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Timo Mitze and Janina Reinkowski[1]

Testing the Neoclassical Migration Model: Overall and Age-Group Specific Results for German Regions

Abstract

This paper tests the empirical validity of the neoclassical migration model in predicting German internal migration flows. We estimate static and dynamic migration functions for 97 Spatial Planning Regions between 1996 and 2006 using key labor market signals including income and unemployment differences among a broader set of explanatory variables. Besides 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 – both at the aggregate level as well as for age-group specific estimates. Thereby, the impact of labor market signals is tested to be of greatest magnitude for workforce relevant age-groups and especially young cohorts between 18 to 25 and 25 to 30 years. This latter result underlines the prominent role played by labor market conditions in determining internal migration rates of the working population in Germany.

JEL Classification: 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 analyze internal and external migration rates at the regional, national and international level. The model puts special emphasis on the labor market dimension of migration and basically relates migration-induced population changes to the relative income (or wage) and employment situation found in the origin and destination region.

In its response, migration works as an equilibrating mechanism for balancing differences among regions with respect to key labor market variables since higher in-migration in a region is expected to reduce the regional wage level due to an increase in labor supply. From the perspective of economic policy making, the empirical implications of the neoclassical migration model are important to assess whether labor mobility can act as an appropriate adjustment mechanism in integrated labor markets facing asymmetric shocks. Though the neoclassical migration model is widely used as a policy simulation and didactic tool, the international empirical evidence so far 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 time dynamic adjustment processes driving the internal migration patterns. We also aim to identify the role of additional factors as well as regional amenities in explaining migratory movements beside key labor market signals. Finally, we focus on the heterogeneity of adjustment processes taking place when migration flows are disaggregated by age groups.

The remainder of the paper is therefore organized as follows: Section 2 sketches the theoretical foundations of the neoclassical migration model. Building on its 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 flows and regional labor market trends. Section 6 presents the empirical results for the total sample as well as for different age groups. Apart from an economic interpretation of the obtained estimation coefficients, we also carefully look at likely model misspecifications such as cross-sectional dependence in the error terms. Section 7 concludes.

2 The Neoclassical Migration Model

Given the complex nature of the decision making 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. Given the scope of this paper, in the following we focus on the latter class which particularly addresses the labor market dimension of migratory flows. However, as for many macro relationships, the neoclassical migration model is also grounded on solid microeconomic foundations. Its derivation starts from a lifetime expected income (utility) maximization approach as specified in the classical work on the human capital model of migration (see Sjaastad, 1962). The human capital model in fact views the process of migration as an investment decision, where the returns to migration in terms of higher wages associated with a new job should exceed the costs involved in moving.

Relaxing the assumption that prospective migrants have perfect information about the wage rates and job availabilities among all potential locations involved in their decision making process, Todaro (1969) proposes a model framework where the migrants discount wages by the probability of finding a job in alternative regions. Throughout the decision making process, each individual compares the expected (rather than observed) income level 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.

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 the unemployment rate in region i (U_i) and a set of further economic and non-economic determinants (X_i). The same setup holds for region j accordingly. Taking costs of moving from region i to j into account (C_{ij}), the individual's decision will be made in favor 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, the model predicts 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 are negatively correlated with net migration as:

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

Core labor market variables may nevertheless not be sufficient to fully predict regional migration flows. We may extend the model by 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). For notational purposes, in the following we refer to the neoclassical migration model solely focusing on labor market conditions as the 'baseline' specification, while the 'augmented' specification also controls for regional amenities and further driving forces such as the regional skill level, population density and commuting flows as a substitute for migratory movements.

The likely impact of additional 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 labor has the same chance of getting a job as educated labor. 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 holds 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 tradable goods). For population density ($POPDENS$), we expect 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 labor market. Thus, the probability of finding employment in region i in the augmented neoclassical migration model takes the following form:[1]

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

Moreover, we also carefully account for alternative adjustment mechanisms such as interregional net commuting flows to restore the inter-regional labor market equilibrium besides migratory movements. As Alecke & Untiedt (2001) point out, the theoretical as well as empirical literature with respect to interregional commuting (different from intraregional commuting) is rather scarce. According to Evers (1989), theoretical models of interregional commuting base the commuting decision on similar driving forces as outlined in the migration framework. We thus expect that these flows are negatively correlated with net in-migration after controlling for common determinants such as regional income differences.

Finally, regional amenities are typically included as a proxy variable for (unobserved) specific climatic, ecological or socio-economic conditions in a certain region. According to the amenity approach regional differences in labor 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, indicating that those regions exhibit higher than average in–migration rates as we would expected after controlling for regional labor market and macroeconomic differences.

3 Econometric Specification

3.1 Functional Form of the Empirical Migration Equation

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

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

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

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.[2] 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, where lower case variables denote logs and $nmr_{ij,t} = log(NM_{ij,t}/POP_{i,t-1})$ as

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

where $e_{ij,t}$ is the model's error term. Taking into account that migration flows typically show a degree of persistence over time, we augment eq.(6) by including one-period lagged values of net migration

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

The inclusion of a lagged dependent variable can be motivated by the existence of social networks in determining internal migration flows over time. 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 gradual adjustment process over time for migration flows out of a particular origin to destination region.

To account for the role played by timely adjustment processes in the endogenous variable, in the context of panel data models specific estimation techniques based on instrumental variables have to be applied. Besides the problem arising from a dynamic model specification, these techniques, in combination with an appropriate lag selection for the further explanatory variables, may also help to minimize the fundamental endogeneity problem in this model setup, which arises from a two-way causality between internal migration and regional labor market variables. We give a detailed discussion of the latter point throughout the outline of the applied estimation techniques in the following.

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)

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

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

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

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

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

3.2 Choice of Estimation Technique and Model Misspecification Tests

For estimation purposes we then have to find an appropriate estimator, which is capable for handling the above described empirical setup. Given the dynamic nature of the neo-classical migration model in eq.(7), 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 on how to estimate a 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 a function of μ_i, also $y_{i,t-1}$ is a function of μ_i and thus $y_{i,t-1}$ as right-hand side regressor in eq.(11) is likewise correlated with the combined error term. Even in the absence of serial correlation of ν_{it} this renders standard λ-class estimators such as OLS, the fixed effects model (FEM) and random effects model (REM) inconsistent (see e.g. Nickel, 1981, Sevestre & Trogon, 1995 or Baltagi, 2008, for an overview).

Next to direct approaches aiming to correct for the bias of the FEM (see e.g. Kiviet, 1995, Everaert & Pozzi, 2007, and the related literature for analytical or bootstrapping-based correction factors), the most widely applied approaches of dealing with this kind of endogeneity typically applies instrumental variable (IV) and generalized methods of moments (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 common tool is the system GMM estimator by Blundell & Bond (1998) as weighted average of first difference and level GMM.

Especially the latter estimators are a good candidate to simultaneously handle the problem arising from the inclusion of the lagged migration variable in our empirical model and the fundamental endogeneity problem induced by two-way causality between migration and labor market variables. In our case, the combination of an appropriate lag selection for the right-hand-side-regressors combined with the IV approach may do so. That is, since we include labor market variables with a lag structure in eq.(7), by definition there cannot be any direct feedback effect from $nmr_{ij,t}$ to labor market variables. However, since $nmr_{ij,t-1}$ enters contemporaneously with respect to the latter, there is still the risk of two-way interdependences due to the dynamic setting of the model. We minimize these potential risks of any endogeneity bias by instrumenting $nmr_{ij,t-1}$ with its lagged values so that the possibility of feedback effects from migration responses to labor market changes as source of estimation bias is limited. This should lead to consistent estimates of the coefficients for the explanatory variables.[3]

We are then also particularily 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, 2009). 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 $\mathrm{Cov}(\nu_{i,t}\nu_{j,t}) \neq 0$ for some t and $i \neq j$ (see Sarafidis & Wansbeek, 2010).

Besides the familiar spatial econometric approach, which assumes certain distance decay in spatial dependence, 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. The common factor model approach is based on the concept of strong cross-sectional dependence, which assumes that all regions, either symmetrically or asymmetrically, are affected rather than just those nearby. Common examples are for instance, regional adjustment processes to common macroeconomic shocks. We introduce a common factor structure for the error term according to eq.(11) in the following way:

[3] Of course, a full account of the simultaneity problem may call for a system approach, which is also likely to increase the estimation efficiency if there are significant cross-correlations in the error terms for functional forms of the migration and labor market variable equations. However, a fully specified system approach goes beyond the scope of this paper.

$$u_{i,t} = \mu_i + \nu_{i,t}, \quad \nu_{i,t} = \sum_{m=1}^{M} \phi_{m,i} \mathbf{f}_{m,t} + \epsilon_{i,t}, \tag{12}$$

where $\mathbf{f}_{m,t} = (f_{1,t,...,f_{M,t})'}$ denotes an $M \times 1$ vector of individual-invariant time-specific unobserved effects, $\phi_i = (\phi_{1,i}, \ldots, \phi_{M,i})'$ 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 on how 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 this type of 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. 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, which is designed for the Arellano & Bond (1991) and Blundell & Bond (1998) GMM estimators, is based on the Diff-in-Hansen test for overidentifying restrictions. The latter is also known as the C-statistic and is defined according to Eichenbaum et al. (1988) as the difference between two Sargan (1958)/Hansen (1982) J-statistics for an unrestricted and restricted IV/GMM-model. 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 form:

$$C_{CD-GMM} = (S_F - S_R) \xrightarrow{d} \chi^2_{h_d}, \tag{13}$$

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-sectional dependence in the model versus the alternative of heterogeneous cross-sectional dependence. If only homogeneous cross-sectional 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).[4]

4 What Does the Empirical Literature Say?

Testing for the empirical validity of the neoclassical migration model yields rather mixed results, when looking at recent empirical evidence for European data. Here, regional (un-)employment disparities 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 (1999) show that the regional wage level corresponds to the theoretically expected signal for the gross outward migration from southern to northern regions. Similar results are found in Fachin (2007).

Napolitano & Bonasia (2010) show that although the coefficients for Italian labor 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 variables are also found significant besides the standard labor market variables in an inter-regional migration model for the Polish transition process (see Ghatak et al., 2008). This indicates that the augmented migration model may be in order.

[4]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 common factor. Sarafidis et al. (2009) propose to likewise test for the exogeneity of a subset of regressors by means of the standard Sargan/Hansen's test for overidentifying restrictions in a first step.

Turning to the case of 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 Büchel & 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.[5] 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, Burda & Hunt, 2001, Hunt, 2006, as well as Alecke et al., 2010). 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 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 Burda & Hunt (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, the authors find that the decline in

[5]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.

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. The study that comes closest to the research focus in this paper is Hunt (2006), who also estimates the migration response to labor market signals by age groups. The author finds that young potential emigrants are more sensitive to wages than older age cohorts. At the same time young age groups are found to be less sensitive to unemployment levels in the origin region. Hunt (2006) argues that the latter finding is likely to drive the migration pattern pooled over all age groups and thus gives a motivation for the dominance of wage rate signals in aggregate data as e.g. reported in Burda & Hunt (2001).

Alecke et al. (2010) apply a Panel VAR to analyze the simultaneous impact of labor 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 labor 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 migration responses to labor market signals (see e.g. Fachin, 2007, and Etzo, 2007).

The recent results for Germany also show that the specific time period used for estimation may significantly impact on the estimation results. Especially for the first years after reunification several structural breaks are in order that partly may partly explain the results between earlier and recent contributions with respect to German internal migration. However, except for Alecke et al. (2010), none of the empirical papers takes into account recent sample observations incorporating information about the second wave of strong East-West outmigration around the year 2001. The allocation of higher weights to recent sample observations may in turn minimize the risk of biasing the results in the light of distinct macro regional structural breaks.[6]

5 Data and Stylized Facts

Given the heterogeneous findings in the international and German empirical literature regarding the neoclassical migration model, we use them as a starting point for an updated regression approach based on German spatial planning units between 1996 and 2006. For

[6]In this paper we account for regional and macro regional results by including East German and state level fixed effects. However, future work should also explicitly test for the poolability of the data for regional subgroups in a partial clustering framework.

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 für Bau-, Stadt-, und Raumforschung, 2010, for details about the concept of Spatial Planning Regions).[7]

We use a set of variables comprising regional net migration, population, real income, the unemployment rate, human capital endowment, international competitiveness of regions and commuting flows. The latter has been included to account for an alternative adjustment mechanism to balance labor market disequilibria. Human capital is defined as the percentage share of regional employment with a university degree (including universities of applied science) in total employment covered by the social security system (*sozialversicherungspflichtig Beschäftigte*).[8] We also include two sets of dummy variables: 1.) binary dummy variables for the 16 federal states to capture macro regional differences (see, e.g., Suedekum, 2004). 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 table 3.

To highlight regional and macro-regional differences for net migration and explanatory variables, figure 1 visualizes spatial differences for the sample means of net in-migration and labor market variables for the period 1996–2006. Net in-migration flows are categorized into labor force relevant age groups between 18 and 65 years as well as non-labour force relevant age groups. For labor force migration, the figure shows that throughout the sample period the East German regions on average lost a considerable fraction of their population levels through net out-migration. Exceptions are the economic core regions around Berlin/Brandenburg and in the south-west of Saxony. Also, the Western regions along the border to East Germany experienced net outflows. On the other hand, the northern West German regions around the urban agglomerations Hamburg and Bremen are among the net recipient regions as well as the western agglomerated regions in the

[7]We restrict our estimation approach to this period since 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.

[8]We also checked for the sensitivity of the results, when using composite indicators of human capital as discussed in Dreger et al. (2009), accounting for human capital potential (measured in terms of high school graduates with university qualification per total population between 18-20 years) as well as science and technology related indicators (e.g. patent intensity). The results did not change though.

Table 1: Variable definition and data sources

Variable	Description	Source
NM	Net migration defined as in- minus outmigration	Destatis (2009)
NM(to18)	Net migration for persons under 18 years	Destatis (2009)
NM(18to25)	Net migration for persons between 18 and 24 years	Destatis (2009)
NM(25to30)	Net migration for persons between 25 and 29 years	Destatis (2009)
NM(30to50)	Net migration for persons between 30 and 49 years	Destatis (2009)
NM(50to65)	Net migration for persons between 50 and 65 years	Destatis (2009)
NM(over65)	Net migration for persons 65 years and above	Destatis (2009)
POP	Population Level	VGRdL (2009)
Y	Gross Domestic Product (real) per Capita	VGRdL (2009)
UR	Unemployment Rate	Federal Employment Agency (2009)
COMM	Net Commuting level defined as in- minus out-commuting	Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR, 2009)
HK	Human Capital level defined as %-share of employees with university degree relative to total employees	BBSR (2009)
INTCOMP	International Competitiveness proxied by foreign turnover relative to total turnover in manufacturing industries	BBSR (2009)
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	BBSR (2009)
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

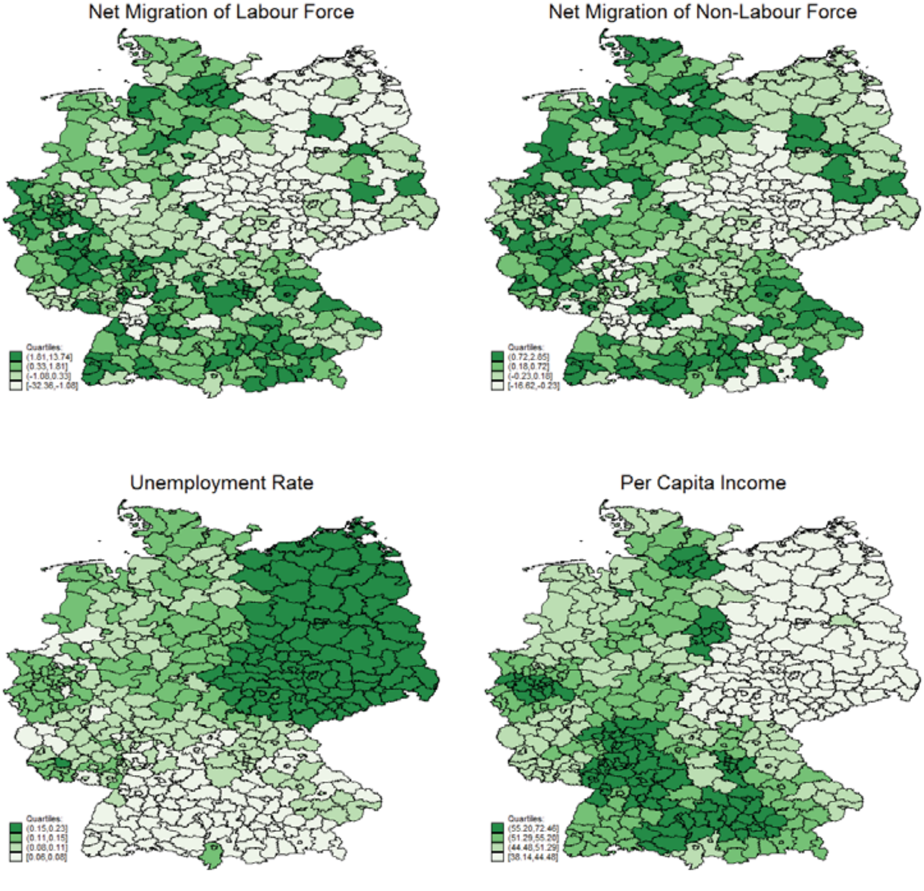
Variable	Obs.	Mean	Std. Dev.	Min	Max	Unit
INM	1067	0.00	7.21	-95.90	37.01	in 1000 persons
INM (to18)	1067	0.00	1.91	-24.41	32.41	in 1000 persons
INM (18to25)	1067	0.00	1.85	-12.97	15.76	in 1000 persons
INM (25to30)	1067	0.00	1.27	-9.93	12.42	in 1000 persons
INM (30to50)	1067	0.00	2.48	-30.99	8.24	in 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-Württemberg, 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:
Sample Means of Net Migration (in 1000), Unemployment Rate (in %), per Capita GDP (in 1000€)



Source: For data description see table 1.

Rhineland (around the metropolitan areas Cologne and Düsseldorf) and the southern West German regions in Baden Württemberg and Bavaria.

Looking at net migration trends for non-labour market relevant age groups, the picture is less clear cut. We see from figure 1 that both the north German coastal regions as well as the southern border regions gain considerable population through net in-migration. This trend may be interpreted in terms of regional amenities such as topographical advantages, which attract migration flows. The relative difference is especially observable for the East German coastal zone in Mecklenburg-Vorpommern. The spatial distribution of real per capita income and unemployment rates nevertheless shows a distinct West-East division. The regions with the highest income levels for the sample period are the northern regions around Hamburg, the Western regions in the Rhineland as well as large parts of the southern states Baden-Württemberg and Bavaria. 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. The opposite case is supposed to hold for large regional unemployment rates. Especially for the East German Spatial Planning Regions high unemployment rates seem to match with net population losses. To check for the correlation of these variables more in depth, the next section presents the results of the estimation exercise.

6 Empirical Results for the Neoclassical Migration Model

6.1 Aggregate Findings

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 check the time series properties of the variables involved in order to avoid the risk of running a spurious regression for non-stationary variables (with moderate $T = 11$). We therefore report test results of different panel unit root tests including recently proposed methods by Levin et al. (2003) and Im et al. (2003) 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, even if the autoregressive parameter is high (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 show, for almost exclusively all variables and test specifications the null hypothesis of non-stationarity of the series under observation can be rejected.[9] Given this overall picture of the panel unit root tests together with the theoretically motivated assumption that migration flows are transitory processes between two labor market equilibria, it seems reasonable to handle the variables as stationary processes so that we can run untransformed regressions without running the risk of spurious regression results.

Table 4: Results of Panel unit root tests (p-values) 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: LLC denotes the test proposed by Levin et al. (2003), IPS is the Im et al. (2003) test, CADF is the test proposed by Pesaran (2007). All unit root tests include 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.

For estimation we start from an unrestricted presentation of the baseline model including the core labor 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 size cannot be rejected on the basis of standard Wald tests. Also, compared to the static specification in column 2, the relative root mean squared error (RMSE) criterion of the model strongly increases if we add a dynamic component to the migration equation. The relative RSME for each estimator is thereby computed as the ratio of the model's RMSE and the static POLS benchmark specification in column 1. A value smaller than one indicate that the model has a better predictive performance than the benchmark POLS.

As discussed above the λ-class estimators are potentially biased in a dynamic specification. Since the coefficient of the lagged dependent variable turns out to be highly significant, we also compute a bias-corrected FEM specification as well as the Arellano & Bond (1991) and Blundell & Bond (1998) system GMM estimators. According to the

[9] 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 ($\tilde{u}_{ij,t}$).

relative RMSE criterion the Blundell-Bond system GMM specification has the smallest prediction error. The coefficients for labor 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 statistics proposed by Arellano & Bond, 1991) 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.

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 Planning 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 labor 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.[10]

The results in table 6 for the period 1996 to 2006 report a statistically significant positive East German dummy, which indicates higher net in-migration balances for the East German Spatial Planning Regions than their labor market performance would suggest. To get further insights we also estimate a specification which includes Federal state level fixed effects. The estimation results for the state dummies in the baseline model are shown in figure 2. 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 Württemberg, Bavaria and Hessen. A Wald test for joint effect of the set of state dummies turns out to be highly significant. However, most important, for both models including the East German dummy and the set of state dummies, the impact of labor market variables is still of expected sign and higher than in the baseline specification. In line with Suedekum (2004) for West Germany, the results thus show that macro regional differences matter, nevertheless there are no qualitative effects on the estimated coefficients that hint to a systematic rejection of the neoclassical migration model.

[10]However, the latter study found that along with a second wave of East-West movements in early 2000 net flows out of East Germany were much higher than expected after controlling for its labor 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.

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***	0.90***	0.78***	0.92***	0.84***	0.88***
			(0.011)	(0.011)	(0.022)	(0.031)	(0.001)	(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***	-0.05	-0.05	-0.32**	-0.28*	-0.53***	-0.19***
		(0.114)	(0.041)	(0.041)	(0.166)	(0.166)	(0.023)	(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	0.12	0.12	-0.26	-0.10	0.25***	0.03**
		(0.314)	(0.108)	(0.112)	(0.372)	(0.374)	(0.066)	(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

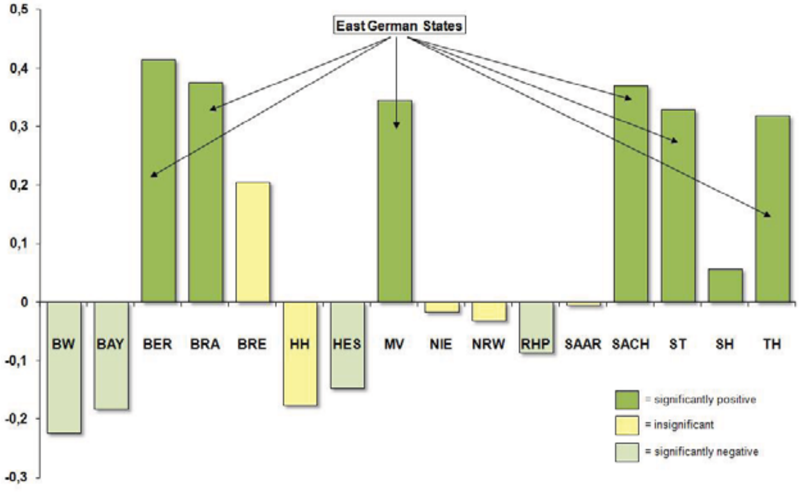
Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. Standard Errors in brackets.

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.

Figure 2: State level effects for German States in the Aggregate Baseline Migration Model



Note: Computations based on table 5.

Regarding the further variables in the augmented variable set, the results show that higher interregional net in-commuting levels are negatively correlated with the net in-migration rate, supporting our basic theoretical expectations from above that both types are alternative adjustment mechanisms to reduce labor market disparities. The binary dummy variables for different settlement types (classified by size of local urban centers and population density, see table 1 for details) reveal 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 favor of a 're-urbanization' process in Germany for the period 1996 to 2006. Similar trends were also reported in Swiaczny et al. (2008).[11]

Finally, testing for the effects of regional human capital endowments and international

[11]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.

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 tested to be insignificant. This finding corresponds to recent results for Spain between 1995–2002, where regional differences in human capital were not found helpful in predicting internal 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 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 show 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, in order to check for the nature of the cross-sectional dependence given the impact of unobserved common factors.

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 we could then apply C_{CD-GMM} from eq.(13) in order to test for the existence of heterogeneous factor loadings 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, hinting at homogeneous responses to common shocks. In sum, the augmented neoclassical migration equation shows to be an appropriate representation of the data generating process and highlights the role of key labor market variables in explaining net in-migration rates for German regions.

6.2 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. We are especially interested to analyze whether the estimated coefficients for the labor market signals change for different age-groups. Indeed, the estimation results show that the migratory response to labor market variables is much higher for workforce relevant age groups. For both the baseline and augmented model, the resulting coefficients for real income and unemployment rate differences together with 95 % confidence intervals are plotted in figure 3.[12]

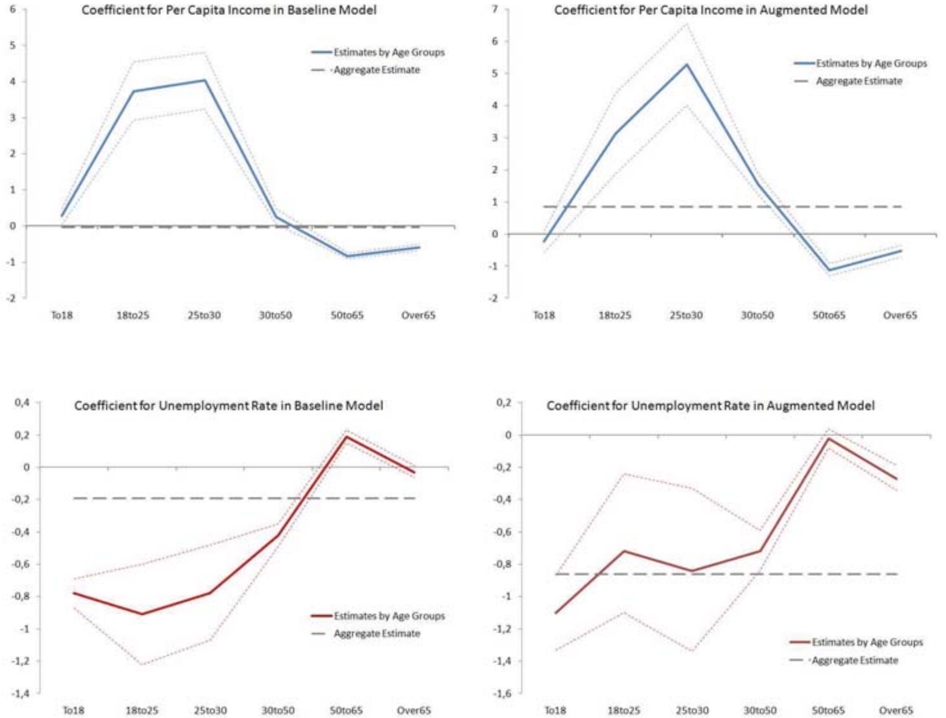
The coefficient for real income differences in figure 3 shows a clear inverted U-shaped pattern when plotted for the different age-groups in ascending order. While for migrants up to 18 year real income difference do not seem to matter, especially for migrants with an age between 18 to 25 years and 25 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 migration responses are found to be very similar for the baseline and augmented migration specification (see figure 3). Similar results were found for regional unemployment rate differences, which show to be almost equally important for age groups up to 50 years. Only for elderly age groups the coefficients turn out to be of smaller size and partly insignificant. 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 the workforce relevant age groups. The results are graphically shown in figure 4 for the baseline migration model.

Finally, table 7 computes the 'relative importance' of the labor market variables by age-groups in determining net migration flows. Thereby, the relative importance refers to the quantification of an individual regressor's contribution in a multiple regression model (see e.g. Grömping, 2006, for an overview). This allows us to further answer the question, in how far our estimation results support the prominent role of labor market conditions in guiding internal migration rates (of the workforce population) in Germany. Table 7 computes two 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 coefficients from the augmented migration model. 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 labor 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 %

[12]Detailed estimation results for the models are given in the appendix.

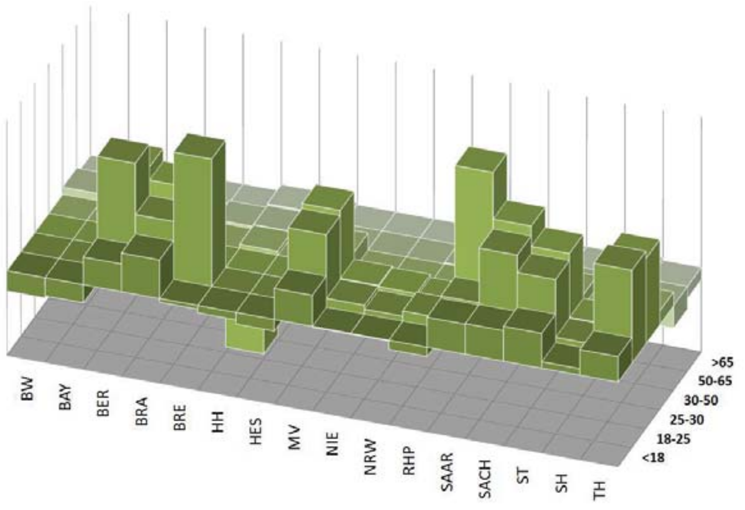
for age-group 25 to 30 years in Specification B). The SYS-GMM thereby on average assigns a stronger weight to real income differences in explaining net in-migration relative to unemployment differences. However, the overall picture confirms our interpretation of the regression tables in assigning a prominent role to labor market imbalances in driving German internal migration.

Figure 3: Coefficients for Income ($\tilde{y}_{ij,t-1}$) und Unemployment Rate Differences ($\tilde{u}_{ij,t-1}$) by Age Groups



Source: Dotted lines denote 95 % confidence intervals.

Figure 4: State level effects in Baseline Migration Model by States and Age



Note: For details of calculation see table A1 and table A2.

Table 7: Relative Contribution of Labor 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 A2 (appendix). 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.

7 Conclusion

In this paper, we have analyzed the explanatory power of the neoclassical migration model for describing aggregate and age-group specific internal migration trends for 97 German Spatial Planning regions throughout the period 1996–2006. Our results based on model specifications for dynamic panel data estimators give strong evidence in favor of the neoclassical inspired Harris-Todaro model. Both real income differences as well as unemployment rate disparities are found to be statistically significant with 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 lower net inflows. Given these responses to labor market signals, migration flows may be seen as a spatial adjustment mechanism and equilibrate regional labor market imbalances.

The results of the standard neoclassical migration model remain stable if commuting flows, regional human capital endowment, the region's international competitiveness as well as differences in the settlement structure 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 persistent structural differences for the two East-West macro regions (by including individual federal state level fixed effects or a combined East German dummy). Most important, the impact of core labor market variables is still of expected sign, when further variables are added. In line with earlier empirical studies, the results thus show that macro regional differences matter, nevertheless there are no qualitative effects on the estimated coefficients that hint to a systematic rejection of the neoclassical migration model.

We finally estimate the migration model for age-group specific subsamples of the data. Here, the impact of labor 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). Computing the 'relative importance' of labor market variables by age-groups in a multiple regression framework with a broader set of controls, our results show that for young cohorts up to 65 % of all migratory movements can be explained by differences in regional income levels and unemployment rates. This latter result underlines the prominent role played by labor market conditions in guiding internal migration rates of the working age population in Germany.

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Appendix

A.1 Baseline and augmented regression results by age groups

Table A1: 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-Württemberg, 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 A2: 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-Württemberg, 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.