The Role of Network Autocorrelation in Modelling German Internal Migration: Spatial Regression versus Filtering in a Dynamic Panel Data Approach

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Abstract

This paper analysis the role of network dependency structures in a dynamic panel data (DPD) model of German internal migration flows since re-unification. As theoretical basis serves a standard neoclassical migration model. We start from its aspatial specification and show by means of residual testing that network autocorrelation effects are highly present. Then, building upon recent empirical work on specifying spatial weighting structures in closed systems of interregional flow data we construct a set of spatial weighting schemes and apply both spatial filtering and spatial regression techniques to control for underlying network autocorrelation. Our results show, that both spatial modelling techniques are able to account for a large part of spatial dependency in the estimation framework. Concerning the economic interpretation of the results we observe that after controlling for spatial dependency a greater role is assigned to regional real wage rate differences relative to unemployment rate signals in directing migration flows. However, in terms of post estimation testing of the spatial filtering and regression specifications we reveal a general trade-off between standard IV consistency and effective spatial modelling. But when we finally combine the two approaches in a unified framework we come to an empirical model that passes both the standard IV diagnostic tests as well as tests for spatial autocorrelation in the residuals. The approach may thus serve as an application-oriented advancement in the DPD field insofar as alternative spatial common factor models are i.) computationally more intensive and ii.) not yet available for the efficient system GMM estimator.

JEL: R23, C31, C33

Keywords: Internal Migration, Dynamic Panel Data, Spatial Filtering, Spatial Lag Model

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1 Introduction

Given the need to account for spatial dependences in regression models with georeferenced data, research in the field of spatial econometrics has evolved rapidly within the last years (see Florax & Van der Vlist, 2003, Anselin, 2007). Unfortunately this is less true for dynamic panel data (DPD) analysis, where econometric theory in fact has most recently devoted huge research efforts on properly capturing the time series properties in dynamic panel data models (see e.g. Breitung & Pesaran, 2008, for an overview), while the spatial dimension is still rather ignored. As Kukenova & Monteiro (2008) point out, so far none of the available DPD estimators allows to consider a dynamic spatial lag panel model with one or more endogenous right hand side variable variables beside the spatial/time lag of the endogenous variable.[1] Given the huge potential for r.h.s. endogeneity (defined as correlation for an exogenous/predetermined regressor with the error term of the model) this is a clear shortcomings 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 consistent 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 the authors show that this augmented SYS-GMM can consistently estimate the spatial lag for standard data settings (large N, small T).

An alternative way to account for spatial autocorrelation in the DPD context is to apply spatial filtering techniques. In a nutshell, similar to the popular filtering approach for time series data with seasonality pattern spatial filtering allows to remove spatial dependences embedded in a set of variables so that the underlying model fulfills the independence assumption for the residual terms. In this sense spatial filtering treats spatial dependence in the data as a nuisance parameter and as entirely independent of the underlying 'spaceless' model to be estimated.[2] In the recent literature predominantly two different types of filtering techniques have been proposed: 1.) the Getis (1990, 1995) and 2.) the Griffith Eigenvector approach (see e.g. Griffith, 1996, 2000 and 2003, as well as Tiefelsdorf & Griffith, 2007 on the latter). While the Getis Filtering approach is a multi-step procedure based upon Ripley's (1977) second order statistic (the so called K function) and the G_i spatial statistic developed by Getis & Ord (1992), the Griffith Eigenvector approach exploits an eigenvector decomposition associated with Moran's I statistic. Linking spatial filtering with DPD estimation, Badinger et al. (2004) were among

[1] 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). Among the few DPD models with spatial error structure or the more general class of spatial common factor models, which also allow to account for r.h.s. endogeneity, is given by Mutl (2006).

[2] A critical discussion of this assumption is e.g. given in Beenstock & Felsenstein (2007).

the first to apply Getis filtered variables in an otherwise unchanged dynamic panel data growth regression approach to analyse the convergence process among EU regions.

In this paper we apply both spatial filtering and spatial regression techniques in a comparative exercise to model internal net migration flows among German states (NUTS1 level) since re–unification. Recently different scholars have hinted at the possible role of spatial autocorrelation in analysing spatial interaction in general and migration in particular (see e.g. Cushing & Poot, 2003, and LeSage & Pace, 2008). Spatial autocorrelation thereby measures the correlation of values for an individual variable, which are strictly attributable to the proximity of those values in geographic space. Of vital importance in the context of interstate migration flows is the appropriate specification of a spatial weighting matrix in order to identify the underlying network autocorrelation structures (see Black, 1992). Different to the design of weight matrices in standard models of spatial dependence the latter network framework requires to shift attention from a two–dimensional space for n regions and $n \times n$ origin (i) and 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 $\{i, j, r, s | i \neq j, r \neq s; i, j = 1 \ldots, n; r, s = 1, \ldots, n\}$. As Fisher & Griffith (2008) point out, the geographical space in which flow origins (such as i and r) on the one hand, and flow destinations (j and s) 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. In this context proximity can e.g. 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. Given its great importance for appropriate mapping spatial dependences in empirical models of dyadic origin-destination flow data, throughout the analysis we will put a special focus on the specification of spatial weighting matrices in the context of network autocorrelation structures for German internal migration flows.

The remainder of the paper is organised as follows: In the next section we briefly outline the neoclassical migration model as starting point for our empirical analysis and motive the likely role of network dependency structures in the modelling framework. The section also discusses how network dependency structures can be translated into a spatial weighting matrix for empirical estimation. In section 3 we present two empirical approaches dealing with spatial autocorrelation in a regression framework, namely the spatial filtering approach in an otherwise unchanged DPD model as well as the direct estimation of a spatial dynamic panel data model using SYS-GMM augmented by a spatial lag variable and consistent orthogonality conditions for the latter. Section 4 gives a short overview of the data used for estimation and presents some stylised facts including a graphical presentation of prominent migration flows between German states. Section 5 discusses the empirical results and section 6 concludes.

2 Network Dependency Structures in Migration Flows

In this section we first briefly outline the underlying neoclassical migration model in its labour market context as starting point for our empirical analysis. According to the neoclassical framework a representative agent will decide to move between two regions if this improves his welfare position relative to the status-quo of not moving. Relevant factors for the agent's rational decision making process are the expected income he would obtain for the case of staying in the home (origin) region (i) and the expected income he would obtain in the alternative (destination) region (j) net of 'transportation' costs when moving from region i to j. 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. The underlying idea of the neoclassical migration model has been formally elaborated in Harris & Todaro (1970) and may be summarized in terms of a stylized equation for net migration flows between region i and region j (NM_{ij}, defined as in-migration relative to out-migration) conditional to a set of explanatory variables as

$$NM_{ij} = f(W_i, W_j, UR_i, UR_j, S_i, S_j, C_{ij}). \tag{1}$$

where W denotes the real wage rate, UR is the unemployment rate, C are the costs of moving from i to j and S is a set of additional economic and non-economic variables that may work as pull or push factors for regional migration flows between i and j. With respect to the theoretically motivated signs for the coefficients of the explanatory variables we expect that an increase in the home country's real wage rate *ceteris paribus* leads to higher net in-flows, while a real wage rate increase in region j results in decreasing net migration flows. On the contrary, an increase in the unemployment rate in region i (j) relative to j (i) has negative effects on the bilateral net in-migration from i to j. 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. A more detailed description of the underlying theoretical migration model used in this paper can be found in Alecke et al. (2009).

In the majority of the empirical literature 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 spatial choice processes, which is then likely to be influenced by a subset of 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 proximate destination regions given unobservable characteristics of origins and destinations in the sample. The associated dependency among flow data is measured in terms 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.

In order to properly account for any form of spatial autocorrelation migration flows should therefore be analysed in the context of network structures, where individual flows are assumed to be related to one another. The dependency relationship among the network flows can then be represented in matrix form corresponding to a spatial weighting matrix in the definition of standard spatial analysis. However as outlined above, while a spatial weighting matrix typically 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 disregard from non-zero flows within each region (typically true for interregional migration data).

To work out the notation and conventions for the description of origin destination flows in a network structure more formally, we may start defining $\mathbf{Z}$ as an $n \times n$ square matrix of interregional flows 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 $i, j = 1, \dots, N$. If we follow LeSage & Pace (2008) and assume that the flows considered reflect a closed system, $\mathbf{Z}$ may then be written as

$$\mathbf{Z} = \begin{pmatrix} o_1 \rightarrow d_1 & o_2 \rightarrow d_1 & \dots & o_n \rightarrow d_1 \\ o_1 \rightarrow d_2 & o_2 \rightarrow d_2 & \dots & o_n \rightarrow d_2 \\ \vdots & \vdots & \ddots & \vdots \\ o_1 \rightarrow d_n & o_2 \rightarrow d_n & \dots & o_n \rightarrow d_n \end{pmatrix}. \tag{2}$$

From $\mathbf{Z}$ we can now produce an $(n^2 \times 1)$ vector of these flows in two ways, either reflecting an origin-centric or destination-centric ordering. For the remainder of the paper we choose the former framework, where the first n elements in the stacked vector $z = vec(\mathbf{Z})$ reflect flows from origin 1 to all n destinations and the the last n elements represent flows from origin n to destinations 1 to n as

$$\begin{array}{ccc} i^o & o^o & d^o \\ 1 & 1 & 1 \\ \vdots & \vdots & \vdots \\ n & 1 & n \\ \vdots & \vdots & \vdots \\ n^2 - n + 1 & n & 1 \\ \vdots & \vdots & \vdots \\ n^2 & n & n, \end{array} \tag{3}$$

where i^o denotes the overall index from $1, \dots, n^2$ in the origin centric ordering scheme. For the case that we assume zero (non-existing) flows within each region, we would have to cut out each row from vector z with $o^o = d^o$. To derive an appropriate weight matrix for the vector z in the context of network spatial autocorrelation or spatial connectivity between origin-destination dyads, Fisher & Griffith (2008) point at the need of shifting attention from a two-dimensional space with $\{i, j | i \neq j; i, j = 1, \ldots, n\}$ to a four dimensional space with $\{i, j, r, s | i \neq j, r \neq s; i, j = 1 \ldots, n; r, s = 1, \ldots, n\}$ as sketched above. The resulting spatial weighting matrix (W^*) is then able to jointly capture a set of origin related interaction effects (W^o) and a set of destination interaction effects (W^d) as

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

Formally, 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

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

The spatial link between i and r may either be measured in terms of a common border or equivalently by defining a threshold distance and operationalizing it in a binary way for i and r to be linked. The spatial weights matrix W^o thus specifies an origin-based neighbourhood 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 neighbour 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 two theoretical concepts, namely 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: These 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 behavioural 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. 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). The basic idea of the competing destinations approach is to model human behaviour 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 thus 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 the competing destinations and the intervening opportunities effects are in order and operate simultaneously so that the aggregated weight matrix W^* may be an appropriate choice for analysing 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) and LeSage & Pace (2008) among others generally support this view.[3] Throughout the rest of the paper we will thus use the combined weight matrix W^* in order to capture network autocorrelation

[3]See Chun (2008) for a more detailed discussion. 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.

effects in German migration flows. Further details about the empirical operationalisation in the specification of the spatial weighting matrix will be given in section 4. In the next section we will first discuss the theoretical concepts of spatial regression and spatial filtering in the context of a dynamic panel data (DPD) model.ication of the spatial weighting matrix will be given in section 4. In the next section we will first discuss the theoretical concepts of spatial regression and spatial filtering in the context of a dynamic panel data (DPD) model.

3 Spatial Regression & Filtering Techniques

3.1 Spatial Regression

In this section we look at different ways to account for spatial autocorrelation in a dynamic panel data model. Following Kukenova & Monteiro (2008) a fairly general way to formulate a first order spatial dynamic panel model is:

$$\begin{aligned} Y_t &= \alpha Y_{t-1} + \rho W_{1t} Y_t + \sum_{m=0}^{k} \beta_m' X_{t-m} + u_t \\ u_t &= \mu + \lambda W_{2t} u_t + \nu_t, \end{aligned} \tag{10}$$

where the endogenous variable Y_t is an $N \times 1$ vector of cross-section units (in our case $N = n^2$ migration flows) for time period t (with the time dimension being $t = 1, \ldots, T$). W_1 and W_2 are $N \times N$ spatial weight matrices (which can – but do not necessarily have to – correspond to each other), Y_{t-1} is the time lagged endogenous variable and X_t is a vector of current and lagged explanatory variables which may either be correlated or uncorrelated with the composed error term u_t. The latter in turn can be decomposed into a time-fixed unobservable effect μ for each cross-section unit and a remainder error term ν_t, where both are assumed to be i.i.d. By adding restrictions to the parameters of the model, we can derive two popular spatial model specifications in form of the dynamic spatial lag model with $\lambda = 0$ and the dynamic spatial error model with $\rho = 0$.

For the remainder of this paper we concentrate on the spatial lag approach, which directly accounts for the relationship of the dependent variable over the N cross sections.[4] That is, similar to the concept of the lagged endogenous variable in time series analysis, the estimated spatial lag coefficient characterizes a contemporaneous correlation between one cross-section observation and geographically proximate further units for the same variable Y. The spatial autoregressive coefficient ρ associated with $W_t Y_t$ then measures the effect of the weighted avera-

[4] Details about 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).

ge of the neighbourhood of cross-section i in terms of $[W_t Y_t]_i = \sum_{j=1}^{N} w(\cdot) Y_{jt}$, where $w(\cdot)$ are the elements of a weighting matrix as defined in section 2 in its row-standardized form according to eq.(9).[5] The spatial lag term allows to determine if the variable Y is (positively/negatively) affected by the Y_t from the other spatially linked cross-sections and the parameter for ρ is assumed to lie within the interval $[-1, 1]$. The latter restriction assures that the variable is spatially stationary (for details see e.g. Kosfeld & Lauridsen, 2009).

One important implication for empirical estimation of a DPD model is that the spatial lag term $W_t Y_t$ is correlated with the model's residuals. To make this point more clear, eq.(10) can be transformed to its reduced form as

$$Y_t = (I_N - \rho W_t)^{-1}(\alpha Y_{t-1} + \sum_{m=0}^{k} \beta'_m X_{t-m} + u_t), \tag{11}$$

which shows that each element of Y_t is a linear combination of all error terms. From an econometric point we thus face an endogeneity problem, which renders standard OLS biased and inconsistent. The solution offered by Kukenova & Monteiro (2008) is simply to treat the spatial lag variable as endogenous (in analogy to the time autoregressive component in the DPD context) and consistently estimate its coefficient ρ by means of appropriate instrumental variables in the context of the Blundell-Bond (1998) SYS-GMM estimator. Though the recent panel econometric literature offers different ways to handle spatial dependence in a dynamic panel data context,[6] Kukenova & Monteiro (2008) make the important point that no one of the existing estimators allows to jointly instrument the spatial lag coefficient $W_t Y_t$, the lagged endogenous variable Y_{t-1} as well as a subset of further endogenous variables among the vector X. Thus, one distinct advantage of the augmented SYS-GMM estimator is that it allows to control for potential r.h.s. endogeneity beside in the time and spatial lag components of the endogenous regressand.

In order show the derivation of consistent moment conditions for the dynamic spatially augmented SYS-GMM estimator it seems convenient switch to the standard notation used in the DPD literature and re-write eq.(10) explicitly for every cross section i (with $i = 1, \dots, N$) as

$$Y_{i,t} = Y_{i,t-1} + \rho [W_{1t} Y_t]_i + \sum_{m=0}^{k} \beta'_m X_{i,t-m} + u_{i,t} \tag{12}$$

In the aspatial SYS-GMM model with $\rho = 0$ consistent instruments can be derived from the so-called 'standard' and 'stationarity' moment conditions. The former condition builds upon

[5] Or in our four-dimensional case $[W_t Y_t]_{ij} = \sum_{r,s=1}^{N} Y_{rs,t}$ 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.

[6] See e.g. Elhorst (2003) for a single equation ML-approach to the reduced form estimation of the first differenced model, as well as Beenstock & Felsenstein (2007) for a multiple equation Panel VAR framework using a spatially augmented LSDVc estimation.

the seminal contribution in Anderson & Hsiao (1981) extended to the GMM framework by Arellano & Bond (1991), and estimates the DPD model from eq.(12) transformed into first differences based on the following moment condition

$$E(y_{i,t-\kappa}\Delta u_{i,t}) = 0 \quad \text{for all} \quad \kappa = 2, \ldots, t-1, \tag{13}$$

which employs sufficient lags of the endogenous variable in levels to consistently instrument the lagged endogenous variable 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 making use of the stationarity moment condition as (see e.g. Arellano & Bover, 1995, Ahn & Schmidt, 1995, and Blundell & Bond, 1998):[7]

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

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 (see e.g. Roodman, 2006):

$$\begin{pmatrix} \Delta y \\ y \end{pmatrix} = \alpha \begin{pmatrix} \Delta y_{-1} \\ y_{-1} \end{pmatrix} + \rho \begin{pmatrix} \Delta WY \\ WY \end{pmatrix} + \beta \begin{pmatrix} \Delta X_{-1} \\ X_{-1} \end{pmatrix} + \begin{pmatrix} \Delta u \\ u \end{pmatrix} \tag{15}$$

Additional instruments beside those derived from sufficiently long time lags for the endogenous variable may also be derived from the vector of explanatory variables X, where the lag structure for each variable in X depends on its exogeneity with respect to the error term. The validity of moment conditions can generally be tested with the help of overidentification tests such as Hansen's (1982) J-Statistic.

Based on the SYS-GMM framework Kukenova & Monteiro (2008) then propose to treat the spatial lag variable as endogenous in analogy to the time autoregressive component and derive consistent instruments based on the adapted standard and stationarity moment conditions according to

$$E([W_{t-\rho}Y_{t-\kappa}]_i)\Delta u_{i,t}) = 0 \quad \text{for all} \quad \kappa = 2, \ldots, t-1, \tag{16}$$

and

$$E(\Delta[W_{t-1}Y_{t-1}]_i u_{i,t}) = 0 \quad \text{for t=3,...,T.} \tag{17}$$

Using a Monte Carlo simulation exercise the authors show that this spatially augmented

[7] The original form in Ahn & Schmidt (1995) is $E(\Delta y_{i,t-1}u_{i,T}) = 0$ for $t = 3, \ldots, T$ derived from a set of non-linear moment conditions. Blundell & Bond (1998) rewrote it as shown eq.(14) for convenience.

SYS-GMM estimator is able to consistently estimate the spatial lag coefficient ρ for standard data assumptions (large N, small T), while only in small sample the coefficient tends to be over-estimated. Another problem may arise if both spatial and time lagged coefficients are close to one, which may induce the problem of multicollinearity. However, the latter problem is again less present for increasing N and fixed T. Finally, the authors find that the presence of exogenous variables reduces the probability of over-estimating the spatial lag term compared to a pure spatial autoregressive model. To sum up, in the absence of alternative estimators to properly handle endogeneity among the spatial lag, time lag and the right hand side regressors the augmented SYS-GMM estimator is a promising and flexible tool for dynamic spatial panel data analysis in standard data settings.

3.2 Spatial Filtering

A rather different estimation strategy for dynamic panel data models has been proposed by Badinger et al. (2004) among others. The authors make use of a two-step procedure, which employs spatial filtering techniques to remove the spatial correlation from the data in a first step and then apply standard (that is spaceless) GMM estimation to make statistical inference on their structural model in a second step. The main difference compared to the dynamic spatial lag model from above is that in this approach the spatial dependence can be viewed as a nuisance parameter and thus as entirely independent of the underlying 'spaceless' model to be estimated. 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 the spatial effects from geographically organized variables (see e.g. Getis & Griffith, 2002). Given their similar empirical performance, 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).[8] Moreover, as Getis & Griffith (2002) argue, the advantage of the Getis approach compared to the Eigenvector filtering is its simplicity and ease of understanding in a regression task. The idea of the spatial filtering approach of Getis (1990, 1995) is based on the consideration of a spatial vector S:

$$S \approx \rho W Y, \tag{18}$$

[8]Empirical applications of the Griffith Eigenvector approach can be found e.g. in Patuelli et al. (2006), Griffith (2007) and Fisher & Griffith, (2008).

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:

$$G_i(d) = \frac{\sum_{j=1}^{N} w_{ij}(d) y_j}{\sum_{j=1}^{N} y_j}, \text{ with } i \neq j. \tag{19}$$

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:

$$E(G_i(d)) = \frac{\sum_{j=1}^{N} w_{ij}(d)}{(N-1)} = \frac{W_i}{(N-1)}, \tag{20}$$

$$Var(G_i(d)) = \frac{W_i(N-1-W_i)}{(N-1)^2(n-2)} \left(\frac{F_{i2}}{F_{i1}^2}\right), \tag{21}$$

where

$$F_{i1} = \frac{\sum_j y_j}{N-1} \text{ and } F_{i2} = \frac{\sum_{j=1} y_j^2}{N-1} - F_{i1}^2. \tag{22}$$

Assuming a normal distribution we can finally derive the test statistic $Z(G)_i$ from the above expressions as as:[9]

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

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

[9] 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.

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:

$$y_i^* = \frac{y_i \times \left(\frac{W_i}{N-1}\right)}{G_i(d)}. \tag{24}$$

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. As described above, 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:

$$max \sum_{i=1}^{N} |Z(G)_i| = max \sum_{i=1}^{N} \frac{|G_i(d) - E[G_i(d)]|}{\sqrt{Var(G_i(d)}} \tag{25}$$

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.

We can thus specify our dynamic panel data model including filtered variables as:[10]

$$Y_t^* = \alpha Y_{t-1}^* + \sum_{j=0}^{k} \beta_j' X_{t-j}^* + u_t^*, \tag{26}$$

and apply standard SYS-GMM estimation under the spatial independence assumption.

[10]Getis & Griffith (2002) additional propose an alternative estimation strategy which reintroduces the spatial component into a final model for the original variable y and the vector of filtered regressors X^* (including the lagged endogenous variable). However, in terms of coefficient estimates we would expect that there is only a small change compared to the entirely spaceless model, as the spatial pattern in the dependent variable should be explained by spatial variables. Moreover, the inclusion of $\ddot{y}$ may be problematic for estimation equation in logarithms, which require a first step spatial filtering in the level of the variables. If the latter exhibits negative autocorrelation for some cross section, $\ddot{y}$ will be negative and cannot be transformed into logs for the second step estimation.

4 Data and Stylised Facts

This section serves to give a short overview of the data employed in this study as well as to present some stylised facts for the intra-German migration patterns since re-unification. German interregional migration data tracks the movement of all resident Germans (including foreigners). Since registration of residency is legally mandated and necessary in order to qualify for transfer benefits, the data should be quite complete and accurate. For the empirical analysis we make use of all available data for the 16 German states between 1991 and 2006, which gives a total of 3840 flow observations. All included monetary variables are denoted in real terms. A full description of the data sources is given in Table 1. Although not reported here, we also care for the time series properties of our data sample. Based on the Im-Pesaran-Shin (1997) panel unit root 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 (for details see Alecke et al., 2009). These results give us a high level of flexibility in terms of employing dynamic panel data estimators using information both in levels and first differences.

<< Table 1 about here >>

Turning to some stylised facts, of particular interest in the recent literature is the descriptive analysis of interstate migration flows between the West and East German macro regions throughout the process of East German economic transition and cohesion (for surveys see e.g. Heiland, 2004, Berentsen & Cromley, 2005, as well as Wolff, 2006). Alongside economic transformation the East German states have witnessed a substantial loss of population through East-West net out-migration. Moreover, East-West migration has not been stable over time and shows two distinct peaks in the early 1990s and around 2001.[11] Thus, to take a first look at the characteristics of intra-German migration flows we compute a set of simple summary statistics that give a first glance of the relative 'performance' of German states. Among the most frequently indicators are (see e.g. Rinne, 1996, for details)

$$w_{i,t}^{inm} := \left(\frac{Inm_{i,t}}{Pop_{i,t}} \right) \tag{27}$$

$$w_{i,t}^{outm} := \left(\frac{Outm_{i,t}}{Pop_{i,t}} \right) \tag{28}$$

[11] The general phenomenon of 'migration volatility' has been subject to considerable research effort recently (see e.g. Manson & Groop, 1996). As Berentsen & Cromley (2005) argue, such ocillative processes with relative brief periods of abrupt systematic change in established migration patterns followed by longer periods during which new migration equilibria will be established are likely to apply to the interstate pattern of migration in Germany as well - given the social, economic and political changes associated with German unification. A detailed account is also given in Alecke et al. (2009).

$$w_{i,t}^{nmr} := \left(\frac{Inm_{i,t} - Outm_{i,t}}{Pop_{i,t}} \right) \tag{29}$$

$$w_{i,t}^{gmv} := \left(\frac{Inm_{i,t} + Outm_{i,t}}{Pop_{i,t}} \right) \tag{30}$$

Eq.(27) and eq.(28) define gross in- and outmigration rates as the number of migrants relative to the population level for region i and time period t and may be seen as general measures of regional (labour market) attraction or distraction respectively. While the net migration rate in eq.(29) is able to identify the 'winning' and 'loosing' regions in the context of population change trough interregional migration, the gross migration value in eq.(30) measures the total migration intensity in the respective regions. The latter is typically positively correlated with the overall economic performance of region i, that is, regions experiencing strong (growth) dynamics typically also have both higher in- and outmigration rates relative to its population level compared with less dynamic regions. Figure 1 and Figure 2 present the above defined indicators for the two German macro regions West and East Germany together with its standard deviation measured as degree of variability in the underlying state level indicators.[12]

<< Figure 1 and 2 about here >>

The figures highlight the different trends in the East and West German aggregates. Looking at in- and outmigration patterns first, in figure 1 the gross in-migration rate of the East German states shows a slight upward trend throughout the 1990s, which has stablized afterwards. On the contrary, the gross outmigration rate for East Germany is much more volatile over time reflecting the above mentioned two peaks in the early 1990s and around 2001. While the former peak may be seen as a direct response to German re-unification, the later coincides with economic stagnation in the East and improving job prospects in the West as well as a gradual fading out of West-East transfers (see e.g. Heiland, 2004, Alecke et al., 2009). In all, during the second wave outmigration rates to the West increased across all East German states and reached levels close to those observed during the first wave after re-unification. For the West German aggregate the time pattern for both rates is rather stable over time. While the population adjusted in-migration rate is almost of the same magnitude for the East and West, the out migration rate for East Germany is much higher over the sample period. This discrepancy between East German in- and outmigration is condensed in the presistently negative net migration rate displayed in figure 2, while for the West German average the net migration rate shows a constant surplus. Finally, the gross migration intensity – reflecting the mobility of the population – is also higher for East Germany especially throughout the 1990s.[13]

[12] The East German aggregate also comprises Berlin due to its geographical location.
[13] Detailed state level indicators according to eq.(27) to eq.(30) are given in the appendix.

If we move from the from the macro-regional to the individual state level, figure 3 displays simple scatterplots for in- and outmigration flows during a fixed time period (we use annual observations 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: That is, 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. Further, data points closer to the origin inhibit smaller gross migration volumes and vice versa. The figure additionally accounts for 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 scatterplot).

<< Figure 3 about here >>

Starting in 1991, figure 3 shows that all East German states are clearly below the diagonal line indicating population losses with Saxony being hit the most. All West German states except Schleswig-Holstein are either on or above the diagonal line indicating net migration inflows. This strong migration response to German re-unification is less present in subsequent periods, where all state values are much closer to the diagonal. However, as already described above in 2001 this trend is partially offset by a second wave of increased East-West migration. 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 (Spätaussiedler), 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. 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.

Analysing migration flows in the context of network structures also allows to identify the (most) significant flows among the full migration matrix for a given time period and thus allows to get a first indication for the possible role of network autocorrelation. 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 simply 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 graphically shown in figure 4. For the year 1991 among the 10 % most prominent flows are Eeast-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). However, as outlined above the latter trend is to some degree distorted by large flows of German resettlers. If we additional include major migration flows up to the 25 % level in the upper right graph of figure 4, 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.

In terms of network autocorrelation figure 4 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 neighbourhood 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 research. 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 themself share a common border. The underlying network paradigma 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.

<< Figure 4 about here >>

The graphical presentation of major migration flows in figure 4 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, which is commonly applied to detect spatial autocorrelation for values of a particular variable.[14] Moran's I basically tests whether observations are random independent drawings from a population with unknown distribution function (see Cliff & Ord, 1973). The 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 operationalisation of the spatial weighting matrix W^*: Here we compare the empirical performance of two types of matrices: 1.) Spatial links are defined by a common border between to states, 2.) we use an optimal distance criterion based on the maximization procedure outlined in eq. 25. Distance between to

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

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 (see the appendix for further details).

<< Table 2 about here >>

Additionally, 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 scatterplot for a standardized variable $\breve{y}$ (with $\breve{y} = [y - \bar{y}]/sd(y)$) against its average neighbours $\breve{y}^s$ 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 5 we therefore finally present such scatterplots for our 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 year we find a highly significant positive slope regression coefficient measuring spatial autocorrelation in the migration data.

<< Figure 5 about here >>

5 Empirical Results

In this section we present the empirical results for different econometric specifications of the neoclassical migration model. We apply both the spatial regression and filtering technique and compare the results with the original specification that assumes independence among the residuals of the model. For the latter benchmark we start from an empirical model as proposed in Alecke et al. (2009), which uses a log-linear form of the stylized migration model in eq.(1).[15] We account both for likely information lags in the transmission process from the explanatory to the endogenous variable, as well as assume that migration flows them self adjust with a lag structure. The inclusion of the time lagged endogenous variable may thereby reflect different channels through which past flows affect current migration (e.g. since migrants serve as

[15]Logs are denotes in small characters.

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, for a detailed discussion). Finally, we restrict the explanatory variables in eq.(31) 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:

$$\begin{aligned} nm_{ij,t} \;=\;& \alpha_0 + \alpha_1 nm_{ij,t-1} + \beta_1 \widetilde{wr}_{ij,t-1} + \beta_2 \widetilde{ur}_{ij,t-1} + \beta_3 \widetilde{ylr}_{ij,t-1} \\ & + \beta_4 \tilde{q}_{ij,t-1} + \beta_5 \widetilde{hc}_{ij,t-1} + \beta_6 \widetilde{\Delta p^l}_{ij,t-1} + e_{ij,t}, \text{ with: } e_{ij,t} = \mu_{ij} + \nu_{ij,t} \end{aligned} \tag{31}$$

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 $e_{ij,t} = \mu_{ij} + \nu_{ij,t}$ is assumed to have the typical one-way error component structure. 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 changes in real labour productivity ($\Delta\widetilde{ylr}$), the labour participation rate ($\tilde{q}$), a human capital index ($\widetilde{hc}$) and the annual growth in land prices ($\Delta\tilde{p}^l$) as explicit control variables out of a broader pool of possible candidates for S_{ij}.[16]

To apply the spatial filtering approach we first have to derive the spaceless components of each variable in the model following the Getis procedure as outline in section 3. As a first indication of the appropriateness of the Getis filtering approach table 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 figure shows for the dependent variable (nm^*) the optimal distance based weighting scheme is much more successful in eliminating spatial dependences from the variable, while for the border based alternative the Moran's I statistic still identifies a significant part of left spatial autocorrelation (in particular for the years 1994 to 1999 in the sample period). Thus, focusing on the distance based filtering output for the exogenous variables of the empirical migration equation table 3 shows on average satisfactory results with some weak indication of remaining spatial autocorrelation only in the filtered component of the real wage rate wr^* (at the 10 % significance level).

<< Table 3 about here >>

The regression results for the model in eq.(31) using (two-step) SYS-GMM are shown in table 4. For both the aspatial, spatial filtered and spatial regression models we report the estimated variables coefficients together with two important types of post estimation tests: A

[16] See Alecke et al. (2009) for a theoretical motivation for the selection of explanatory variables in S. The additional inclusion of annual changes in the price for building may be interpreted as an additional (demand driven) indicator for regional attractiveness. In this case we would expect a positive correlation between in-migration and price development. However, from a classical perspective the variable may also capture the changes in interregional cost of living differentials over time resulting in a likely negative correlation with respect to net in-migration flows. See e.g. Arntz (2006) for a similar empirical approach.

primary concern in model applications including an IV/GMM approach is to carefully check for 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 (see Kelejian & Prucha, 1999, Egger et al., 2005). Both post estimation tests give important hints to identify misspecifications in the empirical modelling approach.

<< Table 4 about here >>

The aspatial migration equation in column I of table 4 serves as a general benchmark for the spatially augmented specifications. The interpretation of the estimated variable coefficients is as follows: The coefficients for labour market variables – real wage rate ($\widetilde{wr}_{ij,t-1}$) and unemployment rate ($\widetilde{ur}_{ij,t-1}$) differentials – turn out statistically significant and of correct signs in line with the neoclassical migration model. That is, 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. In terms of the core labour market variables, migration flows thus have a balancing effect on regional labour market disparities. Also, the inclusion of lagged differences in labour productivity growth turns out to have a highly significant impact on net in–migration with an estimated coefficient sign in line with the theoretical hypothesis, that regions with a relatively high productivity growth performance in the past attract more migrants through likely scale effects.[17] The positive impact of the labour participation rate $\tilde{q}_{ij,t-1}$ on net migration may potentially be interpreted in similar veins, though the theoretically expected link is more vague.

[17]See McCann (2001) for this line of argumentation contrary to the neoclassical growth model. The existence of scale effects e.g. via agglomeration forces than may then indeed act as a pull factor for prospective migrants. In similar veins, new economic geography models with a focus on labour mobility see additional workers migrating to those regions, where clusters/agglomerations have formed in order to benefit from strong home market effects. The influx of labour the stimulates the home market effect even further (see Harris, 2008, for a more detailed overview of the literature.

The negative coefficient for human capital can be basically motivated by an equilibrating effect of regional differences in human capital endowment on net migration flows after controlling for other (common) explanatory labour market factors.[18] However, this latter partial equilibrium view may not reflect the full direct and indirect effect of regional human capital differences on migratory movements e.g. given the empirical link between human capital and productivity growth, which in turn may translate into a positive migration response due to a shock in differences in the regional human capital endowment. Indeed Alecke et al. (2009) find such overall effects in a Panel VAR framework with the help of impulse-response functions. The positive variable coefficient for changes in the average price of building land ($\Delta\tilde{p}^{l}_{ij,t-1}$) may again hint at the role of agglomeration forces in attracting interregional migrants. Finally, the lagged endogenous migration variable enters significantly in the empirical specification in column I, indicating the important role of communication and related linkages supporting the view of a partial adjustment framework in modelling the net migration equation.

Turning to the post estimation tests, the reported J- and C-Statistic based instrument diagnostic tests for the aspatial model in table 4 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 $J_{crit.}, C_{crit.} > 0.05$). 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 (2007). 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 also as benchmark for the spatially augmented regression specifications. Next to the J-Statistic the 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) highly 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 Getis spatial filtering approach as outlined in section 3 and estimate the model in eq.(31) both on the grounds of the border and optimal distance based weighting schemes in column II and III of table 4 respectively. The estimated regression coefficients show some significant changes relative to the aspatial specification. First,

[18] That is, in the related micro literature skilled labour is typically found to be highly responsive to regional wage rate differentials, see e.g. Arntz (2007).

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. If we calculate the implied long-run elasticity for this variable (details are reported in the appendix) 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 both spatial filtered specifications in column II and III.

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 capture the omitted variable effect of relevant network structures in migration flows. If we appropriately account for such network effects, the variable turns insignificant (or weakly significant for some of the spatially augmented specifications, see table 4). From an economic point of view this result may hint at the minor role played by aggregate unemployment rate differentials – as a proxy for the individual risk of being employed – in guiding the agent's migration decision as outlined in section 2. This empirical finding also matches with earlier empirical contributions on German internal migration e.g. in Hunt & Burda (2001), who find that the decline in East-West migration starting from 1992 onwards can almost exclusively be explained by wage differentials and the fast East-West wage convergence, while unemployment differences do not seem to play an important part in explaining actual migration trends. Similar results were obtained by Parikh & Van Leuvensteijn (2003).

This empirical result is also confirmed, if we apply the Getis spatial filtering approach to a more general Panel VAR framework, to check whether a full account of the direct and indirect effects of wage and unemployment rate shocks vary in the aspatial and (distance based) spatially filtered specification.[19] The results for selected impulse-response functions in figure 6 to figure 8 support the impression from above that the effect on net migration in response to a real wage rate shocks is larger relative to aspatial benchmark, while a unit shock in the regional unemployment rate differential lead to migration effects of much smaller magnitude. The figures also show that the spatial filtered PVAR specification is less exposed to persistence (hysteresis effects) in migration responses to wage and labour productivity growth shocks, which improves the economic interpretation of the results in terms of migration as a temporary adjustment mechanism to long run labour market equilibrium.[20]

[19] To compare the results with Alecke et al. (2009) we specify a six equation first order Panel VAR including nm, $\widetilde{ur}$, $\widetilde{wager}$, $\Delta\widetilde{ylr}$, $\widetilde{q}$ and $\widetilde{hc}$. Details about estimation technique are given in Alecke et al. (2009).

[20] However, we do follow this surely interesting research path regarding appropriate spatial econometric modelling tools in a (full information) multiple-equation structural or VAR environment at this point and leave it open for future work in the field. Recent

<< Figures 6 to 8 about here >>

While the estimated coefficient for the regional productivity growth differentials, the regional human capital endowment and changes in the average price for building land are qualitatively in line with the aspatial benchmark, the estimated coefficient for labour participation turns out insignificant in the spatial filtering approach. Looking at the post estimation tests, again 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 4. 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. Again, unemployment and labour participation rate differentials turn out to be insignificant. 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):[21] Here the positive coefficient sign hints at positive spatial autocorrelation effects in line with the theoretical expectations from section 2.

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 criterion based on the IV set of the aspatial benchmark augmented by IVs for the spatial lag variable according to eq.(16) and eq.(17).[22] 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 significantly reduces the estimated coefficient for the spatial lag variable (ρ) and leads to a much higher degree of remaining spatial autocorrelation in the model's residuals. Taken together with the results for the spatially filtered model estimation this in

related advances are e.g. discussed in Mutl (2002) and Beenstock & Felsenstein (2007) for Panel VAR estimates with spatial error and spatial lag structures respectively, as well as Gebremariam (2007) for a more general treatment of multiple-equation panel data estimators with spatial effects. Finally, Jiwattanakulpaisarn (2008) is among the first to apply the Getis spatial filtering approach for Granger causality tests in a Panel VAR framework.

[21] 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.

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

turn may hint at a certain trade-off between IV consistency and effective spatial modelling for both the spatial filtering as well as spatial regression approach.

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

$$Y_t = \alpha Y_{t-1} + \rho W_t Y_t + \sum_{j=0}^{k} \beta_j' X_{t-j}^* + e_t, \tag{32}$$

We use unfiltered values for the endogenous variable and accounting for spatial autocorrelation in terms of the spatial lag variable $W_t Y_t$ mixed with spatially filtered exogenous variables X^*. The results are shown in column VIII and IX in table 4. The empirical specification in column VIII uses the IV set of the aspatial benchmark augmented by additional instruments for the spatial lag variable. The results show that the major difference compared to the pure spatial regression approach is the increased value for ρ. Though the model 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 so that the residual meet the independence assumption. The year-by-year Moran's I values show only in very few years evidence of remaining spatial autocorrelation. Moreover, as first specification the model passes the joint Moran's I test for spatial autocorrelation over the full sample period. And finally, in column IX we are able to further increase the combined model's empirical performance, when we reduce the IV set in such a way the model also passes the standard IV diagnostic tests for the given J- and C-Statistic criteria. As a side effect the improvement in IV consistency additionally pushes the performance of the model in properly capturing spatial dependence – only for two years the Moran's I identifies remaining spatial autocorrelation in the residuals, which is clearly the best empirical track record among all rival specification. The model also clearly passes the Moran's I based test statistic for the whole sample period as well as the Wald GMM test against spatially autocorrelated residuals as suggested by Egger et al. (2005).[23]

Summing up, the obtained results for our migration hint at the further potential of combining spatial filtering and regression techniques in a DPD modelling context (both from a single- as well as multiple-equation perspective), which shows good empirical results and also avoids the need to switch to computationally more intensive estimation strategies – such as estimating more general spatial (Durbin) common factor models based on a multistep approach as e.g. suggested by Mutl (2006) – in order to effectively capture spatial dependences in the structural components of the model.[24]

[23]The authors 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.

[24]Moreover, the approach suggested by Mutl (2006) so far only applies to GMM models in 1. differences according to Arellano & Bond (1991).

6 Conclusion

Various scholars have recently hinted at the huge – and so far unexploited – potential of appropriately capturing spatial autocorrelation in the analysis of interregional migration flows (see e.g. Cushing & Poot, 2003, and LeSage & Pace, 2008). In this paper we take up this point and set up a model of internal migratory movements among German federals states since re-unifications with an explicit reference to its spatial dimension. Starting from a standard aspatial version of the neoclassical migration model in a dynamic panel data context we show by means of the Moran's I statistic applied to the residuals of the econometric specification that spatial autocorrelation is indeed highly present in the modelling approach. The paper then discuss different ways on how to properly account for the identified spatial patterns in applied work: As a first option, Kukenova & Monteiro (2008) propose a direct estimation approach, which augments the standard Blundell-Bond system GMM estimator by a spatial lag variable for the endogenous regressand. The authors derive a set of consistent moment conditions for instrumenting the spatial lag variable and show by means of Monte Carlo simulations that the augmented SYS-GMM yields promising empirical results for standard data assumptions.

An alternative second way to account for spatial autocorrelation is to apply spatial filtering techniques, which intend to remove spatial dependence embedded in a set of variables so that the underlying model fulfills the independence assumption for the residual terms. In this sense 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. In the paper we apply the Getis spatial filtering approach in a two-step estimation exercise, where in the first step the spaceless components are extracted for both the endogenous and exogenous variables and in a second step these filtered components are included in an otherwise unchanged dynamic panel data model. 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 dyadic origin–destination observation. 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 both spatial techniques are able to remove a large part of spatial dependences from our model's residuals. Concerning the estimated elasticities of the core labour market variables in the neoclassical migration model the spatially augmented specifications uniformly assign a greater role to real wage rate differentials (compared to the aspatial benchmark), while regional unemployment rate differences turn out to be only weakly significant – a result that is in line with related empirical work on German internal migration since re-unification. However, for both the the spatial regression and filtering approach we reveal a certain trade-off between instrument consistency (measured by the Hansen J-Statistic overidentification tests) and effective spatial modelling. But when we finally combine the spatial regression and filtering approach in a unified framework we come to an empirical specification that passes both the standard IV diagnostic tests as well as Moran's I and Wald GMM based tests for remaining spatial autocorrelation in the residuals. The latter joint regression and filtering approach may give rise to further improvements in terms of consistent and efficient estimation in the context of dynamic spatial panel data models.

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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 Bemen, 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 contruct artificial time series.

Figure 1: In- and outmigration rates for the German East-West macro-regions together with state level heterogeneity, 1991-2006

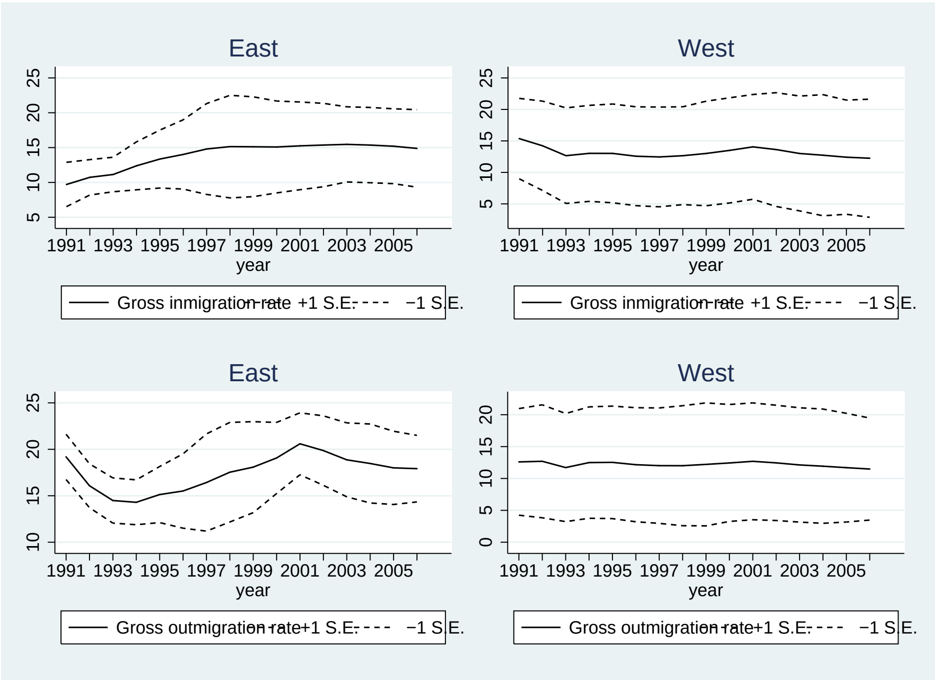


Figure 2: Net migration rate and total migration intensity for the German East-West macro-regions together with state level heterogeneity, 1991-2006

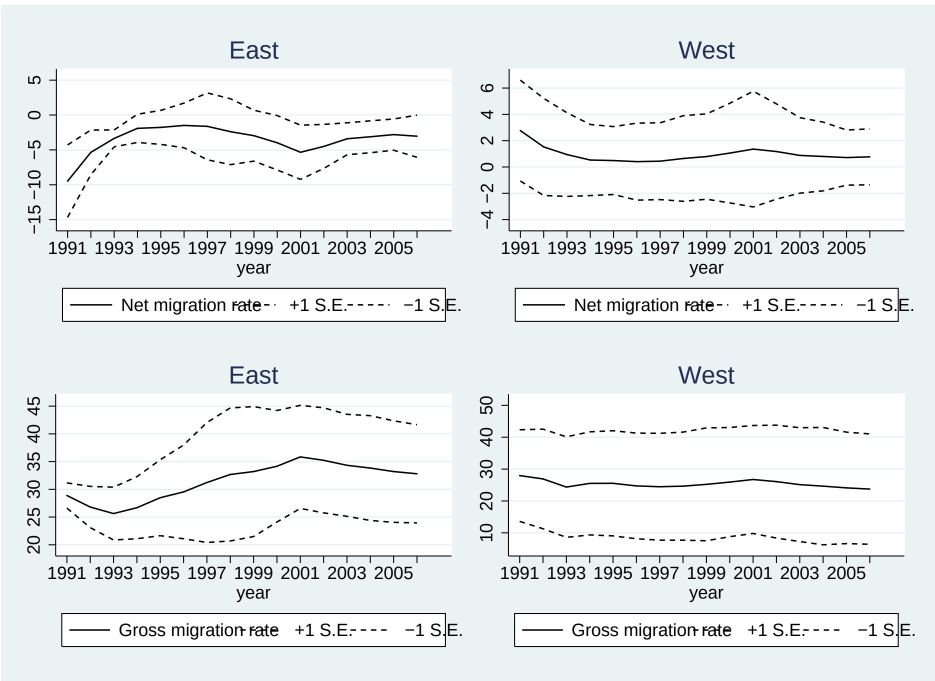


Figure 3: Weighted scatter plots for state level in- and out-migration

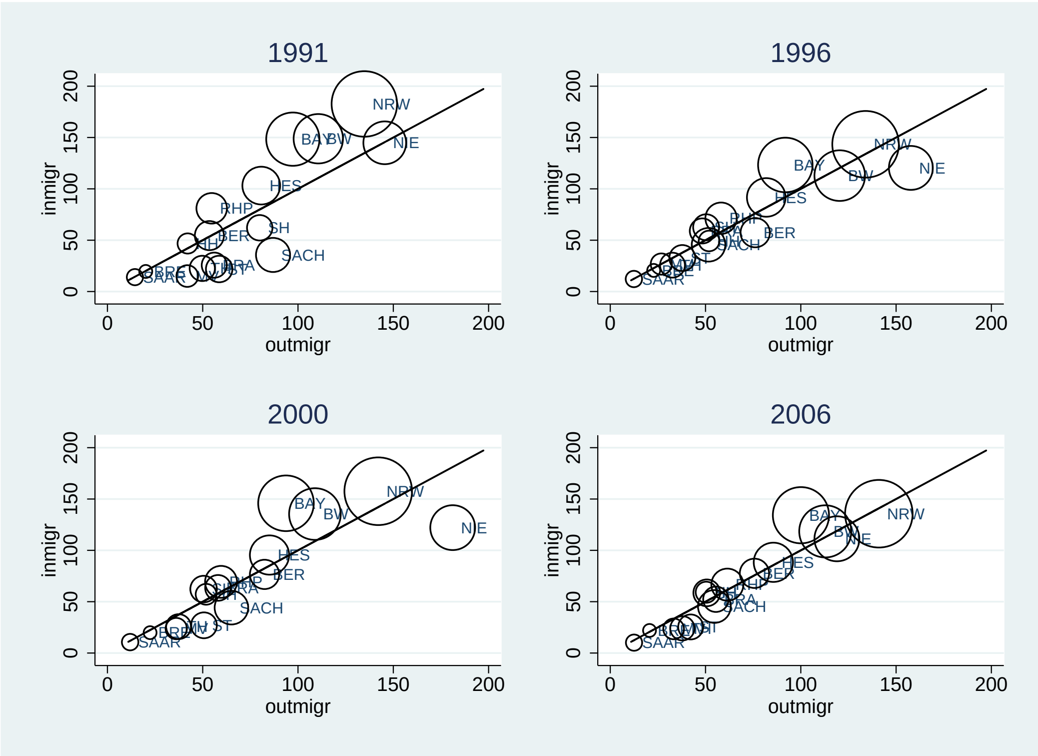


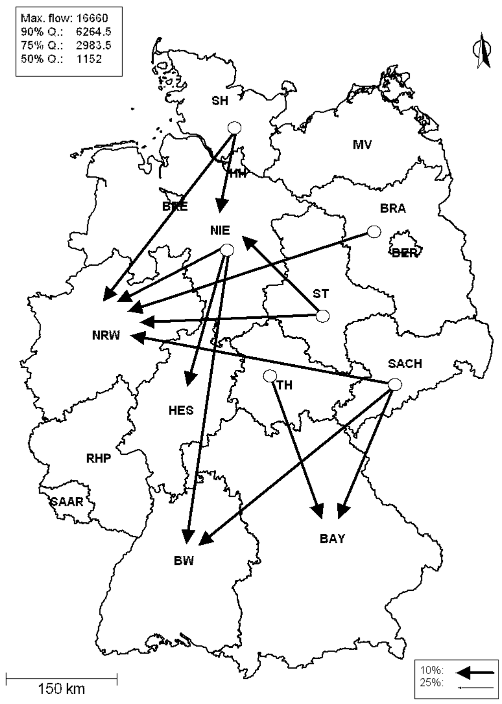
Table 2: $Z(I)$- and $Z(G)$-Statistic for inter-regional net migration rate with alternative weighting matrices

	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)

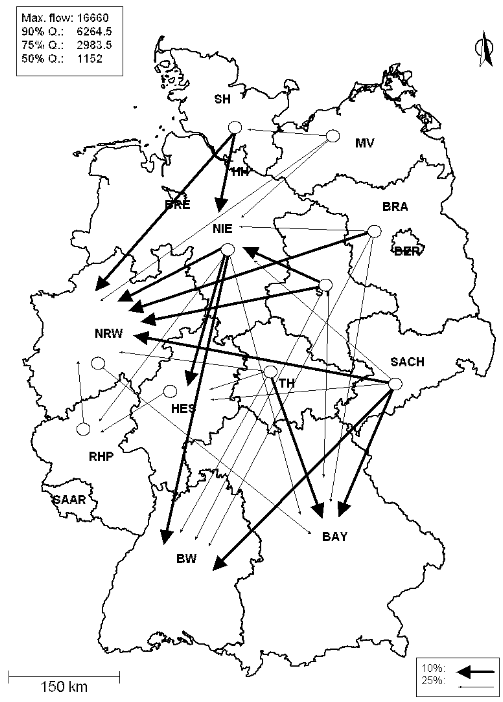
Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. $Z(I)$ and $Z(G)$ are standardized test statistics for Moran's I and Getis-Ord G respectively. d denotes the optimal distance maximising the absolute sum of the (local) $G_i(d)$-statistic according to eq.(19) and is measured in kilometers per fixed units of 25km each.

Figure 4: Prominent migration flows between German states in 1991/2001

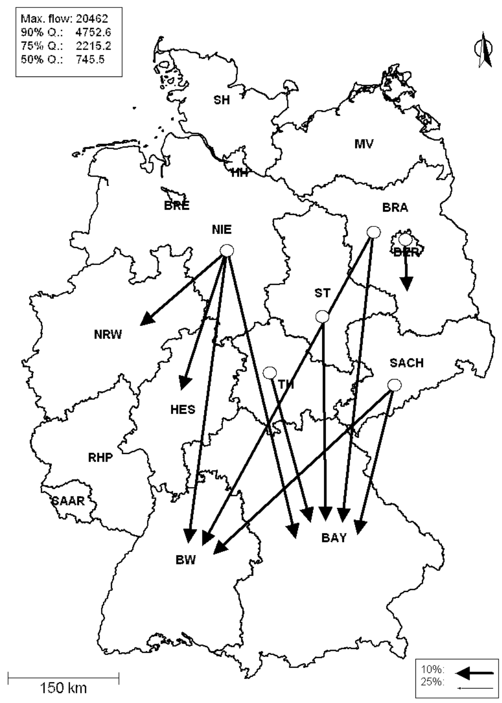
(a) 1991:10 %



(b) 1991:25 %



(c) 2001:10 %



(d) 2001:25 %

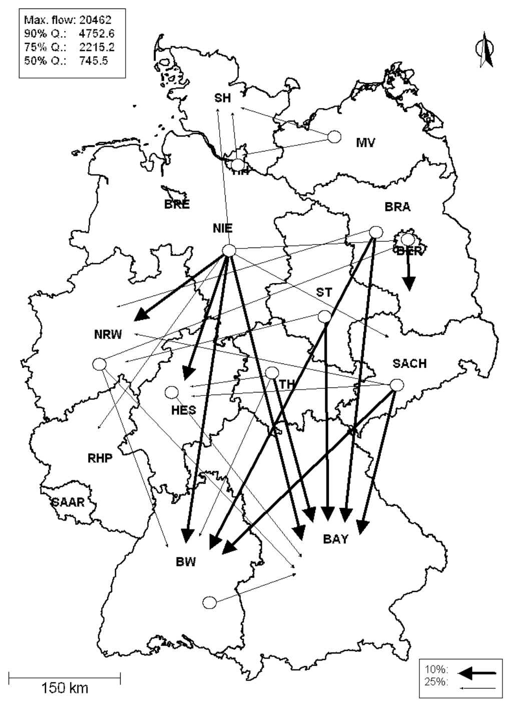
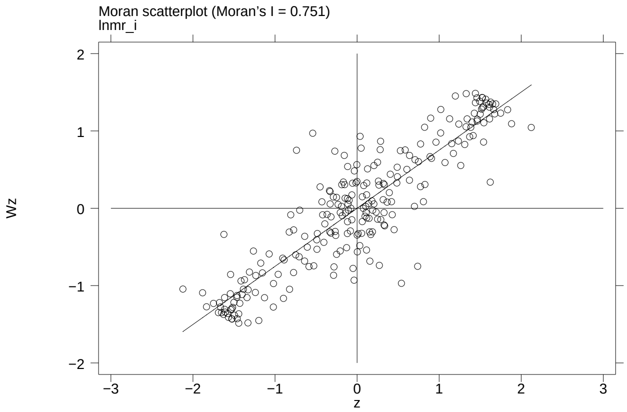
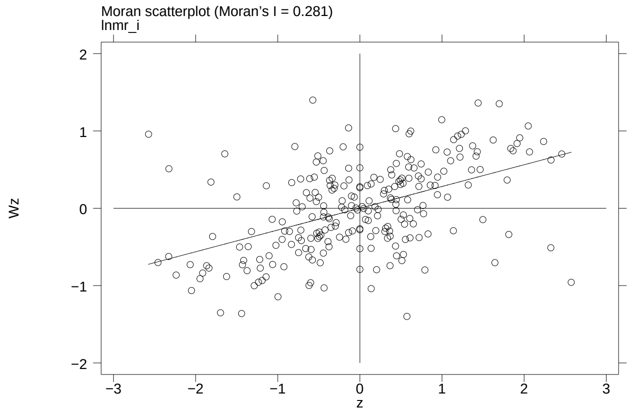


Figure 5: Moran scatterplot for net migration and various years

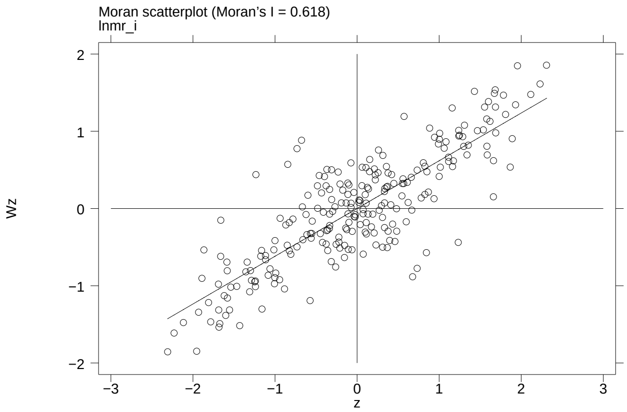
(a) 1991



(b) 1996



(c) 2001



(d) 2006

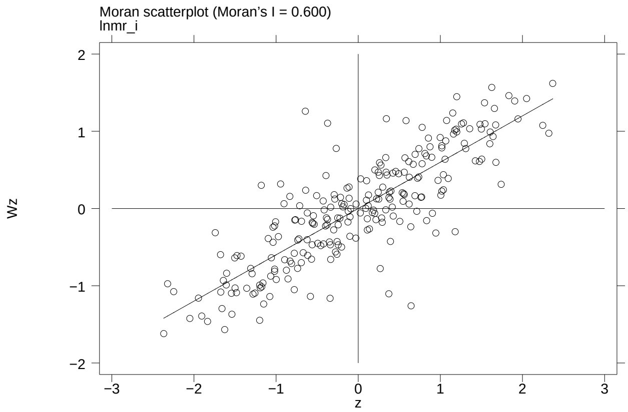


Table 3: Moran's I values for the spatially filtered variables using the Getis approach

	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. In the case geographical distance we use the optimal d-values reported in table 2 for net migration flows. Optimal distance values for the exogenous variables are mostly within the range of the migration variable. Detailed results can be obtained upon request. We do not report filtering results for q and Δp^{l*} since those variable do not show significant autocorrelation effects (see appendix for details).

Table 4: Estimation results of the dynamic migration model using spatial filtering and regression techniques

DPD model:	**Aspatial**	**Spatial Filtering**		**Spatial Regression**				**Combined**	
Weights matrix:	Non	Border	Distance	Border	Distance	Border	Distance	Distance	Distance
	I	II	III	IV	V	VI	VII	VIII	IX
$nm_{ij,t-1}$	0.51***	0.39***	0.36***	0.26***	0.30***	0.43***	0.40***	0.35***	0.29***
	(0.044)	(0.072)	(0.048)	(0.058)	(0.053)	(0.071)	(0.063)	(0.068)	(0.046)
$\widetilde{wr}_{ij,t-1}$	0.21**	0.33**	0.39***	0.39***	0.36***	0.32***	0.30***	0.46***	0.62***
	(0.042)	(0.141)	(0.121)	(0.118)	(0.108)	(0.111)	(0.105)	(0.138)	(0.162)
$\widetilde{ur}_{ij,t-1}$	-0.16***	-0.09	-0.09	-0.01	-0.04	-0.08*	-0.08**	-0.02	-0.08*
	(0.042)	(0.077)	(0.067)	(0.057)	(0.045)	(0.046)	(0.043)	(0.061)	(0.051)
$\Delta\widetilde{ylr}_{ij,t-1}$	0.55***	0.26***	0.37***	0.38***	0.42***	0.51***	0.48***	0.37***	0.68***
	(0.062)	(0.078)	(0.079)	(0.068)	(0.069)	(0.066)	(0.067)	(0.099)	(0.123)
$\tilde{q}_{ij,t-1}$	0.43**	-0.05	-0.06	-0.16	0.09	0.17	0.25	-0.05	-0.11
	(0.207)	(0.168)	(0.174)	(0.235)	(0.216)	(0.243)	(0.201)	(0.223)	(0.189)
$\widetilde{hc}_{ij,t-1}$	-0.03**	-0.02*	-0.01	-0.02*	-0.02*	-0.03***	-0.03***	-0.02	-0.03**
	(0.013)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)
$\widetilde{\Delta p^l}$	0.21***	0.09**	0.11**	0.12***	0.12***	0.17***	0.17***	0.15***	0.18***
	(0.056)	(0.041)	(0.050)	(0.043)	(0.042)	(0.044)	(0.039)	(0.055)	(0.067)
ρ				0.76***	0.58***	0.31**	0.34***	0.70***	0.81***
				(0.110)	(0.107)	(0.147)	(0.127)	(0.177)	(0.113)
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)	61.6 (18)	19.7 (12)
P-value of $J-Stat. > 0.05$	Passed	Failed	Failed	Failed	Failed	Passed	Passed	Failed	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)	27.3 (8)	13.5 (8)
P-value of $C-Stat. > 0.05$	Passed	Failed	Failed	Failed	Failed	Failed	Passed	Failed	Passed

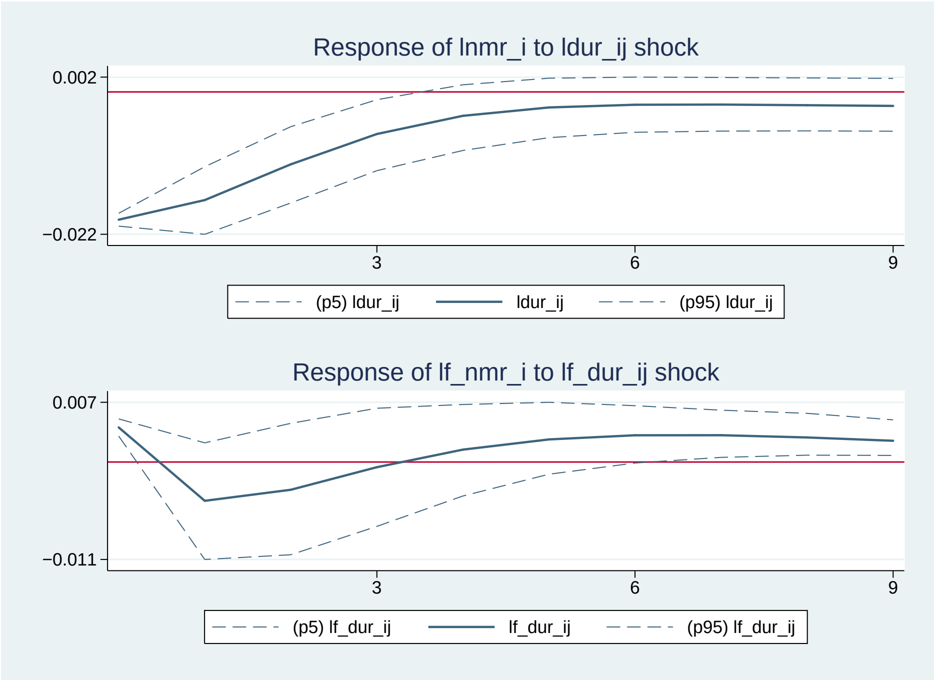
Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level. Standard errors based on Windmeijer's (2005) finite-sample correction. The joint Moran's I statistic based on the average of individual values distributed with zero mean and a standard deviation of $1/\sqrt{m}$, where m is the 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 4 (continued): Estimation results of the dynamic migration model using spatial filtering and regression techniques

DPD model:	**Aspatial**	**Spatial Filtering**		**Spatial Regression**				**Combined**	
Weights matrix:	Non	Border	Distance	Border	Distance	Border	Distance	Distance	Distance
	I	II	III	IV	V	VI	VII	VIII	IX
Moran's I for residuals									
$Z(I)_{1994}$	7.12***	-3.38***	-1.82**	-3.53***	0.08	2.02**	3.27***	0.47	0.93
$Z(I)_{1995}$	2.55***	-4.34***	-0.98	-4.00***	0.58	-1.36*	1.81**	0.02	-0.01
$Z(I)_{1996}$	4.83***	-2.41***	-1.25	-1.77**	0.51	1.90**	2.13**	0.69	0.52
$Z(I)_{1997}$	2.32**	-2.84***	-1.53*	-2.92***	-0.72	-0.36	0.54	-0.44	-0.34
$Z(I)_{1998}$	5.67***	-3.75***	0.03	-3.23***	2.42***	1.31	5.03***	1.38*	1.07
$Z(I)_{1999}$	5.15***	-3.25***	-3.05***	-2.13**	-0.19	1.29	1.84**	-1.81**	-2.26**
$Z(I)_{2000}$	12.67***	-0.61	0.88	-0.42	1.50*	6.97***	4.31***	0.13	-0.97
$Z(I)_{2001}$	11.74***	-2.40***	-0.38	-1.43*	1.78**	5.30***	4.16***	-0.17	0.17
$Z(I)_{2002}$	7.63***	-1.56*	-0.59	-1.78**	1.06	1.80**	3.05***	-0.95	0.92
$Z(I)_{2003}$	7.14***	-2.83***	-2.87***	-1.51*	1.63*	2.05**	4.18***	-0.37	1.28
$Z(I)_{2004}$	7.94***	-1.31*	-0.99	-1.45*	1.71**	2.72***	4.73***	-1.73**	0.93
$Z(I)_{2005}$	10.83***	-2.19**	-0.58	-0.19	6.24***	6.25***	10.39***	1.66**	3.82***
$Z(I)_{2006}$	8.00***	-1.98**	-2.51***	-0.13	1.56*	3.70***	4.19***	-1.96**	-0.25
Moran's I (joint)	**7.19*****	**-2.52*****	**-1.20*****	**-1.88*****	**1.39*****	**2.58*****	**3.81*****	**-0.23**	**0.45**
Efficient Wald GMM	1145.4***	18.7***	7.3**	63.4***	11.1***	355.8***	213.3***	12.8***	2.1
No. of obs.	3120	3120	3120	3120	3120	3120	3120	3120	3120

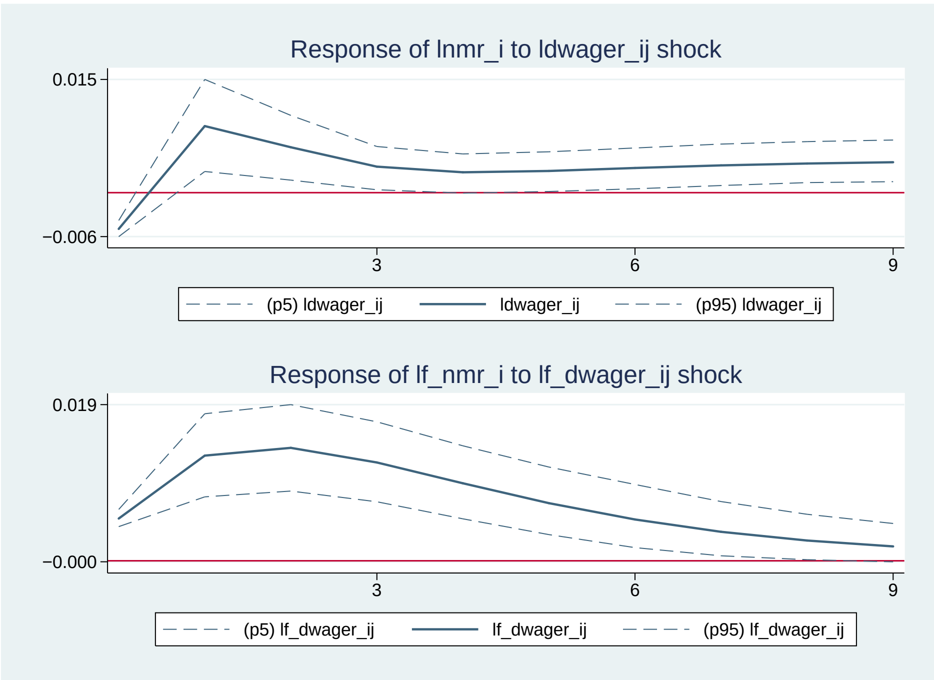
Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level. Standard errors based on Windmeijer's (2005) finite-sample correction. The joint Moran's I statistic based on the average of individual values distributed with zero mean and a standard deviation of $1/\sqrt{m}$, where m is the 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).

Figure 6: Impulse-Response functions for a shock in regional unemployment rate differences on net migration in a PVAR setup for aspatial and spatially filtered variables



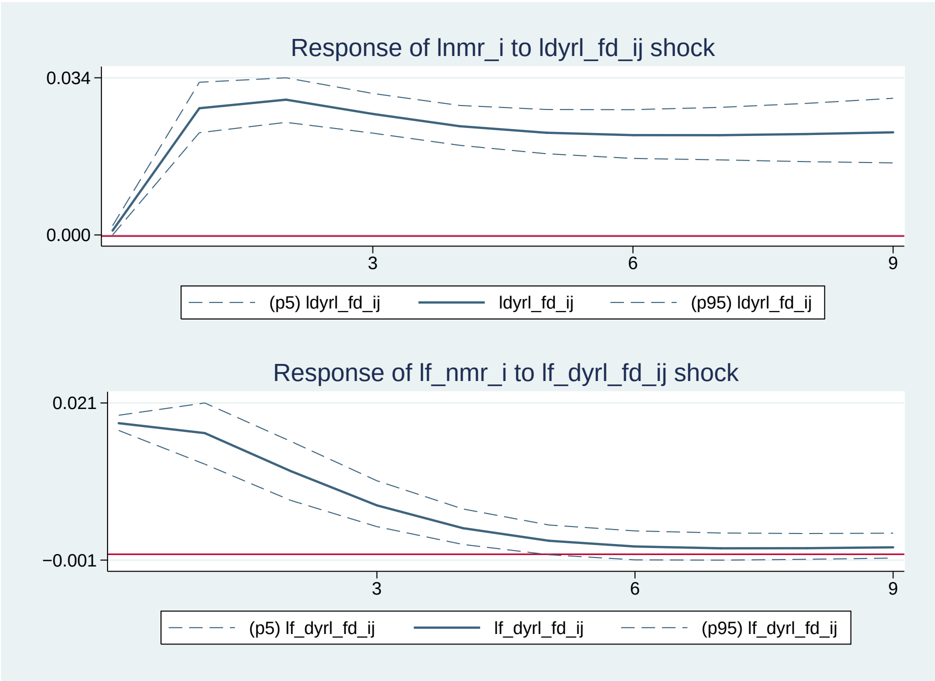
Note: $ldur_{ij}$ = Regional unemployment rate differential (aspatial), $lfdur_{ij}$ = Unemployment rate diff. (spatially filtered). Spatial filtered variables are derived from optimal distances as also in column III of table 4.

Figure 7: Impulse-Response functions for a shock in regional real wage rate differences on net migration in a PVAR setup for aspatial and spatially filtered variables



Note: $ldwager_{ij}$ = Regional wage rate differential (aspatial),$lfdwager_{ij}$ = Wage rate differential (spatially filtered). Spatial filtered variables are derived from optimal distances as in column III of table 4.

Figure 8: Impulse-Response functions for a shock in productivity growth differences on net migration in a PVAR setup for aspatial and spatially filtered variables



Note: $\Delta ldyrl_{ij}$ = Regional productivity growth differential (aspatial), $\Delta lfdyrl_{ij}$ = Productivity growth diff. (spatially filtered). Spatial filtered variables are derived from optimal distances as in column III of table 4.

Table A.1: List of abbreviations used for German states (NUTS1)

BW	**Baden-Württemberg**
BAY	**Bavaria (Bayern)**
BER	**Berlin**
BRA	**Brandenburg**
BRE	**Bremen**
HH	**Hamburg**
HES	**Hessen**
MV	**Mecklenburg-Vorpommern**
NIE	**Lower Saxony (Niedersachsen)**
NRW	**North Rhine-Westphalia (Nordrhein-Westfalen)**
RHP	**Rhineland-Palatinate (Rheinland-Pfalz)**
SAAR	**Saarland**
SACH	**Saxony (Sachsen)**
ST	**Saxony-Anhalt (Sachsen-Anhalt)**
SH	**Schleswig-Holstein**
TH	**Thuringia (Thüringen)**

Table A.2: In-migration rates ($w_{i,t}^{inm}$) at the German state level (NUTS1)

	BW	**BAY**	**BER**	**BRA**	**BRE**	**HH**	**HES**	**MV**
1991	26.21	21.32	31.39	31.92	58.11	53.54	31.73	29.88
1992	24.49	20.58	31.35	31.39	62.40	53.44	31.45	27.95
1993	22.72	18.39	31.50	31.58	59.10	57.43	29.00	27.30
1994	23.26	18.41	33.63	34.11	61.44	58.17	29.70	26.75
1995	23.32	18.69	36.42	38.19	62.86	58.36	29.59	28.20
1996	22.55	17.91	38.49	42.14	63.89	59.18	28.84	29.45
1997	22.17	17.65	43.20	47.13	63.19	60.35	28.96	29.47
1998	22.60	18.34	47.41	48.79	63.12	62.25	29.20	30.87
1999	22.64	18.97	47.30	49.09	65.63	64.51	29.52	32.05
2000	23.28	19.66	47.00	46.73	63.86	63.74	29.80	33.62
2001	24.22	20.85	47.16	47.84	64.53	63.67	30.41	35.82
2002	23.21	19.61	47.33	46.50	66.53	64.14	29.70	36.47
2003	22.05	18.76	46.32	45.04	66.27	63.57	28.81	35.28
2004	21.50	17.97	45.92	45.05	65.79	66.24	28.73	35.09
2005	21.44	18.05	45.20	43.92	63.89	63.61	29.01	33.58
2006	21.54	18.78	45.09	42.24	64.14	62.68	28.62	33.41
	NIE	**NRW**	**RHP**	**SAAR**	**SACH**	**ST**	**SH**	**TH**
1991	39.10	18.23	35.83	26.49	25.95	28.28	53.89	27.90
1992	36.48	17.06	36.05	24.72	22.66	23.70	53.86	26.29
1993	30.28	15.29	33.88	22.42	20.35	22.91	46.95	23.03
1994	35.66	15.93	34.89	23.09	20.65	24.31	48.11	23.20
1995	36.09	15.89	33.84	22.33	21.49	25.53	47.90	23.93
1996	35.68	15.49	32.51	22.73	21.32	25.80	41.33	23.37
1997	35.09	15.29	31.85	22.18	21.69	25.06	41.29	23.67
1998	34.23	15.43	31.75	22.06	21.90	25.94	41.00	23.81
1999	35.50	16.06	31.82	22.01	22.36	26.87	40.89	24.40
2000	38.34	16.65	31.99	21.09	24.59	29.48	40.53	25.83
2001	40.29	16.99	32.41	22.15	26.91	31.77	40.60	27.83
2002	39.18	16.60	32.23	21.71	25.66	30.76	41.11	27.30
2003	36.99	16.24	30.95	20.58	24.49	30.35	40.32	27.13
2004	35.11	15.88	30.97	20.89	23.87	29.23	40.94	26.51
2005	31.94	15.60	31.70	21.03	23.48	28.63	39.28	26.48
2006	28.82	15.33	31.59	21.60	23.47	27.55	38.58	26.67

Note: Data from Destatis & VGRdL, formula see text.

Table A.3: Out-migration rates ($w_{i,t}^{outm}$) at the German state level (NUTS1)

	BW	**BAY**	**BER**	**BRA**	**BRE**	**HH**	**HES**	**MV**
1991	11.18	8.44	15.55	21.89	29.45	25.35	13.93	21.96
1992	11.60	8.81	16.00	20.44	32.01	26.59	14.59	18.03
1993	11.58	8.39	16.75	17.69	32.30	27.60	14.35	16.48
1994	12.03	8.19	18.02	16.06	33.02	29.16	14.32	15.25
1995	12.01	7.90	19.97	17.55	32.54	29.34	13.79	15.27
1996	11.64	7.65	21.95	18.97	33.59	30.35	13.60	14.73
1997	11.38	7.45	25.37	19.97	33.84	30.50	13.70	15.37
1998	11.21	7.53	26.77	20.85	35.10	31.45	13.83	16.84
1999	10.91	7.50	25.60	22.43	35.67	32.01	13.95	17.95
2000	10.38	7.69	24.36	22.32	33.83	30.28	14.04	20.25
2001	10.00	7.91	23.70	24.78	33.51	29.93	14.46	21.93
2002	9.76	8.13	23.82	24.20	32.37	30.58	14.10	21.95
2003	9.76	8.00	24.20	22.62	32.62	30.25	14.04	20.42
2004	9.72	7.95	24.31	22.38	32.04	31.19	13.94	20.11
2005	10.00	7.85	23.24	22.06	31.33	30.47	14.39	19.12
2006	10.51	8.02	22.26	21.72	31.04	28.80	14.08	19.57
	NIE	**NRW**	**RHP**	**SAAR**	**SACH**	**ST**	**SH**	**TH**
1991	19.59	7.74	14.44	13.44	18.40	20.58	30.32	19.20
1992	17.70	7.89	14.61	12.95	14.04	15.32	30.70	14.99
1993	13.00	7.68	14.34	12.14	11.80	13.23	24.61	13.02
1994	18.21	7.88	14.53	12.18	11.31	13.70	24.81	12.79
1995	19.77	7.71	14.45	11.80	11.56	14.18	24.98	13.46
1996	20.24	7.48	14.59	11.45	11.33	13.85	18.42	13.08
1997	19.75	7.40	14.53	11.54	11.37	14.11	18.56	12.90
1998	18.67	7.66	14.53	11.62	12.35	15.46	18.68	13.54
1999	19.94	7.99	14.47	11.58	12.99	16.69	18.54	13.98
2000	22.90	7.89	14.79	11.13	14.64	19.23	18.14	15.29
2001	24.85	7.90	14.97	11.55	16.87	21.14	18.00	16.99
2002	23.66	7.75	14.58	10.80	15.51	19.63	18.25	16.27
2003	21.68	7.63	14.42	10.29	13.82	18.34	18.25	15.84
2004	20.24	7.51	14.48	10.43	13.08	17.64	18.53	15.42
2005	17.92	7.52	14.74	11.04	12.75	17.05	18.11	15.80
2006	14.89	7.81	15.16	11.93	12.83	17.20	17.88	16.30

Note: Data from Destatis & VGRdL, formula see text.

Table A.4: Net migration rates ($w_{i,t}^{nmr}$) at the German state level (NUTS1)

	BW	**BAY**	**BER**	**BRA**	**BRE**	**HH**	**HES**	**MV**
1991	3.86	4.44	0.28	-11.85	-0.79	2.85	3.88	-14.04
1992	1.30	2.95	-0.65	-9.49	-1.62	0.27	2.27	-8.10
1993	-0.45	1.62	-2.01	-3.79	-5.51	2.23	0.30	-5.66
1994	-0.80	2.04	-2.42	1.99	-4.60	-0.15	1.06	-3.76
1995	-0.70	2.88	-3.52	3.10	-2.21	-0.32	2.00	-2.33
1996	-0.73	2.61	-5.40	4.20	-3.29	-1.52	1.63	-0.02
1997	-0.60	2.76	-7.54	7.19	-4.50	-0.64	1.57	-1.27
1998	0.18	3.28	-6.13	7.09	-7.08	-0.65	1.54	-2.80
1999	0.82	3.98	-3.90	4.22	-5.72	0.50	1.62	-3.85
2000	2.53	4.28	-1.72	2.09	-3.81	3.19	1.72	-6.88
2001	4.21	5.03	-0.24	-1.72	-2.50	3.81	1.48	-8.03
2002	3.69	3.35	-0.31	-1.89	1.79	2.98	1.51	-7.43
2003	2.52	2.76	-2.08	-0.19	1.03	3.06	0.73	-5.56
2004	2.06	2.07	-2.70	0.29	1.70	3.86	0.85	-5.13
2005	1.43	2.36	-1.28	-0.20	1.22	2.67	0.23	-4.66
2006	0.53	2.74	0.57	-1.19	2.06	5.07	0.45	-5.73
	NIE	**NRW**	**RHP**	**SAAR**	**SACH**	**ST**	**SH**	**TH**
1991	-0.09	2.75	6.95	-0.38	-10.86	-12.88	-6.76	-10.51
1992	1.08	1.28	6.83	-1.18	-5.41	-6.93	-7.54	-3.69
1993	4.28	-0.07	5.21	-1.86	-3.25	-3.55	-2.26	-3.01
1994	-0.76	0.17	5.83	-1.27	-1.96	-3.09	-1.51	-2.38
1995	-3.44	0.46	4.93	-1.27	-1.62	-2.84	-2.06	-3.00
1996	-4.79	0.53	3.32	-0.18	-1.33	-1.90	4.49	-2.79
1997	-4.41	0.50	2.80	-0.90	-1.05	-3.16	4.17	-2.14
1998	-3.12	0.10	2.69	-1.19	-2.81	-4.98	3.64	-3.27
1999	-4.37	0.08	2.87	-1.15	-3.63	-6.50	3.81	-3.56
2000	-7.46	0.86	2.41	-1.18	-4.70	-8.97	4.26	-4.75
2001	-9.41	1.19	2.47	-0.96	-6.83	-10.51	4.60	-6.15
2002	-8.14	1.11	3.07	0.10	-5.36	-8.51	4.61	-5.23
2003	-6.36	0.98	2.10	0.00	-3.14	-6.32	3.82	-4.55
2004	-5.37	0.86	2.00	0.04	-2.29	-6.04	3.88	-4.34
2005	-3.91	0.56	2.22	-1.04	-2.02	-5.47	3.06	-5.12
2006	-0.96	-0.29	1.28	-2.26	-2.18	-6.84	2.81	-5.93

Note: Data from Destatis & VGRdL, formula see text.

Table A.5: Migration intensity ($w_{i,t}^{gmv}$) at the German state level (NUTS1)

	BW	**BAY**	**BER**	**BRA**	**BRE**	**HH**	**HES**	**MV**
1991	26.21	21.32	31.39	31.92	58.11	53.54	31.73	29.88
1992	24.49	20.58	31.35	31.39	62.40	53.44	31.45	27.95
1993	22.72	18.39	31.50	31.58	59.10	57.43	29.00	27.30
1994	23.26	18.41	33.63	34.11	61.44	58.17	29.70	26.75
1995	23.32	18.69	36.42	38.19	62.86	58.36	29.59	28.20
1996	22.55	17.91	38.49	42.14	63.89	59.18	28.84	29.45
1997	22.17	17.65	43.20	47.13	63.19	60.35	28.96	29.47
1998	22.60	18.34	47.41	48.79	63.12	62.25	29.20	30.87
1999	22.64	18.97	47.30	49.09	65.63	64.51	29.52	32.05
2000	23.28	19.66	47.00	46.73	63.86	63.74	29.80	33.62
2001	24.22	20.85	47.16	47.84	64.53	63.67	30.41	35.82
2002	23.21	19.61	47.33	46.50	66.53	64.14	29.70	36.47
2003	22.05	18.76	46.32	45.04	66.27	63.57	28.81	35.28
2004	21.50	17.97	45.92	45.05	65.79	66.24	28.73	35.09
2005	21.44	18.05	45.20	43.92	63.89	63.61	29.01	33.58
2006	21.54	18.78	45.09	42.24	64.14	62.68	28.62	33.41
	NIE	**NRW**	**RHP**	**SAAR**	**SACH**	**ST**	**SH**	**TH**
1991	39.10	18.23	35.83	26.49	25.95	28.28	53.89	27.90
1992	36.48	17.06	36.05	24.72	22.66	23.70	53.86	26.29
1993	30.28	15.29	33.88	22.42	20.35	22.91	46.95	23.03
1994	35.66	15.93	34.89	23.09	20.65	24.31	48.11	23.20
1995	36.09	15.89	33.84	22.33	21.49	25.53	47.90	23.93
1996	35.68	15.49	32.51	22.73	21.32	25.80	41.33	23.37
1997	35.09	15.29	31.85	22.18	21.69	25.06	41.29	23.67
1998	34.23	15.43	31.75	22.06	21.90	25.94	41.00	23.81
1999	35.50	16.06	31.82	22.01	22.36	26.87	40.89	24.40
2000	38.34	16.65	31.99	21.09	24.59	29.48	40.53	25.83
2001	40.29	16.99	32.41	22.15	26.91	31.77	40.60	27.83
2002	39.18	16.60	32.23	21.71	25.66	30.76	41.11	27.30
2003	36.99	16.24	30.95	20.58	24.49	30.35	40.32	27.13
2004	35.11	15.88	30.97	20.89	23.87	29.23	40.94	26.51
2005	31.94	15.60	31.70	21.03	23.48	28.63	39.28	26.48
2006	28.82	15.33	31.59	21.60	23.47	27.55	38.58	26.67

Note: Data from Destatis & VGRdL, formula see text.

Table A.6: 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.7: 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.map*24*.de*.

Table A.8: Moran's I values for the exogenous variables based on optimal distances

year	wr	ur	yrl	q	hc	p^l
1991	3.28***	3.69***	2.86***	-0.36	0.63	-1.17
1992	2.91***	3.02***	2.47***	1.14	0.91	-0.32
1993	2.43***	2.65***	1.64**	1.18	2.17**	-0.67
1994	2.39***	2.64***	1.56*	0.93	2.49***	-0.73
1995	2.26**	2.97***	1.40*	0.67	3.33***	-1.18
1996	2.24**	3.12***	1.41*	0.62	3.39***	-0.67
1997	2.26**	3.23***	1.79**	0.72	2.65***	-0.65
1998	2.26**	3.64***	1.99**	0.62	3.34***	-0.49
1999	2.28**	3.70***	2.01**	0.75	4.29***	-0.92
2000	2.47***	3.61***	2.10**	1.01	0.68	-0.71
2001	2.53***	3.74***	1.78**	1.11	2.98***	-0.93
2002	2.55***	3.79***	1.29*	1.19	3.53***	0.23
2003	2.67***	3.76***	1.46*	1.11	2.95***	-0.28
2004	2.68***	3.71***	1.79**	0.96	3.57***	-0.37
2005	2.64***	4.05***	1.73**	0.92	4.24***	-0.37
2006	2.69***	3.97***	1.82**	0.80	2.53***	-0.48

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level respectively. 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. Detailed information can be obtained upon request.

Table A.9: Implied long-run coefficients for the empirical models in table 4.

Model:	**Aspatial**	**Spatial Filtering**		**Spatial Regression**				**Combined**	
W^*:	Non	Border	Distance	Border	Distance	Border	Distance	Distance	Distance
	I	II	III	IV	V	VI	VII	VIII	IX
$\widetilde{wr}_{LR}$	0.43	0.54	0.61	0.53	0.51	0.56	0.50	0.71	0.86
$\widetilde{ur}_{LR}$	-0.33	-0.15	-0.14	-0.01	-0.06	-0.14	-0.13	-0.03	-0.08
$\Delta\widetilde{ylr}_{LR}$	1.12	0.43	0.58	0.51	0.60	0.89	0.80	0.57	0.89
$\tilde{q}_{LR}$	0.88	-0.08	-0.09	-0.22	0.13	0.30	0.42	-0.08	-0.25
$\widetilde{hc}_{LR}$	-0.06	-0.03	-0.02	-0.03	-0.03	-0.05	-0.05	-0.03	-0.04
$\widetilde{\Delta p}^{l}_{LR}$	0.43	0.15	0.17	0.16	0.17	0.30	0.28	0.23	0.23

Note: Calculated as $\beta_{i,LR} = \left(\frac{\beta_i}{1-\alpha_1}\right)$ with $i = 1, \ldots, 6$ according to eq.(31).