The Mysteries of the Trade: Interindustry Spillovers in Cities

Analyzing the Causes of MAR-Externalities using Spatial Econometrics Techniques

Wolfgang Dauth*

April 13, 2010

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Theories in regional science predict that related establishments benefit from their mutual proximity due to forward-backward linkages, labor pooling and knowledge spillovers (the Marshallian forces). While the existence of these externalities as a whole is well supported by the empirical literature, there are few studies that discriminate between the single explanations.

Adoption of spatial econometric methods offers an interesting approach to explicitly model interrelations between different industries in the same region. In this context, the strength of these relations is determined by economic closeness rather than by geography. This paper analyzes the dependence of employment growth between 56 industries of the manufacturing and service sectors in five German labor market regions in the years 1989 to 2006. The results suggest that all three of the Marshallian forces can explain agglomeration externalities. The magnitude of these externalities is illustrated by counterfactual steady-state effects and response paths of machinery industries in the Munich region.

JEL-Classification: O47, R11, R12
Keywords: Urban Economics, MAR-Externalities, Interindustry Spillovers, Spatial Econometrics

*IAB Institute for Employment Research and University of Erlangen-Nürnberg, wolfgang.dauth@iab.de

"So great are the advantages which people following the same skilled trade get from near neighbourhood to one another. The mysteries of the trade become no mysteries; but are as it were in the air..." (Marshall, 1890, p. 271)

1 Introduction

At the beginning of the 21st century, for the first time in history, more than half of mankind lives in cities (United Nations DESA, 2008).[1] Even though earth would offer plenty of space for each of its inhabitants, we prefer to crowd ourselves on only a small part of its landmass. In this context, one often thinks of prominent examples like Mumbai, Shanghai or Mexico City. However, this phenomenon is not restricted to such mega cities, but also appears in European industrial nations. In Germany, more than half of the population lives in metropolitan areas[2]. This might be one of the reasons why urban economics is one of the major topics in regional science.[3] What makes living and working in cities so desirable? While quality of live is certainly an aspect for some people, a more convincing explanation should be an economic one.

History and natural advantages offer some explanations (cf. Ellison/Glaeser, 1999), but this is just the beginning of the story. Regional science focuses on agglomeration externalities that exist when actors benefit from their mutual proximity. These effects are self enforcing in a sense that they grow with the size of an agglomeration. One strand of literature on externalities argues that cities with a diversified economic structure offer environments that are particularly creative and foster innovation processes.[4] At the same time, another strand emphasizes the importance of a connection between actors to allow externalities to be effective (i.e. related variety, cf. Frenken/Oort/Verburg, 2007). The key advantage of proximity is the reduction of transportation costs for exchanging goods, people and knowledge. In the literature, these so called MAR-externalities (after Marshall, 1890; Arrow, 1962; Romer, 1986) stem from the proximity of related establishments. While the existence of MAR-externalities is well supported in the empirical literature, their causation is explained mainly theoretically. The most common explanations are that related establishments benefit from being in the same supply chain, sharing a pool of specialized and qualified employees and the transmission of ideas and innovations. Up to now, the empirical literature provided only a small contribution to discriminate between these possible explanations. Instead, it is often argued that while the underlying mechanisms lead to the same result, they are hard to trace due to the "Marshallian

[1] This trend is not going to slow down: in 2050 more than two thirds of mankind will be living in cites.

[2] Source: Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations

[3] In the 2009 North American Meetings of the Regional Science Association International, 30 out of 148 sessions were about urban analysis or urban economics, which makes this by far the most popular topic in the conference program.

[4] e.g. Jacobs (1970), Quigley (1998), Florida (2004)

equivalence" (Duranton/Puga, 2004).

Normally, when MAR-externalities are analyzed, relatedness of establishments is represented by a measure of the agglomeration of establishments that belong to the same industry. However, since official industry classifications like NACE or ISIC are administrative rather than purely functional, this does only take into account a fraction of the possible relationships between establishments.[5] However, while spillovers within the same industry take place inside a black box, information on the nature of the underlying mechanisms of MAR-externalities can be gained from spillovers between industries. This is done by Ellison/Glaeser/Kerr (2010), who make use of this information and analyze how different relations between industries explain interindustrial co-agglomeration. Going one step further, one could presume that these relations enhance productivity and eventually foster employment growth. Thus, when employment in one industry grows, this should have a positive effect on employment in related industries in the same region. Methods of spatial econometrics are capable of explicitly modeling this kind of process, while space is to be interpreted in an economic rather than in a geographic way. With different weights matrices, each representing one of the three explanations for MAR-externalities, it is feasible to discriminate between these explanations and assess their magnitude.

The remainder of the paper is organized as follows. Section 2 provides an overview of the relevant theories concerning agglomeration externalities, while section 3 summarizes the empirical literature that analyzes the different causes of these externalities. Section 4 describes how spatial econometrics methods are used to model interindustry spillovers. Estimation results and steady state effects are presented in section 5 and section 6 concludes.

2 Theoretical Considerations

The question why economic activity is not distributed randomly across space but rather concentrated in a limited number of locations is one of the oldest in regional science. Notable theoretical works on this topic include the famous German scholars von Thünen (1826), Christaller (1933), and Lösch (1940), as well as Hotelling (1929). A widely accepted explanation why establishments from the same industry benefit from their mutual proximity is called MAR-externalities after seminal works from Marshall (1890), Arrow (1962) and Romer (1986). There are three explanations of these externalities (the three Marshallian forces): first, forward-backward linkages are external effects between nearby establishments within the same supply chain. Second, labor pooling, which means that related establishments can draw from a common pool of specialized and qualified employees. Third, knowledge spillovers spread ideas and innovations and thus foster technical change. All of these explanations suggest that spatial concentration leads to an increase

[5]For example, Porter's (2000) definition of a cluster explicitly refers to "firms in related industries".

in productivity. Thus, establishments have pecuniary incentives to seek their mutual proximity.

Knowledge spillovers in particular play a major role in the models of the New Growth Theory (cf. Lucas, 1988; Romer, 1990). Here, input factors are considered to be constant and do not affect growth. Due to the fact that ideas cannot be kept completely secret, technological change spreads among establishments within a region or even between regions and thus leads to endogenous growth.

Finally, the New Economic Geography (cf. Krugman, 1991; Fujita/Krugman/Venables, 1999) presents a closed formal model to explain agglomeration. Within this framework, proximity again saves transport costs. These do not only apply to commodities but also to people and ideas (cf. Glaeser, 2008), which again corresponds to forward-backward linkages, labor pooling and knowledge spillovers. Under certain conditions, the reduction of transport costs leads to self-augmenting processes that further increase concentration and attract even more establishments.

Even though the explanations of MAR-externalities are more than 100 years old, they still apply to modern production processes. At first sight, it might seem like forward-backward linkages lost their importance. However, while fright is cheaper than ever before, saving time plays a crucial role in modern production. Instead of producing intermediate goods and business-related services themselves (at a higher cost), it is efficient for firms to obtain them from external suppliers. Just-in-time delivery and production often necessitate close distances between firms and their suppliers. Flexible production and efficient stockkeeping would hardly be feasible if inputs could not be provided right on-demand. Even when inputs are normally bought from more distant suppliers, local sources can be useful to compensate fluctuations or shortages (cf. Scott, 1986; Feser, 2002). Furthermore, suppliers and buyers often collaborate in design and development of intermediate goods. This cooperation is also facilitated by spatial proximity (cf. Imrie/Morris, 1992; Klier, 1994).

In a time of flexible production, where factor input has to be adjusted to fluctuations in demand, firms can benefit from a pool of specially skilled and experienced personnel. There are several theoretical explanations on how labor pooling provides advantages for co-located establishments. According to Marshall (1890, p. 271), "a localized industry gains a great advantage from the fact that it offers a constant market for skill". Glaeser (2008) calls this "statistical returns to scale". When establishments often experience idiosyncratic shocks, they benefit from labor pooling which irons out these shocks between establishments. This eases adjusting production in response to these shocks (cf. Overman/Puga, 2010), a flexibility that in the long run should increase labor demand. Another advantage can be explained by search and matching theories. With the size of a labor pool, the average quality of matches increases, i.e. the chances of finding good applicants for vacancies improve (cf. Helsley/Strange, 1990). This also motivates workers to acquire more specialized skills (cf. e.g. Becker/Murphy, 1992). Of course, such a labor pool is not restricted to one single industry. Establishments from different industries can have similar production processes or require workers with the same skills, e.g. manufacturing of motor vehicles and manufacturing of other transport equipment. It is very plausible, that an accordingly skilled person would have a good chance to find a job in any of these industries. Thus, establishments from different industries can share a labor pool and, under certain circumstances, benefit from their mutual proximity.

Finally, knowledge spillovers still play a crucial role in supporting technical change. Since they promote productivity by connecting smart people with good ideas, they might be the most important agglomeration economy (Glaeser, 2008). While the transmission of information over the internet is instantaneous and virtually costless, this does not necessarily apply to the transmission of ideas and innovation. In many cases, this kind of knowledge might not even be written down and can only be transmitted by personal contact ("sticky-knowledge", cf. von Hippel, 1994). In this context, knowledge spillovers do not necessarily have to lead to product innovation, but rather to process innovation. If e.g., an establishment slightly improves its production process, others might benefit from the same idea, even if they produce completely different goods. These spillovers can be transmitted through formal as well as informal channels. One could imagine employees of different firms chatting in their spare time and sharing ideas. Grilliches (1979) distinguishes between two kinds of knowledge spillovers: rent spillovers and true knowledge spillovers. The former are associated with the exchange of goods. When the price of a good does not wholly cover its technical advantage, the buyer realizes a rent by obtaining it. These spillovers might be hard to disentangle from forward-backward linkages. True knowledge spillovers on the other hand do not require a business relationship. Here, the knowledge is detached from any kind of merchandize. They can happen between any establishments that use the same kind of knowledge.

Agglomeration is a dynamic process that follows a "circular logic", where external effects increase with the size of an agglomeration, which in turn leads to further agglomeration (cf. Fujita/Krugman/Venables, 1999). Thus, the strength of each of the three Marshallian forces obviously depends on how many related subjects are present in the same region. Cities should be particularly prone to support these interrelations since they offer an environment where many individuals meet in a dense system and interactions should be easier than in rural regions. A further increase in one industry's employment should increase the benefits from forward-backward linkages, labor pooling and knowledge spillovers and eventually result in an increase of employment in related industries.[6] The positive effects of forward-backward linkages and knowledge spillovers on employment growth are quite

[6] At first, externalities should increase productivity. Depending on the price elasticity of demand of an industry's products, this could lead to an increase as well as a decline in employment (cf. Appelbaum/Schettkat, 1995). However, since most industries supply national or even international markets, an increase in the productivity of labor should always increase employment.

plausible. However, this prior is weak in the case of labor pooling.[7] If the three Marshallian forces do exist, we can hypothesize that there are three ways of how employment growth can be related in different industries. This hypothesis will be analyzed empirically in section 5.

3 Literature Review

There is a huge empirical literature analyzing the existence of MAR-externalities. Many of the works in the past 15 years have been motivated by the discussion initiated by Glaeser et al. (1992) and Henderson/Kuncoro/Turner (1995).[8] While these compare the differences in employment between two separate years, other studies use panel data to control for unobserved heterogeneity.[9] All these studies have in common that they analyze externalities that arise from geographic concentration of establishments in the same industry. Most of them find at least some evidence that there are positive effects that arise from proximity. However, they do not try to discriminate between different explanations.

Other studies are dedicated to single ones of the three Marshallian forces. Forni/Paba (2002) create a spillover matrix by regressing the regional employment growth of each Italian 3-digit manufacturing industry on specialization variables of each other industry. They find that most spillovers take place within the same 2-digit aggregate. Additionally, there is a "metal/machinery-layer" that spills over to most other industries. Repeating this procedure for 27 2-digit aggregates, they compare their spillover matrix with an input-output table. It turns out that many spillovers coincide with input-output relations, while many follow an upstream path, i.e. spillovers originate in downstream final industries, while sellers of intermediate goods are recipients. There are two papers that explicitly focus on forward-backward linkages using input-output tables. Amiti/Cameron (2007) analyze the impact of access to suppliers and markets on wages in Indonesian plants. They find that both have a positive effect, while the one of market access is slightly stronger. This contradicts the findings of the previously mentioned work. Both effects decline sharply with distance.[10] López/Südekum (2009) use an input-output matrix to analyze whether the number of close-by establishments from the most important upstream

[7] While the matching argument speaks in favor of a positive relationship, the ironing out of shocks implies that hirings in some establishments are compensated by firings in others, at least in the short run. Furthermore, there could still be competition for the most productive workers, which might even lead to a negative relationship ("labor poaching", cf. Combes/Duranton, 2006).

[8] e.g. Ó'hUallacháin/Sattertwhaite (1992); Combes (2000); Batisse (2002); Südekum (2005); Frenken/Oort/Verburg (2007); Mameli/Faggian/McCann (2008); Otto/Fornahl (2008).

[9] e.g. Henderson (1997); Combes/Magnac/Robin (2004); Blien/Südekum/Wolf (2006); Fuchs (2009); Dauth (2010)

[10] Labor pooling and knowledge spillovers are also taken into account. A labor pool is assumed when staffs have similar education structures, which has a positive effect, while knowledge spillovers are assumed to be confined within the same 5-digit industry and exhibit a negative effect. However, both measures seem to be less convincing than others that are discussed below.

and downstream industries has a positive effect on productivity of Chilean establishments in the manufacturing sector. They find evidence for vertical linkages where downstream buyers benefit from proximity to sellers of intermediate goods, which is in line of the results of Forni/Paba (2002).

To my knowledge, there is only one study that empirically analyzes how labor pooling affects agglomeration. Overman/Puga (2010) show that a measure for idiosyncratic employment shocks, which represents the statistical returns to scale argument from section 2, is positively correlated to an industry's geographical concentration, measured by the Ellison/Glaeser (1997) index. However, there is no discussion on how this affects productivity or employment growth.

In contrast to the lack of studies on labor pooling, there is a huge literature analyzing knowledge spillovers.[11] One of the great challenges in this field is that knowledge spillovers are hard to detect. Especially when one is willing to consider transmission of tacit knowledge one must agree with Krugman (1991) that there is no paper trail to follow. However, there are several approaches that try to uncover these spillovers. One idea is to analyze how highly qualified workers, R&D expenditures or the proximity to universities and research institutions provide positive effects on innovation, productivity or growth (cf. e.g. Anselin/Varga/Acs, 1997; Brenner, 2005; Harhoff, 2000; Bercovitz/Feldman, 2007). Another big strand of this literature argues that there is in fact a paper trail. Patent data provide information on what existing knowledge has been used to create new inventions. When a patent is granted, the patent examiner creates a public document that contains not only technical details but also some information on the inventor. An important part of this information is the citation of other patents.[12] Its purpose is to delimit the scope of how an invention expands the state of the art. Researchers use these citations to measure relationships between patents or inventors. Much of this literature bases on seminal papers by Grilliches (1979) and Jaffe/Trajtenberg/Henderson (1993). The latter work analyzes the geographical localization of patent citations. The authors find that given the patent class, the probability that a citation comes from the same region as the original document is significantly higher compared to a patent from a control group. However, this finding is disputed in the more recent literature. Thompson/Fox-Kean (2005) criticize the selection of the control patents. Using their own method, they find no evidence that patents are localized within countries. On the other hand, Agrawal/Kapur/McHale (2008) confirm that the probability of a citation increases with co-location while spatial proximity also increases the probability of knowledge flows between inventors from different technical fields. An interesting application of patent data is to analyze knowledge spillovers between establishments from different industries. The major difficulty of this endeavor is that patent documents do not contain industrial classifications. Several stud-

[11] For an extensive survey and a classification of older literature cf. Feldman (1999).

[12] Note that it is not the applicant but the examiner who includes the citations.

ies provide concordance tables do assign corresponding ISIC-categories to patent classes (e.g. Verspagen/van Moergastel/Slabbers, 1994; Schmoch et al., 2003). Using his concordance table, Verspagen (1997) analyzes several ways to create matrices that measure the strength of spillovers between pairs of industries and compares their ability to explain common patterns in growth of total factor productivity in different industries.

Obviously, there are several studies that focus on single explanations of MAR-externalities. However, there are only three studies that take into account all three of them and try to assess their relative magnitude. Feser (2002) concentrates on two very unequal manufacturing sectors (farm and garden machinery and measuring and controlling devices), which are examples for conventional and high-tech manufacturing sectors, respectively. The author creates measures for each of the three Marshallian forces, i.e. availability of intermediate inputs/outputs, specialization of the industry's labor force in a 50 mile radius and the public sector innovation rate. His results suggest that labor pooling and knowledge spillovers enhance productivity in the high-tech industry while backward linkages and knowledge spillovers enhance productivity in the conventional manufacturing industry. Even though the restriction to consider only two single industries means some loss of generality, this study sheds some interesting light on the relative importance of the respective explanations for MAR-externalities. Another approach is taken by Rigby/Essletzbichler (2002). In a cross section model, they explore how measures for different kinds of agglomeration influence labor productivity separately in 19 manufacturing industries. The three Marshallian forces are included using three proxies: the concentration of suppliers and buyers, the similarity of the occupational structure of a regional industry's workforce compared to the one of the whole region and the growth of labor productivity in upstream sectors. The last measure is intended to capture rent spillovers that are connected to the actual exchange of goods rather than true knowledge spillovers. The authors find evidence for the importance of forward-backward linkages and technological spillovers but only weak evidence for the effect of labor pooling. Finally, using two different indices Ellison/Glaeser/Kerr (2010) calculate how strongly dyads of manufacturing industries tend to co-agglomerate in the same locations. These indices serve as dependent variables which are regressed on measures for the three Marshallian forces on industry level. The authors find that co-agglomeration indices are higher when the two respective industries have strong input-output relations, when they employ a similarly structured workforce and when they often cite each other's patents. All of the three forces seem to be of similar magnitude.

4 Method and Data

4.1 Estimation Strategy

This paper goes one step beyond the above mentioned work by Ellison/Glaeser/Kerr (2010). While they examine which of the Marshallian forces explain co-location patterns, the present work analyzes their effects on employment growth. The aim is to explicitly model the various external effects to get an impression on how these interrelationships work. As a start, consider a basic model like in Combes/Magnac/Robin (2004) or Blien/Südekum/Wolf (2006):

$$\ln e_{irt} = \phi \ln e_{irt-1} + \mathbf{x}'_{irt}\boldsymbol{\beta} + \epsilon_{irt} \tag{1}$$

The dependent variable $\ln e_{irt}$ is the log employment in industry i $(i = 1, \ldots N)$ in region r $(r = 1, \ldots R)$ at time t $(t = 1, \ldots T)$. $\mathbf{x}_{irt}$ is a vector of control variables including fixed effects for cross-sectional units and periods and ϵ_{irt} is the residual. The lagged dependent $\ln e_{irt-1}$ adds a dynamic component which is necessary due to the persistence of employment. In the literature, this autoregressive term is used to analyze the presence of MAR-externalities. A large ϕ indicates that former employment growth has a large influence on future growth. In this setting, relationships between different industries cannot be taken into account. However, since official industry classifications have not been created according to functional criteria, it is very likely that there are indeed interindustry relationships. These could contain important information on external effects between different firms in the same region. The nature of these relationships could bear evidence on which of the before mentioned Marshallian forces are actually effective.

To take this into account, equation 1 is extended by a spatially lagged dependent variable. In this context, the word 'space' is not to be understood literally in a geographical sense but refers to the methods of spatial econometrics.

$$\ln e_{irt} = \rho \sum_{j \neq i} w_{ij} \ln e_{jrt} + \phi \ln e_{irt-1} + \mathbf{x}'_{irt}\boldsymbol{\beta} + \epsilon_{irt} \tag{2}$$

This spatial lag is the weighted sum of the log employment in all other industries in the same region at time t. The weights w_{ij} are supplied in a weights matrix $\mathbf{W}$, as becomes clear when equation 2 is written in matrix notation:

$$\mathbf{y}_{rt} = \rho \mathbf{W} \mathbf{y}_{rt} + \gamma \mathbf{y}_{r,t-1} + \mathbf{X}_{rt}\boldsymbol{\beta} + \mathbf{c} + \alpha_t \mathbf{l} + \mathbf{V}_{rt}, \tag{3}$$

Note, that this represents all N industries in region r at time t. To obtain an equation for all NRT observations, equation 3 must be stacked RT times. $\mathbf{y}_{rt} = (\ln e_{1rt}, \ln e_{2rt}, \ldots, \ln e_{Nrt})'$ is the vector of the dependent variable, $\mathbf{W}$ is the $N \times N$ weights matrix, $\mathbf{X}_{rt}$ is the $N \times k_x$

matrix of exogenous regressors, $\mathbf{c}$ is an $N\times1$ column vector of industry/region fixed effects, α_t a scalar of the fixed time effect, $\mathbf{l}$ is an $N\times1$ vector of ones and $\mathbf{v}_{nt} = (\epsilon_{1rt}, \epsilon_{2rt}, \ldots, \epsilon_{Nrt})'$ is an i.i.d. error term. The elements of $\mathbf{W}$ quantify the strength of the assumed relationships between any pair of industries within the same region. Since the spatial lag is correlated with the error term, naïve estimators like OLS would lead to biased results. The use of two stage least squares or GMM is conceivable but not available for dynamic panel data yet. Conditioning the likelihood on the first observation, Lee/Yu (2010) are the first to derive a quasi maximum likelihood estimator for this model and show its asymptotic properties. If the kind of interindustry relationship specified by $\mathbf{W}$ does exist, ρ should be significantly greater than zero.

In spatial econometrics, it is important to keep in mind (just like in non-spatial dynamic panel data models) that the structural parameters cannot be interpreted as *effects* any more. Their interpretation is confined to how a change in an x would influence y in the own cell in the short run without taking into account cross-sectional and temporal interrelationships. However, following Franzese/Hays (2007), calculating long-run equilibrium changes of $\mathbf{y}$ is simple. When one assumes that after a shock, all observations converge to a steady-state, $\mathbf{y}_{t-1}$ will eventually be equal to $\mathbf{y}_t$. Assuming stationarity and that the exogenous variables do not change, the reduced form of equation 3 can be solved for $\mathbf{y}_t$:

$$\begin{aligned}\mathbf{y}_t &= \rho\mathbf{W}\mathbf{y}_t + \phi\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{c} + \alpha_t\mathbf{l} + \mathbf{V}_{rt} = (\rho\mathbf{W} + \phi\mathbf{I})\mathbf{y}_t + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{c} + \alpha_t\mathbf{l} + \mathbf{V}_{rt} \\ &= [\mathbf{I} - \rho\mathbf{W} - \phi\mathbf{I}]^{-1}(\mathbf{X}_t\boldsymbol{\beta} + \mathbf{c} + \alpha_t\mathbf{l} + \mathbf{V}_{rt}) = \mathbf{S}\ (\mathbf{X}_t\boldsymbol{\beta} + \mathbf{c} + \alpha_t\mathbf{l} + \mathbf{V}_{rt})\end{aligned} \tag{4}$$

Here, $\mathbf{S}$ is the spatiotemporal multiplier. Each column of this matrix can be interpreted as how a shock in one observation i, increasing ϵ_{irt} by one unit, affects its own outcome and all other observations' $y_{jrT}, j = 1, 2, \ldots, n$. Using the delta-method, it is straightforward to calculate estimates of the standard-errors of these counterfactual effects:

$$\widehat{\mathbf{Var}(\widehat{\mathbf{s}}_i)} = \left[\frac{\partial\widehat{\mathbf{s}}_i}{\partial\widehat{\boldsymbol{\theta}}}\right] \widehat{\mathbf{Var}(\widehat{\boldsymbol{\theta}})} \left[\frac{\partial\widehat{\mathbf{s}}_i}{\partial\widehat{\boldsymbol{\theta}}}\right]', \tag{5}$$

with $\widehat{\boldsymbol{\theta}} \equiv \left[\widehat{\rho}\ \ \widehat{\phi}\right]'$, $\left[\frac{\partial\widehat{\mathbf{s}}_i}{\partial\widehat{\boldsymbol{\theta}}}\right] \equiv \left[\frac{\partial\widehat{\mathbf{s}}_i}{\partial\widehat{\rho}}\ \ \frac{\partial\widehat{\mathbf{s}}_i}{\partial\widehat{\phi}}\right]$, where the vectors $\left[\frac{\partial\widehat{\mathbf{s}}_i}{\partial\widehat{\rho}}\right]$ and $\left[\frac{\partial\widehat{\mathbf{s}}_i}{\partial\widehat{\phi}}\right]$ are the i-th columns of $\widehat{\mathbf{S}}\mathbf{W}\widehat{\mathbf{S}}$ and $\widehat{\mathbf{S}}\widehat{\mathbf{S}}$, respectively.

To calculate response paths as the change of y_{jrt+k} due to a change in y_{irt}, rewrite equation 3 as

$$\mathbf{y}_{rt} = \rho\mathbf{W}\mathbf{y}_{rt} + \gamma\mathbf{M}\mathbf{y}_{rt} + \mathbf{X}_{rt}\boldsymbol{\beta} + \mathbf{c} + \alpha_t\mathbf{l} + \mathbf{V}_{rt}, \tag{6}$$

where $\mathbf{M}$ is a matrix with ones on the lower secondary block-diagonal that creates the temporal lag when multiplied by $\mathbf{y}_{rt}$. Redefine the spatiotemporal multiplier as $S \equiv [\mathbf{I} - \rho\mathbf{W} - \phi\mathbf{M}]^{-1}$ and follow the same procedure as before.

4.2 Variables

To estimate this model, extensive panel data on employment and the economic structure is needed. This is provided by the Establishment History Panel (BHP) of the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research.[13] This data set originates from the mandatory social security notification by German employers. A cross section of the BHP contains each establishment with at least one employee on June 30th in a given year. Data at the establishment level are generated by aggregation of personnel data. The BHP covers almost the entire population of establishments. Exceptions mostly consist of self-employed and civil-servants which are not liable to social security. Unambiguous identification variables allow the cross sections to be combined to a panel data set.

Further preparation of this data set was necessary to solve a problem with the industrial classification. During the observation period, the WZ (for "Klassifikation der Wirtschaftszweige") has several versions, introduced in 1973 (WZ73), 1999 (WZ93), and 2003 (WZ2003). The latter two are very similar, and correspond the the ISIC ("International Standard Industrial Classification"). Changes can easily be harmonized. However, there was a huge break between WZ73 and WZ93. For each establishment that has been observed before and after the break, it is assumed that it did not change its industry. For establishments that closed before the transitional period in 1999, the WZ93 had to be estimated. In each region separately, for each industry class of the WZ73, that of WZ93 where most employees switched when WZ73 was abolished is taken as replacement. This approach can bear some problems due to the restrictive assumptions. However, aggregation of the data in a latter step should minimize these problems.

Next, employment in the public sector has been eliminated. Then the employment data was converted to full time equivalents.[14] Finally, the data was aggregated to functional labor market regions (cf. Eckey/Schwengler/Türck, 2007) and 56 aggregate industries. This industry classification was calculated from the 2-digit ISIC and matches the CPA ("Statistical Classification of Products by Activity in the European Economic Community") that is used in input-output tables of the German and European statistical offices.

The advantages of the BHP's origin are its reliability and completeness. Unfortunately, variables are restricted to those used by social insurance. Other interesting characteristics such as productivity or the establishments' technical state of the inventory are not included. The available data include location, and number of employees separated by gender, qualification, employment status, working hours, and age. It is still possible to use this data do create variables that display the economic structure of the industries and

[13] For detailed information on the BHP cf. Spengler (2008).

[14] The German administrative data only discriminates between full time (39 or more hours per week), minor (less than 18 hours) and major part time (18 to less than 39 hours). Thus, the number of each kind of part time employees is multiplied by 16/39 and 24/39, respectively (cf. Ludsteck, 2006, 275).

regions. The following variables are used as control variables:

- Sector effects:

$$sect_{irt} = \sum_{r'}^{R} e_{ir't} - e_{irt} \tag{7}$$

This controls for growth impulses that take effect on the whole industry in the whole country. To avoid endogeneity, the employment in the own cell is subtracted.

- Diversity:

$$div_{irt} = - \sum_{i'=1, i' \neq i}^{N} \left| \frac{e_{i'rt}}{e_{rt}} - \frac{e_{i't}}{e_t} \right| \tag{8}$$

This is the standard Krugman-diversification Index. It is actually a measure of the absence of diversification in region r multiplied by -1. If the local economic structure exactly equals the one of the whole country it takes a maximum value of zero. Its value becomes more negative, the more specialized a region is. This variable is intended to control for Jacobs externalities.

- Firm size:

$$firmsize_{irt} = e[in\ firms < 20\ employees]_{irt}/e_{irt} \tag{9}$$

The share of employees in small firms controls for the effect of internal economies of scale which could favor growth in larger firms (cf. Combes, 2000). On the other hand McCann (2001) argues that innovation mainly takes place in clusters of small rather than large firms.

- Education:

$$education_{irt} = e[highly\ qualified]_{irt}/e_{irt} \tag{10}$$

Since innovation and entrepreneurship are highly interrelated with human capital, the education of the workforce plays an important role for employment growth. Education is captured by the share of employees with university and technical college degrees. Since both, MAR- and Jacobs-externalities rely on knowledge spillovers, the share of highly educated employees should have a strong impact on employment growth, especially in the presence of these externalities.

- Regional wage level:
To control for the level of wages paid in the region just using mean or median wages seems not to be adequate, since this variable would capture additional effects like productivity differences due to qualification or firm size structures. Instead, following Südekum/Blien (2004) and Blien/Südekum/Wolf (2006), an auxiliary wage regression on establishment level is used to calculate a "neutralized" wage level. For each year separately, the log median wage is regressed on establishment characteristics (size, size squared, proportions of young, male and highly qualified employees)

and dummy variables for regions and industries, respectively. The model is estimated under the constraint that the coefficients of the region dummies, weighted by the regions' shares in total employment, must sum up to zero. This normalization does not change the values of the other coefficients but simplifies the interpretation of the dummy variables: a region with a coefficient significantly greater (smaller) than zero is a "high-wage" ("low-wage") region. These coefficients are used as control variables for the wage level in the main regression.

A variable that captures the development of the employment of the whole region, like the size of employment in all industries, is not included in this model. Combes/Magnac/Robin (2004) and Blien/Südekum/Wolf (2006) argue that his variable controls for a market size effect. However, in this paper's context, the weighted employment size is captured by the "spatial" lag $\mathbf{Wy}_{rt}$. To avoid multicollinearity, the unweighted employment size is left out. The estimation is restricted to five regions: The labor market regions of Munich, Mannheim, Karlsruhe, Hamburg and Hannover. These are the five regions where each of the 56 industry aggregates occurs in each of the 18 years. All of these regions feature the headquarters of well known and prosperous companies and are known for their innovative environments. The choice to take only highly diversified urban regions into account increases the possibility that interactions can be uncovered. While clusters in Porter's (2000) sense might occur in rural areas as well, a larger variety of interindustry relationships is much more likely to be found in these urban centers. This choice of only five regions imposes another restriction: true spatial spillovers, i.e. between regions are not taken into account. However, these labor market regions are defined according to commuting patterns (Eckey/Schwengler/Türck, 2007). It is quite plausible that the distance that individuals are prepared to travel to work on a daily basis is also the distance where most kinds of spillovers take place. Thus, most of the spillovers we are interested in should be confined within these regions.

4.3 Weights Matrices

An important issue are the weights matrices which quantify the potential for spillovers between industries of the same region. Each weights matrix represents one source of externalities, i.e. one of the three Marshallian forces:

forward-backward linkages: To analyze the importance of forward-backward linkages, information on supply relationships is needed. This information is provided by symmetric input-output tables (cf. Bleses, 2007). These are available from the German Statistical Office in the context of national accounting. For this paper, the 2006 table is used. Since input-output tables are only available for the whole country, the same is used for each region. The raw matrix displays which industries (columns) buy an industry's outputs (rows). Two weights matrices are constructed directly with this data: the first refers to upstream relations. Transposing this matrix changes its interpretation. Now each column represents the origin rather than the utilization of goods. Thus, the second matrix represents downstream relations.

Labor pooling: Labor pooling means that firms from different industries access the same pool of accordingly skilled personell. This implies that employees of related industries should be easily interchangeable. Following this intuition, a weights matrix is created according to worker-flows between industries. To create this matrix, the full sample of the employment statistics of the German Federal Employment Agency of the years 1999 to 2006 is used. In this spell data set of all employees subject to social security, employees that change to an establishment in a different industry are identified. Before creating a weights matrix, some more adjustments were made: first using the occupation codes, social and natural scientists, mathematicians, computer scientists and engineers were eliminated from this data set. These employees are likely to posses a high amount of knowledge. When they move to a new employer, they bring this knowledge and thus might create a knowledge spillover. To avoid overlapping with the measurement of knowledge spillovers, these movers are not taken into consideration here. Furthermore, since low-skilled workers and general management mostly require few or only generic skills, they can easily change between any industry without having to acquire special knowledge (cf. Neffke/Henning, 2009). Thus, only skilled non-management staff are considered to be relevant for labor pooling. Using the remaining 19,270,876 cases, a matrix is created that features the numbers of changers between industry pairs.

Knowledge spillovers: To analyze externalities due to knowledge spillovers, it is necessary to find a measure of how strong pairs of industries can take advantage of each others' knowledge. While it is unlikely that e.g., manufacture of wood products benefits from innovations in manufacture of motor vehicles, it is very well plausible that these innovations can be applied in manufacture of transport equipment. One possibility to achieve this are patent citations. However, even if one succeeds in harmonizing the different classifications used in patent and employment data, this can only be done on an even higher level of aggregation than which is used in input-output tables. Moreover, the service sector cannot be taken into account since product classes can only be related to the manufacturing industries which make these products.[15] Another way to identify industries between which knowledge spillovers are likely to take place is to use the social and natural scientists, mathematicians, computer scientists and engineers that were omitted when the weights matrix for labor pooling was created. This time, one can argue that these people do not only change to another industry because their qualification matches to the

[15] Commercial methods on the other hand are generally not patentable.

demands of their new jobs, but that they also bring along knowledge, which is of value to their new employers.[16] Using the 868,173 movers of the aforementioned occupations, again a matrix is created that features the numbers of changers between industry pairs. The more of these changes between industries occur, the more likely knowledge should also find other paths to spill over between establishments of these industries.

Since the data set is a panel of 56 industries in five regions over 17 years, the final weights matrix $\mathbf{W}$ is more complicated than just the raw matrices described above. $\mathbf{W}$ is a square block diagonal matrix with 4760^2 elements. Each 56×56 block consists of one of the raw matrices and represents the economic proximity between industries of the same region at the same time. There is one block per region and year, resulting in $5 \cdot 17 = 85$ blocks. The blocks do not vary between regions and years. This is due to data restrictions: input-output tables are available only for the aggregate country. It is very likely that input-output relations are not equal between regions, but other data quantifying interindustry relations due to forward-backward linkages are not available. While on the one hand the assumption that interindustry spillovers are equal in each region seems very restrictive, on the other hand manufacturing a product like an automobile requires more or less the same inputs no matter if it is made in Hamburg or Munich. Using the same weights for each region, however, might also present an advantage: since the weights matrices are not idiosyncratic for each region, the risk of endogeneity is reduced. All elements on the main diagonal and outside of the blocks are zero. Following the common practice in spatial econometrics, $\mathbf{W}$ is row-standardized, i.e. each row sums up to one. This way, the coefficients ρ of the spatial lags are comparable, regardless of the units of the raw matrices. A final adjustment is to multiply the elements of the row-standardized weights-matrices by the corresponding industry's share in total employment in the respective region in the year 2006. This procedure is non standard but is necessary to take into account the industries' sizes in each region. The intuition is that smaller industries should only cause smaller spillovers.

Table 1 shows correlation coefficients of the dependent variable $\mathbf{y}_{rt}$ and the four spatial lags $\mathbf{W}_d\mathbf{y}_{rt},\ d = 1,2,3,4$, generated by the different weights matrices. There are no extremely high correlations. Thus, it seems legitimate to compare the significance of the different spatial lags in order to infer on the importance of the Marshallian forces which they represent.

[16]To emphasize the argument of valuing their knowledge, it would have been interesting to only consider those movers who increased their wage by changing into another industry. However, German administrative data is censored at the contribution assessment ceiling, which affects a non negligible fraction of the relevant cases.

Table 1: Correlation coefficients of the dependent variable and the “spatial lags”

	dep. var.	fwd. link.	bwd. link	labor p.	knowledge sp.
dependent variable	1				
forward linkages	0.17	1			
backward linkages	0.02	0.04	1		
labor pooling	0.24	0.12	0.53	1	
knowledge spillovers	0.16	0.23	0.47	0.70	1

5 Results

5.1 Baseline Results

Using panel data on 56 aggregate industries in five German regional labor markets in the years 1989 to 2006, the model specified in equation 3 is estimated using the direct approach developed by Lee/Yu (2010). Since this estimator is not capable of including several spatial lags at the same time, the model is estimated four times, with a spatial lag for 1. forward-linkages, 2. backward-linkages, 3. labor pooling, and 4. knowledge spillovers, respectively. Table 2 displays the structural parameters of the four models.

Since the estimator controls for fixed effects of industry/region-cells, the coefficients can be interpreted as how a change in an explaining variable influences the dependent variable of the same observation. The control variables show the expected coefficients and are qualitatively equal between the different models. Note that the structural parameters represent the effects if there was no “spatial” interaction, a situation that is not observable. In order to assess the plausibility of the whole model, the coefficients of the control variables are still discussed briefly. Due to the huge persistence of employment, the temporal lag has a large coefficient which is in line with non-spatial findings of Combes/Magnac/Robin (2004) and Blien/Südekum/Wolf (2006). The effect of the size of the whole industry is significantly positive but quite small. This should be due to the fact that only a small part of total employment (five out of 112 regions) is considered. An increase in diversity in the region does not increase employment. A plausible explanation for this is that the five regions in the sample feature establishments of all industries over the whole observation period. Thus, these regions are highly diversified per definition. Jacobs-type agglomeration effects should already exist in these cities. An increase in diversity should not significantly foster these effects any further. An increase in the share of employees in small establishments has a negative effect on employment. This is evidence for the importance of internal economies of scale. As expected, the share of employees with higher education has a positive effect. Finally, the regional wage level has no effect on employment.

Like the parameters of the control variables, the parameters of the spatial lags can only

Table 2: Results spatial and temporal dynamic panel data estimations.

Dependent variable: log employment	Model 1	Model 2	Model 3	Model 4
temp lag	0.846***	0.844***	0.846***	0.846***
	(94.99)	(94.73)	(94.95)	(94.93)
ln sector	0.138***	0.132***	0.141***	0.142***
	(10.42)	(9.95)	(10.65)	(10.71)
diversity	−0.128	−0.114	−0.140	−0.115
	(−1.12)	(−0.99)	(−1.21)	(−1.00)
ln firm size	−0.085***	−0.085***	−0.085***	−0.085***
	(−18.72)	(−18.90)	(−18.75)	(−18.74)
ln education	0.040***	0.041***	0.040***	0.040***
	(13.13)	(13.42)	(13.12)	(13.21)
wage level	−0.372	−0.386	−0.362	−0.359
	(−1.31)	(−1.36)	(−1.28)	(−1.27)
forward link.	0.706***			
	(3.46)			
backward link.		2.837***		
		(9.30)		
labor pooling			0.978***	
			(4.80)	
knowledge spill.				0.374***
				(3.11)
σ^2	0.012	0.012	0.012	0.012

Bias corrected quasi-ML estimates, z-values in parentheses.
Levels of significance: *** 1 %, ** 5 %,* 10 %.

be interpreted as the immediate effect of an increase in employment in all other industries $j \neq i$ on employment in industry i in the same region, not taking into account any further interactions or adjustment processes. However, the coefficients and z-statistics of the spatial lags do contain some information on the importance of the different interindustry effects. We find that the coefficients of all four spatial lags are significantly larger than zero. The effect of backward linkages is by far the largest. In this case, one could suspect that aside from true spillovers, simple input-output relations explain this large coefficient. When an industry grows, it should also increase its demand for inputs, which then fosters growth of its suppliers. This caveat does not apply to the other models. The spatial lags of forward linkages, labor pooling and knowledge spillovers feature highly significant positive coefficients as well. This is in line with the theory on agglomeration effects. It is reassuring that there are no negative effects to be found, a possibility that could not have been ruled out a priori. In the case of labor pooling, competition for specialized workers could neutralize positive effects. Obviously, this is either not the case or the positive effects outweigh the negative ones. All of the spatial lag coefficients' z-values are qualitatively of the same magnitude. Only the effect of knowledge spillovers seems to be just half the size of the others. However, one should hesitate to draw conclusions on their magnitude yet. This cannot be done without calculating true effects. For now, one can see that all of the Marshallian forces are capable of explaining interindustry relations, which is in line with the findings of Ellison/Glaeser/Kerr (2010). Note, that one should be careful to interpret these interindustry effects separately. The different Marshallian forces are not mutually exclusive but can rather be mixed. Products for example can comprise knowledge that could be of value to the buyer, thus forward linkages might mix with knowledge spillovers. The same might be the case for labor pooling and knowledge spillovers. Even though both weights matrices were created using disjunct sets of job movers, it is also possible that knowledge spills over when non-scientists move to a new employer.

5.2 Calculation and Display of Interindustry Effects

The structural parameters provide evidence that there are interrelationships in employment growth between different industries due to all three of the Marshallian forces. It is now interesting to consider the magnitude of these effects. This is done by calculating counterfactual steady state effects according to equation 4. Doing this creates a huge amount of data. To illustrate the ties between related industries, the presentation is restricted to the Munich region and to industries that produce different kinds of machinery, equipment or vehicles (machinery and equipment n.e.c.; office machinery and computers; electrical machinery and apparatus n.e.c.; radio, television and communication equipment and apparatus; medical, precision and optical instruments, watches and clocks; motor vehicles, trailers and semi-trailers; other transport equipment).[17] These are important industries in Germany. As the recent economic crisis showed rather drastically, a vast number of establishments depend on these industries. Thus, we can assume that they should be particularly prone to be interrelated. Of course, in most cases, physical production does not take place in Munich. However, this city houses headquarters of BMW, MAN, Siemens and many other important firms in machinery industries. Thus, we could argue that spillovers other than mere physical ones should very well take place within this region.

Table 3 shows the reactions (in percent) of seven machinery related industries to a one percent growth of one of the other industries. The highest effects are induced by forward linkages. Note that this particular finding is not completely due to agglomeration effects but can be explained by pure buying relationships. Still, this part of the table visualizes the high dependence of other industries on the car manufacturing industry (the 6th column) and emphasizes the importance of interindustry relations. The elasticities

[17] Other steady state effects are available on request from the author.

Table 3: Counterfactual steady state elasticities in machinery related industries.

	machinery	office	apparatus	communications	instruments	vehicles	transport
forward linkages							
machinery	—	0.000**	0.076***	0.020***	0.006***	0.011***	0.000
office	0.002**	—	0.016***	0.154***	0.001***	0.001	0.000*
apparatus	0.017***	0.001***	—	0.030***	0.009***	0.005***	0.000
communications	0.006***	0.001***	0.025***	—	0.004***	0.007***	0.000
instruments	0.029***	0.002***	0.034***	0.060***	—	0.016***	0.000
vehicles	0.041***	0.000**	0.069***	0.005***	0.001**	—	0.000
transport	0.099***	0.000**	0.033***	0.009***	0.018***	0.009***	—
backward linkages							
machinery	—	0.001***	0.128***	0.023***	0.130***	1.659***	0.181***
office	0.476***	—	0.433***	0.084***	0.355***	0.808***	0.058***
apparatus	0.864***	0.001***	—	0.040***	0.122***	1.910***	0.073***
communications	0.984***	0.034***	0.497***	—	0.547***	0.940***	0.094***
instruments	0.771***	0.001***	0.380***	0.051***	—	0.514***	0.251***
vehicles	0.407***	0.001***	0.090***	0.031***	0.122***	—	0.050***
transport	0.076***	0.001***	0.020***	0.016***	0.026***	0.131***	—
labor pooling							
machinery	—	0.000***	0.036***	0.010***	0.037***	0.060***	0.006***
office	0.056***	—	0.045***	0.022***	0.034***	0.029***	0.002***
apparatus	0.096***	0.001***	—	0.032***	0.060***	0.056***	0.005***
communications	0.060***	0.001***	0.119***	—	0.067***	0.029***	0.003***
instruments	0.092***	0.001***	0.052***	0.032***	—	0.031***	0.004***
vehicles	0.094***	0.000***	0.026***	0.009***	0.021***	—	0.007***
transport	0.082***	0.000***	0.021***	0.008***	0.025***	0.081***	—
knowledge spillovers							
machinery	—	0.000**	0.040***	0.009***	0.029***	0.050***	0.005***
office	0.014**	—	0.023***	0.010***	0.023***	0.012**	0.001*
apparatus	0.041***	0.001***	—	0.070***	0.042***	0.038***	0.003***
communications	0.023***	0.001**	0.056***	—	0.081***	0.018**	0.004***
instruments	0.043***	0.000**	0.057***	0.023***	—	0.022***	0.004***
vehicles	0.063***	0.000*	0.043***	0.005**	0.014***	—	0.009***
transport	0.042***	0.000*	0.032***	0.009***	0.029***	0.063***	—

Levels of significance: *** 1 %, ** 5 %,* 10 %.
Each element represents the long term growth of an industry (rows) induced by a counterfactual 1%growth of another industry (columns)

caused by the other explanations are substantially smaller. The largest elasticity can be found in the second row and fourth column of the forward linkages matrix: when manufacturing of radio, television and communication equipment and apparatus grows by one percent, manufacturing of office machinery and computers will ceteris paribus grow by 0.154 percent after all adjustment mechanisms and interindustry spillovers are completed. The magnitudes of the elasticities are quite heterogenous, depending on the industry pairs they apply to. However, most of them are highly significant and of a non negligible magnitude of roughly 0.05. Thus the major finding of this exercise is that interindustry relations are important to explain employment growth. There is evidence that each of the Marshallian forces can explain these relationships.

Another way to illustrate relations of different industries is to apply tools from social network analysis. Figure 1 displays the strength of interdependencies in employment growth in Munich's machine industries due to knowledge spillovers. The strength of relations is represented by the thickness of the ties, while the industry size in 2006 is represented by the size of the nodes.

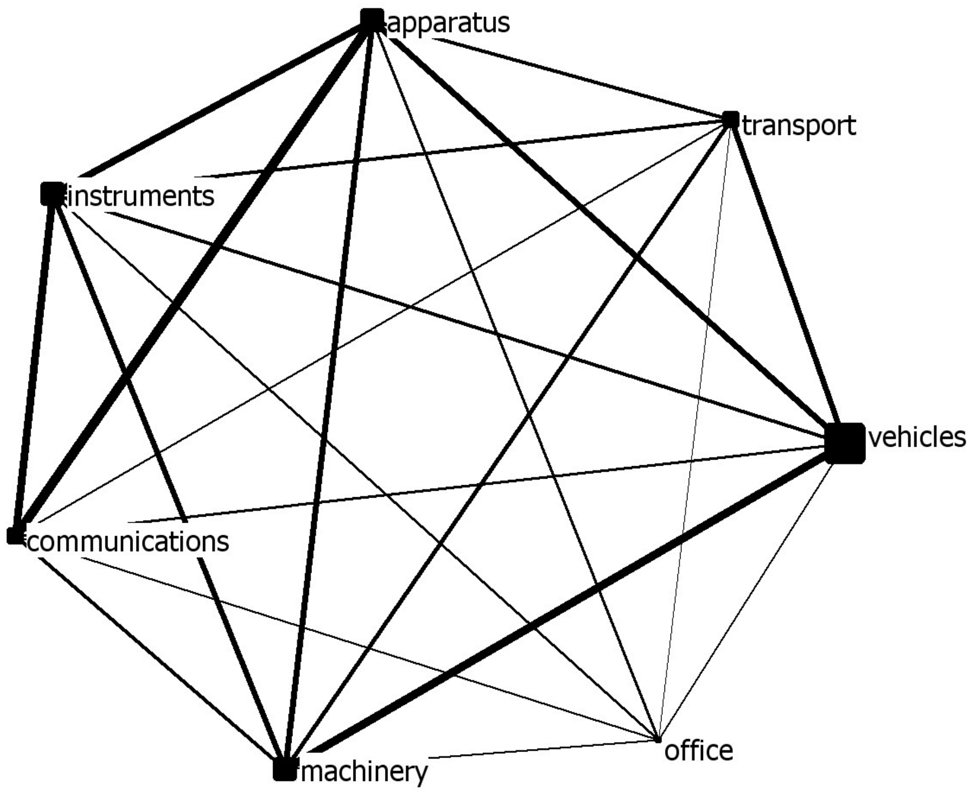

Figure 1: Interdependencies in employment growth after a 1%-shock in all industries.

Taking a closer look at the evolution of a single effect over the time, the response path of the employment in manufacture of other transport equipment to a counterfactual shock of one percent of manufacturing of motor vehicles, trailers and semi-trailers is calculated using the knowledge spillovers matrix. Figure 2 presents the yearly (noncumulative) effects along with their 1% confidence band. We can see that the effect increases steeply at first. After 6 periods, the further development slows down but does not diminish at the end of the observation period. While the cumulative effect after 17 years is an increase by 0.049 percent, it seems to take even longer until the full steady state effect of 0.063 percent is reached. This illustrates that it takes a substantial amount of time for the agglomeration externalities to develop their full impact.

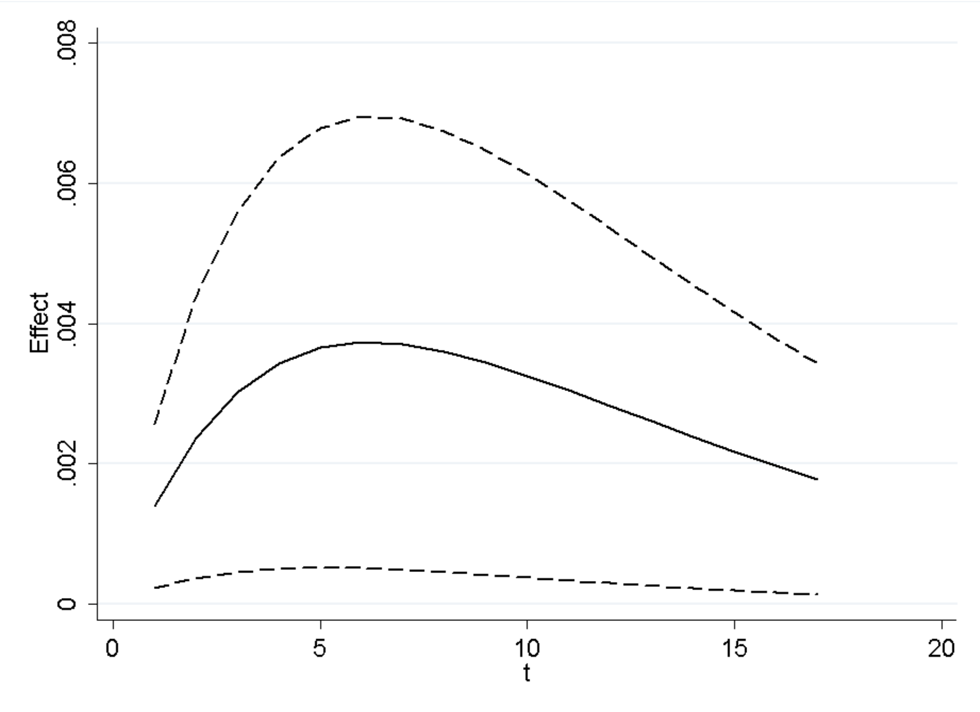

Figure 2: Noncumulative effects of a one percent growth of car manufacturing on manufacture of other transport equipment services.

6 Conclusion

The empirical research in this paper presents a new approach to examine agglomeration externalities as proposed by Marshall (1890), Arrow (1962), and Romer (1986). Empirical evidence found in this work suggests that there are interrelationships within the same region that reach beyond an establishment's own industry. These interindustry relations comprise information on which kind of externalities exist in urban environments. Spatial econometrics methods are capable of explicitly modeling these different types of interindustry relations. The results suggest that forward-backward linkages, labor pooling and knowledge spillovers represented by patterns from input-output matrices and job movers can explain interdependencies in employment growth. Thus, all of the Marshallian forces seem to be of importance, not only to explain co-agglomeration patterns but also to provide positive effects for the further development.

By calculating counterfactual effects, the magnitude of agglomeration externalities could be assessed. Effects were quite heterogenous, depending on the industries that were considered. However, with an elasticity of about 0.05, these effects are substantial and emphasize the importance of cities, where establishments from many different industries are co-located and can interact.

Further research can extend the insights gained in this preliminary work. One important issue would be to search for an alternative weights matrix that represents knowledge spillovers. Future data sets combine patent data and employment data of the respective inventors. This could help to find a suitable weights matrix. Furthermore, this work compares the results of four non-nested models. This makes the assessment of the relative importance of the single Marshallian forces difficult. While the findings suggest that each of them is relevant, it is not possible to isolate the causal effects of the single explanations. Extending the quasi-ML estimator of Lee/Yu (2010) to allow for several different spatial lags would offer interesting possibilities. Finally, the high level of sectoral aggregation is another caveat. It was dictated by the product classification in European input-output matrices. Using US data could provide a finer level of aggregation and thus permit a more detailed view.

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