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# Analysing the spatio-temporal diffusion of economic change – advanced statistical approach and exemplary application

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**Abstract:**

This article presents a spatio-temporal panel vector-autoregressive approach (SptpVAR) as an extended spatial econometric method for analysing spillover effects of regional economic change in time and space. The approach aims to extend the spatial dimension of SpVAR models by capturing the overall cross-regional spillover dynamics over time through additional estimations of effects into neighbouring regions and backward spillover to the source region. By showing how local economic dynamics trigger spillover dynamics in economically linked regions, the results are of particular interest to policy makers. To demonstrate the functioning of the SptpVAR approach, it is applied to 361 German regions using a regional growth model and a regional panel data set in the time-period 2000-2017 in an exemplary application.

**Keywords**: Economic dynamics, Spatial spillover, Spatial econometrics, SpVAR

**JEL Classifications:** C33, O40, R12, R23

# 1 INTRODUCTION

Regional sciences face growing interest in applied spatial econometrics and interest in spatial data analysis tools. Especially the analysis of economic spillover and externalities across regional units is an important topic to understand the spatial dynamics of economic systems. Simultaneously, dynamic flexible vector-autoregressive panel models (pVARs), as one of many methods, have become an essential tool in the empirical analysis of economic systems with interrelated variables and estimation of responses to exogenous shocks, such as economic policy interventions. Although cutting-edge pVAR models are referred to as spatial panel VARs (SpVAR), these models provide scope for improvement in the integration of cross-regional interdependencies among variables and the spatial dissemination of economic effects in neighbouring or economically linked regions (e.g. the models of Beenstock & Felsenstein 2007, Mitze et al, 2018, Eberle et al, 2019). Local economic growth shocks cause spatial externalities in economically linked regions due to various transmission channels that affect the mobility of production factors, such as technology and knowledge diffusion, commuting, or cross-border trade. Thus, effects from a single economic shock can disseminate in space by causing multiplicative effects.

The used SpVAR approaches fall short to capture the complete spatiotemporal dynamics for two reasons: First, only direct spatial effects from neighbouring regions to the analysed region are considered (so-called in-spillover), neglecting economic linkages with larger geographic distance. Second, in most of these cases spatial effects are only used to avoid statistical biases caused by spatially autocorrelated error terms. Further spatial effects over time are usually not analysed (an exception is Wardenburg & Brenner, 2020). This is somewhat inconsistent, because the SpVAR approaches considers indirect effects among the variables included, meaning the effects from one variable to another and from this variable to a third variable and from there back to the first variable are included in the analysis, while effects to the neighbouring region and feedback effects into the initial region are not examined. The reason for this shortcoming in the literature can be found in the complexity of spatial spillover. On the one hand, the spatial structure allows for a large variety of third-order and higher spillover effects. On the other hand, the spillover effects strongly depend on the type of regions involved. In principle, a complete analysis of spatial spillover would require to consider each region with its specific characteristics and neighbours separately, which would imply separate regressions for each region, which usually is not statistically possible without increasing the number of observations.

The purpose of this paper is to develop an approach that is able to capture and analyse spatial spillover processes as far as possible within a rather general statistical approach, integrate them into the resulting impulse-response-functions (IRFs) and estimate the spatial expansion of regional economic shocks over neighbouring and economically linked regions. To this end the SpVAR approach is extended to include the spatial dissemination of local economic shocks over time while considering regional heterogeneity in region types and economic structure. To demonstrate the functioning of the approach, it is applied to the economic development in German regions. The assessment of spatial effects is of particular importance for regional policy makers, since it is important to know how economic policy measures for one region affect other regions.

Using German regional panel data in the time-period 2000 to 2017, we use our recursive SptpVAR to analyse the spatio-temporal dissemination of economic changes, especially local labour demand shocks and productivity growth. The study focusses on the extent to which both variables affect economic development in economically connected regions. A specific interest in this paper is in supra-regional labour market migration in reaction to local economic shocks, that has an intrinsic spatial dimension.

The remainder of the paper succeeds as follows. Section 2 presents the theory on spatial interdependent growth models and cross-regional spillover dynamics as well as spatial VAR models. Section 3 introduces our SptpVAR framework strategy and exemplary data and variables. The empirical results are presented in section 4. Section 5 concludes with a summary.

## 2 THEORETICAL BACKGROUND

As it is widely shown in theoretical and empirical works, the economic development of countries, regions or cities depends to a certain extend on economic processes within nearby regions or countries due to growth spillover and cross-regional interdependencies (e.g. Ertur & Koch, 2007; Grossmann & Helpman, 1991; Howitt, 2000; Rey & Janikas, 2005; Rey & Montouri, 1999). From an observer's perspective this can be seen in historical examples such as the spatiotemporal dissemination of the industrial revolution across England and Europe, but also in the present co-movement in business cycles of neighbouring and economically linked regions (Montoya & de Haan, 2008).

Multi-country growth models explaining spatially interdependent growth by considering cross-unit spillover have been developed in endogenous as well as neoclassical settings. Endogenous growth models that emphasize the role of knowledge and innovation spillover as source of spatially interdependent technological progress are more common (Coe & Helpman, 1995; Ertur & Koch, 2011; Grossmann & Helpman, 1991; Howitt, 2000; Howitt & Mayer-Foulkes, 2005). Basile & Usai (2015) provide a summary on these models. Nevertheless, for the basic mechanisms in our application we build on a neoclassic model that considers the spatial effects of technology and knowledge diffusion and the mobility of further production factors, such as workers that contribute to spatial interdependencies between regions.

## 2.1 Spatial Growth Models

Neoclassic regional growth models build on the Solow-Modell, which explains regional growth of a closed market as a function of Capital (K), Labour (L) and Technology (A) (Solow, 1956). Borts and Stein (1964) advanced this model to the first regional growth model allowing for spatial spillover.

Following Lopez-Bazo et al. (2004) who extend the common neoclassical growth model from Mankiw et al. (1992) by including cross-regional spatial spillover that are mainly caused by technological diffusion, we start with formulating the labour productivity in a simple regional economy *i* in period *t* as:

$$(1)\quad y_{it} = A_{it} k_{it}^{\tau_k} h_{it}^{\tau_h},$$

where *k* and *h* are physical and human capital per labour unit and $\tau_k$ and $\tau_h$ are internal returns to both factors, determined by population growth, technology growth and depreciation rate (Lopez-Bazo et al., 2004). The spatial dimension is integrated trough spatial technology and knowledge diffusion. Thus, $A_{it}$ depends on the technological level of neighbouring regions, which, in turn, depends on physical and human capital intensity in this regions. So $A_{it}$ is defined as:

$$(2)\quad A_{it} = \Delta_t (k_{\rho it}^{\tau_k} h_{\rho it}^{\tau_h})^{\gamma},$$

with the exogenous component $\Delta_t$ that is assumed to be constant over regions and $k_{\rho it}$ and $h_{\rho it}$ denoting the physical and human capital ratios in neighbor regions while $\gamma$ measures the strength of externalities across regions (Lopez-Bazo et al., 2004). Combining (1) and (2), it becomes clear that a region's steady state labour productivity and growth rate depend on capital investments within the region and in its neighbours. Thus, labour productivity in a region profits from investments in neighbouring regions, even without own investments. In consequence, regional growth systems cannot be analysed without incorporating spatial interdependencies. Similar to Mankiw et al. (1992), physical and human capital growth within a region is a function of regional capital accumulation, population and technology growth and depreciation rate. Additionally, due to decreasing returns to capital, investment rates are a decreasing function of capital stocks, while it is an increasing function of capital stocks in neighbouring regions due to externalities across economies, which makes investments more profitable in regions surrounded by regions with high capital intensity (Lopez-Bazo et al. 2004). The authors conclude, that the initial conditions for regional growth within a region equal the ones in Mankiw et al (1992), while externalities across regions cause that growth to depend on the initial productivity and growth rates in their neighbours. As a consequence, the growth rates of two identical economies with identical preconditions may differ if preconditions in their neighbours differ (Lopez-Bazo et al, 2004). The authors argue that spillover do not accelerate the convergence rate across regions as they are a function of parameters within each economy, while persistent inequalities are intensified by more intensive knowledge diffusion among neighbouring strong economies (Lopez-Bazo et al, 2004). In addition, Pfaffermayr (2009) points out, that knowledge and innovation advantages affect neighbouring regions first, but become global within time due to spatial diffusion.

Ertur & Koch (2007) develop a similar spatially augmented growth model based on the Solow-Model (Solow, 1956) with technological interdependence with similar theoretical assumptions as Lopez-Bazo et al. (2004). In their model, a region's steady state real income per worker depends positively on the region's saving rate and negatively on population growth. The same applies for savings and population growth in neighbouring regions due to spatial externalities and technological interdependence.

## 2.2 Factor mobility spillover effects

Both the models of Lopez-Bazo et al. (2004) and Ertur & Koch (2007) focus on knowledge and technological spillover as the only factors that are able to cross regional borders. Pecuniary production factors are still handled as closed economies, ignoring capital and labour mobility and other spillover that have direct impact on the regional steady state by affecting physical and human capital intensity as well as regional population growth (Pfaffermayr, 2012). We argue, that this should also be considered in analysing spatial growth systems.

Capello (2009) identifies three major categories of spatial spillover: Knowledge spillover, industry spillover and growth spillover, pointing out that cross-regional interdependencies are not limited to knowledge spillover. Industry spillover, that may include knowledge spillover, occur on firm level within related industries, if linked firms benefit from value or productivity gains of dynamic, usually large firms without direct compensation through input or output linkages (Barrios et el. 2003). Growth spillover in the most general form summarize all types of growth transmissions between related regions, including knowledge and industry spillover (Capello, 2009, Arora & Vamvakidis, 2005, Cheshire, 1995). Spatial externalities result from the openness and spatial as well as economical limitation of regional economic systems, which are not self-sufficient, but necessarily interact, inter alia, in supply and demand of goods, production factors and common supply chains (Capello, 2009). Thus, local economic volatility that affects the demand and supply of goods and production factors has a direct transmission channel into other regions by increasing the needs for imports from other regions, as additional demand cannot be fully absorbed by local supply. These pecuniary externalities may lead to income and GDP growth in trade-linked regions and further multiplicative effects in those regions as developed in the Export-Growth-Theory (North, 1955). Moreover, regions directly interact via commuting that cause spatial externalities (Shearmur & Motte, 2009). Spending capacities and consumption demands at the place of residence directly depend on the workplace income per worker.

### 2.3. Labour Market Mobility

Migration between regions is modelled as exogenous in the presented neoclassical growth models. However, labour productivity, income per worker and labour market migration are strongly interwoven and migration has large impact on population growth. Therefore, Pfaffermayr (2012) presents an augmented Solow growth model including net-migration, based on the works of Barro & Sala-I-Martin (2004), Sung (2010) and Braun (1993). These postulate (average) income differentials per worker as main driver of migration across regions, whereby individuals migrate towards regions with higher income and job opportunities (Barro & Sala-I-Martin, 2004). Pfaffermayr (2012) models net immigration ξ for a set of regions $y_N$ as:

$$(3)\quad \xi(y_1 \dots, y_N) \approx \kappa\left[(y_i - y_i^*) - \sum_{j=1}^{N} m_{ij}(y_j - y_j^*)\right],$$

where, $m_{ij}$ denotes the exogenous spatial weights, representing that relocations spanning smaller distances are more likely than large distance moves, due to financial and social migration costs and frictions, y* denotes steady state regional income and κ is a parameter reflecting the sensitivity of willingness to migrate at a given spatially weighted average differential income per worker (Pfaffermayr, 2012). Thus, κ is a factor of the individual weighting of locational utilities that result from economic incentives, natural amenities and cultural (manmade) residential amenities (Rodriguez-Pose & Ketterer, 2012, Wardenburg & Brenner, 2020).

The question whether labour market migration has positive or negative effects on regional growth and convergence across regions is answered differently in the literature (Ozgen et al, 2010, Huber & Tondl, 2012, Fratesi & Percoco, 2014). From a neoclassical perspective immigration enhances population growth and therefore reduces economic growth by decreasing the capital-labour ratio and vice versa for emigration. On the other hand, emigration potentially decreases a regions human capital, with negative effects on output and labour productivity. Hence, Pfaffermayr & Fischer (2018) argue that migration accelerates convergence between high and low income regions if human capital of immigrants is not higher than that of natives. Given, that the income differentials result inter alia from higher average human capital in the immigration region, this should apply on average. However, assuming that migrants are particularly high-skilled seeking for additional income rewards brain-drain dynamics reduce the human capital of the sending region and decelerate convergence.

Given these dependencies, an econometric model for analysing the spatial effects in economic growth should consider physical and human capital growth, innovation, labour as well as income and migration. While the possibility of negative spatial externalities is not considered in the mentioned spatial growth literature, their presence in reality is likely due to brain-drain effects and competition between firms in neighbouring regions causing productivity increases in one region negatively affecting other regions

### 2.4 Spatial VAR-Models

Flexible VAR models have their origin in Sims (1980) approach for vector-autoregressive time-series forecasting. Their main advantage is that flexible models are able to estimate mutual time-lagged interaction across dynamic regional variables without making too many a priori restrictions. Holtz-Eakin, Newey and Rosen (1988) adapted Sims approach for panel data VAR (pVAR) estimations. pVARs model economic interdependencies by estimating simultaneous dynamic regression models in which each variable in the system is a dependent variable, depending on lagged values of all variables in the system. Therefore, our starting point is a reduced form simultaneous dynamic first-order panel VAR estimation system in its aggregated form with M estimations, where M equals the number of variables in the system and *i* and *t* represent region and time (Rickmann, 2010):

$$(4)\ \ y_{it} = \mu_i + \tau_t + \mathrm{A}y_{it-1} + \varepsilon_{\mathrm{it}}\,.$$

In this basic form A represents an M*M coefficient matrix. Its values describe the relationship of $y_{it}$ to time-lagged endogenous variables in the system, while $\mu_i$ and $\tau_t$ represent individual and time-fixed effects to control for cross-sectional heterogeneity and global economic dynamics and trade-cycle effects (such as economic crisis) within the panel data set.

This unrestricted model has serious shortcomings as it treats all variables as fully endogenous, which results in over-parametrization and biased impulse-response-functions (Rickmann, 2010). To overcome this problem, the structural VAR model is used. An a-priori causal variable ordering that represents the causal economic structure of variables based on their assumed degree of endogeneity is done (Bernanke, 1986). A subsequent decomposition of the variance-covariance matrix prevents that contemporaneous relations across variables are captured by the instantaneous covariance of the error term (Mitze et al, 2018). The detailed procedure is described in section 3.

Since the presented structural VAR model ignores potential spatial spillover effects, it does not fit regional panel datasets. Beenstock & Felsenstein (2007) and Di Giacinto (2010) proposed ways to calculate coefficients for A that are not biased by spatial autocorrelation by including spatial lag variables as additional independent variables to equation (4):

$$(5)\ y_{it} = \mu_i + \tau_t + A_1 y_{it-1} + H_1 W y_{it-1} + \varepsilon_{\mathrm{it}},$$

where H is an additional M*M matrix of spatial lag coefficients and W is a spatial weight matrix, constant over the M-estimations and over time. In general, further past times (t-2, t-3, …) can be included in Equation (5) implying the use of further coefficient matrices $A_2, H_2, A_3, H_3$ and so on. To keep the presentation of our methodological extension simple and since only one past time is relevant in our application example, we consider only dependencies on time *t-1*. Various analyses of the effects of local economic shocks have used this kind of model (e.g. Eberle et al, 2019). Although, these models are able to correct for exogenous push-in spillover effects, where economic growth results from developments in related regions, they still do not quantify these effects or integrate push-out spillover effects, since the values of H are ignored in the further examination. Wardenburg & Brenner (2020) present an extended spatial indirect SpVAR model and calculate push-in spillover effects by estimating additional impulse-responses representing the effects of a shock in a neighbouring region, based on a one-time growth spillover into the estimated region, however, still ignoring possible later second-order spillover.

Canova & Cicarelli (2009) model a multi-country VAR for multiple time-series based on a global vector-autoregression (GVAR) approach. This approach allows for time variation in the estimated coefficients, but does not explicitly focus on spatial interdependencies. In a restricted GVAR approach Dewachter, Houssa & Torffamo (2012) model a European cross-country VAR which models push-out spillover for Germany under the assumption of a homogenous spatial lag structure. Ramajo, Marquez & Hewings (2017) follow a multiREG-SpVAR that is also based on GVAR methods for seventeen Spanish regions. The model estimates push-in and push-out spillover and explicitly allows for heterogeneity in spillover intensity across regions and allows to identify regions as growth generators with large outward growth spillover. However, this estimation technique ignores effects over time and needs to estimate individual regression systems for every regional unit. Thus, it is not appropriate for data sets with a large number of regions.

In general, within a SpVAR approach all estimation techniques that are used in panel data analysis can be applied. Ellhorst (2012) provides an overview of adequate estimators and their limitations for dynamic panel models pointing out that least-squares models including individual fixed effects and lagged dependent variables (OLS-FE) are biased due to the known Nickell-Bias, especially if t is rather small (<10) (Nickell, 1981). Generalized methods of moments (GMM) estimators have become the most popular alternative, providing consistent estimators under the assumption of strong instrumental variables. However, Kiviet (1995), Hsiao et al. (2002) and Binder et al. (2005) show that GMMs produce noteworthy biases if instruments are weak. Alternatively, transformed likelihood based estimators such as the quasi-maximum likelihood estimator including fixed effects (QML-FE) proposed by Hsiao et al. (2002), and the orthogonal reparametrization approach (OPM) by Lancaster (2002) have been developed considering the incidental parameter problem resulting from maximum-likelihood estimations in dynamic panel models (see Neyman & Scott, 1948). Binder et al. (2005) and Pickup & Hopkins (2020) show, that this estimator outperforms classic OLS-FE, GMMs and the QML-FE estimators especially for small t. However, we find that these estimators face serious problems, if independent variables are not completely exogenous to the lagged dependent variables, what automatically is the case for time-lagged spatial lags of the dependent variable and if partially multicollinearity among independent variables is present. For the sake of simplicity in our application example we use OLS-FE techniques, arguing that the known bias is small with t=17, which is rather preferable against the unknown biases of the other techniques. Furthermore, our focus is not on the estimation technique but on the way in which push-in and push-out spillover can be considered. Our approach for dealing with spillover - presented in Section 3 - can be combined with all kinds of estimators.

### 2.5 Impulse-Response functions

Based on the coefficients of $\mathrm{A}y_{it-1}$ from (5) it is now possible to model impulse-response-functions (IRFs) that illustrate the response of a particular variable to an isolated uncorrelated shock in another variable in the system that includes indirect effects between variables in the system over time. In a non-spatial VAR this is expressed by transforming $\mathrm{A}y_{it-1}$ to its moving-average form, in which $A_T$ represents the dependence on the variable values *T* time steps before, considering *p* past time steps (Lütkepohl 2005):

$$(6)\ \ y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t.$$

Considering the above-mentioned problems with over-parametrization a Choleski decomposition of the covariance matrix is performed following Lütkepohl (2005). This decomposition leads to a matrix A that is premultiplied to eq. (6):

$$(7)\ \ Ay_t = A_1^* y_{t-1} + \cdots + A_p^* y_{t-p} + \varepsilon_t.$$

Considering now the shock element $I_k$ which is a diagonal matrix with unit variance of the input variables, adding ($I_k$ – **A**)$y_t$ to (4) gives

$$(8)\ \ y_t = A_0^* y_t + A_1^* y_{t-1} + \ldots + A_p^* y_{t-p} + \varepsilon_t,$$

where $A_0^*$ equals $I_k$ – **A** and is a lower triangular matrix (Lütkepohl, 2005). Thus, this estimation is recursive and does not allow for instantaneous circular effects, but may contains mutual effects beginning from $y_{t+1}$.

## 3 ECONOMETRIC ADVANCEMENT

In this section we present our technique for extending the presented SpVAR models to a flexible recursive SptpVAR that enables to estimate push-in and push-out spillover corrected impulse-responses for a specific location and its economically connected neighbours over time.

Taking equation (5) as a starting point, we follow the reasoning of Wardenburg & Brenner (2020) that inward spillover intensity per time step is given by the matrix of spatial lag coefficients ($HWy_{it-1}$). This enables to calculate spatial spillover into a region *i* by assuming a shock within a neighbouring region $i_w$ and multiplying it with the spatial lag matrix to get inward effects from an external shock into the calculated region at the next time step of the IRF estimation. In case of two identical economies in terms of size and structure, one could argue, that inward spillover effects from $i_w$ to *i* equal the outward spillover from *i* to $i_w$, which would allow to use the spatial lag matrix to also estimate outward spillover effects. However, allowing for differences in size, the inward spillover effect into *i* is a multiple of the outward spillover to $i_w$, where the multiplier is not known. It could be argued that the multiplier is equal to the size ratio of both economies. However, this relies on the assumption that spillover depend linearly on size. Moreover, the assumption of structural homogeneity in space would be necessary, which is rather unlikely to hold in reality. Economic and geographical characteristics bring strong heterogeneity in the ability to produce and absorb spatial externalities. For example, the more a country's or region's firms and institutions are integrated in cross-border cooperation, innovation systems, commuting and trade, the more is its economic development influenced by the development of other regions. Thus, for example, landlocked regions experience more spatial spillover than coastal regions or islands (Roberts & Deichmann, 2009). Moreover, the infrastructure and accessibility of other regions determine the ability to absorb economic growth and defines the amount of spillover (Durlauf & Johnson, 1995). For example, central regions usually possess a strong linkage to their neighbouring regions. In consequence, the spatial dissemination of shocks strongly depends on the spatial and economic structure of the neighbours and is strongly heterogeneous in space, meaning that a region might be more affected by a shock in a neighbouring region than the other way round, even if both regions are of same size. As a consequence, we argue that calculating outward spillover from a region as equal to inward spillover using spatial lag coefficients from (5) is not correct, although it provides a way to calculate a rough estimation.

To explicitly take into account spatial heterogeneity, we model push-in and push-out spillover effects over time, not only for the regional unit in which the computed shock occurs, but also for spatio-economically linked regions. In order to keep the following calculable, we assume that the spatial weight matrix W contains only values of 0 and 1, meaning that we only distinguish between neighbours and non-neighbours, as done in most studies. Furthermore, it is too complicated to consider the exact structure of the neighbours of one region, so that we treat all direct neighbour regions as a hypothetical single region $i_w$, which influences the developments in the considered region *i* and is influenced by the shock in region *i* due to economic spillover. Assuming that this neighbourhood region $i_w$ surrounds region *i*, we can define a second neighbourhood region $i_{ww}$ (with $i \not\subseteq i_{ww}$) consisting of all neighbours to region $i_w$ (with $i \not\subseteq i_{ww}$). So, $i_{ww}$ can be called the second order neighbourhood of *i.* In the same way further orders of neighbourhood could be build, but in our application further orders do not matter. That might be different in other applications. Figure 1 shows an exemplary neighbourhood structure and the theoretical dissemination of economic shocks in space.

The neighbourhoods $i_w$ and $i_{ww}$ of each region *i* are combinations of original regions and have to be constructed in the dataset. The number of these units equals the number of regions in the dataset for each neighbourhood , $i_w$,


*Figure 1: Dissemination of economic shocks from region I to neighbouring region and higher order neighbours over time.*

$i_{ww}$,(…) since every region has one neighbourhood region at each order of neighbouring. The identification of spatially and economically linked regions is presented in section 3.2. As mentioned above, using summed neighbourhood regions represents a simplification. However, the only more exact version would require to treat all regions separately, implying single regressions for each of them. Using summed neighbourhood regions allows distinguishing regions with different surrounding settlement structure, e.g. big cities with their surrounding and rural regions in the periphery. By this part of the spatial structure and type of neighbouring regions is considered. However, it means that some information on individual regional spillover get lost in summing up neighbourhood regions.

By calculating accurate neighbourhoods instead of calculating spatially weighted lags, we can rewrite equation (5) to:

(9) $y_{it} = \mu_i + \tau_t + A_1 y_{it-1} + H_1 y_{i_w t-1} + \varepsilon_{\mathrm{it}}$,

Where the coefficient matrix $H$ defines the spillover intensity from the combined neighbourhood region $i_w$ into *i.* Again, as in the following, we include only the dependence on the former time step. Of course, further past times could be included in the same way.

We now extend the approach and estimate the autoregressive dynamic effects within the combined regions $i_w$ by formulating an additional M*M autoregressive process congruent to equation (9):

(10) $y_{i_w t} = \mu_{i_w} + \tau_t + C_1 y_{i_w t-1} + G_1 y_{it-1,} + J_1 y_{i_{ww} t-1} + \varepsilon_{i_w \mathrm{t}}$,

where C is a M*M matrix of coefficients representing the autoregressive dependence within $i_w$, $G_,$ is an additional same-size matrix with spatial coefficients representing that the values of $y_{i_w t}$ depend on time-lagged push-out spillover from region $i$, while the matrix J represents analogously push-in spillover from the remaining neighbours $i_{ww}$. A regression equation for $y_{i_{ww} t}$ and even more distant neighbours can be set up similar to (10), dependent on their own lagged values and lagged values of inner and outer neighbours, with corresponding coefficient matrices. The resulting coefficient matrices can be used to calculate spillover corrected IRFs for $i$, $i_w$ and $i_{ww}$. This system can, in theory, be extended without spatial limits. The number of observations is constant over the estimation systems.

Of course, this technique has some difficulties. The most obvious is that individual regions are represented multiple times in the calculated dependent variables of (10), although in different combinations. Thus, regions that have identified neighbourhood relations to many regions have a stronger impact on the calculated dependent variables than those that have only one identified neighbour, which affects the estimation results. Of course, this depends strongly on the chosen definition of neighbourhood. If, e.g., neighbourhood is defined based on commuting, metropolitan cities are linked to many regions, due to size effects and due to the higher amount of weekend-commuter, which means that large cities impact the results of the new developed estimation systems stronger than other regions. However, we believe that this representation of highly connected regions reflects the real spatial spillover structure, because, as argued above, these are drivers of spatial interdependent growth due their high economic integration.

### 3.1 Spatio-temporal IRFs

The information provided by the coefficient matrices from the additional regression systems is used to extend the moving average calculation by including spatial spillover, considering that an initial shock at time $t_0$ leads to spatial spillover not only once, but at every time step in which the effect persists. In principle the IRF values $y_{t0}$ to $y_{t\infty}$ can be calculated by using the moving-average representation as described above in Equation (8), but including the additional spillover terms from Equation (9) and adding similar calculations for the neighbouring regions. For simplicity, we again only consider one past time step (*p=1*) and obtain after the Choleski decomposition analogous to Equation (8) for the considered region:

(11) $y_{it} = A_0^* y_{it} + A_1^* y_{it-1} + H_1 y_{i_w t-1} + \varepsilon_t.$

The IRFs for the neighbouring regions are given by

(12)$y_{i_w t} == C_0^* y_{i_w t} + C_1^* y_{i_w t-1} + G_1 y_{it-1} + J_1 y_{i_{ww} t-1} + \varepsilon_t$

and

(13) $y_{i_{ww} t} = D_0^* y_{i_{ww} t} + D_1^* y_{i_{ww} t-1} + K_1 y_{i_w t-1} + L_1 y_{i_{www} t-1} + \varepsilon_t.$

Further neighbourhoods could be considered in a similar way.

As each IRF needs the estimation results of the next neighbours, all IRFs must be calculated simultaneously. Thus, we practically need to limit the spatial expansion, because otherwise an infinite dimension of estimations would result. Since effect strength will decrease while fuzziness increases with distance, we decided to consider complete estimations up to $y_{i_{ww}t}$, including simplified spatial spillover from $i_{www}$, that are restricted to spatially depend on its inner neighbours, but not its outer neighbours.

In order to show how this effects the IRFs of the considered region *i*, let us consider a shock (change) $y_{i0}$ in this region at time *t=0* and check how this spreads through the equations (assuming all other values to be zero at time *t=0*, as done in IRF calculation). Then, at time *t=1* the values are given by (only presenting the deterministic part, to each value a stochastically determined value has to be added):

$$y_{i1} = A_1 A_0^* y_{i0} \ , \qquad y_{i_w 1} = G_1 A_0^* y_{i0} \qquad \text{and} \quad y_{i_{ww}1} = 0.$$

At time *t=2* spillovers come back from the neighbouring regions:

$$y_{i2} = (A_1^2 + H_1 G_1) A_0^* y_{i0},$$

$$y_{i_w 2} = (C_1 G_1 + G_1 A_1) A_0^* y_{i0} \qquad \text{and} \qquad y_{i_{ww}2} = K_1 G_1 A_0^* y_{i0}.$$

While after two time steps the development in region *i* is only influence by spillover that come back from the neighbouring regions, after four time steps additional spillover coming back from second-order neighbours as well as spillover from the developments that have been triggered in the neighbouring regions add to the developments within the region. The effects of the original shock on region *i* are then given by:

$$y_{i4} = (A_1^4 + H_1G_1A_1^2 + H_1C_1G_1A_1 + A_1H_1G_1A_1 + A_1^2H_1G_1 + A_1H_1C_1G_1 + H_1C_1^2G_1 + H_1G_1H_1G_1 + H_1J_1K_1G_1) * A_0^*y_{i0},$$

This shows that multiple spillover effects occur that play a role for the reaction of a region to shocks (changes) especially in the medium run. All these effects are ignored in the approach that is so far used in the literature.

In order to assess the statistical significance of the estimation results, we conduct a Monte Carlo simulation, in which we draw regions with all their attributed regional and neighbourhood values over years from the original data set until the dataset reaches the same size. Regions can be drawn multiple times. We then estimate the developments after the shock for 500 randomly drawn datasets while holding the initial shock constant and calculate 95% confidence of the IRF values.

We should mention that, despite being sensitive for regional heterogeneity, size effects limit the comparability of effects between the IRFs for *i*, $i_w$ and $i_{ww}$. IRFs indicate responses in %. Thus, the total effects depend on the size and can be approximated by comparing the mean size of the accumulated economies.

## 3.2 Neighbourhood and Spatial Lags

By explicitly modelling also the neighbouring regions, the definitions of regional units and economically linked neighbourhood regions become crucial for the estimation results and the identification of spillover. Like most regional data analysis, we are limited to the use of administrative regions due to data availability. These are mere containers and the spatial expansion of local shocks does not follow local boundaries.

The first problem is the identification of relevant neighbours. Most spatial VARs use a binary Spatial-Durbin model, identifying physically bordering regions as neighbours to calculate spatial-lag variables (e.g. Eberle et al, 2019). As mentioned before, economic interactions are not necessarily based on geographic proximity. However, based on the identified transmission channels, proximity seems to be an important condition for strong market relatedness and spatial connectivity. Moreover, it is important to identify economic linkages that lead to spatial spillover without immediate geographic proximity. In a metropolitan area, for example, regions share economic interactions with the regions core city, even without sharing an administrative border. Furthermore, it must be considered that economic interactions are not evenly distributed across neighbours and not necessarily symmetric. A shock in a large city like Berlin may generate larger impacts on a smaller surrounding city or region than vice versa due to size effects and the accompanying commuting and trade patterns. However, asymmetric spillover are imaginable even for regions of equal size. To identify economic linkages, the economic distance seems to be as relevant as the physical distance.

In order to develop appropriate spatial-weights, we generate a binary spatial weight matrix $W$ in two steps. The first step is to identify spatial proximity using a binary spatial contiguity matrix with $W_{ij}$ = 1 if regions share a border, assuming that physical neighbours automatically share economic externalities. Various instruments can be used to identify further economic linkages. Ramajo et al. (2017) identify economic distance via cross-regional trade linkages. Since we do not have the corresponding data, we consider commuting patterns. We focus on outward-bound commuters, since $y_{it}$ depends on the economic situation at the person's workplace (job-losses, wage gains), whereas economic shocks at the place of residence should not have impact on the workplace. To identify cross-region commuters, we use federal data, that display individuals that are not registered in the regions they life in. These are not necessarily daily commuters, but may be weekend-commuters or people that are registered and work in different places for other reasons. In order to take into account linkages between regions due to commuting, we assign to every region the commuters' target regions, and order these by the share of commuters. Then, we regard all regions at the top of this list as linked regions until a share of more than 80% of the commuters is considered. These regions are added to the neighbourhood matrix, whereby double-counts are excluded to maintain the binary matrix structure.

To limit the before mentioned overrepresentation of metropolitan cities and restrict the number of neighbours, we use another neighbourhood matrix that represents the population-weighted travel distance by car. If this is higher than 90 minutes, regions are not counted as economic neighbours. Obviously substantial economic spillover with greater distance cannot be ruled out, but are, in our opinion, negligible.

The 2$^{nd}$ order neighbourhood matrix V is identified by identifying all regions which are connected to a direct neighbour but are not neighbours of the region itself. A $M$*$M$ matrix results that contains values of 1 for all 2$^{nd}$ order neighbours and values of 0 for all other pairs of regions. The same procedure is done for the 3rd order spatial weights. We further encounter problems with the spatial limitation of datasets here, for example country borders or coasts. In our analysis, non-German regions are not included as neighbours in the dataset due to different information bases and administrative region definition. This limits the number of neighbours (and higher order neighbours), but is not an essential problem for the estimation.

Another issue is the choice of a suitable spatial scale. The smaller the chosen regional unit, the larger the spillover should be compared to the region size. The smaller the economy, the higher the need to import production factors from other regions which extends the need for spatial externalities. While a main concern of former studies was to lose spillover information by using a small regional scale, this is solved by our new approach. Furthermore, in larger regional scales, such as country level analysis, the within-country externalities are not recognized as such. In the case of negative cross-regional (but not cross-country) externalities, these would decrease the estimated responses and would cancel each other out on country level. Hence, choosing rather small regions seems to be advantageous for this method.

### 3.3 Exemplary Data and Variables

The paper's exemplary empirical analysis is based on a balanced panel dataset set including annual data in the spatial unit of all 361 German administrative county regions in the time period 2000 to 2017. County regions are identical o the 401 administrative counties and cities, but district-free cities with a population <100.000 are combined with a neighbourhood region. With few exceptions, these cities are surrounded by just one region with which they are strongly connected, which could distort the results.

The variables utilized in the SptpVAR model are based on the theoretical frameworks in Section 2. Hence, we use the private sector investment rate as a measure of physical capital investments and higher education as measure for human capital. Moreover, we integrate the employment rate and GDP as proxy for the output (labour productivity). As in all similar studies, measuring the technology rate is an essential problem for adequately considering growth models in econometric analysis. We argue, that there is no well-suited measure, since patents – the commonly used indicator with its known advantages and disadvantages – do not have adequate autoregressive characteristics due to high fluctuations and time delays in patent recognition. We argue that regional technology growth should be included in the GDP measure by directly influencing labour productivity. Additionally, the migration rate is included as well as the household income to control for income as the main reason for migration. Spatial lags for every variable are computed as given in Section 3. All variables are used in their natural logarithm form. Table 1 outlines the use of variables and data sources.

TABLE 1: Variable descriptions and Data sources

| Acronym | Variable Description | Data Source |
|---|---|---|
| **INVQ** | Private sector physical capital industry investment rate in the manufacturing, mining and quarrying sector as share of the GDP*<br>*[Industry Investments in € / GDP in €]* | German Federal Statistical Office.<br>GDP: Working Group 'National Accounts of the Federal States. - 'Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder |
| **EMP** | Gross employment rate<br>*[Employed persons/Population aged 15 to 64 years ]* | Institute for Employment Research (IAB)<br>Population data: German Federal Statistic Office |
| **EMP_UNI** | Higher education – Workers with a university degree per economically active working population<br>*[Employed persons with university degree/Population aged 15 to 64 years ]* | German Federal Statistical Office<br>Population data: German Federal Statistic Office |
| **INC** | Mean disposable household income<br>*[Disposable income of private households/population]* | National Accounts of the Federal States ('Volkswirtschaftliche Gesamtrechnungen der Länder')<br>Population data: German Federal Statistic Office |
| **MIG** | Regional net migration rate<br>*[(net migration – $population_{t-1}$)/$population_{t-1}$]* | Migration statistic of the federal government and the federal states<br>Population data: German Federal Statistic Office |
| **GDP** | Nominal GDP per economically active working population<br>*[GDP in €/population aged 15 to 64 years ]* | Working Group 'National Accounts of the Federal States. - 'Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder'<br>Population data: German Federal Statistic Office |

*Remarks:* *Only investments of firms with >=20 working persons are gathered. The missing investments in relation to measured values should not be correlated in space and time, and therefore not produce structural errors.

To verify the actual presence of spatial autocorrelation, we perform a Morans-I test on our database given the spatial weight matrix presented in section 3.2. The results confirm the existence of spatial autocorrelation among all six variables. Another necessary check for pVAR estimation is testing the stationarity condition. The results suggest that unit roots are present in four of six variables, namely employment rate, higher education rate, GDP and income. Hence, we follow Ellhorst (2012) and subtract a time trend from each individual unit in the panel data for the concerned variables. Morans I and IPS test results are given in the Appendix (A1 and A2). The summary of the used variables is given in table 2.

*TABLE 2: Variable summary statistics*

| Nr | Acronym | Observations | Min | 1.Quarter | Mean | 3. Quarter | Max | Std. Dev. |
|---|---|---|---|---|---|---|---|---|
| 1 | **INVQ** | 3610 | -8.194 | -4.335 | -3.967 | -3.560 | -1.496 | 0.651 |
| 2 | **EMP** | 3610 | -1.464 | -0.8845 | -0.723 | -0.587 | 0.411 | 0.256 |
| 2.2 | **EMP_DET** | 3610 | -1.485 | -0.987 | -0.830 | -0.703 | 0.095 | 0.262 |
| 3 | **EMP_UNI** | 3610 | -4.710 | -3.521 | -3.116 | -2.813 | -0.948 | 0.595 |
| 3.2 | **EMP_UNI_DET** | 3610 | -4.773 | -3.866 | -3.442 | -3.127 | -1.253 | 0.595 |
| 4 | **INC** | 3610 | 6.903 | 7.230 | 7.345 | 7.460 | 8.090 | 0.163 |
| 4.2 | **INC_DET** | 3610 | 6.884 | 7.080 | 7.167 | 7.253 | 7.792 | 0.134 |
| 5 | **MIG** | 3610 | -.0405 | -.0011 | .0026 | .0061 | .0592 | .0060 |
| 6 | **GDP** | 3610 | 9.762 | 10.394 | 10.619 | 10.807 | 12.545 | 0.354 |
| 6.2 | **GDP_DET** | 3610 | 9.656 | 10.164 | 10.372 | 10.535 | 11.784 | 0.352 |

*Note: _DET denotes detrended version of the variable.*

As outlined above we need some a priori restrictions towards the causal variable ordering to be able to perform the choleski decomposition of the variance-covariance matrix. The chosen order is as presented in Table 1, based on a Granger-Causality test and additional theoretical assumptions. Test results are given in Appendix-Table A3. It is assumed that the investment rate is the most exogenous variable and cannot be affected by other variables in the same year (but in the following years), while GDP is most endogenous and is contemporaneously affected by all other variables.

## 4 EMPIRICAL RESULTS

The empirical results demonstrate the functioning of our SptpVAR approach and bring some new empirical insights. In this section we present a brief selection of results. The approach provides individual impulse response functions for every pair of variables and regional neighbourhood level (i, $\mathrm{i_w}$ and $\mathrm{i_{ww}}$). All resulting IRFs are listed in the appendix (A4).

Focussing on effects of shocks in the local employment rate, we find that a single shock in the number of jobs within a region has significant positive effects on the local net migration rates in the following years (*Figure 2*). This suggests that at least some of this additional jobs are filled by external workers that move to the region. The results for 1st order and 2nd order neighbours indicate a significant negative development of net migration rates. We therefore see that these neighbours' loose a share of their population to region *i*. Assuming that these were already gainfully employed before or are at least qualified enough to take on a job, these regions forfeit potential growth capital. This finding supports the theoretical assumptions of equation (3), that personal income is a main driver of migration. Furthermore, spatial proximity has an effect, most immigrants into *i* seem to move from neighbouring or economically linked regions. This is an important finding for the assessment of economic policies.

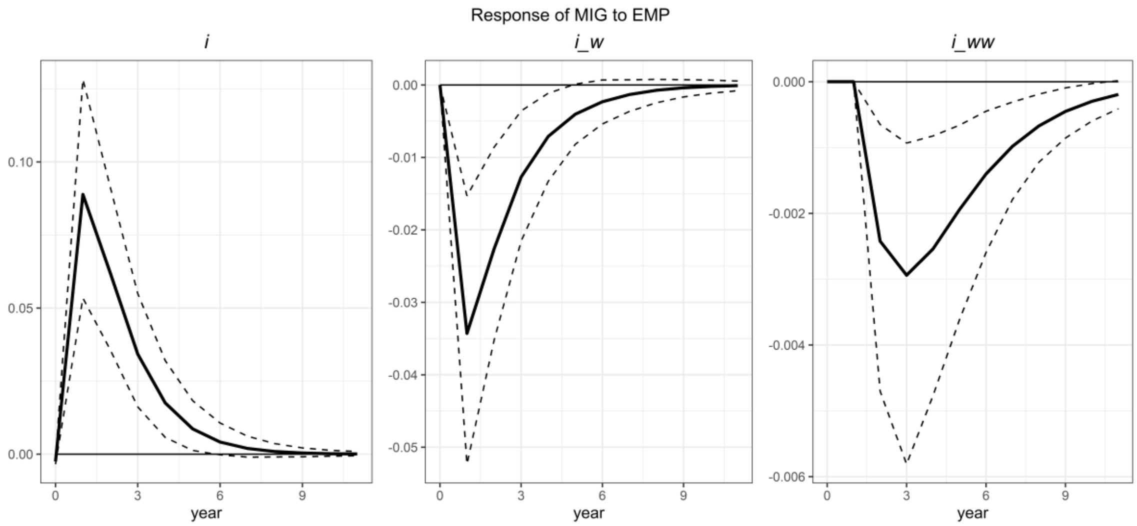


*Figure 2: Responses of Migration to GDP shock. Note: Estimated impulse response functions are solid lines. Dashed lines represent 95% coefficient intervals from Monte Carlo simulations with 500 repetitions. IRFs display responses to orthogonal shocks in the amount of the standard deviations of the impulse variables. Responses are given in %.*

Secondly, we focus on output (GDP) responses to employment shocks, examining the validity of the spatial growth theories presented. In support of the Mankiw growth model (Equation (1)), we find that local labour growth has significant positive effects on the total output within the same region. However, this local shock has no significant effect on neighbouring regions *(Figure 3).* Thus, based on our results, labour growth does not cause spatial externalities that impacts the neighbours total output in a significant way. The same applies for other variables' responses to employment shocks, were we do not find significant spatial effects.

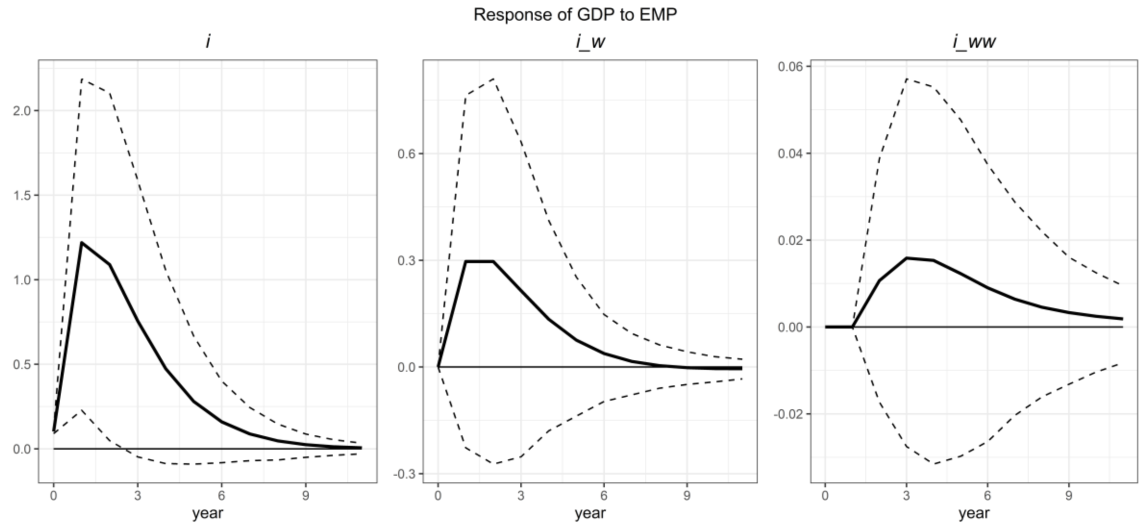


*Figure 3: Responses of GDP to Employment shock. Specifications equal Figure 2.*

We also note that output per working-age population is negatively affected by migration within the same region *(Figure 4).* This indicates that population growth has negative effects on the regions productivity. Based on the presented considerations by Pfaffermayr & Fischer (2018), it means that the average migrant is not as productive as the existing population one year after moving. This explains negative effects on productivity, at least in short term. In consequence, the effects shown in Figure 4 should lead to convergence in productivity across regions. We do not find spatial output effects on local GDP growth.

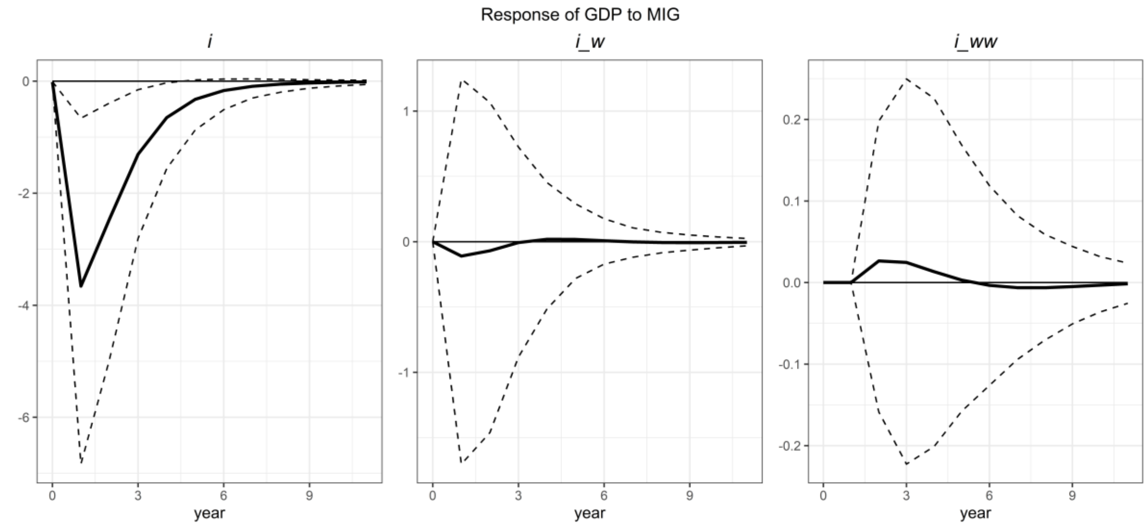


*Figure 4: Responses of GDP to Migration shock. Specifications equal Figure 2.*

Additionally, we are interested in the spatial dissemination of output shocks. We find that GDP growth has on average positive, but not significant effects on its neighbours and no clear impact on $2^{nd}$ order neighbours *(Figure 5).* Thus, we do not find clear evidence for spatial economic externalities within the economic output, against the hypothesis that knowledge driven output growth should spillover into its neighbouring regions causing output growth. It appears that the spatial effects of output growth depend on the nature of the shocks. Assuming that knowledge or technology level spillover cause growth in neighbouring regions, this may not be the case for other growth sources, explaining average positive but not significant growth spillover. Further research using the SptpVAR approach concentrating on this issue could clarify this.

Secondly, we find significant employment growth as a result of GDP shocks (*Figure 5*). The effects are not causing employment growth in neighbouring regions.

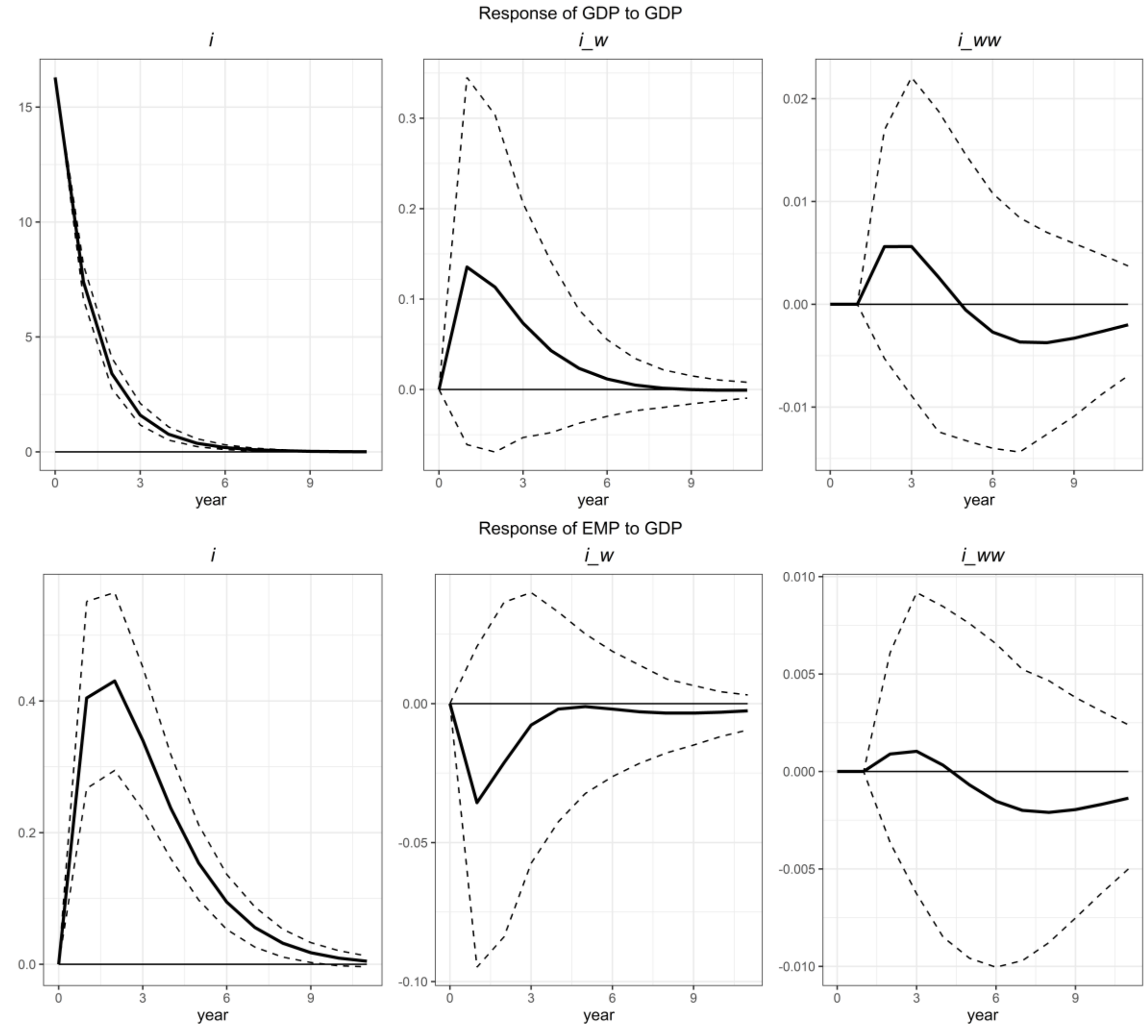

*Figure 5: Responses of GDP to GDP and Employment shocks. Specifications equal Figure 2.*

Nevertheless, GDP growth shows spatial impact in the form of significantly positive migration responses within the region and in both types of neighbouring regions (*Figure 6*). While it is obvious that economically growing regions are attractive for immigrants from other regions, the spatial results somehow seem to contradict the findings from Figure 2. We detect a clear difference between spillover from employment and from GDP growth. Employment growth in a region seems to attract people from surrounding regions into the region, meaning that it leads to quite local migration. In contrast, GDP growth seems to attract people from outside the wider neighbourhood (including second order neighbouring regions) into this neighbourhood, implying long-distance migration. Both effects seem to be connected to suburbanism dynamics, but the latter effect (including second-order neighbours) even goes beyond that.

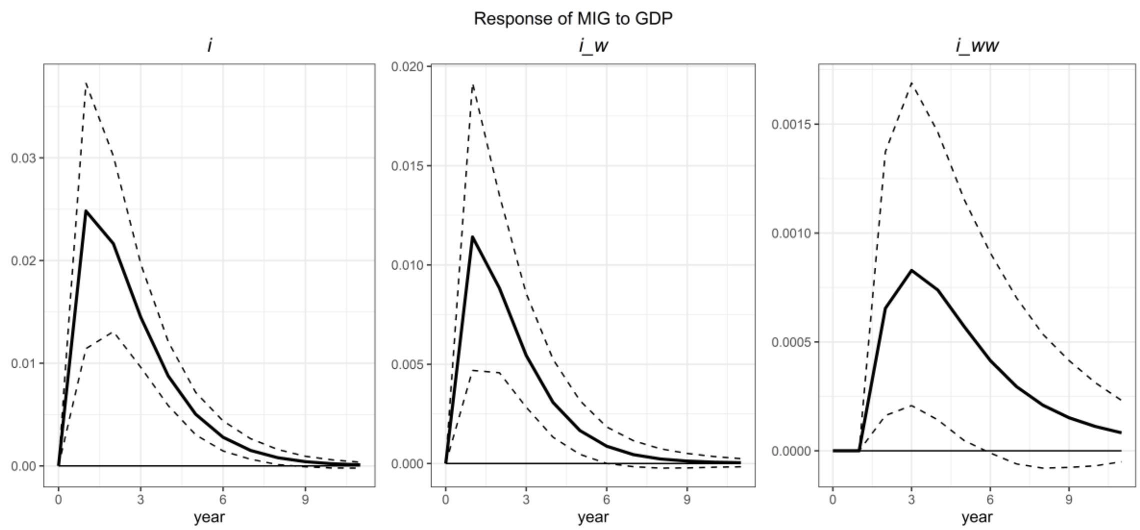


*Figure 6: Responses of Migration to GDP and Employment shock. Specifications equal Figure 2.*

Finally, our estimation reveals that significant effects in neighbouring regions are possible, even if there are no significant local effects. *Figure 7* illustrates that there is no within region reaction of the local employment rate to migration. However, in the direct neighbourhood, the employment rate increases per working age population, although there is no local shock. We believe, that the effect is provoked by emigrants into *i*. If their average employment rate before migration was lower than those of the remaining population in $i_w$, the employment rate within the region increases without new jobs being created.

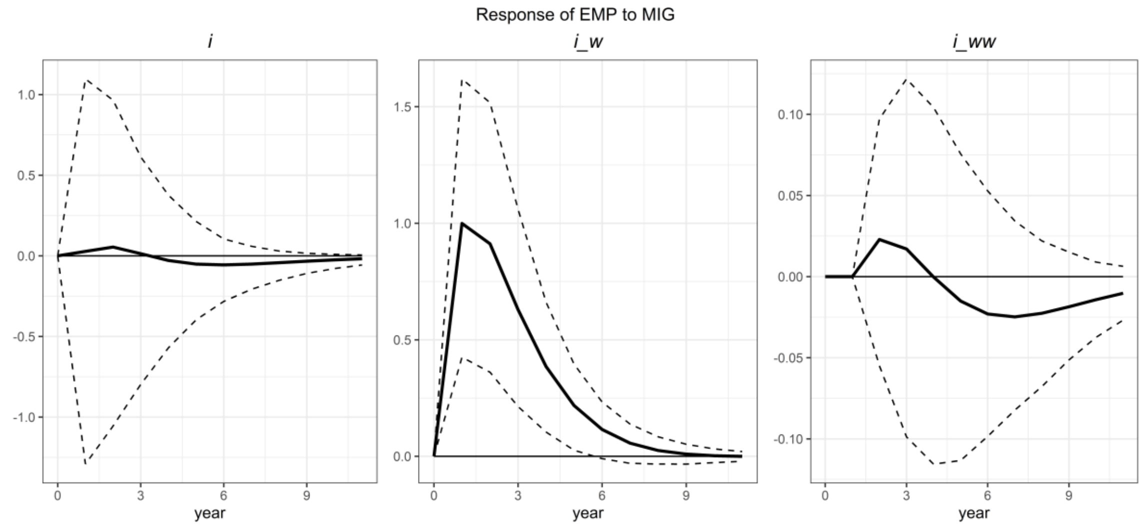


*Figure 7: Responses of Employment to Migration shock. Specifications equal Figure 2.*

## 5 CONCLUSION

The paper aimed to develop a theoretical SpVAR model that extends former approaches by integrating spatial externalities of local economic shocks into the analysis and overcome problems in dealing with spatial effects in regional panel data. We presented an SptpVAR model that does this in a rather general approach that allows to track the spatio-temporal diffusion of local economic change in space as well as in time and incorporates indirect effects not only between variables, but also in space in the resulting IRFs. Furthermore, the proposed approach allows to examine spatial heterogeneity by building subsamples: e.g. studying the subsample of larger cities would imply that the spillover between these cities and their surrounding regions is examined. The functioning of the approach is shown by applying it to a spatial dataset for 361 German regions.

The main advantages of the new approach are that spatial spillover effects resulting from a shock in one region on the surrounding or connected regions and indirect feedback spillover from these regions to the origin region are no longer neglected. Hence, the new approach also provides additional information on spatial spillover structures that are very interesting, for example for the evaluation of regional policy measures.

However, the approach brings some limitations. It still relies on the use of administrative regions as spatial containers, faces problems at the spatial end of the data set (e.g. country borders) and generates rather large regions when calculating higher order neighbourhoods.

Nevertheless, the approach allows for some new interesting empirical insights. We find that positive effects in one region can cause positive or negative spillover in neighbours and linked regions and therefore increase or mitigate the total effects. Our exemplary application shows that spatial spillover are most relevant if migration dynamics are included in the analysis.

We conclude that the SptpVAR has versatile application possibilities in the empirical analysis of dynamic economic systems.

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## Appendix

*TABLE A1: Moran's I test of spatial autocorrelation*

| Variable | INVQ | | EMP | | EMP_UNI | | INC | | MIG | | GDP | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Morans-I** | **p-val** | **Morans-I** | **p-val** | **Morans-I** | **p-val** | **Morans-I** | **p-val** | **Morans-I** | **p-val** | **Morans-I** | **p-val** |
| 2000 | 0.099 | 0.000 | 0.055 | 0.011 | 0.232 | 0.000 | 0.659 | 0.000 | 0.432 | 0.000 | 0.329 | 0.000 |
| 2001 | 0.108 | 0.000 | 0.066 | 0.003 | 0.228 | 0.000 | 0.665 | 0.000 | 0.560 | 0.000 | 0.334 | 0.000 |
| 2002 | 0.119 | 0.000 | 0.072 | 0.002 | 0.224 | 0.000 | 0.661 | 0.000 | 0.502 | 0.000 | 0.335 | 0.000 |
| 2003 | 0.137 | 0.000 | 0.075 | 0.001 | 0.217 | 0.000 | 0.660 | 0.000 | 0.283 | 0.000 | 0.338 | 0.000 |
| 2004 | 0.134 | 0.000 | 0.077 | 0.001 | 0.216 | 0.000 | 0.656 | 0.000 | 0.316 | 0.000 | 0.336 | 0.000 |
| 2005 | 0.122 | 0.000 | 0.085 | 0.000 | 0.213 | 0.000 | 0.651 | 0.000 | 0.231 | 0.000 | 0.348 | 0.000 |
| 2006 | 0.143 | 0.000 | 0.077 | 0.000 | 0.216 | 0.000 | 0.635 | 0.000 | 0.251 | 0.000 | 0.339 | 0.000 |
| 2007 | 0.151 | 0.000 | 0.074 | 0.001 | 0.216 | 0.000 | 0.633 | 0.000 | 0.422 | 0.000 | 0.338 | 0.000 |
| 2008 | 0.173 | 0.000 | 0.069 | 0.002 | 0.217 | 0.000 | 0.635 | 0.000 | 0.315 | 0.000 | 0.345 | 0.000 |
| 2009 | 0.142 | 0.000 | 0.063 | 0.005 | 0.219 | 0.000 | 0.593 | 0.000 | 0.232 | 0.000 | 0.335 | 0.000 |
| 2010 | 0.164 | 0.000 | 0.060 | 0.007 | 0.220 | 0.000 | 0.620 | 0.000 | 0.290 | 0.000 | 0.328 | 0.000 |
| 2011 | 0.196 | 0.000 | 0.062 | 0.005 | 0.213 | 0.000 | 0.629 | 0.000 | 0.277 | 0.000 | 0.332 | 0.000 |
| 2012 | 0.220 | 0.000 | 0.064 | 0.004 | 0.219 | 0.000 | 0.652 | 0.000 | 0.380 | 0.000 | 0.331 | 0.000 |
| 2013 | 0.149 | 0.000 | 0.063 | 0.005 | 0.225 | 0.000 | 0.652 | 0.000 | 0.410 | 0.000 | 0.332 | 0.000 |
| 2014 | 0.128 | 0.000 | 0.065 | 0.004 | 0.225 | 0.000 | 0.672 | 0.000 | 0.257 | 0.000 | 0.335 | 0.000 |
| 2015 | 0.130 | 0.000 | 0.069 | 0.002 | 0.224 | 0.000 | 0.668 | 0.000 | 0.091 | 0.000 | 0.345 | 0.000 |
| 2016 | 0.133 | 0.000 | 0.072 | 0.002 | 0.223 | 0.000 | 0.660 | 0.000 | 0.162 | 0.000 | 0.335 | 0.000 |
| 2017 | 0.143 | 0.000 | 0.076 | 0.001 | 0.225 | 0.000 | 0.649 | 0.000 | 0.223 | 0.000 | 0.340 | 0.000 |

*TABLE A2: IPS unit-root test statistics*

| Variable | IPS-test statistic | p-vale |
|---|---|---|
| **INVQ** | -31.711 | 0.000 |
| **EMP** | 39.812 | 1 |
| **EMP_DET** | -17.622 | 0.000 |
| **EMP_UNI** | 24.398 | 1 |
| **EMP_UNI_DET** | -25.224 | 0.000 |
| **INC** | 27.116 | 1 |
| **INC_DET** | -31.393 | 0.000 |
| **MIG** | -13.440 | 0.000 |
| **GDP** | 32.813 | 1 |
| **GDP_DET** | -33.162 | 0.000 |

*Note: Number of regions = 361, t= 10, test based on Im Pesaran & Shin (2003): H0: presence of unit roots. _DET donates detrended version of the variable.*

*TABLE A3: Panel Granger Causality Test (lag=1)*

| **GRANGER CAUSES** | **INVQ** | | ***EMP_DET*** | | **EMP_UNI_DET** | | **INC_DET** | | **MIG** | | **GDP_DET** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | value | p-value | *value* | *p-value* | value | p-value | value | p-value | value | p-value | value | p-value |
| **INVQ** | x | x | 9.94 | 0.00 | 4.03 | 0.00 | 0.09 | 0.926 | 1.23 | 0.219 | 1.66 | 0.097 |
| **EMP_DET** | 1.08 | 0.284 | x | x | 9.29 | 0.00 | 18.43 | 0.000 | 8.29 | 0.000 | 8.48 | 0.000 |
| **EMP_UNI_DET** | 1.06 | *0.288* | -1.17 | 0.243 | x | x | 7.76 | 0.000 | 4.00 | 0.000 | 2.95 | 0.003 |
| **INC_DET** | 0.39 | 0.696 | 3.76 | 0.000 | 22.90 | 0.000 | x | x | 2.74 | 0.006 | 2.819 | 0.005 |
| **MIG** | 1.11 | 0.266 | 9.04 | 0.000 | -1.21 | 0.225 | 1.77 | 0.075 | x | x | 6.04 | 0.000 |
| **GDP_DET** | 4.12 | 0.000 | 0.57 | 0.568 | 3.89 | 0.000 | 6.71 | 0.000 | -3.11 | 0.756 | x | x |

*Note: Test as given in Dumitrescu/Hurlin (2012).*
*Granger Causality Test is performed for every region; Alternative hypothesis = Granger causality given for at least one reg*

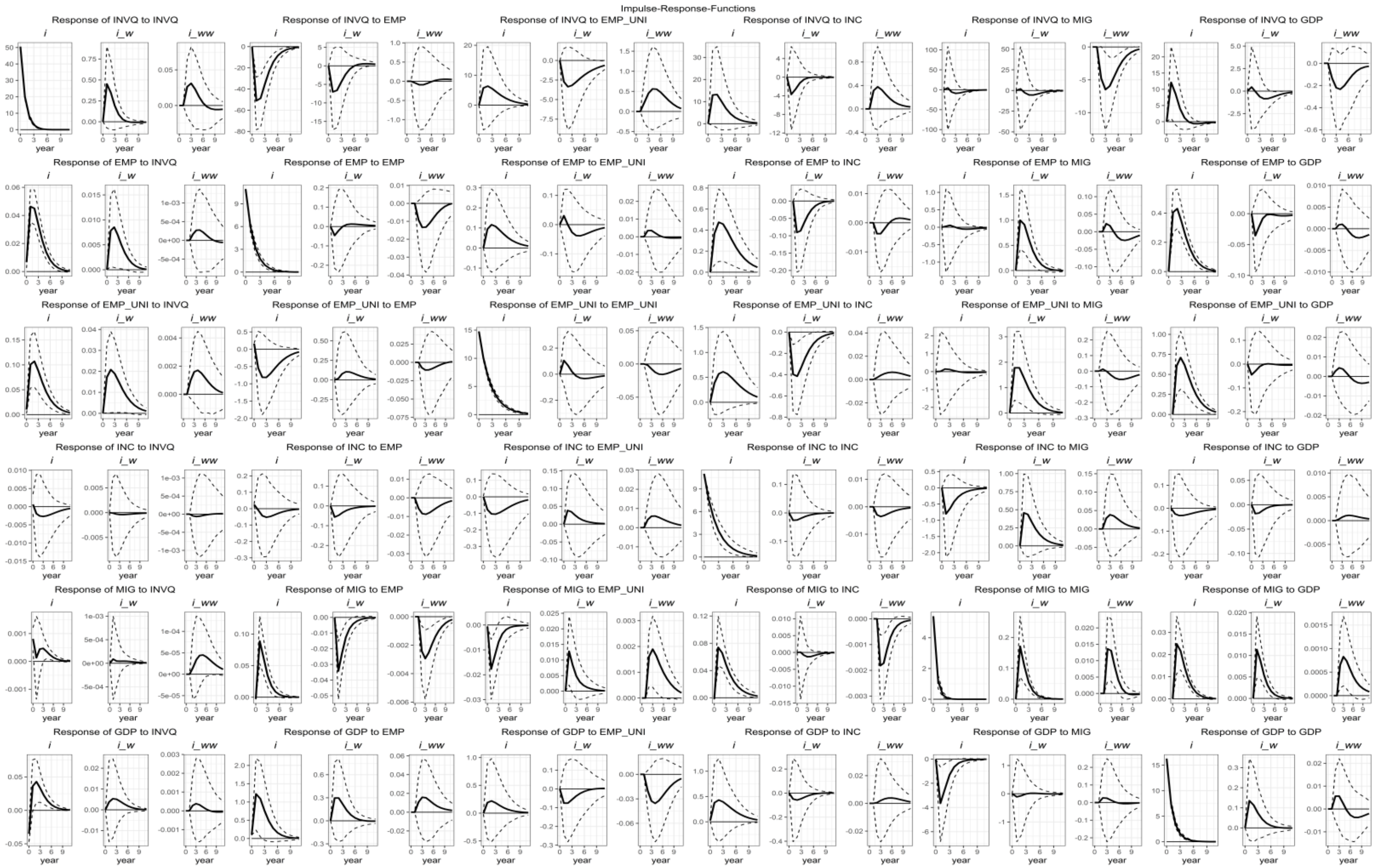


*Figure A4: Complete set of IRFs in the estimated SptpVAR System. Specifications equal Figure*

*TABLE A5: Core-Models - i is dependent variable*

| | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | (invq) | (emp) | (empl_uni) | (inc) | (mig) | (gdp) |
| plm::lag(invq, 1) | 0.412*** | 0.003*** | 0.007*** | -0.001 | -0.00003 | 0.002 |
| | (0.012) | (0.001) | (0.001) | (0.001) | (0.0001) | (0.001) |
| plm::lag(emp, 1) | -0.864*** | 0.565*** | -0.049* | -0.011 | 0.014*** | 0.128*** |
| | (0.255) | (0.012) | (0.026) | (0.011) | (0.003) | (0.027) |
| plm::lag(empl_uni, 1) | -0.111 | -0.015*** | 0.664*** | -0.011** | -0.001 | 0.020* |
| | (0.109) | (0.005) | (0.011) | (0.005) | (0.001) | (0.012) |
| plm::lag(inc, 1) | 0.469** | 0.047*** | 0.070*** | 0.701*** | 0.021*** | 0.008 |
| | (0.224) | (0.010) | (0.023) | (0.010) | (0.003) | (0.024) |
| plm::lag(mig, 1) | -0.832 | 0.085* | 0.034 | -0.005 | 0.153*** | -0.164 |
| | (1.050) | (0.048) | (0.105) | (0.047) | (0.013) | (0.113) |
| plm::lag(gdp, 1) | 0.124 | 0.030*** | 0.019* | -0.006 | 0.005*** | 0.462*** |
| | (0.111) | (0.005) | (0.011) | (0.005) | (0.001) | (0.012) |
| plm::lag(spinvq, 1) | 0.048* | -0.0004 | 0.004 | -0.001 | 0.0001 | -0.005** |
| | (0.025) | (0.001) | (0.002) | (0.001) | (0.0003) | (0.003) |
| plm::lag(spemp, 1) | 1.121** | 0.097*** | 0.199*** | 0.010 | -0.024*** | -0.198*** |
| | (0.498) | (0.023) | (0.050) | (0.022) | (0.006) | (0.053) |
| plm::lag(spempl_uni, 1) | -1.036*** | -0.106*** | -0.111*** | 0.036*** | -0.003 | 0.046* |
| | (0.242) | (0.011) | (0.024) | (0.011) | (0.003) | (0.026) |
| plm::lag(spinc, 1) | 0.411 | 0.024 | -0.108*** | -0.143*** | -0.010** | -0.124*** |
| | (0.381) | (0.018) | (0.038) | (0.017) | (0.005) | (0.041) |
| plm::lag(spmig, 1) | -3.801** | 0.420*** | 0.917*** | 0.013 | 0.189*** | -0.156 |
| | (1.762) | (0.081) | (0.177) | (0.079) | (0.022) | (0.189) |
| plm::lag(spgdp, 1) | 0.110 | 0.014 | 0.012 | -0.003 | 0.010*** | 0.059** |
| | (0.230) | (0.011) | (0.023) | (0.010) | (0.003) | (0.025) |
| Observations | 6,137 | 6,137 | 6,137 | 6,137 | 6,137 | 6,137 |
| R2 | 0.181 | 0.432 | 0.468 | 0.469 | 0.073 | 0.254 |
| Adjusted R2 | 0.125 | 0.394 | 0.432 | 0.433 | 0.011 | 0.204 |
| F Statistic (df = 12; 5748) | 105.676*** | 364.648*** | 421.142*** | 423.546*** | 37.761*** | 163.402*** |
| Note: | | | | *p<0.1; **p<0.05; ***p<0.01 | | |

*TABLE A6: 1st neighbor models - $i_w$ is dependent variable*

| | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | spinvq) | (spemp) | (spempl_uni) | (spinc) | (spmig) | (spgdp) |
| plm::lag(invq, 1) | 0.017*** | 0.001** | 0.002*** | -0.0001 | 0.00003 | 0.002** |
| | (0.006) | (0.0003) | (0.001) | (0.0004) | (0.0001) | (0.001) |
| plm::lag(emp, 1) | -0.164 | 0.001 | 0.031** | -0.018** | -0.007*** | 0.009 |
| | (0.124) | (0.006) | (0.012) | (0.008) | (0.002) | (0.014) |
| plm::lag(empl_uni, 1) | -0.058 | -0.008*** | -0.009* | 0.002 | 0.003*** | -0.004 |
| | (0.052) | (0.003) | (0.005) | (0.003) | (0.001) | (0.006) |
| plm::lag(inc, 1) | -0.025 | -0.011** | -0.023** | 0.010 | 0.001 | 0.00001 |
| | (0.107) | (0.005) | (0.011) | (0.007) | (0.002) | (0.012) |
| plm::lag(mig, 1) | 0.167 | 0.066** | 0.099** | 0.070** | 0.038*** | -0.012 |
| | (0.503) | (0.026) | (0.049) | (0.034) | (0.008) | (0.058) |
| plm::lag(gdp, 1) | -0.014 | -0.007** | -0.010** | -0.008** | 0.002*** | 0.009 |
| | (0.053) | (0.003) | (0.005) | (0.004) | (0.001) | (0.006) |
| plm::lag(spinvq, 1) | 0.496*** | 0.001** | 0.003** | -0.001 | -0.00002 | -0.001 |
| | (0.012) | (0.001) | (0.001) | (0.001) | (0.0002) | (0.001) |
| plm::lag(spemp, 1) | -1.480*** | 0.532*** | -0.150*** | -0.059*** | 0.049*** | -0.123*** |
| | (0.313) | (0.016) | (0.031) | (0.021) | (0.005) | (0.036) |
| plm::lag(spempl_uni, 1) | 0.155 | 0.024*** | 0.769*** | 0.041*** | -0.036*** | 0.116*** |
| | (0.145) | (0.007) | (0.014) | (0.010) | (0.002) | (0.017) |
| plm::lag(spinc, 1) | 0.611*** | 0.032*** | 0.017 | 0.456*** | -0.001 | 0.010 |
| | (0.185) | (0.009) | (0.018) | (0.012) | (0.003) | (0.021) |
| plm::lag(spmig, 1) | -1.405 | 0.047 | 0.155* | 0.034 | 0.311*** | 0.066 |
| | (0.860) | (0.044) | (0.084) | (0.058) | (0.014) | (0.099) |
| plm::lag(spgdp, 1) | 0.437*** | 0.058*** | 0.087*** | 0.063*** | 0.016*** | 0.459*** |
| | (0.112) | (0.006) | (0.011) | (0.008) | (0.002) | (0.013) |
| plm::lag(sp2invq, 1) | 0.113*** | -0.001 | 0.003 | -0.002 | 0.0005* | 0.0005 |
| | (0.016) | (0.001) | (0.002) | (0.001) | (0.0003) | (0.002) |
| plm::lag(sp2emp, 1) | 1.452*** | 0.175*** | 0.254*** | 0.133*** | -0.048*** | 0.098** |
| | (0.344) | (0.018) | (0.034) | (0.023) | (0.005) | (0.040) |
| plm::lag(sp2empl_uni, 1) | -0.987*** | -0.094*** | -0.100*** | -0.015 | 0.019*** | -0.069*** |
| | (0.167) | (0.009) | (0.016) | (0.011) | (0.003) | (0.019) |

| | | | | | | |
|---|---|---|---|---|---|---|
| plm::lag(sp2inc, 1) | 0.909*** | -0.100*** | -0.149*** | -0.170*** | -0.020*** | -0.153*** |
| | (0.280) | (0.014) | (0.028) | (0.019) | (0.004) | (0.032) |
| plm::lag(sp2mig, 1) | -7.109*** | 0.861*** | 1.352*** | 0.523*** | 0.144*** | 0.327** |
| | (1.263) | (0.064) | (0.124) | (0.085) | (0.020) | (0.146) |
| plm::lag(sp2gdp, 1) | -0.058 | 0.014* | 0.060*** | -0.015 | 0.015*** | -0.015 |
| | (0.163) | (0.008) | (0.016) | (0.011) | (0.003) | (0.019) |
| Observations | 6,137 | 6,137 | 6,137 | 6,137 | 6,137 | 6,137 |
| R2 | 0.281 | 0.541 | 0.597 | 0.280 | 0.200 | 0.251 |
| Adjusted R2 | 0.232 | 0.509 | 0.569 | 0.230 | 0.145 | 0.200 |
| F Statistic (df = 18; 5742) | 124.603*** | 375.713*** | 472.683*** | 123.753*** | 79.716*** | 107.142*** |
| Note: | | | | *p<0.1; **p<0.05; ***p<0.01 | | |

*TABLE A7: 2nd neighbor models - $\boldsymbol{i}_{ww}$ is dependent variable*

| | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | (Sp2invq) | (sp2emp) | (sp2empl_uni) | (sp2inc) | (sp2mig) | (sp2gdp) |
| plm::lag(spinvq, 1) | 0.066*** | -0.001*** | -0.0003 | -0.002*** | -0.0005*** | 0.001 |
| | (0.008) | (0.0004) | (0.001) | (0.001) | (0.0001) | (0.001) |
| plm::lag(spemp, 1) | 0.371* | 0.012 | -0.010 | -0.013 | -0.013*** | 0.068*** |
| | (0.216) | (0.011) | (0.024) | (0.014) | (0.003) | (0.024) |
| plm::lag(spempl_uni, 1) | -0.212** | -0.047*** | -0.006 | -0.003 | 0.003** | -0.044*** |
| | (0.101) | (0.005) | (0.011) | (0.007) | (0.001) | (0.011) |
| plm::lag(spinc, 1) | -0.076 | -0.007 | -0.051*** | -0.045*** | -0.006*** | -0.016 |
| | (0.126) | (0.007) | (0.014) | (0.008) | (0.002) | (0.014) |
| plm::lag(spmig, 1) | -2.882*** | 0.179*** | 0.318*** | 0.276*** | 0.076*** | 0.152** |
| | (0.595) | (0.031) | (0.066) | (0.039) | (0.008) | (0.066) |
| plm::lag(spgdp, 1) | 0.253*** | 0.009** | 0.025*** | 0.014*** | 0.001 | 0.014 |
| | (0.078) | (0.004) | (0.009) | (0.005) | (0.001) | (0.009) |
| plm::lag(sp2invq, 1) | 0.475*** | 0.003*** | 0.008*** | -0.002** | 0.0004** | 0.002 |
| | (0.011) | (0.001) | (0.001) | (0.001) | (0.0002) | (0.001) |
| plm::lag(sp2emp, 1) | -1.117*** | 0.606*** | 0.016 | 0.046** | 0.005 | -0.059* |
| | (0.284) | (0.015) | (0.032) | (0.019) | (0.004) | (0.032) |
| plm::lag(sp2empl_uni, 1) | -0.660*** | -0.011* | 0.674*** | 0.017** | -0.018*** | 0.118*** |
| | (0.125) | (0.007) | (0.014) | (0.008) | (0.002) | (0.014) |
| plm::lag(sp2inc, 1) | 0.424** | -0.018* | -0.054** | 0.344*** | 0.018*** | -0.126*** |
| | (0.204) | (0.011) | (0.023) | (0.014) | (0.003) | (0.023) |
| plm::lag(sp2mig, 1) | -0.022 | 0.310*** | 0.264** | -0.090 | 0.357*** | -0.120 |
| | (0.924) | (0.048) | (0.103) | (0.061) | (0.013) | (0.103) |
| plm::lag(sp2gdp, 1) | 0.424*** | 0.060*** | 0.128*** | 0.078*** | 0.013*** | 0.425*** |
| | (0.120) | (0.006) | (0.013) | (0.008) | (0.002) | (0.013) |
| plm::lag(sp3invq, 1) | 0.049*** | -0.0004 | 0.005*** | -0.002** | -0.0004* | -0.002 |
| | (0.014) | (0.001) | (0.002) | (0.001) | (0.0002) | (0.002) |
| plm::lag(sp3emp, 1) | 1.674*** | 0.132*** | 0.197*** | 0.114*** | -0.019*** | -0.066** |
| | (0.302) | (0.016) | (0.034) | (0.020) | (0.004) | (0.034) |
| plm::lag(sp3empl_uni, 1) | -0.870*** | -0.066*** | -0.074*** | -0.028*** | 0.011*** | 0.017 |
| | (0.130) | (0.007) | (0.014) | (0.009) | (0.002) | (0.014) |

| | | | | | | |
|---|---|---|---|---|---|---|
| plm::lag(sp3inc, 1) | -0.447* | -0.083*** | -0.124*** | -0.197*** | -0.026*** | -0.145*** |
| | (0.246) | (0.013) | (0.027) | (0.016) | (0.003) | (0.027) |
| plm::lag(sp3mig, 1) | -4.735*** | 0.796*** | 1.003*** | -0.110 | 0.146*** | 0.155 |
| | (1.105) | (0.058) | (0.123) | (0.073) | (0.015) | (0.123) |
| plm::lag(sp3gdp, 1) | 0.029 | 0.017** | 0.061*** | 0.042*** | 0.001 | 0.076*** |
| | (0.133) | (0.007) | (0.015) | (0.009) | (0.002) | (0.015) |
| Observations | 6,137 | 6,137 | 6,137 | 6,137 | 6,137 | 6,137 |
| R2 | 0.318 | 0.610 | 0.558 | 0.227 | 0.302 | 0.245 |
| Adjusted R2 | 0.271 | 0.584 | 0.527 | 0.174 | 0.255 | 0.193 |
| F Statistic (df = 18; 5742) | 148.668*** | 499.556*** | 402.046*** | 93.532*** | 138.280*** | 103.239*** |

Note: *p<0.1; **p<0.05; ***p<0.01