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The mysteries of the trade: employment effects of urban interindustry spillovers

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Abstract

Theories in regional science predict that related establishments benefit from their mutual proximity due to forward-backward linkages, labor market 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 separate explanations. This paper introduces a new approach to assess the importance and magnitude of each of the Marshallian forces separately. Instead of measuring external economies of scale that take place within single industries, it models spillovers that happen between co-located industries. To this end, methods of spatial econometrics are adopted to measure interindustry relationships in employment growth between 55 industries of the manufacturing and service sectors in the labor market regions of the five largest cities in western Germany in the years 1989 to 2006. In this context, the strength of these relations is determined by economic closeness rather than by geography. The results suggest that each of the three Marshallian forces help to explain agglomeration externalities.

Zusammenfassung

Theorien der Regionalforschung sagen voraus, dass Betriebe von ihrer gegenseitigen räumlichen Nähe profitieren, wenn sie in einer Lieferbeziehung stehen, einen gemeinsamen Arbeitsmarkt haben, oder es zur Übertragung von Wissen kommt (die drei Marshall'schen Kräfte). Während die Existenz dieser externen Effekte als Ganzes durch die empirische Literatur gestützt wird, gibt es nur wenige Studien, welche zwischen den einzelnen Erklärungen unterscheiden. Diese Arbeit stellt einen neuen Ansatz vor, um die Bedeutung und die Größenordnung der einzelnen Marschall'schen Kräfte zu beurteilen. Anstatt externe Skalenerträge innerhalb einzelner Wirtschaftszweige zu messen, werden Beziehungen zwischen verschiedenen Branchen am gleichen Ort modelliert. In einer empirischen Untersuchung werden Wechselwirkungen in der Beschäftigungsentwicklung von 55 Wirtschaftszweigen in den Arbeitsmarktregionen der fünf größten Städte Westdeutschlands im Zeitraum von 1989 bis 2006 gemessen. Dazu werden Methoden der räumlichen Ökonometrie angepasst, wobei in diesem Kontext die Stärke der Wechselwirkungen durch die ökonomische anstelle der geographischen Nähe bestimmt wird. Die Ergebnisse deuten darauf hin, dass jede der drei Marschall'schen Kräfte dazu beitragen kann, Agglomerationsvorteile zu erklären.

JEL classification: O47, R11, R12

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"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

Even in a time where transport costs diminish and communication is fast and almost costless, the geographic concentration of firms from the same industry is remarkably strong (cf. Krugman, 1991; Ellison/Glaeser, 1997). Since this kind of agglomeration occurs particularly often in cities (cf. Dauth, 2010), there must be advantages that compensate for higher costs due to land rents, congestion or the urban wage premium. This paper introduces a new empirical approach to shed light on which mechanisms can explain the advantages that firms gain from agglomeration.

History and natural advantages offer some first explanations on how cities emerged and attracted a large share of economic activity, but this is just the beginning of the story (cf. Ellison/Glaeser, 1999). Regional science focuses on agglomeration externalities that arise 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.[1] This paper, however, focuses on another strand of literature that emphasizes the importance of a connection between agents to allow externalities to be effective (i.e. related variety, cf. Frenken/Oort/Verburg, 2007). So called MAR-externalities (after Marshall, 1890; Arrow, 1962; Romer, 1986) stem from the proximity of related establishments. There are three theoretical explanations on how these externalities work: co-located establishments benefit from being in the same supply chain, sharing a pool of specialized and qualified employees and the transmission of ideas and innovations. In the literature, these explanations are referred to as the three Marshallian forces: forward-backward-linkages, labor market pooling and knowledge spillovers. Up to now, a large part of the empirical literature in this field has not adequately discriminated between these possible explanations. Instead, it is often argued that while all of the underlying mechanisms lead to the same result, they are hard to separate due to "Marshallian equivalence" (Duranton/Puga, 2004).

There is a huge empirical literature analyzing MAR-externalities. Many papers in the past 15 years have been motivated by the discussion initiated by Glaeser et al. (1992) and Henderson/Kuncoro/Turner (1995).[2] While these compare the differences in employment between two separate years, other studies use panel data to control for unobserved heterogeneity.[3] All of these studies have in common that they analyze externalities that arise from geographic concentration of establishments that belong to the same industry. Most

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

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

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

of them find evidence that there are positive effects that arise from proximity. However, spillovers within the same industry take place inside a black box. Particularly in administrative employment data, there is not enough information to allow conclusions on what causes these spillovers. A way to deal with this problem and gain more information is to consider interindustry spillovers instead. There are several possibilities how establishments from different industries can be related that correspond to the theoretical explanations of MAR-externalities.[4] To distinguish between different kinds of interindustry relations allows to draw conclusions on how MAR-externalities work and to assess their magnitude.

To this end, López/Südekum (2009) use an input-output matrix to analyze whether the number of close-by establishments from the most important upstream 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. However, they only analyze one of the Marshallian forces. In fact, only a very small number of studies take into account all three of them at the same time. Feser (2002) concentrates on two very dissimilar manufacturing sectors (farm and garden machinery and measuring and controlling devices), which are examples for conventional and high-tech manufacturing sectors, respectively. His results suggest that labor market pooling and knowledge spillovers enhance productivity in the high-tech industry while backward linkages and knowledge spillovers enhance productivity in the conventional manufacturing industry. A notable study is done by Ellison/Glaeser/Kerr (2010). They use two different indices to 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.

This study contributes to the literature in various ways: first, a new approach to model interindustry spillovers is introduced. Theories in regional science predict that agglomeration externalities follow a circular logic, i.e. they increase with the size of an agglomeration. Thus, employment growth in one industry provides positive external effects for related industries. The magnitude of these effects can be measured by extending the empirical model by a term that captures linkages between different industries within the same region. Second, the three explanations for MAR-externalities are analyzed separately. The empirical approach allows to specify the patterns of relatedness of industries in different ways. Each way represents one of the Marshallian forces. This allows to compare their importance and magnitude. Finally, methods of spatial econometrics are adopted to take into the account the endogeneity of interindustry linkages in employment growth. In this context however, the strength of interdependence between cross sectional observations is determined by economic closeness rather than geographical proximity.

The key results of this paper are that each of the three Marshallian forces helps to ex-

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

plain agglomeration externalities. The long-run elasticity of an industry's employment with respect to the growth of another industry is roughly 0.038.

The remainder of the paper is organized as follows. Section 2 provides an overview of the relevant theories concerning agglomeration externalities. Section 3 describes how spatial econometrics methods are adapted to model interindustry spillovers. Estimation results and steady state effects are presented in section 4 and section 5 concludes.

2 Theoretical Considerations

The question why economic activity is not distributed randomly across space but is instead concentrated in a limited number of locations is one of the oldest in regional science. Notable early theoretical studies on this topic include contributions by 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 refers to MAR-externalities after seminal works by Marshall (1890), Arrow (1962) and Romer (1986). There are three explanations of these externalities (the three Marshallian forces): first, proximity of establishments within one supply chain leads to external economies of scale, which are often referred to as forward-backward linkages. Second, co-located establishments can draw from a common pool of specialized and qualified employees. This is called labor market pooling. Third, knowledge spillovers spread ideas and innovations and thus foster technical change. All of these explanations suggest that spatial concentration leads to an increase in productivity. Thus, establishments have pecuniary incentives to seek mutual proximity.

Even though some of the explanations of MAR-externalities are more than 100 years old, they arguably still apply to modern production processes. While fright is cheaper than ever before, saving time plays a crucial role in modern production. Just-in-time delivery and production often necessitate close distances between firms and their suppliers. Even if inputs are usually 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). Note that these linkages are not restricted to firms within the same industry. Input-output tables allow to analyze how closely different industries are related which forms the base for forward-backward linkages.

In a time of flexible production, where factor inputs have to be adjusted to fluctuations in demand, firms can benefit from a pool of a specially skilled and experienced workforce. There are several theoretical explanations on how labor market 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 market 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. Thus, establishments that share a labor pool can benefit from their mutual proximity.

Cities play a particularly important role supporting knowledge spillovers since they "promote productivity by connecting people to smart people with good ideas" (Glaeser, 2008: p. 149). 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. Jaffe/Trajtenberg/Henderson (1993) and Agrawal/Kapur/McHale (2008) show that spatial proximity increases the probability of knowledge spillovers in general as well as the probability that knowledge flows between agents from different technical fields. 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. They can happen between any establishments that use the same kind of knowledge, even if they belong to completely different industries.

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 market pooling and knowledge spillovers and eventually result in an increase of employment in related industries.[5] The positive effects of forward-backward linkages and knowledge spillovers on employment growth are quite plausible. However, this prior is weak in the case of labor market pooling.[6] Altogether the Marshallian forces, i.e. forward-backward linkages, labor market pooling and knowledge spillovers offer three explanations why employment growth can be related between industries. These three explanations will be analyzed empirically in section 4.

[5] 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 rather than a closed regional economy, an increase in the productivity of labor should always increase employment.

[6] 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).

3 Method and Data

3.1 Estimation Strategy

We explicitly model how employment growth in one industry affects employment growth in other industries due to the Marshallian forces. As a starting point, 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 strength of intraindustry spillovers, which indicate the presence of MAR-externalities. If these are at work, employment growth in an industry/region cell increases agglomeration externalities which in turn, following a circular logic, foster future employment growth in the same cell. In this case, ϕ would be large (cf. Combes/Magnac/Robin, 2004). However, as the discussion in section 2 shows, spillovers do not only occur within one industry, but between different industries as well. These interindustry spillovers could contain important information on external effects between firms from different industries in the same region. The nature of these relationships could bear evidence on which of the before mentioned Marshallian forces are effective. If employment growth is interrelated between industries, the model in equation 1 misses a term and is thus misspecified.

To take this into account, equation 1 is extended by the weighted sum of the log employment in all other industries in the same region r at time t. The weights of each industry's log employment depend on how strongly two industries interact. Each one of the Marshallian forces is taken into account by a corresponding weighting scheme.[7]

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

The weights w_{ij} enter the equation in form of a weight matrix $\mathbf{W}$, as becomes clear when equation 2 is written in matrix notation:

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

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 a $N \times N$ weight matrix, $\mathbf{X}_{rt}$ is the $N \times k_x$ matrix of exogenous regressors, $\mathbf{c}$ is an $N \times 1$ column vector of industry/region fixed effects, α_t a scalar of the fixed time effect, $\mathbf{l}$ is an $N \times 1$ vector of ones and $\mathbf{v}_{rt} = (\epsilon_{1rt}, \epsilon_{2rt}, \ldots, \epsilon_{Nrt})'$ is a vector of i.i.d. error terms.

7 Section 3.3 provides details on how these weights are determined.

The elements of **W** quantify the strength of the assumed relationships between any pair of industries within the same region. If the kind of interindustry relationship specified by **W** does exist, the coefficient ρ should be significantly greater than zero. If the model did not contain the interindustry term $\mathbf{Wy}_{rt}$, GMM estimation techniques developed by Arellano/Bond (1991) or Blundell/Bond (1998) would be appropriate to avoid the Nickell (1981) bias due to the presence of a serially lagged dependent variable. However, if $\rho \neq 0$, $\mathbf{Wy}_{rt}$ is correlated with the error term due to the two-dimensional nature of interindustry effects (industry i affects industry j and vice versa, cf. Anselin (1988)). Thus, another estimator must be used to obtain consistent results. This way to model cross sectional dependence is very similar to the spatial autoregressive model in spatial econometrics (cf. Anselin, 1988). The main difference is how the weights are determined. In spatial econometrics, in most cases the weights are given by contiguity of regions or distance functions. In the present context, the term 'space' is not to be understood literally in a geographic sense but rather in an economic one. Two co-located industries are considered to be close if they are in an economic relationship. Following the terminology of spatial econometrics, where $\mathbf{Wy}_{rt}$ is called the spatial lag, this term will be called the industry lag, henceforth. Thus, using a matrix of economic rather than geographic weights, spatial econometrics tools can be used to obtain consistent estimates for the parameters of equation 3.

In spatial econometrics the endogeneity of $\mathbf{Wy}_{rt}$ is dealt with by using two stage least squares or maximum likelihood techniques. However, the presence of a temporally lagged dependent variable complicates the estimation. The use of two stage least squares or GMM is conceivable but no consistent estimator for dynamic panel data with fixed effects is available yet. Lee/Yu (2010) are the first to derive a quasi maximum likelihood estimator for this model and to show its asymptotic properties. Fixed effects for both, industry/region cells and years are estimated jointly with the other parameters.[8]

It is important to keep in mind (just like in non-spatial dynamic panel data models) that the estimated structural parameters cannot be interpreted as marginal 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 **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 $\mathbf{y}_t$:

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

Here, **S** is the spatiotemporal multiplier. Each column of this matrix can be interpreted as how a shock in one observation i's error term (e.g. the formation of a new establish-

[8] Lee/Yu (2010) also propose an alternative approach where a transformation of the data eliminates the time fixed effects. This procedure leads to efficient results if the number of cross-sectional units NR is relatively smaller than the number of periods T, which is not the case here. However, this transformation requires the weight matrix **W** to be row normalized, i.e. that the elements of each row sum up to one, which is a major restriction.

ment) that permanently increases y_{irt} by one unit, affects its own outcome and all other observations' $y_{jrT}, j = 1, 2, \ldots, n$ after all adjustment mechanisms and feedback loops are concluded. 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+l} due to a change in y_{irt}, rewrite equation 3 as

$$\mathbf{y}_{rt} = \rho \mathbf{W} \mathbf{y}_{rt} + \phi \mathbf{M} \mathbf{y}_{rt} + \mathbf{X}_{rt}\boldsymbol{\beta} + \mathbf{c} + \alpha_t \mathbf{I} + \mathbf{v}_{rt}, \tag{6}$$

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.

3.2 Data

To estimate the model in equation 2, extensive panel data on employment of regional industries and their 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.[9] This data set originates from the mandatory social security notification by German employers. Since this source is used to calculate retirement pensions, the data is highly reliable and complete. A cross-section of the BHP contains information on each German 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 German employees. 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. The data used for this analysis covers the years 1989 to 2006 and the functional labor market regions of the five largest cities in Western Germany: Hamburg, Munich, Cologne, Frankfurt/Main and Stuttgart. All of these regions feature the headquarters of well known and prosperous companies and are known for their innovative environments. The decision 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. Using only five regions imposes a restriction: true spatial spillovers, i.e. between regions are not taken into account. However, labor market regions are defined according to commuting patterns (Eckey/Schwengler/Türck, 2007). It is quite plausible that the distance that individuals are willing to travel to work on a daily basis is also the distance where most kinds of spillovers take place. Thus, most of the

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

spillovers we are interested in should be confined within these regions.

Some further steps are necessary to prepare the data from the BHP. First, two different industry classifications are harmonized to allow using a large number of cross sections. This is done following the procedure introduced in Dauth (2010). The result is a classification which conforms to the International Standard Industrial Classification (ISIC). Next, employment in agriculture and the public sector is eliminated. Then the employment data is converted to full time equivalents.[10] The data is aggregated to functional labor market regions (cf. Eckey/Schwengler/Türck, 2007). The level of industrial aggregation is dictated by the availability of input-output data. This data is used to construct weight matrices for forward-backward linkages (cf. section 3.3). However, the German as well as the European statistical office calculate input-output tables only on relatively highly aggregated levels of the Statistical Classification of Products by Activity in the European Economic Community (CPA). In order to harmonize the CPA and the ISIC, the whole data has to be aggregated to 55 industries. Finally, the small industry "manufacture of tobacco products" is excluded from the analysis because it does not exist in some of the considered regions.

3.3 Weight Matrices

Since the focus of this analysis is to model interindustry relations that constitute the existence of MAR externalities, it is essential to find weight matrices that embody the sources of these externalities. The aim is to create distinct weighting schemes, each representing one of the three Marshallian forces. This way, four different weight matrices are generated:

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 weight matrices are constructed: 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 market pooling: labor market pooling means that firms from different industries use the same pool of adequately skilled personnel. This implies that employees of related industries should be easily interchangeable. Following this intuition, a weight 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

[10] The German administrative data only discriminates between full time, minor (less than 18 hours) and major part time (at least 18 hours but not full time). Following Ludsteck (2006), the number of each kind of part time employees is multiplied by $16/39$ and $24/39$, respectively.

identified. Before creating a weight matrix, some more adjustments are made: first, using the occupation codes, social and natural scientists, mathematicians, computer scientists and engineers are 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 very generic skills, they can easily change industries without having to acquire special knowledge (cf. Neffke/Henning, 2009). Thus, only skilled non-management staff are considered to be relevant for labor market pooling. Using the remaining 19,270,876 cases, a matrix is created that features the numbers of movers between pairs of industries.

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 plausible that the same innovations can be applied in manufacture of transport equipment. One possibility to measure 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 a 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.[11] 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 weight matrix for labor market pooling was created. One can argue that these people do not only change to another industry because their qualification matches to the demands of their new jobs, but that they also bring along knowledge, which is of value to their new employers.[12] Using the 868,173 movers of the aforementioned occupations, again a matrix is created that features the numbers of movers 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 55 industries in five regions over 17 years, the final weight matrix **W** is more complicated than just the raw matrices described above. **W** is a square block diagonal matrix with 4675^2 elements. Each 55×55 block $\mathbf{W}_{rt}$ 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 raw matrices do not vary between regions and years. This is due to data restrictions:

[11] Commercial methods are generally not patentable.

[12] 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.

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 across regions 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 weight 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.

Before the weight matrices can be used to measure interindustry spillovers, some more adjustments are necessary. The raw matrices are measured in different units (Euros and persons, respectively). To make the ρ coefficients comparable, all matrices are row normalized, i.e. the elements of each row sum up to one. Even though this is treated as standard in spatial econometric theory, it is in fact not common practice in empirical studies (cf. Plümper/Neumayer, 2009). Row normalization is unproblematic when all cross-sectional units are about the same size and thus induce effects of the same magnitude. In this context, however, agglomeration effects can be expected to depend on industry size. Large and small industries should cause effects of different strength when they grow by e.g. one percent. This is taken into account by multiplying the elements of the row normalized weight matrices by the corresponding industry's share in total employment in the respective region. To avoid endogeneity of this weighting scheme, the previous year's employment share is used. Note that due to this procedure, the industry lag is a weighted sum rather than a weighted average of the other industries' dependent variables. The ρ coefficients are still quantitatively comparable but cannot be interpreted directly any more. A ρ larger than one does not indicate a spatial unit-root, as it would in the case of a purely row normalized weight matrix.

Table 1: Correlation coefficients of the dependent variable and the industry lags

	Dep var	Fwd link	Bwd link	Labor market p.	Know. spill.
Dependent variable	1				
Forward linkages	0.18	1			
Backward linkages	-0.08	-0.06	1		
Labor market pooling	0.07	0.03	0.50	1	
Knowledge spillovers	0.03	0.18	0.44	0.68	1

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

3.4 Control Variables

To control for other determinants of regional employment growth, information on the size and the economic structure of the observation cells and the aggregate industries and regions which they belong to is needed. However, the BHP data offers only limited information. Interesting characteristics such as productivity or the establishments' technical state of the inventory are not available. The data include location, as well as number of employees separated by gender, qualification, employment status, working hours, and age. Thus, it is possible to create variables that indicate the economic structure of industries and regions.

Following Blien/Südekum/Wolf (2006) and Dauth (2010), the following variables are used as control variables: $sect_{irt} = \sum_{r'}^{R} e_{ir't} - e_{irt}$ controls for growth impulses that affect an industry in the entire country. To avoid endogeneity, the employment in the own cell is subtracted. Cities also provide a beneficial environment due to a diversified and thus creative economic structure (cf. Jacobs, 1970; Florida, 2004). Thus, the "Krugman-diversification index" $div_{irt} = -\sum_{i'=1,i'\neq i}^{N} \left| \frac{e_{i'rt}}{e_{rt}} - \frac{e_{i't}}{e_t} \right|$ is included to control for these so-called Jacobs externalities. The share of employees in small establishments $firmsize_{irt} = e[in\ firms < 20\ employees]_{irt}/e_{irt}$ controls for internal economies of scale as opposed to external economies. Since many modern industries depend on human capital, the education of the workforce is important to foster employment growth. Education is captured by the share of employees with university and technical college degrees $education_{irt} = e[highly\ qualified]_{irt}/e_{irt}$. To control for the regional wage level, mean or median wages would not be adequate since they also contain structural differences of the industries and their workforces. Thus, following Blien/Südekum/Wolf (2006) and Dauth (2010), an auxiliary wage regression at the establishment level is run for each year, where log median wages are regressed on the establishments' size and sector as well as on the age, gender and qualification structure of their workforces. The coefficients of regional dummy variables, which are constrained to sum up to zero, can be interpreted as the "neutralized" wage level and serve as the values of the variable $wagelevel$ 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 such a variable controls for a market size effect. However, in this paper's context, the weighted employment size in all other industries is already captured by the industry lag $\mathbf{Wy}_{rt}$. To avoid multicollinearity, the unweighted employment size is left out.

4 Results

4.1 Baseline Results

Using panel data on 55 aggregate industries in five German regions in the years 1989 to 2006, the model specified in equation 3 is estimated. Since the number of observation groups is larger than the number of periods, the time fixed effects can be estimated using the direct approach developed by Lee/Yu (2010), which does not rely on the assumption that the weight matrices are row normalized. This estimator is not capable of including several industry lags jointly. Hence, the model is estimated four times, with a lagged term for 1. forward-linkages, 2. backward-linkages, 3. labor market pooling, and 4. knowledge spillovers, respectively. Since most correlations between industry lags are quite low (cf. table 1), omitted variable bias due to not including the other lags does not seem to pose a severe problem. Table 2 displays the structural parameters of the four models.

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

Dependent variable: log employment	Model 1	Model 2	Model 3	Model 4
Temp lag	0.868***	0.864***	0.868***	0.868***
	(96.98)	(96.45)	(97.04)	(97.02)
Ln sector	0.124***	0.117***	0.126***	0.127***
	(9.54)	(9.03)	(9.71)	(9.77)
Diversity	−0.019	−0.077	−0.032	−0.033
	(−0.15)	(−0.62)	(−0.26)	(−0.27)
Ln firmsize	−0.085***	−0.085***	−0.085***	−0.085***
	(−17.65)	(−17.68)	(−17.68)	(−17.67)
Ln education	0.042***	0.044***	0.042***	0.042***
	(11.77)	(12.31)	(11.74)	(11.74)
Wagelevel	−0.134	−0.229	−0.176	−0.158
	(−0.67)	(−1.15)	(−0.88)	(−0.79)
Forward link.	0.798***			
	(3.53)			
Backward link.		3.040***		
		(9.61)		
Labor Market Pooling			0.911***	
			(4.18)	
Knowledge spill.				0.529***
				(3.58)
σ^2	0.012	0.012	0.012	0.012

Number of observations: 4675
Bias corrected quasi-ML estimates, z-values in parentheses.
Fixed effects included for both, industry/region cells and years.
Levels of significance: *** 1 %, ** 5 %,* 10 %.

Since the estimator controls for fixed effects of industry/region-cells, the coefficients indicate how a change in an explaining variable influences the dependent variable of the same observation. The control variables show the expected signs and are qualitatively equal between the different models. Note that the structural parameters represent the effects in a situation without interindustry interaction, which is not observable. In order to assess the plausibility of the model, the coefficients of the control variables will nevertheless be discussed briefly: Due to the persistence of employment, the temporal lag has a large coefficient which is in line with non-spatial findings of Combes/Magnac/Robin (2004), Blien/Südekum/Wolf (2006) and Dauth (2010) and is well below unity. The effect of the industry size is significantly positive but smaller than in prior studies. This should be due to the fact that only five urban regions rather than the entire country are considered. The elasticity of employment growth with respect to industry employment growth seems to be heterogenous and smaller in cities than in rural regions. An increase in regional diversity does not increase employment. A plausible explanation may be that the five regions in the sample are already highly diversified. Jacobs-type agglomeration effects should already exist in these cities. Apparently, an increase in diversity does not significantly foster these effects any further. An increase in the share of employees in small establishments reduces employment. This is evidence for 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.

Similarly, the parameters of the industry lags can only 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 industry lags do contain some information on the importance of the different interindustry effects. The coefficients of all four industry lags are significantly larger than zero, while 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 also increases its demand for inputs, which then fosters growth of its suppliers. This caveat does not apply to the other models. The industry lags of forward linkages, labor market 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 market 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 industry lag coefficients' z-values are qualitatively of the same magnitude. Only the effect of knowledge spillovers seems to be somewhat smaller than the others. However, one should hesitate to draw conclusions on their magnitude yet. This cannot be done without calculating steady state effects that take into account interindustry relations and their feedback. 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 market pooling and knowledge spillovers. Even though both weight 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.

4.2 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 considerable 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; office machinery and computers; electrical machinery and apparatus; radio, television and communication equipment and apparatus; medical, precision and optical instruments, watches and clocks; motor vehicles, trailers and semi-trailers; other transport equipment).[13] These are important industries in Germany. As the recent economic crisis showed rather drastically, a vast number of establishments depend on these industries.

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 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 0.226 percent in the long run. The magnitudes of the elasticities are quite heterogenous, depending on the industry pairs they apply to. However, most of them are highly significant and amount to 0.038.[14] Thus the major finding of this exercise is that interindustry relations are important to foster employment growth. There is evidence that each of the Marshallian forces contributes to explain these relationships.

To illustrate relations of different industries, 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. One can see that for example the small industry manufacturing of office machinery and computers is relatively isolated while the medium sized industry electrical machinery and apparatus has strong relations to most other machinery industries. The network structure of this figure emphasizes the empirical insight that for some industries' establishments, it seems to be highly important not to be isolated but to be able to interact with others. Cities are the ideal environment for these interactions due to the strong density of co-located industries.

To appreciate the importance of interindustry spillovers due to MAR externalities, it is also important to see how long it takes until these effects reach their steady state levels. 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 a one percent growth 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 seven years, 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 0.080 percent, it seems to take even longer until the full steady state effect of 0.132 percent

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

[14] This is the unweighted average of all effects in Table 3, except for the ones that stem from backward linkages.

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

	Machinery	Office	Electrical	Communications	Instruments	Vehicles	Transport
Forward linkages							
Machinery	—	0.001**	0.135***	0.030***	0.009***	0.017***	0.000
Office	0.003**	—	0.029***	0.226***	0.002***	0.001	0.000*
Electrical	0.029***	0.003***	—	0.045***	0.013***	0.008***	0.000
Communications	0.011***	0.002***	0.044***	—	0.006***	0.011***	0.000
Instruments	0.051***	0.004***	0.062***	0.089***	—	0.025***	0.000
Vehicles	0.070***	0.000**	0.123***	0.008***	0.001**	—	0.000
Transport	0.169***	0.000*	0.060***	0.014***	0.027***	0.014***	—
Backward linkages							
Machinery	—	0.002**	0.262***	0.045***	0.218***	2.721***	0.237***
Office	1.044***	—	0.814***	0.141***	0.555***	1.765***	0.107***
Electrical	1.548***	0.003***	—	0.072***	0.221***	3.224***	0.118***
Communications	1.740***	0.058***	0.882***	—	0.798***	1.835***	0.147***
Instruments	1.333***	0.003***	0.661***	0.079***	—	1.079***	0.321***
Vehicles	0.796***	0.002**	0.205***	0.056***	0.207***	—	0.082***
Transport	0.186**	0.003***	0.057**	0.030***	0.054***	0.315**	—
Labor market pooling							
Machinery	—	0.001***	0.054***	0.013***	0.047***	0.080***	0.006***
Office	0.083***	—	0.067***	0.027***	0.044***	0.041**	0.003**
Electrical	0.138***	0.001***	—	0.039***	0.076***	0.076***	0.005***
Communications	0.088***	0.001***	0.177***	—	0.085***	0.040**	0.004***
Instruments	0.133***	0.001***	0.078***	0.039***	—	0.042***	0.005***
Vehicles	0.135***	0.000**	0.039***	0.011***	0.027***	—	0.008***
Transport	0.119***	0.000**	0.032***	0.010***	0.032***	0.108***	—
Knowledge spillovers							
Machinery	—	0.001**	0.095***	0.019***	0.058***	0.105***	0.009***
Office	0.039**	—	0.059***	0.020***	0.047***	0.030**	0.003*
Electrical	0.092***	0.003***	—	0.130***	0.082***	0.081***	0.005***
Communications	0.057***	0.001***	0.130***	—	0.157***	0.040***	0.007***
Instruments	0.099***	0.001**	0.132***	0.045***	—	0.050***	0.008***
Vehicles	0.140***	0.001*	0.101***	0.012**	0.031***	—	0.016***
Transport	0.097***	0.001*	0.077***	0.020***	0.058***	0.132***	—

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)

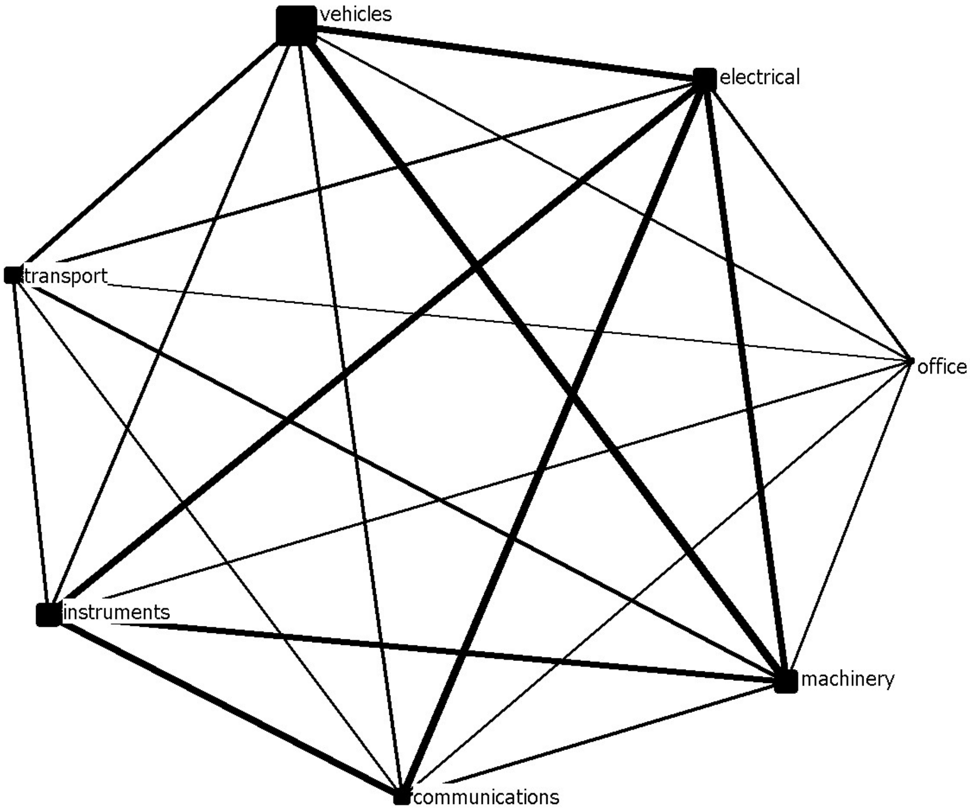

Figure 1: Interdependencies in employment growth due to knowledge spillovers between machinery industries in Munich.

is reached. This illustrates that it takes a substantial amount of time for agglomeration externalities to develop their full impact.

5 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 inform about the kind of externalities in urban environments. The adaption of spatial econometrics methods allows to explicitly model these different types of interindustry relations. The results suggest that forward-backward linkages, labor market 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 further development.

By calculating counterfactual effects, the magnitude of agglomeration externalities can be assessed. Effects are quite heterogenous, depending on the industries that are considered. However, with an elasticity of up to about 0.23, these effects are substantial. These findings strongly emphasize the importance of interactions between firms not only within an industry but also between different industries. Thus, regions should not specialize on sin-

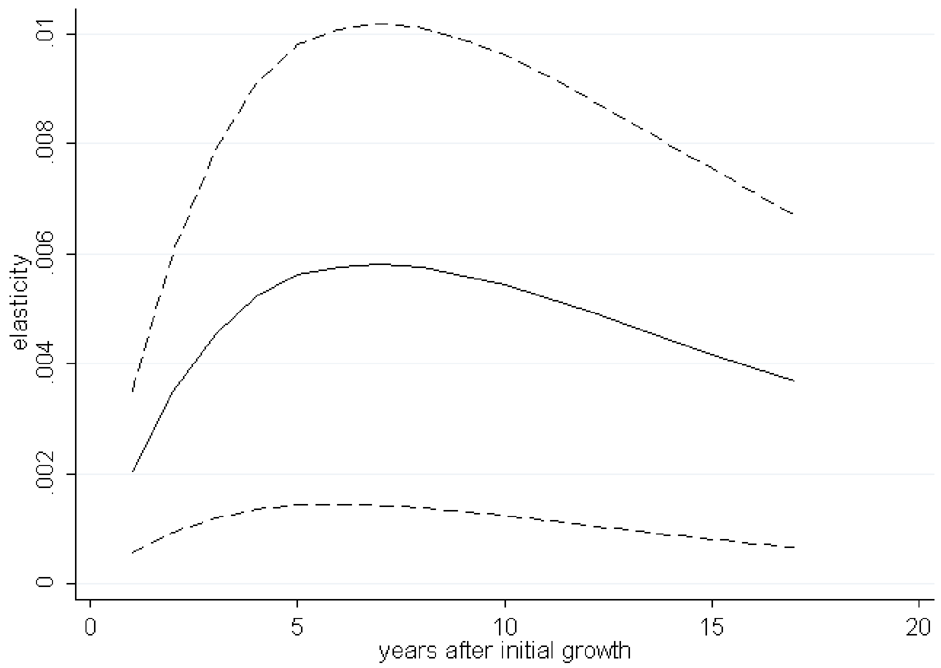

Figure 2: Noncumulative effects of a one percent growth of car manufacturing on manufacture of other transport equipment.

gle industries but rather provide a dense network of interrelated industries. This should not be confused as evidence for Jacobs-type urbanization externalities. It is not just undirected economic diversity that induces the externalities discussed in this paper. There rather has to be an underlying relationship between industries for these mechanisms to be effective. Exchanging goods, people and ideas embodies these relationships. Cities are of particular importance since they offer dense environments that facilitate these exchanges.

Further research can extend the insights gained in this analysis. One important issue would be to search for an alternative weight matrix that represents knowledge spillovers. Data sets that combine patent data and employment data of the respective inventors could help to find a suitable weight matrix. However, this kind of data is not available yet. This study compares the results of four non-nested models, which renders 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 industry 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. US data could provide a finer level of aggregation and permit a more detailed view.

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