at income convergence after integration, our analysis includes the preintegration years as well. In this way, we are able to capture the distributional impact of integration. In addition, our approach particularly takes spatial interrelatedness across regions into account while examining per capita income convergence. Following Barro et al. (1991), many studies consider macroeconomic fundamentals such as physical capital, human capital and infrastructure key factors that explain economic variations and convergence (Mankiw, Romer, and Weil 1992; Button 1998; Ding, Haynes, and Liu 2008). But as Quah (1996) points out, neighborhood effect is potentially a stronger

driving force behind economic convergence (or divergence) than many macroeconomic factors. Above that, we allow for dynamic processes through time in our estimations aside of the spatial interrelationships for the purpose of addressing certain potential biases in our results. Finally, our study suggests a new way of looking at the mechanisms that explain convergence. Economic convergence can take place through different channels; for instance, factor mobility (Barro and Sala-I Martin 1992), technological spillovers (Ertur and Koch 2007), institutions such as the EU and trade agreements (Armstrong 1995; Chiquiar 2005), regional policies (Cappelen et al. 2003; Hansen and Teuber 2011) and agglomeration (Marquez and Hewings 2003; Geppert and Stephan 2008). Findings from this study suggest that economies with relatively simple production structures and short production chains are more likely to suffer negative distributional effects from regional integration. These negative effects may cause divergence or a slowdown in convergence in the short run, as we observe in our results.

The subsequent sections will introduce the background of the EACU and the Belarusian economy, followed by a review of the literature on the economic impacts of free trade agreements. Next, we explain our empirical approach, the data, and elaborate on our empirical results. Finally, the conclusion section discusses the policy implications of our findings alongside potential avenues for future research.

Belarus and the Eurasian Customs Union

Customs unions require a high level of coordination and inflict strict constraints on the sovereignties and policy preferences of member countries (Schiff and Winters 2003), and inefficient customs unions can cause negative political consequences. Tarr (2016) and Schiff and Winters (2003) mention several unfavorable outcomes resulting from unreasonably disproportionate income distribution caused by defective economic integration projects, such as the closure of the borders among the East African Customs Union members, and – albeit being an extreme case subject to diverse factors – the American civil war to some extent. The European Union on the other hand, stands as a relatively successful project.

Turning back to the EACU, while Russia and Belarus have been already highly harmonized in terms of their tariff lines (De Souza 2011), trade disputes involving non-tariff measures have nevertheless taken place between the two countries regarding the standards of certain products (Tarr 2016). Unlike Russia and Kazakhstan which are major oil exporters in the region, Belarus is a small open economy. As a neighbor of the EU, about 50% of its exports and over half of its imports are with Russia (UN Comtrade 2018). As a consequence, Belarus is in a fragile position in relation to trade shifts that can involve the Russian Federation, as it is the CIS country with the highest trade dependency to

Russia (Tochitskaya and De Souza 2009). More specifically, Belarusian economic growth heavily relies on refining and exporting cheaply imported oil and gas from Russia (Tarr 2016). This dependency suggests that the EACU has more implications for Belarus than for the other member countries, rendering the country an ideal case for studying the effects of the customs union.

The early economic effects of the EACU have been ambiguous due to the already existing strong level of economic integration between Belarus and Russia (De Souza 2011). Some decipherment of these early impacts (for the union as a whole) are presented by Isakova, Koczan, and Plekhanov (2016) who observed that the EACU caused a decrease in Kazakhstan's imports from China, an increase in the imports from the other EACU members, and a small decrease in the imports of Belarus from the EU. Regarding the drop in the imports from EU, it would be useful to highlight the argument by Tarr (2016) that an increase in external tariffs would impede the import of technology into the EACU zone from advanced economies.

With the objective of addressing the above mentioned ambiguity regarding the economic consequences of the EACU, particularly in relation to the Belarusian economic geography, we compiled an original data set from the official statistical reports for all 118 "raions" of Belarus (henceforth referred to as regions) for the period 2005–2014. The fact that the EACU was accepted on 27 November 2009 and launched on 1 January 2010 makes it convenient to study the direct effects of the customs union. As Isakova, Koczan, and Plekhanov (2016) points out, this short policy window of about one month circumvents the identification problem related to the endogenous nature of the tariff, an empirical issue difficult to tackle and often ignored when studying the impacts of regional integration. We discuss our data in detail in Section 4.

Theoretical background and empirical approach

Spatial effects of regional integration

Generally, a free trade agreement or a customs union applies the same to all regions of an economy. However, its impact on the economic activity in each location is shown to vary.[2] Solidifying this argument, Krugman and Livas Elizondo (1996) theoretically established the effects of nation-wide trade policies – within the New Economic Geography (NEG) framework – on the formation of large metropolises in the developing world. Theory and empirics have identified inter-regional labor mobility and trade costs as factors affecting the firm incentives for spatial concentration (Krugman 1991; Monfort and Nicolini 2000; Paluzie 2001; Behrens et al. 2007), together with the role of proximity of national economic cores to supra-national economic centers (Paelinck and Polèse 1999). To illustrate, a decline in trade barriers between countries can stimulate businesses to relocate to new locations, leading to the development

of clusters, through a reduction in the prices of intermediate good imports and the enhancement of the market access of local firms to larger markets (Schiff and Winters 2003; Puga and Venables 1998). Aside of the removal of trade barriers and the harmonization of tariff lines, economic integration also enables the common usage of transit infrastructure and trade routes (Tochitskaya and Kirschner 2014). Within this framework, Tochitskaya (2010), argued that EACU participation may increase the importance of Belarus as a transit country, and that further spatial effects may emerge in the form of locational advantages which influence investment inflows resulting from regional economic integration. This being said, the internal non-oil trade flows within the EACU countries are subject to various problems due to the lack of infrastructural harmonization and quality (Shcherbanin and Golovaneva 2013).

From an empirical point of view in relation to economic geography, the influence of an external political agreement on the internal spatial economic structure of a country has been documented by several authors. The commonly examined cases are the North American Free Trade Agreement (NAFTA) and the European Union (EU). For instance, Paelinck and Polèse (1999) compare how NAFTA has affected the sub-regional economic activity in Mexico and Canada. Their results imply that the spatial effects of trade-based economic integration depends on the relative locations of the economic cores of the member countries and the general core of the union. In another study that looks at the effects of NAFTA, Baylis, Garduño- Rivera, and Piras (2012) observe that rich border regions in Mexico have benefited from trade integration unlike the more densely populated areas. For the case of the EU on the other hand, studies mostly focus on the convergence among the regions within the union as a whole, probably thanks to the availability of standardized regional data across nations. As a result, there is a plethora of studies on EU regional convergence. However, unlike the research on the NAFTA countries, studies focusing exclusively on the effect of the EU on convergence within a single country are scarce. Nevertheless, several EU-wide studies that also elaborate on within-country trends can be singled out; such as Martin (2001) who observe divergence in regional employment growth in the EU countries during the period 1975–1998, and Armstrong (1995) who finds that the within-country convergence speeds in the EU decreased after the 1960s (the study covers the period 1950–1999), a result supported by the findings of Cuadrado-Roura (2001).

Focusing on the economic effect of customs unions, Venables (2003) theorizes that the effect of a customs union on regional disparities will depend on the comparative advantage of its members with the rest of the world (Venables 2003). The key insight from the theory is that if the members have to divert their trade from a more productive-efficient nonmember to a less productive-efficient member, this trade diversion effect will harm the members of the customs union. Furthermore, if comparative advantage is associated with income, the membership is likely to lead to divergence of income within

the customs union composed of low-income countries because of the trade diversion effect (Venables 2003, 748). The theory, however, mainly concerns convergence among member states and does not predict the distributional effect within a country.

Given that the EACU primarily lifted the trade barriers between the member countries and imposed a single external tariff to nonmembers, it is expected to affect economic convergence or divergence directly through trade. Because internal and external tariff rates have been reduced (Isakova, Koczan, and Plekhanov 2016), consumers and downstream industries can obtain consumption goods and intermediate inputs from other countries with lower prices. The people of Belarus may also gain from a boost in exports, because the import prices of intermediate inputs are lower. Nevertheless, these economic benefits distribute unequally over space, depending on the comparative advantage of the Belarusian economy and the industrial structure of a region. A region will benefit more from the EACU if it was importing high-tariff inputs for production before joining the EACU. On the other hand, a region may not gain much when it does not rely on imported products, although its demand may shift to the lower price products or inputs. In contrast, a region may lose because of trade diversion; that is, it shifts its demand from a more efficient supplier to a less efficient one because of the tariffs. The tariff rate of some products and inputs can also become higher if the external common tariff rate was higher than the ones prevailed.

Most industries in Belarus are legacies of the Soviet era. They are outdated, inefficient and internationally uncompetitive (Savchenko 2009). Economic activities too are distributed unequally over space, and regional disparities remain a perpetual economic feature of the country. In Belarus the formation of production patterns in regions and the clustering of firms gravitate toward more industrialized areas, in particular to cities and capital regions of oblasts such as Minsk, Homyel and Vitebsk.[3] Since most economic activities of the country are concentrated in the major cities, it is expected that these economic centres would become the winners of the EACU, thereby contributing to agglomeration processes and divergence among Belarusian regions.

Certainly, the Eurasian integration may offer significant trade privileges for peripheral regions and prompt the centrifugal effect of resource distribution. However, in order to maximize this effect, certain conditions have to be met. Firstly, the resources of the economy should be mobile in order to utilize emerging opportunities in the border regions, and secondly, the border regions should establish business networks with the agglomerating centers to support forward and backward linkages (Niebuhr and Stiller 2002). The latter condition highlights the need of linkage maintenance for expanding and efficient production, which is especially important in industrially-oriented regional economies. Moreover, it also implies that the benefits of positive externalities from economic centers are more likely to fall into the areas

located closer to the capital regions, which means that these areas gain more benefits from regional integration. Thus, the gains in the border zone are expected to be less, even if all other factors would be the same.

Regional β-convergence, technological spillovers, and spatial effects

Our empirical analysis is rooted in the theoretical foundation of the β-convergence approach established by Barro and Sala-i Martin (Barro et al. 1991; Barro and Sala-I Martin 1992; Sala-I Martin 1996b), and its panel expansion substantiated by Islam (1995). β-convergence equations lead to empirical results that answer whether (and how fast) per capita income differentials across regions diminish over time. This type of convergence analysis is based on the Solow (1956) and Swan (1956) neo-classical growth model which is about a single economy converging to a steady-state level of output growth that can be equal to zero. This growth rate can be positive if there is exogenous technological progress that is labor-augmenting. Such convergence is anticipated – albeit for a single economy – by the neo-classical framework due to the assumption of diminishing marginal products of capital investments.

β-convergence of economies may only happen under certain conditions such as similar technology and common structural characteristics (Mankiw, Romer, and Weil 1992). To test whether such conditions play a role, growth-convergence equations are generally augmented through the addition of theoretically supported variables. In a subnational regional context, where the relative locations of economies are obvious factors that influence their economic outcomes, a further augmentation to the model is through the consideration of spatial effects. Formally referred to as spatial dependence, these effects are caused by various types of spillovers in a geographical framework (Anselin 1988a). A comprehensive formalization of these spill-overs is rigorously presented by Ertur and Koch (2007) who formulate the occurrence of technological spillovers through spatial connections. An older, less-rigorous argument underlining spillovers among regions resulting from technological progress is given by Armstrong and Taylor (2000). Regarding the study of regional income convergence in particular, as earlier mentioned, Quah (1996) has shown that space-related spillover effects play a more important role in regional income distribution dynamics compared to macroeconomic factors.

Aside of actual spatial spillover effects caused by real socioeconomic phenomena such as the diffusion of technology and knowledge, trade, and migration, spatial dependence can also be a by-product of data if the correspondence between the market processes over space and the spatial units such as administrative regions is imperfect (Anselin and Rey 1991; Rey 2001). It is therefore imperative to include spatial effects in regional convergence analyses, as shown by Rey and Montouri (1999) and Rey and Dev (2006), among others. We therefore estimate conditional convergence model

parameters where convergence is conditioned on a set of regional socioeconomic variables – discussed in Section 4 – together with region-specific and time-specific unobserved effects. We then include spatial effects on top of the aforementioned factors for the purpose of incorporating the geographic dimension as an additional feature of conditional convergence. Finally, a dynamic panel estimation approach (discussed below) is adopted to strengthen the economic rationality of our findings.

Estimation

The analysis is in the form of a panel data model with annual observations on all the 118 regions of Belarus over the period 2005–2014 (the details of our data are presented in Section 4). The sample ends in 2014 because a more extensive reintegration project, the Eurasian Economic Union, was established in 2015. Our approach involves dividing the data into two parts: before (2005–2009) and after (2010–2014) the joining of Belarus into the EACU, and comparing the parameter estimates and the speeds of conditional convergence between the two periods. This technique is then reinforced with a dummy variable approach using the full sample (2005–2014) and allowing for interaction effects between the explanatory variables and a binary variable E_t which takes the value of zero for the years 2005–2014, and equals one for the years 2010–2014. Based on the foundation outlined in Section 3.2, we present the baseline panel β-convergence model in Equation 1 – which we apply on the preaccession and postaccession periods, before extending our estimation to the combined sample which includes the observations from both periods. The divided sample approach is particularly useful in the context of the spatial models which we present in the subsequent specifications, as it allows us to concentrate on disentangling the direct and indirect effects caused by spatial interactions, while avoiding the further fragmentation of effects that would be introduced by the dummy variable interactions with the spatially lagged and non-lagged explanatory variables. This naturally comes at a cost, which we discuss below and address through additional estimation methods.

$$\ln(y_{it}) = \theta + (1+\beta)\ln(y_{i,t-1}) + \sum_{k=1}^{m}\gamma_k x_{k,it} + \mu_i + \eta_t + \xi_{it} \tag{1}$$

In Equation 1, y_{it} denotes the per capita income in region i at time t. θ is a constant term, and β is the convergence parameter (it is summed with 1 as a result of expressing the left-hand-side as a level rather than a growth rate). The coefficient $1+\beta$ equals e^{-bT} where b is known as the speed of convergence, the key parameter that we estimate, and T is the number of years between two observations and equals to one in our panel setting (Sala-I Martin 1996a). The speed of convergence is related to the half-life of convergence

which is the time it would take for half of the current per capita income gaps to be eliminated and is equal to $\frac{\ln(2)}{b}$ (Barro et al. 1991; Arestis, Baddeley, and McCombie 2007). x_k denotes the k explanatory variables that are used to augment the model into a conditional convergence specification, where the effect of each x_k is measured through its parameter γ_k and $k = 1, \ldots, m$. Convergence is further conditioned on the unobserved region-specific effects absorbed by the fixed effects term μ_i, and on the year-specific effects η_t. Finally, the idiosyncratic error term of the model is denoted as ξ_{it}.

The aforesaid spatial effects enter our estimation in five alternative ways. The per capita income level of a given region may depend on the economic activity that takes place in all other regions j, and their effects can depend on how far they are from region i (Elhorst, Piras, and Arbia 2010). The Spatial Autoregressive Model (SAR; Anselin 1988b) takes this possibility into account by including the per capita income levels of all other regions – weighed by distance. This possible spatial dependence in the dependent variable would be captured by the coefficient ρ in the term $\rho \sum_{j=1}^{N} w_{ij} \ln(y_{jt})$ in the below SAR specification (Equation 2). The term w_{ij} is the row-normalized inverse Euclidean distance between the regional capitals of regions i and j, and is an element of the spatial weight matrix W. Each diagonal element (where $i = j$) of W is equal to zero as there is no distance from a given region to itself. W is an $N \times N$ matrix where N is the number of regions (118; $i = 1, \ldots, N$, $j = 1, \ldots N$). In order to ensure conformability in a panel setting, W is expanded such that in our estimations the weight matrix is $I_T \otimes W$ where I_T is an identity matrix of length T as $t = 1, \ldots, T$ (Millo et al. 2012).

$$\ln(y_{it}) = \theta + \rho \sum_{j=1}^{N} w_{ij} \ln(y_{jt}) + (1 + \beta) \ln(y_{i,t-1}) + \sum_{k=1}^{m} \gamma_k x_{k,it} + \mu_i + \eta_t + \xi_{it} \quad (2)$$

The Spatial Error Model (SEM; LeSage and Pace 2009) tests whether there is spatial dependence among the errors which would imply the existence of spatially clustered omitted variables (Ward and Gleditsch 2008). The disturbances ξ_{it} are now defined as in the SEM specification in Equation 3. Spatial dependence in this error term is observed by the parameter λ. The remaining i.i.d. error term is $\vartheta_{it} \sim N(0, \sigma^2_{\vartheta})$.

$$\begin{aligned} \ln(y_{it}) &= \theta + (1 + \beta) \ln(y_{i,t-1}) + \sum_{k=1}^{m} \gamma_k x_{k,it} + \mu_i + \eta_t + \xi_{it} \\ \xi_{it} &= \lambda \sum_{j=1}^{N} w_{ij} \xi_{jt} + \vartheta_{it} \end{aligned} \quad (3)$$

The Spatial Autoregressive Combined model (SAC; Kelejian and Prucha 1998) brings together the two preceding models such that both the SAR and SEM

specifications are nested within the SAC as shown in Equation 4. The SAC model would reduce to the SAR equation if $\lambda = 0$, to the SEM specification if $\rho = 0$, and to the nonspatial base model (Equation 1) if $\rho = \lambda = 0$.

$$\begin{aligned} \ln(y_{it}) &= \theta + \rho \sum_{j=1}^{N} w_{ij} \ln(y_{jt}) + (1+\beta) \ln(y_{i,t-1}) + \eta_t + \xi_{it} \\ \xi_{it} &= \lambda \sum_{j=1}^{N} w_{ij} \xi_{jt} + \vartheta_{it} \end{aligned} \tag{4}$$

Furthermore, spatial dependence may exist through the explanatory variables. This type of spatiality is initially explored in a Spatial Durbin Model (SDM; Anselin 1988b) where the spatially lagged counterparts of all explanatory variables are added into the specification such that:

$$\begin{aligned} \ln(y_{it}) = \theta + \rho \sum_{j=1}^{N} w_{ij} \ln(y_{jt}) + (1+\beta) \ln(y_{i,t-1}) + \sum_{k=1}^{m} \gamma_k x_{k,it} + \sum_{k=1}^{m} \delta_k \sum_{j=1}^{N} w_{ij} x_{k,jt} \\ + \mu_i + \eta_t + \xi_{it} \end{aligned} \tag{5}$$

Finally, the SDM can be augmented so that it nests the SAC model (LeSage and Pace 2009). Halleck Vega and Elhorst (2015) label this specification which comprises all types of spatial effects as the General Nesting Spatial model (GNS; Equation 6):

$$\begin{aligned} \ln(y_{it}) = \theta + \rho \sum_{j=1}^{N} w_{ij} \ln(y_{jt}) + (1+\beta) ln(y_{i,t-1}) + \sum_{k=1}^{m} \gamma_k x_{k,it} + \sum_{k=1}^{m} \delta_k \sum_{j=1}^{N} w_{ij} x_{k,jt} \\ + \mu_i + \eta_t + \xi_{it} \xi_{it} = \lambda \sum_{j=1}^{N} w_{ij} \xi_{jt} + \vartheta_{it} \end{aligned} \tag{6}$$

The above models incorporate regional fixed effects and therefore are prone to the Nickell (1981) bias (also referred to as the dynamic panel bias). This would result in an underestimation of the coefficient $1 + \beta$, because it is greater than zero as we shall see in our estimation results. Therefore, an upward bias in the estimate of the convergence speed would be present, leading to the biased estimation of half-lives as shorter than in actuality. In consequence, our estimates of the convergence parameter may be subject to a distortion which is of order $1/T$ – that is, decreasing in the length of the time period in our panel (Nickell 1981). Generally, in a nonspatial setting, variants of the generalized method of moments (GMM) estimation are used to deal with this type of bias (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998). Furthermore, an additional type of bias would be present in the estimation of the spatial parameter (ρ) if the estimation

method of the spatial models is ordinary least squares (OLS). On this point, maximum likelihood estimation (MLE) stands out as a frequently used approach for thwarting the expected inconsistency and bias while providing asymptotic efficiency (Elhorst 2003).[4] Elhorst, Piras, and Arbia (2010) show that even though GMM is effective in reducing this bias, the resulting bias in the estimated spatial term would be large; that is to say, relative to an estimate resulting from an MLE approach.

Turning back to the Nickell bias, it may be possible that our convergence speed estimates for the preaccession and postaccession periods will be distorted to a similar degree as a result of the dynamic panel bias. If this is true, the possible consequences of the Nickell bias on the interpretation of our findings may be alleviated – as our interest lies mainly in the comparison of the two periods. However, our estimates of the speed of convergence for these periods will still be subject to the earlier discussed overestimation. In order to eliminate the Nickell bias, we estimate the full-sample specification using System-GMM (Arellano and Bover 1995; Blundell and Bond 1998) along with fixed effects and two-stage least square (2SLS) models for comparison. On the other hand, since our divided-sample models emphasize on the spatial terms, we use MLE for the estimation of the spatial models.

A final but essential point that requires consideration in the estimation of spatial models is the existence of direct and indirect effects. LeSage and Pace (2009) first indicated that in spatial models, explanatory variables exhibit a direct effect, as well as an indirect effect. Continuing on this line, Elhorst (2010) demonstrates that it is imperative to differentiate between the indirect and direct effects in models with spatial terms. In a spatial model where observed units are regions, the observed direct effect of a variable belonging to specific region is the change it causes in the dependent variable for the same region, and the indirect effect is the change it causes on the dependent variable in the other regions (Elhorst 2014). More specifically, Elhorst (2014) shows how these effects are contained in a matrix of partial derivatives of which the average of the diagonal elements summarizes the direct effect, and the average of the row or column sums of the off-diagonal elements summarize the indirect effect. For the GNS and SDM estimations in particular, the indirect and direct impacts of explanatory variables are contingent upon the coefficients of the covariates with spatial lags, namely, the estimates of the δ_k's (Elhorst 2014; Golgher and Voss 2016). In line with this account, we have calculated the speeds of convergence based on the direct effect of $y_{i,t-1}$ for all our models, rather than using the point estimates reported in the output tables. We report the direct and indirect effects of the model covariates based on our preferred spatial specification, the GNS model, which has the most comprehensive structure, and yields the highest log-likelihood value for both periods.

The dataset and the choice of model variables

The fundamental theoretical setting of conditional convergence analysis suggests conditioning the model on: the share of capital, the rate of productivity growth, depreciation rate, and population growth (Sala-I Martin 1996a). Empirical convergence studies build upon these theoretical suggestions by altering or enhancing this set of economic characteristics. The diversity in the choice of variables is attributable to the contextual focus of the research, the availability of data, and often depends on whether the observations are nations or regions. The variable selection in our study is also subject to the same considerations. For regional per capita income (y), we use the regional revenue per capita, and condition convergence on several regional characteristics. As capital stock figures are unavailable at the regional level, we use fixed capital investments and denote it as K. Mankiw, Romer, and Weil (1992) have shown that human capital can play a significant role in explaining the differences in productivity levels between economies. In line with their approach, we use the percentage of full-time students enrolled in colleges in the regional population (H) as an indicator of the level of human capital in a region.

As earlier discussed, technological progress is an integral part of the theoretical convergence framework. There is no clear-cut measure available for the technological differences across Belarusian regions. We propose that the industrialization level in a region may provide information regarding its relative technological sophistication, and include the share of industrial production in a region (I) to account for this regional characteristic. The agglomeration of manufacturing labor is a central theme in the new economic geography literature (Krugman 1991; Krugman and Livas Elizondo 1996; Fujita and Krugman 2004). When a region becomes more urbanized, agricultural activity is replaced – to some extent – by manufacturing and the services industry. With respect to economic convergence, DiCecio and Gascon (2010) empirically show that the level of urbanization has been an important determinant of regional disparities in the US. Alongside the theoretical and empirical suggestions, and subject to the availability of data for the Belarusian regions, we account for manufacturing agglomeration through the use of the share of the urban population (U) in our analysis. Finally, we also consider the relative weights of public and private economic activity in a region. Beugelsdijk and Eijffinger (2005) argue (and support with empirical findings) that an increase in the productivity of a region may attract private investment which in turn increases income per capita. In our models, we represent private economic activity in each region with the share of private firms in the total number of private and public companies (P).

The above presented indicators constitute the set of k explanatory variables in the term $x_{k,it}$ which appears in Equations 5 and 6. As discussed in Section 3.3, it is highly likely that variables observed in individual regions will affect each other across space. Therefore, they all enter the estimation also in the

Table 1. Variable definitions.

Variable	Definition
y	Revenues from sales of products, goods, works and services, divided by population in constant 2004 prices (millions of BYR).
K	Investments in fixed capital in constant 2004 prices (billions of BYR).
I	Volume of industrial production divided by regional revenue (both variables in constant 2004 prices, billions of BYR).
P	Share of private companies, at the end of the year, in the total number of private and public (state) companies.
H	Percentage in the regional population of full-time college students enrolled at the beginning of the academic year.
U	Share of urban population.

Source: National Statistical Committee of Belarus (2014, 2015).

Table 2. Descriptive statistics.

Variable	Mean	St. Dev.	Min	Max
y_{it}	8.22	6.69	1.73	60.75
K_{it}	105.01	147.75	5.13	1,501.52
I_{it}	0.40	0.20	0.07	2.01
P_{it}	0.42	0.15	0.10	1.00
H_{it}	4.99	3.74	0.90	22.80
U_{it}	0.48	0.18	0.00	1.00
$N = 118$, $T = 10$				

Source: National Statistical Committee of Belarus (2014, 2015).

form of spatial lags, through the term $\sum_{j=1}^{N} w_{ij}x_{k,it}$. The variable definitions are summarized in Table 1, and their descriptive statistics are presented in Table 2. All variables vary across regions and years. All data has been obtained from the statistical yearbooks of the National Statistical Committee of Belarus (issued in 2014 and 2015).

A descriptive look to the Belarusian economic geography

In order to elucidate the regional economic outcomes in Belarus with respect to the EACU, we begin by discovering the spatial patterns in the country. For this aim, we present descriptive illustrations depicting the distribution of income, alongside the identification of spatial clusters and spatial outliers as formalized by Anselin (1995). For the purpose of observing the variation through time, we examine the Local Indicators of Spatial Association (LISA; Anselin 1995) for three snapshots in time: the first year in our data, the year of establishment of the EACU, and the final year in our data.[5,6]

The geographical distribution of income per capita (in millions of BYR) is presented in the maps in the upper row of Figure 1 where darker shades of blue represent higher per capita income levels. For all the three years, we observe that regions with high per capita income levels are located mostly in the central parts of Belarus; around the capital Minsk, and several southern regions. These regions, among others, are exclusively identified in the LISA

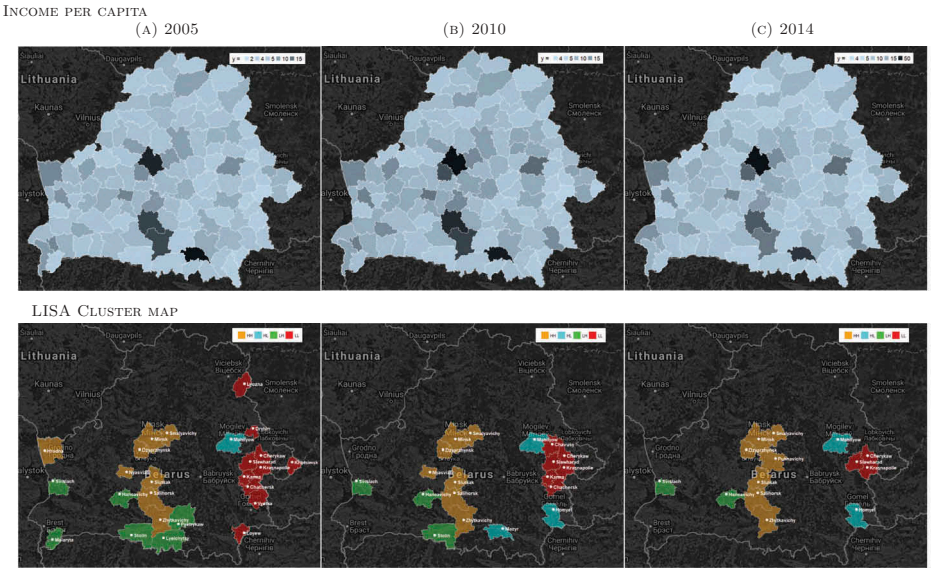

Figure 1. Income per capita and the spatial clusters in Belarus.

cluster maps presented in the bottom row. The LISA cluster maps identify four types of spatial clusters partly based on the categorization made by the Moran Scatterplots in Figure 2. The Moran Scatterplots (Anselin 1995) for the three years plot $\ln(y_i)$ against its own spatial lag (denoted by $W \ln y$ in the graphs) and include a fitted regression line representing the Global Moran's I statistic (Moran 1950; Cliff and Ord 1972) for the corresponding year. The associated p-values for the Global Moran's I statistics for the years 2005, 2010, and 2014 are all significant at the 0.01 level (reported under the figures), indicating the existence of global spatial dependence across regions in terms of their per capita incomes. These significant Moran's I results reinforce the necessity for the usage of spatial estimation models for accurately assessing the convergence process in Belarus.

The LISA cluster maps depend on the significance of the spatial association of each region with its surroundings such that only regions with Local Moran's I p-values less than 0.05 are colored.[7] Each category, shown in yellow, blue, green, and red, highlight the cores of spatial clusters based on the type of spatial association they have with their surrounding regions (Anselin, Syabri, and Kho 2006). The HH category marks the core of the spatial cluster where regions with higher-than-average per capita income are significantly clustered with other regions which also have an average per capita income that is higher than the country average. The HL category includes regions that have high income despite being surrounded by low income regions. In contrast, LH clusters are those where poor regions are surrounded by richer ones. Finally, LL regions mark the cluster cores where poor regions are grouped together.

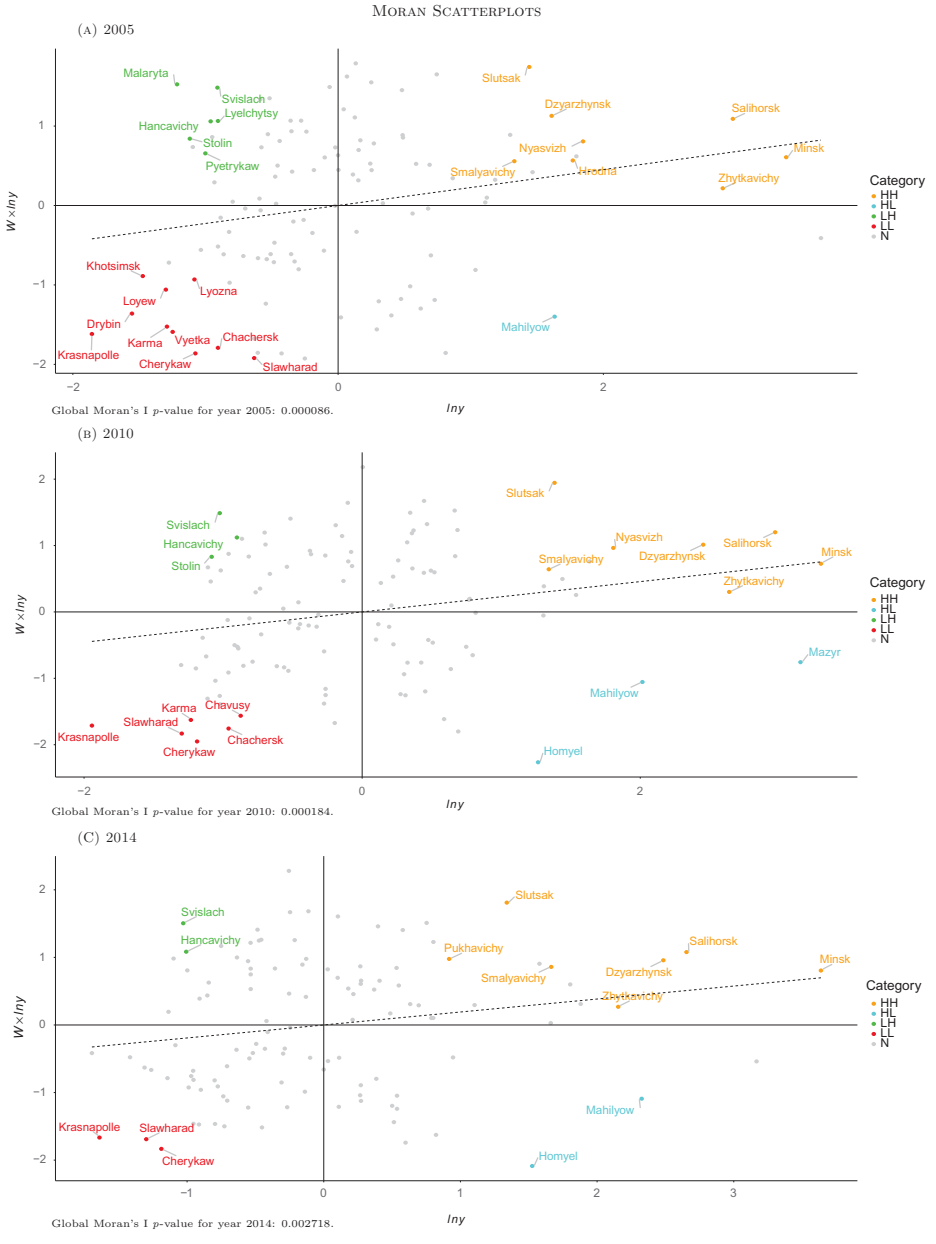

Figure 2. Moran scatterplots.

We therefore identify the areas with significant spatial association (i.e., spatial cluster cores) in Belarus, and designate these clusters in the Moran scatterplots where the grsy dots are regions with no significant Local Moran's I statistics (denoted as "N" in the graphs).

The spatial cores of the Belarusian economy have been subject to some changes, especially after 2010, the EACU membership year. The LH cluster in the south (shown in green) has ceased to exhibit a highly significant spatial

correlation as of 2014. However, the HH clusters around and in the south of Minsk, and the cluster around Hrodna were persistent. Similarly, the LL category cluster cores close to the borders with Russia and Ukraine are identified, though with decreasing significance, particularly in 2014. We then observe regions with significant negative spatial association with their surrounding economies, HL type regions and LH type regions. Svislach, which is located at the border with the EU (Poland), has been remaining in the latter category throughout our sample period. Mahilyow and Homyel stand out as regions falling into the former category, and are high-income cores surrounded by poorer regions.

As a final descriptive look, we follow the trajectories of the spatial cluster cores and spatial outliers (i.e. regions with significant Local Moran's I p-values) in Figure 3. Each line graph displays (in natural logarithms) how the income per capita of the regions in the cores of these clusters has evolved over time. In the period before the EACU membership, the LH and LL clusters (green and red) seem to have had similar directions to those of the high income clusters. However, they become flatter after 2010, which may imply divergence, or a slowdown in convergence. The trend in regional inequalities is represented specifically in the overlaid coefficient of variation (CV) line, which uses the information not only from the clusters and outliers, but from all other regions as well. As an indicator of what is referred to as σ-convergence in the convergence literature (Sala-I Martin 1996a, 1996b), the trend in the CV further implies that EACU membership may have hindered regional convergence in Belarus; a steady decline in the variation of regional per capita income over years is no longer visible after 2010. This visual hint implies that EACU membership may have affected poorer Belarusian regions differently, relative to the richer ones. We therefore elaborate particularly on the difference in the speeds of convergence in the pre-EACU and EACU periods that result from our empirical analysis Section 6.

Empirical results

The empirical results of the models with spatial terms discussed in Section 3.3 are presented in Tables 3 and 4, where the former reports the findings for the pre-EACU period, and the latter for the EACU period. The six columns of each table report the nonspatial (base), SAR, SEM, SAC, SDM, and the GNS models, respectively. As earlier mentioned, the spatial models should be interpreted based on the direct and indirect effects of the model covariates rather than relying solely on their point estimates. We investigate the results of all the spatial models in conjunction with the direct and indirect effects based on the GNS results, which are presented in Table 5.[8]

First and foremost, we observe that there has been regional β-convergence in Belarus during both periods, as can be concluded from the estimates

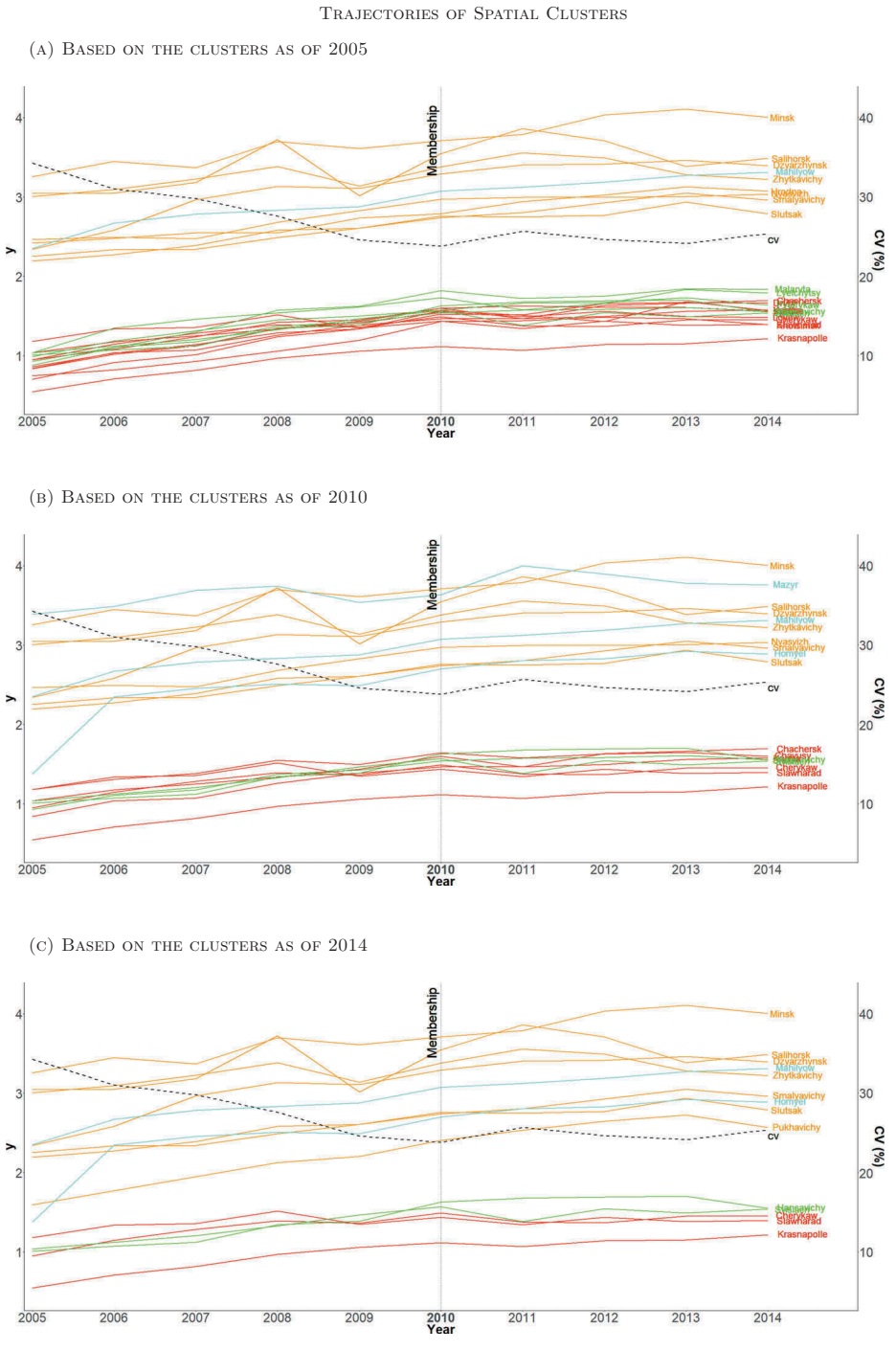

Figure 3. Trajectories of spatial clusters.

of $(1+\beta)$ in all results. The speeds of convergence associated with the coefficient estimates of $\ln(y_{i,t-1})$ are reported in the lower part of each table. Regardless of the model specification, all estimations for the pre-EACU

Table 3. Estimation results for the pre-EACU period.

	Base	SAR	SEM	SAC	SDM	GNS
$lny_{i,t-1}$	0.193***	0.192***	0.191***	0.192***	0.192***	0.192***
	(0.0417)	(0.0413)	(0.0415)	(0.0414)	(0.0421)	(0.0420)
lnK_{it}	0.0416*	0.0429*	0.0419*	0.0428*	0.0466**	0.0455**
	(0.0222)	(0.0220)	(0.0219)	(0.0220)	(0.0225)	(0.0226)
l_{it}	−0.374***	−0.372***	−0.376***	−0.372***	−0.361***	−0.360***
	(0.0767)	(0.0760)	(0.0763)	(0.0762)	(0.0780)	(0.0776)
P_{it}	0.114	0.118	0.121	0.119	0.0866	0.0860
	(0.0929)	(0.0920)	(0.0910)	(0.0923)	(0.0978)	(0.0981)
H_{it}	0.0617***	0.0606***	0.0602***	0.0605***	0.0582***	0.0586***
	(0.0166)	(0.0164)	(0.0165)	(0.0165)	(0.0167)	(0.0166)
U_{it}	0.828	0.833	0.809	0.830	0.868	0.865
	(0.558)	(0.553)	(0.554)	(0.554)	(0.573)	(0.571)
$\sum_{j=1}^{N} w_{ij} \ln y_{j,t-1}$					−0.224	−0.278
					(0.543)	(0.529)
$\sum_{j=1}^{N} w_{ij} \ln K_{jt}$					0.207	0.207
					(0.218)	(0.204)
$\sum_{j=1}^{N} w_{ij} l_{jt}$					0.0115	0.175
					(0.963)	(0.968)
$\sum_{j=1}^{N} w_{ij} P_{jt}$					0.0764	0.0781
					(0.711)	(0.662)
$\sum_{j=1}^{N} w_{ij} H_{jt}$					−0.278	−0.281
					(0.207)	(0.194)
$\sum_{j=1}^{N} w_{ij} U_{jt}$					0.432	0.659
					(7.903)	(7.499)
ρ		−0.35538		−0.323	−0.446	−0.207
		(0.33520)		(0.492)	(0.359)	(0.498)
λ			−0.282	−0.0400		−0.317
			(0.339)	(0.454)		(0.535)
Convergence Speed	1.644	1.649	1.655	1.650	1.642	1.646
Half-life (years)	0.421	0.420	0.419	0.420	0.422	0.421

Observations: 472, Observations per region: 4.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

period yield very similar convergence speeds and half lives – calculated using the earlier discussed direct effects of $\ln(y_{i,t-1})$ – on average of 1.64 and 0.42, respectively. The convergence speed and half life averages for the EACU period estimations are 0.70 and 0.97 respectively, with insubstantial differences across models. Therefore, our primary result is that the half-lives estimated for the pre-EACU period are all lower than those presented in Table 4, which are for the EACU period. This result is consistent with our earlier descriptive observations regarding the σ-convergence process and the per capita income trends of the spatial clusters and outliers. However, while the differences between the periods in terms of the convergence speeds and half lives are evident, we calculate extraordinarily high and unrealistic speeds of convergence in general. As predicted in Section 3.3, this may be caused by an underestimation – as a result of the Nickell bias – of the coefficient estimate of the lagged

Table 4. Estimation results for the EACU period.

	Base	SAR	SEM	SAC	SDM	GNS
$\ln y_{i,t-1}$	0.495***	0.495***	0.498***	0.498***	0.483***	0.485***
	(0.0408)	(0.0405)	(0.0407)	(0.0407)	(0.0408)	(0.0409)
$\ln K_{it}$	0.0244**	0.0242**	0.0242**	0.0243**	0.0254**	0.0254**
	(0.00993)	(0.00989)	(0.00987)	(0.00989)	(0.00987)	(0.00987)
I_{it}	−0.113***	−0.113***	−0.113***	−0.113***	−0.0945***	−0.0942***
	(0.0298)	(0.0296)	(0.0295)	(0.0295)	(0.0300)	(0.0299)
P_{it}	0.102	0.0988	0.0930	0.0933	0.0729	0.0705
	(0.100)	(0.100)	(0.101)	(0.101)	(0.100)	(0.100)
H_{it}	0.0243	0.0237	0.0234	0.0235	0.0213	0.0215
	(0.0216)	(0.0215)	(0.0215)	(0.0216)	(0.0219)	(0.0219)
U_{it}	0.648**	0.644**	0.635**	0.634**	0.615**	0.610**
	(0.307)	(0.305)	(0.305)	(0.305)	(0.304)	(0.304)
$\sum_{j=1}^{N} w_{ij} \ln y_{j,t-1}$					−1.097**	−1.170**
					(0.456)	(0.463)
$\sum_{j=1}^{N} w_{ij} \ln K_{jt}$					0.208*	0.205*
					(0.113)	(0.109)
$\sum_{j=1}^{N} w_{ij} I_{jt}$					0.289	0.326
					(0.341)	(0.337)
$\sum_{j=1}^{N} w_{ij} P_{jt}$					2.880***	2.849***
					(0.995)	(0.961)
$\sum_{j=1}^{N} w_{ij} H_{jt}$					0.264	0.240
					(0.211)	(0.205)
$\sum_{j=1}^{N} w_{ij} U_{jt}$					4.149	4.044
					(3.124)	(3.013)
ρ		0.0908		−0.0459	−0.0520	0.0908
		(0.243)		(0.342)	(0.268)	(0.377)
λ			0.175	0.202		−0.208
			(0.239)	(0.307)		(0.442)
Convergence Speed	0.703	0.702	0.698	0.697	0.725	0.727
Half-life (years)	0.986	0.987	0.993	0.994	0.956	0.953

Observations: 590, Observations per region: 5.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 5. Direct and indirect effects – GNS model.

		$\ln y_{i,t-1}$	$\ln K_{it}$	I_{it}	P_{it}	H_{it}	U_{it}
Pre-EACU	Direct	0.193***	0.045	−0.361***	0.086	0.059***	0.864
		(0.042)	(0.023)	(0.077)	(0.099)	(0.017)	(0.568)
	Indirect	−0.264	0.164	0.207	0.05	−0.244	0.399
		(0.443)	(0.177)	(0.789)	(0.553)	(0.176)	(6.235)
EACU	Direct	0.483***	0.026**	−0.094***	0.075	0.022	0.616**
		(0.041)	(0.01)	(0.03)	(0.101)	(0.022)	(0.304)
	Indirect	−1.237**	0.228	0.349	3.136**	0.266	4.503
		(0.665)	(0.149)	(0.4)	(1.519)	(0.229)	(3.68)

Standard errors in parenthesis.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

dependent variable. Following our below presented elaboration on the remaining noteworthy findings from the spatial models, we shall proceed to address this issue directly through the use of additional estimation methods.

Our second empirical observation from the spatial estimations is based on the SDM and GNS findings, and is consistent with the direct and indirect effects reported for the GNS in Table 5: spatially lagged previous per capita income has been negatively impacting the income per capita of a given region since the entry of Belarus to the EACU. In other words, since EACU membership, regions which are located close to other regions that had above average per capita income levels in the previous period are expected to have lower per capita income. This result implies regional competition with a spatial dimension, meaning richer regions may ingest the economic activity of their neighbors. Therefore, further insight is unearthed regarding the slowdown of regional convergence in Belarus that took place after its EACU membership. The main implication is that economic activity has been shifting from poorer areas to surrounding richer regions after 2010; hence, a spatial mechanism is attested.

Another effect of EACU membership seems to occur in relation to fixed capital investments ($\ln K_{i,t}$). We observe positive effects of this variable on regional per capita income – with slight and varying significance across the models – during the pre-EACU period. This effect persists and becomes somewhat more noticeable after the EACU establishment year (i.e., robustly significant at the 5% level), although with smaller elasticity. The difference between periods for this variable is more pronounced in the GNS direct and indirect effect findings, where no significant effect is observed for the pre-EACU period. We also notice a slightly significant spatially lagged coefficient estimate for $\ln K_{i,t}$. If this effect is truly present, it may be due to the spatial continuity and spillover effects of infrastructure investments (Zheng et al. 2013). However, an indirect effect of fixed capital investments over space is not supported by the direct and indirect estimates for this variable, as reported in Table 5.

The share of industrial production had a negative and significant coefficient estimate before 2010, implying that regions which are less industrialized had higher per capita incomes. The effect has become weaker while remaining significant after 2010. This being the case, the share of private companies in a region (P_{it}) is positive but insignificant in all models. However, the spatial lag of this variable is found to be significant by the SDM and GNS indirect effect estimations for the period following EACU membership. Thus, own private sector activity is less important for a region than being a part of a general cluster of private sector activity, given EACU membership. This result suggests that the effects of economic integration favor spatial clusters in Belarus when it comes to business activity. All in all, EACU membership has made the spatial dimension more prominent, both through the promotion of clustering and the emergence of a geographic competition effect.

We observe an intriguing result regarding the effect of the share of students (H_{it}). While a positive and significant effect is observed in all models for the pre-EACU period, there is no evidence of an impact following EACU

membership. In other words, the positive effect of student share on regional income per capita is no longer present after international economic integration. Conversely, stronger evidence for the effect of agglomeration, represented by the urbanization level, is observed for the EACU period compared to the pre-EACU years. Therefore, the relatively more urbanized regions of Belarus have benefited more from economic integration.

While we have obtained the above discussed elucidating information regarding the particular spatial processes thanks to the spatial estimations, we nevertheless observe in Tables 3 and 4 that their inclusion does not change our findings regarding the speed of convergence. For instance, the half-lives estimated by the nonspatial model and the GNS model are the same for the pre-EACU period, with only a minuscule difference after the third decimal digit. Similarly, the difference between the half-lives estimated by these models is only 12 days for the EACU period. More importantly, the speed of convergence is found to be slower for the period after EACU membership in all spatial model variants. However, in all models, the previously discussed dynamic panel bias emerges as a critical issue due to the apparent overestimation of the speeds of convergence.

The robustness of the convergence speed and half-life estimates to all the different specifications of spatial effects allows us to particularly concentrate on coping with the dynamic panel bias for the purpose of obtaining a more precise estimate of the convergence speed through the implementation of a GMM approach on a nonspatial specification. Furthermore, by setting aside the spatial effects and therefore evading the indirect and direct impacts introduced by these effects, we are able to combine both periods into one sample and focus on the impacts of the covariates across the two periods through a dummy variable scheme, where the dummy E_t takes the value zero for the pre-EACU period, and one for the EACU period. In essence, laying aside the spatial terms which ultimately do not effect the estimation of $\ln(y_{i,t-1})$ avoids further complications that would arise from the necessity to distinguish the changes in the slope estimates across the two periods in the presence of yet an additional layer of indirect impacts stemming from the spatial effects (which in turn would also be interacted with E_t). Finally, using one undivided sample and interacting each covariate with the aforementioned dummy variable enables us to see whether the difference in the speeds of convergence across the two periods is statistically significant.[9]

We address the Nickell bias through the use – as instruments – of the lagged first-differences and the lagged levels of variables with clear endogeneity implications in a System-GMM (Sys-GMM) framework. The instrumented variables are previous income per capita, investments – as they may be endogenously determined by $y_{i,t-1}$ and/or y_{it}, and I_{it} since it includes y_{it} as a scaling factor, together with the interactions of these variables with the dummy E_t. For comparison, a 2SLS estimation with fixed effects where the

same variables are instrumented using their lagged levels, and a fixed effects (FE) estimation is presented. The Sys-GMM estimation uses lag limits of (1,3) for avoiding instrument proliferation and keeping the number of instruments below the number of regions (based on the model that includes all dummy interactions). The results for the full sample for the FE, Instrumental Variable Fixed Effects (IV-FE), and the Sys-GMM models are presented in Table 6.

Each of the three estimation methods shown in Table 6 presents the results for two separate extended versions of Equation 1. Firstly, the model is augmented with the period dummy E_t, and its interaction with lagged per capita regional income, $y_{i,t-1}$. Secondly, the interactions of all explanatory variables with the period dummy are added to the model. Because there are two different sets of fixed effects for the earlier presented split sample estimations (pre-EACU, EACU), the latter approach is not fully quantitatively equivalent, but conceptually analogous to our earlier strategy of dividing the sample across the two periods in a nonspatial setting. Moreover, it allows the model to have higher degrees of freedom. The former approach on the other hand only explores how the effect of $y_{i,t-1}$ differs across the two periods and does not allow for any change in the effects of the remaining explanatory variables across the pre-EACU and EACU periods. Henceforth, we refer to the model augmented only with $y_{i,t-1} \times E_t$ as the "restricted specification," and label the model including the interactions of all covariates with E_t as the "full interaction specification." For each model, we report the implied speeds of convergence for the two separate periods in the lower section of Table 6.

The restricted FE model sustains the earlier implication of a slowdown in convergence after EACU membership, with seemingly overestimated implied convergence speeds as the models estimated by FE and IV-FE are once again vulnerable to the dynamic panel bias. The remaining coefficient estimates for the explanatory variables are treated as unconditional, as they do not depend on the period dummy E_t, and yield similar results to our earlier findings for the pre-EACU period. The full interaction FE results on the other hand, do not find a significant difference regarding the convergence process between the pre-EACU and EACU periods. Because the positive trend in the Belarusian income per capita is already captured by our time dummies, a standalone interpretation of the coefficient estimate of E_t would be inaccurate.

While the estimates for I_{it} and $I_{it} \times E_t$ support our previous observations on industrialization, $U_{it} \times E_t$ yields results contrary to our earlier findings regarding urbanization. Being a naive attempt to cope with the potential endogeneity posed by several explanatory variables, the restricted IV-FE model does not find a significant difference in terms of the convergence speed across the two periods. The augmented, full interaction version of this estimation approach yields a higher convergence speed for the EACU period, but the half-lives are still unrealistic, with a tiny difference of only about two months.

Table 6. FE, IV, and GMM Estimation results – full sample.

	FE		IV-FE		Sys-GMM	
	Restricted	Full Interaction	Restricted	Full Interaction	Restricted	Full Interaction
$\ln y_{i,t-1}$	0.525***	0.547***	0.415***	0.469***	0.952***	0.929***
	(0.0629)	(0.0626)	(0.0996)	(0.109)	(0.015)	(0.0205)
$\ln y_{i,t-1} \times E_t$	0.0371***	−0.0308	0.0264	−0.0972**	0.0384***	0.0497**
	(0.0118)	(0.0211)	(0.0254)	(0.0377)	(0.0097)	(0.0232)
$\ln K_{it}$	0.0313***	0.00276	0.0295	−0.0793	0.0295***	0.0372***
	(0.00970)	(0.0194)	(0.0244)	(0.0535)	(0.0076)	(0.0128)
I_{it}	−0.161***	−0.282***	−0.0628	−0.251	−0.1304***	−0.0411
	(0.0563)	(0.0661)	(0.150)	(0.188)	(0.0355)	(0.0463)
P_{it}	0.137	0.0150	0.176**	0.0315	0.0702	0.108
	(0.0842)	(0.0995)	(0.0843)	(0.102)	(0.0490)	(0.0906)
H_{it}	0.0277***	0.0378***	0.0367***	0.0606***	−0.0030*	−0.00534***
	(0.00851)	(0.0116)	(0.0117)	(0.0199)	(0.0016)	(0.00189)
U_{it}	0.256	0.583**	−0.172	0.294	0.0247	0.0288
	(0.366)	(0.289)	(0.525)	(0.433)	(0.0277)	(0.0404)
E_t	−0.0622	−0.126*	−0.00460	−0.290**	−0.1806***	−0.126***
	(0.0380)	(0.0690)	(0.0649)	(0.147)	(0.0221)	(0.0465)
$\ln K_{it} \times E_t$		0.0306		0.113**		−0.00690
		(0.0193)		(0.0472)		(0.0138)
$I_{it} \times E_t$		0.125***		0.105		−0.00674
		(0.0440)		(0.102)		(0.0499)
$P_{it} \times E_t$		0.160*		0.191*		−0.0830
		(0.0893)		(0.104)		(0.106)
$H_{it} \times E_t$		−0.00196		−0.00959		0.00280
		(0.00292)		(0.00754)		(0.00223)
$U_{it} \times E_t$		−0.0962**		−0.0797		−0.0289
		(0.0379)		(0.0657)		(0.0404)
Convergence speed – before	0.645	0.603	0.881	0.758	0.049	0.074
Half-life (years) – before	1.075	1.149	0.787	0.914	14.160	9.367
Convergence speed – after	0.577	0.661	0.819	0.99	0.0094	0.022
Half-life (years) – after	1.201	1.049	0.846	0.7	73.35	31.507
Observations	1062	1062	944	944	1062	1062
Obs. per region	9	9	8	8	9	9
No. of instruments			3	6	106	111
AR1 test (p val.)					0.00000762	0.00000729
AR2 test (p val.)					0.400	0.428
Hansen test (p val.)					0.258	0.293
GMM Lag limits					1,3	1,3

Instrumented variables: $\ln y_{i,t-1}$, $\ln y_{i,t-1} \times E_t$, $\ln K_{it}$, $\ln K_{it} \times E_t$, I_{it}, $I_{it} \times E_t$.
Year dummies included in all estimations.
The number of instruments is below the number of groups (118) in all IV and GMM estimations.
Heteroskedasticity robust SE's in parentheses: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

The Sys-GMM results on the other hand confirm that the dynamic panel bias was indeed a major issue in our earlier estimations that focused on avoiding bias that may arise from the omission of spatial terms, which in turn lead to the estimation of unrealistically high speeds of convergence and short half-lives. According to the results from the restricted and full interaction Sys-GMM estimations, there is a clear and substantial setback in the process of regional

convergence. The restricted model results imply half-lives of 14.16 and 73.35 years for the pre-EACU and EACU periods, respectively. According to the full interaction model, the half-life for the pre-EACU period is 9.37 years while for the EACU period, it increases to 31.5 years. Therefore, both model specifications find that the half-life of convergence more than doubled upon the entry of Belarus into the EACU. The more realistic half-lives that our Sys-GMM models imply are not very different from those estimated by Kholodilin, Oshchepkov, and Siliverstovs (2012) in their study on Russian regions where they allow for separate convergence processes for different types of spatial clusters, and estimate half-lives of about 14–22 years for the Russian regions in the HH category, and 25–34 years for those in the LL category.

The findings of the Sys-GMM estimations regarding a slowdown are consistent with our earlier descriptive and inferential results in general, and yield realistic speeds of convergence. It is however imperative to note that despite the clear improvement in terms of realism regarding the convergence speed estimates, the Sys-GMM estimations are subject to bias due to omitted but relevant spatial terms. Particularly for the EACU period, we had observed evidence for the existence of spatial dependence through several model covariates in the SDM and GNS results. It follows that, while our finding regarding a slowdown in convergence is mostly robust to the inclusion of control variables and to the various estimation methods (except for the full interaction FE and IV-FE models), the results regarding the control variables themselves should not be overinterpreted. Considering this fact, we can argue that the decrease in the magnitude and increase in the significance of $\ln K_{it}$ across the two periods in the spatial models is reflected to the full interaction Sys-GMM results as a total loss of significance. However, as highlighted earlier, this finding comes from a specification where the spatial lag of this variable ($\sum_{j=1}^{N} w_{ij} \ln K_{it}$) is omitted. In relation to I_{it}, we had earlier observed that all else fixed, being less industrialized had a positive impact on per capita income levels but this effect became less after EACU membership. In the Sys-GMM results, this effect is still visible, but not in a significant form. The cluster effect of private sector share is naturally not distinguishable unlike in the models where the spatial lag of this variable is included, and the impact of own P_{it} remains insignificant. The only clear contrast of the Sys-GMM results to the findings from the other estimation methods is the reversed sign on H_{it}. On the other hand, in accord with the spatial model results for the EACU period, the coefficient estimate $H_{it} \times E_t$ is positive but not significant; any effect that human capital had before membership became insignificant after membership according to all models. Finally, we no longer observe results suggesting that the effect of the level of urbanization in a region became prominent upon membership.

Conclusion

In this study, we made an initial diagnosis of the distributional effects of the EACU on the Belarusian economic geography. According to The World Bank (2018), EACU membership has corresponded to an increase in the income per capita of Belarus as a whole. However, a spatial economic look has shown us that regional experiences vary. We observed that economic convergence in Belarus has slowed down after the country's entrance to the EACU. In line with the previous research in the literature, we observed the existence of spatial dependence in the convergence process. More specifically, we observed evidence for competition among regions – characterized by their relative locations over space – that became prominent after EACU membership.

As an alternative empirical approach, given that the inclusion of spatial terms in our estimations did not affect the estimated convergence speeds (while providing valuable data regarding specific spatial processes), we estimated models that particularly aim to cope with the dynamic panel bias that was apparent in our results in the form of unrealistically high convergence speed estimates. The System GMM estimations have confirmed the slowdown in convergence across the two periods. For the period after EACU membership, the results have identified half-lives of convergence that are more than twice of the pre-EACU levels.

Our above summarized analysis yielded novel evidence regarding the internal regional effects of external regional economic integration, a central feature of the global economy. Nevertheless, research on the impacts of economic integration on the economic geographies of individual countries has been limited, particularly apart from the cases of EU and NAFTA countries. Alongside with the new economic geography literature, our findings suggest that the distributional impacts of regional integration depend on the trade and production structure of a country. In the case of Belarus, oil and food productions are the main tradables of the country. And similar to other post-Soviet economies, its production process is relatively simple and its production chains are relatively short and fragmented. Although some sectors of the Belarusian economy benefit from the reduction of trade barriers (i.e. petroleum products and foods), the gains unevenly fall into a few sectors. The simple production structure substantially limits the benefits which could spill over to the upstream or downstream industries in other geographical areas. Consequently, instead of creating positive network externalities which could lead to a big push (Murphy, Shleifer, and Vishny 1989), regional integration produces clear winners and losers in Belarus, such that development happens only in some regions. Production activities flourish only in some regions, and regions become spatial substitutes as highlighted by the negative spatial effect present in our econometric results. In parallel, our analysis showed that the economic geography of Belarus is defined by a significant core-periphery structure, and the results from the spatial models

imply that urban regions have benefited more from the EACU relative to less urbanized areas. This may be due to the relatively simple economic structure of the economy. Low production complementarity between sectors benefited only a few regions. Without making the pie larger, EACU created both winners and losers and hence reduced the speed of convergence.

Focusing particularly on our spatial models, significant implications to economic geography research can be deduced. As Martin and Ottaviano (2001) show, agglomeration and growth are mutually self-reinforcing processes. Agglomeration stimulates growth as it reduces the cost of innovation through externalities. Growth also fosters agglomeration as it benefits new firms by reducing transportation costs. An empirical study by Braunerhjelm and Borgman (2004) on Sweden finds that regions with a higher degree of concentration in the production of goods and services experience stronger regional growth. In the context of regional income disparities, Ozguzel (2018) shows that agglomeration is related to spatial inequalities in production. Our spatial results highlight agglomeration as a driving force for growth, which leads industries and economic activities to grow but disperse. On the one hand, reduced agglomeration may harm economic growth and damage the overall competitiveness of an economy in the long run. On the other hand, the lack of dispersion deepens regional disparities, which is socially undesirable.

Altogether, our findings imply further avenues for research toward exploring the reasons behind our results. Why did the EACU intensify regional competition and why some regions in Belarus benefited from it while others did not is an issue that requires detailed examination. Region or industry level case studies can be informative in understanding the regional characteristics that played determining roles in this framework. Furthermore, future research that identifies the conditions under which equitable growth can be achieved would help policy makers to enhance the benefits of regional integration.

Notes

1. Regarding socioeconomic topics other than per capita income distribution, important region-level evidence is presented by Nefedova, Slepukhina, and Brade (2016) on migration for the period 1990–2013, Karachurina and Mkrtchyan (2015) on population distribution through 1989 to 2009, and Fateyev (2000) on employment and privatization for Belarus in the 1990s.
2. See for instance Hanson (1998) and Behrens et al. (2007).
3. Minsk, Homyel, and Vitebsk oblasts in total account for about half of the industrial output of the country (National Statistical Committee of the Republic of Belarus, a). In contrast, a large portion of agricultural production clusters exist in the Brest and Hrodna (Grodno) oblasts in the west of the country.
4. The usage of MLE is common in the estimation of spatial panel models despite not being robust to assumptions regarding the distribution of the data. This method has been used, among others, by Pfaffermayr (2012), Ertur and Musolesi (2012), Baltagi

and Bresson (2011), Lee and Yu (2010a), Lee and Yu (2010b), Debarsy and Ertur (2010), and Elhorst and Freret (2009).

5. The descriptive and empirical analyses in this study have been applied using the R and Stata 15 software. For calculating the direct effects and their significances, we refer to the equations presented in Table 2.1 in Elhorst (2014) and use the postestimation feature of the Stata 15 command spxtregress (StataCorp LLC 2017), which yields the same impact sizes – for the SAR model – when the effects are calculated based on the routine presented by Piras (2014) who uses the impacts function of the spdep package developed Bivand et al. (2011). The instrumental variable estimations were conducted using the xtivreg2 command developed by Schaffer (2012), and the system-GMM models are estimated using the xtabond2 routine by Roodman (2009). The following R packages and functions were also used for the various steps of our study: plm Croissant et al. (2008), splm by Millo et al. (2012), ggmap by Kahle and Wickham (2013), the Moran.I function by Paradis, Claude, and Strimmer (2004), the localmoran function by Bivand et al. (2011), and the spDists function described in Bivand et al. (2008). All statistical maps have been overlaid on the base map obtained from Google maps (2017). Our R and Stata codes can be made available to reviewers if requested.
6. Belarus is a founding member of the EACU. Therefore, its membership year is the year of establishment of the EACU (2010).
7. The Global Moran's I statistic is $I = \left(\frac{n}{\sum_i \sum_j w_{ij}}\right) \sum_i \sum_j w_{ij} z_i z_j / \sum_i z_i^2$ where w_{ij} are the spatial connectivity terms discussed in Section 6 and the z_i are deviations from the mean per capita income. The local Moran's I statistic for each region i is calculated as $I_i = z_i \sum_j w_{ij} z_j$.
8. As previously stated, the GNS model, which serves as our basis for the calculation of direct and indirect effects, is our most comprehensive spatial specification, and the one with the highest log-likelihood values for both the pre-EACU and EACU periods (566.6 and 719.5, respectively).
9. We would like to thank an anonymous referee for suggesting this approach.

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