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Network Dependency in Migration Flows

A Space-time Analysis for Germany since Re-unification

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Timo Mitze[1]

Network Dependency in Migration Flows – A Space-time Analysis for Germany since Re-unification

Abstract

The contribution of this paper is to analyse the role of network interdependencies in a dynamic panel data model for German internal migration flows since re-unification. So far, a capacious account of spatial patterns in German migration data is still missing in the empirical literature. In the context of this paper, network dependencies are associated with correlations of migration flows strictly attributable to proximate flows in geographic space. Using the neoclassical migration model, we start from its aspatial specification and show by means of residual testing that network dependency effects are highly present. We then construct spatial weighting matrices for our system of interregional flow data and apply spatial regression techniques to properly handle the underlying space-time interrelations. Besides spatial extensions to the Blundell-Bond (1998) system GMM estimator in form of the commonly known spatial lag and unconstrained spatial Durbin model, we also apply system GMM to spatially filtered variables. Finally, combining both approaches to a mixed spatial filtering-regression specification shows a remarkably good performance in terms of capturing spatial dependence in our migration equation and at the same time qualify the model to pass essential IV diagnostic tests. The basic message for future research is that space-time dynamics is highly relevant for modelling German internal migration flows.

JEL Classification: R23, C31, C33

Keywords: Internal migration, dynamic panel data; Spatial Durbin Model; GMM

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1 Introduction

This paper aims to take an explicit account of spatial interdependencies in dynamic panel data (DPD) models to explain German internal migration flows since re-unification. While research in the field of spatial econometrics has evolved rapidly within the last years (see Florax & Van der Vlist, 2003, Anselin, 2007), applications to dynamic processes for panel data are still at an experimental stage. Nevertheless, a proper handling of spatial autocorrelation besides controlling for time dynamic adjustment processes may have important implications from a statistical as well as theoretical perspective.[1] Regarding the latter point, different scholars have already pointed out the likely role played by spatial autocorrelation in analyzing migration (see e.g. Cushing & Poot, 2003, and LeSage & Pace, 2008 & 2009). Spatial autocorrelation measures the correlation of values for an individual variable, which are strictly attributable to the proximity of those values in geographic space. Depending on its source, spatial interdependences may either be captured through a spatial lag term of the dependent variable, the explanatory variables and/or the error term. In this paper we take a general perspective and apply both the spatial lag as well as the unconstrained spatial Durbin model, which augments the spatial lag approach by additionally controlling for spatially lagged terms of the exogenous variables.

Concerning the proper choice of the estimation strategy, Kukenova & Monteiro (2009) point out that so far none of the available estimators allows to consider a dynamic spatial lag panel model with additional endogenous right hand side variables beside the spatial/time lag of the endogenous variable.[2] Given the potential source of right hand side endogeneity – defined as correlation for any regressor with the error term of the model – this is a clear shortcoming for empirical application. The authors therefore propose an estimation strategy that starts from the standard Blundell-Bond (1998) system GMM approach (SYS-GMM) and augments the latter estimator by valid instruments for the spatial lag variable – both for the equations in levels and first differences.

The main advantage of this estimation approach is that it stays within the flexible SYS-GMM framework (which is now available for many econometric software packages) combined with an explicit treatment of spatial issues. Using a Monte Carlo simulation exercise, Kukenova & Monteiro (2009) show that this augmented SYS-GMM can consistently estimate the spatially augmented specifications for standard data settings (large N, small T). First applications of a spatial dynamic panel model estimated by GMM

[1] The importance of timely adjustment processes in modelling internal migration flows for Germany has recently been shown by Alecke et al. (2010).

[2] Throughout the paper the term 'spatial lag' is used to indicate the presence of a 'spatially lagged dependent variable' among the right hand side regressors of a mixed regressive spatial autoregressive model (see e.g. Ward & Gleditsch, 2008).

are given in Bouayad-Agha & Vedrine (2010) as well as Elhorst et al. (2010). The latter authors also show, how to effectively combine the GMM approach with alternative estimation techniques to increase the estimator's overall performance.

Of vital importance in the context of migration flow modelling is also the appropriate specification of a spatial weighting matrix in order to identify the underlying spatial – or in this context – spatial network autocorrelation structures (see Black, 1992). Different to the design of weight matrices in standard models of spatial dependence, the framework for modelling network flows requires to shift attention from a two–dimensional space for n regions and $n \times n$ origin–destination pairs to a four dimensional space with $n^2 \times n^2$ origin-destination linkages. As Fisher & Griffith (2008) point out, the geographical space in which flow origins on the one hand, and flow destinations on the other hand are located, may both be a source of spatial dependence in the level of flows originating and/or terminating in regions nearby. Proximity can be defined as first-order origin or destination related contiguity, specified by a spatial weighting matrix of the form that it explicitly accounts for the cumulative impact of origin and destination interaction effects.

The contribution of this paper is thus twofold: First, given its importance for mapping spatial dependencies in empirical models of origin-destination flow data, throughout the analysis we will put a special focus on the specification of spatial weighting matrices for internal migration flow data. We then use the derived spatial variables for a time-space analysis of German migration dynamics. While time dynamic models are by now standard, the analysis augments the existing body of empirical research by an explicit account of space. Of particular interest is, whether the effect of regional labour market signals, which are typically found to be an important driving force of internal migration flows in standard model specification, also hold for spatially upgraded versions. Second, given the novelity of econometric tools for a joint handling of time-space dynamic processes, the paper also explores ways, how to efficiently estimate these complex relationships.

The remainder of the paper is organized as follows: In the next section we outline our empirical estimation strategy, starting from a short description of the neoclassical migration model. We then demonstrate how network dependency structures can be translated into a spatial weighting matrix for empirical estimation and discuss different methods to spatially upgrade dynamic panel data estimators. After a brief overview of the data used for estimation and some stylized facts of migration flows between German states in section 3, section 4 then estimates the different spatial dynamic panel models by means of SYS-GMM. These include spatial lag and spatial Durbin model specifications as well as standard SYS-GMM to spatially filtered variable as a benchmark case. We also report the performance of mixed spatial filtering-regression techniques. Section 5 concludes.

2 Econometric Model Specification

2.1 Neoclassical Migration: A Benchmark Model

In this section we briefly outline the neoclassical migration model as a starting point for our empirical analysis. According to the neoclassical framework, a representative agent decides to move between two regions if this improves his welfare position relative to not moving. Relevant factors for this decision are the expected incomes in the home (origin) and alternative (destination) region net of 'transportation' costs for the case of moving. Expected income in turn can be expressed a function of the wage rate and the probability of being employed, where the latter is inversely related to the regional unemployment rate. This underlying idea has been formally elaborated in Harris & Todaro (1970) and may be summarized in terms of a stylized equation for net in-migration flows between region i and region j (NM_{ij}) conditional on a set of explanatory variables as[3]

$$NM_{ij} = f(WR_i, WR_j, UR_i, UR_j, S_i, S_j, C_{ij}), \tag{1}$$

where WR denotes the real wage rate, UR is the unemployment rate, C are the costs of moving and S is a set of additional economic and non-economic variables that may work as pull or push factors for regional migration flows. We expect that an increase in the home region's real wage rate *ceteris paribus* leads to higher net in-flows, while a real wage rate increase in region j results in lower net in-migration flows to region i. By contrast, an increase in the unemployment rate in region i relative to j has negative effects on net in-migration to i. Costs of moving between the two regions are typically expected to be an impediment to migration and are thus supposed to be negatively correlated with net migration.

For empirical application eq.(1) is typically specified in a log-linear form. In addition to the explanatory factors in the stylized migration equation, we also account for likely information lags in the transmission process from the explanatory to the endogenous variable, as well as assume that migration flows themselves adjust with a lag structure. The inclusion of the time lagged endogenous variable has proven to be an important factor in the adjustment path of German migration flows (see e.g. Alecke et al., 2010) and may reflect different channels through which past flows affect current migration (e.g. since migrants serve as communication links for friends and relatives left behind), which in turn has a potential impact on prospective migrants who want to live in an area where they share cultural and social backgrounds with other residents (see e.g. Chun, 1996,

[3]Where positive values indicate a net surplus in region i.

for a detailed discussion). We restrict explanatory variables to enter as inter–regional differences resulting in a triple-indexed model specification (ij, t), where the index ij for each exogenous variable denotes regional difference between region i and region j, t is the time index:[4]

$$\begin{aligned} nm_{ij,t} &= \alpha nm_{ij,t-1} + \beta_1 \widetilde{wr}_{ij,t-1} + \beta_2 \widetilde{ur}_{ij,t-1} + \beta_3 \widetilde{\Delta ylr}_{ij,t-1} \\ &\quad + \beta_4 \tilde{q}_{ij,t-1} + \beta_5 \widetilde{hc}_{ij,t-1} + \beta_6 \widetilde{\Delta p^l}_{ij,t-1} + \mu_{ij} + \nu_{ij,t} \end{aligned} \tag{2}$$

where $\tilde{x}_{ij,t}$ for any variable $x_{ij,t}$ is defined as $\tilde{x}_{ij,t} = (x_{i,t} - x_{j,t})$. The error term is assumed to have the typical one-way error component structure $(\mu_{ij} + \nu_{ij,t})$. Net migration is defined as in- minus out-migration for each period as $nm_{ij,t} = (inm_{ij,t} - outm_{ij,t})$. Next to the core labour market variables in terms of real wages $(\widetilde{wr})$ and unemployment rates $(\widetilde{ur})$ we include growth in real labour productivity $(\widetilde{\Delta ylr})$, the labour participation rate $(\tilde{q})$, a human capital index $(\widetilde{hc})$ and the annual growth in land prices $(\Delta \widetilde{p}^l)$ as control variables. To account for differences in the standards of living, we explicitly deflate real wages by regional consumer prices (see e.g. Roos, 2006, for details).

2.2 Network Dependency Structures in Migration Flows

In the majority of empirical applications, migration flows between an origin and a destination region are typically assumed to be independent of other migration flows associated with different origin destination pairs. However, as Chun (2008) points out, an individual migration decision may be seen as a result of choice processes in space, which is likely to be influenced by other migration flows at the macro level. In this sense, outflows from a particular origin may be correlated with other outflows that have the same origin and geographically proximate destination regions given unobservable characteristics of origins and destinations in the sample. The associated dependency among flow data is measured in terms of network autocorrelation. If empirical model building does not account for such network autocorrelation effects in mapping migration flows, results are likely to be biased and may lead to unreliable conclusions (see e.g. LeSage & Pace, 2008).

In order to properly account for any form of spatial autocorrelation, we will analyse migration flows in the context of network structures, where individual flows are assumed to be related to one another. The relationship among network flows can then be arranged in a spatial weighting matrix. However, while a standard spatial weighting matrix typically

[4]In the following, logs are denoted by small characters.

has an $n \times n$ dimension for an underlying tessellation containing n spatial regions, the dimension of a network weighting matrix becomes $(n^2 \times n^2)$ – or analogously $[(n^2 - n) \times (n^2 - n)]$ in a system of n region if we abstract from non-zero flows within each region, which is typically true for interregional migration data.

Formally, we follow LeSage & Pace (2008) and define $\mathbf{M}$ to be an $n \times n$ square matrix of interregional migration flows in a closed system from each of the n origin regions to each of the n destination regions, where the columns represent different origins (o_i) and the rows represent destinations (d_j) with $i, j = 1, \ldots, N$ as

$$\underset{(n \times n)}{\mathbf{M}} = \begin{pmatrix} o_1 \rightarrow d_1 & o_2 \rightarrow d_1 & \ldots & o_n \rightarrow d_1 \\ o_1 \rightarrow d_2 & o_2 \rightarrow d_2 & \ldots & o_n \rightarrow d_2 \\ \vdots & \vdots & \ddots & \vdots \\ o_1 \rightarrow d_n & o_2 \rightarrow d_n & \ldots & o_n \rightarrow d_n \end{pmatrix}. \tag{3}$$

Taking an origin-centric perspective, we can then construct a stacked $(n^2 \times 1)$ vector $m = vec(\mathbf{M})$, whose first n elements reflect flows from origin 1 to all n destinations and whose last n elements represent flows from origin n to destinations 1 to n. The resulting research task is to specify a spatial weight matrix for the vector m to capture spatial connectivity between origin-destination flows. In this context, Fisher & Griffith (2008) point at the need to shift attention from a two–dimensional space for n regions and $n \times n$ origin (i), destination (j) pairs $\{i, j | i \neq j; i, j = 1, \ldots, n\}$ to a four dimensional space with $n^2 \times n^2$ origin-destination linkages $\{i, j, r, s | i \neq j, r \neq s; i, j = 1 \ldots, n; r, s = 1, \ldots, n\}$. An appropriate spatial weighting matrix (W^*) should then be able to jointly capture a set of origin related interaction effects (W^o) and a set of destination interaction effects (W^d) as

$$W^* = W^o + W^d \tag{4}$$

The elements w^o of the origin-based spatial weights matrix W^o can be defined as

$$w^o(i, j; r, s) = \begin{cases} 1 \text{ if } j = s \text{ and } c(i, r) = 1, \\ 0 \text{ otherwise,} \end{cases} \tag{5}$$

where $c(i, r)$ is the element of a conventional $(n \times n)$ link matrix with

$$c(i, r) = \begin{cases} 1 \text{ if } i \neq r \text{ and } i \text{ and } r \text{ are spatially linked to each other,} \\ 0 \text{ otherwise.} \end{cases} \tag{6}$$

In this framework, the spatial link between origins i and r may either be measured in terms of a common border or equivalently by defining a threshold distance and operationalize it in a binary way for i and r to be linked. The spatial weights matrix W^o thus specifies an origin-based neighborhood set for each origin-destination pair (i,j). According to Fisher & Griffith (2008) each element $w^o(i,j;r,s)$ defines an origin-destination pair (r,s) as being a neighbor of (i,j) if the origin regions i and r are contiguous spatial units and $j = s$. In similar veins the specification of the destination based spatial weights matrix W^d consists of the following elements w^d as

$$w^d(i,j;r,s) = \begin{cases} 1 \text{ if } i = r \text{ and } c(j,s) = 1, \\ 0 \text{ otherwise,} \end{cases} \tag{7}$$

where

$$c(j,s) = \begin{cases} 1 \text{ if } j \neq s \text{ and } j \text{ and } s \text{ are spatially linked to each other,} \\ 0 \text{ otherwise.} \end{cases} \tag{8}$$

The full weighting matrix W^* can be used in its binary – or alternatively – row-standardized form, where the latter elements $\bar{w}^*$ are subject to the following transformation as

$$\bar{w}^*(ij;r,s) = \left[w^*(i,j;r,s) \Bigg/ \sum_{\substack{r',s'=1 \\ (r',s')\neq(i,j)}}^{n^2} w^*(i,j;r',s') \right]. \tag{9}$$

Applied to the field of migration research Chun (2008) argues that the use of the full weighting matrix W^* associated with simultaneous origin- and destination-related interaction effects can be motivated by theoretical concepts such as the 'intervening opportunities' and 'competing destinations' model. In this logic the specification of W^o – linking network flows from spatially linked origins to one particular destinations – is supposed to mirror the effect of intervening opportunities in the path of migratory movements from an origin to a pre-selected destination: Here, movements of people in space are modelled upon the idea that the number of migration flows between two regions is determined by the availability of different intervening opportunities (such as the number of available jobs etc.) existing between the origin and the destination. Under the assumption that migrants move as short a distance as possible, the intervening opportunities model then provides a behavioral argument of spatial search in sequential form, where the spatial arrangement of regions – predominately around an origin – has great influence on the number of potential intervening opportunities (for details see e.g. Freymeyer & Ritchey, 1985, Chun, 2008). Thus, given that intervening opportunities exist in regions that are located between an origin and destination, migration flows to one particular destination from a number of origins, which are spatially close to each other, are likely to be correlated.

Likewise, the specification of the destination-related weighting matrix W^d in eq.(7) and eq.(8) can be motivated by competing destinations effects from the perspective of a particular origin region (see e.g. Fotheringham, 1983, Hu & Pooler, 2002). The basic idea of the competing destinations approach is to model human behavior as a spatial choice process based on the assumption that the actual choice occurs through hierarchical information processing since migrants are supposed to be only able to evaluate a limited number of alternative at a time. Hence, prospective migrants tend to simplify the alternatives by categorizing all alternatives into clusters, where the probability that one destination in a certain cluster will be chosen is related to the other regions in that cluster. This clustering effect in turn requires that spatial proximity of destinations has an influence on the destination choice of migrants from one particular origin. The competing destinations approach reflects a two-stage decision process, where the attractiveness of all defined groups of destinations is evaluated and a particular group is chosen in a first step. In the second step then the individual destination will be selected out of this group.

For empirical application it is reasonable to assume that both effects are in order and operate simultaneously so that the aggregated weight matrix W^* may be an appropriate choice for analyzing the range of cumulative network effects in migration flows. Recent research results on closely related modes of network modelling e.g. given in Guldmann (1999), Almeida & Goncalves (2001), Hu & Pooler, 2002, and LeSage & Pace (2008) among others generally support this view.[5] Throughout the rest of the paper we will thus use the combined weight matrix W^* in order to capture network autocorrelation effects in German migration flows. Further details about the empirical operationalization in the specification of the spatial weighting matrix will be given in section 3.

2.3 Spatial Upgrading of Dynamic Panel Data Models

Given the likely importance of space and time interdependences in migration flows, in this section we propose an estimation strategy, which is able to account for spatial dependence in a dynamic panel data model. As Bouayad-Agha & Vedrine (2010) point out, estimation methods for the simultaneous treatment of space and time interrelations must deal with three main and potentially linked problems: First, serial dependence at each point in time; second, spatial dependence at each point of time; and finally, unobservable effects

[5] LeSage & Pace (2008) additionally discuss the impact on regression results if either W^* or separate matrices for W^o and W^d are included in the spatial model.

specific to space and time periods. Recently, different approaches to deal with these problems have been proposed: Elhorst (2005) proposes a maximum likelihood estimator (MLE) for spatial lag panel models, Lee & Yu (2010) as well as Yu et al. (2008) study asymptotic quasi-maximum likelihood estimator (QMLE) properties. Fixed-Effect type IV based methods are applied for instance in Beenstock & Felsenstein (2007) as well as Korniotis (2009).

Building upon recent advances in using GMM methods for DPD processes, Bouayad-Agha & Vedrine (2010) as well as Kukenova & Monteiro (2009) suggest extensions to the Arellano-Bond (1991) and Blundell-Bond (1998) estimators by additional moment conditions for the inclusion of spatially lagged variables. The latter GMM approach has the advantage that it can easily deal with any type of right hand side endogeneity in terms of correlation of regressors with the composed error term. Using Monte Carlo simulations, Kukenova & Monteiro (2009) show that in the presence of endogenous covariates, the bias of the spatial lag (ρ) remains relatively low for GMM estimators, while the endogeneity bias arising from correlated regressors may grow large, if it is not corrected. In this general setup, the spatially augmented SYS-GMM estimator in the spirit of Blundell-Bond (1998) clearly dominates in terms of unbiasedness for many variables. Given their supportive finite sample properties, in the following we focus on SYS-GMM based methods in estimating a spatial dynamic panel model.

We start from a fairly general space-time dynamic specification, which accounts for time lags, spatial lags and time-spatial lags of the endogenous and exogenous variables as

$$\begin{aligned} y_{i,t} &= \alpha y_{i,t-1} + \rho \sum_{j \neq i} w_{ij} \times y_{j,t} + \phi \sum_{j \neq i} w_{ij} \times y_{j,t-1} \\ &\quad + \sum_{m=0} \beta_m x_{i,t-m} + \sum_{m=0} \gamma_m \sum_{j \neq i} w_{ij} \times x_{j,t-m} + \mu_i + \nu_{i,t} \\ with \quad & \nu_{i,t} = \lambda \sum_{i} w_{ij} \times \nu_{i,t} + \nu_{i,t}, \end{aligned} \tag{10}$$

where the endogenous $y_{i,t}$ and exogenous variable $x_{i,t}$ vary in the cross-section $i = 1, \ldots, N$ and time series $t = 1, \ldots, T$) dimension. $w_{i,j}$ are elements of a spatial weight matrix W, which we assume, is equal for all variables. The model contains two error components, namely a time-fixed unobservable effect μ_i for each cross-section unit and a time-varying error term $\nu_{i,t}$. The parameter ρ, ϕ, γ_m and λ measure the degree of spatial dependence in the model. Given that eq.(10) is a combination of a time and spatial autoregressive model, we need to ensure that the resulting process is stationary. As Kukenova & Monteiro (2009) point out, the stationarity restrictions in this model are stronger than the individual restrictions imposed on the coefficients of a pure spatial or time dynamic model. Here, covariance stationarity requires that the summation of the time autoregressive parameter α and the spatial lag coefficients ρ and ω satisfies the following condition:

$$|\alpha| < 1 - \rho\omega_{max} - \phi\omega_{max} \quad \text{if} \quad \rho, \phi \geq 0, \tag{11}$$

$$|\alpha| < 1 - \rho\omega_{min} - \phi\omega_{min} \quad \text{if} \quad \rho, \phi < 0, \tag{12}$$

where ω_{min} and ω_{max} are the smallest and highest characteristic root of the spatial weight matrix W. The spatial effects are then assumed to lie between $\frac{1}{\omega_{min}}$ and $\frac{1}{\omega_{max}}$.[6]

By adding restrictions to the parameters of the model, we can derive commonly known spatial model specifications with additional time dynamics such as the:

- spatial Durbin model (SDM) with $\lambda = 0$ and
- spatial Durbin error model (SDEM) with $\rho = 0$ and $\phi = 0$.

The difference between the two specifications is that besides spatial lags of the exogenous variables the SDEM allows only for spatial dependency in the error term $\nu_{i,t}$, while the SDM includes spatial lags of the dependent variable as well. In both model specifications, the additional spatial structure may be seen as a 'catch all' variable for cross-sectional dependence, which has not been captured by the spatial lags of the exogenous variables. The main difference between them is that the SDEM allows to a address the source of spatial dependence more carefully. In a hierarchical manner, further restrictions to both the SDM and SDEM can be imposed yielding the

- spatial lag (or autoregressive) model (SAR) with $\lambda = 0$ and $\sum_{m=1}\gamma_m = 0$ as a restricted form of the SDM $\rightarrow$ SAR and
- spatial error model (SEM) with $\rho = 0$, $\phi = 0$ and $\sum_{m=1}\gamma_m = 0$ as restricted form of the SDEM $\rightarrow$ SEM.

For the remainder of this paper we concentrate on specifications based on the spatial lag (SAR) and spatial Durbin model (SDM) approach.[7] Especially the latter model may be seen as a general modelling framework, which allows to test for the validity of different restrictions (see also Mur & Angulo, 2006, Elhorst, 2010).

[6] While most of the spatial econometrics literature constrains a spatial lag variable to lie between -1 and +1, this may be too restrictive given that for row-normalized spatial weight matrices the smallest eigenvalue can be bigger than -1.

[7] Details about time dynamic panel data estimators of the spatial error type model are e.g. given in Mutl (2006). The author derives a multi step estimation strategy for the Arellano-Bond (1991) type GMM estimator based on a consistent estimator of the spatial autoregressive parameter as proposed in Kapoor et al. (2007).

Similar to the concept of the lagged endogenous variable in time series analysis, the estimated spatial lag coefficients characterize a contemporaneous correlation between one cross-section observation and geographically proximate further units for the same variable. The spatial lag coefficient of the dependent variable, for instance, measures the effect of the weighted average of the neighborhood of cross-section i as $\sum_{j=1}^{n} w_{ij} \times y_{j,t}$.[8] Additionally, the inclusion of spatial lags of exogenous variables allows for the possibility of spatial spillovers from these variables to the endogenous regressor in the model.

With respect to the included time and spatial lags of the endogenous variables in eq.(10), we can distinguish between 'space-time recursive', 'dynamic' and 'simultaneous' combinations (see Anselin et al., 2007). In the following we restrict our analysis to the 'time-space simultaneous' model, which sets $\phi = 0$ but includes a time and spatial lag of the dependent variable. As Parent & LeSage (2009) point out, the latter restriction imposes $\omega = -\rho \times \alpha = 0$. We do not put any restrictions on the space-time dynamics of the exogenous variables included in our model. The choice of combination of time and spatial lags of the dependent variable has important implications for the formulation of valid moment conditions in the course of GMM estimation (see Bouayad-Agha & Vedrine, 2010).

Another important implication for empirical estimation of a DPD model is that the spatial lag term of the endogenous variable is correlated with the model's composed error term (see e.g. Kukenova & Monteiro, 2009). From an econometric point we thus have to treat this term as endogenous (in analogy to the time autoregressive component in the DPD context). The solution of GMM based estimators is then to obtain an estimate for ρ by means of appropriate instrumental variables in the context of the Arellano-Bond (1991) or Blundell-Bond (1998) SYS-GMM estimator. While the latter model only estimates the DPD model after first differencing to get rid of the unobservable individual effects μ_i, the latter approach tries to retain the level information of the variables by appropriate instrument selection.

Focusing on the Blundell-Bond (1998) SYS-GMM estimator, consistent instruments can be derived from the so-called 'standard' and 'stationarity' moment conditions. The former condition builds upon the seminal contribution in Anderson & Hsiao (1981) extended to the GMM framework by Arellano & Bond (1991), and estimate an aspatial DPD model as in eq.(2) transformed into first differences based on the following moment condition

[8] In the four-dimensional case of our migration flow data we may write $\sum_{r,s=1}^{n^2} w(i,j;r,s) \times y_{rs,t}$ with $ij \neq rs$. For the sake of notational simplicity we keep the two-dimensional (i,j)-index throughout the remainder of this section. However, the extension to the four dimensional space $(i,j;r,s)$ to measure origin-destination flows is straightforward.

$$E(y_{i,t-s}\,\Delta u_{i,t}) = 0 \quad t = 3,\ldots,T \quad s = 2,\ldots,t-1, \tag{13}$$

which employs sufficient lags of the endogenous variable in levels (starting from $y_{i,t-2}$) to serve as own instruments for $\Delta y_{i,t-1}$ in the first differenced equation (for details see Arellano & Bond, 1991). Additionally, the model can be augmented by appropriate instruments in first differences for the equation in levels, making use of the stationarity moment condition as (see e.g. Arellano & Bover, 1995, Ahn & Schmidt, 1995, and Blundell & Bond, 1998):

$$E(\Delta y_{i,t-1}\,u_{i,t}) = 0 \quad t = 3,\ldots,T. \tag{14}$$

The latter moment condition rests on certain assumptions about the initial period observation $y_{i,0}$ for panel data settings with only few time periods. Both in the pure panel time-series as well time-space panel literature the importance of the initial condition has been stressed (see e.g. Parent & LeSage, 2009). Rather than taken the initial period observation as given (see e.g. Elhorst, 2005, for an ML estimator with exogenous $y_{i,0}$), the literature typically assumes mean stationarity of $y_{i,0}$ based on the following assumption for its data generating process $y_{i,0} = \mu_i/(1-\alpha) + \xi_{i,0}$ with $E(\mu_i\,\xi_{i,0}) = 0$ and $E(\xi_{i,0}\,\nu_{i,t}) = 0$ (for further details see e.g. Hsiao, 2003).[9]

Further instruments beside those derived from sufficiently long time lags for the endogenous variable may also be derived from each explanatory variable x, where the set of valid instruments for each variable depends on its correlation with respect to the error term. The consistenty of moment conditions based on y and x can generally be tested with the help of overidentification tests such as Hansen's (1982) J-Statistic and the Difference-in Hansen's J-Statistic. The latter also allows to test on the validity of the level equation in the addition to the first difference equation ofthe Arellano-Bond (1991) GMM estimator. Augmenting the instrument set by transformations of $x_{i,t}$, then the following moment conditions apply for the first differenced equation:

– If $x_{i,t}$ is strictly exogenous,

$$E(x_{i,t\pm s}\,\Delta u_{i,t}) = 0 \quad t = 3,\ldots,T \quad \forall s. \tag{15}$$

[9] One also has to note that eq.(14) is derived as a linearization of the original stationarity condition proposed by Ahn & Schmidt (1995) from a set of non-linear conditions given by $E(\Delta y_{i,t-1} u_{i,T}) = 0$ for $t = 3,\ldots,T$.

– If $x_{i,t}$ is weakly endogenous (predetermined),

$$E(x_{i,t-s}\,\Delta u_{i,t}) = 0 \quad t = 3, \ldots, T \quad s = 1, \ldots, t-1. \tag{16}$$

– If $x_{i,t}$ is strictly endogenous,

$$E(x_{i,t-s}\,\Delta u_{i,t}) = 0 \quad t = 3, \ldots, T \quad s = 2, \ldots, t-1. \tag{17}$$

For the level equation of the SYS-GMM estimator in eq.(14) we may formulate valid moment conditions as:

– If $x_{i,t}$ is strictly exogenous,

$$E(\Delta x_{i,t}\,u_{i,t}) = 0 \quad t = 2, \ldots, T. \tag{18}$$

– If $x_{i,t}$ is weakly or strictly endogenous

$$E(\Delta x_{i,t-1}\,u_{i,t}) = 0 \quad t = 3, \ldots, T. \tag{19}$$

The SYS-GMM estimator then jointly employs both eq.(13) and eq.(14) for estimation. Though labeled 'system' GMM, the estimator in fact treats the (stacked) data system as a single-equation problem since the same linear functional relationship is believed to apply in both the transformed and untransformed variables as:

$$\begin{pmatrix} \Delta y \\ y \end{pmatrix} = \alpha \begin{pmatrix} \Delta y_{-1} \\ y_{-1} \end{pmatrix} + \rho \begin{pmatrix} \Delta WY \\ WY \end{pmatrix} + \beta \begin{pmatrix} \Delta X_{-1} \\ X_{-1} \end{pmatrix} + \begin{pmatrix} \Delta u \\ u \end{pmatrix} \tag{20}$$

Turning to the spatially augmented SYS-GMM specification, equivalent moment conditions can be defined for the spatial lag of each variable, conditional upon the underlying correlation of x and y. Since Kukenova & Monteiro (2010) have shown that the spatial lag of the dependent variable is endogenous, a natural means for estimation of the SYS-GMM estimator in eq.(14) is to build internal instruments using time lags for both the equation in first differences as well as levels. Moreover, as Bouayad-Agha & Vedrine (2010) point out, we can make use of spatially weighted exogenous $x_{i,t}$ variables to instrument $\sum_{i \neq j} w_{ij} \times y_{i,t-s}$. The latter attempt aims at identifying the exogenous part of the spatial lag variability by means of a spatially weighted model. Assuming strict exogeneity of current and lagged values for $x_{i,t}$, then the full set of potential moment conditions for the spatial lag of $y_{i,t-1}$ is given by

– First differenced equation:

$$E\left(\sum_{i\neq j} w_{ij} \times y_{i,t-s}\ \Delta u_{i,t}\right) = 0 \quad t = 3,\ldots,T \quad s = 2,\ldots,t-1, \tag{21}$$

$$E\left(\sum_{i\neq j} w_{ij} \times x_{i,t\pm s}\ \Delta u_{i,t}\right) = 0 \quad t = 3,\ldots,T \quad \forall s. \tag{22}$$

– Level equation:

$$E\left(\sum_{i\neq j} w_{ij} \times \Delta x_{i,t}\ u_{i,t}\right) = 0 \quad \text{for all} \quad s = 2,\ldots,T \quad \text{and} \quad t = 3,\ldots,T, \tag{23}$$

$$E\left(\sum_{i\neq j} w_{ij} \times \Delta y_{i,t}\ u_{i,t}\right) = 0 \quad t = 3,\ldots,T. \tag{24}$$

One has to note that the consistency of the SYS-GMM estimator relies on the validity of these moment conditions. Moreover, in empirical application we have to carefully account for the 'many' and/or 'weak instrument' problem typically associated with GMM estimation, since the instrument count grows as the sample size T rises. We thus put special attention to this problem and use restriction rules specifying the maximum number of instruments employed as e.g. proposed by Bowsher (2002) and Roodman (2009).

Accounting for spatial lags of the endogenous and exogenous variables finally leads to the SDM representation of the neoclassical migration model from eq.(2)

$$\begin{aligned} nm_{ij,t} \;=\; & \alpha nm_{ij,t-1} + \rho \sum_{j\neq i} w_{ij} \times nm_{ij,t-1} + \beta_1 \widetilde{wr}_{ij,t-1} + \gamma_1 \sum_{j\neq i} w_{ij} \times \widetilde{wr}_{ij,t-1} \\ & + \beta_2 \widetilde{ur}_{ij,t-1} + \gamma_2 \sum_{j\neq i} w_{ij} \times \widetilde{ur}_{ij,t-1} + \beta_3 \widetilde{ylr}_{ij,t-1} + \gamma_3 \sum_{j\neq i} w_{ij} \times \widetilde{ylr}_{ij,t-1} \\ & + \beta_4 \tilde{q}_{ij,t-1} + \gamma_4 \sum_{j\neq i} w_{ij} \times \tilde{q}_{ij,t-1} + \beta_5 \widetilde{hc}_{ij,t-1} + \gamma_5 \sum_{j\neq i} w_{ij} \times \widetilde{hc}_{ij,t-1} \\ & + \beta_6 \widetilde{\Delta p^l}_{ij,t-1} + \gamma_6 \sum_{j\neq i} w_{ij} \times \widetilde{\Delta p^l}_{ij,t-1} + \mu_{ij} + \nu_{ij,t} \end{aligned} \tag{25}$$

One finally has to note, that the regression parameters of the explanatory variables from eq.(25) cannot be interpreted directly as elasticities. As LeSage & Pace (2009) point out, unlike the parameters from a linear regression model, in models containing spatial lags of the explanatory or dependent variables the interpretation becomes richer and more complicated given that spatial regression models expand the information set to include information from neighboring regions/observations. The authors propose a categorization based on the average direct, indirect and total effect for each regressor. The latter effect measures both the direct effect in terms of the impact of changes in the ith observation for a variable x, as well as the indirect effect, which arises from spatial spillovers of changes in the observations for all neighbouring regions j. Since we are moreover dealing with a time dynamic specification, in order to get long-run total effects as a combination of time and space interdependencies, we additionally have to correct for α. Taking the spatial lag model (SAR) as an example, the average total long-run effect $\bar{M}(x)_{total,LR}$ of a variable x can then be calculated as

$$\bar{M}(x)_{total,LR} = n^{-1}\iota_n' S_x(W)\iota_n = (1 - \alpha - \rho)^{-1}\beta_x \tag{26}$$

where $S_x(W) = (I_n - \alpha - \rho W)^{-1}\beta_x$ and ι_n is a constant term vector of ones and I_n is an n-dimensional identity matrix for the number of observations. Different from the spatial lag model, in the case of the spatial Durbin model total long-run impacts arising from changes in a variable x exhibit a greater deal of heterogeneity due to the presence of the additional term $(W \times \gamma_x)$ in the calculation of the total effects with $S_x(W)$ given by $S_x(W) = (I_n - -\rho W)^{-1}(I_n\beta_x + W\gamma_x)$. Thus, while the SAR has a common global multiplier of all β_x, total effects over space and time have in the SDM have to be calculated taking all the individual parameters γ_x of the explanatory variable spatial lag terms into account (for details see e.g. LeSage & Pace, 2009, Elhorst, 2010).

3 Data and Stylized Facts

German interregional migration data tracks the movement of all residents in Germany. For the empirical analysis we use data for the 16 German states between 1991 and 2006. All monetary variables are denoted in real terms. A full description of the data sources is given in Table 1. We also take account for the time series properties of our data sample. Based on the Im-Pesaran-Shin (2003) and Pesaran (2007) panel unit roots test we find that for all variables we can reject the null hypothesis of non-stationarity for a wide range of different testing set-ups (detailed test statistics are reported in Alecke et al., 2010).

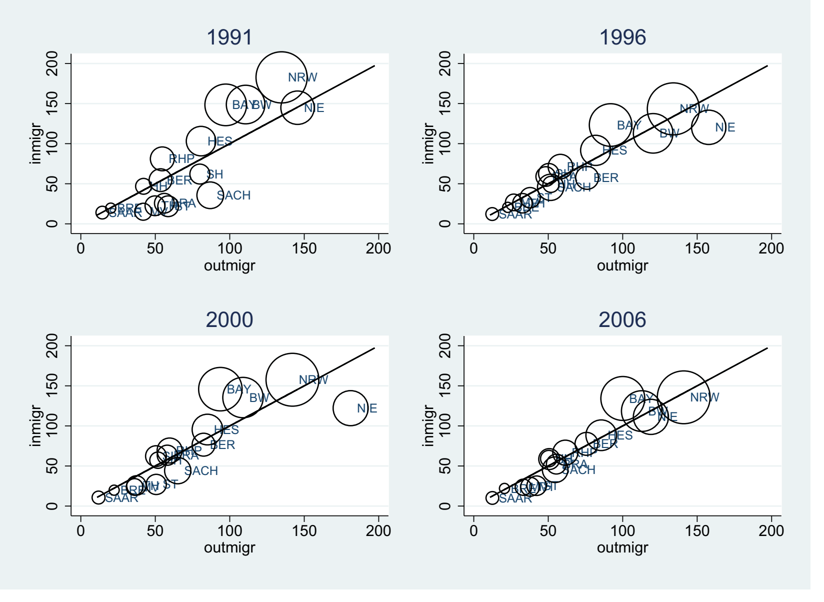
Turning to the stylized facts of German internal migration, figure 1 displays scatter plots for in- and outmigration flows of German states for 1991, 1996, 2001 and 2006. The interpretation of the figure is straightforward: The closer data points are to the diagonal (45-degree line), the more balanced are their net migration patterns: For data points on the diagonal net migration is equal to zero, while the area above (below) the diagonal indicate positive (negative) net migration flows. Data points closer to the origin inhibit smaller gross migration volumes and vice versa. The figure additionally accounts for

Table 1: Data description and source

Variable	Description	Source
$outm_{ijt}$	Total number of outmigration from region i to j	Destatis (2008)
inm_{ijt}	Total number of in-migration from region i to j	Destatis (2008)
$y_{i(j)t}$	Gross domestic product in region i and j respectively	VGRdL (2008)
$py_{i(j)t}$	GDP deflator in region i and j respectively	VGRdL (2008)
$ylr_{i(j)t}$	Real labour productivity defined as $(yl_{j,t} - py_{j,t})$	VGRdL (2008)
$pop_{i(j)t}$	Population in region i and j respectively	VGRdL (2008)
$emp_{i(j)t}$	Total employment in region i and j respectively	VGRdL (2008)
$unemp_{i(j)t}$	Total unemployment in region i and j respectively	VGRdL (2008)
$ur_{i(j)t}$	Unemployment rate in region i and j respectively defined as $(unemp_{i,t} - emp_{i,t})$	VGRdL (2008)
$pcpi_{i(j)t}$	Consumer price index in region i and j respectively based on Roos (2006) and regional CPI inflation rates	Roos (2006), RWI (2007)
$wr_{i(j)t}$	Real wage rate in region i and j respectively defined as wage compensation per employee deflated by $pcpi_{i(j)t}$	VGRdL (2008)
$q_{i(j)t}$	Labour market participation rate in region i and j respectively defined as $(emp_{i,t} - pop_{i,t})$	VGRdL (2008)
$hc_{i(j)t}$	Human capital index as weighted average of: 1.) high school graduates with university qualification per total pop. between 18-20 years ($hcschool$), 2.) number of university degrees per total pop. between 25-30 years ($hcuni$), 3.) share of employed persons with a university degree relative to total employment ($hcsvh$), 4.) number of patents per pop. ($hcpat$): $hc = 0,25 * hcsvh + 0,25 * hcschool + 0,25 * hcuni + 0,25 * hcpat$	Destatis (2008)
$pland_{i(j)t}$	Average price for building land per qm in i and j, in Euro	Destatis (2008)

Note: All variables in logs. For Bremen, Hamburg and Schleswig-Holstein no consumer price inflation rates are available. We took the West German aggregate for these states, this also accounts for Rhineland-Palatine and Saarland until 1995. In order to construct time series for the price of building land (p^l) no state level data before 1995 was available. Here we used the 1995-1999 average growth rate for each state to derive the values for 1991-1994. For Hamburg and Berlin only very few data points were available. Here we took the price per qm in 2006 and used national growth rates to construct artificial time series.

Figure 1: Weighted scatter plots for state level in- and out-migration



Note: BW = Baden-Wuerttemberg, 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

population size by weighting the size of the data point (circle) with its absolute population value for the respective period. The figure confirms the tendency that populous states on average have higher absolute gross migration flows (moving towards the upper right of the scatter plot).

Starting in 1991, figure 1 shows that all East German states are clearly below the 45-diagonal line indicating population losses with Saxony being hit the most. This underlines that alongside economic transformation the East German states have witnessed a substantial loss of population through East-West net out-migration West German states are either on or above the diagonal line indicating net migration inflows. This strong migration response to German re-unification is less present in 1996, where all state values are much closer to the diagonal. However, in 2001 a second wave of increased East-West out-migration can be observed.[10] Towards the sample end in 2006 interregional migration flows among German states again seem to be more balanced than in the early 1990s and around 2001.

Analyzing migration flows in the context of network structures allows to identify the (most) significant flows among the full migration matrix for a given time period. As Kipnis (1985) points out, there are different methods to define threshold values for significant flows, ranging from single arbitrary measures to complex index computations such as flow maximization. In the following, we highlight the 10 % and 25 % largest net flows among all migratory movements for a single year of our data sample. The results for the years 1991 and 2001 are shown in figure 2. For the year 1991 among the 10 % most prominent flows are East-West migratory movements directed to the large West German states North-Rhine Westphalia (NRW), Baden–Wurttemberg (BW) and Bavaria (BAY). Next to the dominant East-West pattern there are also significant North-South movements with large net out-migration flows from Schleswig–Holstein (SH) and Lower Saxony (NIE). If we additionally include major migration flows up to the 25 % level in the upper right graph of figure 2, the distinct East-West net out-migration trend becomes even more visible. Though the latter trend is also shown for migratory movements in 2001, now flows are much more directed towards the southern states in Germany. This may potentially be a response to their much better economic performance throughout the late 1990s compared to other (Western) states such as North-Rhine Westphalia.

Searching for empirical support of the theoretical network concepts in terms of the intervening opportunities and competing destinations model, figure 2 shows the following picture: Taking net migration flows for Saxony-Anhalt (ST) in 2001 as an example, we see that the state has a large net outflow to Bavaria (among the 10 % most significant flows). However, not only Saxony-Anhalt also the Eastern (Brandenburg, Saxony, Thuringia) and Western states (Lower Saxony) in the geographical neighborhood of Saxony-Anhalt have significant outflows directed to Bavaria. If we take the common border criteria as a measure of spatially linked regions, the spatial autocorrelation pattern inhibit in these flows is well captured by the origin-related weighting matrix in the definition eq.(5) and eq.(6) reflecting the intervening opportunities approach of migration modelling. Likewise, if we look at the 10 % significant outflows of Brandenburg (BRA) for 2001, these are both directed to the southern states Bavaria and Baden-Wurttemberg, which themselves

[10] The strong negative outlier effect of the West German state Lower Saxony (Niedersachsen) is due to the specific migration pattern of German resettlers from Eastern and Southern Europe (Spaetaussiedler), which are legally obligated to first move to the central base Friesland in Lower Saxony and only subsequently migrate to other states. Hence, taking also external migration for Niedersachsen into account this negative effect vanishes.

share a common border. The underlying network paradigm can now be described in terms of a destination-based weighting scheme according to eq.(7) and eq.(8) reproducing the migrant's choice process in line with the competing destination model. Analogously, we can identify a range similarly directed origin-destination flows in accordance to the intervening opportunities and competing destinations framework.

The graphical presentation of major migration flows in figure 2 already provides a first indication of importance to properly account for spatial dependence. As a more formal test we use the Moran's I statistic to detect spatial autocorrelation for values of a particular variable.[11]. Inference for spatial autocorrelation is carried out on the basis of the asymptotically normal standardized $Z(I)$-value. The results of the test statistic together with the corresponding $Z(G)$-value of the Getis-Ord G-statistic for the dependent variable (net migration flows) are given in table 2.

To compute the test statistics we also need an operationalization of the spatial weighting matrix W^*. We compare the empirical performance of two types of matrices: 1.) Spatial links are defined by a common border between states, 2.) An optimal distance criterion based on a maximization procedure of the Getis & Ord (1992) $G_i(d)$-statistic (details are given in the appendix). Distance between to states is thereby calculated as the road distance in kilometers between a population weighted average of major city pairs for each pairwise combination of regions. A detailed list of the cities included in the sample and the resulting distance matrix are given in the appendix. We also allow that the optimal distance (d) potentially varies with each year of the sample period from 1991 to 2006. As the table shows, for both types of weighting matrices we identify significant spatial autocorrelation effects among net migration flows for all years. Similar results were also obtained for the exogenous variables.

We can give the Moran's I statistic a graphical interpretation to clarify to spatial association among individual values for each variable (see Ward & Gleditsch, 2008). Using a scatter plot for a standardized variable $\breve{y}$ (with $\breve{y} = [y - \bar{y}]/sd(y)$) against its average neighbors $\breve{y}^s$ the distribution of observations in the four quadrants around the mean of $\breve{y}$ and $\breve{y}^s$ captures a picture of the spatial association of the variable y. If there is no spatial clustering the individual values of y^s should not systematically vary with y. On the contrary, for positive spatial association observations above (below) the means of y should correlate with high (low) values for y^s. Fitting a regression line to this scatter plot, its slope coefficient shows the value for Moran's I correlation given the original variable y and the weighting matrix W^*. In figure 3 we present such scatter plots for our

[11] As a related measure, we also use the (global) Getis-Ord G-statistic.

Figure 2: Prominent migration flows between German states in 1991/2001

(a) 1991:10 %

(b) 1991:25 %

(c) 2001:10 %

(d) 2001:25 %

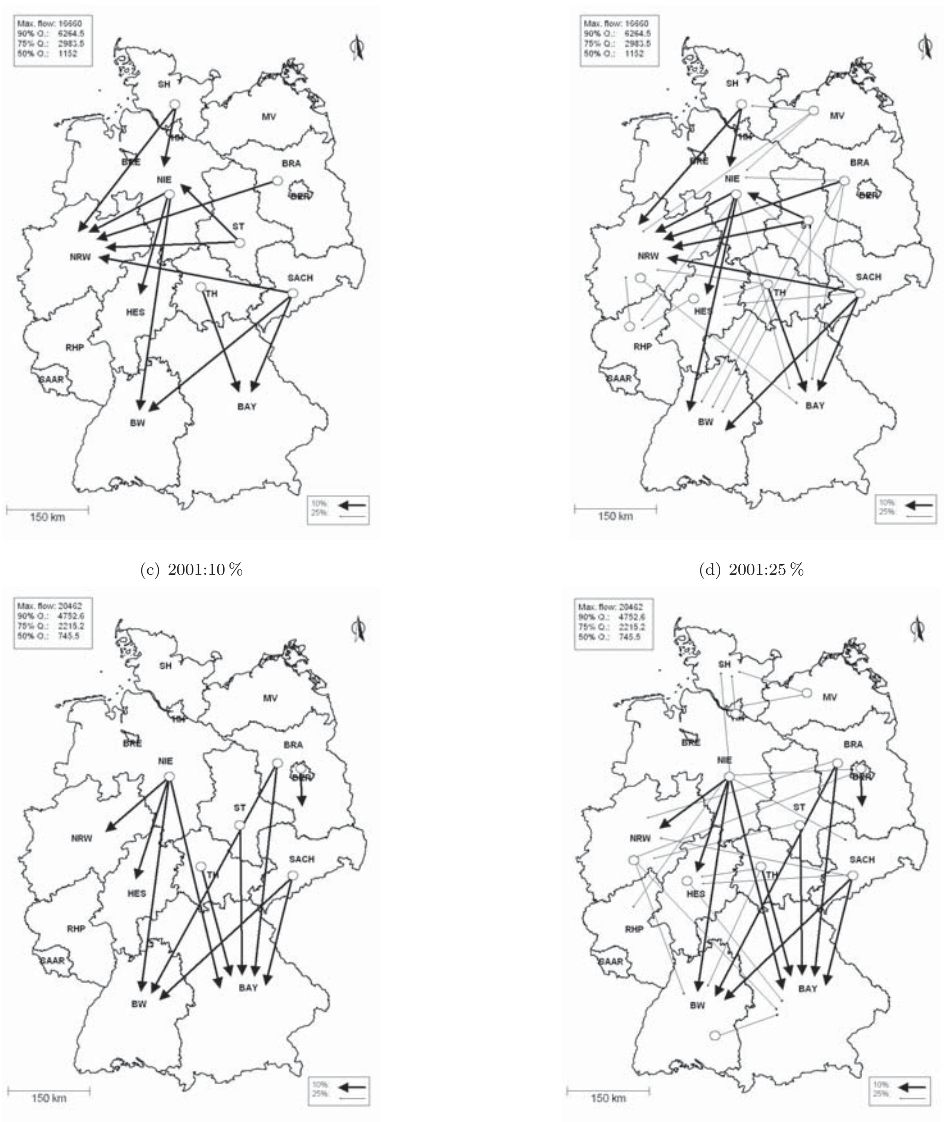


Table 2: $Z(I)$- and $Z(G)$-Statistic for inter-regional net migration rate with alternative weighting matrices

	Common Border				**Optimal distance**				
year	$Z(I)$	P-value	$Z(G)$	P-value	d	$Z(I)$	P-value	$Z(G)$	P-value
1991	23.33***	(0.00)	15.05***	(0.00)	250	16.97***	(0.00)	12.22***	(0.00)
1992	21.62***	(0.00)	10.74***	(0.00)	250	14.99***	(0.00)	8.42***	(0.00)
1993	16.52***	(0.00)	5.53***	(0.00)	275	14.87***	(0.00)	7.22***	(0.00)
1994	12.74***	(0.00)	3.44***	(0.00)	275	10.14***	(0.00)	40.8***	(0.00)
1995	10.47***	(0.00)	2.98***	(0.00)	350	11.62***	(0.00)	4.89***	(0.00)
1996	9.96***	(0.00)	3.20***	(0.00)	350	11.30***	(0.00)	4.81***	(0.00)
1997	10.44***	(0.00)	3.85***	(0.00)	350	11.14***	(0.00)	5.08***	(0.00)
1998	14.41***	(0.00)	4.98***	(0.00)	350	14.88***	(0.00)	7.06***	(0.00)
1999	17.02***	(0.00)	6.85***	(0.00)	275	14.31***	(0.00)	7.68***	(0.00)
2000	19.07***	(0.00)	9.05***	(0.00)	275	15.32***	(0.00)	9.38***	(0.00)
2001	20.39***	(0.00)	10.79***	(0.00)	275	16.42***	(0.00)	10.99***	(0.00)
2002	19.19***	(0.00)	9.39***	(0.00)	275	19.92***	(0.00)	10.79***	(0.00)
2003	17.80***	(0.00)	7.26***	(0.00)	275	15.48***	(0.00)	8.26***	(0.00)
2004	17.57***	(0.00)	6.87***	(0.00)	275	16.93***	(0.00)	9.16***	(0.00)
2005	17.91***	(0.00)	6.09***	(0.00)	275	15.74***	(0.00)	7.51***	(0.00)
2006	18.87***	(0.00)	6.08***	(0.00)	250	15.08***	(0.00)	6.74***	(0.00)

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. $Z(I)$ and $Z(G)$ are standardized test statistics for Moran's I and Getis-Ord G respectively. d denotes the optimal distance maximizing the absolute sum of the (local) $G_i(d)$-statistic and is measured in kilometers per fixed units of 25km each.

net migration flows and its spatial lag together with the slope of Moran's I for the four sample periods 1991, 1996, 2001 and 2006. The figure shows that for all years we find a highly significant positive slope regression coefficient measuring spatial autocorrelation in migration data.

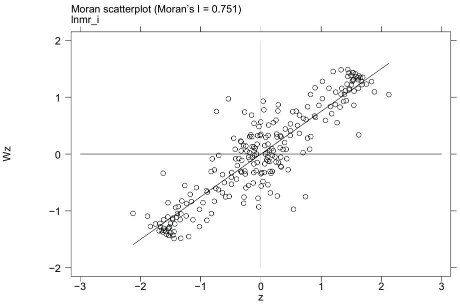
4 Empirical Results

The regression results for the aspatial benchmark model from eq.(2) and subsequent spatial extensions are shown in table 3. Beside the spatial lag specification of the extended SYS-GMM approach we also report regression results from standard SYS-GMM estimation after variables have been spatially filtered using a method proposed by Getis (1995). Spatial filtering treats the spatial dependence in the data as a nuisance parameter and as entirely independent of the underlying 'spaceless' model to be estimated.[12] For both the aspatial, spatial filtered and spatial lag regression models we report the estimated variable coefficients together with two important types of post estimation tests: A primary concern in model applications including an IV/GMM approach is to carefully check for

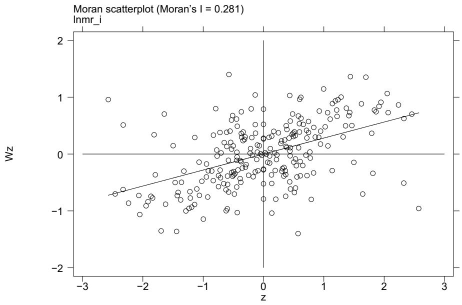
[12] A detailed description of the the spatial filtering approach based on Getis (1995) is given in the appendix.

Figure 3: Moran scatter plot for net migration and various years

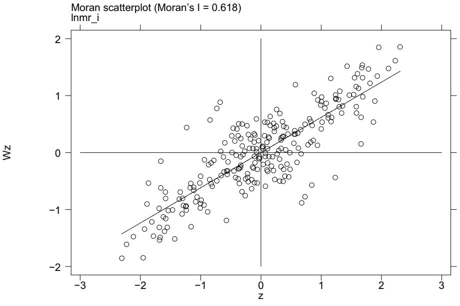
(a) 1991



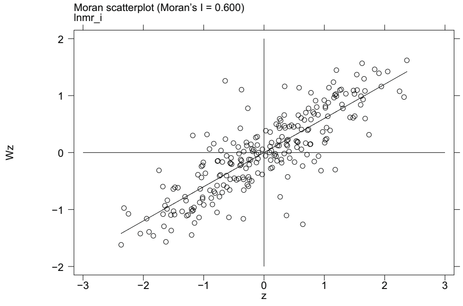
(b) 1996



(c) 2001



(d) 2006



the instrument consistency of the chosen specification – e.g. given that in the unrestricted GMM framework the number of IVs may become large relative to the total number of observations. We therefore guide instrument selection based on the widely applied Sargan (1958) / Hansen (1982) overidentification test (J-Statistic) as well as the C-statistic (or also 'Diff-in-Sargan/Hansen') as numerical difference of two J-Statistics isolating IV(s) under suspicion (see Eichenbaum et al., 1988, for details). The J-Statistic is the value of the GMM objective function, evaluated at the efficient (in our case two-step) GMM estimator.

In an overidentified model the J-Statistic allows to test whether the model satisfies the full set of moment conditions, while a rejection implies that IVs do not satisfy orthogonality conditions required for their employment. In similar veins the C-Statistic is typically employed to judge about the consistency of the instrument set in the level equation as extension of the standard Arellano-Bond (1991) approach in first differences. A second type of post estimation testing explicitly looks at the likely bias introduced by spatial autocorrelation in the residuals of the empirical models. Here we calculate Moran's I statistic for both each individual year and as a joint measure for the whole sample period, as well as a Wald GMM test for spatial autocorrelation in the model's error term (see Kelejian & Prucha, 1999, Egger et al., 2005). Egger et al. (2005) show on the basis of Monte Carlo simulations that GMM based Wald tests tend to perform well irrespective of the underlying error distribution and thus are a well-equipped alternative to the frequently used Moran's I test under GMM circumstances.[13] Both post estimation tests give important hints to identify misspecifications in the empirical modelling approach.

[13] We use a rather simple way to compute an overall measure of Moran's I for panel data. Alternative ways exploiting the spatiotemporal dimension of the data are e.g. discussed in Lopez et al. (2009).

Table 3: Estimation results of the dynamic migration model using spatial filtering and spatial lag model

DPD model:	**Aspatial**	**Spatial Filtering**		**Spatial Lag Model**			
Weights matrix:	None	Border	Distance	Border	Distance	Border	Distance
	I	II	III	IV	V	VI	VII
$nm_{ij,t-1}$	0.51***	0.39***	0.36***	0.26***	0.30***	0.43***	0.40***
	(0.044)	(0.072)	(0.048)	(0.058)	(0.053)	(0.071)	(0.063)
$\widetilde{wr}_{ij,t-1}$	0.21**	0.33**	0.39***	0.39***	0.36***	0.32***	0.30***
	(0.042)	(0.141)	(0.121)	(0.118)	(0.108)	(0.111)	(0.105)
$\widetilde{ur}_{ij,t-1}$	-0.16***	-0.09	-0.09	-0.01	-0.04	-0.08*	-0.08**
	(0.042)	(0.077)	(0.067)	(0.057)	(0.045)	(0.046)	(0.043)
$\Delta\widetilde{ylr}_{ij,t-1}$	0.55***	0.26***	0.37***	0.38***	0.42***	0.51***	0.48***
	(0.062)	(0.078)	(0.079)	(0.068)	(0.069)	(0.066)	(0.067)
$\tilde{q}_{ij,t-1}$	0.43**	-0.05	-0.06	-0.16	0.09	0.17	0.25
	(0.207)	(0.168)	(0.174)	(0.235)	(0.216)	(0.243)	(0.201)
$\widetilde{hc}_{ij,t-1}$	-0.03**	-0.02*	-0.01	-0.02*	-0.02*	-0.03***	-0.03***
	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
$\widetilde{\Delta p^l}$	0.21***	0.09**	0.11**	0.12***	0.12***	0.17***	0.17***
	(0.056)	(0.041)	(0.050)	(0.043)	(0.042)	(0.044)	(0.039)
ρ				0.76***	0.58***	0.31**	0.34***
				(0.110)	(0.107)	(0.147)	(0.127)
Instrument diagnostics							
Hansen J-Statistic	23.2 (15)	41.4 (15)	46.9 (15)	51.9 (19)	40.1 (19)	27.3 (17)	27.5 (18)
P-value of $J-Stat. > 0.05$	Passed	Failed	Failed	Failed	Failed	Passed	Passed
C-Stat. for IV in LEV	8.2 (7)	24.5 (7)	19.0 (7)	23.4 (8)	17.1 (8)	18.6 (8)	10.7 (8)
P-value of $C-Stat. > 0.05$	Passed	Failed	Failed	Failed	Failed	Failed	Passed

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level. Standard errors (in brackets) are based on Windmeijer's (2005) finite-sample correction. The joint Moran's I statistic based on the average of individual values distributed with zero mean and a standard deviation of $1/\sqrt{m}$, where m is the number of included values. For the efficient Wald GMM test we run an auxiliary regression on each two-step GMM residual as $u = \kappa W u + \epsilon$ and test for the significance of κ according to a Wald F-test with $H_0 : \kappa = 0$ as in Egger et al. (2005).

Table 3 (continued): Estimation results of the dynamic migration model using spatial filtering and spatial lag model

DPD model:	**Aspatial**	**Spatial Filtering**		**Spatial Lag Model**			
Weights matrix:	Non	Border	Distance	Border	Distance	Border	Distance
	I	II	III	IV	V	VI	VII
Moran's I for residuals							
$Z(I)_{1994}$	7.12***	-3.38***	-1.82**	-3.53***	0.08	2.02**	3.27***
$Z(I)_{1995}$	2.55***	-4.34***	-0.98	-4.00***	0.58	-1.36*	1.81**
$Z(I)_{1996}$	4.83***	-2.41***	-1.25	-1.77**	0.51	1.90**	2.13**
$Z(I)_{1997}$	2.32**	-2.84***	-1.53*	-2.92***	-0.72	-0.36	0.54
$Z(I)_{1998}$	5.67***	-3.75***	0.03	-3.23***	2.42***	1.31	5.03***
$Z(I)_{1999}$	5.15***	-3.25***	-3.05***	-2.13**	-0.19	1.29	1.84**
$Z(I)_{2000}$	12.67***	-0.61	0.88	-0.42	1.50*	6.97***	4.31***
$Z(I)_{2001}$	11.74***	-2.40***	-0.38	-1.43*	1.78**	5.30***	4.16***
$Z(I)_{2002}$	7.63***	-1.56*	-0.59	-1.78**	1.06	1.80**	3.05***
$Z(I)_{2003}$	7.14***	-2.83***	-2.87***	-1.51*	1.63*	2.05**	4.18***
$Z(I)_{2004}$	7.94***	-1.31*	-0.99	-1.45*	1.71**	2.72***	4.73***
$Z(I)_{2005}$	10.83***	-2.19**	-0.58	-0.19	6.24***	6.25***	10.39***
$Z(I)_{2006}$	8.00***	-1.98**	-2.51***	-0.13	1.56*	3.70***	4.19***
Moran's I (joint)	**7.19***	**-2.52***	**-1.20***	**-1.88***	**1.39***	**2.58***	**3.81***
Efficient Wald GMM	1145.4***	18.7***	7.3**	63.4***	11.1***	355.8***	213.3***
No. of obs.	3120	3120	3120	3120	3120	3120	3120

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level. Standard errors (in brackets) are based on Windmeijer's (2005) finite-sample correction. The joint Moran's I statistic based on the average of individual values distributed with zero mean and a standard deviation of $1/\sqrt{m}$, where m is the number of included values. For the efficient Wald GMM test we run an auxiliary regression on each two-step GMM residual as $u = \kappa W u + \epsilon$ and test for the significance of κ according to a Wald F-test with $H_0 : \kappa = 0$ in the spirit of Egger et al. (2005).

The aspatial migration equation in column I of table 3 serves as a general benchmark for the spatially augmented specifications. For most variables we find statistically significant coefficients in line with the theoretical predictions of the neoclassical migration model, e.g. a real wage increase in region i relative to region j leads to increased net in-migration flows, while a relative increase in the regional unemployment rate has the opposite effect. Turning to the post estimation tests, the reported J- and C-Statistic based instrument diagnostic tests for the aspatial model in table 3 report the outcome of a downward testing approach to reduce the number of included instruments in such a way that both critical J- and C-Statistic criteria are satisfied (with P-value for $J_{crit.} > 0.05, C_{crit.} > 0.05$).

The applied downward testing approach thereby has two distinct features: First, we reduce the total number of IVs by using collapsed rather than uncollapsed instruments as suggested in Roodman (2009). Second, based on the collapsed IV specification we finally reduce the number of instruments using a C-statistic based algorithm, which is able to subsequently identify those IV subsets with the highest test results (see Mitze, 2009, for details). This gives us a model with a total of 15 overidentifying restrictions, which passes the Hansen J-Statistic criteria. We use this instrument set as benchmark for the spatially augmented regression specifications. Next to the J-Statistic, the aspatial benchmark model in column I also passes the C-Statistic criterion for the chosen IV set in the level equation, which supports our modelling strategy to use the generally more efficient SYS-GMM approach compared to standard GMM in first differences. However, contrary to the IV diagnostic tests the results for tests of spatial dependence in the residuals (both Moran's I and Wald GMM) clearly reject the null of independent observations for each individual year as well as for the joint sample period.

The latter poor result for the aspatial model calls for an explicit account of the spatial dimension in our DPD model context. We start with the spatial filtering approach and estimate the model in eq.(2) both on the grounds of a common border and optimal distance based weighting schemes in column II and III of table 3 respectively. The estimated regression coefficients show some significant changes relative to the aspatial specification. First, the estimated coefficient of the lagged endogenous variable is substantially reduced though still significant. On the contrary, the parameter for regional wage rate differentials turns out to be higher. However, if we calculate the implied long-run elasticity for this variable in table 4 we see that due to the two opposed effect the long-run elasticity of regional real wage rate differentials with respect to net migration flows remains roughly in line with the aspatial benchmark for the spatial filtered specifications (see table 4).

However, interestingly the effect of unemployment rate differentials though being still negative turns out statistically insignificant in the estimated models based on the Getis filtering approach. The results are broadly in line with recent findings for internal US migration rates reported in Chun (2008): Here the author finds that the magnitude of the unemployment rate coefficient drops significantly, when moving from an aspatial to a spatial filtered (origin constrained) migration model. One way to interpret this result is that unemployment rate differences in the aspatial model also capture the omitted variable effect of other relevant economic and social factors, which arise through network structures in migration flows (as for instance outlined in the competing destinations model). If we appropriately account for network effects, the variable loses predictive power. One likely example is the provision of cultural goods, which is typically negatively correlated with the unemployment rate, but may well be an alternative spatially heterogeneous attractor of migration flows – especially for highly educated prospective migrants.

Looking at the post estimation tests, the optimal distance based weighting matrix shows a much better performance compared to the common border specification as already found for the filtering exercise of the endogenous variable reported in table 3. For the spatial filtering approach in column III only some few years still show significant spatial autocorrelation patterns when applying Moran's I to the model's residuals, while the border based approach in column II is less effective. However, both filtered specifications do not pass the joint Moran's I test as well as fail to pass the standard J- and $C-$Statistic based IV diagnostic tests based on the same set of IVs as the aspatial benchmark (the latter results are rather robust to changes in the IV set).

If we look at the estimation results of the dynamic spatial lag regression approach in column IV and V they are both qualitatively and quantitatively much in line with the spatial filtering approach. Total long-run effects for each explanatory variable are also reported in table 4. One advantage of the spatial regression compared to the spatial filtering approach is that we can additionally give an interpretation for the parameter estimate for the spatial lag variable (ρ):[14] Here the positive coefficient sign hints at positive spatial autocorrelation effects in German migration flows, giving rise to spillover effects motivated by theories of intervening opportunities and competing destinations.

With respect to the post estimation test for spatial autocorrelation in the residuals the results for the spatial lag model mirror the findings of the spatial filtering approach that the optimal distance weighting matrix is much better equipped to filter out spatial dependences from the model. However, again the models fail to pass the J- and C-Statistic

[14]However, as Kosfeld & Lauridsen (2009) point out, that one must be cautious when wishing to interpret the autoregressive parameter (ρ) as an autocorrelation coefficient in time series analysis. While for maximum likelihood estimation the likelihood function ensures that the autoregressive parameter lies within a fixed interval, in IV estimation there is no guarantee for the latter leading to uncertain areas of interpretation and inference.

criterion based on the IV set of the aspatial benchmark augmented by IVs for the spatial lag variable.[15] In column VI and VII we therefore try to reduce the number of instruments for the spatial lag variable using the C-Statistic based downward testing approach. In column VII we manage to reduce the number of instruments so that both the J- and C-Statistic criterion is passed. However, this reduces the estimated coefficient for the spatial lag variable (ρ) and leads to a higher degree of remaining spatial autocorrelation in the model's residuals indicated by Moran's I values. As the long-run total effects for the spatial lag model from column VII in table 3 show for instance, differences in the wage rate and regional labour productivity have a higher impact compared to the aspatial benchmark specification, when accounting for spatial dependencies in the model.

Table 4: Total effects ($\bar{M}(x)_{total,LR}$) for the explanatory regressors in the empirical migration model

Model:	**Aspatial**	**Spatial Filtering**	**Spatial Lag Model**
W^*:	None	Distance	Distance
	I	III	VII
$\widetilde{wr}_{total,LR}$	0.43	0.61	1.15
$\widetilde{ur}_{total,LR}$	-0.33	-0.14	-0.31
$\Delta\widetilde{ylr}_{total,LR}$	1.12	0.58	1.85
$\tilde{q}_{total,LR}$	0.88	-0.09	0.96
$\widetilde{hc}_{total,LR}$	-0.06	-0.02	-0.12
$\widetilde{\Delta p}^{l}_{total,LR}$	0.43	0.17	0.65

Note: Calculated according to $\bar{M}(x)_{total,LR}$ from eq.(26) for $x = 1, \ldots, 6$.

The latter result may hint at the potential role played by spatial spillover effects from other variables besides the dependent one. We thus test for the improvement in the empirical results if we estimate the unconstrained spatial Durbin model according to eq.(25). The regression results are shown in table 5. Here we only focus on weighting matrices derived from optimal distances. The results show, that most of the spatial lags of the explanatory variables turn out to be significant: For instance, a rise in the unemployment rate differential in neighbouring regions shows to have a positive effect on the region's net inmigration rate. The opposite holds for changes in labour productivity growth and the labour participation rate in neighbouring regions.

We see that the spatial Durbin model in column VIII is also very successful in capturing spatial dependence in the migration equation. As first specification the model passes the joint Moran's I test for spatial autocorrelation over the full sample period as well as the

[15]Therefore the number of overidentifying restrictions increases from 15 to 19.

GMM-based Wald test to detect spatially autocorrelation in the error terms. However, given the large number of instruments employed, the model is not able to pass the essential IV diagnostic tests. If we reduce the number of instruments, we come back to the old problem that the model passes the J test, but at the same time the performance in terms of capturing the existing spatial dependence in the model significantly worsens. Taken together, this may hint at a certain trade-off between IV consistency and effective spatial modelling for both the spatial filtering as well as spatial regression approaches (both the spatial lag as well as spatial Durbin model).

As a final exercise we test for the impact on the empirical results if we combine the spatial filtering and spatial regression approach in the following way:

$$Y_t = \alpha Y_{t-1} + \rho W_t Y_t + \sum_{j=0}^{k} \beta_j^{*\prime} X_{t-j}^{*} + u_t, \tag{27}$$

Here we use unfiltered values for the endogenous variable and account for spatial autocorrelation in terms of the spatial lag variable $W_t Y_t$, moreover we use spatially filtered exogenous variables X^*. The empirical specification in column XI and XII have the potential advantage that they reduce the number of instrument counts and multicollinearity among regressors since no spatial lags besides the dependent variable are included. If the researcher's primary interest is to get an interpretation of spatial spillovers from the parameter coefficient of the endogenous variable, while at the same time retain well-behaved residuals, this mixed filtering-regression approach may be a feasible strategy.

Although the mixed model with the IV set from the benchmark specification first fails to pass the J- and C-Statistic criteria it is remarkably good in terms of capturing spatial dependence in the structural parameters of the model. As the annual Moran's I values show only in very few year there some evidence of remaining spatial autocorrelation. Moreover, as it was the case for the spatial Durbin model, the mixed filtering-regression specification passes the joint Moran's I test for spatial autocorrelation over the full sample period. Finally, in column XII we are able to reduce the IV set in such a way that the model also passes the standard IV diagnostic tests for the given J- and C-Statistic criteria.

Additionally, this improvement in the standard tests for instrument validity goes in line with a good performance in properly capturing spatial dependence: Only rarely the annual Moran's I identifies remaining spatial autocorrelation in the residuals, which is among the best empirical track record among all rival specification. The model also passes the Moran's I based test statistic for the whole sample period as well as the GMM-based Wald test for spatial autocorrelation in the model's error term. Finally, the model also passes the stability condition from eq.(11) requiring $|\alpha + \rho| < 1$, while model specifications

Table 5: Estimation results for spatial Durbin model and a mixed spatial regression-filtering model

DPD model:	**Spatial Durbin Model**			**Mixed Filt. & Reg.**	
Weights matrix:	Distance VIII	Distance IX	Distance X	Distance XI	Distance XII
$nm_{ij,t-1}$	0.31***	0.23***	0.20***	0.35***	0.20**
	(0.043)	(0.078)	(0.073)	(0.068)	(0.085)
$\widetilde{wr}_{ij,t-1}$	0.36*	0.22	-0.60	0.46***	0.68***
	(0.215)	(0.269)	(0.485)	(0.138)	(0.151)
$W \times \widetilde{wr}_{ij,t-1}$	0.16	0.28	1.24**		
	(0.283)	(0.348)	(0.641)		
$\widetilde{ur}_{ij,t-1}$	-0.31**	-0.16	-0.58***	-0.02	-0.01
	(0.123)	(0.140)	((0.195)	(0.061)	(0.054)
$W \times \widetilde{ur}_{ij,t-1}$	0.56***	0.31**	0.84***		
	(0.152)	(0.156)	(0.264)		
$\Delta\widetilde{ylr}_{ij,t-1}$	0.67***	0.70***	0.27*	0.37***	0.63***
	(0.129)	(0.137)	(0.145)	(0.099)	(0.108)
$W \times \Delta\widetilde{ylr}_{ij,t-1}$	-0.44***	-0.53***	0.11		
	(0.149)	(0.159)	(0.182)		
$\tilde{q}_{ij,t-1}$	0.46	0.95***	1.16**	-0.05	0.05
	(0.306)	(0.358)	(0.492)	(0.223)	(0.182)
$W \times \tilde{q}_{ij,t-1}$	-0.81***	-1.02***	-1.30***		
	(0.275)	(0.364)	(0.488)		
$\widetilde{hc}_{ij,t-1}$	-0.02	-0.06	-0.12***	-0.02	-0.01
	(0.038)	(0.041)	(0.041)	(0.014)	(0.026)
$W \times \widetilde{hc}_{ij,t-1}$	0.02	0.05	0.10**		
	(0.041)	(0.043)	(0.044)		
$\widetilde{\Delta p^l}$	-0.01	0.23*	1.29***	0.15***	0.18***
	(0.036)	(0.121)	(0.251)	(0.055)	(0.061)
$W \times \widetilde{\Delta p^l}$	0.04	-0.27	-2.13***		
	(0.062)	(0.196)	(0.418)		
ρ	0.80***	0.76***	0.80***	0.70***	0.79***
	(0.081)	(0.127)	(0.116)	(0.177)	(0.123)
Hansen J-Statistic	121.6 (48)	71.2 (28)	32.3 (22)	61.6 (18)	25.8 (16)
P-value of $J - Stat. > 0.05$	Failed	Failed	Passed	Failed	Passed
C-Stat. for IV in LEV	25.8 (14)	26.5 (12)	17.5 (9)	27.3 (8)	4.1 (7)
P-value of $C - Stat. > 0.05$	Failed	Failed	Failed	Failed	Passed
$Z(I)_{1994}$	0.417	1.04	1.21	0.47	0.11
$Z(I)_{1995}$	0.33	1.22	1.26	0.02	1.17
$Z(I)_{1996}$	1.41*	2.22**	1.51*	0.69	1.42*
$Z(I)_{1997}$	-0.69	0.59	2.83***	-0.44	0.67
$Z(I)_{1998}$	2.38***	3.83***	4.04***	1.38*	2.25**
$Z(I)_{1999}$	-1.63	-0.23	0.91	-1.81**	-1.61*
$Z(I)_{2000}$	-0.54	0.67	5.03***	0.13	-0.23
$Z(I)_{2001}$	0.58	1.41*	2.88***	-0.17	0.36
$Z(I)_{2002}$	-0.51	0.29	1.24	-0.95	-0.67
$Z(I)_{2003}$	-0.28	0.42	3.45***	-0.37	1.38*
$Z(I)_{2004}$	-1.11	-0.13	2.69***	-1.73**	-0.98
$Z(I)_{2005}$	1.52*	3.01***	8.31***	1.66**	1.34*
$Z(I)_{2006}$	0.84	2.59***	4.07***	-1.96**	-1.43*
Moran's I (joint)	**0.21**	**1.30***	**3.03***	**-0.24**	**0.29**
Efficient Wald GMM	2.4	15.8***	123.2***	12.8***	2.2

with larger instrument sets as in column VII (though performing well in capturing spatial dependence) may face problems with respect to this criteria.

Summing up, the obtained regression results for our migration model show that both time and space are important dimensions to account for in our empirical analysis. Applying different estimation techniques in a GMM framework, we observe a general trade-off between essential IV diagnostic tests and remaining spatial dependence in the residuals. As best alternative from the perspective of standard IV and spatial dependence diagnostic tests serves a mixed filtering-regression approach, which allows to quantify the effect of spillovers from spatially linked migration flows, as well as shows a good model fit in terms of essential IV diagnostic tests and well-behaved residuals.

5 Conclusion

In this paper we have explored the potential role of spatial autocorrelation in the analysis of interregional migration flows for Germany since re-unification. Though there is a huge body of literature dealing with structural determinants of German internal migration, no test for the role of time-space dynamic processes has been done. Starting from a standard aspatial specification of the neoclassical migration model in a dynamic panel data context, we show that spatial autocorrelation is highly present. The paper then discuss how to properly account for the identified spatial patterns in applied work: We basically follow an estimation strategy, which augments the standard Blundell-Bond (1998) system GMM estimator by spatial lags of the endogenous and explanatory variables. This estimator has recently been shown to perform both well in Monte Carlo simulations (see e.g. Kukenova & Monteiro, 2009) as well as empirical applications (see e.g. Bouayad-Agha & Vedrine, 2010). We apply extended SYS-GMM to a spatial lag as well as an unconstrained spatial Durbin model approach. An alternative way to account for spatial interdependence is to apply spatial filtering techniques, which intend to remove spatial dependence embedded in a set of variables.

In order to apply the spatial regression and filtering techniques we construct a set of binary spatial weighting matrices (both based on common borders as well as optimal geographical distances derived from a threshold measure) for our migration flow data. The latter requires to shift attention from a two–dimensional space for n regions and $n \times n$ origin-destination pairs to a four dimensional space with $n^2 \times n^2$ origin-destination linkages. Based on these network autocorrelation structures we then set up a framework for specifying a combined spatial weights matrix that that is able to simultaneously capture both origin- as well destination related interaction effects.

The regression results show that the different spatial techniques are able to remove a large part of spatial dependences from our model's residuals. In terms of the spatial extension of the SYS-GMM estimator the spatial Durbin model shows the best performance in capturing spatial dependences among migration flows. However, since it employs a large number of instruments, we observe a trade-off between instrument consistency (measured by the Hansen J-Statistic overidentification tests) and effective spatial modelling. Finally, applying a mixed spatial filtering-regression approach to reduce the number of instrument counts, this specification passes both standard IV diagnostic tests as well as Moran's I and Wald GMM based tests for remaining spatial autocorrelation in the residuals. The latter approach may give rise to further improvements in terms of consistent and efficient estimation of dynamic spatial panel data models and is in line with earlier findings such as Elhorst et al. (2010), who propose a mixture of different estimation techniques in complex models with space-time dynamics.

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Appendix

A Spatial Filtering

Similar to the idea of filtering seasonality out of time series data spatial filtering techniques convert variables that are spatially autocorrelated into spatially independent variables and a residual – purely spatial – component. Among the commonly applied spatial filtering techniques is the Getis (1990, 1995) as well as the Griffith (1996, 2003) Eigenvector spatial filtering approach. A recent empirical comparison of both filtering techniques has shown that both approaches are almost equally equipped for removing spatial effects from geographically organized variables (see e.g. Getis & Griffith, 2002). For the remainder of the paper we rely on the Getis approach, which has been applied in variety of empirical research contexts (see e.g. Badinger & Url, 1999, Badinger et al., 2004, Iara & Traistaru, 2003, Battisti & Di Vaio, 2008, and Mayor & Lopez, 2008). The idea of the spatial filtering approach is based on the consideration of a spatial vector S:

$$S \approx \rho W Y, \tag{28}$$

which takes the place of both the spatial weights matrix W and the spatial lag coefficient ρ for variable Y and allows the conversion of the dependent variable into its non-spatial equivalence as $Y^* = (Y - S)$. Once the filtering exercise has computed a set of non-spatial variables the second step regression task can be performed under the independence assumption yielding unbiased estimation results for the underlying model. To derive the set of spatially 'cleaned' variables the Getis approach uses the local statistic $G_i(d)$ by Getis & Ord (1992) defined as:

$$G_i(d) = \frac{\sum_{j=1}^{N} w_{ij}(d) y_j}{\sum_{j=1}^{N} y_j}, \text{ with } i \neq j. \tag{29}$$

The $G_i(d)$-statistic calculates the ratio between the sum of the y_j values included within a distance d from region i and the sum of the values in all the regions excluding i. It thus measures the concentration of the sum of values in the considered area and would increase their result when high values of variable y are found within a distance d from i. For empirical application one has to note that the use of this approach is limited by the nature of the $G_i(d)$-statistic which requires all variables to have a natural origin and be positive. Thus, as Getis & Griffith (2002) point out, some typical variables such as those represented by standard normal variates or percentage changes cannot be used. Moreover, the matrix of spatial weights has to be binary (not row-standardized). Getis

& Ord (1992) additionally deduce the expressions of the expected value for $G_i(s)$ and its variance under the spatial independence hypothesis as:

$$E(G_i(d)) = \frac{\sum_{j=1}^{N} w_{ij}(d)}{(N-1)} = \frac{W_i}{(N-1)}, \tag{30}$$

$$Var(G_i(d)) = \frac{W_i(N-1-W_i)}{(N-1)^2(n-2)} \left(\frac{F_{i2}}{F_{i1}^2}\right), \tag{31}$$

where

$$F_{i1} = \frac{\sum_j y_j}{N-1} \text{ and } F_{i2} = \frac{\sum_{j=1} y_j^2}{N-1} - F_{i1}^2. \tag{32}$$

Assuming a normal distribution we can finally derive the test statistic $Z(G)_i$ from the above expressions as as:[16]

$$Z(G)_i = \frac{G_i(d) - E[G_i(d)]}{\sqrt{Var(G_i(d))}}. \tag{33}$$

According to Getis (1995) the filtered variables can then be computed from the $G_i(d)$-statistic in the following way: Since its expected value $E[G_i(d)]$ represents the value in location i when the spatial autocorrelation is absent, the ratio $G_i(d)/E[G_i(d)]$ is used in order to remove the spatial dependence included in the variable. The spatially uncorrelated component of variable y can then be derived as:

$$y_i^* = \frac{y_i \times \left(\frac{W_i}{N-1}\right)}{G_i(d)}. \tag{34}$$

The difference between the original y and the filtered variable y^* is a new variable $\ddot{y} = (y - y^*)$ that represents purely spatial effects embedded in y.

As Badinger & Url (1999) point out, the choice of an appropriate distance d is essential for filtering. The optimal distance can thereby be interpreted as the radius of an area where spatial effects maximize the probability of deviations between observations and expected values. One option to set up this radius is in terms of border regions. Alternatively, using geographical distance between regions, Getis (1995) suggests to choose the d-value which maximizes the absolute sum of the normal standard variate of the $G_i(d)$-statistic:

[16] The underlying null hypothesis of $Z(G)_i$ states that the values within a distance d from i are a random sample drawn without replacement from the set of all possible values.

$$max \sum_{i=1}^{N} |Z(G)_i| = max \sum_{i=1}^{N} \frac{|G_i(d) - E[G_i(d)]|}{\sqrt{Var(G_i(d)}} \quad (35)$$

Finally, Getis (1995) outlines four criteria to assess the effectiveness of the spatial filter in removing spatial dependence. First, there should be no spatial correlation in y^*. Second, if y is a variable with spatial dependence embedded in it, then $\ddot{y}$ is a spatially autocorrelated variable. Third, in any regression model where all variables have been filtered using an appropriate distance d, residuals are not spatially associated. Fourth, theoretically motivated explanatory variables in a regression equation should be statistically significant after spatial dependence has been removed.

As a first indication of the appropriateness of the Getis filtering approach table A.3 reports the results of the Moran's I test statistics applied to the filtered variables (except those being tested spatially independent, namely $\tilde{q}$ and $\Delta\tilde{p}^l$). As the table shows for the dependent variable (nm^*) the optimal distance based weighting scheme is much more successful in eliminating spatial dependences compared to the border based alternative.

Table A.1: Moran's I values for the spatially filtered variables using the Getis approach

	Border	**Optimal distance**				
year	nm^*	nm^*	wr^*	ur^*	yrl^*	hc^*
1991	0.66	0.07	-1.05	-1.07	-2.05**	-0.91
1992	-0.84	-0.94	-1.21	-1.11	-1.76**	-0.86
1993	-1.90**	0.12	-1.39*	-1.12	-1.35*	-0.89
1994	-3.23***	-1.44*	-1.41*	-1.07	-0.89	-0.89
1995	-3.38***	0.98	-1.46*	-1.05	-0.65	-0.93
1996	-2.73***	-0.70	-1.43*	-0.98	-0.43	-0.87
1997	-2.83***	-0.74	-1.37*	-0.90	-0.30	-0.74
1998	-2.65***	1.25	-1.38*	-0.73	-0.26	-0.97
1999	-1.65**	-0.94	-1.36*	-0.66	-0.06	0.63
2000	0.04	0.83	-1.29*	-0.65	-0.04	-1.21
2001	-0.10	1.43*	-1.28*	-0.59	-0.16	-0.92
2002	-0.09	1.42*	-1.28*	-0.58	-0.13	-0.86
2003	-1.18	0.22	-1.27	-0.71	0.02	-0.86
2004	-1.13	0.08	-1.23	-0.76	0.12	-0.78
2005	-2.02**	0.05	-1.25	-0.65	-0.01	-0.55
2006	-0.27	-1.07	-1.26	-0.63	-0.02	-0.83

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. For both endogenous and exogenous variables we use information in levels and the exogenous variables are filtered in their original form. The optimal distance values are: $wr = 300km$, $ur = 400km$, $yrl = 225km$, $q = 225km$, $hc = 450km$, $p^l = 350km$ and kept constant over the sample periods. A sensitivity analysis with time-varying d-values did not change the results significantly. We do not report filtering results for q and Δp^{l*} since those variable do not show significant autocorrelation effects.

Table A.2: Major cities among German states based on population levels in 2006

No.	Rank	**City**	**Pop. in 2006**	**Pop. weight**	**State**
1	1	Stuttgart	593923	0.389	Baden-Württemberg
2	2	Mannheim	307914	0.202	Baden-Württemberg
3	3	Karlsruhe	286327	0.188	Baden-Württemberg
4	4	Freiburg	217547	0.143	Baden-Württemberg
5	5	Ulm	120925	0.079	Baden-Württemberg
6	1	München	1294608	0.557	Bavaria
7	2	Nürnberg	500855	0.215	Bavaria
8	3	Augsburg	262512	0.113	Bavaria
9	4	Würzburg	134913	0.058	Bavaria
10	5	Regensburg	131342	0.057	Bavaria
11	1	Berlin	3404037	1.000	Berlin
12	1	Potsdam	148813	0.472	Brandenburg
13	2	Cottbus	103837	0.329	Brandenburg
14	3	Frankfurt/Oder	62594	0.199	Brandenburg
15	1	Bremen	547934	1.000	Bremen
16	1	Frankfurt/Main	652610	0.550	Hessen
17	2	Wiesbaden	275562	0.232	Hessen
18	3	Kassel	193518	0.163	Hessen
19	4	Fulda	63916	0.055	Hessen
20	1	Hamburg	1754182	1.000	Hamburg
21	1	Rostock	199868	0.550	Mecklenburg-Vorpommern
22	2	Schwerin	96280	0.265	Mecklenburg-Vorpommern
23	3	Neubrandenburg	67517	0.186	Mecklenburg-Vorpommern
24	1	Hannover	516343	0.512	Lower Saxony
25	2	Braunschweig	245467	0.244	Lower Saxony
26	3	Osnabrück	163020	0.162	Lower Saxony
27	4	Wilhelmshaven	82797	0.082	Lower Saxony
28	1	Köln	989766	0.368	North Rhine-Westphalia
29	2	Dortmund	587624	0.218	North Rhine-Westphalia
30	3	Essen	583198	0.217	North Rhine-Westphalia
31	4	Münster	272106	0.101	North Rhine-Westphalia
32	5	Aachen	258770	0.096	North Rhine-Westphalia
33	1	Mainz	196425	0.345	Rhineland-Palatine
34	2	Ludwigshafen	163560	0.287	Rhineland-Palatine
35	3	Koblenz	105888	0.186	Rhineland-Palatine
36	4	Trier	103518	0.182	Rhineland-Palatine
37	1	Saarbrücken	177870	1.000	Saarland
38	1	Leipzig	506578	0.403	Saxony
39	2	Dresden	504795	0.402	Saxony
40	3	Chemnitz	245700	0.195	Saxony
41	1	Halle(Saale)	235720	0.506	Saxony-Anhalt
42	2	Magdeburg	229826	0.494	Saxony-Anhalt
43	1	Kiel	235366	0.527	Schleswig-Holstein
44	2	Lübeck	211213	0.473	Schleswig-Holstein
45	1	Erfurt	202658	0.497	Thuringia
46	2	Gera	102733	0.252	Thuringia
47	3	Jena	102494	0.251	Thuringia

Table A.3: Distance matrix for German states based on population weighted inter-city connections in road kilometers

	BW	**BAY**	**BER**	**BRA**	**BRE**	**HH**	**HES**	**MV**	**NIE**	**NRW**	**RHP**	**SAAR**	**SACH**	**ST**	**SH**	**TH**
BW	0															
BAY	262	0														
BER	672	523	0													
BRA	673	518	88	0												
BRE	633	650	375	440	0											
HH	667	666	279	364	110	0										
HES	231	308	527	556	424	473	0									
MV	802	701	207	291	278	152	596	0								
NIE	529	541	295	351	130	177	310	345	0							
NRW	410	501	521	584	273	363	234	555	265	0						
RHP	207	339	619	639	483	553	163	715	427	251	0					
SAAR	226	378	745	758	590	690	255	847	544	349	146	0				
SACH	579	461	210	202	431	450	388	398	417	534	505	615	0			
ST	549	416	150	200	295	317	351	316	261	416	497	592	206	0		
SH	732	745	316	398	192	76	510	181	272	447	629	754	523	396	0	
TH	440	317	269	293	391	418	247	433	359	411	369	471	145	163	487	0

Note: For further details about included cities see table A.6. Inter-city distances in road kilometers calculated with the help of *www.map24.de*.