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Human Capital Mobility and Convergence – A Spatial Dynamic Panel Model of the German Regions

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Abstract

Since the fall of the iron curtain in 1989, the migration deficit of the Eastern part of Germany has accumulated to 1.8 million people, which is over ten percent of its initial population. Depending on their human capital endowment, these migrants might either – in the case of low-skilled migration – accelerate or – in high-skilled case – impede convergence. Due to the availability of detailed data on regional human capital, migration and productivity growth, we are able to test how geographic mobility affects convergence via the human capital selectivity of migration. With regard to the endogeneity of the migration flows and human capital, we apply a dynamic panel data model within the framework of β-convergence and account for spatial dependence. The regressions indicate a positive, robust, but modest effect of a migration surplus on regional productivity growth. After controlling for human capital, the effect of migration decreases; this decrease indicates that skill selectivity is one way that migration impacts growth.

Keywords: human capital mobility, regional growth, spatial panel models

JEL Classification: R23, R11, C23

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Humankapitalmobilität und Konvergenz – Ein räumliches Panelmodell für Deutschland

Zusammenfassung

Seit dem Fall des Eisernen Vorhanges im Jahr 1989 ist das Binnenmigrationsdefizit des östlichen Teils von Deutschland auf rund 1,8 Millionen Menschen angewachsen. Dies bedeutet, dass Ostdeutschland in den letzten 20 Jahren infolge der Abwanderung nach Westdeutschland rund zehn Prozent seiner Ausgangsbevölkerung verloren hat. Es stellt sich die Frage, inwieweit dies Auswirkung auf die Geschwindigkeit des innerdeutschen Konvergenzprozesses hatte. Abhängig vom Humankapital der Migranten kann die Nettoabwanderung – im Falle von geringqualifizierter Migration – einen Konvergenzprozess beschleunigen oder – im hochqualifizierten Fall – behindern. Detaillierte, für einen langen Zeitraum verfügbare Informationen über den regionalen Humankapitalbestand, die Zu- und Abwanderungsströme sowie das Produktivitätswachstum erlauben es, den Effekt einer möglichen Humankapitalselektivität der Binnenmigration auf den innerdeutschen Konvergenzprozess im Rahmen eines räumlich-dynamischen Panelmodells zu überprüfen. In einem ersten Ansatz ist ein signifikant positiver Einfluss von Zuwanderungsgewinnen auf das regionale Wachstum festzustellen. Werden Unterschiede im Humankapital berücksichtigt, reduziert sich dieser Einfluss jedoch stark. Die Ergebnisse sprechen somit gegen die Hypothese, dass Wanderungsbewegungen die Angleichung regionaler Disparitäten befördern.

Schlagwörter: Humankapitalmobilität, regionales Wachstum, räumliche Panelmodelle

JEL-Klassifikation: R23, R11, C23

1 Introduction

According to the standard neoclassical framework with homogenous labour, migration should accelerate economic convergence. To improve their income position, people move from poor to rich destinations, thereby increasing capital intensity, productivity, and wages in the poorer origin and reducing it in the destination economy (BARRO and SALA-I-MARTIN, 1995). However, more complex models point to forces that counteract this equalising mechanism (DRINKWATER *et al.*, 2003). Within new economic geography models, a broad range of agglomeration mechanisms cause increasing rather than decreasing wages and income in the rich destination region whereas the region of origin – due to the lack of economies of scale – falls behind (FAINI, 1996; FUJITA *et al.*, 1999; HENDERSON and WANG, 2005). Moreover, because out-migration lowers the marginal product of capital, it creates disincentives for gross capital formation in the economy that, in the case of a low-income economy, will dominate the standard neoclassical equilibrating effect (RAPAPPORT, 2005). Finally, and most likely most importantly, the skill selectivity of migrants – typically referred to as *brain drain* – is considered to be one crucial reason why labour mobility works against the optimistic prediction of the standard neoclassical model (KANBUR and RAPOPORT, 2005; FRATESI and RIGGI, 2007). If migrants are taken from the very upper tail of the human capital distribution, the region of origin might suffer even in a human capital augmented neoclassical model. The divergence outcome can be strengthened by human capital externalities, which are elaborated in the new growth models.[1]

Using the neoclassical concept of ß-convergence, which was introduced by BARRO and SALA-I-MARTIN (1992) and MANKIW *et al.* (1992), the present paper empirically addresses the question of whether and how the spatial mobility of human capital affects the long-run steady state as well as the transitional dynamics towards the steady state. This paper tests the neoclassical hypothesis that migration accelerates convergence toward the steady state (*convergence hypothesis*). In addition, this paper provides evidence regarding the proposition that a permanent migration-induced human capital inflow increases the steady state of a region (*steady state hypothesis*). Finally, this paper elucidates the empirical content of the hypothesis that a positive skill selection of migrants affects convergence and the steady state (*selectivity hypothesis*).

To empirically test these migration-related hypotheses, several serious problems must be resolved (NIEBUHR *et al.*, 2012). The main difficulty is caused by the endogeneity of the migration variable in growth regressions. Because migrants react to (expected) income opportunities, changing the regional growth prospects could be the driver rather than the effect of migration flows. Second, the heterogeneity of regions can bias the results if the migration decisions are correlated with unobserved regional amenities that are relevant to regional growth. Third, within a small scale regional setting, the dependence of the growth rates between spatially related units must be taken

1 On contrary, the recent brain drain literature points to the positive feedback effects of skill-selective out-migration on the origin economy that are primarily created by remittances, trade networks, return migration and, most notably, increased incentives for human capital formation in the home region (MOUNTFORD, 1997; STARK *et al.*, 1998; KANBUR and RAPOPORT, 2005).

into account. Fourth, the human capital content of migration is typically unobserved. Therefore, it is not straightforward to disentangle the role of the skill selectivity of migration in regional growth.

The purpose of the present analysis is to provide empirical evidence on the effect of migration on regional growth while *accounting for the four problems mentioned*. Addressing these topics simultaneously, we extend the previous literature, which incorporates only one or two of these crucial concerns.[2] Methodologically, we apply a dynamic panel approach of ß-convergence for managing the endogeneity of migration as well as regional heterogeneity. Furthermore, and extending the basic specification, we augment the model by implementing a spatially lagged dependent variable to solve the problem of spatial dependence. Fourth, concerning skill selectivity, our data set allows for a precise measurement of a region's human capital endowment. By controlling human capital, we are able to identify the role of the migrants' skills in income growth and convergence.

Finally, focusing on the case of the reunified Germany allows a high variation of regional disparities, growth rates, and human capital flows to be exploited. Whereas regional income disparities in the first years after the fall of the iron curtain predominantly occurred along the East-West divide, twenty years after the reunification, the picture has become more diverse even if the rich East German districts still rank below the poor West German districts (BLUM *et al.*, 2010). Because of the high spatial mobility of human capital during transition – the internal migration deficit of the Eastern part of Germany has accumulated to 1.8 million mostly young and well-educated people since 1989 (ibid.) – Germany appears to be a highly appropriate case for testing the impact of skill-selective migration on the evolution of regional disparities (NIEBUHR *et al.*, 2012).

2 Literature

The number of studies analysing the catch-up processes within the β-convergence framework developed by BARRO and SALA-I-MARTIN (1992) and MANKIW *et al.* (1992) is so great that one can get a general idea of the findings only on the basis of meta-analysis techniques. Using the meta studies performed by ABREU *et al.* (2005a) and DOBSON *et al.* (2006), the major results found in this literature can be identified.[3] ABREU *et al.* (2005a) count 1,650 published English-language studies within the *EconLit* database that calculate a rate of convergence. The random sample of this set, which is analysed by the authors, contains 48 studies. The average convergence rate found is 4.3% per year. Regarding our approach – a panel analysis on the basis of regional data – the authors show that the use of regional, rather than country data, significantly increases the convergence rate by 1.1

2 See the review of OZGEN *et al.* (2010). One exception is the paper of OSTBYE and WESTLUND (2007), which addresses regional heterogeneity as well as the endogeneity and skill selectivity of migration in Norway and Sweden.

3 An alternative approach revealing the dependence of the estimated ß-coefficients on different estimation strategies is performed by ARBIA *et al.* (2008). These authors apply the most frequently used regression models to the same dataset and are able to explain a notable part of the variety of results in the empirical literature by the chosen estimation technique.

percentage point. Additionally, splitting the entire sample period into shorter time units and estimating a panel leads to a further increase in the convergence rate. However, the length of the time unit of one growth episode in the panel has a significant negative impact on the estimate of the convergence coefficient. The longer the period is, the smaller the convergence coefficient. Moreover, a fixed-effect approach controlling for differences in steady states and implying a conditional convergence concept substantially increases the measured speed of convergence.

In contradiction to this meta-analysis, DOBSON *et al.* (2006) do not draw a random sample from a broadly defined set of convergence studies but restrict their analysis to a group of more rigorously selected analyses of the β-convergence of per capita income. After applying the corresponding criteria, they obtain 79 papers and calculate an average convergence rate of 2.1% – almost identical to the 2% rule of SALA-I-MARTIN (1996). However, splitting the sample into cross-national and intra-national studies shows that, on average, the calculated speed of convergence is higher at the sub-national level (1.6% for the cross-national vs. 2.5% for the intra-national studies). Furthermore, the meta-regressions for the cross-national level reveal that conditioning on the steady state (either due to fixed effects or due to the inclusion of steady state determining variables) speeds up the estimated convergence rate. Again, there is some evidence that a shorter time span leads to larger estimates for the convergence coefficient. Finally, controlling for spatial dependence reduces the estimate for the β-coefficient. Interestingly, the meta-regression on the basis of regional, i.e., intra-national analyses does not fully support these conclusions. Most of the significant effects for the cross-national analyses become non-significant in the sample for regional studies, even though the sign of the estimators remains almost unchanged.

Evaluating both meta-analyses, one would suppose that our basic approach – an intra-national panel model with relatively short time units that control for individual effects – would yield a substantially higher coefficient of convergence than 2%. In contrast, the implementation of a spatial variable should reduce the convergence speed according to the literature.

With respect to the primary conceptual objective of our paper, i.e., the impact of migration on regional convergence, few empirical analyses can be found. The meta-analysis of OZGEN *et al.* (2010) refers to nine published studies and three working papers addressing this question. However, none of these studies simultaneously address the crucial issues of the migrants' skill selectivity, the endogeneity of migration, regional heterogeneity, and spatial dependence. According to the authors, the overall effect of net migration on the regional growth rate is positive, but small. An increase of 1 percentage point in the net migration rate increases the per capita growth rate by 0.1 percentage points. Moreover, the effect of controlling for net migration in the convergence regression increases the speed of catching up. Yet, the effect is very small. Altogether, these general findings are more in favour of an endogenous than a neoclassical growth model.

However, a closer look reveals that more reliable studies that take into account the potential endogeneity of migration and use panel data models to address the omitted time-invariant variables find a less positive impact for migration on growth. Consistent with these findings, it can be observed that introducing the net migration rate into convergence analyses controlling for regional fixed effects and potential endogeneity bias shifts the β-coefficient substantially more downward than the shift observed in studies without fixed effects. Methodologically, our analysis is primarily related to the paper of OSTBYE and WESTERLUND (2007), even if we extend their approach by accounting for spatial dependence.[4] Therefore, this study is an appropriate reference point for our undertaking. The authors investigate how migration affects convergence for 20 Norwegian and/or 25 Swedish regions. The authors apply a five-year-unit panel data model for the period from 1980 to 2000 that controls for endogeneity and unobserved heterogeneity. To some extent, the results of the paper support the general findings of the meta-analysis of OZGEN *et al.* (2010) – the study is, of course, included in the meta-analysis. For the net migration rate, the authors estimate positive coefficients for Sweden as well as Norway; yet, neither estimate is statistically significant. Surprisingly, including net migration rates reduces the point estimate for the β-coefficient. This result no longer holds for Norway if a measure for the regional human capital stock is included; in this case, the sign of the net migration rate variable in the convergence equation becomes negative. This change in sign points to a major conceptual issue, i.e., the educational composition of migration. If educational attainment is held constant then, at least in Norway, migration has the same effect on growth as a pure increase in the population.

With respect to the geographical focus on German regions, our analysis is primarily related to the labour market related study of NIEBUHR *et al.* (2012), answering the question about whether internal migration acts an equilibrating force in terms of regional unemployment and wages. The authors apply a GMM based dynamic panel approach and account for the spatial correlation of the error term. According to their results, labour mobility strengthens the equilibrating forces with respect to the unemployment rates. On the contrary, spatial mobility does not appear to contribute to a faster wage convergence between German regions. Altogether, NIEBUHR *et al.* conclude that their findings are consistent with the standard neoclassical perspective on mobility rather than with the effects caused by skill-selective migration.

3 Empirical approach

3.1 β-convergence in a dynamic panel framework

Estimating β-convergence in a panel setting goes back at least to ISLAM (1995). The advantages of using a panel approach are, *prima facie*, very promising. First, the problem of omitted variables can be controlled, particularly with respect to the differences in the initial level of technology between

4 Surprisingly, OSTBYE and WESTERLUND found only modest evidence for the existence of spatial correlation in growth and migration rates. However, the reliability of the applied Moran's I statistic is disputable in cases of substantial spatial dependence generated by a spatial autoregressive DGP (LI *et al.*, 2007).

the regions. Second, endogeneity and measurement errors can be addressed (ISLAM, 2003; BOND *et al.*, 2001). In our context, the β-convergence equation is given by

$$\log y_{iT} - \log y_{i0} = a + b\ log y_{i0} + \gamma_m m_i + \gamma_h h_i + \varepsilon_i \text{ with } b = e^{-\beta T} - 1 \quad (1)$$

Here, variable y_i represents the (initial and/or final) gross value added per worker in region *i*. The term m_i measures the net migration rate and h_i represents the regional stock of human capital in region *i*. In a dynamic panel setting with more than one observed growth period equation, (1) can be analogously expressed as follows:

$$\log y_{it} = \alpha + \rho_1 \log y_{it-1} + \theta_m m_{it} + \theta_h h_{it} + \mu_i + d_t + \varepsilon_{it} \text{ with } \rho_1 = e^{-\beta t} \quad (2)$$

The ß-coefficient is assumed to be constant over the entire sample period. The variable μ represents the regional fixed effects, e.g., capturing differences in the initial level of technology or other unobserved fixed parameters leading to dissimilar regional steady states; *d* are time effects. Yet, these fixed effects could also account for region- and period-specific measurement errors (BOND *et al.*, 2001).

Estimating model (2) allows the hypotheses proposed in the introduction to be tested:

(1) *Convergence effect*. The effect of migration on convergence can be assessed by estimating equation (2) with and without the migration term. If the ß-coefficient substantially decreases (ρ_1 increases) after controlling for migration, it indicates that migration has a convergence accelerating effect.

(2) *Steady state effect*. The long-run impact of migration can be directly tested by the sign and magnitude of the migration parameter θ_m. With a positive parameter, enduring net migration gains should shift the steady state outward. Calculating the temporal multiplier for the migration parameter $\theta_m * (1 - \rho_1)^{-1}$ provides a straightforward interpretation of the magnitude of the long-run impact.

(3) *Selectivity effect*. To identify the effect of the migrants' skill selectivity, the model is estimated both including and excluding the human capital variable. If migration drives regional growth mainly through human capital import, then the coefficient of the migration variable should diminish after implementing the human capital variable.

3.2 Estimation technique

For consistently estimating equation (2), a panel technique that transcends the common methods of a within group, first difference or random effects panel estimator must be applied.[5] The

[5] Of course, estimating the model with OLS and neglecting the individual effect will lead to a correlation of the lagged dependent variable with the error term in equation (2) and, therefore, to an estimation bias. The correlation

inconsistency of the random effects estimator is due to the obvious correlation between the individual effect and the lagged dependent variable. Therefore, the constitutive orthogonality condition is violated. Regarding the within estimator, a related argument holds. By subtracting the mean of every variable, the error term becomes correlated with the lagged dependent variable – in other words, the orthogonality condition between the regressor and the error term is violated. The same problem occurs by differencing equation (2). Interestingly, according to NICKELL (1981) and HSIAO (1986), the correlation between the error term and the regressor in the simple OLS case produces an upward bias of the estimate; the opposite is true for the within group estimator. So, as BOND *et al.* (2001) note, determining that the estimated parameter is between those extremes appears to be a reasonable test for the validity of results.

To overcome the violation of the orthogonality condition, an instrumental estimation of equation (2) in first differences was proposed by ARELLANO and BOND (1991) and applied to the growth context by CASELLI *et al.* (1996). The general strategy is to instrument the differenced variable with its lagged levels. However, as shown by BOND *et al.* (2001), even this estimator in first differences is problematic within the context of growth models. Using the lagged levels as instruments for the first differences might cause a weak instruments problem. In particular, within the context of growth regressions, the time series are typically persistent and the number of time periods is small, which leads to a low correlation between the instruments and the instrumented variable. Instead, BOND *et al.* (2001) suggest applying a System-GMM approach that contains a level and a difference version of equation (2). In the level equation, the lagged dependent variable is instrumented by the first differences and, vice versa, in the difference equation, the first differences are instrumented by the lagged levels (BLUNDELL and BOND 1998). Therefore, the weak instruments problem can be minimised.[6] For consistency in the System-GMM approach, the relevant moment conditions must hold. Firstly, to ensure the validity of the lagged levels as instruments for the first differences, the error terms in the original level equation ε must be serially uncorrelated. Secondly, to allow the lagged differences to serve as instruments in the level equation, the initial conditions – i.e., the deviations of the initial output from the steady state – must not systematically correlate with the individual effects (DURLAUF *et al.,* 2005).

Moreover, the System-GMM approach is also appropriate in our regional growth context because it allows other endogenous regressors to be included in the model – in our case, the net migration rate as well as the human capital variable. The endogenous variable is instrumented using own lagged levels and differences. Hence, we can address not only the endogeneity of the lagged dependent but also of the other crucial variables in the model. As we will now see, even the

occurs because i) the lagged dependent variable depends itself on the individual effect μ_i and ii) the error term ε_{it} also contains the individual effect. The upward estimation bias resulting from the correlation between individual effects in the error term and the lagged regressor was discussed by HSIAO (1986).

6 Unfortunately, within the context of a dynamic panel data setting, a straightforward test of weak instruments is not available.

implementation of a spatially lagged endogenous regressor does not affect the consistency of the System-GMM approach.

3.3 Implementing spatial dependence

Within the last ten years, it has become standard to account for spatial dependence in empirical regional growth models (FINGELTON and LOPEZ-BAZO, 2006; LESAGE and FISCHER, 2008). According to ANSELIN (1988), spatial dependence is defined as the "existence of a functional relationship between what happens at one point in space and what happens elsewhere."[7] Two basic types of spatial dependence can be distinguished: a *substantive* and a *nuisance* form (ANSELIN and REY, 1991). The second type typically stems from the arbitrariness of the administrative boundaries of spatial units. The problem of measurement errors arises in this context. In contrast, the first type refers to substantial spatial interactions between (neighbouring) locations. Here, economic factors or the economic outcome of one region exert an influence on the outcome in other locations. The first type is econometrically implemented as a spatial lag or a cross-regressive model; the second type as spatial error model (REY and MONTOURI, 1999).

With respect to *dynamic panel* β-convergence models, spatial effects have been ignored in the majority of the analyses.[8] A first exception was the approach of BADINGER *et al.* (2004), who account for spatial dependence in a dynamic panel GMM setting by *spatial filtering*. Within this two-step approach, to separate the spatial effects, the relevant variables were transformed according to filtering methods. A more straightforward approach that directly implements a spatial component in the regression equation was recently performed by BOUAYAD-AGHA and VEDRINE (2010). These authors account for the spatial lag and/or error dependence within a dynamic panel analysis of β-convergence for European regions within the framework of a GMM difference approach. A recent alternative accounting for spatial correlation by inclusion of a spatially lagged dependent variable is performed by YU and LEE (2012) for the US economy. Yet, their spatial dynamic panel model does not include other endogenous regressors on the right hand side such as migration, which is important for the present analysis.

Neglecting spatial autocorrelation may work like an omitted variable bias (LESAGE and PAGE, 2009, 27ff.) In our analysis, this consequence appears to be a major concern because net migration is likely to be correlated with unobserved variables. Even if we treat migration as an endogenous variable in the System-GMM estimation a separate representation of the spatial effect is reasonable. One way of exemplifying the correlation between the productivity of adjacent regions and migration refers to the role of technological spillovers. Productivity enhancing knowledge flows from neighbouring regions should drive wages in the region stimulating in-migration from more

7 According to ANSELIN (1988: 11ff.), two basic types of spatial effects must be distinguished: spatial heterogeneity and spatial dependence. Spatial heterogeneity is related to the lack of "structural stability of various phenomena over space," resulting in spatially varying functional forms and parameters.

8 However, in a broader context spatially augmented panel models are more common. See LEE and YU (2010) for an overview as well as ELHORST (2012) for a typology of dynamic spatial panel models.

distant areas. Taking these spatial interactions seriously is a necessary pre-condition for obtaining unbiased results. More specifically, we follow the suggestion of MONTEIRO and KUKENOVA (2009), who show that directly estimating the System-GMM with a spatially lagged dependent variable works reasonably well and outperforms the alternative estimation strategies in terms of biasedness and efficiency, at least for the specification of our primary interest. We prefer the spatial lag over the error specification because the lag model provides a meaningful interpretation and – as FINGELTON and LOPEZ-BAZO (2006) argue – is the most appropriate for the analysis of *conditional* convergence. Furthermore, the consequence of neglecting spatial dependence in the error term only concerns the *efficiency* of the estimator. In contrast, when ignoring substantive spatial dependence within variables the estimator will lose its property of being *consistent* (ELHORST, 2012).

The spatial and dynamic autoregressive lag model with the term W representing the spatial weights matrix is given by the following:

$$\log y_{it} = \alpha + \rho_1 \log y_{it-1} + \rho_2 (W \log y_{it}) + \theta_m m_{it} + \theta_h h_{it} + \mu_i + d_t + \varepsilon_{it} \qquad (3)$$

ABREU *et al.* (2005b) and LESAGE and PAGE (2009) point to the specifics in interpreting the θ parameters in a spatial lag model. Because the effect of an increase of, say, the net migration rate in region i disperses, in the first step, to the neighbouring regions and, in a second step, to the neighbours' neighbours and, therefore, back to the origin region, the initial increase of y_i is only a part of the total induced effects in the other regions $i \neq j$ as well as in the own region i. To account for these additional spatial spillovers when interpreting the parameters, we rely on the concepts developed by LESAGE and PAGE (2009, 34ff.).

Basically, LESAGE and PAGE distinguish between the *direct* and the *total* effect of changes in the variables. The direct effect measures the increase in the dependent variable y in region i induced by an increase in the independent variable m in region i. Note that this effect also includes feedback loops running via the initial impact of region i on its neighbour j followed by the return effect of region j on its neighbour i.[9] The total effect includes the entire outcome of an increase of m in region i in this region *and* in regions $j \neq i$. To calculate these measures, one must rely on the product of the parameter of interest and the spatial multiplier matrix $\theta_m * (I - W\rho_2)^{-1}$, which results from the reduced form transformation of (3) with respect to y_{t}. The main diagonal of the matrix contains the direct effect for every region; the sample size standardised trace of the diagonal is a suitable measure of the direct effect. The other cells contain the indirect effects resulting from a change of m in i on the outcome in region j. The sample size standardised row sum of the matrix, therefore, can be interpreted as the total effect of a change in m in region i.

9 ABREU *et al.* (2005b) apply a somewhat different terminology. Their direct effects do not include the impact induced by the feedback relationship with neighbours.

Because a spatial dynamic model not only comprises spatial interactions but also temporal correlation, the interpretation of the parameters – at least with a long-term perspective – should also account for the temporal effect represented by ρ_1.[10] According to ELHORST (2012), the long-run direct effect of a change of m in region i at time t can be calculated by augmenting the spatial multiplier matrix to $(I - \rho_1 I - W\rho_2)^{-1}$ and multiplying by θ_m. The main diagonal contains the effect of a change in the net migration rate in region i at time t on the steady state outcome y of region i including the spatial feedback effect of the neighbouring regions.

3.4 Specification and model selection

The consistency of the (System-) GMM estimator relies on the validity of the moment conditions that are applied, particularly on the orthogonality and the relevance of the instruments in the level and difference equation. Therefore, the specification tests are of decisive importance and should guide the selection of the most credible model. The following criteria partly proposed by ROODMAN (2009a, b) must be met to consider a particular specification to be valid:

i. The number of instruments is considerably smaller than the number of regions.

ii. The Hansen J test does not reject the H_0 of the valid instruments.

iii. The Difference-in-Hansen J test for the instruments' validity of the excluded subgroups in the level equation – particularly the subgroup of instruments stemming from the dependent variable y – is not rejected.

iv. The second differences of residuals are not serially correlated (AR (2) test statistic is insignificant).

v. The parameter of the time-lagged income per worker lies between the Within Group and the OLS value.

Furthermore, we follow ROODMAN'S (2009a) suggestion and estimate dynamic panel models with time dummies. We restrict the number of instruments by imposing limitations on the lag structure. With respect to the special set of differenced instruments in the System-GMM level equation, ROODMAN draws attention to a particular problem of the instruments' validity. He proposes to test the orthogonality condition by the Difference-in-Hansen J test for the subgroup of instruments – especially the Δy – in the level equation. If the J statistic significantly increases when the subgroup of previously excluded instruments is included, it might indicate a violation of the moment

10 Of course, the diffusion of the spatial effects also takes several periods until it culminates in a new steady state.

condition. Then, the System-GMM should be invalid and only the differenced equation should be estimated.[11]

3.5 Data

Even if we implement a spatially lagged dependent variable in our extended specification, we try to identify the convergence effect of human capital migration on a regional level where the urban sprawls and/or the spatial urban-suburban commuting relationships should play only a minor rule. Therefore, our analysis focuses on the regional level of *functional* spatial units and not on *administrative* districts. We aggregate data for the 439 NUTS-3 German administrative districts ('Landkreise und kreisfreie Städte') into 97 spatial planning regions ('Raumordnungsregionen'). Because we aggregate districts into functionally defined regions, a sample is generated with a lower number of regions but more *homogenous* spatial units.

In our analysis, we use data for the 1993 to 2008 period stemming from the Federal Statistical Office and the states' statistical offices ('Länder'). For each of the NUTS-3 regions of Germany and for every year of the sample period, the analysis contains information on the total gross value added and the working population. The gross value added is measured in current prices; the annual values are averaged over the time span of one panel period. The migration data are provided by the regional migration statistics of the Federal Statistical Office. Because we concentrate on internal migration, we include only the migration flows *between* German districts. However, these flows also include the movements of foreigners within Germany. Because we aggregate data from the 439 NUTS-3 regions into larger functional spatial units, we could only use the net migration rates and are not able to distinguish between the gross inflow and outflow of migrants. Because we are interested in the productivity effect, i.e., the growth of gross value added per worker, we only consider migrants between the ages of 25 to 65 years.

In our data set, we directly observe the age but not the human capital of the migrants. To disentangle the human capital effect of the migrants, we consider a variable that measures the human capital endowment of the region's workforce. More specifically, we design a variable representing the share of employees with an academic degree in the region's entire workforce. The data are taken from the employment statistics of the German Federal Employment Agency covering all employees registered in the German social security system.

To take spatial dependencies into account, we must map the economic interactions of the neighbouring regions. For simplicity, we apply a row standardised contiguity matrix between the 97 spatial planning regions. To check the sensitivity of the results, we alternatively use a distance-based weighting matrix that is determined by the inverse average travelling time by car between the

11 BOUAYAD-AGHA and VEDRINE (2010) estimate their dynamic panel model of β-convergence of the European regions as a Difference-GMM because the Difference-in-Hansen J test is highly significant. However, the cost of fewer but valid instruments appears to be – at least in the context of growth regressions – a weak instruments problem (BOND *et al.*, 2001).

centres of the 97 regions in 2006. To avoid unreasonable neighbourhood relationships over large distances, the cells of the matrix are set to zero for all travelling times above two hours. The resulting matrix is row-standardised.

A crucial question considers the choice of length for the panel intervals. Altogether, we can only observe a short time span of 16 years between 1993 and 2008. One natural division is to split this time span into four growth periods of four years each. In the literature, five-year time intervals are typically generated (ISLAM, 2003). Yet, there is no clear criterion for deciding the minimum interval length. In our case, if we opt for longer intervals, we must restrict the number of intervals per region to three, which appears to be a greater drawback than applying a time span of only four years. However, to check the robustness of the results, we also estimate the model for two-year panel periods. These periods are quite short in the context of growth regressions. The advantage is a substantial increase in the number of observed time spans from four to eight.

4 Results

4.1 Basic model

Table 1 displays the results of the System-GMM estimation without accounting for spatial effects. In this parsimonious specification, only the second lag is used as an instrument in the difference equation. Because the lag dependent, the migration and the human capital variables are treated as endogenous; first lags are not valid instruments and must be neglected. Column (1) represents the full model when net migration rates and regional human capital are included. In column (2), the model is estimated neglecting the net migration rate. In column (3), the human capital variable is omitted.

Before turning to the estimates, a closer look at the specification tests is necessary. First, in all of the models, the number of instruments is small in comparison to the number of regions. Thus, the problem of "too many instruments" (ROODMAN, 2009b) appears not to be prevalent. Therefore, the Hansen J statistic is an appropriate guide to assess the validity of the instruments. The general Hansen J statistic is far from being significant. Additionally, the difference-in-Hansen J tests do not create scepticism with respect to the validity of the differenced instruments in the level equation. Therefore, the System-GMM approach is the preferred estimation strategy. Moreover, at least for the models including human capital, the coefficient for the lagged dependent variable lies between the OLS and the Within-Group (WG) estimates. All in all, the specification tests appear to support the specification even if the evidence related to the serial correlation of errors based on the AR (2) test is not available due to the insufficient number of panel periods.

Table 1: System-GMM estimation without spatial effects, 1993-2008 (four 4-year periods)

	Full model (1)	Net migration excluded (2)	Human capital excluded (3)
$\ln y_{t-1}$ *Test* $\ln y_{t-1} = 1$	**0.811** [0.000]***	**0.814** [0.000]***	**0.919** [0.412]
ß	*0.052*	*0.051*	*0.021*
Net migration rate	**0.153** [0.069]*		**0.191** [0.067]*
Regional human capital	**0.880** [0.000]***	**0.918** [0.000]***	
Regions/observations	97/291	97/291	97/291
Shortest /longest lag	2/2	2/2	2/2
Number of instruments	11	7	7
Specification tests			
Hansen J	4.36 [0.499]	2.41 [0.300]	0.83 [0.661]
Difference in Hansen J ($\Delta \ln y$ valid in level equation)	0.57 [0.449]	0.18 [0.647]	0.16 [0.692]
Difference in Hansen J (Δ migration and/or Δ human capital valid in level equation)	4.35 [0.360]	2.41 [0.300]	0.83 [0.661]
OLS estimate for $\ln y_{t-1}$	0.846	0.849	0.847
WG estimate for $\ln y_{t-1}$	0.545	0.545	0.561

Notes: Significance levels * 10%, ** 5%, *** 1%; p-values in parentheses. Time dummies are included. Lag dependent, migration, and human capital variables are treated as endogenous; thus, only second and deeper lags are used. An AR (2) test is not feasible due to an insufficient number of panel periods. The estimations are performed by the Roodman's xtabond2 package in STATA. See ROODMAN (2009a). For comparison with other studies, the ß-coefficient is re-calculated for a one-year period.

Source: Own calculation.

In the full specification (1), the β-coefficient is approximately 5%. Within the range of the OLS and the WG estimator, the β-coefficient lies relatively close to the OLS estimator. The size of the coefficient appears to be close to the other estimates from sub-national panel convergence models. Quite reasonably, the 5% is considerably above the BARRO and SALA-I-MARTIN 2% rule of thumb for cross-country estimates of convergence. Another convincing result is the significant impact of human capital endowment – measured as the proportion of workers with an academic degree – on regional growth. According to specifications (1) and (2), a one percentage point increase in that proportion raises the productivity in the subsequent period by slightly below one percent.

Firstly, with respect to the hypotheses to be tested, we find no notable *convergence effect* from net migration. Comparing columns (1) and (2) shows that the coefficient of convergence is not affected by the omission of the migration variable. Interestingly, the coefficient of convergence reacts sharply to the drop of the human capital variable (see column (3)). If regional human capital is controlled for, the speed of convergence is almost twice as high as in the specification without human capital.

Secondly, the regressions provide evidence for a positive effect of net migration on the long-run *steady state*. Across almost all specifications, a one percentage point increase in the net migration rate fosters productivity within the 4-year period by the small amount of 0.10-0.25 percent; the long-run effect accumulates to over 2 percent. The effect is consistent with the results from other countries (see section 2). From this perspective, one might conclude that migration causes long-run divergence in the sense that regions with considerable migration gains will achieve higher long-run productivity levels than regions that lose population through out-migration.

Thirdly, our analysis is in favour of a modest *selectivity effect*. The coefficient of migration increases when the human capital measure is omitted (columns (1) vs. (2)). Even if the rise is not dramatic, it indicates that human capital, and thus the skill selectivity of migration is one channel through which migrants influence productivity.

4.2 Spatial model

Although no direct test of spatial dependence in the context of a dynamic panel model is available (BOUAYAD-AGHA and VÉDRINE, 2010), the Moran's I statistics for the main variables reveal substantial spatial correlation within the data (Appendix table A2). Furthermore, we test for spatial dependence by applying the LM tests developed by DEBARSY and ERTUR (2010) to the (static) fixed effects panel version of our model. As table A3 in the appendix shows, spatial dependence seems to be a major concern in our data (*significant joint test*). Moreover, on the basis of the LM tests for the static panel version, a decision in favour of the model including a spatially lagged dependent variable can be made.[12] This choice is supported by the theoretical reasoning in section 3.3. In addition, the spatially lagged dependent model provides us with meaningful propositions regarding spatial spillovers.

Turning to the spatial augmented model in table 2, the System-GMM specification tests are somewhat less favourable. The general Hansen J test rejects the hypothesis of valid instruments at the conventional level of 5%. The difference-in-Hansen J test rejects the exogeneity of instruments in most of the relevant cases. Consequently, the results must be interpreted very cautiously.

12 The test for the absence of spatially correlated residuals when allowing for a spatially lagged dependent variable cannot be rejected whereas the test for the absence of spatial correlation of the dependent variable when allowing for spatially correlated residuals has to be rejected.

Table 2: System-GMM System estimation with spatial lag, 1993-2008 (four 4-year periods)

	Full model (1)	Net migration excluded (2)	Human capital excluded (3)
$\ln y_{t-1}$	**0.645**	**0.652**	**0.610**
Test $ln\, y_{t-1} = 1$	[0.000]***	[0.020]**	[0.000]***
ß	*0.110*	*0.107*	*0.123*
W $\ln y_t$	**0.231** [0.342]	**0.224** [0.343]	**0.164** [0.529]
Net migration rate	**0.144** [0.091]*		**0.245** [0.147]
Regional human capital	**1.123** [0.000]***	**1.134** [0.000]***	
Regions/observations	97/291	97/291	97/291
Shortest /longest lag	2/2	2/2	2/2
Number of instruments	15	11	11
Specification tests			
Hansen J	17.90 [0.022]**	11.69 [0.039]**	11.63 [0.040]**
Difference in Hansen J ($\Delta \ln y$ and $\Delta W \ln y$ valid in level equation)	6.03 [0.110]	3.68 [0.299]	9.31 [0.025]**
Difference in Hansen J (Δ migration and/or Δ human capital valid in level equation)	17.11 [0.002]***	11.03 [0.004]***	8.49 [0.014]**
OLS estimate for $\ln y_{t-1}$	0.776	0.776	0.810
WG estimate for $\ln y_{t-1}$	0.384	0.384	0.407

Notes: Significance levels * 10%, ** 5%, *** 1%; p-values in parentheses. Time dummies are included. Lag dependent, spatial lag, migration, and human capital variables are treated as endogenous; thus, only second and deeper lags are used. AR (2) test is not feasible due to an insufficient number of panel periods. The estimations are performed via the xtabond2 package in STATA. See ROODMAN (2009a). A row-standardised contiguity matrix is used. For comparison with other studies, the ß-coefficient is re-calculated for a one-year period.

Source: Own calculation.

Yet, there is good news in the rather stable effect of migration. Even if the significance of the estimates is somewhat low, the magnitude of the coefficients is quite similar to those of table (1). However, because the interpretation of the effects within a spatial lag model should consider the spatial feedback loops, it is more accurate to compare the effect of the non-spatial model of table 1 with the (short-run) average direct spatial effect calculated in table 3. Including the spatial relationships does not change the overall result. Therefore, the primary interesting finding of our analysis is not jeopardised through the implementation of spatially lagged productivity levels. Moreover, the increased size of the coefficients for migration in specifications without human capital (columns (1) vs. (3)) is confirmed. Finally – consistent with the non-spatial model – omitting migration does not affect the coefficient of convergence.

The most astonishing aspect of table 2 is the impact of the spatially lagged term on the β-coefficient. Controlling for the productivity of the relevant regions surrounding the own district doubles the speed of convergence from 5% to 10%. The effect of the neighbouring regions on regional growth itself is substantial but imprecisely estimated. Altogether, the convergence process appears to exhibit a spatial and a temporal effect. A region not only grows faster because the distance to its steady state is higher; it also benefits if the neighbouring regions exhibit high productivity levels.

If regions with similar levels of productivity tend to cluster[13], then neglecting the spatial effect in estimating the β-convergence will reduce the speed of convergence because the very productive regions exhibit high growth rates – not because of the gap between the initial levels and the steady state but because of spillovers from the surrounding high level regions. Taking the spatial effect into account – as in the augmented model of table 2 – increases the parameter for the coefficient of convergence.[14]

Table 3: Average short-run spatial and long-run effects of changes in net migration

Net migration rate	Full model (1)	*Non-spatial full model, table 1* *(2)*
Effect net of spatial spillovers [θ_m]	*0.144*	*0.153*
Short run spatial effect		
Average direct effect	0.146	*0.153*
Average total effect	0.187	*0.153*
Long run effect		
Average direct effect	1.164	*2.263*

Notes: The short-run spatial direct effect is calculated by dividing the trace of the matrix K by the number of regions. The matrix K is computed by multiplying θ_m with the spatial multiplier matrix $[I - \rho_2 W]^{-1}$. For the long-run effect, the spatial multiplier matrix is extended to $[I - \rho_1 I - \rho_2 W]^{-1}$. The sample size standardised row sum of the matrix K represents the total effect. For comparison, column (2) refers to the non-spatial full model shown in table 1. See section 3.3.

Source: Own calculation.

13 The correlation between the productivity level and its spatial lag is approximately 0.8.

14 For an analogous result on the level of the European regions, see BOUAYAD-AGHA and VÉDRINE (2010).

4.3 Robustness check

To test the reliability of our results, we perform various estimations applying different specifications. First, we use a different lag structure, exploiting a deeper lag as an instrument for the difference as well as the level equation of the System-GMM estimator. Appendix table A4 displays the results for the non-spatial model; table A5 shows the spatial augmented regressions. Regarding the non-spatial model, no remarkable changes appear. With respect to the spatial augmented specification, the spatial lag and the ß coefficient increase. However, the impact of migration appears to be quite unaffected by the changes; only the variance of the estimate increases.

Second, we test the sensitivity of our analysis in terms of the choice of the spatial weights matrix (see Appendix table A6). Instead of a contiguity matrix, we implement a distance-based weighting matrix based on the inverse average travelling time by car between the centres of the regions. Again, the modification of the specification does not affect the results – at least in terms of the net migration rate which can be seen by comparison of the short run average direct and total effect of migration between the first column of table 3 and the first column of table A6 (full model).

Third, we extend the number of observations per region by shortening the panel period from four to two years (see Appendix tables A7 and A8). Hence, we obtain eight growth periods per region. Although the outcome variable y could be driven by many short-term factors during this time span that are not related to the determinants of long-run growth, this strategy allows the number of instruments to be increased even if we restrict the maximum length of the lags according to the basic specification for comparability. The main discrepancy of the specification with more but shorter panel periods concerns the selectivity hypothesis. Whereas in all previous specifications, the effect of migration on the steady state is reduced when human capital is controlled for, no substantial difference can be observed in tables A7 and A8.

5 Conclusions

Our analysis suggests that there is a considerable convergence of German regions in the period of 1993 to 2008. Because we apply a dynamic panel approach, the tested type of convergence is the *conditional* one, i.e., the speed of adjustment to the own regional steady state. If steady states between regions differ, conditional convergence does not necessarily imply absolute convergence, i.e., higher growth rates for lagging regions and lower growth for regions that are ahead. Regarding our primary research question – the impact of migration on regional growth and convergence – we find significant and robust effects. After controlling for the initial level of productivity, increasing regional migration rates appear to accelerate regional productivity leading to a higher steady state. The effect is weaker if the human capital endowment of the regions is accounted for. This result indicates that the migration effect is at least partly attributable to the human capital selectivity of migrants.

With respect to regional convergence, migration is supposed to cause long-run divergence in the sense that the regions with considerable human capital gains achieve higher productivity. A transitional impact on the speed of convergence to the steady state is not verified by our analysis. Furthermore, the results concerning the effect of migration still hold in the spatially augmented model. Furthermore, if initial productivity is controlled for, the contemporaneous productivity of the neighbouring regions fosters the own productivity level. Thus, convergence exhibits a temporal as well as a spatial dimension. Neglecting the spatial dimension underestimates the speed of convergence because even the near steady state regions grow quickly due to the substantial spatial spillovers from their near steady state neighbours.

Regarding the impact of migration on growth and convergence as well as the role of skill selectivity, our results are consistent with the previous analyses (OZGEN *et al.*, 2010) even if most of these analyses do not account for the serious methodological problems mentioned in the introduction. The positive, but fairly small effect of migration on growth and the long-run steady state is consistent with the empirical literature. Contrary to our results, most studies find that controlling for net migration increases the speed with which regions catch up; however, these effects are very small. We rather support the outcome of OSTBYE and WESTERLUND (2007), who find that the growth effect of net migration is reduced after controlling for human capital, a result that points to the crucial role of the migrants' skill composition. Moreover, our findings concerning the spatial dimension of convergence are confirmed by BOUAYAD-AGHA and VÉDRINE (2010) in their recent analysis of the convergence of European regions.

From a methodological perspective, we must point to some potential for further research. First, it would be useful to have a longer time span to increase the length of one panel period from four years to – say – ten years. Otherwise, there could be too much noise or there could be business cycle effects within the short period data. Second, a direct measure of the migrants' human capital endowment would be more reliable that tests the hypotheses concerning the skill selectivity of migration. Bearing these limitations in mind, our analysis, nevertheless, has generated some quite robust insights into the impact of migration on regional growth.

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7 Appendix

Table A1: Description and summary statistics of variables

	(1) Mean of 97 regions	(2) Coefficient of variation	(3) Minimum region	(4) Maximum region
y_t ≡ Gross value added per worker of period t (mean of four years; in constant prices)				
t_1 (1993-1996)	41,110	6,817	27,436	58,154
t_2 (1997-2000)	43,894	6,293	32,246	61,734
t_3 (2001-2004)	46,018	5,869	34,810	65,502
t_4 (2005-2008)	48,674	6,040	37,237	69,041
Growth rate$_t$ ≡ $1/3[(\ln y)_t - (\ln y)_{t-1}]$				
t_1 (1993-1996)	-	-	-	-
t_2 (1997-2000)	0.0232	0.0153	-0.0121	0.0599
t_3 (2001-2004)	0.0166	0.0146	-0.0163	0.0558
t_4 (2005-2008)	0.0188	0.0090	-0.0050	0.0494
Net migration rate$_t$ ≡ Total net migration over period t in relation to the initial population (25-65 years)				
t_1 (1993-1996)	0.0060	0.0322	-0.1379	0.0899
t_2 (1997-2000)	0.0044	0.0306	-0.1620	0.0943
t_3 (2001-2004)	0.0043	0.0210	-0.0520	0.0487
t_4 (2005-2008)	-0.0017	0.0161	-0.0359	0.0375
Regional human capital$_t$ ≡ Share of employees with an academic degree in relation to the entire workforce (mean of four years)				
t_1 (1993-1996)	0.0669	0.0243	0.0304	0.1440
t_2 (1997-2000)	0.0736	0.0238	0.0360	0.1492
t_3 (2001-2004)	0.0800	0.0250	0.0406	0.1600
t_4 (2005-2008)	0.0867	0.0265	0.0456	0.1737

Notes: Migration statistics without the spatial planning region of Goettingen due to inflated out-migration rates reflecting the *pro forma* assignment of refugees to that region.

Source: Own calculation.

Table A2: Spatial dependence structure Moran's I statistics (z-scores)

	(1) Log GVA per worker (4 year mean)	(2) Growth rate of (1)	(3) Migration rate (4 year total)	(4) Human capital (4 year mean)
t_1 (1993-1996)	10.750 [0.000]***	-	-0.259 [0.796]	6.198 [0.000]***
t_2 (1997-2000)	10.011 [0.000]***	7.774 [0.000]***	0.818 [0.413]	4.121 [0.000]***
t_3 (2001-2004)	9.369 [0.000]***	8.682 [0.000]***	0.751 [0.453]	2.947 [0.003]**
t_4 (2005-2008)	9.342 [0.000]***	2.844 [0.005]**	4.078 [0.000]***	2.070 [0.039]*

Notes: Significance levels * 5%, ** 1%, *** 0.1%; p-values in parentheses. A 97x97 row standardised contiguity matrix is used.

Source: Own calculation.

Table A3: LM tests for spatial dependence (fixed effects panel model)

LM test (DEBARSY and ERTUR, 2010)	LM-Statistic	p-value
Joint test of spatial correlation (H0: absence of spatially correlated residuals *and* spatial correlation of the dependent variable)	181.9	<0.01
Spatial correlation in residuals (H0: absence of spatial correlation in residuals)	175.4	<0.01
Spatial correlation of the dependent variable (H0: absence of spatial correlation of the dependent variable)	172.0	<0.01
Spatial correlation in residuals when spatial correlation of the dependent variable is accounted for (H0: absence of spatial correlation in residuals)	0.3	0.62
Spatial correlation of the dependent variable when spatial correlation in residuals is accounted for (H0: absence of spatial correlation of the dependent variable)	318.7	<0.01

Notes: Significance levels * 5%, ** 1%, *** 0.1%; p-values in parentheses. A 97x97 row standardised contiguity matrix is used. The tests developed in DEBARSY and ERTUR (2010) are performed via the MATLAB code provided by Debarsy and Ertur for the Econometrics toolbox of LeSage (http://www.spatial-econometrics.com).

Source: Own calculation.

Table A4: System-GMM estimation without spatial effects, 1993-2008 (four 4-year periods, more lags used)

	Full model (1)	Net migration excluded (2)	Human capital excluded (3)
$\ln y_{t-1}$	**0.840**	**0.849**	**0.870**
Test $ln\, y_{t-1}$ *= 1*	[0.000]***	[0.000]***	[0.182]
ß	*0.044*	*0.041*	*0.035*
Net migration rate	**0.130** [0.056]*		**0.183** [0.051]*
Regional human capital	**0.533** [0.012]**	**0.549** [0.006]***	
Regions/observations	97/291	97/291	97/291
Shortest /longest lag	2/3	2/3	2/3
Number of instruments	13	8	8
Specification tests			
Hansen J	9.39 [0.226]	6.11 [0.107]	2.93 [0.176]
Difference in Hansen J ($\Delta\ln y$ valid in level equation)	1.70 [0.193]	1.81 [0.178]	0.75 [0.387]
Difference in Hansen J (Δ migration and/or Δ human capital valid in level equation)	4.85 [0.303]	6.11 [0.107]	0.08 [0.961]
OLS estimate for $\ln y_{t-1}$	0.846	0.849	0.847
WG estimate for $\ln y_{t-1}$	0.545	0.545	0.561

Notes: Significance levels * 10%, ** 5%, *** 1%; p-values in parentheses. Time dummies are included. Lag dependent, migration, and human capital variables are treated as endogenous; thus, only second and deeper lags are used. AR (2) test is not feasible due to an insufficient number of panel periods. The estimations are performed by the Roodman's xtabond2 package in STATA. See ROODMAN (2009a). For comparison with other studies, the ß-coefficient is re-calculated for a one-year period.

Source: Own calculation.

Table A5: System-GMM estimation with spatial effects, 1993-2008 (four 4-year periods, more lags used)

	Full model (1)	Net migration excluded (2)	Human capital excluded (3)
$\ln y_{t-1}$ *Test* $ln\, y_{t-1}$ *= 1*	**0.468** [0.000]***	**0.475** [0.000]***	**0.404**
ß	*0.190*	*0.186*	*0.227*
W $\ln y_t$	**0.557** [0.002]***	**0.553** [0.002]***	**0.554** [0.014]**
Net migration rate	**0.106** [0.191]		**0.225** [0.199]
Regional human capital	**1.196** [0.000]***	**1.197** [0.000]***	
Regions/observations	97/291	97/291	97/291
Shortest /longest lag	2/3	2/3	2/3
Number of instruments	18	13	13
Specification tests			
Hansen J	21.25 [0.031]**	17.76 [0.013]**	16.27 [0.023]**
Difference in Hansen J ($\Delta\ln y$ and W $\ln y_t$ valid in level equation)	2.53 [0.469]	2.68 [0.444]	4.27 0.234
Difference in Hansen J (Δ migration and/or Δ human capital valid in level equation)	14.68 [0.005]***	12.25 [0.002]***	5.45 [0.065]*
OLS estimate for $\ln y_{t-1}$	0.776	0.776	0.810
WG estimate for $\ln y_{t-1}$	0.384	0.384	0.407

Notes: Significance levels * 10%, ** 5%, *** 1%; p-values in parentheses. Time dummies are included. Lag dependent, migration, and human capital variables are treated as endogenous; thus, only second and deeper lags are used. An AR (2) test is not feasible due to an insufficient number of panel periods. The estimations are performed by the Roodman's xtabond2 package in STATA. See ROODMAN (2009a). For comparison with other studies, the ß-coefficient is re-calculated for a one-year period.

Source: Own calculation.

Table A6: System-GMM estimation with spatial lag, 1993-2008 (Distance-based W-Matrix; four 4-year periods)

	Full model (1)	Net migration excluded (2)	Human capital excluded (3)
$\ln y_{t-1}$	**0.541**	**0.545**	**0.556**
Test $\ln y_{t-1} = 1$	[0.005]***	[0.005]***	[0.025]**
ß	*0.154*	*0.152*	*0.147*
W $\ln y_t$	**0.406**	**0.403**	**0.231**
	[0.125]	[0.116]	[0.467]
Net migration rate	**0.129**		**0.249**
	[0.109]		[0.152]
Short run spatial effects of net migration			
Short run average direct effect	*0.133*		*0.251*
Short run average total effect	*0.218*		*0.324*
Regional human capital	**1.428**	**1.433**	
	[0.000]***	[0.000]***	
Regions/observations	97/291	97/291	97/291
Shortest /longest lag	2/2	2/2	2/2
Number of instruments	15	11	11
Specification tests			
Hansen J	10.07	6.23	9.33
	[0.260]	[0.285]	[0.097]
Difference in Hansen J	3.00	1.00	5.61
($\Delta\ln y$ and W $\ln y_t$ valid in level equation)	[0.391]	[0.801]	[0.132]
Difference in Hansen J (Δ migration and/or	9.18	5.62	8.76
Δ human capital valid in level equation)	[0.057]*	[0.060]*	[0.013]**
OLS estimate for $\ln y_{t-1}$	0.806	0.806	0.837
WG estimate for $\ln y_{t-1}$	0.387	0.387	0.412

Notes: Significance levels * 10%, ** 5%, *** 1%; p-values in parentheses. Time dummies are included. Lag dependent, spatial lag, migration, and human capital variables are treated as endogenous; thus, only second and deeper lags are used. The estimations are performed via the xtabond2 package in STATA. See ROODMAN (2009a). The row-standardised distance matrix W is calculated on the basis of the inverse travelling time by car. Distances over 120 minutes are set to zero. For comparison with other studies, the ß-coefficient is re-calculated for a one-year period.

Source: Own calculation.

Table A7: System-GMM estimation without spatial effects, 1993-2008 (eight 2-year periods)

	Full model (1)	Net migration excluded (2)	Human capital excluded (3)
$\ln y_{t-1}$ *Test* $ln\, y_{t-1}$ = *1*	**0.917** [0.000]***	**0.918** [0.000]***	**0.931** [0.014]**
ß	*0.044*	*0.043*	*0.036*
Net migration rate	**0.131** [0.006]***		**0.115** [0.004]***
Regional human capital	**0.371** [0.000]***	**0.387** [0.000]***	
Regions/observations	97/679	97/679	97/679
Shortest /longest lag	2/2	2/2	2/2
Number of instruments	35	23	23
Specification tests			
AR(2)	-1.81 [0.070]*	-1.81 [0.070]*	-1.76 [0.078]*
Hansen J	32.17 [0.153]	21.04 [0.101]	21.37 [0.092]*
Difference in Hansen J ($\Delta\ln y$ valid in level equation)	5.42 [0.366]	12.98 [0.024]**	6.35 [0.274]
Difference in Hansen J (Δ migration and/or Δ human capital valid in level equation)	10.22 [0.597]	10.17 [0.118]	4.12 [0.661]
OLS estimate for $\ln y_{t-1}$	0.913	0.914	0.912
WG estimate for $\ln y_{t-1}$	0.713	0.713	0.713

Notes: Significance levels * 10%, ** 5%, *** 1%; p-values in parentheses. Time dummies are included. Lag dependent, migration, and human capital variables are treated as endogenous; thus, only second and deeper lags are used. The estimations are performed by the Roodman's xtabond2 package in STATA. See ROODMAN (2009a). For comparison with other studies, the ß-coefficient is re-calculated for a one-year period.

Source: Own calculation.

Table A8: System-GMM estimation with spatial lag, 1993-2008 (eight 2-year periods)

	Full model (1)	Net migration excluded (2)	Human capital excluded (3)
$\ln y_{t-1}$	**0.772**	**0.775**	**0.769**
Test $\ln y_{t-1}$ *= 1*	[0.000]***	[0.000]***	[0.000]***
ß	*0.129*	*0.128*	*0.131*
W $\ln y_t$	**0.201**	**0.199**	**0.155**
	[0.009]***	[0.014]**	[0.027]**
Net migration rate	**0.108**		**0.089**
	[0.010]***		[0.003]***
Regional human capital	**0.571**	**0.563**	
	[0.000]***	[0.000]***	
Regions/observations	97/679	97/679	97/679
Shortest /longest lag	2/2	2/2	2/2
Number of instruments	47	35	35
Specification tests			
AR(2)	-1.67	-1.67	-1.76
	[0.095]*	[0.096]*	[0.078]*
Hansen J	49.31	45.25	36.06
	[0.069]*	[0.008]*	[0.071]*
Difference in Hansen J	15.11	17.06	11.94
($\Delta\ln y$ and W $\ln y_t$ valid in level equation)	[0.178]	[0.106]	[0.369]
Difference in Hansen J (Δ migration and/or	12.97	9.96	7.63
Δ human capital valid in level equation)	[0.371]	[0.126]	[0.266]
OLS estimate for $\ln y_{t-1}$	0.879	0.879	0.901
WG estimate for $\ln y_{t-1}$	0.607	0.607	0.607

Notes: Significance levels * 10%, ** 5%, *** 1%; p-values in parentheses. Time dummies are included. Lag dependent, spatial lag, migration, and human capital variables are treated as endogenous; thus, only second and deeper lags are used. The estimations are performed via the xtabond2 package in STATA. See ROODMAN (2009a). For comparison with other studies, the ß-coefficient is re-calculated for a one-year period.

Source: Own calculation.