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Abstract

This paper assess the empirical validity of the neoclassical migration model to predict German internal migration flows driven by regional labour market disparities. We estimate static and dynamic migration functions for 97 Spatial Planning Regions between 1996–2006 using key labour market signals including income and unemployment differences among a broader set of explanatory variables. Beside an aggregate specification we also estimate the model for age-group related subsamples. Our results give empirical support for the main transmission channels identified by the neoclassical framework: That is, regional differences in the real income show the expected effect on the net inmigration rate, while the link between regional unemployment rate differentials and net inmigration is negative. The results remains stable if further variables are added to the model. Net in-commuting shows a negative correlation with in-migration underlying the substitutive nature of the two variables. Moreover an increasing level of international competitiveness attracts further in-migration flows. We also find heterogeneity for different types of settlement structure and the East-West macro regions by including federal state level fixed effects or an East German dummy. The results broadly hold for age-group specific estimates. Here, the impact of labour market signals is tested to be of greatest magnitude for workforce relevant age-groups and especially young cohorts from 18 to 25 and 25 to 30 years. This latter result underlines the prominent role played by labour market conditions in determining internal migration rates of the working population in Germany.

JEL: R23, C31, C33

Keywords: German Internal Migration, Harris-Todaro Model, Dynamic Panel Data

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1 Introduction

There are many theories aiming to explain, why certain people migrate and others do not. However, the neoclassical model remains still the standard workhorse specification to analyse internal and external migration rates at the regional, national and international level. The model puts special emphasis on the labour market dimension of migration and basically relates migration-induced population changes as a response to relative income (or wage) and employment situations found in the origin and destination region. Migration then itself works as an equilibrating mechanism for balancing differences among regions with respect to key labour market variables since higher in-migration in a region is expected to reduce the regional wage level due to an increase in labour supply. From the perspective of economic policy making the empirical implications of the neoclassical migration model are important to assess whether labour mobility can act as an appropriate adjustment mechanism in integrated labour markets facing asymmetric shocks. Though the neoclassical migration model is widely used as a theoretical and didactic tool, the international empirical evidence provides rather mixed results.

In this paper, we therefore aim to check the validity of the neoclassical migration model using a panel of 97 German regions for the period 1996 – 2006. We are especially interested in taking a closer look at the role played by dynamic adjustment processes driving the internal migration patterns. We also aim toto identify likely role played by additional factors as well as regional amenities in explaining migratory movements beside key labour market signals and focus on the heterogeneity of adjustment processes taking place when migration flows are disaggregated by age groups.

The remainder of the paper is therefore organised as follows: Section 2 skteches the theoretical foundations of the neoclassical migration model leading to a functional form of the neoclassical migration model that can be estimated for the panel of German regions. Building on the theoretical underpinnings section 3 discusses the estimation approach with a special focus on dynamic panel data models. Section 4 then presents a selected literature review for empirical studies dealing with the determinants of internal migration flows. Section 5 describes the data used and displays stylized facts for German internal migration and labour market trends. Section 6 presents the empirical results. Apart from an economic interpretation of the obtained estimation coefficients, we also carefully look at any model misspecification such as cross-sectional dependence in the error terms of our model. An augmented sensitivity analysis for disaggregated migration models by age groups is performed in Section 7. Section 8 concludes.

2 The neoclassical migration model

Theories of migration try to explain what drives population flows. Given the complex nature of the decision process individuals face, there is a large variety of theoretical models available to explain the actual migration outcome. These models may either be classified as micro- or macroeconomic in nature. While micro behavioural models focus on dominant factors at the individual level (such as the human capital model as outlined for example in Sjaastad, 1962), macroeconomic models especially focus on the labour market dimension of migratory flows.

Given the strong need for a solid microeconomic foundation of many macro relationships, the neoclassical migration framework also starts from a micro-founded lifetime expected income (utility) maximization approach as specified in the classical work done on the human capital model of migration. The latter model in fact views the process of migration as an investment where the returns to migration in terms of higher wages associated with a new job exceed the costs involved in moving. Relaxing the assumption that the potential migrant has perfect information about the wage rates and job availabilities among all potential locations involved in his decision making process, Todaro (1969) was among the first to propose a model where the potential migrant discounts wages by the probability of finding a job in respective regions. From this follows that throughout the decision making process, the individual compares the expected (rather than known) income he would obtain for the case he stays in his home region (i) with the expected income we would obtain in the alternative region (j) and further accounts for 'transportation costs' of moving from region i to j.

In their seminal paper, Harris & Todaro (1970) further formalize this idea: The authors set up a model where the expected income from staying in the region of residence Y_{ii}^E is a function of the wage rate or income in region i (Y_i) and the probability of being employed ($Prob(EMP_i)$). The latter in turn is assumed to be a function of unemployment rate in region i (U_i) and a set of potential variables related both to economic and non-economic factors (X_i). The same set of variables - with different subscripts for region j accordingly - is also used to model the expected income from moving to an alternative region. Thus, taking costs of moving from region i to j into account (C_{ij}), the individual's decision will be made in favour of moving to region j if

$$Y_{ii}^E < Y_{ij}^E - C_{ij}, \tag{1}$$

where $Y_{ii}^E = f(Prob(EMP_i), Y_i)$ and $Y_{ij}^E = f(Prob(EMP_j), Y_j)$. The potential migrant weights the proposed wage level in the home and target regions with the individual probability of finding employment. Using this information, we can set up a model for the regional net migration rate (NM_{ij}) defined as regional in-migration flows to i from j relative to outmigration flows from i to j (possibly normalized by the regional population level), which has the following general form:

$$INM_{ij} - OUTM_{ij} = NM_{ij} = f(Y_i, Y_j, U_i, U_j, X_i, X_j, C_{ij}). \tag{2}$$

With respect to the theoretically motivated signs of the explanatory variables we expect that an increase in the home country wage rate (or, alternatively, the real income level) *ceteris paribus* leads to higher net migration inflows, while a wage rate increase in region j results in a decrease of the net migration rate. On the contrary, an increase in the unemployment rate in region i (j) has negative (positive) effects on the bilateral net migration from i to j. The costs of moving from i to j are typically expected to be an impediment to migration and thus are negatively correlated with net migration as:[1]

$$\frac{\partial NM_{ij}}{\partial Y_i} > 0; \frac{\partial NM_{ij}}{\partial Y_j} < 0; \frac{\partial NM_{ij}}{\partial U_i} > 0; \frac{\partial NM_{ij}}{\partial Uj} < 0; \frac{\partial NM_{ij}}{\partial C_{ij}} < 0. \tag{3}$$

Core labour market variables may nevertheless not be sufficient to predict regional migration flows. Recent extensions of the model therefore include further driving forces of migration such as human capital, the regional competitiveness, housing prices, population density and environmental conditions, among others (see e.g. Napolitano & Bonasia, 2010, for an overview). We refer to the neoclassical migration model focusing solely on labour market conditions as the 'baseline' specification, while the 'augmented' specification also controls for regional amenities and further driving forces such as population density and commuting flows as a substitute for migratory movements.

Moreover, regional amenities are typically included as a proxy variable for (unobserved) specific climatic, ecological or social conditions in a certain region. According to the amenity approach regional differences in labour market signals then only exhibit an effect on migration after a critical threshold has been passed. Since in empirical terms it is often hard to operationalize amenity relevant factors, Greenwood et al. (1991) propose to test the latter effect by the inclusion (macro-)regional dummy variables in the empirical model. For the long run net migration equation amenity-rich regions then should have dummy coefficients greater than zero (and vice versa), indicating that those regions exhibit higher than average in–migration rates as we would expected after controlling for regional labour market and macroeconomic differences.

[1]The migration effect of the vector of further economic variables $X_{(i,j]}$ is a priori not clear.

The baseline and augmented migration equations can then either be applied at the micro-, regional or macroeconomic level. The advantage of studies at the macro level is that an analysis of the elasticity of migration with respect to income and unemployment changes gives important information about the size of the adjustment process taking place of balance cross-regional labour market difference through labour migration. In the next section, we therefore estimate the short and long-run impact of alterations in unemployment rates and incomes on migration. Using a flexible estimation approach we also seek to determine whether economic disparities appear to be necessary but not sufficient condition for observed migration processes. The latter hypothesis would give rise to a significant role played by other factors such as local amenities besides labour market signals.

The likely impact of these latter variables in the augmented neoclassical framework can be sketched as follows: Taking human capital as an example, it may be quite reasonable to relax the assumption of the Harris-Todaro model that uneducated labour has the same chance of getting a job as educated labour. Instead, the probability of finding a job is also a function of the (individual but also region specific) endowment with human capital (HK). The same logic accounts for regional competitiveness ($INTCOMP$): Here, we expect that those regions with a high competitiveness are better equipped to provide job opportunities than regions lagging behind (where regional competitiveness may e.g. be proxied by the share of foreign turnover relative to total turnover in sectors with internationally tradeable goods). For population density ($POPDENS$), we expect in general a positive impact of agglomeration forces on net flows through an increased possibility of finding a job, given the relevance of spillover effects e.g. from a large pooled labour market. Thus the probability of finding employment in region i in the augmented neoclassical migration model takes the following form:[2]

$$\begin{aligned} Prob(EMP_i) \;&=\; f[U_i, HK_i, INTCOMP_i, POPDENS_i], \\ & with: \quad \frac{\partial NM_{ij}}{\partial HK_i} > 0; \frac{\partial NM_{ij}}{\partial INTCOMP_i} > 0; \frac{\partial NM_{ij}}{\partial POPDENS_i} > 0. \end{aligned} \tag{4}$$

Finally, we also carefully account for alternative adjustment mechanisms to restore the inter-regional labour market equilibrium such as net commuting flows as substitute to migratory movelents. Here we expect that these flows are negatively correlated with net inmigration.

[2]The opposite effect on NM_{ij} holds for an increase in $HK \uparrow$, $INTCOMP \uparrow$ and $POPDENS \uparrow$ in region j.

3 Econometric Specification

For the empirical estimation of the neoclassical migration model we start from a core specification as e.g. applied in Puhani (2001) and set up a model for the net migration rate as:

$$\left(\frac{NM_{ij,t}}{POP_{i,t-1}}\right) = A_{i,t}\left(\frac{U_{i,t-1}^{\alpha_1}Y_{i,t-1}^{\alpha_2}}{U_{j,t-1}^{\alpha_3}Y_{j,t-1}^{\alpha_4}}\right), \tag{5}$$

where net migration rate between i and j is defined as regional net balance NM for region i relative to the rest of the country j, POP is the region's i population level, t is the time dimension.[3] A is a (cross-section specific) constant term. In the empirical literature a log-linear stochastic form of the migration model in eq.(5) is typically chosen as (where lower case variables denote logs) and $nmr_{ij,t} = log(NM_{ij,t}/POP_{i,t-1})$:

$$\begin{aligned} nmr_{ij,t} &= \alpha_0 + \alpha_1 y_{i,t-1} + \alpha_2 y_{j,t-1} \\ &+\alpha_3 u_{i,t-1} + \alpha_4 u_{j,t-1} + \alpha_5 \mathbf{X} + e_{ij,t}, \end{aligned} \tag{6}$$

where the error term $e_{ij,t} = \mu_{ij} + \nu_{ij,t}$ has the typical error component structure. Taking into account that migration flows typically show some time persistence, we augment eq.(6) by the lagged value of net migration as:

$$\begin{aligned} nmr_{ij,t} &= \beta_0 + \beta_1 nmr_{ij,t-1} + \beta_2 y_{i,t-1} + \beta_3 y_{j,t-1} \\ &+\beta_4 u_{i,t-1} + \beta_5 u_{j,t-1} + \beta_6 \mathbf{X} + u_{ij,t}, \end{aligned} \tag{7}$$

The inclusion of a lagged dependent variable can be motivated by the existence of social networks in determining internal migration flows over time: That is, Rainer & Siedler (2009) for example find for German micro data that the presence of family and friends is indeed an important predictor for migration flows in terms of communication links, which may result in a time dependence of the adjustment path for migration flows out of particular origin to destination regions. Finally, in applied work one typically finds a restricted version of eq.(7) where net migration is regressed against regional differences of explanatory variables of the form (see e.g. Puhani, 2001)

[3] See e.g. Maza & Villaverde (2004) for a similar definition of the dependent variable.

$$nmr_{ij,t} = \gamma_0 + \gamma_1 nmr_{ij,t-1} + \gamma_2 \tilde{y}_{ij,t-1} + \gamma_3 \tilde{u}_{ij,t-1} + \gamma_4 \mathbf{X} + u_{ij,t}, \tag{8}$$

where $\tilde{x}_{ij,t}$ for a variable $x_{ij,t}$ denotes $\tilde{x}_{ij,t} = x_{i,t} - x_{j,t}$. The latter specification implies the following testable restrictions of the unrestricted model in eq.(8), for which we will account for in the empirical estimation:

$$\beta_2 = -\beta_3, \tag{9}$$

$$\beta_4 = -\beta_5. \tag{10}$$

For estimation purposes we then have to find an appropriate estimator, which accounts for the above described empirical setup. Given the dynamic nature of the neoclassical migration model in eq.(8) we can write the specified form in terms of a more general dynamic panel data model as (in log-linear specification):

$$y_{i,t} = \alpha_0 + \alpha_1 y_{i,t-1} + \sum_{j=0}^{k} \beta_j' X_{i,t-j} + u_{i,t}, \quad \text{with:} \quad u_{i,t} = \mu_i + \nu_{i,t}, \tag{11}$$

again $i = 1, \ldots, N$ (cross-sectional dimension) and $t = 1, \ldots, T$ (time dimension). $y_{i,t}$ is the endogenous variable and $y_{i,t-1}$ is one period lagged value. X_i is the vector of explanatory time-varying and time invariant regressors, $u_{i,t}$ is the combined error term, where $u_{i,t}$ is composed of the two error components μ_i as the unobservable individual effects and $\nu_{i,t}$ is the remainder error term. Both μ_i and $\nu_{i,t}$ are assumed to be i.i.d. residuals with standard normality assumptions.

There are numerous contributions in the recent literature with respect to the single equation estimation of the dynamic model of the above type, which especially deal with the problem introduced by the inclusion of a lagged dependent variable in the estimation equation and its built-in correlation with the individual effect: That is, since y_{it} is also a function of μ_i, $y_{i,t-1}$ is a function of μ_i and thus $y_{i,t-1}$ as right-hand side regressor in eq.(11) is correlated with the error term. Even in the absence of serial correlation of ν_{it} this renders standard OLS, FEM and REM models biased and inconsistent (see e.g. Nickel, 1981, Sevestre & Trogon, 1995 or Baltagi, 2008, for an overview).

Next to various attempts to correct for the bias of the FEM (see e.g. Kiviet, 1995, Everaert & Pozzi, 2007, and the related literature for analytically or bootstrapping-based correction factors), the most widely applied approaches of dealing with this kind of endogeneity typically applies IV and GMM based techniques. While the first generation of models used transformations in first differences, latter extensions also account for the information in levels, when setting up proper estimators. A widely applied technique is the System GMM estimator by Blundell & Bond (1998), which builds consistent instruments based on the following orthogonality conditions:

$$E(y_{i,t-\rho}\Delta u_{i,t}) = 0 \quad \text{for all} \quad \rho = 2, \ldots, t-1, \tag{12}$$

where Δ is the difference operator defined as $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$. Eq.(12) is also called the 'standard moment condition' and is widely used in empirical estimation. However, one general drawback of dynamic model estimators in first differences is their poor empirical performance especially for a high persistence in the autoregressive component such as growth models (see Munnel, 1992, and Holtz-Eakin, 1994, for poor empirical estimates of a production function in FD, Bond et al. (2001) for growth equation estimates). Bond et al. (2001) argue that first difference IV/GMM estimators can be poorly behaved, since lagged levels of the time series provide only 'weak instruments' for sub-sequent first-differences.

$$E(\Delta y_{i,t-1}u_{i,t}) = 0 \quad \text{for t=3,...,T.} \tag{13}$$

Rather than using lagged levels of variables as instruments for the equation in first difference according to eq.(12), eq.(13) defines an orthogonality condition for the model in level that uses instruments in first differences. Blundell & Bond (1998) propose the system GMM estimator as combination of both orthogonality conditions.

In our estimation design we are especially interested in testing for the appropriateness of the chosen IV approach and apply test routines that account for the problem of many and/or weak instruments in the regression (see e.g. Roodman, 2006). Moreover, as it is typically the case with regional data we are especially aware of the potential bias induced by a significant cross-sectional dependence in the error term of the model. There are different ways to account for such error cross-sectional dependences implying

$$Cov(\nu_{i,t}\nu_{j,t}) \neq 0 \quad \text{for some } t \text{ and } i \neq j \tag{14}$$

(see e.g. Sarafidis & Wansbeek, 2010, for an overview). Besides the familiar spatial approach, recently the common factor structure approach has gained considerable attention. The latter specification assumes that the disturbance term contains a finite number of unobserved factors that influence each individual cross-section separately. In terms of the above described combined residual term of the dynamic panel data model in eq.(11), we are able to introduce a common factor structure for the error term in the following way:

$$u_{i,t} = \mu_i + \nu_{i,t}, \quad \nu_{i,t} = \sum_{m=1}^{M} \phi_{m,i}\mathbf{f}_{m,t} + \epsilon_{i,t}, \tag{15}$$

where $\mathbf{f}_{m,t} = (f_{1,t,\dots,f_{M,t})'}$ denotes an $M \times 1$ vector of individual-invariant time-specific unobserved effects, $\phi_i = (\phi_{1,i}, \dots, \phi_{M,i})'$ is an $M \times 1$ vector of factor loadings and $\epsilon_{i,t}$ is a pure idiosyncratic error component with zero mean and constant variance. Cross-sectional dependence in turn leads to inconsistent estimates if regressors are correlated with the unspecified common variables or shocks. There are different proposals in the literature to account for unobserved factors. For dynamic panel estimators with short time dimension, Sarafidis & Robertson (2009) propose to apply time-specific demeaning which alleviates the problem of parameter bias if the variance of the individual factor loadings for the common factor models is small. Alternatively, if the impact of the common factor varies considerably by cross-sections, there are different estimation techniques, which account for cross-sectional dependence by using cross-section averages of the dependent and independent variables as additional regressors (see e.g. Pesaran, 2006).

Recently, various testing procedures have been developed to check for the presence of cross-sectional dependence. Among the most commonly applied routines is Pesaran's (2007) extension to the standard Breusch & Pagan LM test. The so-called Cross-Section Dependence (CD) test is based on the pairwise correlation coefficient of residuals from a model specification that ignores the potential presence of cross-sectional dependence. However, as Sarafidis & Wansbeek (2010) point out, the CD-Test has the weakness that it may lack power to detect the alternative hypothesis under which the sign of the elements of the error covariance matrix is alternating (thus for positive and negative correlation in the residuals, e.g. for factor models with zero mean factor loadings). Moreover, the test statistic requires normality of the residuals. Thus, Sarafidis et al. (2009) propose an alternative testing procedure that does not require normality and is valid for fixed T and large N. The testing approach designed for the Arellano-Bond (1991) and Blundell-Bond (1998) GMM estimators is based on Sargan's difference-test statistic for overidentifying restrictions. The aim of the test is to examine whether there is still (heterogeneous) cross-sectional dependence in the residuals after time-specific demeaning in the logic of Sarafidis & Robertson (2009). The test has the following simple (C-Statistic based) form:[4]

$$C_{CD-GMM} = (S_F - S_R) \xrightarrow{d} \chi^2_{h_d}, \tag{16}$$

[4] Where the C-statistic is defined according to Eichenbaum et al. (1988) as the difference between two Sargan/Hansen J-statistics for an unrestricted and restricted IV/GMM-model.

where h_d is the number of degrees of freedom of the test statistic as difference between the set of instruments (number of moment conditions) in the full model (S_F) and the restricted model (S_R), where the GMM model has either the Arellano-Bond or the Blundell-Bond form augmented by time-specific dummy variables. The corresponding null hypothesis of the Sargan's difference-test tests is that there is homogeneous cross-section dependence in the model versus the alternative of heterogeneous cross-section dependence as:[5]

$$H_0 : \text{Var}(\phi_i) = \sum \phi = 0 \quad \text{versus:} \quad H_1 : \sum \phi \neq 0. \tag{17}$$

The restricted (sub-)set of moment conditions thereby only includes instruments from regressors in the vector $X_{i,t}$ (according to eq.(11)) that remain strongly exogenous in the sense that their factor loadings are mutually uncorrelated with the cross-section specific parameter of the the common factor. Sarafidis et al. (2009) propose to likewise test for the exogeneity of a subset of regressors by means of the standard Sargan's/Hansen's test for overidentifying restrictions in a first step.[6]

Before estimating the model and testing for the appropriateness of alternative specification we first discuss recent findings in the empirical literature and present some stylized facts of German internal migration and regional economic and social characteristics. We also check for the time-series properties of the variables involved in order to avoid any spurious regression problem associated with non-stationary data.

4 What does the empirical literature say?

Testing for the empirical validity of the (baseline) neoclassical migration model for internal migration in European countries yields rather mixed results:[7] Regional disparities in (un-)employment are often shown to be important factors in determining migratory flows. On the contrary, the influence of regional wage or income levels is difficult to prove in many empirical examinations (see e.g. Pissarides & McMaster, 1990, as well as Jackman and Savouri (1992) for British regions; Westerlund, 1997, for inter-regional migration in Sweden, Devillanova & Garcia-Fontes, 2004, for Spain). Only for the Italian case Daveri & Faini (1998) show that the regional wage level corresponds to the theoretically expected signal for the gross outward migration from southern to northern regions. Similar

[5] If only homogeneous cross-section dependence is present the inclusion of time-specific dummies variables is sufficient to remove any bias in the estimation approach, see e.g. Sarafidis & Robertson (2009).

[6] One has to note that instruments derived from transformations the lagged endogenous regressor cannot be included in the subset of strictly exogenous moment conditions to test for the null hypothesis of homogeneous cross-section dependence.

[7] This section draws on Alecke et al., 2010.

results are found in Fachin (2007). Napolitano & Bonasia (2010) show that although the coefficients for Italian labour market variables in the neoclassical migration model shows the expected sign, due to the complexity of the internal migration process, the baseline Harris-Todaro approach neglects important variables such as agglomeration forces measured by population density and human capital. The latter variable is also found significant besides the standard labour market variables in an inter-regional migration model for the Polish transition process (see Ghatak et al., 2008).

For German interregional migration, Decressin (1994) examined gross migration flows for West German states up to 1988. His results show that a wage increase in one region relative to others causes a disproportional rise in the gross migration levels in the first region, while a rise in the unemployment in a region relative to others disproportionally lowers the gross migration levels. Decressin does not find a significant connection between bilateral gross migration and regional differences in wage level or unemployment when purely cross-sectional estimate are considered. Difficulties in proving a significant influence of regional wage decreases on the migratory behavior within Germany are also found in earlier empirical studies based on micro-data directly addressing the motivation for individual migratory behavior in Germany. Among these are Hatzius (1994) for the West German states, and Schwarze and Wagner (1992), Wagner (1992), Burda (1993) and Buechel & Schwarze (1994) for East Germany. Subsequent studies succeed in qualifying the theoretically unsatisfactory result of an insignificant wage influence: Schwarze (1996) shows that by using the expected wage variables instead of the actual ones, the wage drop between East German and West German states has a significant influence on the migratory behavior.[8] In a continuation of Burda (1993), Burda et al. (1998) also indicates a significant non-linear influence on household income.

Contrary to earlier evidence, in recent macroeconomic studies with an explicit focus on intra-German East-West migration flows, regional wage rate differentials are broadly tested to significantly affect migration flows (see e.g. Parikh & Van Leuvensteijn, 2003, Hunt, 2000, as well as Burda & Hunt, 2001). The study of Parikh & Van Leuvensteijn (2003) augments the core migration model with regional wage and unemployment differentials as driving forces of interregional migration by various indicators such as regional housing costs, geographical distance and inequality measures. For the sample period 1993 to 1995, the authors find a significant non-linear relationship between disaggregated regional wage rate differences and East-West migration (of a U-shaped form for white-collar

[8]This result is also confirmed in Brücker & Trübswetter (2004). The latter study also focuses on the role of self-selection in East-West migration, finding that East-West migrants receive a higher individual wage compared to their non-migrating counterparts after controlling for the human capital level.

workers and of inverted U-form for blue-collar workers), while unemployment differences are tested be insignificant. The relationship between income inequality and migration did not turn out to be strong.

According to Hunt (2000) and Hunt & Burda (2001), wage rate differentials and especially the fast East-West convergence are also a significant indicator in explaining observed state-to-state migration patterns. Using data from 1991 to 1999, Hunt & Burda (2001) find that the decline in East-West migration starting from 1992 onwards can almost exclusively be explained by wage differentials and the fast East-West wage convergence, while unemployment differences do not seem to play an important part in explaining actual migration trends.[9] In a recent application, Alecke et al. (2010) apply Panel VAR techniques to analyse the simultaneous impact of labour market variables to migration and vice versa for German Federal States between 1991 and 2006. The results broadly support the neoclassical migration model and show that migration itself has an equilibrating effect on labour market differences. The authors also find evidence for structural differences between the West and East German macro regions in the migration equation, similar to findings for an Italian 'empirical puzzle' with a distinct North-South division in terms of the magnitude of the migration response with respect to labour market signals (see e.g. Fachin, 2007, and Etzo, 2007).

5 Data and stylized facts of German internal migration

Given the heterogeneity found in the international empirical literature in predicting interregional migration flows, we take these results as a starting point for an updated regression approach based on German spatial planning units between 1996 and 2006. For empirical estimation we use regional data for the 97 German Spatial Planning Regions (so called *Raumordnungsregionen*) as the level of analysis for spatial migration processes within Germany (see e.g. Bundesinstitut fuer Bau-, Stadt-, und Raumforschung, 2010, for details about the concept of Spatial Planning Regions). The time period used for estimation ranges from 1996 to 2006. We have chosen to restrict our estimation approach to this period since the regional boundaries of the German Spatial Planning Regions have changed before and after, which may introduce a measurement problem that is likely to bias our empirical results.

We use variables for regional net migration, population, real income, the unemployment rate, human capital endowment, international competitiveness of regions and commuting

[9] For a critical reflection of the results of Hunt & Burda (2001) see e.g. Yellen (2001) and Wolff (2006).

flows. The latter has been included to account for an alternative adjustment mechanism to balance labour market disequilibria. We also include two sets of dummy variables into the migration model: 1.) binary dummy variables for the 16 federal states to capture macro regional differences. This may be especially important to account for structural differences between West and East Germany (see e.g. Alecke et al., 2010, for recent findings); 2.) binary dummy variables for different regional settlement types ranging from metropolitan agglomerations to rural areas (in total 7 different categories based on their absolute population size and population density). As Napolitano & Bonasia (2010), point out variables measuring population density may be an important factor in explaining the regional amenities. Variable definitions and descriptive statistics are provided in table 1 to 3.

<<< Table 1 to table 3 about here >>>

In order to show some distinct regional and macro-regional differences for net migration and explanatory variables, figure 1 to figure 6 additionally visualize the above shown descriptive statistics for net migration and labour market variables. As figure 1 shows for both periods 1996 and 2006, the net in-migration flows show a high level of persistence with huge net losses for the northern south-western regions in East Germany. Also, the Western regions along the border to East Germany experienced net outflows. On the other hand the northern West German Spatial Planning Regions around the urban agglomerations Hamburg and Bremen are among the net inflow regions as well as the western agglomerated regions in the Rhineland (around the metropolitan areas Cologne and Duesseldorf) and the southern West German regions in Baden Wuerttemberg and Bavaria. Among the few regions in East Germany with net migration inflows is the belt of regions around Berlin. Looking at net migration trends by age-groups in figure 2 and 3 the graphs show that especially net outflows of the East German regions are especially prevailing for the age-group of young persons between 18 and 25 years. This may give a first indication that the labour market situation is poor in terms of qualification and employment for the young workforce. For the other workforce relevant age-groups, the spatial distribution of net in- and out-flow regions is more heterogeneous, while especially the middle German regions lose population due to internal migration throughout the period 1996 to 2006. Looking at the broad picture for the elderly age-groups (50 to 65, as well as above 65 years), here we see that both the north German coastal regions as well as the southern regions close to Austria and Switzerland gain considerable population through net in-migration. This trend may be interpreted in terms of regional amenities via special topographical advantages, which guide migration flows.

The spatial distribution of regional labour market variables is shown in figure 4 for real income in the periods 1996 and 2006 as well as regional unemployment rates (figure 5) for the same time period. Figure 4 for real income per capita shows a clear West-East division, which remains rather stable over time. The regions with the highest income levels both in 1996 and 2006 are the northern regions around Hamburg, the Western regions in the Rhineland as well as large parts of the southern Federal States Baden-Wuerttemberg (especially around Stuttgart) and Bavaria (around Munich). Since these regions were also found to have large net in-migration flows (both overall as well as for the workforce relevant age-groups), this may give a first hint at the positive correlation of migration flows and regional income levels as suggested by the neoclassical migration model.

As figure 5 shows for regional unemployment rates, here a strong negative correlation with net migration inflows may be expected especially for the East German Spatial Planning Regions, which face on average much higher rates than the West German counterparts. Again this picture remains relatively stable over time. Finally, figure 6 plots the classification of regional settlement type according to the BBSR definition (see table 1). Compared to the highly agglomerated areas around the urban centers Hamburg, Berlin, Stuttgart and Munich also large parts of Nordrhine-Westphalia show a strong agglomeration of population. On the contrary, especially the northern parts in East Germany as well as South-Eastern regions in Bavaria are classified as rural areas. The same also holds for the middle German regions in the state-level border zones of Thuringia, Hessen and Bavaria. These graphical findings thus support the hypothesis from above that regions with a high population density on average attract further migrants.

<<< Figure 1 to figure 6 about here >>>

6 Empirical Results for the Neoclassical Migration Model

For the migration model of eq.(7) and eq.(8) we apply different static and dynamic panel data estimators. Before estimating the empirical migration model we look at the time series properties of the variables involved in order to avoid the risk of running a spurious regression for non-stationary variables (with $T = 11$). We therefore report the test results of different panel unit root tests including the Levin-Lin-Chu (2003) and Im-Pesaran-Shin (2003) unit root tests as well as Pesaran's (2007) CADF test. The latter approach has the advantage that it is relatively robust with respect to cross-sectional dependence in the variable (see e.g. Baltagi et al., 2007, as well as de Silva et al., 2009, for extensive Monte Carlo simulation evidence). As the results in table 4 shows for almost exclusively all variables and test specifications, the null hypothesis of non-stationarity of the series under observation can be rejected. Only for the (rest of the country) aggregate of the unemployment rate the Levin-Lin-Chu test could not reject the null of non-stationarity. However, the LLC-test rejects the null hypothesis of an integrated time series if the unemployment rate is transformed into regional differences ($\tilde{u}_{ij,t}$). Thus, given the overall picture presented by the panel unit root tests it seems reasonable to handle the variables as stationary processes so that we can also run regressions in levels (as it is the case for Blundell-Bond System GMM) without running the risk of spurious regression results. The estimation results are reported in the next section.

<<< Table 4 about here >>>

For estimation we start from an unrestricted presentation of the baseline model including the core labour market variables real income (y) and unemployment rates (u) and test for parameter constraints according to eq.(9) and eq.(10). As the results in table 5 show for almost all model specifications the null hypothesis for equal parameter cannot be rejected on the basis of standard Wald tests. Compared to the the static specification in column 2, the (relative) RMSE criterion of the model strongly increases if we add a dynamic component to the migration equation. The RSME for each equation is thereby computed as the ratio compared to the RMSE of the static POLS benchmark specification in column 1. As discussed above the POLS, REM and FEM estimators are biased for dynamic panel data models. We thus compute a corrected FEM specification as proposed e.g. in Kiviet (1995) as well as the Arellano-Bond (1991) und Blundell-Bond (1998) system GMM estimators. According to the relative RMSE criterion the Blundell-Bond system GMM specification has the smallest forecast error. The coefficients for labour market signals are statistically significant and of expected signs. Moreover the SYS-GMM specification passes standard tests for autocorrelation in the residuals (m_1 and m_2 statistic) as well as the Hansen J-statistic for instrument validity. The reported C-statistic for the exogeneity of the instruments in the level equation shows the validity of the augmented approach in extension to the standard Arellano-Bond first differenced model.

<<< Table 5 about here >>>

We then use the SYS-GMM approach to test for the significance of different extensions of the baseline Harris-Todaro model. We start by including a dummy variable for the East German Spatial Planing Regions (see table 6). The motivation for this approach is to test for the significance of the so-called East German empirical puzzle, where a relatively high degree of migratory interregional immobility was found to coexist with large regional labour market disparities. Fachin (2007) and Etzo (2007) report similar results to hold for Italian South-North migration trends, while Alecke & Untiedt (2000) as well as Alecke et al. (2010) identify such effects for German East-West migration throughout the 1990s. However, the latter study found that along with a second wave of East-West movements in early 2000 net flows out of East Germany on the contrary were much higher than expected after controlling for its weak labour market and macroeconomic performance. Since this trend was accompanied by a gradual fading out of economic distortions, this supports the view of "repressed" migration flows for that period. As the result in table 6 show for the period 1996 to 2006 we find a statistically significant positive East German dummy, which indicates higher net in-migration balances for the East German Spatial Planning Regions than their labour market performance would suggest. To get further insights we also estimate a specification which includes Federal state level fixed effects. The results for the state dummies in the baseline model are reported in table 7 (column 1) and are graphically shown in figure 7. The fixed effects for federal states, which represent remaining time-fixed macro regional influential factors for the regional net in-migration rate, are statistically significant for many cases.

<<< Table 6 and table 7 about here >>>

<<< Figure 7 about here >>>

As the figure highlights, for all six East German state dummies we get statistically significant and positive coefficients. Negative coefficients are found for the West German states Baden Wuerttemberg, Bavaria and Hessen. A Wald test for joint effect of the set of state dummies turns out to be highly significant. For both models (including the East German dummy and the set of state dummies), the impact of labour market variables is of expected sign and higher than in the baseline specification.

We then also add further variables as discussed above. Here, the results show that higher net in-commuting levels are negatively correlated with the net in-migration rate, indicating that both types are alternative adjustment mechanisms to reduce labour market disparities. Adding a set of binary dummy variables for different settlement types (classified by size of local urban centers and population density, see table 1 for details) reveals further structural differences in inter-regional migration patterns. Next to rural areas with low population density, agglomeration regions of Type 2 and 4 also show significantly lower net in-migration rates relative to benchmark category Type 1 (highly agglomerated area with regional urban center above 100,000 persons and population density above 300 inhabitants/sqm). This may hint at the role played by regional centers of agglomeration in attracting migration flows and may be interpreted in favour of a 'reurbanisation' process in Germany for the period 1996 to 2006. Similar trends were also reported in Swiaczny et al. (2008).[10] Finally, testing for the effects of regional human capital endowments and international competitiveness shows mixed results. While the proxy for the latter variable in terms of foreign turnover relative to total turnover in manufacturing sector industries shows the expected positive effect on net in-migration, the regional endowment with human capital is insignificant. This finding corresponds to recent results for Spain between 1995–2002, where regional differences in human capital do not help to explain migration flows (see Maza & Villaverde, 2004). The latter may be explained by the fact that not the region specific stock of human capital but rather the individual endowment of the prospective migrant is the appropriate level of measurement. However, the latter variable is not observable for regional data.

In order to check for the appropriateness of our augmented SYS-GMM specifications, we perform a variety of of postestimation tests for instrument appropriateness, temporal and cross-sectional dependence of the error term. The test results are reported in table 6. With respect to IV appropriateness and temporal autocorrelation of the error terms, all model specifications shows satisfactory results. In order to control for cross-sectional error dependence due to unobserved common factors, we first add year dummies to our model specification, which also turn out to be jointly significant. We then apply the Sargan's difference test for the SYS-GMM model (C_{CD_GMM}) as described above, which tests for the nature of the cross-sectional dependence given unobserved common factors as being homogeneous our heterogeneous among regions. In order to run the test, we first need to judge whether the set of explanatory variables (excluding instruments for the lagged endogenous variable) is exogenous with respect to the combined error term. This can be easily tested by means of a Sargan/Hansen J-statistic based overidentification test. As the results in table 6 show, only those model specification which include fixed state effects pass the overidentification test for the vector of explanatory variables. For these equations

[10]The authors argue that throughout the process of demographic change in Germany city core regions may gain in demographic terms from young migrants, while suburban and rural areas are expected to face increasing migration losses.

we could then apply C_{CD_GMM} from eq.(16) in order to test for the existence of heterogeneous factor loading for the common factor structure of the error terms as proposed by Sarafidis et al. (2009). The test results do not indicate any sign of misspecification after including period-fixed effects for standard significance levels. In sum, the augmented neoclassical migration equation shows to be an appropriate representation of the data generating process and highlights the role of key labour market variables in explaining net in-migration rates for German Spatial Planning regions.

7 Sensitivity analysis: Disaggregate estimates by age groups

Given the supportive findings for the neoclassical migration model at the aggregate level, we finally aim to check for the sensitivity of the results when different disaggregated age groups are used. Detailed results for the baseline and augmented specification of the migration model are shown in table A.1 and table A.2 in the appendix.[11] We are especially interested to analyse whether the estimated coefficients for the labour market signals change for different age-groups. Indeed, the results show that the migratory response to labour market variables is much higher for workforce relevant age groups. The resulting coefficient size for real income and unemployment rate differences together with 95 % confidence intervals for the estimated models are plotted in figure 8 and figure 9.

<<< Figure 8 and Figure 9 about here >>>

The coefficient for real income differences in figure 8 shows a clear inverted U-shape when plotted for the different age-groups in ascending order. While for migrants up to 18 year real income difference do not seem to matter, especially for migrants with an age between 18 to 25 years and 25 to 30 years the estimated coefficient is statistically significant and much higher compared to the overall migration equation from table 6. For older age-groups the effect reduces gradually. The results are found to be very similar for the baseline and augmented migration specification (see figure 8). Similar results were found for regional unemployment rate differences, which are found to be almost equally important for age groups until 50 years and only show much smaller and partly insignificant coefficient signs for elderly age groups. If we look at the distribution of the state-level fixed effects for each estimated age-group specification, the estimation results show that the positive dummy variable coefficients for the East German states particularly hold for

[11] For the augmented migration model we choose a specification including commuting flows as well as settlement structure and state level fixed effects in order to guarantee a high number of observations in the sample.

the workforce relevant age groups. The results are graphically shown in figure 10 for the baseline migration model (detailed results for the estimated coefficients of the baseline and augmented specification are reported in the the appendix).

<<< Figure 10 about here >>>

Finally, table 8 computes the 'relative importance' of the labour market variables by age-groups with respect to net migration flows. Thereby, the relative importance refers to the quantification of an individual regressors contribution to a multiple regression model (see e.g. Groemping, 2006, for an overview). This allows us to further answer the question, in how far our estimation results support the prominent role of labour market conditions in guiding internal migration rates (of the workforce population) in Germany. Table 8 calculates to specifications either based on the squared correlation of the respective regressor with the dependent variables (univariate R^2, specification A) as well as the standardized estimated SYS-GMM coefficents from the augmented migration model in table A.2. This latter metric for assessing the relative importance of regressors has the advantage over the simple benchmark in specification A since it accounts for the correlation of regressors. As the table shows both methods assign a significant share for the two key labour market variables in predicting migration flows, especially for the workforce population (up to 50 % joint contribution in Specification A for age-group 18 to 25 years and even up to 65 % for age-group 25 to 30 years in Specification B). The SYS-GMM thereby on average assigns a stronger weight to real income differences in explaining net in-migration relative to unemployment differences. However, the overall picture confirms our interpretation of the regression tables in assigning a prominent role to labour market imbalances in driving German internal migration.

<<< Table 8 about here >>>

8 Conclusion

In this paper we analysed the explanatory power of the neoclassical migration model in describing aggregate and age-group specific internal migration trends for 97 German Spatial Planning regions throughout the period 1996–2006. Our estimation results based on model specifications for dynamic panel data estimators give strong evidence in favour for the neoclassical inspired Harris-Todaro model. Both real income differences as well as unemployment rate disparities are found to be statistically significant with the expected signs. That is, a real income increase in region i relative to region j leads to higher net migration inflows to i from j; on the contrary, a rise in the regional unemployment rate in i leads to low net inflows. Given these responses to labour market signals, migration flows act as a spatial adjustment mechanism and equilibrate regional labour market differences. The results of the standard neoclassical migration model remain stable if commuting flows, the regional human capital endowment, the region's international competitiveness as well as population density are added as further explanatory variables. The inclusion of the regional net in-commuting rate shows a negative correlation with migration underlying the substitutive nature of the two variables. Also, an increasing level of international competitiveness attracts further in-migration flows. We also find heterogeneity for different types of regional settlement structure proxied by population density and we observe structural differences for the two East-West macro regions (by including individual federal state level fixed effects or an combined East German dummy). We also estimate the model for age-group specific subsamples of the data. Here the impact of labour market signals is found to be of greatest magnitude for workforce relevant age-groups (18 to 25, 25 to 30 and 30 to 50 years). This latter result underlines the prominent role played by labour market conditions in guiding internal migration rates (of the working age population) in Germany.

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Table 1: Variable definition and data sources

Variable	Description	Source
NM	Net migration defined as in- minus outmigration	German Statistical Office
NM(to18)	Net migration for persons under 18 years	German Statistical Office
NM(18to25)	Net migration for persons between 18 and 24 years	German Statistical Office
NM(25to30)	Net migration for persons between 25 and 29 years	German Statistical Office
NM(30to50)	Net migration for persons between 30 and 49 years	German Statistical Office
NM(50to65)	Net migration for persons between 50 and 65 years	German Statistical Office
NM(over65)	Net migration for persons 65 years and above	German Statistical Office
POP	Population Level	VGRdL
Y	Gross Domestic Product (real) per Person	VGRdL
UR	Unemployment Rate	Federal Employment Agency
COMM	Net Commuting level defined as in- minus outcommuting	German Statistical Office
HK	Human Capital level defined as %-share of employees with university degree relative to total employees	German Statistical Office
INTCOMP	International Competitiveness proxied by foreign turnover relative to total turnover in manufacturing industries	German Statistical Office
EAST	Binary dummy variable for regions in East Germany	own calculation
STATE	Set of binary dummies for each of the 16 Federal States	own calculation
TIME	Set of year specific time dummies for sample period 1996 to 2006	own calculation
SETTLE	Set of binary dummies for types of settlement structure with: *Type1:* Highly agglomerated area with regional urban center above 100.000 persons and population density above 300 inhabitants/sqm *Type2:* Highly agglomerated area with regional urban center above 100.000 persons and population density below 300 inhabitants/sqm *Type3:* Agglomerated area with population density above 200 inhabitants/sqm *Type4:* Agglomerated area with regional urban center above 100.000 persons and population density between 100-200 inhabitants/sqm *Type5:* Agglomerated area without regional urban center above 100.000 persons and population density between 150-200 inhabitants/sqm *Type6:* Rural area with population density above 100 inhabitants/sqm *Type7:* Rural area with population density below 100 inhabitants/sqm	Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR)
i	index for region i (region in focus)	
j	index for region j (rest of the country aggregate)	
t	time index	

Table 2: Descriptive statistics for continuous variables in the sample

Variable	Obs.	Mean	Std. Dev.	Min	Max	Unit
INM	1067	0.00	7.21	-95.90	37.01	in 1000 persons
INM (to18)	1067	0.00	1.91	-24.41	32.41	in 1000 persons
INM (18to25)	1067	0.00	1.85	-12.97	15.76	in 1000 persons
INM (25to30)	1067	0.00	1.27	-9.93	12.42	in 1000 persons
INM (30to50)	1067	0.00	2.48	-30.99	8.24	in 1000 persons
INM (50to65)	1067	0.00	0.91	-10.61	1.82	in 1000 persons
INM (over65)	1067	0.00	0.62	-7.05	1.23	in 1000 persons
POP	1067	848.10	607.13	226.29	3466.52	in 1000 persons
Y	1067	51.23	7.49	34.02	80.01	in 1000 Euro
UR	1067	11.84	4.94	4.37	26.18	in %
COMM	873	-33.49	37.44	-177.73	36.31	in 1000 persons
HK	873	7.30	2.71	2.88	16.81	in %
INTCOMP	946	30.05	11.42	0.82	61.12	in %

Table 3: Descriptive statistics for binary variables in the sample

Variable	Obs.	% with $X = 1$
EAST	1067	23.7
Federal State Level Dummies		
BW	1067	12.4
BAY	1067	18.5
BER	1067	1.0
BRA	1067	5.2
BRE	1067	1.0
HH	1067	1.0
HES	1067	5.1
MV	1067	4.1
NIE	1067	13.4
NRW	1067	13.4
RHP	1067	5.1
SAAR	1067	1.0
SACH	1067	5.1
ST	1067	4.1
SH	1067	5.1
TH	1067	4.1
Settlement Type Dummies		
Type1	1067	15.5
Type2	1067	15.5
Type3	1067	17.5
Type4	1067	17.5
Type5	1067	8.2
Type6	1067	15.4
Type7	1067	10.3

Note: BW = Baden-Wurttemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia.

Figure 1: Spatial Distribution of Net In-Migration Flows for German Regions

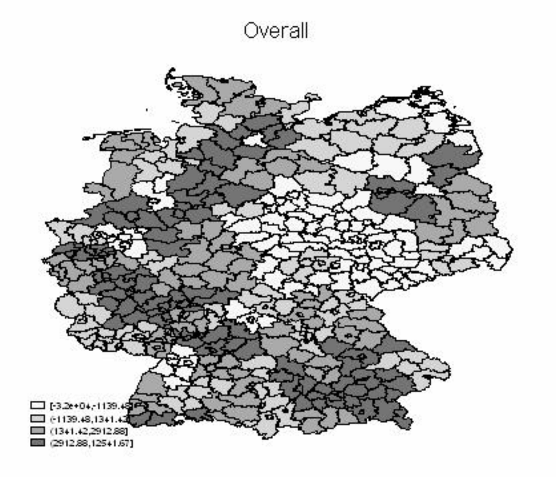


Figure 1: 1996

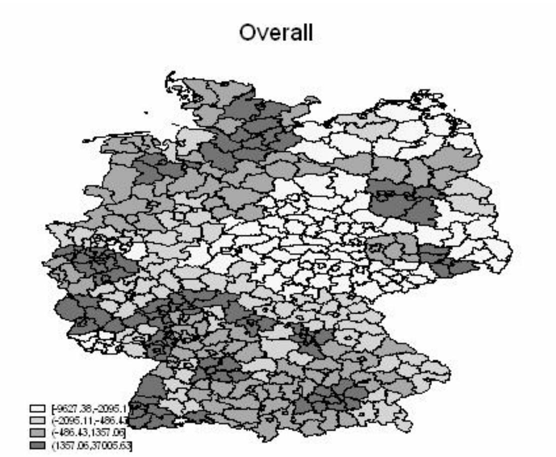


Figure 2: 2006

Figure 2: Net In-Migration by Age Groups for German Regions in 1996

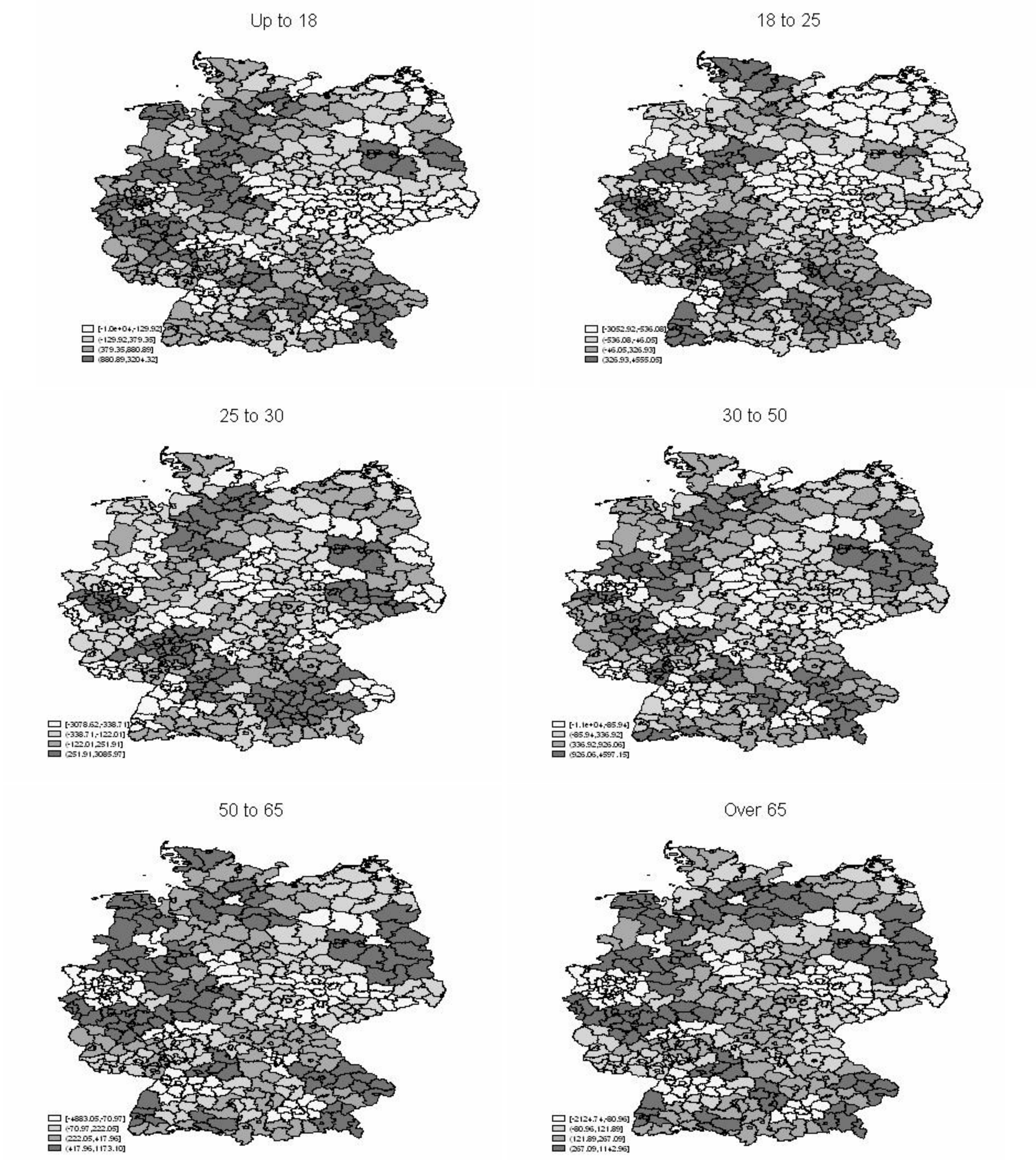


Figure 3: Net In-Migration by Age Groups for German Regions in 2006

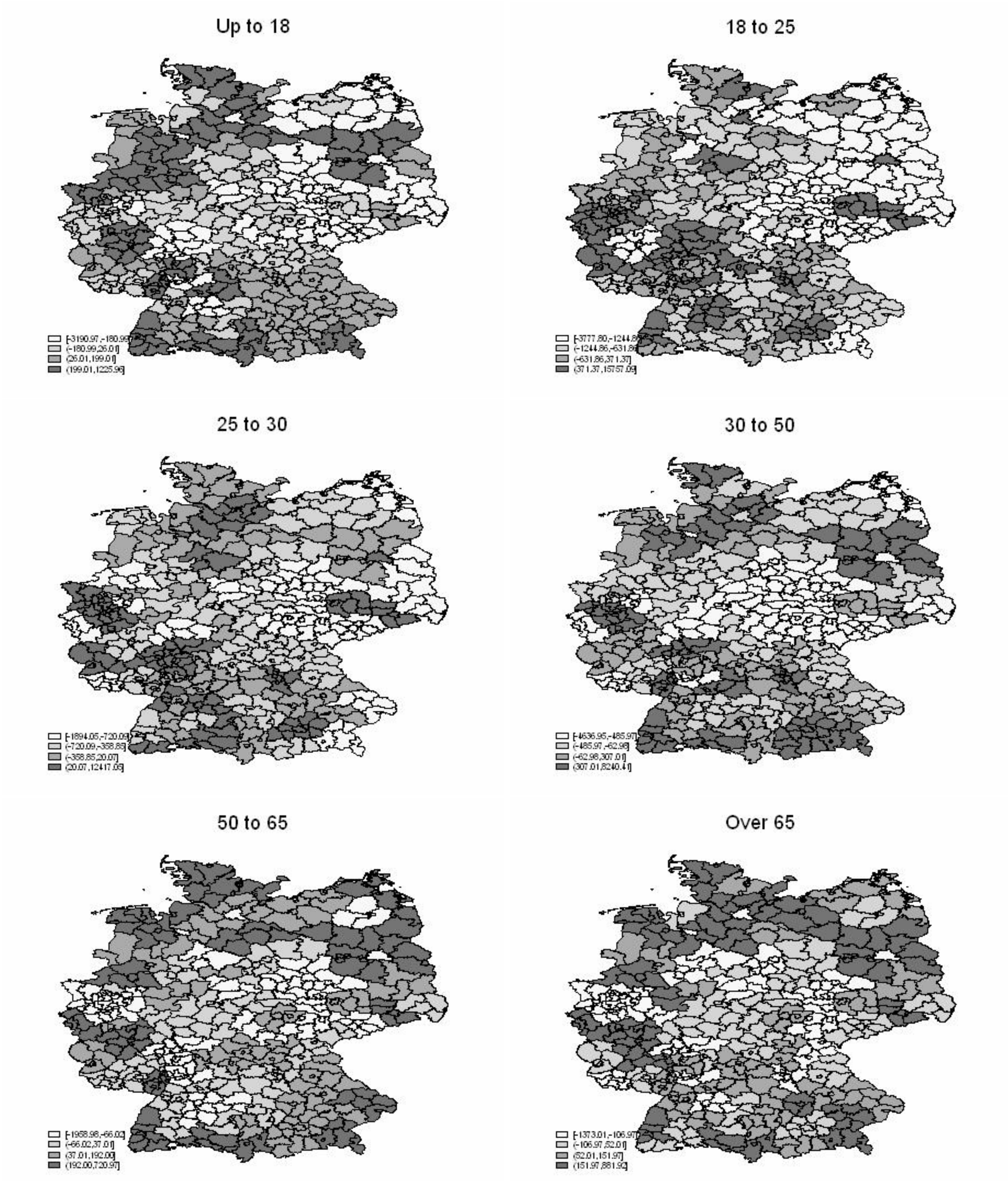


Figure 4: Spatial Distribution of Real Income in German Regions

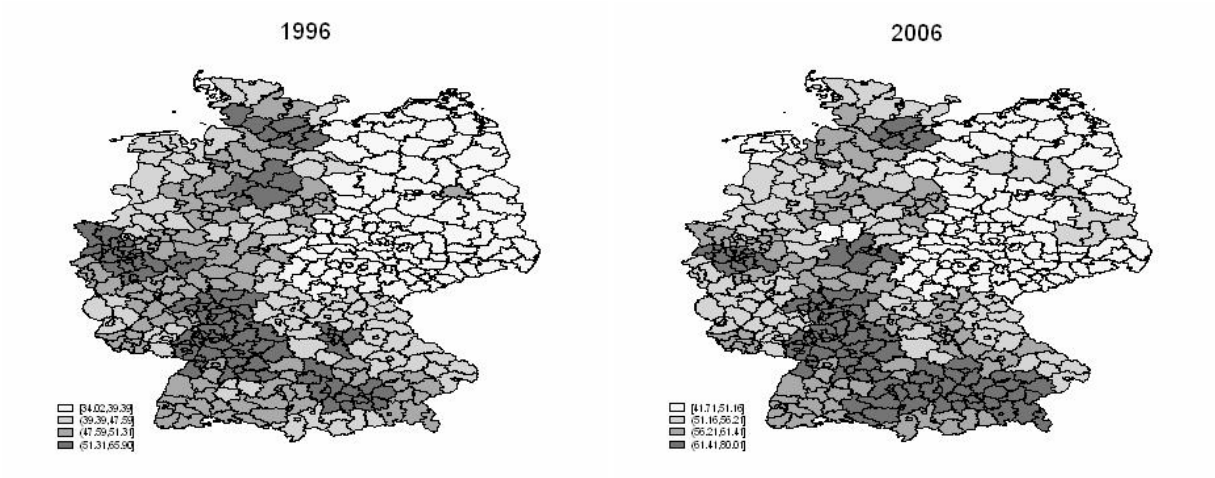


Figure 5: Spatial Distribution of Unemployment Rate in German Regions

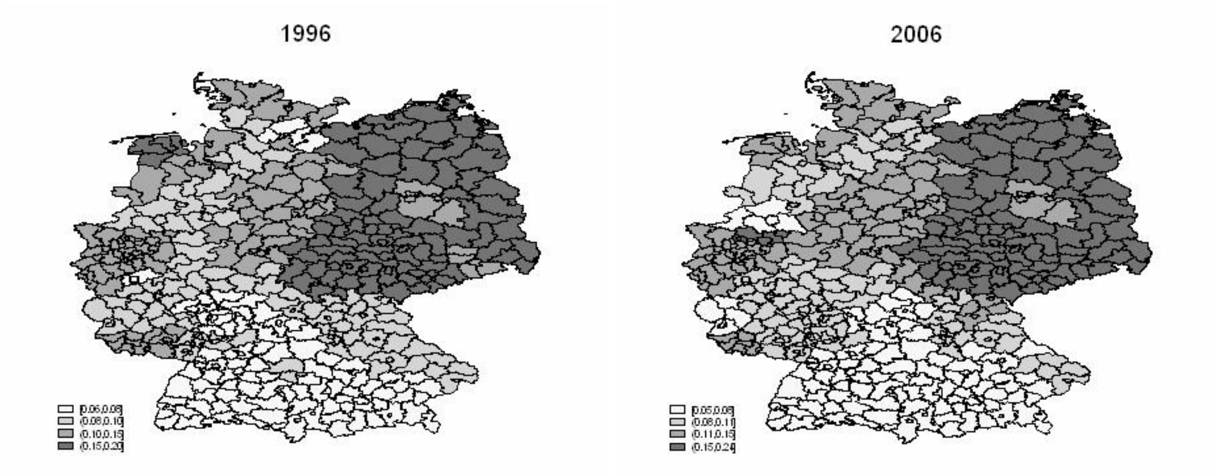
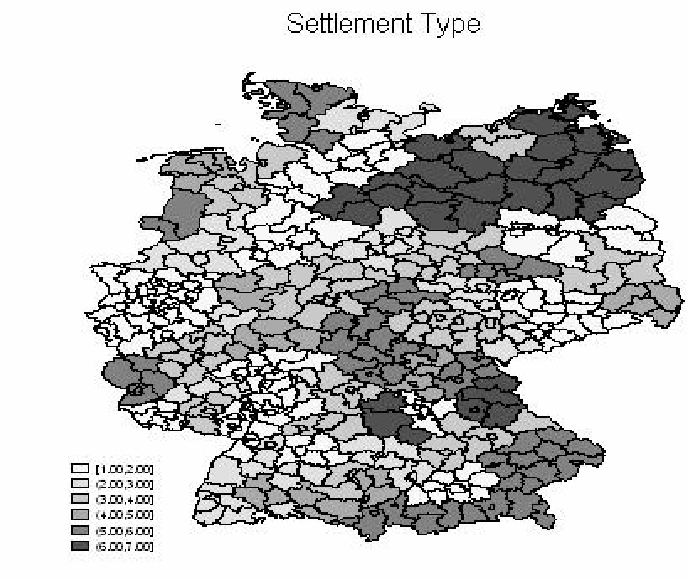


Figure 6: Regional Settlement Structure by Size of Urban Centres and Population Density



Note:
Type1 = Highly agglomerated area with regional urban center above 100.000 persons and population density above 300 inhabitants/sqm
Type2 = Highly agglomerated area with regional urban center above 100.000 persons and population density below 300 inhabitants/sqm
Type3 = Agglomerated area with population density above 200 inhabitants/sqm
Type4 = Agglomerated area with regional urban center above 100.000 persons and population density between 100-200 inhabitants/sqm
Type5 = Agglomerated area without regional urban center above 100.000 persons and population density between 150-200 inhabitants/sqm
Type6 = Rural area with population density above 100 inhabitants/sqm
Type7 = Rural area with population density below 100 inhabitants/sqm

Table 4: Results of Panel unit root tests for variables in the migration model

Test used:	**p-val. LLC**	**Lags**	**p-val. IPS**	**Lags**	**p-val. CADF**	**Lags**
	H_0: **All series are non-stationary**					
$nm_{ij,t}$	(0.00)	1.47	(0.03)	1.47	(0.00)	1.00
$u_{i,t}$	(0.00)	3.20	(0.00)	3.20	(0.00)	1.00
$u_{j,t}$	(0.99)	3.81	(0.00)	0.22	(0.00)	1.00
$y_{i,t}$	(0.00)	1.35	(0.00)	1.35	(0.00)	1.00
$y_{j,t}$	(0.00)	0.00	(0.00)	0.00	(0.00)	1.00
$\tilde{u}_{ij,t}$	(0.00)	3.30	(0.00)	3.30	(0.00)	1.00
$\tilde{y}_{ij,t}$	(0.00)	1.44	(0.00)	1.44	(0.00)	1.00

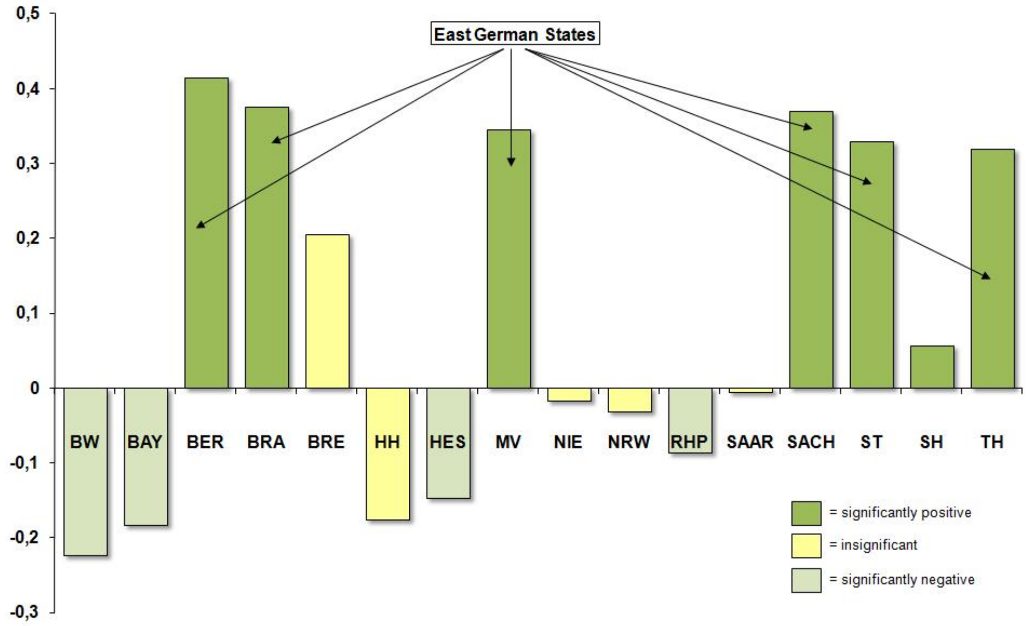
Note: Including a constant term; optimal lag length selected according to the AIC information criterion for the LLC and IPS test. The Pesaran CADF test includes one lag and a potential time trend in the estimation equation.

Table 5: Baseline Specifications of the Neoclassical Migration Model for German Spatial Planning Regions

Dep. Var.: $nm_{ij,t}$	**POLS**	**POLS**	**POLS**	**REM**	**FEM**	**FEMc**	**AB-GMM**	**SYS-GMM**
$nm_{ij,t-1}$			0.90*** (0.011)	0.90*** (0.011)	0.78*** (0.022)	0.92*** (0.031)	0.84*** (0.001)	0.88*** (0.001)
$u_{i,t-1}$	-0.74*** (0.114)							
$u_{j,t-1}$	0.64* (0.399)							
$\tilde{u}_{ij,t-1}$		-0.72*** (0.114)	-0.05 (0.041)	-0.05 (0.041)	-0.32** (0.166)	-0.28* (0.166)	-0.53*** (0.023)	-0.19*** (0.006)
$y_{i,t-1}$	0.07 (0.315)							
$y_{j,t-1}$	-0.14 (0.378)							
$\tilde{y}_{ij,t-1}$		0.07 (0.314)	0.12 (0.108)	0.12 (0.112)	-0.26 (0.372)	-0.10 (0.374)	0.25*** (0.066)	0.03** (0.014)
No. of obs.	1067	1067	1067	1067	1067	1067	1067	1067
No. of groups	97	97	97	97	97	97	97	97
No. of years	11	11	11	11	11	11	11	11
$\beta_{u_i} = -\beta_{u_j}$	(0.83)		(0.60	(0.42)	(0.11)	(0.19)	(0.00)	(0.14)
$\beta_{y_i} = -\beta_{y_j}$	(0.76)		(0.60)	(0.24)	(0.39)	(0.59)	(0.58)	(0.14)
m_1 and m_2							(0.42)/(0.24)	(0.35)/(0.24)
J-Stat. Overall							Passed	Passed
C-Stat. LEV-EQ								Passed
Time Dummies (11)	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relative RMSE	1	1.07	0.38	0.38	0.41	0.39	0.43	0.38

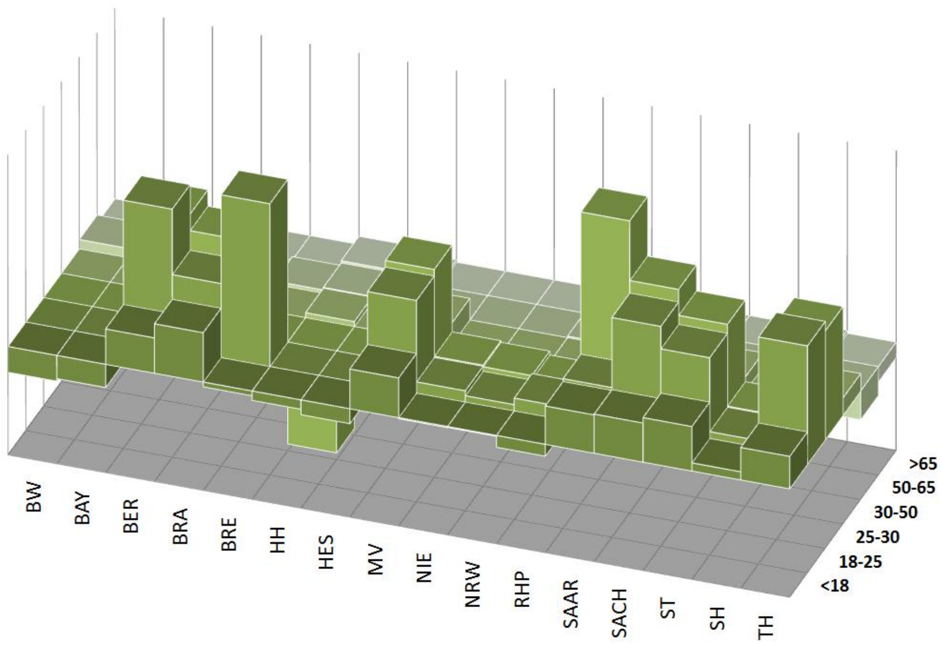
Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. Standard Errors in brackets.

Figure 7: State level effects for German States in the Aggregate Baseline Migration Model



Note: For details of calculation see table 7.

Figure 10: State level effects Effects in Baseline Migration Model by States and Age



Note: For details of calculation see table A.1 and table A.2.

Table 6: Augmented Neoclassical Migration Model for German Spatial Planning Regions

$nm_{ij,t}$	SYS-GMM					
$nm_{ij,t-1}$	0.87***	0.87***	0.89***	0.87***	0.86***	0.89***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
$\tilde{u}_{ij,t-1}$	-0.33***	-0.52***	-0.25***	-0.58***	-0.86***	-0.86***
	(0.008)	(0.022)	(0.030)	(0.034)	(0.060)	(0.058)
$\tilde{y}_{ij,t-1}$	0.47***	0.48***	0.30***	1.25***	0.84***	1.05***
	(0.046)	(0.11)	(0.047)	(0.118)	(0.172)	(0.225)
$EAST$	0.29***			0.63***		
	(0.016)			(0.045)		
$COMM$			-0.02***	-0.02***	-0.05***	-0.05***
			(0.002)	(0.002)	(0.006)	(0.007)
HK						0.004
						(0.011)
$INTCOMP$						0.05**
						(0.021)
	Type of Settlement Structure					
Type 2				-0.07**	-0.53***	-0.40***
				(0.035)	(0.143)	(0.126)
Type 3				0.01	-0.10	-0.02
				(0.039)	(0.083)	(0.088)
Type 4				-0.12***	-0.24***	-0.16*
				(0.041)	(0.085)	(0.082)
Type 5				0.02	-0.12	-0.01
				(0.049)	(0.088)	(0.095)
Type 6				-0.05	-0.08	0.04
				(0.047)	(0.094)	(0.107)
Type 7				-0.05	-0.29***	-0.15
				(0.045)	(0.110)	(0.117)
No. of obs.	1067	1067	873	873	873	753
Time Dummies (11)	167.9***	12.4***	32.3***	12.8***	16.5***	6.4***
State Dummies (16)	No	21.7***	No	No	26.6***	27.8***
m_1	(0.38)	(0.37)	(0.50)	(0.57)	(0.55)	(0.64)
m_2	(0.24)	(0.24)	(0.21)	(0.20)	(0.20)	(0.20)
J-Stat. Overall	(0.52)	(0.67)	(0.16)	(0.12)	(0.31)	(0.22)
C-Stat. LEV-EQ	(0.99)	(0.99)	(0.76)	(0.63)	(0.97)	(0.57)
C-Stat. Exog. Var.	(0.07)	(0.99)	(0.00)	(0.00)	(0.33)	(0.11)
C-Stat. CD-GMM		(0.58)			(0.35)	(0.57)

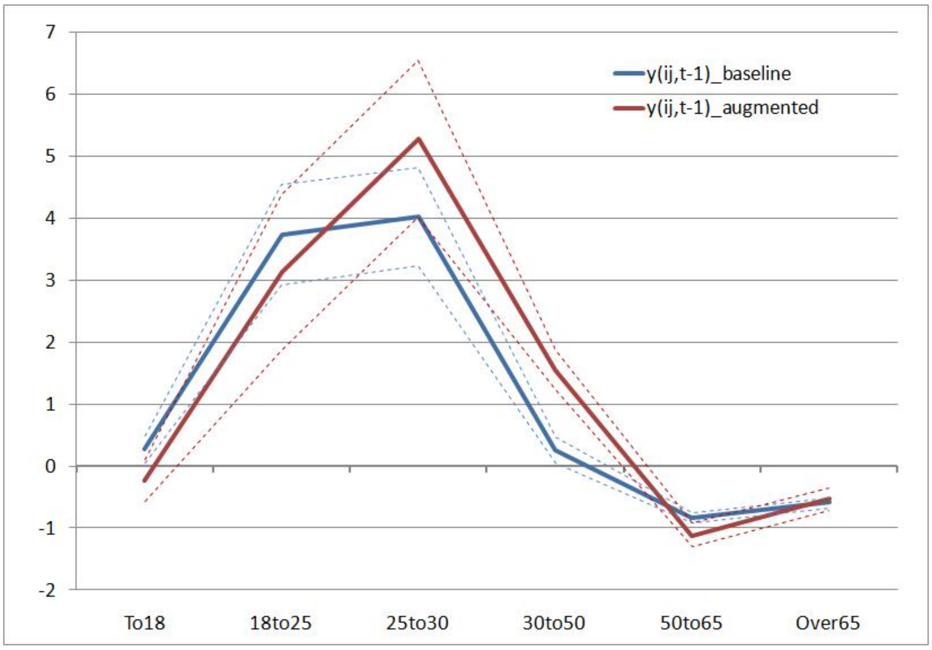
Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. In the regressions including the regional settlement structure the dummy for higly agglomerated areas of Type1 is excluded and thus serves as the benchmark category for the further settlement type dummies. Standard Errors in brackets. For m_1, m_2, J- and C-Statistic test results p-values are reported.

Table 7: Estimated state level effects in Migration Models

Model:	Baseline	Augmented
BW	-0.22*** (0.023)	-0.27*** (0.079)
BAY	-0.18*** (0.019)	-0.39*** (0.119)
BER	0.42** (0.188)	1.12*** (0.264)
BRA	0.38*** (0.045)	0.63*** (0.137)
BRE	0.20 (0.255)	1.23** (0.492)
HH	-0.18 (0.346)	1.08* (0.553)
HES	-0.15*** (0.030)	-0.32** (0.125)
MV	0.34*** (0.045)	0.53*** (0.125)
NIE	-0.02 (0.021)	-0.05 (0.105)
NRW	-0.03 (0.026)	0.02 (0.059)
RHP	-0.09*** (0.023)	-0.67*** (0.129)
$SAAR$	-0.01 (0.254)	-0.49 (0.583)
$SACH$	0.37*** (0.052)	0.79*** (0.174)
ST	0.33*** (0.047)	0.23* (0.133)
SH	0.06** (0.024)	0.07 (0.107)
TH	0.32*** (0.037)	0.19 (0.154)

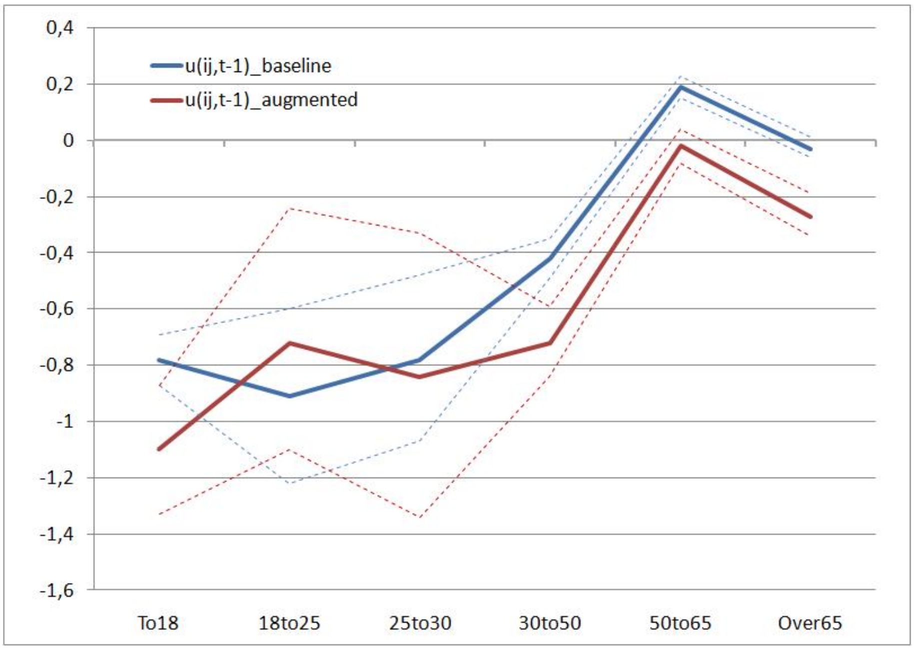
Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. BW = Baden-Wurttemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia. Baseline results according to column 8 in table 5, augmented model results according to column 5 in table 6.

Figure 8: Coefficients for Real Income Differences ($\tilde{y}_{ij,t-1}$) by Age Groups



Note: For details of calculation see table A.1 and table A.2. Dotted lines are 95 % convidence intervals.

Figure 9: Coefficients for Unemployment Rate Differences ($\tilde{u}_{ij,t-1}$) by Age Groups



Note: For details of calculation see table A.1 and table A.2. Dotted lines are 95 % convidence intervals.

Table 8: Relative Contribution of Labour Market Variables in Explaining Migration Flows

	Specification A			**Specification B**		
Age-Group	$y_{ij,t-1}$	$u_{ij,t-1}$	Joint	$y_{ij,t-1}$	$u_{ij,t-1}$	Joint
Up to 18	1 %	3 %	4 %	0 %	19 %	19 %
18 to 25	29 %	21 %	50 %	19 %	8 %	27 %
25 to 30	18 %	14 %	31 %	54 %	11 %	65 %
30 to 50	1 %	5 %	6 %	5 %	8 %	13 %
50 to 65	1 %	1 %	1 %	2 %	0 %	2 %
Over 65	1 %	0 %	2 %	1 %	1 %	2 %

Note: Specification A is based on the computation of the squared correlation of the respective regressor with the dependent variables (univariate R^2). Specification B is calculated using the estimated SYS-GMM coefficent from the augmented migration model specification in table A.2. The estimation coefficient for regressor x_k is further standardized as $\hat{\beta}_{standardized,k} = \hat{\beta}_k \frac{\sqrt{s_{kk}}}{\sqrt{s_{yy}}}$, where s_{kk} and s_{yy} denote the empirical variances of regressor x_k and the dependent variable y respectively. As long as one only compares regressors within models for the same y, division by $\sqrt{s_{yy}}$ is irrelevant.

Table A.1: Baseline Migration Model based on System GMM Estimation

$nm_{ij,t}$	**To18**	**18to25**	**25to30**	**30to50**	**50to65**	**Over65**
$nm_{ij,t-1}$	0.87***	0.86***	0.86***	0.87***	0.90***	0.88***
	(0.001)	(0.005)	(0.004)	(0.002)	(0.001)	(0.002)
$\tilde{u}_{ij,t-1}$	-0.78***	-0.91***	-0.78***	-0.42***	0.19***	-0.03
	(0.044)	(0.156)	(0.148)	(0.036)	(0.019)	(0.018)
$\tilde{y}_{ij,t-1}$	0.28**	3.73***	4.03***	0.25**	-0.83***	-0.59***
	(0.112)	(0.406)	(0.395)	(0.102)	(0.042)	(0.043)
BW	-0.31***	-0.35***	-0.37***	-0.17***	0.11***	0.01
	(0.035)	(0.093)	(0.093)	(0.018)	(0.016)	(0.011)
BAY	-0.28***	-0.21***	-0.20***	-0.15***	0.07***	-0.01
	(0.031)	(0.075)	(0.077)	(0.018)	(0.016)	(0.009)
BER	0.42***	1.67**	1.32	0.12	-0.17***	-0.02
	(0.144)	(0.721)	(0.937)	(0.187)	(0.054)	(0.068)
BRA	0.59***	0.89***	1.12***	0.36***	-0.24***	-0.06***
	(0.044)	(0.171)	(0.156)	(0.052)	(0.019)	(0.018)
BRE	-0.06	1.95***	-0.38	-0.03	0.04	-0.10***
	(0.256)	(0.610)	(0.470)	(0.161)	(0.107)	(0.133)
HH	-0.11	-0.12	-1.22	-0.12	0.07	0.09
	(0.410)	(0.712)	(1.133)	(0.018)	(0.125)	(0.160)
HES	-0.18***	-0.22*	-0.27**	-0.12***	0.09***	0.03
	(0.045))	(0.133)	(0.110)	(0.018)	(0.031)	(0.027)
MV	0.48***	1.11***	1.19***	0.26***	-0.31***	-0.12***
	(0.047)	(0.171)	(0.164)	(0.051)	(0.022)	(0.021)
NIE	-0.01	0.14**	0.15**	-0.02	-0.05***	-0.04***
	(0.020)	(0.065)	(0.057)	(0.017)	(0.011)	(0.007)
NRW	-0.01	0.08	0.13*	-0.02	-0.01	-0.01
	(0.035)	(0.065)	(0.071)	(0.019)	(0.010)	(0.008)
RHP	-0.14***	0.15	0.08	-0.08***	0.02	-0.04***
	(0.035)	(0.102)	(0.089)	(0.017)	(0.026)	(0.014)
$SAAR$	0.46	0.49	2.20**	0.07	0.11	0.03
	(0.384)	(0.764)	(1.062)	(0.153)	(0.176)	(0.082)
$SACH$	0.47***	1.33***	1.49***	0.24***	-0.33***	-0.15***
	(0.055)	(0.194)	(0.177)	(0.052)	(0.028)	(0.022)
ST	0.53***	1.06***	1.17***	0.25***	-0.35***	-0.15***
	(0.088)	(0.177)	(0.178)	(0.051)	(0.020)	(0.021)
SH	0.10***	0.18*	0.19***	0.07***	0.07***	0.03
	(0.030)	(0.094)	(0.056)	(0.013)	(0.013)	(0.007)
TH	0.39***	1.42***	1.31***	0.21***	-0.34***	-0.18***
	(0.058)	(0.212)	(0.173)	(0.048)	(0.019)	(0.018)
No. of obs.	1067	1067	1067	1067	1067	1067
Time Dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. BW = Baden-Wurttemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia.

Table A.2: Augmented Migration Model based on System GMM Estimation

$nm_{ij,t}$	**To18**	**18to25**	**25to30**	**30to50**	**50to65**	**Over65**
$nm_{ij,t-1}$	0.86***	0.85***	0.87***	0.87***	0.90***	0.84***
	(0.002)	(0.006)	(0.006)	(0.003)	(0.002)	(0.003)
$\tilde{u}_{ij,t-1}$	-1.10***	-0.72***	-0.84***	-0.72***	-0.02	-0.27***
	(0.117)	(0.239)	(0.256)	(0.061)	(0.032)	(0.035)
$\tilde{y}_{ij,t-1}$	-0.23	3.13***	5.28***	1.55***	-1.12***	-0.53***
	(0.175)	(0.633)	(0.369)	(0.157)	(0.097)	(0.090)
$COMM$	-0.10***	-0.06***	-0.04**	-0.01**	-0.02***	-0.03***
	(0.010)	(0.014)	(0.015)	(0.005)	(0.002)	(0.003)
BW	-0.19	-0.28	-0.85***	-0.39***	0.14***	-0.02
	(0.136)	(0.229)	(0.179)	(0.068)	(0.046)	(0.037)
BAY	-0.59***	-0.37	-0,98***	-0.39***	0.05	-0.11**
	(0.193)	(0.261)	(0.237)	(0.077)	(0.056)	(0.052)
BER	1.41***	1.02	0.81	0.59**	0.02	0.49***
	(0.481)	(1.182)	(1.157)	(0.279)	(0.136)	(0.186)
BRA	0.59***	0.37	065*	0.71***	-0.18***	0.04
	(0.164)	(0.365)	(0.350)	(0.103)	(0.046)	(0.055)
BRE	1.95**	2.76	-1.37	0.24	0.08	0.39
	(0.782)	(2.015)	(0.934)	(0.458)	(0.211)	(0.435)
HH	1.00	1.07	-1.23*	-0.41	0.35	0.09
	(1.173)	(1.183)	(0.629)	(0.424)	(0.368)	(0.611)
HES	-0.18	-0.33	-0.86***	-0.39***	0.13**	0.01
	(0.209)	(0.248)	(0.198)	(0.072)	(0.058)	(0.057)
MV	0.26*	0.41	0.76**	0.63***	-0.16***	-0.02
	(0.133)	(0.288)	(0.312)	(0.084)	(0.048)	(0.059)
NIE	-0.26*	-0.17	-0.52**	-0.06	0.05	-0.08**
	(0.139)	(0.264)	(0.198)	(0.083)	(0.047)	(0.033)
NRW	0.06	0.09	-0.12	-0.05	0.03	0.01
	(0.076)	(0.183)	(0.157)	(0.056)	(0.032)	(0.028)
RHP	-1.31***	-0.71***	-0.91***	-0.32***	-0.09*	-0.38***
	(0.226)	(0.247)	(0.286)	(0.089)	(0.051)	(0.066)
$SAAR$	-0.11	0.17	0.86	-0.33	0.26	0.06
	(0.736)	(1.279)	(1.361)	(0.488)	(0.249)	(0.227)
$SACH$	0.57***	0.96**	1.21***	0.75***	-0.34***	-0.08
	(0.188)	(0.405)	(0.403)	(0.115)	(0.061)	(0.066)
ST	-0.23	0.13	0.54	0.56***	-0.31***	-0.23***
	(0.176)	(0.321)	(0.352)	(0.088)	(0.048)	(0.055)
SH	0.11	-0.22	-0.56***	-0.02	0.09**	0.06
	(0.165)	(0.266)	(0.211)	(0.089)	(0.046)	(0.043)
TH	-0.45*	0.46	0.77**	0.53***	-0.34***	-0.18*
	(0.256)	(0.306)	(0.360)	(0.102)	(0.067)	(0.102)
No. of obs.	873	873	873	873	873	873
Time Dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes
Settlement Type (6)	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. BW = Baden-Wurttemberg, BAY = Bavaria, BER = Berlin, BRA = Brandenburg, BRE = Bremen, HH = Hamburg, HES = Hessen, MV = Mecklenburg-Vorpommern, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SACH = Saxony, ST = Saxony-Anhalt, SH = Schleswig-Holstein, TH = Thuringia.