Industrial Structure and Regional Employment Dynamics

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Wolfgang Dauth

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Preface

In economics, it is essential to keep in mind that events are usually not independent but have causes and consequences. This is of particular importance when the economic analysis is carried out at the disaggregate level of cities or regions because "everything is related to everything else, but near things are more related than distant things" (Waldo R. Tobler's "first law of geography"). Since I started working at IAB, I have been fascinated by analyzing these interactions that would stay hidden if we analyzed only aggregate countries. The result of my research constitutes this book, a slightly revised version of my dissertation, which has been accepted by the University of Erlangen-Nuremberg in June 2012.

It would have been impossible to accomplish this project without the support of many people. Foremost, I thank my supervisor Regina T. Riphahn, who never hesitated to share her experience of practicing empirical research and how to succeed in academia. I immensely benefitted from her advice. My second supervisor, Uwe Blien, has always been an outstanding mentor for me. Working under his wings, I had the time I needed to focus on my research and on top of this a dedicated supporter in any situation. I owe special thanks to him.

For the longest period of my research, I was member of the joint graduate programme (GradAB) of IAB and the University of Erlangen-Nuremberg and received a scholarship from IAB. I strongly benefitted from being able to discuss my work with the fellow GradAB members and being part of this close-knit group. In particular, I thank Daniel D. Schnitzlein and Heiko Stüber for mutual inspiration and for being good friends.

Simultaneously to my scholarship, I worked as a junior researcher at IAB. I thank all colleagues from the departments "Regional Labour Markets" and "Regional Research Network". Being part of these research departments meant access to knowledge and advice on a vast range of topics. I am especially grateful to Katja Wolf and Stefan Fuchs who more than supported my research. They were great role models and their advice and support helped me keep my sanity more than once during the past years.

In the summer of 2011, I spent two months as a visiting scholar at the Harvard Kennedy School of Government in Cambridge, USA. Working at this world famous institution was one of the greatest experiences in my whole live. I thank William R. Kerr and Edward L. Glaeser for inviting me and giving me indispensable advice.

The fourth chapter of this book stems from a joint project with Jens Südekum and Sebastian Findeisen. I am grateful for having been able to work with these outstanding scholars.

Finally, I thank my family and in particular my parents for their tremendous support and for believing in my accomplishment long before I did. I also thank Christine, who has been a constant source of motivation and support, especially during the final, stressful months.

Wolfgang Dauth
Schwabach, October 2012

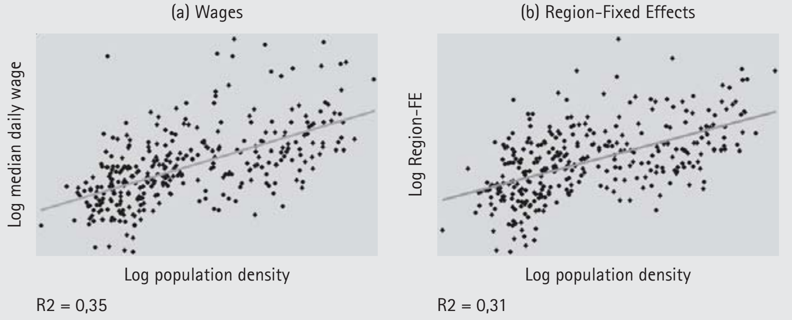
1 Introduction

Several textbooks in the field of regional science start by presenting variations of the same stylized fact: Mankind is not spread evenly across the earth's landmass. While this fact itself is not surprising at all, comparing the world's population and land areas to more tangible dimensions does reveal some fascinating insights.[1] The United Nations estimate that in 2010, there were 6,895,889,018 human beings on earth, sharing 136,147,854 square kilometers of land. If all of us were living in households of four, each household could own a piece of land as large as eleven soccer fields. Even if all of these hypothetical households decided to move to France and Germany, each one could have a piece of land of more than 500 square meters, a comfortable lot for a single family house. Yet, mankind prefers to crowd together much more closely. In 2010, for the first time in history, more than half of all people were living in urban areas and projections suggest that this share will rise to two thirds by 2050. Of course, there are many different explanations why people chose to live close to other people. But as far as most traditional theories in economics are concerned, cities should not exist.

Living, working, and producing in cities is much more expensive than in rural regions. For example, a simple regression of log median wages on log population density in 2008 in Western Germany yields a positive correlation and an R-square of 0.35 (see Figure 1.1a). Even if gender, age, nationality, industry, and establishment size are held constant in a Mincer-type regression, the R-square of the region-fixed effects regressed on log population density is still 0.31 (see Figure 1.1b). On the other hand, the wage premium in urban areas is largely compensated by much higher rents and real estate prices. Hence, if we just considered prices, we would have to conclude that "cities should fly apart" (Lucas, 1988, p. 38), since both firms and workers would have incentives to move to less densely populated regions with lower prices and rents. Of course, there are plenty of explanations why cities are not just places of congestion and high costs. From the perspective of economic theory, most explanations boil down to the insight that space does matter.

1 All calculations on this page are based on data from the "World Population Prospects: The 2010 Revision" and the "World Urbanization Prospects: The 2009 Revision" of the United Nations, Department of Economic and Social Affairs. Brakman/Garretsen/van Marrewijk (2001) and Glaeser (2008), for example, present similar calculations.

Figure 1.1: Correlation of regional wages and population density in 413 German regions



Source: IAB Sample of Integrated Labour Market Biographies (SIAB).

1.1 The German school of regional science

In order to take into account the spatial dimension in economic models, one must allow for increasing returns to scale and imperfect competition. Long into the 20th century, this has been avoided in most mainstream economic models.[2] Nonetheless, the idea that distance between economic subjects is of importance is nothing new. In fact, there has even been an early *German School of Regional Science*. Almost 200 years ago, von Thünen (1826) combined insights from his work in agriculture with classical economics in his pioneering work on the theory of industrial location. Assuming a ring-shaped region with a city at its center, he models landprices in the rural hinterland as a function of revenue, transport tariffs and distance from the center. His model predicts the distance from the central city within which each agricultural commodity can be produced: The higher the transport costs are in relation to a product's price, the closer to the center its production will be located. Thus, heavy products like lumber or perishable fruits will be produced closer to the center than grain or expensive meat products. Even though this model is outdated and depends on restrictive assumptions, it still helps to explain the structure of modern cities in the "monocentric city model" (Alonso, 1960).

About 100 years later, Weber (1922) focused on the geographic location of firms relative to competitors. The effective price (price ex works plus transport costs) increases with distance. In a one-dimensional simplification, this is graphically represented by a Y-shaped function with the firm in the center. If there is more than one firm on the market, each firm's sales depend on where these Ys intersect, that is, their respective distance to the customers. Beyond a certain distance, transport

2 An important exception is the rather small field of Urban Economics pioneered by Henderson (1974).

costs will be too high and customers will buy at the competitors. This model shows that lower productivity (in terms of a higher price ex works than the competing firms) can be compensated by being located closer to the customers. In subsequent work, Hotelling (1929) shows that this alone leads to agglomeration of economic activity. If a market area for a standardized product is linear and homogenous, the best location for a new firm is right next to an already established one, exactly splitting the incumbent's market area in half.[3]

Probably the most prominent works of early German scholars in this field are from Christaller (1933) and Lösch (1940). They also assume market areas being homogenous and customers being distributed evenly across space. In the presence of fixed-costs, each firm must sell a minimum quantity just to break even. Thus, each single firm has a circular minimum market area with a certain number of customers. Another circle defines the maximum market area. Beyond this distance, transport costs are prohibitively high. Since there is excess demand beyond this maximum distance, other firms can exist there as long as each firm has a market area large enough to cover its fixed-costs. In equilibrium, each firm has zero profits and a market area in the shape of a hexagon.[4] The size of these hexagons varies between different commodities, depending on their durability, value, etc. and how far individuals would travel to obtain them. This leads to a hierarchical system of central places which is consistent with the empirical geographical structure of modern economies (the so-called *Number-Average Size Rule*, see Mori/Smith, 2011). For example, while grocery stores are distributed almost evenly across space, more specialized stores are primarily located in mid-sized or larger cities. Finally, higher-tier services, such as art galleries or international airports, can only be found in large cities.

1.2 From transport costs to Marshallian externalities

These early theories on industrial location have made important contributions to explain the historical economic structure of industrialized nations. All of them hinge on the costs it takes to haul a product from the seller to the buyer. However, in the last decades, transport costs have strongly diminished. In 2011, the cost of shipping a standard twenty by eight foot (6.1 by 2.4 meters) container from Asia to Europe reached a historic low of merely 700 $ (Economist, 2011). One might

3 He also argues that the same logic explains why firms have incentives to make their variations not too distinctive from the competitors' products or why politicians from opposite parties prefer to lean to the middle instead of taking definitive positions.

4 Any other regular shape, i.e., any other polygon or circle, would imply the existence of either positive profits or areas not being supplied by any firm.

indeed wonder what Christaller's (1933) system of central places would look like if it were virtually irrelevant where producers and buyers are located. Some people even proclaim that modern transportation and communication technology caused the "Death of distance" (Cairncross, 1997).

This conclusion might be premature, since physically transporting goods is not the only activity being facilitated when economic subjects are close to each other. Proximity also increases the mobility of people and ideas. In his seminal treatise on economics, Marshall (1920) discusses the benefits arising in industrial agglomerations, that is, when a number of related firms are co-located in the same region. 120 years after the first edition has been published, his words sound somewhat poetical, but his ideas are still up to date:

> "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, 1920, § IV.X.7)

These *mysteries of the trade* stand for economies of scale, external to single establishments but internal to a region as a whole. Marshall distinguishes between three different sources of externalities. First, an agglomeration of firms from the same industry creates a market size effect for their suppliers. Again, if there are transport costs, firms can specialize to cater for the specific needs of customers and benefit from internal economies of scale:[5]

> "For subsidiary industries devoting themselves each to one small branch of the process of production, and working it for a great many of their neighbors, are able to keep in constant use machinery of the most highly specialized character, and to makeit pay its expenses…" (Marshall, 1920, § IV.X.8)

Second, an industrial agglomeration creates a large labor market for specifically trained workers. Marshall's idea is that demand shocks are less harmful in larger labor markets: If workers are laid-off in one firm, they are more likely to find a job in another one (as long as shocks are not correlated between firms). Employers also benefit from being able to choose from a larger pool of potential employees:

> "… a localized industry gains a great advantage from the fact that it offers a constant market for skill. Employers are apt to resort to any place where they

5 This is also the underlying force creating agglomeration externalities in the model framework of the New Economic Geography (see Krugman, 1991b; Fujita/Krugman/Venables, 1999).

> are likely to find a good choice of workers with the special skill which they require; while men seeking employment naturally go to places where there are many employers who need such skill as theirs and where therefore it is likely to find a good market." (Marshall, 1920, § IV.X.9)

Finally, proximity also facilitates the diffusion of knowledge and ideas:

> "... inventions and improvements in machinery, in processes and the general organization of the business have their merits promptly discussed: if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas." (Marshall, 1920, § IV.X.7)

On the one hand, one might argue that this point is not important any more given today's possibilities of instantaneous and virtually costless communication, which have made the world a much smaller place. On the other hand, there is an abundance of empirical studies showing that this only applies to the transmission of formal information but not to the transmission of tacit knowledge. In his homage to "our greatest invention", Glaeser (2011) points out that one of the most important functions of cities is to connect smart people. People can come up with good ideas anywhere, but often it takes interaction with other people to spread these ideas and create a commercial value. To this day, the three Marshallian forces – forward-backward linkages, labor market pooling, and knowledge spillovers – provide the basis for modeling the microfoundations of the economies of agglomeration (see Duranton/Puga, 2004).

1.3 The modern role model

The most cited modern example on how these Marshallian forces work is probably Silicon Valley (see Saxenian, 2006, for an extensive portrait of this region). The region south of the San Francisco Bay Area around Palo Alto is without doubt the center of computer technology hosting headquarters of countless high tech firms. Obviously, all these firms benefit from the physical proximity to each other, despite facing some of the highest rents and wages in the United States. Of course firms in Silicon Valley require barely any physical inputs for production. But the high density of law firms, venture capitalists and other service providers, specialized to the specific needs of highly innovative young enterprizes, clearly suggests forward-backward linkages playing a role beyond traditional manufacturing. Silicon Valley is also very attractive to a constant stream of highly qualified workers from the US and anywhere else in the world. IT experts know about the job abundance in this area. In the case of lay-offs or if workers try to advance their position, other jobs can be easily found literally in the neighborhood of the old employer. And finally, the extremely high density of smart people from different firms and the nearby universities promotes the spillovers of new ideas and new products.

Silicon Valley is the role model which a high number of regions try to mimic,[6] but none is as successful as the original. Still, agglomeration externalities are an important force in any city or region where related firms are co-located, albeit most likely to a more modest degree than in Silicon Valley. In a recent New York Times article, for example, an Apple executive explained that it is not cheap work which makes electronics companies offshore their production to Asia:

> "You need a thousand rubber gaskets? That's the factory next door. You need a million screws? That factory is a block away. You need that screw made a little bit different? It will take three hours." (Barboza/Lattman/Rampell, 2012)

This also highlights another aspect of forward-backward linkages: Shipping a container from Asia to Europe might cost only 700 $, but according to Hapag-Lloyd's web page, it takes around 30 days for a cargo ship to travel this distance. Thus, transport is still costly – if not in Euros, then in time. As reality shows, being close to suppliers makes production more flexible, which is of particular importance in times of modern production processes and shortening product life cycles.

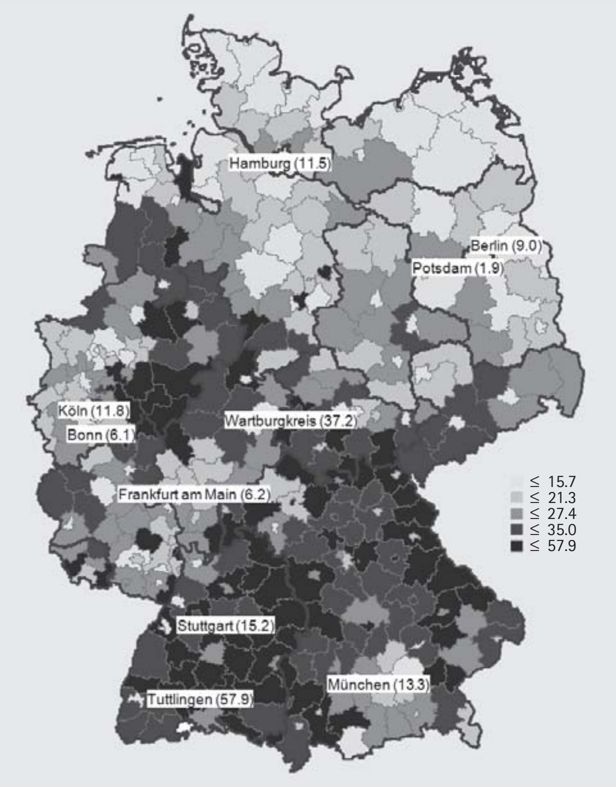
1.4 Regional disparities in Germany

One might wonder if these agglomeration externalities are as important in Germany as in other countries, since it is a comparably small country. You could easily travel between any two German cities by train or car within one day. So why not consider Germany as one large agglomeration? If this were the case, we should expect to observe a quite homogenous distribution of economic outcomes, since it would not matter where exactly firms or workers are located. But in fact, the opposite is true. Twenty years after the German Reunification, Eastern Germany has not yet caught up with the West. But even within Western Germany, regional disparities have a magnitude comparable to disparities between countries of the European Union. In March 2012, unemployment rates in Western Germany ranged from 1.4 percent in Eichstätt to 16.6 percent in Bremerhaven. This spread is of a similar magnitude as the variation of European national unemployment rates, ranging

6 There are 50 items on Wikipedia's *list of places with "Silicon" names.*

from 4.2 percent in Austria to 23.6 percent in Spain.[7] One of the major explanations why regional unemployment rates differ so strongly originates from the regional economic structure, which also varies substantially. Figure 1.2 displays the regional variation of the share of employees working in the manufacturing sector. This share varies between 1.9 percent in Potsdam and 57.9 percent in Tuttlingen, with a minimum of 6.1 percent in Bonn for Western Germany. While cities have lower manufacturing shares in general, one can also recognize an interesting feature of Germany's industrial distribution: Despite the secular shift of employment from manufacturing to modern service industries, prosperous regions still have relatively high manufacturing shares. This becomes particularly obvious in Eastern Germany, where low manufacturing shares do not suggest a modern service sector, but are rather a symptom of an underdeveloped economic structure, where the large service sector mostly consists of retail trade and elementary services.

Figure 1.2: Percentage of employees in the manufacturing sector, March 2012



Source: Statistics Department of the German Federal Employment Agency.

7 Sources: Statistics Department of the German Federal Employment Agency and Eurostat.

Even at this aggregate sectoral level, the pronounced regional disparities become apparent. Regions differ in many dimensions, where unemployment and manufacturing are only two examples. One might ask if there is a connection between the industrial structure of a region and its economic welfare. Is there an ideal industry mix that promotes a good development in the long run? This question is difficult to answer since the stories of many very successful regions are hard to imitate. Silicon Valley, for example, is a huge success, but it is hard to imagine that another IT cluster will be equally successful. Freising is another example of a region with enormous employment growth rates in the past two decades. Yet, this success is exclusively due to the fact that Germany's second largest airport has been built there from scratch in the late 1980ies.

Even if it is almost impossible for regional policy to deliberately set the seed for an exceptionally successful development, it is still important to know what drives regional evolutions. In the past decades, all industrialized nations have undergone a huge structural change. Employment in the manufacturing sector has substantially declined, while many jobs have been created in the service sector. One of the most common explanations for this process is the increasing trade integration with emerging countries. Traditional manufacturing has suffered from competition in low wage countries. In Germany, industries like manufacturing of shoes or wearing apparel have almost completely vanished and it is unlikely that these jobs will ever come back (Artuc/Chaudhuri/McLaren, 2010). Yet, in the German case, this story is more complicated than in other high-income countries like the US. The German economy is certainly affected by import competition from emerging countries, but Germany is also one of the biggest exporters in the world. While some industries are indeed no longer competitive, firms in other industries manage not only to survive but are also world market leaders in their respective niches. Many of these highly productive exporting firms are neither high tech firms nor large multinational corporations. They are mid-sized firms, the so-called German "Mittelstand", and focus on more traditional manufacturing such as machine construction, industrial chains, or high-pressure cleaners (Economist, 2010). They are successful by focusing on niches, being constantly innovative and offering a quality that cannot (yet) be matched by competitors from low-wage countries. But of course, large corporations, most notably from the automobile industry, also account for a large share of Germany's trade surplus. While Volkswagen is striving to become the world's largest car maker, the whole industry experiences strong growth rates both in output and employment. This provides huge benefits for the German economy and in particular for the large number of automotive suppliers.

There are many examples suggesting that the German economy as a whole is well suited for the challenges of structural change and trade integration. But strong regional disparities show that some regions prosper, while others experience a substantial decline in employment and have difficulties to retain or recover their prosperity. To a large extend, the industrial structure will determine how a region can face these challenges. Economies of agglomeration can increase productivity in incumbent firms, facilitate the adjustment to structural change, and withstand competition from abroad. Furthermore, depending on which manufacturing industries are located within a region, international trade could both be a thread or an opportunity for the evolution of local employment.

1.5 Organization of this dissertation

This dissertation examines the issue of regional employment dynamics from two perspectives. The first perspective focuses on whether the industrial structure of a region is related to employment growth. In line with Marshall (1920), economies of agglomeration can increase productivity in related firms being co-located in the same region. There is already a huge body of literature, both on identifying agglomeration and on measuring the magnitude of these externalities. However, different approaches yield very different results, especially if the effects of agglomeration on employment growth are analyzed. The first study, *Agglomeration and Regional Employment Dynamics* contributes to the literature by combining two distinctive but familiar strands. First, I calculate two different indices to identify observations where agglomeration externalities are expected to be particularly strong. These particular local industries either belong to national industries with a tendency to concentrate geographically or are industrial agglomerations, that is, several plants from one industry being located in the same region. Second, I augment the dynamic panel data model of Combes/Magnac/Robin (2004) and Blien/Südekum/Wolf (2006) to analyze the inertia of employment dynamics in these agglomerations. This allows for a direct test of the existence and magnitude of within-industry externalities. I find evidence that employment growth is indeed more persistent in industrial agglomerations. An earlier version of this study has been awarded the Edwin-von-Böventer-Preis for the best paper presented by a PhD-Student at the 47th Winter Seminar of the German speaking section of the Regional Science Association International (RSAI) in Matrei/Osttirol, Austria, and has been accepted for publication in *Papers in Regional Science*.

The approach of the first study treats agglomeration externalities like a "black box". It allows to measure the effects of these externalities but provides no explanation on what exactly causes them. This is a common problem in empirical studies in this field, where the "Marshallian equivalence" hinders us to distinguish forward-backward linkages, labor market pooling, and knowledge spillovers

(Glaeser/Gottlieb, 2009). The innovation of the second study, *The Mysteries of the Trade: Inter-industry Spillovers in Cities,* is to analyze spillovers between different but co-located industries. This provides additional heterogeneity, since these spillovers can differ, depending on which of the Marshallian forces are considered. Some industries can be related via forward-backward linkages while others benefit from labor market pooling, for instance, even though they do not exchange any goods. This additional heterogeneity is utilized to measure the magnitude of each of the Marshallian forces. Manufacturing of aircraft does not sell a large part of its products directly to manufacturing of motor vehicles. If firms from both industries are located in the same region, they are not likely to benefit from their proximity due to forward-backward linkages (as opposed to manufacturing of machines, for example). But an innovation in one firm, say a more efficient way to process aluminium, could be also applied in another firm. The chance that people learn about the ideas of employees from another firm increases if both firms are located in the same region. To analyze inter-industry spillovers, I adapt a spatial econometrics estimator to the case where proximity between industries is determined by economic relations rather than geography. Each of the Marshallian forces is taken into account by a weights matrix representing the relations of industry-pairs. The results suggest that employment dynamics in ten large urban areas are correlated between different industries due to the three Marshallian forces, while labor market pooling seems to provide the strongest externalities. An earlier version of this study has been awarded several prices for the best paper submitted by a PhD Student at the 4th World Conference of the Spatial Econometrics Association, in Chicago, USA; the 50th Anniversary European Congress of the RSAI in Jönköping, Sweden; and the 50th Anniversary Meeting of the Western Regional Science Association in Monterey, USA.

The second perspective in this dissertation focuses on the reaction of regional employment on the increasing trade integration with emerging countries from the East. Empirical studies on labor market effects of trade mostly focus on the level of aggregate industries or single firms. Since there is strong variation in regional specialization, both in aggregate manufacturing vs. non-manufacturing as illustrated in Figure 1.2, and also within the manufacturing sector, regions are differently exposed to international trade integration. In a recent study, Autor/Dorn/Hanson (2011) relate imports from China, measured on the industry level, to regions in the United States according to their industrial structure. They conclude pessimistically that import competition from China displaces jobs in the manufacturing sector. In joint work with Sebastian Findeisen (University of Zurich) and Jens Südekum (University of Duisburg-Essen) on *The Rise of the East and the Far East: German Labor Markets and Trade Integration*, we extend this analysis by several dimensions.

Like in the US, imports from China to Germany have risen enormously in the last two decades, but so have Germany's exports to China as well. Furthermore, while China is Germany's largest single trade partner among emerging countries, trade integration with Eastern Europe as a whole is even stronger. We thus analyze the effects of both imports and exports from/to China and Eastern Europe on several regional labor market outcomes, including manufacturing employment and wage inequality. We find that, for the average region, the opportunities of exporting to Eastern countries more than offset the losses induced by import competition.

2 Agglomeration and regional employment dynamics

(Wolfgang Dauth)

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2.1 Introduction

In most industrialized countries, firms tend to concentrate in close proximity to other firms from the same industry. Aside from history or coincidence, there must be an economic explanation for why such industrial agglomerations exist, even though there are many competitors for labor, space, and infrastructure. According to the theory of agglomeration economies, spatial proximity between firms facilitates the exchange of goods, workers, and information, which in turn fosters productivity. This paper contributes to the empirical literature on the economies of agglomeration by combining two distinctive but familiar strands. In the first, authors like Ellison/Glaeser (1997) construct statistical measures to identify the geographic concentration of industries and regions where such industrial agglomerations are located. The second analyzes the external effects that arise from the proximity between firms or people. In most of the existing econometric literature, sophisticated measures that have been established in the former strand are not used in the latter.

In this paper, I first briefly discuss different approaches to identify agglomeration and present some stylized facts for Germany. I then use these results in a dynamic panel data model to explicitly allow for the inertia of employment growth to distinguish between agglomerations and non-concentrated local industries. The results suggest that after an initial positive shock, growth is significantly more persistent in industrial agglomerations. The second contribution of this paper is that it deals with the issue of spatial dependence. Due to the detailed level of regional and sectoral aggregation, current spatial autoregressive panel data methods are difficult to apply. Still, I control for characteristics of neighboring regions to prevent possible bias in the coefficients of the agglomeration effects. Finally, I reconsider previous findings, using a much more detailed industry classification. Other studies only distinguish between a small number of highly aggregated industries. As this means combining very different industries in the same aggregate, agglomeration patterns may not be recognized. To this end, I create a time-consistent classification of 191 manufacturing and service industries to cover the full observation period.

In the theoretical literature, there is consensus that both the concentration of firms from the same industry as well as a diversified economic structure lead to positive external effects. Important empirical works by Glaeser et al. (1992) and Henderson/Kuncoro/Turner (1995) distinguish localization and urbanization externalities and analyze their effect on employment growth. Using basically the same model, both parties obtain rather different results. While the former do not find localization effects, the latter do, especially for older, well-established firms. Again, using similar models, this discussion has been continued in numerous studies, which also come to different conclusions.[1] These studies explicitly control for localization, mostly using simple location quotients, allowing for a straightforward inference on the (non-)existence of agglomeration effects on employment growth. Their major caveat is that they only use a cross-sectional approach: Growth between two years is explained by conditions of the first year. While this avoids methodical problems, it is not possible to use fixed effects in order to control for unobservable heterogeneity between local industries. Other studies use panel data and analyze employment growth over a series of years.[2] In this case, growth is regarded as dynamic, which means that inertia and growth in the past affect further evolutions.

This study contributes to the discussion on how to measure agglomeration effects and assess their magnitude. I use extensive panel data, covering all German employees subject to social security from 1989 to 2006 to analyze the impact of agglomeration effects on dynamic employment growth. The units of observation are local industries, that is, the aggregates of all employees in a three-digit industry in a NUTS 3 region. The main question is, whether there are agglomeration externalities that increase the long-term effects of initial employment growth. First, I measure agglomeration according to two definitions: I use the Ellison/Glaeser (1997) index to identify aggregate industries that are geographically concentrated, and the cluster index of Sternberg/Litzenberger (2004) to identify industrial agglomerations, that is, local industries where a substantial share of an industry's employment is concentrated (see O'Donoghue/Gleave, 2004, for a more detailed definition of industrial agglomerations). Then I use this information in the subsequent empirical analysis to allow the strength of dynamic employment growth to vary between agglomerated and non-agglomerated observations. The empirical evidence suggests that dynamic growth is indeed stronger in industrial agglomerations, while the fact that an entire industry tends to concentrate geographically does not significantly influence the dynamic growth of employment in this industry in all regions.

1 Cf. Ó'hUallacháin/Sattertwhaite (1992); Combes (2000); Südekum (2005); Frenken/van Oort/Verburg (2007); Mameli/Faggian/McCann (2008).

2 Cf. Henderson (1997); Combes/Magnac/Robin (2004); Blien/Südekum/Wolf (2006); Fuchs (2011).

2.2 Empirical strategy

2.2.1 Microfoundations of agglomeration economies

Explanations for why related firms benefit from being located close to each other are as old as Alfred Marshall's (1920) seminal treatise and are often called the three Marshallian forces or MAR externalities (Marshall, 1920; Arrow, 1962; Romer, 1986). A concentration of similar firms attracts specialized suppliers. Proximity reduces transport costs (Krugman, 1991b) and enables firms to benefit from sharing suppliers that have increasing returns to scale (Abdel-Rahman/Fujita, 1990). Apart from suppliers and an adequate infrastructure, specialized services like accountants, attorneys or advertising agencies may also be more readily available in industrial agglomerations (Quigley, 1998). However, the reduction of transport costs is not restricted to commodities but also applies to the mobility of people and ideas. The former can be explained by a highly specialized labor supply in one particular region. Search costs for qualified personnel are reduced and there is a higher probability of successful matches (Helsley/Strange, 1990). Specialized workers from elsewhere have the incentive to move to such regions due to better job and wage opportunities. Proximity also promotes the spillover of knowledge and technologies between establishments. This could happen through both formal and informal channels (Cohen/Morrison Paul, 2005; Henderson, 2007). The possibility of these spillovers decreases sharply with increasing distance (Griliches, 1979; Jaffe/Trajtenberg/Henderson, 1993).

All of these effects are expected to increase the productivity of firms located near related firms. From a static point of view, this provides incentives for firms to locate near each other, which leads to the geographic concentration of industries. From a dynamic point of view, however, the observation of geographic concentration alone does not provide sufficient evidence for the presence of agglomeration externalities: If these effects lose their importance in a specific industry due to reduced transport costs or modern communication technologies, for instance, the costs of relocation will prevent concentrated structures from quickly becoming dispersed. In this paper, I take the economic structure observed at the beginning of the period as given due to history, regional endowments or static agglomeration effects. If dynamic MAR externalities are at work, a circular logic as described by theoretical models like the New Economic Geography (NEG, Fujita/Krugman/Venables, 1999) should be observable, and agglomeration should be self-enforcing. Industrial agglomerations should then have a stronger productivity growth, and grow faster than other local industries in the long run.

Another class of economies of agglomeration appears in urban environments, where diversity attracts creative people, helps to create new ideas and protects the local economy from demand shocks in single industries. It is important to bear in mind that these Jacobs externalities (Jacobs, 1970) and MAR externalities are not mutually exclusive. While employment in some industries can be concentrated in a city, the rest of the city's employment can still be diversified, leading to the existence of both externalities at the same time (cf. Rosenthal/Strange, 2004). Hence, it is important to control for externalities of urbanization when analyzing the magnitude of MAR externalities.

Only a fraction of all local industries consists of a number of co-located establishments large enough that one would expect them to be subject to MAR externalities. The others account only for a minor share of employment in dispersed industries, where economies of agglomeration are of little importance. In Section 2.3, I present indices to identify local industries where MAR externalities are more likely to take effect. This allows for a direct test of these externalities: If MAR externalities exist in some local industries, long-run inertia of employment growth should be larger in these observations due to the self-enforcing nature of these externalities as described by theoretical models like the NEG. Thus, employment growth in the past should have a stronger effect on employment growth in the future.

2.2.2 Estimation method and variables

The following empirical analysis focuses on the magnitude of dynamic MAR externalities, while controlling for Jacobs externalities. The observation cell is the aggregate number of employees in a local industry, that is, industry i ($i = 1 \ldots N$) which is located in region r ($r = 1 \ldots R$). The approach used by Blien/Südekum/Wolf (2006) and in part also by Combes/Magnac/Robin (2004) serves as a starting point. Basically, log employment $\ln e_{irt}$ is regressed on its own value at time $t-1$ and on control variables:

$$\begin{aligned}\ln e_{irt} = {} & \beta_0 + \alpha \ln e_{irt-1} + \beta_1 \ln sect_{irt} + \beta_2 \ln size^{cf}_{rt} + \beta_3 div_{irt} \\ & + \beta_4 \ln firmsize_{irt} + \beta_5 \ln education_{irt} + d_t + c_{ir} + u_{irt}\end{aligned} \tag{2.1}$$

where e_{irt} is employment in region r in industry i at time t, *sect* the aggregate industry i employment in Western Germany, $size^{cf}$ the aggregate employment in the region, *div* the degree of diversity in region r, and *firmsize* the share of employment in firms with fewer than 20 employees. d_t is a general time effect that controls for macroeconomic shocks that affect the economy as a whole and are thus not connected to agglomeration effects. c_{ir} is a time invariant fixed effect for each local industry which captures unobserved location attributes such as resource endowments, culture, geographical location or historical developments.

Including the lagged dependent variable $\ln e_{irt-1}$ means that adjustment processes and thus dynamic externalities can be effective. Since this term is correlated with the error term in the fixed effects model, its coefficient is biased towards zero (see Nickell, 1981). To approach this problem, I apply a first difference panel approach. This has two advantages: First, following Anderson/Hsiao (1982) and Arellano/Bond (1991), it provides internal instruments. The first differenced lagged dependent variable $\ln e_{irt-1} - \ln e_{irt-2}$, which is correlated with the first differenced error term $u_{irt} - u_{irt-1}$, can be instrumented by further lags of the level values of the same variable. Second, subtracting the natural logs of employment in t and $t-1$, $\ln e_{irt} - \ln e_{irt-1}$, is a good approximation of the growth rate of employment between these years. Fixed effects are still controlled for, as they are eliminated by differentiation. This model allows a straightforward interpretation of the coefficients as effects on the employment growth rate. However, it has to be kept in mind that all regressors are now measured in differences as well. Thus, the effects of stock values on growth cannot be determined.

Combes/Magnac/Robin (2004) and Blien/Südekum/Wolf (2006) argue that a very large coefficient of the lagged dependent variable (one or greater than one) can be interpreted as evidence for MAR externalities. Only then would employment follow an explosive growth path, as the theory predicts.[3] On the other hand, an estimated coefficient considerably smaller than one (but greater than zero) would imply mean reversion, which would indicate convergence in the long run. This should hold true for the majority of all local industries where economies of agglomeration are not relevant.

The crucial drawback of this specification is that it restricts the autoregressive parameter to be equal for all observations. If MAR externalities actually exist, they should only be effective for local industries that feature some kind of agglomeration. To take this into account, the model is extended by the term $\lambda_{i(r)t-1}(\ln e_{irt-1} - \ln e_{irt-2})$ where $\lambda_{i(r)t}$ is an indicator variable for agglomeration. $\lambda_{i(r)t}$ takes the value of one if a local industry is subject to geographic concentration according to the indices presented in Section 2.3. Otherwise, it takes the value of zero. Thus, the estimation model becomes:

3 However, in this case, the autoregressive process would be non-stationary and neither of the prevalent estimation methods would lead to reasonable results. Thus, this finding is not likely to occur.

$$
\begin{aligned}
\ln e_{irt} - \ln e_{irt-1} = {} & \alpha_1(\ln e_{irt-1} - \ln e_{irt-2}) + \alpha_2 \lambda_{i(r)t-1}(\ln e_{irt-1} - \ln e_{irt-2}) \\
& + \beta_1(\ln sect_{irt} - \ln sect_{irt-1}) + \beta_2(\ln size^{cf}_{rt} - \ln size^{cf}_{rt-1}) \\
& + \beta_3(div_{irt} - div_{irt-1}) + \beta_4(\ln firmsize_{irt} - \ln firmsize_{irt-1}) \\
& + \beta_5(\ln education_{irt} - \ln education_{irt-1}) + \Delta d_t + u_{irt} - u_{irt-1}
\end{aligned} \tag{2.2}
$$

This allows the effect of previous growth to be of different magnitude, depending on whether an observation is localized or not. Thus, the presence of MAR externalities can be tested directly, which was not possible before. If the coefficient of the interaction term α_2 is significantly greater than zero, this presents evidence that former growth has a larger effect on future development in industrial agglomerations than it has in dispersed industries. Adding the two coefficients α_1 and α_2 gives the joint effect for dynamic growth in local industries that either belong to geographically concentrated national industries or are industrial agglomerations themselves.

Equation (2.2) can be estimated using the Generalized Method of Moments. Aside from the lagged dependent variable, the interaction term is also correlated with the error term and also has to be instrumented by lagged values. The main requirement for the instruments to be valid is no higher order autocorrelation in the first differenced error term. $u_{irt} - u_{irt-1}$ follows an MA(1) process by construction, but serial correlation at order two or higher indicates that the moment conditions are not valid. A further problem of the Arrelano/Bond-estimator can occur when the autoregressive process is almost non-stationary, that is, when the coefficient of the lagged dependent variable is close to unity. This can also be expected to happen in this context, at least for observations with $\lambda_{i(r)t-1} = 1$. Blundell/Bond (1998) approach this problem by using further lags of the first-differenced lagged dependent variable as additional instruments and estimating a system of two equations: One in differences and one in levels. This approach will also be used in the following empirical analysis.

The control variables are defined as follows (see Blien/Südekum/Wolf, 2006):

- Sector effects:

$$sect_{irt} = \sum_{r'}^{R} e_{ir't} - e_{irt} \tag{2.3}$$

  This controls for growth impulses that take effect in the industry as a whole throughout the country. To avoid endogeneity, employment in the own local industry is subtracted.
- Regional size: Aggregate regional employment is included to control for regional shocks. This variable could be endogenous if growth of different local industries is directly or indirectly related. This may very well be the case, since the externalities described in Section 2.2.1 are not necessarily restricted to one

industry. As an alternative, I use a proxy for counterfactual employment growth similar to that used by Blanchard/Katz (1992). Based on employment in the first year, $size_{rt}^{cf}$ is the aggregate employment in region r at time t if all local industries have developed according to their annual national growth rates.

- Diversity:

$$div_{irt} = -\sum_{i'=1,\, i' \neq i}^{N} \left| \frac{e_{i'rt}}{e_{rt}} - \frac{e_{i't}}{e_{t}} \right| \tag{2.4}$$

This is the standard Krugman diversification index, which is actually a measure of the absence of diversification in region r multiplied by -1. If the local economic structure exactly equals that of the country as a whole, it takes a maximum value of zero. The more specialized a region is, the more negative its value becomes. This variable controls for Jacobs externalities.

- Firm size:

$$firmsize_{irt} = e[in\ firms < 20\ employees]_{irt} / e_{irt} \tag{2.5}$$

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

- Education:

$$education_{irt} = e[highly\ qualified]_{irt} / e_{irt} \tag{2.6}$$

Innovation and entrepreneurship, which are two important determinants of growth, are highly related to human capital. Education is captured by the share of employees with university and technical college degrees. Since both MAR and Jacobs externalities rely on knowledge spillovers, it is particularly important to control for the presence of highly qualified personnel. Note that this variable could be both predetermined (i.e., be the result of earlier employment dynamics) and correlated with agglomeration. This would be the case if local industries which have grown particularly fast attracted more highly educated workers, as have local industries that tend to agglomerate. If this biases the coefficient of this variable, correlation with the agglomeration measure $\lambda_{i(r)t-1}$ could also bias the coefficient of the interaction term. To deal with this problem, I use temporally lagged values of the same variable as internal instruments, purging the correlation of *education* with the error terms of previous periods.

Finally, I take into account the possibility of spatial dependence between observations. If the influence of neighboring regions were not controlled for, the coefficients of this model could be biased upwards. In general, spatial econometrics models would permit the modeling of spatial correlation in the dependent variable or the error term (see Anselin, 1988; LeSage/Pace, 2009) and appropriate estimators are available even for dynamic panel data models (see Lee/Yu, 2010). Yet, the fact that the economic structure varies strongly between regions and in some cases even between years poses a problem similar to that of missing data, which renders contemporary ML or GMM estimators unfeasible (see Koch, 2010). As an alternative approach, I include spatial lags of $size^{cf}$, *diversity, firmsize*, and *education* in the model. For each industry and time period, I construct a separate, contiguity-based spatial weight matrix W_{it}. If two regions that host firms from the same industry share a common border, the respective element is one, and if not, zero. This matrix is row standardized and has zeros on the main diagonal. Multiplying it with the matrix of control variables for each region produces the weighted arithmetic averages of the controls of all other regions.

There are two further issues that should be kept in mind regarding the empirical strategy of this study: First, employment growth might not be the first choice for analyzing agglomeration effects. An increase in productivity only leads to employment growth if the demand for an industry's products is sufficiently elastic (see Appelbaum/Schettkat, 1995; Combes/Magnac/Robin, 2004). If this is not the case, regressing employment growth on a measure of localization could produce downward biased estimates (see Cingano/Schivardi, 2004). Since disaggregated data on productivity are rarely available, I follow a large strand of the literature and analyze the effects on employment growth nevertheless. Blien/Südekum/Wolf (2006) argue that even if specific theories on agglomeration effects cannot be tested, the results of this kind of analysis are still useful to explain how the local economic structure affects one of the most important outcomes for regional policy. The second issue concerns the causal direction of agglomeration and employment growth. In this paper, I analyze whether employment growth is stronger in an agglomeration. One could also argue that stronger employment growth causes or increases agglomeration. This concern is weakened to a certain degree by the temporal logic of the empirical strategy I apply in this study. Using panel data, I analyze the effects on future employment dynamics caused by employment growth and agglomeration patterns in the previous years.

2.2.3 Data

For the following analysis, I use data from the Establishment History Panel (BHP) of the Research Data Center of the German Federal Employment Agency (see Spengler, 2008, for detailed information). This data set is based on the mandatory registration of all employees subject to social security. The individual data on June 30th in each year is aggregated at the establishment level, resulting in a panel data set containing almost all German establishments with information on industry, location, and workforce composition. Eastern Germany is excluded due to being a transformation economy with strongly subsidized structures during most of the observation period. Since this kind of panel analysis requires a time-consistent classification of industries, I apply the procedure proposed by Eberle et al. (2011) to harmonize different classifications and to obtain the official German equivalent of NACE Rev. 1 for all years of observation.

The data set is aggregated to the number of full-time equivalents in 326 administrative districts in Western Germany (Landkreise und kreisfreie Städte – NUTS 3 regions, comparable to counties) and 191 three-digit industry classes from 1989 to 2006.

2.3 Geographic concentration of industries in Germany

Before turning to the analysis of agglomeration effects, it is useful to first take a look at the basic facts concerning the geographic concentration of industries in Western Germany. To this end, I apply two approaches: First, I use Ellison and Glaeser's (1997) EG-index to identify industries that are geographically concentrated. This index measures the deviation of the geographic distribution of an industry's employment from a random distribution. Its main advantage is its robustness to the industry's organization, that is, a small number of single, large firms does not lead the EG to indicate agglomeration. The authors suggest both a test whether an industry's employment significantly diverges from a random distribution and more conservative threshold values indicating substantial and strong geographic concentration (0.02 and 0.05, respectively). Note that it is not possible to determine the sites where firms of highly concentrated industries are located. To add this regional dimension, I use the cluster index (CI) of Sternberg/Litzenberger (2004) as the second measure. The CI is the product of three regional ratios, each normalized by the corresponding national ratio: The number of employees in the local industry divided by the regional population, the number of employees in the local industry divided by the regional surface area, and the number of establishments in the local industry divided by the number of its workers.[4] If each of these ratios is at least four times larger than in the aggregate country, the CI exceeds its threshold of 64 ($CI > 4^3 = 64$) and the local industry is identified as an industrial agglomeration.[5]

In 2006, 101 out of 191 industries in the manufacturing and service sectors were significantly localized according to the EG-index. This is more than half of all the industries observed and confirms Krugman's (1991a) observation that localization is rather the norm than an exception. However, the mean EG is 0.0052 and thus considerably smaller than the threshold of 0.02, which would indicate substantial concentration. Only 21 industries exceed this threshold, while seven industries have an EG larger than 0.05. Thus, most German industries seem to be localized, but not very strongly. Table 2.1 shows the 21 industries with EG-values larger than 0.02. While there are some high-tech industries, there are also many industries that have to make their location decisions according to geographical aspects like proximity to coasts or transportation routes. However, there are also manufacturing and service industries which one would not a priori have expected to be geographically concentrated.

Table 2.1: Geographically concentrated industries 2006, measured by the EG-index

EG	Industry code WZ93	
0.1330	611	Sea and coastal water transport
0.0869	152	Processing and preserving of fish and fish products
0.0857	263	Manufacture of ceramic tiles and flags
0.0747	335	Manufacture of watches and clocks
0.0716	671	Activities auxiliary to financial intermediation
0.0639	362	Manufacture of jewelery and related articles
0.0552	652	Other financial intermediation
0.0489	921	Motion picture and video activities
0.0448	622	Non-scheduled air transport
0.0431	176	Manufacture of knitted and crocheted fabrics
0.0410	732	Research and experimental development and social sciences and humanities
0.0385	632	Other supporting transport activities
0.0355	334	Manufacture of optical instruments and photographic equipment
0.0350	924	News agency activities
0.0349	172	Textile weaving
0.0340	262	Manufacture of non-refractory ceramic goods other than for construction purposes
0.0263	660	Insurance and pension funding, except compulsory social security
0.0257	351	Building and repairing of ships and boats
0.0251	300	Manufacture of office machinery and computers
0.0249	612	Inland water transport
0.0204	202	Manufacture of veneer sheets, plywood and other panels and boards

Source: IAB Establishment History Panel (BHP).

4 See Appendix A.1 for details on how to construct these indices.

5 The robustness ofthe estimation results regarding the choice of these rather arbitrary thresholds is checked in Section 2.4.2.

Table 2.2 displays the local industries with the highest CI values in 2006. Many industries that have high EG values can be recognized. The mean CI is 38.80 with a median of 1.11. 3.40 percent of all local industries have CI values greater than 64. Compared to the previous finding that over 50 percent of all industries are geographically concentrated, industrial agglomeration seems to be restricted to a relatively small number of observations, which is consistent with the intuition. Figure A.1 in the Appendix shows the regional distribution of local industries with CI values greater than 64. Many rural areas host either very few industrial agglomerations or none at all, while greater numbers of industrial agglomerations are located only in cities.[6] It is obvious that industrial agglomerations are not isolated but rather co-exist with other agglomerations of different industries. This fact should be kept in mind when I analyze agglomeration effects later.

Table 2.2: The 20 local industries with the highest CI values in 2006

CI	District	Industry code WZ93
361699	Bottrop	Manufacture of coke oven products
167291	Bremerhaven	Processing and preserving of fish and fish products
87691	Pirmasens	Manufacture of footwear
61844	Pforzheim	Manufacture of watches and clocks
39305	Pforzheim	Manufacture of jewellery and related articles
27852	Frankfurt am Main	Scheduled air transport
24977	Duisburg	Manufacture of coke oven products
24927	Merzig-Wadern	Manufacture of ceramic tiles and flags
24779	Trier	Manufacture of tobacco products
22701	Peine	Processing of nuclear fuel
19722	Bayreuth	Manufacture of tobacco products
11449	Straubing	Manufacture of sports goods
10856	Kaufbeuren	Miscellaneous manufacturing n.e.c.
9539	Remscheid	Manufacture of cutlery, tools and general hardware
9446	Emden	Transport via pipelines
8930	Solingen	Manufacture of cutlery, tools and general hardware
8904	Zollern-albkreis	Manufacture of knitted and crocheted fabrics
8714	Kassel	Manufacture of railway and tramway locomotives and rolling stock
8532	Wilhelms-haven	Transport via pipelines
8145	Emden	Building and repairing of ships and boats

Source: IAB Establishment History Panel.

6 This might be due to the method of calculating the CI: It is more difficult for local industries to take on high CI values in large, sparsely populated regions.

Geographical concentration appears to be a very common phenomenon in Germany and concerns more than half of all industries in the manufacturing and service sectors. However, most of this concentration is rather weak and only a small fraction of all observations is substantially concentrated. The remainder of this paper is dedicated to the question whether employment dynamics in these localized industries or industrial agglomerations differ from those in other local industries.

2.4 Estimation results

2.4.1 Baseline results

Using the above-mentioned data on all employees subject to social security in manufacturing and service industries from 1989 to 2006, I estimate equation (2.2) using the Blundell/Bond (1998) system estimator. I construct the interaction term by multiplying the log employment level $\ln e_{irt}$ with a dummy variable $\lambda_{i(r)t}$ that takes the value of one if the national industry has an EG index of larger than 0.02 or if the local industry has a CI index of larger than 64. I estimate the model separately for each of the two indices. The two indices represent different meanings of the term agglomeration. The EG index takes on large values if an aggregate industry shows a tendency to concentrate geographically. Hence, local industries could have $\lambda_{i(r)t} = 1$ even if they are not industrial agglomerations, as long as the whole industry is concentrated. Since the CI index, by contrast, varies between industries and regions, one would a priori expect the CI interaction term to have a larger coefficient.

In order to allow for the interpretation of long-run effects, I add another lag of the dependent variable and the interaction term. I also add two lags for the control variables.[7] The endogenous regressors are instrumented by one additional lag of their first differences and levels, respectively.

Table 2.3 displays the short run and steady state estimates of the two models. For the lagged dependent and the interaction term, I construct long-run effects by adding the lag coefficients. For the exogenous variables, I obtain the long-run effects by dividing the sum of all coefficients of one variable by the temporal multiplier: $\frac{\beta_{k,t} + \beta_{k,t-1} + \beta_{k,t-2}}{1 - \alpha_{1,t-1} - \alpha_{1,t-2}}$.[8]

7 I also estimated models with three or four lags. However, neither the contemporaneous effects nor the long-term effects changed substantially. Thus, I use the parsimonious version with two lags. This also allows the most efficient use of the rather small number of available periods.

8 Hence, the steady state effects only apply to observations with $\lambda_{i(r)t-1} = 0$. For the others, the steady state effects would be slightly larger: $\frac{\beta_{k,t} + \beta_{k,t-1} + \beta_{k,t-2}}{1 - \alpha_{1,t-1} - \alpha_{1,t-2} - \alpha_{2,t-1} - \alpha_{2,t-2}}$.

Table 2.3 Results of the dynamic panel data system estimation

Dependent variable: ln employment					
		Model 1		Model 2	
		coeff.	z/χ^2 (1)-value	coeff.	z/χ^2 (1)-value
ln e	long run	0.778 ***	95.75	0.748 ***	82.60
ln e * EG	long run	0.002	0.55	.	.
ln e * CI	long run	.	.	0.044 ***	8.09
ln sect	contemp.	0.881 ***	37.66	0.889 ***	37.58
	long run	0.792 ***	699.30	0.864 ***	862.68
ln size^{cf}	contemp.	0.150 ***	2.63	0.129 **	2.24
	long run	0.438 ***	11.82	0.248 **	3.88
diversity	contemp.	0.324 ***	8.13	0.319 ***	7.99
	long run	0.437 **	4.21	0.356 *	3.54
ln firmsize	contemp.	-0.059 ***	-38.51	-0.058 ***	-38.43
	long run	-0.086 ***	175.51	-0.083 ***	208.55
ln education	contemp.	0.104 ***	8.72	0.111 ***	9.02
	long run	0.167 ***	110.16	0.171 ***	127.37
W * ln size^{cf}	contemp.	-0.023 **	-2.29	-0.022 **	-2.24
	long run	-0.031	0.26	-0.020	0.13
W * diversity	contemp.	-0.007	-0.16	-0.007	-0.17
	long run	-0.131	0.22	-0.149	0.36
W * ln firmsize	contemp.	0.005 ***	4.56	0.005 ***	4.71
	long run	0.015 **	4.29	0.016 **	6.11
W * ln education	contemp.	-0.003 ***	-3.37	-0.003 ***	-3.33
	long run	-0.009 *	3.07	-0.006	2.04
Time dummies		YES ***		YES ***	
Observations		679,796		679,796	
Groups		47,291		47,291	
AR(1)		-18.611***		-17.119***	
AR(2)		-0.321		-0.817	
Sargan		975.843***		906.887***	

z-values based on heteroscedasticity consistent standard errors.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: IAB Establishment History Panel (BHP).

The extremely large Sargan statistic is somewhat disturbing. It rejects the null hypothesis that the instruments are valid. However, Combes/Magnac/Robin (2004) and Blien/Südekum/Wolf (2006) had no such problems despite using the same instruments and, in the case of the latter study, the same data. The only major difference is the number of observations. Due to the much smaller level of aggregation, the number of observations in the current study is about ten times larger. This might cause the Sargan test to overreject (see Andersen/Sørensen, 1996;

Hansen/Heaton/Yaron, 1996). When the size of the data set is reduced by randomly deleting groups, the null is no longer rejected. Moreover, the Arellano-Bond test for zero autocorrelation in the first-differenced errors does not indicate higher-order autocorrelation. Thus, the main requirement for the moment conditions to be valid is fulfilled. One other concern might be multicollinearity between the temporal lags of the explaining variables. While the stock values are of course quite stable, correlations between the differenced values are rather small (while the absolute value of none of the correlation coefficients is greater than 0.44, most lie between 0.1 and 0.2.).

Since the coefficients of the lagged variables should not be interpreted separately, I only describe the steady state effects, which occur after all adjustment mechanisms are completed. The lagged dependent variable has a long-run coefficient of 0.778 (0.748), which is very close to the result obtained by Blien/Südekum/Wolf (2006) for manufacturing industries. Industries that are substantially localized according to the EG index (Model 1) do not exhibit stronger dynamic growth. This can be explained by the definition of the EG index: It only varies between industries but not between regions. The concentration of an industry as a whole does not create externalities for all of its establishments. Turning to Model 2, the long run coefficient of the lagged dependentvariable is larger by 0.044 in industrial agglomerations. Adding both coefficients still yields a steady state effect significantly smaller than unity, so non-stationarity does not pose a problem in this model. Hence, even in industrial agglomerations, there is no explosive growth. A positive shock does not result in indefinite growth, but still leads to a higher steady state employment level. This is compatible with theoretical NEG models, where a "no black hole condition" prevents self-enforcing processes from becoming excessively strong (see Fujita/Krugman/Venables, 1999). To gain an impression of the additional effect in agglomerations, it is useful to perform a back-of-the-envelope calculation similar to that of Blien/Südekum/Wolf (2006). In non-agglomerated local industries, an initial exogenous shock of one percent leads to a 0.748 percent increase in the growth rate of the following year and increases the level of employment by approximately 3.97 percent $\left(=\frac{1\,\%}{1-0.748}\right)$ in the long run. In an industrial agglomeration, this long-run effect increases considerably to 4.81 percent $\left(=\frac{1\,\%}{1-(0.748+0.044)}\right)$. This means that in industrial agglomerations, shocks like the foundation of new plants or the extension of old plants are more persistent and have significantly larger long-run effects on further employment growth. This finding is in line with the theory of MAR externalities: Positive employment shocks could reinforce the Marshallian externalities of forward-backward linkages, labor market pooling, and knowledge spillovers, which strengthen a local industry's development in the long run.

The control variables have coefficients that are similar in size to those obtained by Blien/Südekum/Wolf (2006). In the long run, additional employment growth by one percent in the aggregate industry increases growth in the single observation by 0.792 percent (0.864 percent) – keeping everything else constant. A one percent shock of aggregate regional employment (represented by the counterfactual employment if all local industries had grown according to national rates) increases employment growth in the local industry by 0.438 percent (0.248 percent). Since the contemporaneous coefficient of this variable is substantially smaller (around 0.12), it seems as if it takes longer for regional shocks to take effect. Growth of diversity also has a positive and significant effect on employment growth in the long run. Thus, an increase of a regional economy in size and diversification creates an environment that favors employment growth, which is evidence for the importance of Jacobs externalities. However, it has to be kept in mind that it is unclear whether this result is identified by diversified cities or by rural areas increasing their economic diversity. The next subsection offers more insights into this matter. In addition, note that the long run coefficients of $ln\,size^{cf}$ and *diversity* are smaller in Model 2 than in Model 1. This corresponds to the observation that there are multiple industrial agglomerations in many regions. By controlling for different growth paths in industrial agglomerations, these two variables seem to loose importance. An increase in the growth of the share of small firms has a negative effect, which supports the hypothesis that internal economies of scale have positive effects on growth. The education variable has a positive coefficient, highlighting the importance of human capital for employment growth.

The lower part of Table 2.3 displays the coefficients of the spatially lagged covariates. A positive shock on aggregate regional employment in neighboring regions has a negative but small effect which becomes insignificant in the long run, while an increase in diversity has no significant effect across regional borders at all. An increase in the share of employment in small establishments in neighboring regions has a positive effect. It seems as if this variable represents a different mechanism than the share of employment in small plants in the own region: An increase in the share of employment in larger plants could have negative effects in neighboring regions due to an increase in productivity of competing firms. Finally, the spatially lagged human capital variable has a negative but very small coefficient that becomes insignificant in the long run.

2.4.2 Robustness checks

To validate the robustness of the results, I first include both interaction terms in the model simultaneously. The results of Model 3 in Table A.1 show that the coefficient of the CI interaction term becomes a little smaller while the coefficient of the lagged dependent variable increases in size. Still, the inertia after an initial shock is substantially stronger in industrial agglomerations than in non-agglomerated observations.

Ellison/Glaeser (1997) favor higher levels of regional aggregation to calculate their index. Their index does not consider agglomeration across regional borders, which could pose a problem if co-location takes place in regional entities larger than NUTS 3 regions. By adding spatially lagged covariates in the baseline model, I attempt to control for this spatial dependence. Alternatively, Model 4 estimates the effects for a higher level of regional aggregation. Instead of using 326 districts, the data are aggregated to 112 labor market regions (see Eckey/Schwengler/Türck, 2007). These regions are defined according to daily commuting patterns, which should also be the relevant regional scale for most other regular transactions than going to work. Thus, most kinds of spillovers are unlikely to reach further than beyond these regions' borders.

Indeed, there are some remarkable changes. While the EG interaction term is virtually zero, the CI interaction term has a much smaller long-run effect. To explain this, one has to keep in mind that aggregating the observations to a higher regional scale means that the regions' economic structures become more similar. Consequently, some industrial agglomerations stay hidden and thus MAR externalities are more difficult to identify. Another interesting result is the change in the effects of *ln size*^{cf} and *diversity*. In the long run, both coefficients are smaller than before and insignificant. Both variables have been used to measure Jacobs externalities, which are only effective in cities. Since labor market regions are not confined to cities but also include their partly rural hinterland, these effects become blurred. The fact that their effect is reduced when the difference between urban and rural regions is less pronounced presents some evidence that *ln size*^{cf} and *diversity* did capture Jacobs externalities in the previous models. Consequently, the lower level of aggregation seems to be the appropriate choice for measuring agglomeration effects.

Finally, I check whether the results depend on the rather arbitrary choice of thresholds for $\lambda_{i(r)t}$. Table A.2 displays the results of the model with simultaneous interactions when thresholds are lowered (Model 5) or raised (Model 6). For the EG, the new thresholds are 0.01 and 0.05 respectively, the latter being the value indicating strong concentration according to Ellison/Glaeser (1997). For the CI, I chose thresholds where all factors of the index are three times and five times as large as in the aggregate country, $3^3 = 27$ and $5^3 = 125$, respectively. Yet, the main results remain stable, which confirms that the conclusions do not hinge on the exact cutoff values that determine whether a local industry is considered to be an agglomeration or not.

2.5 Conclusion

In this paper, I present some new insights into how to measure the magnitude of agglomeration economies arising from the proximity of firms in the same industry. In previous studies, there was no consensus on how to control for agglomeration in a dynamic panel data framework. Blien/Südekum/Wolf (2006), for example, argue that the considerable inertia that local industries exhibit after an exogenous shock might be potentially due to MAR externalities. Since they cannot observe mean reversion in the absence of these effects, it remains unclear how strong these externalities are. Using indices to identify local industries that are particularly likely to be subject to MAR externalities, I find that inertia is indeed significantly stronger in industrial agglomerations than in other local industries. The difference in the persistence of employment growth is about 4.4 percentage points, which results in a considerably stronger growth in the long run.

It might still be delicate to attribute this finding completely to the presence of MAR externalities. Since many industrial agglomerations coexist in cities, part of this effect could also be due to Jacobs externalities, even though diversity and aggregate regional shocks are controlled for. For a direct interpretation, I should have used productivity as the dependent variable rather than employment growth. Since other studies find no evidence of MAR externalities (Glaeser et al., 1992) or even negative effects of specialization (Cingano/Schivardi, 2004), this result is still remarkable. The finding that industrial agglomerations have a higher degree of persistence in employment dynamics is in line with Henderson/Kuncoro/Turner (1995), who argue that if an industry is well established in a region, MAR externalities are important to sustain this industry. This insight is of major importance to regional policymakers or planners. The results suggest that explosive growth is reserved for special cases like Silicon Valley. Nonetheless, benefits from agglomeration can help local industries to persist in structural change and international competition.

3 The mysteries of the trade: Inter-industry spillovers in cities *(Wolfgang Dauth)*

"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, 1920, § IV.X.7)

3.1 Introduction

In spite of their age, Alfred Marshall's (1920) "Mysteries of the Trade" still serve as the base for the modern theoretical microfoundations of agglomeration economies. 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. These explanations for the presence of agglomeration externalities are commonly referred to as the three Marshallian forces: Forward-backward linkages, labor market pooling, and knowledge spillovers. While they are well established in theory (Duranton/Puga, 2004; Glaeser, 2008), there is only a sparse literature that distinguishes empirically these explanations (Puga, 2010). In particular, there is as yet no consensus on their relative importance (Glaeser/Gottlieb, 2009).

Yet, this is one of the central questions in agglomeration economics: Can we empirically decompose the phenomenon of agglomeration into its single explanations? Ideally, we could eventually say that each of them accounts for a certain percentage, say agglomeration economies are to X percent explanation A, to Y percent explanation B, and to Z percent explanation C (and a residual). To achieve this, it is necessary to model each part in a way that makes it comparable to the others and ensure that the individual parts can be isolated from each other. In this paper, I propose a new way to carry out the first task.

This study contributes to the literature in various ways: First, I introduce a new approach to empirically model external economies of scale across different industries. If these externalities increase with the size of an agglomeration, as proposed by the New Economic Geography as in Fujita/Krugman/Venables (1999), employment growth in one industry should provide positive external effects for related industries. To measure the magnitude of these multipliers, I augment the empirical model by adding a term that captures linkages between different local industries. Second, I analyze the three microfoundations of agglomeration externalities separately. The empirical approach allows to specify different patterns of inter-industry relations, representing each one of the Marshallian forces. Since each of them is modeled in a similar fashion, this allows for a comparison of their importance and magnitude. Finally, I adapt methods of spatial econometrics to account for the endogeneity of inter-industry linkages in employment growth. In this context, however, the strength of interdependence between cross-sectional observations is determined by economic rather than geographical proximity. Thus, methods of spatial econometrics serve as a central part of the empirical strategy.

The key results of this paper indicate that each of the three Marshallian forces helps to explain agglomeration externalities, while labor market pooling seems to be the most important one. The long-run effect on a local industry's employment with respect to the growth of a related local industry is an increase in the employment growth rate by roughly 0.026 percentage points.

A large empirical literature on agglomeration externalities in the past 15 years has been motivated by the discussion initiated by Glaeser et al. (1992) and Henderson/Kuncoro/Turner (1995).[1] Most of these studies find evidence that there are positive effects in general which arise from proximity of establishments within the same industry. However, up to now, the majority of the empirical literature in this field has not adequately discriminated between the different explanations for agglomeration externalities. Instead, it is often argued that while all of the underlying mechanisms lead to the same result, they are hard to separate due to the "Marshallian equivalence" (Duranton/Puga, 2004).

While a large number of studies focus on individual Marshallian forces,[2] only a handful analyze all three of them simultaneously in order to gain information on their relative importance. One way to do this is presented by Audretsch/Feldman (1996) and Rosenthal/Strange (2001), who examine which factors are correlated with the geographic concentration of industries. They find that concentration is positively correlated to the importance of transport costs, the share of skilled employees and the ratio of R&D-expenditure to sales, which is evidence for the importance of the three Marshallian forces.

Another way to deal with the Marshallian equivalence is to consider spillovers that happen between different industries.[3] Analyzing inter-industry spillovers rather than within-industry spillovers offers additional heterogeneity since the different agglomeration externalities operate trough different channels. While two

1 See Combes/Magnac/Robin (2004); Blien/Südekum/Wolf (2006); Frenken/van Oort/Verburg (2007); Fuchs (2011), for recent examples.

2 See Rosenthal/Strange (2004) for a survey of this literature.

3 For example, Porter's (2000) definition of a cluster explicitly refers to "firms in related industries", rather than to just a single industry.

plants, one making cars and the other one producing aircraft, do not exchange many of their products, for example, they could still benefit from having access to the same pool of qualified personnel. Measuring the magnitude of the different linkages could help to discriminate between the underlying microfoundations and thus overcome the Marshallian equivalence.

To this end, Feser (2002) concentrates on the two very dissimilar manufacturing sectors farm and garden machinery, as well as measuring and controlling devices, which are examples of 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. Rigby/Essletzbichler (2002) analyze how the Marshallian forces affect labor productivity separately for 19 manufacturing industries. They are represented by three proxies: The concentration of suppliers and buyers, the similarity of the occupational structure of a regional industry's workforce compared to that of the whole region, and the growth of labor productivity in upstream sectors.[4] They find evidence for the importance of forward-backward linkages and technological spillovers but only weak evidence for the effect of labor market pooling. The study by Ellison/Glaeser/Kerr (2010) is certainly also related to this paper. They use two different indices to calculate how strongly pairs of manufacturing industries tend to co-agglomerate in the same locations. These indices serve as dependent variables which are regressed on proxies for the three Marshallian forces on the industry level. The authors find that co-agglomeration indices take on higher values if 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.

In this empirical literature, there is no consensus on how inter-industry spillovers caused by the Marshallian forces should be modeled. This is most likely due to data restrictions. While it is straightforward to model spillovers that happen within an industry, it is difficult to obtain information on how firms from different industries are related. In the case of forward-backward linkages, there is some agreement that this is best achieved by input-output data. But with regard to labor market pooling or knowledge spillovers, most studies resort to more indirect measures, which pose the danger that the effects are not comparable any more between the different microfoundations. This study uses both a new method and exclusive data to model relations between 55 industries in ten large urban areas.

4 The last measure is intended to capture rent spillovers that are embodied in the actual exchange of goods rather than true knowledge spillovers (Griliches, 1979).

These relations are determined at the national level by input-output relations, the mobility of skilled workers, and the mobility of people in highly innovative occupations. The key finding of this paper is that employment dynamics are correlated between local industries due to these relations, which is evidence for each of the three Marshallian forces. Labor market pooling seems to provide the strongest multiplier.

The remainder of the paper is organized as follows. Section 3.2 briefly discusses the theoretical background. Section 3.3 describes how spatial econometrics methods are adapted to model inter-industry spillovers and introduces the data set. Estimation results, steady state effects, and robustness checks are presented in Section 3.4 and Section 3.5 concludes.

3.2 Theoretical background

Modern methods of manufacturing that include just-in-time delivery and production often necessitate close distances between firms and their suppliers. If transport costs are large enough, buyers benefit from having access to a variety of intermediate suppliers with increasing returns to scale (Abdel-Rahman/Fujita, 1990). But even if inputs are usually bought from more distant suppliers, local sources can be useful to compensate fluctuations or shortages (Scott, 1986; Feser, 2002). Furthermore, suppliers and buyers often collaborate in the design and development of intermediate goods, which is also facilitated by spatial proximity (Imrie/Morris, 1992; Klier, 1994). Establishments that share a common pool of specifically qualified personnel find it easier to adjust production in response to demand shocks (Overman/Puga, 2010), a flexibility that can increase labor demand in the long run. Another advantage of labor market pooling is the increase of the average quality of matches with the number of potential employers and employees (Helsley/Strange, 1990). This also motivates workers to acquire more specialized skills (see e.g., Becker/Murphy, 1992). Finally, proximity facilitates the transmission of innovation and ideas. 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 spills over between agents from different technical fields, leading to both product and process innovation.

More than 120 years after Marshall first introduced his ideas on the "mysteries of the trade", the underlying mechanisms – sharing, matching, and learning – still provide the theoretical microfoundations to explain agglomeration economies (Duranton/Puga, 2004). What these three mechanisms have in common is them requiring linkages between firms. If firms have nothing in common at all, it is unlikely that they will benefit from their mutual proximity by exchanging goods, attracting specialized employees, or spreading ideas.

From a single plant's point of view, the strength of each of the three Marshallian forces depends on how many related plants are located in the same region. If a local industry's employment grows, the benefits from forward-backward linkages, labor market pooling, and knowledge spillovers increase for all plants of this industry as well as in related industries. At first, these externalities enhance productivity, and if demand is sufficiently elastic, this also leads to an increase in employment (Appelbaum/Schettkat, 1995).[5] This consideration provides an approach to analyze the existence and the magnitude of the Marshallian forces. If employment dynamics are correlated between co-located industries which are in the same supply-chain, hire workers from the same labor market, or use the same kind of knowledge, then there is evidence that the underlying externalities are indeed effective.

3.3 Empirical strategy

3.3.1 Estimation method

Before inter-industry effects are taken into account, the basic model as proposed by Combes/Magnac/Robin (2004) or Blien/Südekum/Wolf (2006) serves as a starting point:

$$\ln e_{irt} = \phi \ln e_{irt-1} + \mathbf{x}'_{irt}\beta + \varepsilon_{irt} \tag{3.1}$$

The dependent variable $\ln e_{irt}$ is the log employment in local industry i ($i = 1, \dots N$) in region r ($r = 1, \dots R$) at time t ($t = 1, \dots T$). $\mathbf{x}_{irt}$ is a vector of control variables including fixed effects for cross-sectional units and periods, and ε_{irt} is the residual. The lagged dependent variable $\ln e_{irt-1}$ adds a dynamic component to take into account the inertia of employment. In the empirical literature, this autoregressive term is used to indicate the strength of spillovers within industries, which indicate the presence of agglomeration externalities. If a shock on employment in a local industry increases agglomeration externalities, the long run effects of this shock on further employment dynamics should be larger than in absence of agglomeration effects and ϕ would take on a large value (Combes/Magnac/Robin, 2004). Yet, there is no information on what causes these externalities. This paper's focus

5 Since most industries supply national or even international markets rather than a closed regional economy, this should always be the case.

is on inter-industry spillovers rather than on intra-industry spillovers. Since their magnitude is likely to vary depending on which industries are involved and how they are related, there is additional heterogeneity that helps to disentangle the underlying mechanisms.

If agglomeration externalities are at work, there is cross-sectional dependence in employment dynamics between industries and the model in equation (3.1) is misspecified. I take this into account by including the weighted sum of the log employment in all other industries $j \neq i$ in the same region r at time t as displayed in equation (3.2). The weights depend on how strongly two industries interact with each other. Each of the Marshallian forces is represented by a corresponding weighting scheme. Section 3.3.3 provides details on how these weights are determined.

$$\ln e_{irt} = \rho \sum_{j \neq i} w_{ij} \ln e_{jrt} + \phi \ln e_{irt-1} + \mathbf{x}'_{irt} \beta + \varepsilon_{irt} \tag{3.2}$$

The weights w_{ij} enter the equation in the form of a weight matrix $\mathbf{W}$, as becomes clear when equation (3.2) is written in matrix notation:

$$\mathbf{y}_{rt} = \rho \mathbf{W} \mathbf{y}_{rt} + \phi \mathbf{y}_{rt-1} + \mathbf{X}_{rt} \beta + \mathbf{c} + \alpha_t \mathbf{l} + \mathbf{v}_{rt}, \tag{3.3}$$

Note that this represents all N industries in region r at time t. To obtain an expression for all NRT observations, equation (3.3) must be stacked RT times. $\mathbf{y}_{rt} = (\ln e_{1rt}, \ln e_{2rt}, ..., \ln e_{Nrt})'$ is the vector of the dependent variable, $\mathbf{W}$ is an $N \times N$ 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 is a scalar of the time fixed effect, $\mathbf{l}$ is an $N \times 1$ vector of ones, and $\mathbf{v}_{rt} = (\varepsilon_{1rt}, \varepsilon_{2rt}, ..., \varepsilon_{Nrt})'$ is a vector of i.i.d. error terms.

The elements of $\mathbf{W}$ quantify the strength of the assumed relationships between any pair of industries within the same region. If the kind of inter-industry relationship specified by $\mathbf{W}$ does exist, the coefficient ρ should be significantly greater than zero. If the model did not contain the inter-industry term $\mathbf{W}\mathbf{y}_{rt}$, 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 $\rho \neq 0$, $\mathbf{W}\mathbf{y}_{rt}$ is correlated with the error term due to the two-dimensional nature of inter-industry effects (industry i affects industry j and vice versa).[6] Thus, another

6 Lagging this term by one period would solve the problem of endogeneity but restricts inter-industry spillovers to be static. To model multiplier effects that spread across co-located industries and induce retroactive effects on the original industry, it is necessary to include this term contemporaneously.

estimator must be used to obtain consistent results. The approach to model cross-sectional dependence as described above is very similar to a spatial autoregressive model (see Anselin, 1988; LeSage/Pace, 2009). The main difference is how the weights are determined. Usually, in spatial econometrics, 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 connected by an economic relationship. Following the terminology of spatial econometrics, where $\mathbf{Wy}_{rt}$ is called the spatial lag, I will henceforth call this term the industry lag. Thus, I use a matrix of economic rather than geographic weights, and apply spatial econometrics tools to obtain consistent estimates for the parameters of equation (3.3).

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 and there is no consistent IV estimator for dynamic panel data with fixed effects available yet. Lee/Yu (2010) are the first to derive a quasi-maximum likelihood estimator for this kind of model and to show its asymptotic properties. Fixed effects for both local industries and years are estimated jointly with the other parameters. One restriction of this approach is that it only allows to include a single weight matrix at a time.[7] Consequently, it is not possible to take into account the Marshallian forces simultaneously. This has to be kept in mind in Section 3.4, when the different estimates are interpreted.

It is also important to consider (just as in non-spatial dynamic panel data models) that the estimated structural parameters can no longer be interpreted as marginal effects. Their interpretation is restricted to how a change in a covariate would influence y in one local industry in the short run without taking into account cross-sectional and temporal interrelationships. However, calculating long-run equilibrium changes of y is simple (cf. Franzese/Hays, 2007).[8] These can be interpreted as the long-run effects of the counterfactual growth of a local industry on employment in all other industries in the same region.

7 In general, it is possible to include several weight matrices, as Lacombe (2004) did for cross-section data. However, no such estimator has as yet been developed for more complex dynamic panel data models.

8 For details see Appendix B.1.

3.3.2 Data

To estimate the model in equation (3.3), extensive panel data on employment in 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 are highly reliable and complete. A cross-section of the BHP contains information on each German establishment with at least one employee on June 30th of a given year. Data at the establishment level are generated by aggregation of worker data. The BHP covers almost the entire population of German employees, exceptions mostly being the self-employed and public officials who are not liable to social security. Unambiguous identification variables allow the cross-sections to be combined to form a panel data set. The data used for this analysis covers the years 1989 to 2008 and the functional labor market regions of the ten major urban agglomerations in Western Germany: The Ruhr district, Hamburg, Munich, Cologne/Bonn, Frankfurt am Main, Stuttgart, Bremen, Düsseldorf, Hannover and Nuremberg. Using only ten regions imposes the restriction that true spatial spillovers, that is, those between regions, are not taken into account. Since the regional classification is defined according to commuting patterns (Eckey/Schwengler/Türck, 2007), this problem is less severe at this level than at more detailed levels of aggregation. It is quite plausible that the distance, which individuals are willing to travel to work on a daily basis, is also the distance where most agglomeration spillovers take place. This is also the distance that is regarded as the geographic scope of agglomeration externalities (Duranton/Overman, 2005). Thus, most spillovers should be confined within these regions.

I aggregate the data to the number of full-time equivalents in local industries in the ten major urban labor market regions. The level of industrial aggregation is 56 industries of the manufacturing and service sectors. This is dictated by the availability of input-output data I use to construct weight matrices for forward-backward linkages in Section 3.3.3. Both the German and the European statistical offices only calculate input-output tables at relatively highly aggregated levels of the Statistical Classification of Products by Activity in the European Economic Community (CPA). Finally, I exclude the small industry "manufacture of tobacco products" from the analysis because it does not exist in some of the regions considered.

9 See Spengler (2008) for detailed information on the BHP.

3.3.3 Weight matrices

Since the focus of this analysis is to model inter-industry relations that indicate the existence of agglomeration externalities, it is essential to find weight matrices that embody the sources of these externalities. The objective is to create distinct weighting schemes, each representing one of the three Marshallian forces. To this end, I generate four different weight matrices:

- **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 (Bleses, 2007). These are available from the German Statistical Office in the context of national accounting. For this study, I use the 2006 table. Since no regional input-output tables are available, I use the national table for each region. The raw matrix displays which industries (columns) buy another industry's outputs (rows). I construct two weight matrices: The first refers to upstream relations. Transposing this matrix changes its interpretation: Now each column represents rather the origin than the utilization of goods. Thus, the second matrix represents downstream relations. This approach is similar to López/Südekum (2009) who use an input-output matrix to analyze the positive effect of proximity to establishments from the most important upstream and downstream industries on the productivity of Chilean manufacturing establishments. However, while López/Südekum (2009) restrict their analysis to forward-backward linkages, this study applies the same logic to each of the Marshallian forces.
- **Labor market pooling:** Labor market pooling means that firms from different industries benefit from accessing the same pool of adequately skilled personnel. This implies that employees from related industries are easily interchangeable. Following this implication, I create a weight matrix according to worker-flows between industries. To this end, I use the full sample of the employment statistics of the German Federal Employment Agency for the years 1999 to 2006. In this spell data set of all employees subject to social security, I identify employees who move to an establishment of a different industry. Then I use information on occupations to eliminate social and natural scientists, mathematicians, computer scientists and engineers from this dataset. These employees are likely to possess a large amount of knowledge. When they move to a new employer, they take this knowledge with them and might thus create a knowledge spillover. I eliminate these specific movers to avoid an overlap with the measurement of knowledge spillovers. Furthermore, since low-skilled tasks and general

management mostly require few or very generic skills, unqualified workers and managers can move between industries more easily without having to acquire special knowledge (Neffke/Henning, 2009). Thus, I consider only skilled non-management staff to be relevant for labor market pooling. Using the remaining 19,270,876 cases, I construct a matrix that represents the number of movers between pairs of industries.

- **Knowledge spillovers:** To analyze externalities due to knowledge spillovers, it is necessary to find a measure for the extent to which firms from different industries can take advantage of each other's knowledge. Patent citations provide a way to find explicit evidence of knowledge being used to produce new innovations. Since patents mostly relate to product innovation which is connected to a commercial value, this might still not be an appropriate approach in this study's context. Process innovation and the creation or advancement of skills are much more frequent and come closer to the idea of knowledge being a production factor as suggested by Lucas (1988), but might never be patented. Thus, using patent data means that only a selective part of all potential knowledge spillovers is taken into account. Moreover, it is usually not possible to relate patents to industries of the service sector. Official patent data are classified by product classes that can only be related to those manufacturing industries which make these products. An alternative way to identify industries between which knowledge spillovers are likely to take place is to consider the mobility of those social and natural scientists, mathematicians, computer scientists, and engineers who were omitted when the weight matrix for labor market pooling was created. Following Fosfuri/Rønde (2004) and Power/Lundmark (2004), it appears save to assume that these people not only change to another industry because their qualifications match the demands of their new jobs, but because they also bring knowledge with them, which is of value to their new employers.[10] Using the 868,173 movers of these knowledge intensive occupations, I again create a matrix that represents the number of movers between industry pairs. The more of these changes between industries occur, the more likely it is that establishments benefit from each others' knowledge and that they find further ways to learn from each other.[11]

10 To emphasize the argument of valuing their knowledge, it would have been interesting to consider only those movers who increased their salary by moving to another industry. However, German administrative data are censored at the contribution assessment ceiling for social security, which affects a particularly large fraction of this group of high skilled employees.

11 A more detailed discussion on different ways to quantify the potential for knowledge spillovers between industries is presented in Appendix B.2.

Since the data set is a panel of 55 industries in ten regions over 19 years, the final weight matrix, **W**, is more complex than just the raw matrices described above. **W** is a square block diagonal matrix with a total of $10,450^2$ elements. Each 55×55 block, $\mathbf{Wy}_{rt}$, consists of one of the raw matrices and represents the economic proximity between industries from the same region at the same time. There is one block per region and year, resulting in $10 \cdot 19 = 190$ blocks. All elements on the main diagonal and outside the blocks are zero. The raw matrices do not vary between region and year. This is due to data restrictions: Input-output tables are only available for the aggregate country. Yet, using the same weights for each region also entails an advantage: Since the weight matrices are not idiosyncratic for each region, the risk of endogeneity is reduced.

Before I use the weight matrices to measure inter-industry spillovers, some more adjustments are necessary. The raw matrices are measured in different units (Euros and persons, respectively). To make the ρ coefficients comparable, I row-normalize all matrices, that is, I transform the elements of each row to 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 (Plümper/Neumayer, 2010). 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 are expected to depend on the size of the local industry. Large and small local industries should cause effects of different strength when they grow by one percent, for example. 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. This way, the uneven distribution of industries over the observed regions is taken into account. To avoid endogeneity of this weighting scheme, I use the previous year's employment share. Note that due to this procedure, the industry lag is a weighted sum rather than a weighted average of the values of the dependent variable in the other industries. The ρ coefficients are still quantitatively comparable but can no longer be interpreted directly. 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 3.1: 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	0.28	0.34	1		
Labor market pooling	0.27	0.72	0.55	1	
Knowledge spillovers	0.21	0.69	0.52	0.89	1

Source: IAB Establishment History Panel (BHP).

Table 3.1 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 $\mathbf{y}_{rt}$-vector with the different weight matrices. As expected, there is some correlation between the different industry lags. Obviously, when there is an exchange of either goods, people, or ideas between different industries, there is also a higher probability of an exchange of the others. This has to be kept in mind when the effects of the different linkages are interpreted.

3.3.4 Control variables

To control for other determinants of regional employment dynamics, information on the size and the economic structure of local industries, national aggregate industries, and regions is required. However, the BHP data offers only limited information due to its administrative origin. Interesting characteristics such as productivity or the establishments' technical state of inventory are not available. The BHP contains information on location, industrial affiliation, as well as on the composition of the workforce with regard to gender, qualification, employment status, working hours, and age. Thus, it is possible to create variables that indicate the economic structure of industries and regions.

In line with the empirical literature (e.g., Blien/Südekum/Wolf, 2006), I use the following standard control variables: $sect_{irt} = \sum_{r'}^{R} e_{ir't} - e_{irt}$ controls for growth impulses that affect an industry throughout the country. To avoid endogeneity, I subtract the employment in the own local industry. 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 allow for further employment growth. I capture this 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 are inadequate since they also contain structural differences between industries and their workforces. Thus, in line with Blien/Südekum/Wolf (2006), I run an auxiliary wage regression at the establishment level 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.

I do not include a variable that captures the development of employment in the aggregate region in this model. Combes/Magnac/Robin (2004) and Blien/Südekum/Wolf (2006) argue that such a variable controls for market size effects. However, in the empirical model applied here, the weighted employment size in all other local industries is already captured by the industry lag $\mathbf{Wy}_{rt}$. To avoid multicollinearity, I omit the unweighted employment size in this study.

3.4 Results

3.4.1 Baseline results

I estimate the model specified in equation (3.3) using panel data on 55 aggregate industries for ten German regions in the years 1989 to 2008. Since the number of observation groups is larger than the number of periods, time fixed effects can be estimated using the direct approach developed by Lee/Yu (2010), which does not require that the weight matrices are row-normalized. This estimator is not capable of including several industry lags jointly. Thus, I estimate the model four times, with a term for (1) forward linkages, (2) backward linkages, (3) labor market pooling, and (4) knowledge spillovers, respectively. Table 3.2 displays the structural parameters of the four models.

Since the model includes local industry fixed effects and the main variables are in natural logarithms, the coefficients can approximately be interpreted as the effects on employment growth rates. The control variables show the expected signs and are qualitatively equal in the different models. Due to the persistence of employment, the serial lag has a large coefficient which is in line with the findings of Combes/Magnac/Robin (2004) and Blien/Südekum/Wolf (2006), but 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 ten urban regions are considered rather than the entire country. 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 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.

Table 3.2: Results of spatial and temporal dynamic panel data estimations

Dependent variable: ln employment				
Temp lag	0.887 ***	0.886 ***	0.887 ***	0.887 ***
	(163.56)	(163.43)	(163.64)	(163.65)
ln sector	0.096 ***	0.095 ***	0.096 ***	0.097 ***
	(12.13)	(11.96)	(12.19)	(12.26)
ln firmsize	-0.059 ***	-0.059 ***	-0.059 ***	-0.059 ***
	(-20.82)	(-20.85)	(-20.82)	(-20.8)
ln education	0.027 ***	0.027 ***	0.026 ***	0.027 ***
	(11.06)	(11.08)	(11.02)	(11.05)
Wage level	-0.015	-0.022	-0.025	-0.021
	(-0.13)	(-0.19)	(-0.21)	(-0.18)
Forward linkages	0.342 **			
	(2.33)			
Backward linkages		0.671 ***		
		(3.26)		
Labor market pooling			0.427 ***	
			(3.00)	
Knowledge spillovers				0.184 *
				(1.80)
σ^2	0.011 ***	0.011 ***	0.011 ***	0.011 ***
	(72.28)	(72.28)	(72.28)	(72.28)
Observations:	10,450	10,450	10,450	10,450

Bias corrected quasi-ML estimates, z-values in parentheses.
Fixed effects for local industries and years included.
Levels of significance: *** 1 %, ** 5 %, * 10 %.

Source: IAB Establishment History Panel (BHP).

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 information about the importance of the different inter-industry effects. The coefficients of each of the four industry lags are significantly larger than zero. The effect of backward linkages is by far the largest, while the effect of knowledge spillovers is significant only at the ten percent level. In the case of backward linkages, one could suspect that aside from true spillovers, simple supply chain relations explain this large coefficient. When an industry grows, it also increases its demand for inputs, which then fosters growth of its suppliers. Thus, one should hesitate to interpret this particular finding in favor of agglomeration economies. This caveat does not apply to the other models. The industry lags of forward linkages, labor market pooling and knowledge spillovers have 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 (Combes/Duranton, 2006). Obviously, this is either not the case or the positive effects outweigh the negative ones.

Labor market pooling has the largest coefficient and also the largest z-value. This provides some first evidence that this might be the most important one of the Marshallian forces, while forward linkages and knowledge spillovers cause somewhat smaller inter-industry effects. Of course, the necessity to estimate separate models is a caveat in this analysis, since the correlation of the different inter-industry effects is not accounted for. Hence, it is difficult to tell if the coefficients differ significantly and to make inference on their relative magnitude. This is important to keep in mind, since the different Marshallian forces are not mutually exclusive but can operate simultaneously. 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 I have created both weight matrices using disjunct sets of job movers, it is also possible for knowledge to spill over when non-scientists move to a new employer. Yet, the differences in the coefficients are still substantial, even though there is some correlation between the different industry lags. While the results suggest that all of the Marshallian forces are capable of explaining inter-industry relations, which is in line with the findings of Ellison/Glaeser/Kerr (2010), there is also evidence that they differ in strength.

3.4.2 Calculation and display of inter-industry effects

The structural parameters provide evidence that there are interrelationships in employment growth between different industries due to each of the three Marshallian forces. They also suggest an ordered importance of the different Marshallian forces. However, from the perspective of policymakers the most prominent question concerns the absolute magnitude of agglomeration effects. How strongly do establishments in cities benefit from the proximity to other establishments from different industries? It is obvious that the benefits from inter-industry linkages vary between industries and regions. In particular, they depend on how strongly an industry is related to others and on the size of the industries that cause these effects. To receive an impression of the magnitude of these effects, I calculate steady state multipliers.[12] These effects illustrate the additional employment growth that is induced by the counterfactual growth of one percent of an industry in the same city, after all adjustment mechanisms and interactions are completed. This procedure creates a considerable amount of data: One effect and its uncertainty estimate for each industry pair in each city for each of the Marshallian forces. For reasons of brevity, I focus on a case study of mechanical engineering industries in Munich. The industries considered here are manufacturing of (i) machinery and equipment, (ii) office machinery and computers, (iii) electrical machinery and apparatus, (iv) radio, television and communication equipment and apparatus, (v) medical, precision and optical instruments, watches and clocks, (vi) motor vehicles, trailers and semitrailers, and (vii) other transport equipment.[13] These are very important industries in Germany. As the recent international economic crisis showed rather drastically, a decline of these industries can cause negative effects in a vast number of establishments in various other industries (Möller, 2010).

Table 3.3 shows the reactions (in percent) of seven machinery-related industries to a one percent growth of one of the other industries. The strongest effects stem from forward linkages. Note that this particular finding is not completely due to agglomeration effects but can also 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 sixth column) and emphasizes the importance of inter-industry relations in general. The multipliers caused by the other linkages 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 0.199 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 significant and roughly amount to 0.026.[14] Thus, the major finding of this exercise is that inter-industry relations are important for fostering employment growth. There is evidence that each of the Marshallian forces contributes to explaining these relationships.

12 See Franzese/Hays (2007) and Appendix B1.

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

14 This is the unweighted average of all significant effects in Table 3.3, except for the ones that stem from backward linkages.

Table 3.3: Counterfactual steady state elasticities in machinery related industries

	Machinery	Office	Electrical	Communi-cations	Instruments	Vehicles	Transport
Forward linkages							
Machinery	–	0.000 *	0.051 **	0.025 **	0.006 **	0.009 **	0.000
Office	0.001 *	–	0.011 **	0.199 **	0.001 **	0.000	0.000
Electrical	0.015 **	0.001 **	–	0.039 **	0.008 **	0.004 **	0.000
Communi-cations	0.006 **	0.001 **	0.016 **	–	0.003 **	0.006 **	0.000
Instruments	0.027 **	0.002 **	0.023 **	0.078 **	–	0.014 **	0.000
Vehicles	0.037 **	0.000 *	0.046 **	0.006 **	0.001 *	–	0.000
Transport	0.090 **	0.000	0.022 **	0.012 **	0.017 **	0.008 **	–
Backward linkages							
Machinery	–	0.000 *	0.030 ***	0.007 **	0.044 ***	0.623 ***	0.071 ***
Office	0.106 **	–	0.115 ***	0.037 ***	0.137 ***	0.144 **	0.008 *
Electrical	0.329 ***	0.000 ***	–	0.016 ***	0.035 ***	0.689 ***	0.018 ***
Communi-cations	0.372 ***	0.018 ***	0.147 ***	–	0.234 ***	0.242 ***	0.023 **
Instruments	0.306 ***	0.000 ***	0.118 ***	0.027 ***	–	0.093 **	0.099 ***
Vehicles	0.139 ***	0.000	0.018 ***	0.013 ***	0.043 ***	–	0.013 ***
Transport	0.007	0.000	0.001	0.003	0.003	0.011	–
Labor market pooling							
Machinery	–	0.000 **	0.020 ***	0.010 **	0.028 ***	0.044 ***	0.004 ***
Office	0.039 **	–	0.025 ***	0.024 ***	0.025 **	0.019 **	0.001 **
Electrical	0.073 ***	0.001 ***	–	0.036 ***	0.048 ***	0.041 ***	0.003 **
Communi-cations	0.043 **	0.001 ***	0.071 ***	–	0.053 ***	0.019 **	0.002 **
Instruments	0.070 ***	0.001 ***	0.030 ***	0.036 ***	–	0.020 **	0.003 **
Vehicles	0.072 ***	0.000 **	0.014 ***	0.009 **	0.015 **	–	0.005 ***
Transport	0.061 ***	0.000 **	0.011 **	0.008 **	0.018 **	0.060 ***	–
Knowledge spillovers							
Machinery	–	0.000	0.025 *	0.012	0.027 *	0.033 *	0.003 *
Office	0.011	–	0.029 *	0.011	0.011	0.003	0.000
Electrical	0.036 *	0.001	–	0.033 *	0.040 *	0.025 *	0.002 *
Communi-cations	0.015	0.000	0.096 *	–	0.031 *	0.006	0.001
Instruments	0.030 *	0.001 *	0.034 *	0.057 *	–	0.009	0.003 *
Vehicles	0.039 *	0.000	0.023 *	0.009	0.013	–	0.004 *
Transport	0.029	0.000	0.013	0.016 *	0.020 *	0.036 *	–

Levels of significance: *** 1 %, ** 5 %,* 10 %.

Each element represents the additional long-term growth of an industry (rows) induced by the counterfactual one percent growth of another industry (columns).

Source: IAB Establishment History Panel (BHP).

3.4.3 Robustness checks

To validate the robustness of the results with regard to the choice of weight matrices and regions, I carry out several robustness checks. First, I create alternative weight matrices. The weight matrices used in the previous sections to estimate the main results follow a vector concept. This means that it is the direction of the underlying linkages that is important. For example, I take into account if one industry sells goods to another industry, but not vice versa. To allow spillovers to be directional is a virtue of this approach. Ellison/Glaeser/Kerr (2010), for instance, were not able to tell if industry pairs co-agglomerate because both industries benefit from proximity or if this only stems from one industry. However, this might be debatable in the case of labor market pooling and knowledge spillovers. These linkages do not require particular transactions that could have a definite direction. Hence, I create alternative matrices in line with Ellison/Glaeser/Kerr (2010). In these new raw matrices, for each pair of industries, the maximum value applies to both directions, for example $Input\_max_{ij} = max(Input_{i \rightarrow j}, Input_{j \rightarrow i})$. The new weight matrices are symmetric by construction and follow the non-directional pooling concept. Table 3.4 displays the coefficients of the industry lags for these alternative matrices. All of the coefficients are roughly half a standard deviation smaller than their counterparts in Table 3.2 and the coefficient of knowledge spillovers is no longer significant. This result suggests that direction indeed matters. If establishments from two industries have an advantage from being co-located, sometimes the establishments from one industry seem to benefit more than those from the other one. It is also interesting to see that the order of both the coefficients and their z-values remains unchanged.

Table 3.4: Robustness check: Pooling concept

Dependent variable: ln employment				
Forward linkages	0.291 **			
	(2.14)			
Backward linkages		0.570 ***		
		(3.13)		
Labor market pooling			0.376 ***	
			(3.08)	
Knowledge spillovers				0.138
				(1.57)
Observations:	10,450	10,450	10,450	10,450

Bias corrected quasi-ML estimates, z-values in parentheses.
Fixed effects for local industries and years included.
Levels of significance: *** 1 %, ** 5 %,* 10 %.

Source: IAB Establishment History Panel (BHP).

Another issue that might need clarification is the choice of the ten major urban areas in Germany. To test the robustness with regard to the choice and number of regions, I estimate the models with the original (vector-concept) weight matrices, using only the five largest cities in Germany. Since the omitted cities are considerably smaller and less dense, the effects should be stable or even increase. Indeed, Table 3.5 shows that all of the inter-industry effects have strongly increased. This provides evidence that agglomeration economies are particularly strong in denser urban areas. Again, the order of the coefficients remains stable. It is also interesting to note that when I use these coefficients to calculate steady state effects along the lines of Section 3.4.2, the magnitudes of inter-industry effects in Munich remain almost unchanged. The restriction to a smaller set of cities thus affects the overall coefficients but does not produce different results for the individual cities.

Table 3.5: Robustness check: Ruhr district, Hamburg, Munich, Cologne/Bonn, Frankfurt

Dependent variable: ln employment				
Forward linkages	0.591 ***			
	(3.18)			
Backward linkages		1.605 ***		
		(5.92)		
Labor market pooling			0.768 ***	
			(4.34)	
Knowledge spillovers				0.390 ***
				(3.03)
Observations:	5,225	5,225	5,225	5,225
Bias corrected quasi-ML estimates, z-values in parentheses. Fixed effects for local industries and years included. Levels of significance: *** 1 %, ** 5 %,* 10 %.				
Source: IAB Establishment History Panel (BHP).				

Finally, I relax the restriction that no spillovers take place between cities. Table 3.6 displays the coefficients of the four industry lags that result from different specifications of the weight matrices and the choice of regions. In the first model, I adjust the weight matrix to allow for interactions of different industries, both within and between regions. To this end, I fill the blocks off the main block-diagonal, that were all zeroes in the previous models, with the inter-industry matrices, and weight them down by the inverse distances in multiples of 50 kilometers. Since 50 kilometers is about the distance that has been found the most relevant for agglomeration economies according to Duranton/Overman (2005), regions that are less than this distance apart are not weighted down. The first column shows no significant inter-industry effects. One explanation is probably that agglomeration externalities are contained within regions. Considering linkages between regions might add too much noise and render the effects within regions unrecognizable. This is supported by the second column, where I only allow for spillovers between regions, that is, all elements on the main block-diagonal are zero. This model also does not yield any significant coefficients. In columns three and four, I carry out the same procedure, but now only the six regions that have common borders are considered.[15] Here, it might be particularly problematic to restrict the spillovers to not take effect between regions. Only in the case when spillovers between regions are allowed (see Model S4 in Table 3.6), backward linkages and labor market pooling yield moderately large and significant coefficients. This also implies that agglomeration externalities mostly operate within regions and sharply decline with distance. Even when I consider only contiguous but relatively large regions, no significant inter-industry effects are perceptible.

Table 3.6: Robustness check: Alternative specifications of the weight matrices

Dependent variable: ln employment				
	Model S1	**Model S2**	**Model S3**	**Model S4**
Forward linkages	0.022	0.055	0.065	0.155
	(0.44)	(0.80)	(0.93)	(1.52)
Backward linkages	0.051	0.131	0.153	0.352 **
	(0.70)	(1.27)	(1.50)	(2.36)
Labor market pooling	0.045	0.085	0.076	0.170 *
	(0.94)	(1.25)	(1.14)	(1.74)
Knowledge spillovers	0.018	0.037	0.044	0.098
	(0.54)	(0.79)	(0.94)	(1.42)
Observations:	10,450	10,450	6,270	6,270

Bias corrected quasi-ML estimates, z-values in parentheses.
Fixed effects for local industries and years included.
Levels of significance: *** 1 %, ** 5 %,* 10 %.

Model S1: Spillovers within and between regions.
Model S2: Spillovers only between regions.
Model S3: Spillovers within and between regions, only contiguous regions.
Model S4: Spillovers only between regions, only contiguous regions.

Source: IAB Establishment History Panel (BHP).

15 In two cases, three regions share common borders: Hamburg, Bremen, and Hannover in Northern Germany, and the Ruhr district, Düsseldorf, and Cologne/Bonn in North Rhine-Westphalia.

3.5 Conclusion

For a long time, there has been consensus that firms benefit from the proximity to related firms and that Marshall's (1920) explanations are still valid. However, most of the empirical literature focuses on spillovers that happen within industries. In this paper, I present a new approach to analyze spillovers between different industries. This approach provides additional information on the mechanisms that cause agglomeration externalities. If one industry grows, the benefits for firms in other industries located close by increase as well. Yet, this effect varies depending on which industries are involved and how they are related. For example, the co-location of two industries could generate large external effects from forward-backward linkages but only lesser effects from labor market pooling and knowledge spillovers. To analyze this in an econometric model, I adapt methods of spatial econometrics. In this context, the distance between cross-sectional observations is determined by economic rather than geographic proximity. The results imply 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 dynamics between local industries in urban environments. Thus, each of the Marshallian forces seem to be important, not only to explain co-agglomeration patterns but also to provide positive effects for further development. Labor market pooling can be interpreted, albeit with some caution, as the strongest Marshallian force with regard to fostering employment growth in related industries, while knowledge spillovers have the smallest impact.

By calculating long run effects, the magnitude of the economies of agglomeration can be assessed. Multipliers are quite heterogenous, depending on the industries considered. However, with an elasticity of up to 0.2, these effects are substantial. These findings strongly emphasize the importance of interactions between firms, not only within an industry but also between different industries. This has also an important implication for regional policy: Policies that support the regional specialization on single industries might not be efficient. Instead, a favorable regional economic structure should provide a dense network of interrelated industries. This should not be interpreted as evidence for Jacobs-type urbanization externalities. It is not simply undirected economic diversity that creates the externalities discovered in this paper. Rather, there 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 should 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 with employment data of the respective inventors could help to find a suitable weight matrix. However, this kind of data is not yet available. The high level of sectoral aggregation might also hide some of the strongest effects. The industry classification was dictated by the product classification in European input-output matrices. Data from the United States could provide a finer level of aggregation and permit a more detailed view. Finally, congestion costs could be taken into account more explicitly. There might very well be a maximum city size, where further growth of some local industries hinders long run growth in others. While this might reduce the benefits from agglomeration in general, forward-backward linkages, labor market pooling and knowledge spillovers, as analyzed in this study's empirical framework, can still yield positive effects.

4 The rise of the East and the Far East: German labor markets and trade integration

(Wolfgang Dauth, Sebastian Findeisen, Jens Südekum)

4.1 Introduction

Among the central forces that have spurred globalization in the last decades is certainly the rise of Eastern Asian countries, especially China, in the world economy. The substantial rise of trade with China, and its perceived competitiveness, have led to major concerns in the traditional Western market economies about possible adverse effects for domestic labor markets. This "fear" is particularly high on the agenda in the United States, where numerous studies have addressed the impact of trade integration with East Asia on US wage inequality, offshoring, innovation, et cetera.[1]

From the perspective of Germany, which consistently ranks among the most open economies in the world and for a long time held the unofficial title of the export world champion, China's rise also had a major impact. Starting from almost zero trade in the late 1980s, the German import volume from China has risen dramatically to more than 50 Billion Euros in 2008 (see Figure 4.1). This corresponds to a growth rate of 1,628 percent, which is far higher than for any other trading partner (see Table 4.1). However, although Germany runs a trade deficit vis-a-vis China despite an overall trade surplus, the magnitude of this deficit is much smaller than in the US case. This is because German exports to China have also risen by about 900 percent, from almost zero in 1988 to some 30 Billion Euros in 2008, which is much faster than the rise of US exports. The "rise of China" therefore led to two major impacts for the German economy: Increased import competition, particulary in such sectors as textiles, toys, or lower-tier office and computer equipment, but at the same time a substantial rise in market opportunities for the classical German export sectors, most notably automobiles, specialized manufacturing, and the electronic and medical industries.

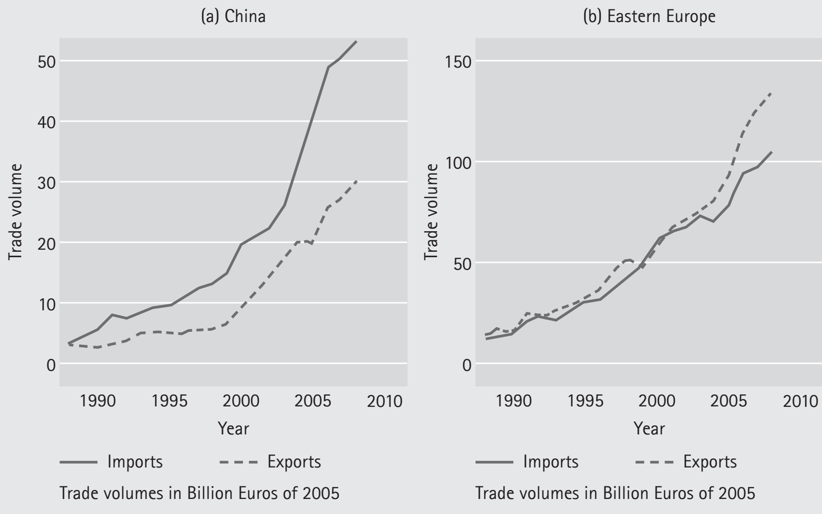
In addition to the "rise of China", Germany was affected by another major facet of globalization that at least economically had a much milder impact in North America, namely the fall of the Iron Curtain with the subsequent transformation of the former socialist countries into market economies. Overall, the rise of German exports to Eastern Europe even outpaced export growth to China. Import growth from Eastern Europe also has been substantial, exceeding

1 See, among others, Feenstra/Hanson (1999); Harrigan (2000); Feenstra/Wei (2010); Harrison/McLaren/McMillan (2010); Ebenstein et al. (2011).

800 percent during the period 1988 to 2008.[2] For the German economy, import competition and export market opportunities therefore increased not only from the Far East, but also from the East much closer by.

In this paper, we analyze the impacts of these major trade liberalizations from the perspective of small-scale German regions. There is substantial variation in sectoral employment patterns at the regional level, also within the manufacturing sector where commodity trade occurs. Given these initial specializations, regions are thus differently exposed to import competition and export opportunities arising from Eastern European and Asian countries. We relate changes in key local labor market variables to measures of import and export exposure that reflect the local industry mix. Afterwards, we complement this aggregate analysis with a disaggregate approach at the level of individual workers, analyzing how trade exposure affects employment stability within regions, local industries, and plants.

Figure 4.1: German trade volumes with China and Eastern Europe, 1988 to 2008



Source: United Nations Commodity Trade Statistics Database (UN comtrade).

2 To obtain a geographically stable region, we consider Eastern Europe to comprise the countries Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, and the former USSR or its succession states Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan. The increase in trade volumes between the US and these countries is negligible, at least in comparison to the German numbers. The sectoral structure of German trade with Eastern Europe differs from trade with China – see Tables C.1 and C.2 in the Appendix. Although the export sectors are mostly the same, there is more intra-industry and vertical trade as the top imported items are automobile parts and electric apparatus.

Table 4.1: Changes in German trade volumes, 1988 to 2008 (in Billion Euros of 2005)

	China		Eastern Europe	
Period	**Imports**	**Exports**	**Imports**	**Exports**
1988	3.1	3.0	11.0	13.3
1998	12.9	5.6	42.0	51.0
2008	53.1	30.1	103.8	134.0
Growth	**1628.3 %**	**893.2 %**	**843.9 %**	**905.3 %**
	Other Asian dev. countries		**Rest of the World**	
Period	**Imports**	**Exports**	**Imports**	**Exports**
1988	5.0	5.1	289.4	402.1
1998	12.5	7.5	357.7	506.9
2008	20.0	16.3	490.2	842.7
Growth	296.5 %	219.0 %	69.4 %	109.6 %

Source: United Nations Commodity Trade Statistics Database (UN comtrade).

In the literature, there are several approaches to identify the impacts of trade shocks. One approach uses industries at the national level as the unit of observation and analyzes how trade affects wages in general equilibrium, taking into account that inter-sectoral labor mobility may also involve a loss of specific human capital (Feenstra/Hanson, 1999; Harrigan, 2000; Robertson, 2004; Poletaev/Robinson, 2008; Blum, 2008). This literature is based on the view that labor markets adjust instantaneously or very rapidly to a new equilibrium, even after major perturbations. Another prominent approach looks at finer levels of disaggregation and is based on the presumption that the adjustment to major trade shocks is sluggish and may require more time. In that case, the differential impacts on firms, occupations or regions may be informative about the short- to medium-run effects of trade liberalization. Within that string of literature, Bernard/Jensen/Schott (2006), Verhoogen (2008), Amiti/Davis (2012), and Bloom/Draca/Van Reenen (2011) have analyzed trade shocks at the level of plants and firms, whereas Artuc/Chaudhuri/McLaren (2010), McLaren/Hakobyan (2010), and Ebenstein et al. (2011) use the industry and occupation level.

Our work is most closely related to the literature that identifies the impact of trade shocks at the regional level, see Chiquiar (2008), Kovak (2011), Topalova (2010), and in particular, Autor/Dorn/Hanson (2011). The latter (henceforth labeled as ADH) separate the US into 722 regions and analyze the differential performance of these regions depending on their exposure to import competition from China. To account for unobserved shocks that simultaneously affect imports and regional performance, they use imports of other high-income countries to construct an instrument for US regional import exposure. Their main finding is that regions with an industry mix that strongly exposes them to competition from China have experienced severe negative impacts on their labor markets, such as rising unemployment, lower labor force participation, or increasing reliance on disability and other transfer benefits. At the same time, they find that Chinese trade shocks induced relatively small cross-regional population shifts. This low labor mobility, in turn, supports the view that regions can be treated as "sub-economies" of the US across which the adjustment to trade shocks works far from instantaneously, so that the cross-regional variation in import exposure and labor market performance is a useful source of identification. Our analysis for German regions makes use of this empirical approach pioneered by ADH. Since regional labor mobility in Germany is traditionally much lower than in the US (Bertola, 2000), that approach indeed seems especially well applicable in our context.

Given the substantial differences in the aggregate trade developments between Germany and the US, we pay particular attention to two aspects that ADH did not focus on: Exports and Eastern Europe. The "rise of China", facilitated by substantial productivity gains and the Chinese WTO accession, and for that matter also the "rise of Eastern Europe" that was due to similar causes, not only imply an exogenous increase in import exposure from the point of view of a single German region. They also imply an increase in new export opportunities that regions, specialized in the "right" type of industries, can take advantage of. Our results in fact suggest that both aspects are crucial for understanding how German local labor markets were affected by, and adjusted to trade exposure in the past two decades.

Consistent with ADH, we also find a negative causal effect of import exposure on manufacturing employment in German regions.[3] That is, regions specialized in import competing sectors saw a decline in manufacturing employment attributable to the impact of trade. This effect is significant only for import exposure from Eastern Europe, however, while the rising penetration from China apparently had no major impact. Furthermore, we find that this negative impact is more than offset by a positive causal effect of export exposure. Regions specialized in export-oriented sectors were able to build up manufacturing employment as a result of the new trade opportunities. Again, this effect is more pervasive for Eastern Europe than for China. Overall, our empirical analysis suggests that the impact of the rising trade exposure with China and Eastern Europe was positive for manufacturing employment in Germany.[4] Quantitatively, the impact is highly important. We

3 To control for unobserved demand and supply shocks, we implement an instrumental variable strategy using trade flows from other high-income countries with Eastern Europe and China as an instrument for German import and export exposure. Our identification strategy is discussed in Section 4.2.

4 This finding differs substantially from ADH's main conclusion for the US. They find a much stronger negative impact for import penetration from China, also when they "net out" import and export exposure. That is, manufacturing employment in US regions did not seem to benefit significantly from export opportunities in China.

calculate that without these trade liberalizations, the total share of manufacturing employment in the German working age population would approximately be 1.54 percentage points lower in 2008 than it actually is. This corresponds to (at least) some 770,000 manufacturing jobs that would have disappeared over the period 1988 to 2008 without the rise of the East. We also find that trade has – on aggregate – reduced between-group wage inequality, lowered unemployment and led to employment gains in non-manufacturing sectors.

Finally, the analysis at the individual level allows for a more detailed look on the causal effects of trade. Here, we use cumulative spell information from administrative social security data. We find that a higher export exposure of the own job raises the probability of staying employed within the same plant or local industry. Analogously, higher import exposure raises the probability that a job is terminated. Overall, however, we find that trade has led to a higher stability of employment relationships.

The rest of this paper is organized as follows. Section 4.2 describes the empirical approach. Section 4.3 is devoted to the analysis of manufacturing employment at the regional level, while Section 4.4 looks at further regional labor market outcomes. Section 4.5 presents the worker level analysis, and Section 4.6 concludes.

4.2 Theory and estimation strategy

4.2.1 The model

Similarly as in ADH, we use the model by Eaton/Kortum (2002) as the theoretical background for our estimation strategy. Consider an industry *j* in a German region *i*.[5] The total output of that local industry is, in general equilibrium, equivalent to the total sales to all destination markets. Specifically, output Q_{ij} of a local industry in that Ricardian framework can be written as

$$Q_{ij} = A_{ij} \sum_n \frac{X_{nj} \tau_{nij}^{-\theta}}{\phi_{nj}}$$

where A_{ij} is the cost-adjusted productivity, X_{nj} is expenditure in the destination market *n* on industry *j*'s good, τ_{nij} are bilateral trade costs between the origin region *i* and the destination market *n*, and ϕ_{nj} is a measure for the toughness of competition in market *n* and industry *j*.

5 Regions are 413 NUTS 3 regions: "Landkreise und Kreisfreie Städte", comparable to US counties.

Our main aim is to identify the impact of the rise of China, or respectively, of Eastern Europe on the local markets in Germany.[6] Suppose China (indexed by C) experiences growth in cost-adjusted productivity and/or declining bilateral trade costs, for example, from joining the WTO. This will raise China's competitiveness and, from the point of view of a German local industry, displace sales in all relevant markets, including the own local market, the markets in the other German regions, and in the foreign export destinations. Formally, the impact on the output of a German local industry is

$$\hat{Q}_{ij} = -\sum_{n} \frac{X_{nij}}{Q_{ij}} \frac{X_{ncj}}{X_{nj}} \left(\hat{A}_{Cj} - \hat{\tau}_{nCj}\right) \tag{4.1}$$

where $\left(\hat{A}_{Cj} - \hat{\tau}_{gCj}\right)$ represents the rise in Chinese productivity and the declining trade costs. In applying equation (4.1), we focus on the displacement effects that occur in the other German markets, neglecting the trade diversion in foreign countries. Limiting the summation across destinations n to the markets within Germany (indexed by G), and summing across all industries j we obtain the following direct impact of China's rise on output in a German region i:

$$\hat{Q}_{i} = -\sum_{j} \frac{Q_{ij}}{Q_{i}} \frac{X_{Gij}}{Q_{ij}} \frac{X_{GCj}}{X_{Gj}} \left(\hat{A}_{Cj} - \hat{\tau}_{GCj}\right) \tag{4.2}$$

where $X_{Gij}\ /Q_{ij}$ captures the dependence of regional industry ij on sales in Germany, and where $X_{GC\,j}\ /X_{Gj}$ is the relative importance of China as a supplier of industry j's goods in Germany. The "rise of China" of course triggers numerous indirect effects in general equilibrium, such as adjustments in factor prices that in turn affect trade flows. However, similarly as ADH, our focus is on the identification of the direct impact of this exogenous trade shock, and on the analysis how German regions adjust to this shock along different margins.

To take equation (4.2) to the data, we proxy regional output by total regional employment in an initial time period t, $Q_i = E_{it}$, and analogously we use region i's initial share in total industry j employment to proxy for the local industry's share in total German sales in that industry, $X_{Gij}/X_{Gj} = E_{ijt}/E_{jt}$. Finally, to proxy $X_{GCj}\left(\hat{A}_{Cj} - \hat{\tau}_{GCj}\right)$, we use the total change in Chinese imports to Germany (in constant Euros of 2005) that was observed in industry j between time periods t and $t+1$. Using equation (4.2), we can then compute the following measure:

$$\Delta\left(ImE\right)_{it}^{C} = \sum_{j} \frac{E_{ijt}}{E_{jt}} \frac{\Delta Im_{jt}^{C}}{E_{it}} \tag{4.3}$$

6 For illustrative purposes we consider the rise of China in the theoretical model, i.e., changes in Chinese cost-adjusted productivity and trade costs. All arguments apply analogously to the rise of Eastern Europe.

This term captures the change in (potential) exposure of region i to imports from China, given the region's initial pattern of industry specialization.

Figure C.1 in the Appendix illustrates this increasing import exposure across German regions for the period 1998 to 2008, both with respect to China and Eastern Europe. The average increase in exposure to Chinese imports over that time period was 1,903 €, while for Eastern Europe it was 1,848 €. As can be seen from the maps, the industrial structure of Eastern Germany in 1998 was such that there was little potential import competition, neither from China nor from Eastern Europe. The West was, by and large, exposed more strongly to imports although there is substantial regional variation within Western Germany. Notice also, that the correlation between Chinese and Eastern European import exposure across German regions is only about 0.3. That is, many regions had industry structures that exposed them quite strongly to the imports from one area, but not from the other.

Turning to export exposure, it is clear that the rise of China (respectively, of Eastern Europe) also creates different potentials for German regions to exploit those new market opportunities, depending on the initial industrial structures. In an analogous way as for imports, it can be shown that the rise of China as an export destination for German goods has the following direct impact on output in a German region i:

$$\hat{Q}_i = \sum_j \frac{Q_{ij}}{Q_i} \frac{X_{Cij}}{Q_{ji}} \left(\hat{X}_{Cj} - \hat{\tau}_{CGj}\right)$$

Here, $X_{C\,ij} / Q_{ij}$ is the dependence of the local industry ij on sales in China, and $\hat{X}_{Cj} - \hat{\tau}_{CGj}$ represents the rise of the German industry j driven by gains in Chinese demand and the decline in bilateral trade costs. Using $Q_i = E_i$ and $X_{C\,ij} = (E_{ij} / E_j)\, X_{CGj}$, the export exposure of a German region i is thus given by

$$\Delta\left(ExE\right)_{it}^{C} = \sum_j \frac{E_{ijt}}{E_{jt}} \frac{\Delta Ex_{jt}^{C}}{E_{it}} \tag{4.4}$$

Figure C.2 in the Appendix illustrates the increase in potential export exposure of German regions, both with respect to China and Eastern Europe. The average increase in export exposure for China was 1,037 €, while for Eastern Europe that number reached 3,714 €. The map furthermore shows that Eastern Germany is again relatively little affected. Within Western Germany, there is substantial regional variation in the exposure to new export opportunities, yet with a clearly visible concentration in the south and southwest where the automobile and machinery sectors are highly concentrated.

4.2.2 Instrumental variable strategy

In the empirical analysis we aim to identify the causal effect of the rise of China and, respectively, of Eastern Europe on the economic performance of German regions. More specifically, we regress the change of regional manufacturing employment, wage inequality, and other variables, between t and $t+1$ on the change of regional import and export exposure over the same time period.

The main challenge for this exercise is the endogeneity of trade exposure, in particular the presence of unobserved supply and demand shocks that simultaneously affect import/export exposure and regional economic performance. To address those concerns, we employ an instrumental variable (IV) strategy that is close in spirit to the approach by ADH. To instrument German regional import exposure from China (equation 4.3), we construct the following variable for every German region i:

$$\Delta\left(ImE_{Inst}\right)_{it}^{C} = \sum_{j} \frac{E_{ijt-1}}{E_{jt-1}} \frac{\Delta Im_{jt}^{C-other}}{E_{it-1}} \qquad (4.5)$$

Here, $\Delta Im_{jt}^{C-other}$ are changes in trade flows of industry j's goods from China to other countries (see below). Similarly, for regional export exposure we construct the following instrumental variable that uses changes in exports of other countries to China:

$$\Delta\left(ExE_{Inst}\right)_{it}^{C} = \sum_{j} \frac{E_{ijt-1}}{E_{jt-1}} \frac{\Delta Ex_{jt}^{C-other}}{E_{it-1}} \qquad (4.6)$$

The identification strategy (4.5) is based on the idea that China's rise in the world economy induces a supply shock and rising import penetration for all trading partners, not just for Germany. Constructing a regional measure of import exposure by using those import flows of other countries therefore identifies the exogenous component of rising Chinese competitiveness and purges the effects of possible other shocks that simultaneously affect German imports and regional performance variables.[7] The logic of the instrument for export exposure is similar. As China becomes more integrated into the world trading system, it becomes a more attractive export destination for all countries, not just for Germany. Using (4.6) as an instrument for (4.4) thus purges the impacts of other unobservable shocks that simultaneously affect German exports and labor market performance, and thereby identifies the causal impact of the rise of export opportunities to China on German

7 Notice that the import values of the other trading countries are distributed across the German regions according to lagged sectoral employment shares from period $t-1$. This is done in order to tackle potential issues of measurement error or reverse causality, if employment reacted to anticipated trade.

local labor markets. The instruments for Eastern European ("EE") import/export exposure are constructed analogously, and use changes in trade flows of other countries with Eastern European economies.

The quality of the instruments hinges, in particular, on three important conditions. First, they must have explanatory power in order to avoid a weak instrument problem. Second, the supply and demand shocks in those countries should not too strongly be correlated with those of Germany, since otherwise the instruments do not purge the internal shocks and the estimated coefficients are still biased. Third, in order for the exclusion restriction not to be violated, there should not be an independent effect of the trade flows of those other countries with China and Eastern Europe on German regions other than through the exogenous rise of China/Eastern Europe.

To take those conditions into account, it is important to consider which countries are included in the "instrument group" whose trade flows are used to construct (4.5) and (4.6). We adopt the following approach: We focus on developed countries with a similar income level as Germany, but we exclude all direct neighbors as well as all members of the European Monetary Union. This is for two reasons. First, supply and demand shocks in such countries (e.g., France or Austria) are likely to be too similar to those in Germany, hampering the identification. Second, since those countries are highly integrated with Germany in an economic union where exchange rate alignments are impossible, it is likely that changes in trade flows between those countries and China/Eastern Europe also directly affect regional performance in Germany. Our final "instrument group" consists of Australia, Canada, Japan, Norway, New Zealand, Sweden, the United Kingdom, and the United States. Below we conduct several robustness checks where we change the countries that are included.

4.3 Trade exposure and manufacturing employment

4.3.1 Data

For the analysis at the regional level, we combine two main data sources. The German labor market data at the regional and local industry level come from the IAB-Establishment History Panel (BHP, see Spengler, 2008) which includes the universe of all German establishments with at least one employee subject to social security. This data set consists of an annual panel with approximately 2.7 million yearly observations on establishments aggregated from mandatory notifications to social security in the years from 1975 to 2008. Due to the administrative origin, the data are restricted to information relevant for social security (structure of workforce with regard to age, sex, nationality, qualification, occupation, wage) but at the same time are highly reliable and available on a highly disaggregated level.

Information on international trade is taken from the United Nations Commodity Trade Statistics Database (Comtrade). This data contains annual international trade statistics of over 170 reporter countries detailed by commodities and partner countries. Trade flows are converted into Euros of 2005 using exchange rates supplied by the German Federal Bank. We merge these two data sources by harmonizing industry and product classifications. The correspondence between 1031 SITC rev. 2/3 product codes and the employment data (101 NACE 3-digit equivalent industry codes) is provided by the UN Statistics Division and allows unambiguously matching 92 percent of all commodities to industries. Trade values of ambiguous cases are partitioned into industries according to national employment shares in 1978. We omit all industries related to agriculture, mining, and fuel products, since they would lead to extreme values in the main explanatory variables, which represent the increase in trade exposure per worker.

Table 4.2: Means and standard deviations of main variables

	1988–1998		1998–2008	
	Outcome variables			
10-year change manuf. employment/ working age pop. in %-points	-2.51	(2.71)	-0.15	(2.21)
	Trade exposure			
Δ import exposure				
Eastern Europe	1.80	(1.00)	1.85	(1.30)
China	0.59	(0.52)	1.90	(1.88)
Δ export exposure				
Eastern Europe	2.17	(1.01)	3.71	(2.27)
China	0.13	(0.11)	1.04	(0.82)
	Control variables			
Initial shares in total labor force				
Manuf. of food products	3.83	(2.18)	3.35	(2.06)
Manuf. of consumer goods	6.33	(5.46)	3.88	(3.28)
Manuf. of producer goods	14.37	(8.89)	11.97	(7.47)
Manuf. of capital goods	14.82	(10.72)	11.57	(9.15)
Routine occupations	41.34	(4.46)	36.42	(4.41)
High skilled	4.30	(2.43)	7.09	(3.76)
Foreigners	6.46	(3.71)	5.86	(4.26)
Women	38.50	(13.98)	40.41	(13.35)

Trade exposure in 1,000 € per worker. Control variables in percent.
Source: IAB Establishment History Panel (BHP) and UN comtrade.

4.3.2 Baseline specification: Manufacturing employment growth

We estimate the effect of trade exposure on local labor markets by running specifications of the form:

$$\Delta y_{it} = \gamma_t + \beta_1 \Delta(ImE)_{it}^{C/EE} + \beta_2 \Delta(ExE)_{it}^{C/EE} + \mathbf{x}'_{it}\beta_3 + e_{it} \tag{4.7}$$

That is, we relate changes in the regional outcome variable y_{it} between time periods t and $t+1$ to changes in (potential) regional import and export exposure (from China, or respectively, from Eastern Europe) during the same time period, while controlling for start-of-period regional control variables $\mathbf{x}'_{it}$. In the baseline specification of this section, the dependent variable is the decennial change in manufacturing employment as a share of the working age population in region i, $y_{it} = E_{it}^{M/WP}$. In the next section we consider further outcome variables, such as changes in regional population sizes, wage inequality, or unemployment. Detailed data for regional sectoral employment is available from 1978 onwards. Since much of the rise of China and Eastern Europe occurred after 1990, we use 1988 as our starting point and thus observe data for two time periods (1988 to 1998 and 1998 to 2008) for each region. This timing also allows us to use employment lagged by ten years in the construction of our instruments as discussed above. Eastern German regions are only included for the second decade 1998 to 2008, because sectoral employment data for these regions only became available in the mid-1990s. We report robustness checks excluding all Eastern German regions.

In the vector $\mathbf{x}'_{it}$ we include several region-decade specific controls, such as the start-of-period shares of employees in five broad groups of manufacturing industries,[8] and dummies for the 16 German federal states. We also allow for decade specific growth trends by a time dummy γ_t. Table 4.2 reports some descriptive statistics for the main variables.

Eastern Europe

We start our analysis by focussing on the impact of Eastern European trade exposure on manufacturing employment across German regions. The first three columns of Table 4.3 show OLS specifications where we do not instrument for import and export exposure. Column (1) includes only a parsimonious set of controls and shows a positive relationship with export and a negative relationship between import exposure and manufacturing employment growth.

8 These are manufacturing of food products, consumer goods, producer goods, and capital goods, which might mean revert over time.

Table 4.3: Trade exposure with Eastern Europe and manufacturing employment

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ import exposure	-0.048	-0.052	-0.013	-0.564**	-0.599**	-0.594**
	(0.19)	(0.18)	(0.19)	(0.24)	(0.24)	(0.24)
Δ export exposure	0.368*	0.382**	0.326*	0.638***	0.669***	0.630***
	(0.19)	(0.16)	(0.17)	(0.24)	(0.23)	(0.24)
% food manuf.	0.233***	0.031	0.026	0.225***	0.021	0.016
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
% consumer goods	-0.101***	-0.122***	-0.115***	-0.091***	-0.117***	-0.110***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
% producer goods	-0.052***	-0.084***	-0.084***	-0.047**	-0.082***	-0.082***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
% capital goods	-0.067**	-0.059**	-0.055*	-0.061*	-0.056*	-0.052*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
% routine occupations		-0.081	-0.084		-0.069	-0.074
		(0.06)	(0.06)		(0.05)	(0.05)
% high skilled		-0.170***	-0.175***		-0.173***	-0.178***
		(0.04)	(0.03)		(0.03)	(0.03)
% foreigners		-0.060***	-0.059***		-0.059***	-0.058***
		(0.01)	(0.01)		(0.01)	(0.01)
% women		-0.039	-0.036		-0.018	-0.015
		(0.04)	(0.04)		(0.04)	(0.04)
Federal state dummies	Yes	Yes	–	Yes	Yes	–
Time dummy	Yes	Yes	–	Yes	Yes	–
State and time interaction	–	–	Yes	–	–	Yes
R-square	0.354	0.462	0.484	0.204	0.332	0.226
First stage (KP)				21.914	23.866	23.757
p Hansen				0.078	0.210	0.317

Observations: 739. Standard errors clustered by administrative districts and years in parentheses. All control variables are shares in total employment. % high skilled of labor force defined as the fraction of the workforce with a university degree. % routine occupations defined as basic activities according Blossfeld (1987). Levels of significance: *** 1 %, ** 5 %, * 10 %.

Source: IAB Establishment History Panel (BHP) and UN comtrade.

In the second column we add controls for the initial composition of the labor force, namely the start-of-period share of high-skilled, foreigners and women. Furthermore, motivated by the literature on job off-shoring (e.g., Antras/Garicano/Rossi-Hansberg, 2006; Grossman/Rossi-Hansberg, 2008), we include the percentage of routine intensive occupations (represented by basic activities in the taxonomy of Blossfeld (1987)). As can be seen, export exposure is still estimated to have a positive and significant effect, whereas the relationship with import competition is around zero. Finally, in column (3) we use interacted federal state x time period dummies instead of separate state/time dummies. This specification is the most demanding one, as it is only identified by within state-time variation. As can be seen, the coefficients of trade exposure decline slightly but remain qualitatively robust.

The OLS coefficients reported in the first three columns are confounded with unobservable supply and demand shocks that can simultaneously affect employment and trade flows in Germany. To identify the causal effect of the rise of Eastern Europe on German manufacturing employment, we therefore use the instrumental variable estimation as described before. For ease of comparison, we use the same specifications for the IV estimation in columns (4) to (6) as for the OLS estimations.

The impact of import exposure from Eastern European trade on German manufacturing employment is now estimated between -0.564 and -0.599, which is both statistically and economically significant. The results indicate that the sources of bias for the OLS estimates seem to be quantitatively important and responsible for driving the OLS estimates towards zero. Similarly, the coefficient for export exposure rises in magnitude, and is now estimated between 0.638 and 0.669. These coefficients reflect the change of manufacturing employment in percentage points, induced by an increase in trade exposure of 1,000 €. Table 4.3 reports the Kleibergen-Paap Wald rk F statistic to diagnose a potential weak instrument problem.[9] With values above 20, the results suggest that we face no such weak instrument bias – the values are well above the critical values compiled by Stock/Yogo (2002) (for the i.i.d. case) and the rule-of-thumb value of 10 suggested by Staiger/Stock (1997). Hansen's J test for overidentifying restrictions also indicates the validity of the instrument set, at least for the full specifications. The other estimated coefficients have the expected sign and do not differ much across the different specifications. There is evidence for mean reversion across regions in manufacturing of capital goods, producer goods, and consumer goods. A higher share of high skilled and female workers in the local labor force is negatively related to manufacturing employment growth, which also appears to be economically plausible.

In our preferred specification from column (6), the estimates imply that increased import competition from Eastern Europe led, for the average region, to a 1.07 percentage point decline in manufacturing employment between 1988 and 1998, and to a 1.10 percentage point decline between 1998 and 2008. Access to Eastern European markets, on the other hand, has increased manufacturing employment by 1.37 percentage points on average between 1988 and 1998, and by 2.34 percentage points between 1998 and 2008. Hence, Eastern Europe trade integration has in the aggregate led to an increase of manufacturing employment in Germany, stemming from the increased Eastern European demand for German goods.

9 The Kleibergen-Paap statistic (Kleibergen/Paap, 2006) is appropriate for use in the presence of non-i.i.d. errors, as opposed to the Cragg-Donald F statistic for the i.i.d. case.

China

Turning to the impact of trade exposure with China, the OLS estimates reveal a highly significant and large correlation between export exposure and manufacturing employment growth. The coefficients are in fact several times larger than the corresponding ones for Eastern European export exposure. In contrast, import exposure from China does not seem to be correlated with changes in manufacturing employment; the effect is estimated to be close to zero, and with small standard errors.

Table 4.4: Trade exposure with China and manufacturing employment

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ import exposure	0.055	0.050	0.020	0.019	-0.016	-0.066
	(0.07)	(0.06)	(0.06)	(0.07)	(0.08)	(0.09)
Δ export exposure	1.709***	1.770***	1.656***	1.448***	1.624***	1.510***
	(0.39)	(0.37)	(0.41)	(0.51)	(0.48)	(0.51)
% food manuf.	0.264***	0.052	0.046	0.260***	0.048	0.041
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
% consumer goods	-0.084***	-0.110***	-0.103***	-0.079***	-0.102***	-0.092***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
% producer goods	-0.049***	-0.085***	-0.085***	-0.045***	-0.081***	-0.081***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
% capital goods	-0.088***	-0.084***	-0.079***	-0.077***	-0.076***	-0.071***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
% routine occupations		-0.105**	-0.102**		-0.101**	-0.098**
		(0.05)	(0.05)		(0.05)	(0.05)
% high skilled		-0.157***	-0.163***		-0.157***	-0.163***
		(0.03)	(0.03)		(0.03)	(0.03)
% foreigners		-0.058***	-0.058***		-0.058***	-0.058***
		(0.01)	(0.01)		(0.01)	(0.01)
% women		-0.029	-0.026		-0.029	-0.025
		(0.04)	(0.04)		(0.04)	(0.04)
Federal state dummies	Yes	Yes	–	Yes	Yes	–
Time dummy	Yes	Yes	–	Yes	Yes	–
State and time interaction	–	–	Yes	–	–	Yes
R-square	0.408	0.520	0.532	0.286	0.421	0.320
First stage (KP)				18.577	18.121	21.187
p Hansen				0.094	0.130	0.198

Observations: 739. Standard errors clustered by administrative districts and years in parentheses. All control variables are shares in total employment. % high skilled of labor force defined as the fraction of the workforce with a university degree. % routine occupations defined as basic activities according to Blossfeld (1987). Levels of significance: *** 1 %, ** 5 %, * 10 %.

Source: IAB Establishment History Panel (BHP) and UN comtrade.

When using the instrumental variable approach, we find that the coefficient for import exposure turns negative, which is consistent with an upward bias of the OLS coefficient that we have also found before. Still, the coefficient is clearly not significant. Import exposure from China therefore does not seem to affect the German manufacturing sector, a finding that is in stark contrast to the effects found for the US case. With respect to export exposure, the IV estimate decreases somewhat, compared to its OLS counterpart, but overall it remains highly statistically significant and fairly large. This suggests that the overall impact of trade with China was largely positive for the German manufacturing sector as a whole. There is no evidence for substantial employment losses resulting from stronger import competition due to the rise of China. Rather, we find that the newly arising export opportunities in China have strengthened manufacturing employment in Germany.

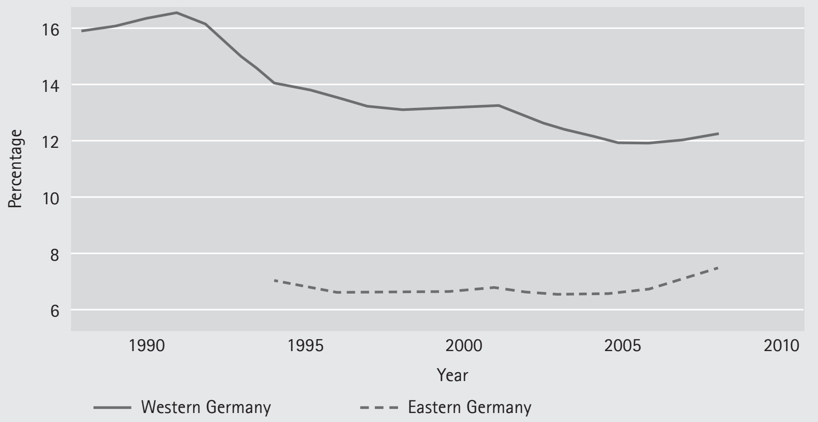
Benchmarking the impact of trade liberalization

If the estimated coefficient for export exposure is much larger for China than for Eastern Europe, one has to note that the overall economic impact of export exposure is actually larger for Eastern Europe. This is due to a much more pronounced and more rapid growth of trade integration with Eastern Europe. Table 4.2 shows that while the average export exposure with Eastern Europe increased by 3,714 € per worker between 1998 and 2008 and 2,174 € between 1988 and 1998, the corresponding decennial changes for China have been only 1,037 € and 134 €, respectively. Using mean exposure, this translates into manufacturing employment increases of 0.20 percentage points for the period 1988 to 1998, and 1.57 percentage points for the period 1998 to 2008. These numbers are somewhat more modest than the 1.37 and 2.34 percentage points that we have found for Eastern Europe earlier on. Intuitively, it seems that trade with Eastern Europe had more immediate consequences for German manufacturing employment than trade with China. This result is consistent with standard gravity forces of international trade, as the Eastern European market is located closer by.

To set these numbers into perspective, it is important to note that the manufacturing sector has been declining in Germany over the period 1988 to 2008. Figure 4.2 shows that, in Western Germany, the share of manufacturing employment (measured in full-time equivalents) in the working age population dropped substantially over the past two decades, from 16 percent in 1988 to around 12 percent in 2008.

Trade exposure with Eastern Europe has increased that share by roughly 0.3 percentage points in the first, and by roughly 1.24 percentage points in the second half of the observation period. In absolute terms, this corresponds to 131,927 (full-time equivalent) manufacturing jobs in the first, and 641,730 jobs in the second decade that would not exist in Germany without the rise of Eastern Europe as a trading partner.

Figure 4.2: Percentage of manufacturing employees in working age population



Source: IAB Establishment History Panel (BHP).

Robustness checks

Instrument group: How robust are our results with respect to the definition of the "instrument group" of countries whose trade flows with China and Eastern Europe are used in the definition of equation (4.5) and (4.6)? The validity of our identification approach hinges on the ability of the instrument to purge domestic shocks that simultaneously affect German regional employment and trade patterns. As explained above, we have therefore excluded direct neighbors of Germany as well as members of the European Monetary Union and used trade flows of Australia, Canada, Japan, Norway, New Zealand, Sweden, the United Kingdom, and the United States.

There is still the concern that there might be an independent effect of the trade flows between China/Eastern Europe and those "instrument group" countries on German regions, which in turn would violate the exclusion restriction. To check the robustnessof our results, we re-estimate our baseline model with varying instruments (Tables C.3 and C.4). In column (1), we omit the USA from the instrument set. If there are such independent effects of an instrument country, they should be strongest in the case of the USA, the world's largest economy and a major trading partner of Germany. Yet, the coefficients change only slightly compared to the baseline specification. This suggests that our baseline instrument does not violate the exclusion restriction.

In column (2), we only use US trade flows to instrument German import/export exposure. In that case, we obtain substantial deviations of the estimated coefficients from the baseline results. Furthermore, the small Kleibergen-Paap statistics indicate that this specification suffers from a weak instrument problem. US trade patterns with Eastern Europe and China seem to be quite different from Germany's pattern of trade with these economies. This speaks in favor of specifying an overidentified model as in the baseline specification, where the trade patterns of several countries are taken into account, rather than a model where identification comes from the trade pattern of a single country only. Column (3) conveys a similar message. Here, we add up all instruments instead of specifying an overidentified model. The results are similar to those in column (2). This is due to the fact that this aggregate instrument is dominated by the trade flows of the large US economy, while adding smaller countries with varying trade patterns introduces noise. Finally, in column (4), we consider a placebo test by including only such countries in the instrument group, whose economic structures are totally dissimilar from Germany's. More specifically, we only use Cyprus, Iceland, and the United Arab Emirates to construct the instrument. As expected, the Kleibergen-Paap statistics indicate that these results are strongly biased due to weak instruments.

Summing up, the robustness checks suggest that our baseline specification indeed leads to a credible identification, as the adopted instrument has both explanatory power in the first stage and does not violate the important conditions for validity.

Particular industries: Next, we check the sensitivity of our results to the omission of specific industries. We construct twenty new data sets. In each data set, one of the most important industries when it comes to bilateral trade values in 2008 for Eastern Europe and China, respectively, is dropped at the start of the whole data preparation process. Then we re-estimate the baseline model and obtain the results reported in Tables C.5 and C.6. We find that leaving out the automobile industry (which is by far the most important trade sector for the German economy) strongly decreases the coefficients for both import and export exposure to Eastern Europe. This highlights the importance of the car industry for both German manufacturing employment and trade. Omitting other industries, however, does not lead to a notable change in our estimated IV coefficients, compared to the baseline findings. Also, in the analysis for Chinese trade exposure we obtain robust results, an exception being the specification where we leave out "manufacture of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines". This industry aggregate includes manufacturing of pumps, valves, bearings, gears, etc. and is directly connected to the automotive industry by its role as a supplier of intermediate inputs. However, we believe the results of these robustness checks should be treated with some caution. Due to its sheer size and close integration with many other industries, a German economy without the automotive sector is downright unimaginable. Simply omitting this sector from the data set results in an economic structure that does most likely not conform with the structure that would actually have evolved if there would have never been an automotive sector in Germany. In other words, simply omitting big industries, makes for a bad counterfactual how trade exposure affects employment without these industries.

Regional classification: Turning to the issue of Western versus Eastern Germany, we have included all 413 (Eastern and Western) German regions in the baseline. Since we have data for Eastern Germany only after the German reunification, there are thus only 326 regions available in the first period. As a robustness check, we exclude all Eastern German regions also in the second period. The coefficients in Tables C.7 and C.8 are slightly larger than in our baseline estimation, but all conclusions are qualitatively unchanged. Finally, we investigate the robustness of our results with respect to the regional level of analysis. As an alternative to the 413 administrative NUTS 3 regions, we consider 147 local labor market areas (Eckey/Schwengler/Türck, 2007), which are comparable constructs to the US commuting zones used by ADH. The resulting coefficients in Tables C.9 and C.10 are only marginally larger than in our baseline specification. We thus prefer to stick to the more detailed regional level that offers more heterogeneity.

4.4 Other regional labor market indicators

4.4.1 Population shifts

If labor were perfectly mobile across regions, workers would respond instantaneously to trade shocks by relocating between regions. The differential response of employment across local labor markets would then be less informative about the effects of trade liberalization, while the impacts would become visible in regional migration patterns or adjustments of local population sizes. In their analysis on the impact of Chinese import exposure in the US, ADH emphasize that there seems to be a sluggish adjustment of population across local labor markets.

That is, US labor markets seem to have adjusted mainly at the employment margin while there have been little population shifts in response to the (potential) Chinese import competition.

Traditionally, it is argued that regional labor mobility is even lower in Germany than in the US (see Bertola, 2000), so that we may expect a similar pattern in our case. To investigate this issue, we exchange the outcome variable and consider the 10-year change in (log) regional populations. Table 4.5 reports the results for the impact of trade exposure with respect to Eastern Europe and China on population shifts within Germany. For brevity we no longer report OLS estimates, but turn directly to the effects identified by our IV estimation approach.

Table 4.5: Population shifts

	Dependent variable: 10-year change in ln headcounts	
	Eastern Europe trade	**China trade**
Δ import exposure	-0.298	-0.451***
	(0.28)	(0.11)
Δ export exposure	-0.026	-0.223
	(0.16)	(0.31)
R-square	0.174	0.183
First stage (KP)	23.757	21.187
p Hansen	0.185	0.027

Observations: 739. Standard errors clustered by administrative districts and years in parentheses. IV estimates, including federal state and time interactions and all controls described in Section 4.3.2. All coefficients and standard errors are multiplied by 100.
Levels of significance: *** 1 %, ** 5 %, * 10 %.

Source: Federal Statistical Office, BHP, and UN comtrade.

For the case of Eastern European trade exposure, we find no evidence for induced population changes. This result is in line with ADH's findings for the US case, and suggests that German regional labor markets indeed respond to the rise of Eastern Europe at the employment margin rather than through spatial labor mobility. For trade with China, results are consistent for export exposure. There seems to be no population movement towards regions with industrial structures that allow them to benefit particularly from the export opportunities in the Chinese markets, despite sizable employment gains in those regions as reported above in Table (4.4).

However, for import penetration from China, we do find a robustly negative impact. That is, regions with industrial structures that strongly exposed them to (potential) Chinese import competition did lose population over the period 1988 to 2008. More specifically, a region with average import exposure of 1,927 € per worker lost 0.87 percent of its population due to the rise of China. Interestingly, recall from Table 4.4, that we have not found any economically or statistically significant effects of the same variable on manufacturing employment.

Why do German local labor markets respond differently to import penetration from China and from Eastern Europe? The reason may be that imports from China occur mostly in sectors that were on a secular decline in Germany even before the rise of China in the global economy really kicked in. Workers formerly employed in sectors such as lower-tier manufacturing, wearing apparel, basic electronics, and so on, had weak labor market prospects already in the 1980s. Regions specialized in those sectors were subject to net emigration already before. The rise of Chinese import exposure seems to have accelerated the emigration out of those regions, which may explain why we find little adjustments at the employment margin for this case.

4.4.2 Between-group wage inequality

Next we investigate the effects of trade exposure on regional wage inequality. We augment our data set with daily wage quantiles of all male employees in the manufacturing sector, as reported in the mandatory social security notifications. This data stems from the full sample of all employees on June 30th for each year. The unique identifier of the notifying establishments, as well as data on employment status and qualification allow us to calculate wage quantiles for specific regions, industries, and worker groups. Since these data stem from notifications to social security, wages are extremely accurate.

Table 4.6: Trade exposure and wage inequality in the manufacturing sector

	Dependent variables: 10-year change in ln daily wage differentials					
	Eastern Europe trade			China trade		
Quantile spread	50/15	85/50	85/15	50/15	85/50	85/15
Δ import exposure	1.136***	0.255	1.391***	0.072	-0.021	0.052
	(0.31)	(0.40)	(0.48)	(0.12)	(0.14)	(0.19)
Δ export exposure	-0.830***	-0.837***	-1.667***	-0.694*	-1.763***	-2.457***
	(0.22)	(0.25)	(0.27)	(0.38)	(0.57)	(0.62)
R-square	0.025	0.166	0.107	0.040	0.164	0.133
First stage (KP)	23.757	23.757	23.757	21.187	21.187	21.187
p Hansen	0.053	0.662	0.486	0.320	0.577	0.791

Observations: 739. Standard errors clustered by administrative districts and years in parentheses. Coefficients and standard errors multiplied times 100. IV estimates, including federal state and time interactions and all controls described in Section 4.3.2. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Source: Statistics Department of the German Federal Employment Agency, BHP, and UN comtrade.

Table 4.6 summarizes how trade exposure affects wage inequality. We focus on 50/15, 85/50 and 85/15 quantile log spreads.[10] At this point, we do not distinguish further between different worker groups, so the focus is on the causal effect of trade exposure on *between-group* wage inequality.

For trade with Eastern Europe, we find that import exposure raises wage inequality, particularly in the upper and the lower tail of the distribution. Export exposure, in contrast, decreases inequality. These results go hand in hand with our previous findings for employment adjustments. When trade exposure positively affects employment, this tends to decrease wage inequality and vice versa. The results are also in line with standard reasoning along the lines of the Stolper-Samuelson theorem. The German manufacturing sector tends to use low-to-medium skilled employees intensively, whereas the most high-skilled workers are intensively used in advanced service industries. For the export oriented German manufacturing sectors, trade exposure thus disproportionately raises the wages of those low-to-medium skilled workers, thus decreasing overall wage inequality. The opposite happens in manufacturing industries where Germany has a comparative disadvantage and faces import competition from Eastern Europe. Turning to the impact of China, we find no effect of import exposure on the wage structure, but a dampening effect of export exposure on wage inequality. This is again consistent with our previous results for employment adjustments, which arise only for export exposure. Chinese import competition seems to be mainly absorbed by population shifts across regions, hence we observe neither wage nor employment adjustments.

Evaluating these changes at the average trade exposure across regions over the 20 year period, we find that trade integration with Eastern Europe has actually decreased lower-tail (50/15), upper tail (85/50), and overall (85/15) wage inequality.[11] Chinese export exposure had a similar overall impact. Dustmann/Ludsteck/Schönberg (2009) use the same administrative data as we do, and document an increase in the three quantile spreads of the total wage distribution for the period from 1990 to 2004. Our results suggest that rising trade opportunities in the East have actually worked *against* this general trend of rising wage inequality, while import competition (at least with respect to Eastern Europe) has contributed to it. Our results are also in line with the findings of Schank/Schnabel/Wagner (2007), who document that especially

10 We use the 85 percent quantile instead of the more popular 90 percent quantile, since wages are right-censored at the upper earnings limit in the statutory pension fund.

11 We also find weak evidence that trade integration with Eastern Europe affects wage inequality in non-manufacturing industries in a similar way, although unsurprisingly, the coefficients are smaller in magnitude (see Appendix Table C.12).

relatively low-skilled blue collar workers benefit from the German exporter wage premium. In fact, when distinguishing further the wages of blue- and white collar workers, we find stronger effects for the former group (see Appendix, Table C.11).

4.4.3 Non-manufacturing employment and unemployment

The final regional labor market indicators that we investigate are changes in regional non-manufacturing employment and total regional unemployment. Both for Eastern Europe and China, we find that export exposure tends to raise non-manufacturing employment. Economically, this suggests that the rise of export opportunities not only has direct positive effects on employment and wages within the tradable goods sectors, but that there are also indirect effects on other local industries that produce non-tradable goods. The intuition may be that workers, who experience wage gains as a result of increased export exposure, spend more on local goods and services which in turn boosts demand for labor there. By a similar mechanism, total regional unemployment goes down in regions with strong export exposure.

Table 4.7: Further local labor market outcomes and trade exposure to Eastern Europe

	Dependent variables: 10-year change in /working age pop. in %-points			
	non-manuf. employment	unemployment	non-manuf. employment	unemployment
	Eastern Europe trade		China trade	
Δ import exposure	-0.549	0.089	-0.153	-0.061*
	(0.36)	(0.08)	(0.13)	(0.03)
Δ export exposure	0.522**	-0.183***	0.556	-0.350***
	(0.25)	(0.07)	(0.37)	(0.12)
R-square	0.165	0.073	0.182	0.084
First stage (KP)	23.757	23.757	21.187	21.187
p Hansen	0.145	0.262	0.071	0.290

Observations: 739. Standard errors clustered by administrative districts and years in parentheses. IV estimates, including federal state and time interactions and all controls described in Section 4.3.2. Levels of significance: *** 1 %, ** 5 %, * 10 %.

Source: Statistics Department of the German Federal Employment Agency, BHP, and UN comtrade.

For import exposure, the effects work in the opposite direction: Non-manufacturing employment tends to decrease, while unemployment (at least for the case of

Eastern Europe) increases. The effects are imprecisely estimated, however. For Chinese import exposure, we even find a small (and weakly significant) negative effect on unemployment which is counter-intuitive. This, however, could stem from the induced population shifts discussed above. German regions strongly exposed to Chinese import competition have faced outward migration. This decrease in regional labor supply, in turn, has apparently led to slight decreases in the regional unemployment rate.

4.5 Worker level evidence

The analysis has so far focussed on the impact of trade exposure on regional labor market aggregates. In this section, we extend our analysis along the lines of Autor et al. (2012) to the individual level, using detailed micro data on employment and wage histories of German manufacturing workers.

From the perspective of a single worker, trade liberalization may increase the risk of displacement, if the own job is subject to high (potential) import competition. An extensive literature (Topel, 1990; von Wachter/Bender, 2006; Sullivan/von Wachter, 2009) documents that, if displaced workers have to find new jobs and acquire human capital specific to their new employers, this in turn can lead to adverse effects on employment biographies in terms of reduced employment and earnings spells. On the other hand, export opportunities can have a countervailing stabilizing effect on individual employment relationships. Workers who are involved in the production of goods that are increasingly in demand from abroad, might face a lower probability of job termination. Holding everything else constant, they may even be able to accumulate firm- and industry-specific human capital and raise their long-term labor market prospects.

4.5.1 Data and variables

We use the Sample of Integrated Labour Market Biographies (SIAB, cf. Dorner et al., 2010). This data stems from all German social security notifications in the years 1975 to 2008. A two percent random sample has been drawn from all persons who have either been employed or officially registered as job-seekers resulting in an individual-level spell data set with information on age, sex, nationality, qualification, occupation, wage, unemployment benefits, spell durations, etc. This data is highly accurate even on a daily base due to its original purpose of calculating retirement pensions. Since the notifications of employees are passed by their employers, establishment level data from the Establishment History Panel (BHP) can be merged to this data set. To match this data with the periods considered at the regional level, we analyze individuals who have been employed in the manufacturing sector either in the year 1988 or 1998 and construct our dependent variable as cumulative days in employment over the following ten years. We only consider persons who were of working age (22–64 years) in the respective period.

The trade exposure indices are constructed similarly as before. Yet, we now construct them at the industry level, in order to measure trade exposure at the level of an individual worker. The intuition is that manufacturing workers often have acquired sector- and occupation-specific human capital, so that they cannot switch instantaneously between occupations and industries. The change in import penetration per worker from either China or Eastern Europe (indexed by k) over the period $t = \{1988 - 1998, 1998 - 2008\}$ in a German industry j is defined as

$$\Delta IP_{jt} = \frac{\Delta M_{jt}^{k}}{E_{jt}} \tag{4.8}$$

where ΔM_{jt}^{k} is the change in imports from $k = \{\text{China, Eastern Europe}\}$ to Germany over period t, and E_{jt} is total employment in industry j at the beginning of the period. Analogously, we define the change in export opportunities per worker in industry j as

$$\Delta EP_{jt} = \frac{\Delta X_{jt}^{k}}{E_{jt}} \tag{4.9}$$

where ΔX_{jt}^{k} is the respective change in exports of industry j from Germany to area k.

Our focus is the identification of the causal effect of the rise of China/Eastern Europe on individual worker biographies in German manufacturing. Hence, we again rely on a instrumental variable approach for identification. We construct the following instruments:

$$\Delta IP_{ijt} = \frac{\Delta M_{j-3t}^{oc/c}}{E_{j-3t-3}} \text{ and } \Delta EP_{ijt} = \frac{\Delta X_{j-3t}^{oc/c}}{E_{j-3t-3}} \tag{4.10}$$

where we use the trade flows of the same set of countries as in the previous section. We use lagged employment shares of the sectors where workers were employed three years prior to the start of the period to avoid a possible influence of sorting of workers due to anticipation of future trade exposure.

To control for differences across broader manufacturing sectors, we again use a dummy variable for the broad manufacturing industry group (see above), and we include dummies to control for year of birth and interaction terms for federal states and time periods. Additionally, we use standard human capital variables of a Mincer-type wage regression. Since import and export exposure only vary across industries, one could worry that they capture industry-level effects that correlate with the change in trade exposure. To mitigate this multi-level problem, we also include further industry-level control variables (Herfindahl-Index, the Ellison/Glaeser (1997) agglomeration-index, share of plants younger than two years, average establishment size, share of highly qualified employees, and share of employees older than 50) in the regression. Throughout, we cluster standard errors at the industry-time level.

Table 4.8: Means and standard deviations of main variables for manufacturing workers

	1988–1998		1998–2008	
		Outcome variables		
Cumulative years of employment	7.50	(3.03)	7.85	(2.96)
Cumulative years of employment in original establishment	5.68	(3.72)	5.58	(3.90)
Cumulative years of employment in original 3-digit industry	6.10	(3.67)	6.21	(3.82)
Cumulative years of employment in original labor market region	7.04	(3.28)	7.17	(3.39)
		Trade exposure		
Δ imports from Eastern Europe per worker in $t = 0$	4.74	(4.92)	6.61	(9.42)
Δ exports to Eastern Europe per worker in $t = 0$	5.92	(5.54)	13.16	(10.81)
Δ imports from China per worker in $t = 0$	1.55	(3.85)	6.60	(20.26)
Δ exports to China per worker in $t = 0$	0.39	(0.96)	3.86	(4.40)

Trade exposure measured in 1,000 € per worker.
Source: IAB Sample of Integrated Labour Market Biographies (SIAB), BHP, and UN comtrade.

4.5.2 Results

The first two columns in Table 4.9 display the effects of an increase in Eastern European trade exposure on the total number of days in employment over a 10 year period. While column (1) refers to the OLS estimation, we implement our IV strategy in column (2). Notice that the first-stage diagnostics show that we do not encounter a weak instrument problem.

The interpretation of the export exposure coefficient in column (2) is that a 1,000 € increase in industry exports per worker increases the expected time of employment over 10 years by 2.01 days ($= 0.55 \cdot \frac{365}{100}$), ceteris paribus. Given that the average worker in manufacturing has faced an increase of export exposure by more than 13,000 € over a ten year period, this implies that expected employment at the worker level has increased by about 26 days due to increasing export exposure to Eastern Europe. Interestingly, there is no comparable negative effect caused by imports from Eastern Europe.

Table 4.9: Eastern European trade exposure and individual employment

	Dependent variable: 100 x cumulative years of employment over 10 year period				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
	total	total	plant	3-digit ind.	region
Δ imports from Eastern Europe	0.29	-0.22	-2.14***	-1.86***	-0.40
per worker in $t = 0$	(0.37)	(0.32)	(0.75)	(0.65)	(0.42)
Δ exports to Eastern Europe	0.36	0.55*	1.91***	1.13*	0.72*
per worker in $t = 0$	(0.25)	(0.30)	(0.71)	(0.62)	(0.40)
Employment in manuf. of	-16.28	-16.09	-21.81	-36.74*	-14.85
consumer goods in $t = 0$	(10.34)	(10.12)	(16.35)	(19.66)	(12.12)
Employment in manuf. of	9.77*	9.85*	20.93*	-14.13	15.77**
producer goods in $t = 0$	(5.41)	(5.40)	(10.81)	(10.75)	(6.97)
Employment in manuf. of	17.36***	17.75***	31.14**	-6.21	23.53***
capital goods in $t = 0$	(5.86)	(5.95)	(14.13)	(12.94)	(7.50)
Female	-179.12***	-179.37***	-124.44***	-146.00***	-158.70***
	(3.58)	(3.46)	(4.87)	(5.30)	(4.13)
Foreign citizen	-53.36***	-53.17***	-28.37***	-36.35***	-39.44***
	(2.83)	(2.83)	(4.13)	(4.16)	(3.29)
Low skilled	-29.81***	-29.50***	-16.74***	-22.08***	-18.57***
	(2.07)	(2.06)	(2.97)	(2.97)	(2.46)
High skilled	33.38***	33.33***	-43.68***	-23.79***	-33.55***
	(3.42)	(3.43)	(5.32)	(7.25)	(5.94)
Industry level controls	Yes	Yes	Yes	Yes	Yes
R-square	0.197	0.113	0.084	0.085	0.086
First stage (KP)		35.485	35.485	35.485	35.740
p Hansen		0.578	0.870	0.734	0.552

Observations: 185,337. Standard errors clustered by 186 industry x start of period cells in parentheses. Control variables include dummy variables for start of period tenure, plant size, year of birth and federal state period fixed effects. Models (3) – (5) consider cumulative employment only within the original establishment, 3-digit industry, and region, respectively.
Levels of significance: *** 1 %, ** 5 %, * 10 %.

Source: SIAB, BHP, and UN comtrade.

Table 4.10: China trade exposure and individual employment

	Dependent variable: 100 x cumulative years of employment over 10 year period				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
	total	total	plant	3-digit ind.	region
Δ imports from China	0.02	-0.04	-0.46*	-0.42*	-0.17
per worker in $t = 0$	(0.09)	(0.10)	(0.26)	(0.24)	(0.15)
Δ exports to China	2.18***	1.60**	5.13***	5.21***	2.90***
per worker in $t = 0$	(0.56)	(0.63)	(1.79)	(1.90)	(0.86)
Employment in manuf. of	-13.84	-14.13	-14.07	-29.18	-9.94
consumer goods in $t = 0$	(10.18)	(10.28)	(14.31)	(18.41)	(11.74)
Employment in manuf. of	11.49**	11.43**	24.03***	-13.41	17.44***
producer goods in $t = 0$	(5.05)	(5.14)	(8.95)	(9.03)	(6.03)
Employment in manuf. of	15.33***	16.65***	23.81**	-17.81	20.01***
capital goods in $t = 0$	(5.40)	(5.51)	(12.07)	(11.11)	(6.39)
Female	-178.87***	-178.88***	-122.00***	-143.98***	-156.73***
	(3.51)	(3.49)	(4.66)	(5.19)	(4.00)
Foreign citizen	-53.01***	-53.03***	-28.54***	-36.59***	-39.96***
	(2.81)	(2.80)	(4.04)	(4.09)	(3.24)
Low skilled	-29.42***	-29.40***	-17.16***	-22.60***	-18.38***
	(2.04)	(2.03)	(2.95)	(2.90)	(2.41)
High skilled	33.49***	33.47***	-42.92***	-23.05***	-32.12***
	(3.41)	(3.40)	(5.21)	(7.15)	(5.87)
Industry level controls	Yes	Yes	Yes	Yes	Yes
R-square	0.197	0.113	0.087	0.088	0.087
First stage (KP)		5.670	5.670	5.670	5.670
p Hansen		0.475	0.156	0.078	0.456

Observations: 185,337. Standard errors clustered by 186 industry x start of period cells in parentheses. Control variables include dummy variables for start of period tenure, plant size, year of birth and federal state period fixed effects. Models (3) – (5) consider cumulative employment only within the original establishment, 3-digit industry, and region, respectively.
Levels of significance: *** 1 %, ** 5 %, * 10 %.

Source: SIAB, BHP, and UN comtrade.

Our data permits us to further disaggregate the effect, and to investigate how trade exposure affects job stability for individual workers at the plant-, industry-, or region-level. Such effects might not be visible when looking only at total employment spells, since individuals might have changed jobs across plants, industries, or regions without a significant period of unemployment. The results reported in columns (3) to (5) indeed show that trade exposure with Eastern Europe has caused significant job turnover that is not observable at the aggregate level. Increased exposure to import competition by 1,000 € reduces the expected time spent with the original employer by 7.8 days and, respectively, the original 3-digit industry by 6.8 days. That is, import exposure has causally increased job churning both within and across industries. On the other hand, rising export exposure by 1,000 € raised job stability at the plant and industry level by 7.0 days and 4.1 days, respectively. Moreover, employees in industries with high export exposure are less likely to relocate to another region. These findings are in line with and complementary to the results from the regional level discussed in the previous sections.

For trade exposure with China, we obtain similar results. In column (2) we find that an increase in export exposure again has a positive effect on overall days of employment, while there is virtually no effect of import competition. When we take a more detailed view at job stability within the original plant, industry, or region (columns (3) to (5)), we again find that (potential) import competition reduces, while export exposure raises individual employment stability.

4.6 Discussion and conclusion

The past decades have seen a strong increase in the volume of international trade. Deregulation and the abolishment of trade barriers as well as drastic reductions in transport costs have led to a steadily increasing integration of national economies. In this paper, we focus on two major facets of globalization: China's explosive ascent and the rise of Eastern Europe after the fall of the Iron Curtain. Understanding the consequences of those developments for the labor markets in the traditional Western market economies is crucial, both from an economic and a political point of view.

We analyze the causal impact of the rise of China and Eastern Europe on the performance of local labor markets in Germany during the period 1988 to 2008, using an instrumental variable approach pioneered by Autor/Dorn/Hanson (2011). At the regional level, Germany is characterized by strong disparities in local industrial structures. These initial structures determine how the regions were affected by the rising trade exposure that kicked in since the mid 1990s. Two main messages can be derived from our analysis: First, the rise of Eastern Europe had much more immediate consequences for the German economy than the rise of China. Second, overall, the rise in trade exposure has largely benefited the German economy along various margins, and our analysis provides a rich portray on how these gains from trade actually come about.

On the one hand, we find that the increase of import exposure (particularly from Eastern Europe) per se had negative consequences for German local labor markets. In particular, regions strongly exposed to import competition from the East had to face lower employment (both in the manufacturing sector and beyond), higher wage inequality, higher unemployment, and lower job stability at the individual level. Yet, since Germany is one of the world's leading exporting economies, this threat of import competition is not the end of the story. The rising trade openness in the East created new opportunities for German firms to export their goods to these emerging economies. Regions with the "right" industrial structures, namely such with high potential export exposure to the East, thus benefited substantially from those new market opportunities and experienced sizable employment gains, lower wage inequality, lower unemployment, and higher individual job stability. In the aggregate, those positive impacts have offset the threats arising from import competition.

Our results for the German economy differ quite substantially from the findings of Autor/Dorn/Hanson (2011) for the United States. Trade liberalization with China is likely to bring about welfare gains also for the US case, for example, through gains in productivity or consumption diversity. Yet, they stress that in the short-to-medium run, the US economy has to face severe adverse effects on local labor markets, even when taking into account that the rise of China not only creates import penetration but also new export opportunities. The situation of Germany seems to be quite different, as the overall labor market consequences are largely positive even in the medium run – a finding that may be explained by the fact that overall trade with China is much more balanced in the German than in the US case. Furthermore, our analysis suggests that focusing only on China provides an incomplete picture at least for the German case. Due to its geographical location, the rise of Eastern Europe had a much stronger impact on German local labor markets.

In our main analysis, we assign sector level trade data to German regions according to their initial industrial structures. This approach has the caveat that we can only observe the potential trade exposure with the East. It is not possible to directly relate trade flows to specific firms or local industries. Hence, we have to assume that all firms in a sector are affected more or less uniformly. Another caveat is that we cannot observe disaggregate within-group effects. For example, the analysis of wage inequality would clearly gain from distinguishing further between sector-occupation groups. Further research could also complement our findings at the industry level and apply a similar empirical strategy. This would allow to directly focus on the effects on specific worker groups.

An advantage of our approach is that it allows to analyze the local adjustments to trade exposure along many different margins. Our main focus on manufacturing employment is interesting, because in most industrialized countries, there has been a long-run trend of structural change where employment secularly shifted away from the manufacturing sector and towards modern service industries. Our results suggest that trade with the East has per se decelerated this declining trend, because the export opportunities in the East saved at least 700,000 manufacturing jobs in Germany that would otherwise (without the rise of the East) have disappeared. This preservation of the manufacturing sector can include a wide range of more narrowly defined industries. We do find evidence, however, that the automotive sector is of particular importance. This is not necessarily only due to the extraordinary success of the German luxury car makers like BMW, Audi, and Mercedes Benz, but also to the crowd of mid-sized suppliers, the typical German "Mittelstand", that strongly depend on these corporations.

5 Summary and conclusion

Regional disparities within Germany have a magnitude comparable to disparities between countries of the European Union. While Germany as a whole is one of the strongest economies in the world, there is huge variation in regional evolutions in the past decades. Hereby, the regional industrial structure is an important factor that can determine the future development of regional employment. Some regions are specialized in the "wrong" mix of declining industries. Jobs that are destroyed there are often not replaced by jobs in more successful industries. But then, other regions have an industrial structure that is beneficial for resident industries and provides favorable conditions for further growth.

This dissertation presents three studies that examine two important aspects relevant for the support of the regional industrial structure for regional evolutions. First, economies of agglomeration may give local industries an advantage in terms of higher productivity over industries located in other regions. Under certain conditions, this higher productivity can result in employment growth. Regions providing these economies of agglomeration can have more favorable employment dynamics and be better prepared against the challenges of structural change. Second, the regional industrial structure determines the extent to which regions are exposed to the effects of international trade. This can be a bone or a bane, since trade integration means that domestic producers face a more fierce competition but also that there is the opportunity to reach more customers.

The first study investigates the existence and magnitude of external effects emerging from the agglomeration of establishments from the same industry. While the existence of these so-called Marshallian externalities is well accepted both in the empirical and theoretical literature, there is only consensus that they foster productivity. The evidence on employment effects is ambiguous (Cingano/Schivardi, 2004). However, from a regional policymaker's perspective, the question whether agglomeration externalities can foster employment growth is probably more important. The model framework used in this study bases on papers by Combes/Magnac/Robin (2004) and Blien/Südekum/Wolf (2006). Both use a dynamic panel data model of local industries and find that there is considerable inertia in employment dynamics. They argue that while there is no explosive employment growth, part of this inertia can be explained by economies of agglomeration. Yet, they cannot tell to what extent. Both studies restrict their effects to be equal across all observations. This implies that an exogenous shock which increases a local industry's employment by one percent is supposed to have the same effect regardless of the industries and regions under consideration. Take manufacturing of food products in a rural region and automotive parts in the vicinity of a large car maker as two antithetic examples. If economies of agglomeration actually exist, they should be stronger in the automotive agglomeration than in the highly dispersed industry. In the first study, this consideration is the basis of the identification strategy: First, I identify local industries where agglomeration externalities are expected to be particularly strong. Then, I analyze if inertia of employment growth is actually stronger there than in non-agglomerated local industries. Indeed, I find that there is an economically and statistically significant difference. Positive employment shocks are more persistent in industrial agglomerations and lead to a higher level of employment in the long run.

A first implication for regional policy is that it is not efficient to subsidize greenfield development. A single new plant in a rural region might or might not turn out to be successful in the long run, however, there could be a higher impact on regional employment if it were located near similar plants. Having access to specialized suppliers, a dense labor market, and the possibility of learning from others, can be an important asset and should be taken into account when politicians and planers attempt to regulate the industrial structure of a region.

However, considering only single industries might be shortsighted. Both theoretical and empirical studies tend to focus on external economies of scale which operate only within local industries because they are easier to handle. Yet, there is actually no reason to believe that spillovers are restricted to work within single industries only. Most buyer-seller relations happen in fact between different industries. And plants from different industries may still share a common labor market and benefit from learning from each other's ideas. The second study presents a new way of analyzing how employment dynamics are related across industries. This contributes to the insights of the first study in two ways. First, the additional heterogeneity of inter-industry spillovers provides a new approach to disentangle the three most common explanations for the existence of economies of agglomeration. Second, it shows that employment growth in one local industry can be fostered by growth in other industries. Hence, it might also be inefficient for regional planners to support the agglomeration of a single industry. The insights gained in the second study emphasize the need to provide a well-balanced, diversified industrial structure for a region to be successful. Yet, these externalities should not be confused with economies of urbanization as endorsed in well known contributions by Jacobs (1970), Florida (2004), and Glaeser (2011). The idea of urbanization is that growth and innovation are best spurred in the creative environment of dense but highly diversified cities. While this is certainly important, the externalities analyzed in this dissertation hinge on actual relations between plants or people. A term that probably best describes the difference is "related variety" (see Frenken/van Oort/Verburg, 2007). While economies of urbanization are subject to large cities, any region could provide a favorable industrial structure, where firms can locate near related firms. In order to support this kind of industrial structure, regional policy must assure to not focus too strongly on single industries, even if this is tempting in the case of modern growth industries.

In the third study, the focus is shifted towards the effect of the increasing trade integration with emerging countries in the East on German regions. The structure of resident industries determines how strongly regions are exposed to the effects of international trade. If, for example, a region is dominated by industries that produce non-tradable goods, aggregate employment should hardly be affected by trade. Even if a single industry declines due to the lacking ability to compete on the world market, workers might easily find jobs in other industries. By contrast, if a region specializes in the production of goods that are internationally traded, the rise of emerging countries can be both an opportunity for and a threat to the whole region. This study concentrates on trade with China and Eastern Europe, which are the most important trade partners for Germany. It is important to keep in mind that we are not interested in the overall effects of international trade. There is no doubt that many jobs in manufacturing were lost to low-wage countries. Yet, it would be a fairly futile exercise to wonder what would have become of German manufacturing if there were no trade at all. Instead, we are interested in the causal effects of the rise of China and Eastern Europe. The fall of the Iron Curtain, China's accession to the WTO, the steadily increasing wealth of their citizens: All these events fostered the integration of the respective countries and German markets. We try to attach a number to the question on what trade with these countries means for German regions. We find evidence that the net effects of trade with these countries have in fact been favorable for Germany. For the average region, exports to both China and Eastern Europe had positive effects on manufacturing employment. These effects seem to be stronger than the corresponding negative effects of imports. Hence, Germany as a whole seems to benefit from trade integration. Still, regional disparities in the industrial structure imply that winners and losers of this development exist. Sonneberg and Coburg, for example, belong to the regions with the highest increase in import exposure from China. Being located close-by but on different sides of the Inner German border, both industrial regions have been specialized in the manufacturing of toys, furniture, and other low-tier products. Manufacturing of these products declined, which led to high unemployment rates and strong outward migration of people in working age searching for new jobs. Schweinfurt, by contrast, is one of the winners of this development. This region used to have a strong manufacturing base in firms producing ball bearings, an essential part for any kind of wheeled vehicle. After these firms suffered a substantial decline in the 1990ies, the industrial base of Schweinfurt regained its former strength in the last decade (see Blien/Dorner, 2011, for further information on the evolution of this region). The main products manufactured in this region are still ball bearings but there is also manufacturing of other automotive parts and medical appliances. Since these are also products with a high demand abroad, the rise of the East certainly contributed to the resurrection of this region.

However, it is difficult to derive recommendations for regional politicians and planners. For the aggregate country, trade is obviously nothing to be afraid of. But for single regions, this statement might not hold. One lesson is certainly that a region's structure should not be concentrated too strongly on just a few industries. A decline of these industries might tear down the whole region. On the other hand, a well-balanced structure could facilitate job-matching in other industries. And as the example of Schweinfurt shows, a region's capability to shift production to new or different products helps to adjust to structural change and to compete with competition from abroad.

It is almost impossible to stem the forces of international trade or structural change. Subsidizing declining industries is mostly inefficient or even harmful. However, there is no empirical evidence that structural change leads to job losses per se (cf. Findeisen/Südekum, 2008). It is important for regional policy to ensure that regions undergo the process of structural change without any frictional losses. The literature on this topic is scarce, but the case study on Boston by Glaeser (2005) emphasizes that a modern infrastructure and a qualified workforce are vital for a region to "reinvent itself" and to shift its sectoral composition away from declining to emerging industries. The results of the first part of this dissertation imply that an agglomeration of one or more industries along with firms from other but related industries are the ideal environment for a sustainable development. Of course, there is no panacea, no single strategy that can be successfully applied to every region. Yet, policymakers do acknowledge the need for a targeted and integrated regional policy, as supported, for instance, by the advisors in social matters to the Bavarian prime minister (Kommission "Anforderungen aus dem zweiten Bayerischen Sozialbericht", 2011). While regional planners should ensure a modern infrastructure and adequate transport connections, universities and technical colleges could specialize their course catalogues to produce graduates specifically trained for the reginal economy's requirements. Labor market policy can also contribute by helping workers in declining industries to learn the skills they need to find jobs in other industries even before they are in danger of being laid-off. The results from the second part of this dissertation imply that structural change does not necessarily mean a complete shift of jobs away from manufacturing towards service industries – at least not to the extend as it is the case in other countries. Due to the opportunities to export to the rising countries in the East, the German manufacturing sector will continue to provide jobs for skilled and high-skilled workers. Coping with the consequences of structural change thus seems a little more manageable than in other high-income countries.

It is up to further research to combine the two aspects of agglomeration and trade. The specialization of a whole region in only in a few industries might accelerate its decline. This is what happened to Schweinfurt in the 1990ies: Since about half of all workers were employed in manufacturing of ball bearings, the decline of this industry affected a large share of all employees rather than only some of them. Since there were not enough other industries to absorb laid-off workers, the demand for non-traded goods also declined more rapidly and the whole region fell into a crisis. Since aggregate employment increased in most countries in the past decades, very few empirical studies have dealt with this question. Yet, the increased inertia of employment dynamics in industrial agglomerations could function in two ways: While positive shocks have a larger long term effect, negative shocks might be amplified as well. On the other hand, it is reasoned that the benefits from Marshallian externalities are particularly strong in well established, "old" industries (see Henderson/Kuncoro/Turner, 1995). In times of trade-induced structural change, firms in industrial agglomerations can have an advantage over isolated firms and thus have a higher chance to survive. They can find it easier to adapt to the challenge of import competition and focus on specific niches. While most toys, wearing apparel, shoes, furniture, and low-tier electronics are not produced in Germany any more, there are still some German firms left in these industries. Many of them are even geographically concentrated, for example manufacturing of toys in Fürth or shoes in Pirmasens. These firms manage to compete on the world market by concentrating on niches and offering innovative products with high quality standards. Maybe the benefits from forward-backward linkages, labor market pooling, or knowledge spillovers contribute to their success.

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A Appendix for Chapter 2

A.1 Calculation of the EG and CI indices

EG Index: An intuitive measure for geographical concentration of an industry is

$$G = \sum_{r=1}^{R} (x_r - s_r)^2 \tag{A.1}$$

where x_r is region r's share of overall employment and s_r is region r's share of the respective industry's aggregate employment. G shows to what extend the geographic distribution of an industry's employment differs from the geographic distribution of overall employment. Like the Gini coefficient, G takes the value of zero if both distributions are identical, and the value of one if an industry is localized in only one region. Ellison/Glaeser (1997) criticize that G is not adequate to measure geographical concentration that has not evolved by coincidence but rather by benefiting from agglomeration externalities. They demonstrate this with a "dartboard approach": If you throw ten darts randomly at a map with nine regions, you will inevitably observe agglomeration in at least one region. The appropriate benchmark distribution ought to account for the number of regions and the size of an industry's establishments. To this end, they augment the index G from Equation A.1 with the industry's structure:

$$EG = \frac{G - (1 - \sum_{r=1}^{R} x_r^2)\, H}{(1 - \sum_{r=1}^{R} x_r^2)\,(1 - H)} \tag{A.2}$$

where H is the industry's Herfindahl index of plant size distribution $H = \sum_{b=1}^{B} z_b^2$, with the z_b plant b's share of the industry's employment. This index is derived from a theoretical model of site selection, where two different forces lead to agglomeration: Spillovers and natural resources. Although it cannot disentangle these forces, the EG index is widely used in the literature to analyze the causes of agglomeration.[1] To allow for hypothesis testing, Ellison/Glaeser (1997) suggest that G has an expected value of $E(G) = (1 - \sum_{r=1}^{R} x_r^2)\, H$ in absence of agglomeration effects. The variance of G is given by:

$$\sigma_G^2 = 2\left\{H^2\left[\sum_{r=1}^{R} x_r^2 - 2\sum_{r=1}^{R} x_r^3 - (\sum_{r=1}^{R} x_r^2)^2\right] - \sum_{b=1}^{B} z_b^4\left[\sum_{r=1}^{R} x_r^2 - 4\sum_{r=1}^{R} x_r^3 - 3\,(\sum_{r=1}^{R} x_r^2)^2\right]\right\}$$

1 E.g., Maurel/Sédillot (1999); Rosenthal/Strange (2001); Bertinelli/Decrop (2005); Alecke et al. (2006); Alecke/Untiedt (2008).

For a more conservative approach, Ellison/Glaeser (1997) propose that a value higher than 0.02 should be regarded as an indicator that an industry is substantially geographically concentrated, while a value above 0.05 even indicates strong concentration.

CI Index: In principle, the location quotient

$$LQ_{ir} = \frac{e_{ir} / \sum_{i=1}^{N} e_{ir}}{\sum_{r=1}^{R} e_{ir} / \sum_{i=1}^{N} \sum_{r=1}^{R} e_{ir}}$$

that relates the share of employment in local industry *ir* in total employment in region *r* to the share of total employment in industry *i* in total national employment, is suited to identify industrial agglomerations (O'Donoghue/Gleave, 2004). Litzenberger/Sternberg (2006) develop the cluster index CI that is based on the LQ,[2] but extents it by some features:

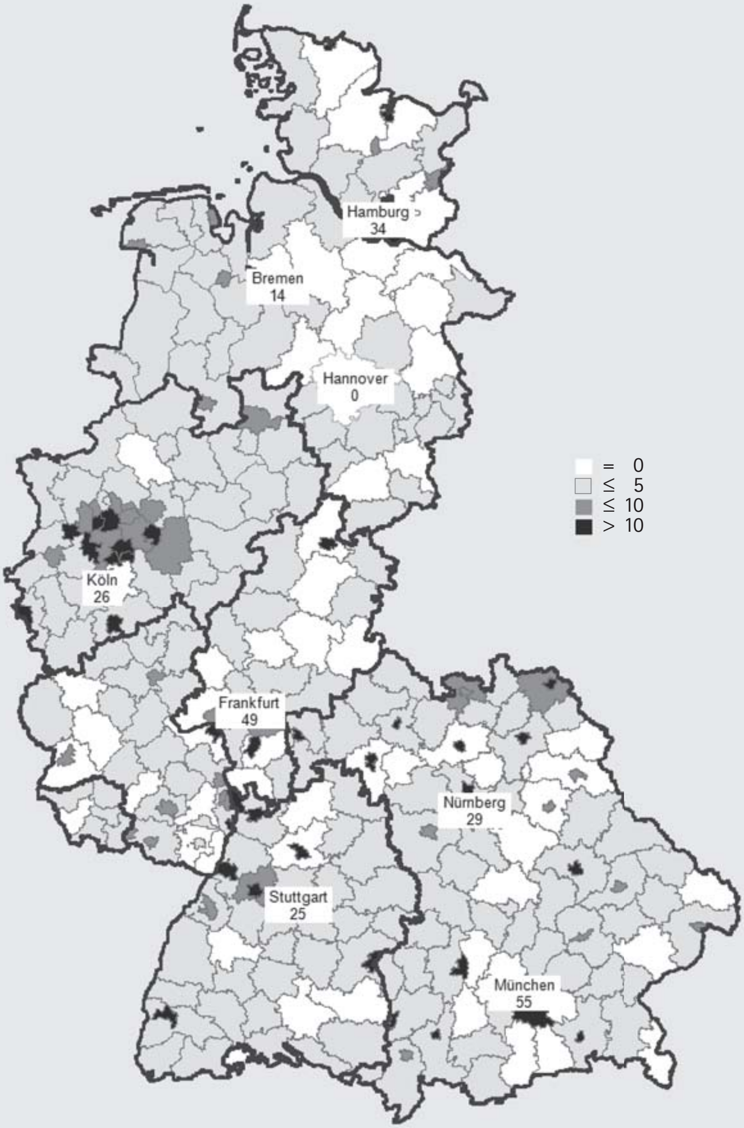
$$CI_{ir} = \frac{\frac{e_{ir}}{a_r}}{\frac{\sum_{r=1}^{R} e_{ir}}{\sum_{r=1}^{R} a_r}} \times \frac{\frac{e_{ir}}{z_r}}{\frac{\sum_{r=1}^{R} e_{ir}}{\sum_{r=1}^{R} z_r}} \div \frac{\frac{e_{ir}}{b_{ir}}}{\frac{\sum_{r=1}^{R} e_{ir}}{\sum_{r=1}^{R} b_{ir}}}$$

where *e* is employment, *a* surface area, *z* population, and *b* the number of establishments, while *i* and *r* denote industry and region, respectively. The index can be decomposed in three parts (the three ratios in the first equation), which represent several properties of industrial agglomerations: A region has to feature a higher density of employment in a certain industry in relation to area and population, compared to the aggregate country. Since the first two ratios can be large in the presence of one single huge establishment, this is accounted for by dividing by the ratio of the mean establishment size in the local industry to the one in the national industry. Due to the multiplicative relation, the CI takes the value of one if the structure of the local industry equals the one of the aggregate country. Sternberg/Litzenberger (2004) suggest that a local industry is an industrial agglomeration if each ratio is four times larger than in the aggregate country ($CI = 4^3 = 64$).

2 This is the case if region *r*' share of population in the national population equals region *r*'s share of the labor force in the national labor force, which holds true at least by approximation.

A.2 Regional distribution of industrial agglomerations in Germany

Figure A.1: Number of industrial agglomerations per region in 2006



Source: IAB Establishment History Panel (BHP).

A.3 Further results

Table A.1: Robustness checks (I)

Dependent variable: ln employment							
		Model 3			**Model 4**		
		Simultaneous interactions			Regional aggregation		
		coeff.		**z/χ2** (1)-value	coeff.		**z/χ2** (1)-value
ln e	long run	0.773	***	93.54	0.781	***	55.42
ln e * EG	long run	0.002		0.47	0.000		-0.07
ln e * CI	long run	0.038	***	7.52	0.023	***	2.91
ln sect	contemp.	0.883	***	37.61	0.528	***	2.79
	long run	0.806	***	771.29	0.970	***	537.94
ln size^{cf}	contemp.	0.156	***	2.75	0.216	**	2.06
	long run	0.450	***	16.14	0.257		2.18
Diversity	contemp.	0.325	***	8.12	0.233	***	3.24
	long run	0.406	*	3.78	0.226		0.37
ln firmsize	contemp.	-0.059	***	-38.80	-0.054	***	-22.98
	long run	-0.085	***	181.46	-0.084	***	57.50
ln education	contemp.	0.104	***	8.93	0.146	***	6.97
	long run	0.156	***	102.98	0.211	***	76.26
W * ln size^{cf}	contemp.	-0.023	**				
	long run	-0.029					
W * diversity	contemp.	-0.005					
	long run	-0.131					
W * ln firmsize	contemp.	0.005	***				
	long run	0.016	**				
W * ln education	contemp.	-0.003	***				
	long run	-0.008	*				
Time dummies		YES	***		YES	***	
Observations		679796			272870		
Groups		47291			18244		
AR(1)		-19.216	***		-9.384	***	
AR(2)		0.122			-0.375		
Sargan		1085.572	***		411.179	***	

z- and χ2 (1)-values based on heteroscedasticity consistent standard errors.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Model 3 uses both interaction terms of Model 1 and 2 from Table 3 simultaneously.
Model 4 uses regional data aggregated to 112 labor market regions instead of 326 districts.
Source: IAB Establishment History Panel (BHP).

Table A.2: Robustness checks (II)

Dependent variable: ln employment							
		Model 5			**Model 6**		
		Lower thresholds for λ			**Higher thresholds for λ**		
		coeff.		**z/χ2 (1)-value**	**coeff.**		**z/χ2 (1)-value**
ln e	long run	0.762	***	85.43	0.768	***	90.69
ln e * EG	long run	-0.000		-0.14	-0.003		-0.73
ln e * CI	long run	0.049	***	10.21	0.041	***	6.52
ln sect	contemp.	0.877	***	37.53	0.870	***	37.43
	long run	0.786	***	921.43	0.811	***	914.98
ln size^{cf}	contemp.	0.148	***	2.58	0.145	**	2.58
	long run	0.277	**	5.60	0.347	***	11.50
Diversity	contemp.	0.336	***	8.30	0.329	***	8.19
	long run	0.448	**	5.02	0.502	**	5.96
ln firmsize	contemp.	-0.058	***	-38.71	-0.058	***	-38.70
	long run	-0.082	***	180.73	-0.086	***	193.10
ln education	contemp.	0.106	***	9.23	0.111	***	9.45
	long run	0.150	***	104.35	0.170	***	121.22
W * ln size^{cf}	contemp.	-0.027	***	-2.66	-0.023	**	-2.32
	long run	-0.073		1.62	-0.037		0.39
W * diversity	contemp.	-0.009		-0.19	-0.012		-0.28
	long run	-0.119		0.20	-0.168		0.39
W * ln firmsize	contemp.	0.006	***	5.18	0.005	***	4.49
	long run	0.020	***	8.50	0.015	**	4.26
W * ln education	contemp.	-0.002	***	-3.08	-0.002	***	-3.17
	long run	-0.007		2.00	-0.007		1.99
Time dummies		YES	***		YES	***	
Observations		679796			679796		
Groups		47291			47291		
AR(1)		-19.381	***		-17.977	***	
AR(2)		0.500			-0.219		
Sargan		1078.199	***		1038.932	***	

z- and χ2 (1)-values based on heteroscedasticity consistent standard errors.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Model 5 uses thresholds of *EG* > 0.01 and *CI* > 27
Model 6 uses thresholds of *EG* > 0.05 and *CI* > 125

Source: IAB Establishment History Panel (BHP).

B Appendix for Chapter 3

B.1 Calculation of counterfactual steady state effects

Assuming that all observations converge to a steady-state after a shock, $\mathbf{y}_{t-1}$ will eventually equal $\mathbf{y}_t$. Assuming stationarity and holding the exogenous variables constant, the reduced form of equation (3.3) can be solved for $\mathbf{y}_t$:

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

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 establishment), 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, calculating estimates of the standard errors of these counterfactual effects is straightforward:

$$\widehat{\mathbf{Var}(\hat{s}_i)} = \left[\frac{\partial \hat{s}_i}{\partial \hat{\theta}}\right] \widehat{\mathbf{Var}(\hat{\theta})} \left[\frac{\partial \hat{s}_i}{\partial \hat{\theta}}\right]' \tag{B.2}$$

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

B.2 Alternative ways to quantify knowledge spillovers

Since the weighting schemes for knowledge spillovers and for labor market pooling have been created using a similar logic, further discussion of the alternatives might be appropriate. A natural way to quantify knowledge spillovers between establishments is to use patent citations. When a patent is filed, existing knowledge that has been used to create the innovation is also noted. This has been the foundation of a large amount of the literature on knowledge spillovers initiated by Griliches (1979) and Jaffe/Trajtenberg/Henderson (1993). However, most of these studies are restricted to the effects of spillovers on further innovations instead of other economic outcomes because of technical problems such as harmonizing different classifications. Concordance tables such as the one provided by Verspagen/van Moergastel/Slabbers (1994) require the data to be aggregated at a very high level and do not account for innovation in service industries. Furthermore, studies using patent data tend to consider only a handful of innovative industries, since the significance of patenting varies between industries. While, for example, car manufacturers might patent an engine as a whole, chemical firms tend to file separate patents for single molecular chains. Filing a patent also depends on a strategic decision: To do so means to reveal that there has been an innovation in the first place. Thus, while patent citations indeed provide interesting possibilities to track knowledge flows, they seem inadequate for this study's purpose of analyzing spillovers across different industries of the manufacturing and service sectors.

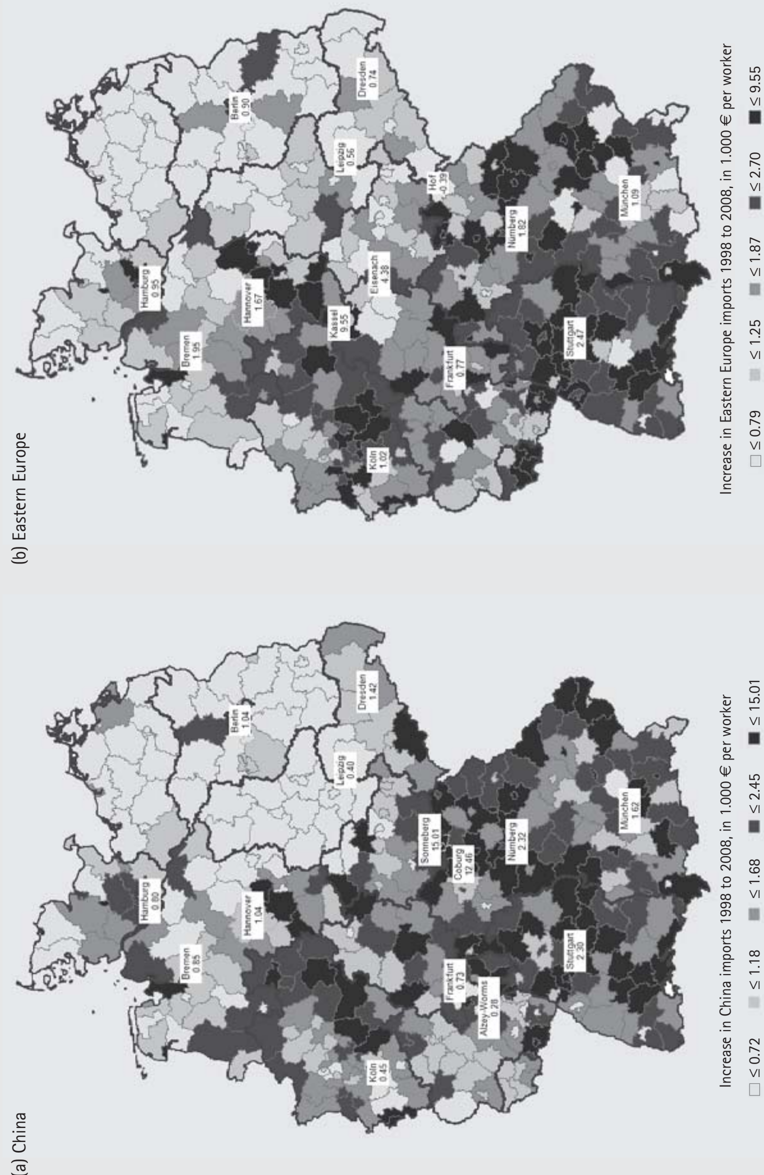
Other studies, I like Amiti/Cameron (2007), assume that knowledge spillovers only take place within the same industry. While this does not fulfill the intention of this study to model inter-industry spillovers explicitly, it poses the danger of confusing the effects of the different Marshallian forces, since all of them should be particularly strong within industries in general. In another study that analyzes the relative importance of the Marshallian forces, Rigby/Essletzbichler (2002) use the productivity growth in upstream industries as a measure for knowledge spillovers. The implication behind this is that if an innovation is not completely reflected in the sales price, the customer receives a rent from buying it. This creates a rent spillover as suggested by Griliches (1979), but also neglects the idea that people learn from each other aside from formal channels or transactions.

Using the mobility of workers as a proxy for the likelihood of knowledge spillovers thus appears to be a reasonable second-best solution. If the same skilled people are able to work in different fields, knowledge might also find other paths to spill over between these industries.

C Appendix for Chapter 4

C.1 Increase in regional trade exposure

Figure C.1: Change in import exposure 1998 to 2008

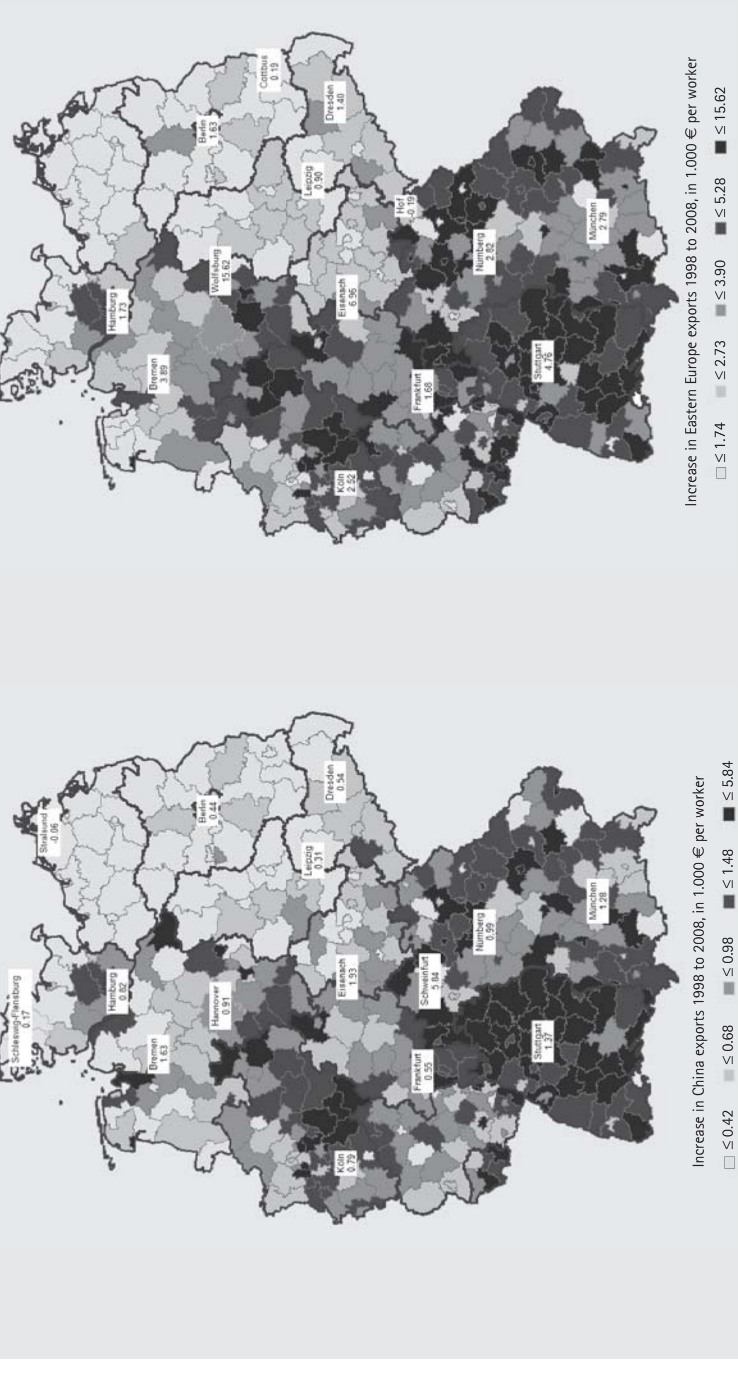


Source: BHP and UN comtrade.

Figure C.2: Change in export exposure 1998 to 2008

(a) China

(b) Eastern Europe



Source: BHP and UN comtrade.

C.2 The sectoral composition of German trade

Table C.1: Trade volumes of the top ten sectors in trade with Eastern Europe

	Industry	2008	1998	1988
Imports from Eastern Europe				
111	Extraction of crude petroleum and natural gas*	20700	2340	1460
341	Manuf. of motor vehicles	7100	4440	76
343	Manuf. of parts and accessories for motor vehicles and their engines	6830	1610	11
274	Manuf. of basic precious and non-ferrous metals	4280	1940	992
271	Manuf. of basic iron and steel and of ferro-alloys (ECSC1)	3510	949	402
316	Manuf. of electrical equipment n.e.c.	3350	1260	26
361	Manuf. of furniture	3260	2260	449
291	Manuf. of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines	3080	727	85
241	Manuf. of basic chemicals	3010	1300	442
287	Manuf. of other fabricated metal products	2500	1190	75
Exports to Eastern Europe				
341	Manuf. of motor vehicles	13300	3970	248
343	Manuf. of parts and accessories for motor vehicles and their engines	9180	2610	92
295	Manuf. of other special purpose machinery	7830	3400	1250
291	Manuf. of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines	5390	1500	413
252	Manuf. of plastic products	5280	2090	577
241	Manuf. of basic chemicals	4990	1540	989
292	Manuf. of other general purpose machinery	4500	1710	447
287	Manuf. of other fabricated metal products	4030	1360	128
244	Manuf. of pharmaceuticals, medicinal chemicals and botanical products	3950	1000	245
312	Manuf. of electricity distribution and control apparatus	3900	1440	155

Trade volumes measured in Million Euros of 2005. *: This industry and all other industries related to agriculture, mining, and fuel products are omitted in the empirical analysis.

Source: UN comtrade.

Table C.2: Trade volumes of the top ten sectors in trade with China

	Industry	2008	1998	1988
Imports from China				
300	Manuf. of office machinery and computers	8630	1160	12
182	Manuf. of other wearing apparel and accessories	4950	1900	704
365	Manuf. of games and toys	3280	658	46
323	Manuf. of television and radio receivers, sound or video recording or reproducing apparatus and associated goods	2930	700	171
321	Manuf. of electronic valves and tubes and other electronic components	2920	123	2
322	Manuf. of television and radio transmitters and apparatus for line telephony and line telegraphy	1740	172	8
287	Manuf. of other fabricated metal products	1510	390	40
177	Manuf. of knitted and crocheted articles	1360	199	24
241	Manuf. of basic chemicals	1200	335	115
297	Manuf. of domestic appliances n.e.c.	1190	392	10
Exports to China				
341	Manuf. of motor vehicles	3530	238	209
295	Manuf. of other special purpose machinery	3220	1050	590
291	Manuf. of machinery for the production and use of mechanical power, except aircraft, vehicle and cycle engines	2740	248	108
294	Manuf. of machine-tools	1900	376	306
312	Manuf. of electricity distribution and control apparatus	1650	277	54
343	Manuf. of parts and accessories for motor vehicles and their engines	1640	114	31
292	Manuf. of other general purpose machinery	1570	388	112
353	Manuf. of aircraft and spacecraft	1310	182	11
332	Manuf. of instruments and appliances for measuring, checking, testing, nav. and other purposes, except industrial process control equipment	1220	168	84
311	Manuf. of electric motors, generators and transformers	1200	83	26

Trade volumes measured in Million Euros of 2005.

Source: UN comtrade.

C.3 Further results

Table C.3: Robustness checks: Variations in instrumental variables (Eastern Europe results)

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points			
	Leave out USA	Only USA	Just identified	Only CY, IS, UAE
Δ import exposure	-0.584**	-1.602***	-1.108**	-0.326
	(0.26)	(0.52)	(0.49)	(0.53)
Δ export exposure	0.608**	0.500	0.697**	0.661*
	(0.26)	(0.44)	(0.35)	(0.35)
R-square	0.227	0.011	0.157	0.237
First stage (KP)	21.030	8.201	12.579	3.518
p Hansen	0.124			0.391

Observations: 739. Standard errors clustered by administrative districts and years in parentheses.
IV estimates, including federal state and time interactions and all controls described in Section 4.3.2.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: BHP and UN comtrade.

Table C.4: Robustness checks: Variations in instrumental variables (China results)

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points			
	Leave out USA	Only USA	Just identified	Only CY, IS, UAE
Δ import exposure	-0.058	-0.148	-0.123	0.034
	(0.09)	(0.13)	(0.10)	(0.14)
Δ export exposure	1.474***	-0.734	0.181	-0.972
	(0.51)	(1.34)	(0.87)	(0.85)
R-square	0.321	0.129	0.247	0.095
First stage (KP)	24.429	3.322	13.961	12.003
p Hansen	0.401			0.521

Observations: 739. Standard errors clustered by administrative districts and years in parentheses.
IV estimates, including federal state and time interactions and all controls described in Section 4.3.2.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: BHP and UN comtrade.

Table C.5: Robustness checks: Drop most important industries for trade with Eastern Europe

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points				
Omitted industry	**Motor vehicles**	**Parts for motor vehicles**	**Spec. purp. machinery**	**Plastic products**	**Basic chemicals**
Δ import exposure	-0.311	-0.603***	-0.627**	-0.539**	-0.502**
	(0.21)	(0.22)	(0.25)	(0.24)	(0.25)
Δ export exposure	0.480	0.462*	0.604***	0.590**	0.676***
	(0.30)	(0.24)	(0.23)	(0.24)	(0.23)
R-square	0.252	0.252	0.208	0.238	0.233
First stage (KP)	24.591	22.398	22.745	23.905	18.286
p Hansen	0.270	0.172	0.384	0.262	0.366
Omitted industry	**El. equipment n.e.c.**	**Furniture**	**Rubber products**	**El. control apparatus**	**Wearing apparel**
Δ import exposure	-0.596**	-0.667***	-0.657***	-0.596**	-0.657**
	(0.24)	(0.25)	(0.25)	(0.23)	(0.26)
Δ export exposure	0.662***	0.627***	0.460**	0.631***	0.630***
	(0.24)	(0.24)	(0.23)	(0.24)	(0.24)
R-square	0.239	0.239	0.218	0.224	0.229
First stage (KP)	22.414	24.467	20.015	23.075	25.822
p Hansen	0.204	0.217	0.443	0.339	0.192

Observations: 739. Standard errors clustered by administrative districts and years in parentheses.
IV estimates, including federal state and time interactions and all control variables.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: BHP and UN comtrade.

Table C.6: Robustness checks: Drop most important industries for trade with China

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points				
Omitted industry	**Office machines**	**Wearing apparel**	**Toys**	**Communication devices**	**TV and radio devices**
Δ import exposure	-0.024	-0.065	-0.060	-0.087	-0.060
	(0.11)	(0.09)	(0.09)	(0.10)	(0.09)
Δ export exposure	1.529***	1.494***	1.500***	1.487***	1.476***
	(0.51)	(0.50)	(0.51)	(0.51)	(0.49)
R-square	0.321	0.315	0.321	0.313	0.334
First stage (KP)	47.755	24.152	13.318	17.713	31.931
p Hansen	0.208	0.199	0.254	0.267	0.316
Omitted industry	**Motor vehicles**	**Spec. purp. machinery**	**Mach. for prod. of mech. power**	**Machine tools**	**El. control apparatus**
Δ import exposure	-0.082	-0.087	-0.105	-0.071	-0.074
	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)
Δ export exposure	1.238*	1.513***	0.475	1.547***	1.522***
	(0.65)	(0.51)	(0.44)	(0.52)	(0.52)
R-square	0.326	0.309	0.248	0.314	0.318
First stage (KP)	25.274	21.551	28.774	21.784	22.201
p Hansen	0.300	0.254	0.479	0.207	0.286

Observations: 739. Standard errors clustered by administrative districts and years in parentheses.
IV estimates, including federal state and time interactions and all control variables.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: BHP and UN comtrade.

Table C.7: Robustness checks: Only Western Germany (Eastern Europe results)

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	2SLS	2SLS	2SLS
Δ import exposure	-0.037	-0.047	-0.008	-0.608**	-0.649***	-0.645***
	(0.19)	(0.19)	(0.19)	(0.24)	(0.24)	(0.23)
Δ export exposure	0.376**	0.394**	0.338*	0.666***	0.712***	0.674***
	(0.19)	(0.16)	(0.17)	(0.24)	(0.23)	(0.24)
Individual controls	–	Yes	Yes	–	Yes	Yes
Federal state dummies	Yes	Yes	–	Yes	Yes	–
Time dummy	Yes	Yes	–	Yes	Yes	–
State and time interaction	–	–	Yes	–	–	Yes
R-square	0.267	0.398	0.424	0.213	0.346	0.237
First stage (KP)				22.383	24.879	24.822
p Hansen				0.086	0.164	0.183

Observations: 652. Standard errors clustered by administrative districts and years in parentheses.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: BHP and UN comtrade.

Table C.8: Robustness checks: Only Western Germany (China results)

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ import exposure	-0.007	-0.008	-0.045	-0.024	-0.067	-0.125
	(0.07)	(0.06)	(0.06)	(0.08)	(0.08)	(0.09)
Δ export exposure	1.745***	1.825***	1.706***	1.487***	1.680***	1.571***
	(0.39)	(0.37)	(0.41)	(0.51)	(0.48)	(0.51)
Individual controls	–	Yes	Yes	–	Yes	Yes
Federal state dummies	Yes	Yes	–	Yes	Yes	–
Time dummy	Yes	Yes	–	Yes	Yes	–
State and time interaction	–	–	Yes	–	–	Yes
R-square	0.333	0.469	0.484	0.304	0.446	0.347
First stage (KP)				105.380	119.311	157.232
p Hansen				0.183	0.222	0.282

Observations: 652. Standard errors clustered by administrative districts and years in parentheses.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: BHP and UN comtrade.

Table C.9: Robustness checks: Labor market regions (Eastern Europe results)

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ import exposure	-0.409**	-0.286*	-0.268	-0.854***	-0.670***	-0.650***
	(0.19)	(0.16)	(0.17)	(0.22)	(0.17)	(0.17)
Δ export exposure	0.444**	0.510***	0.444***	0.719***	0.766***	0.701***
	(0.18)	(0.15)	(0.15)	(0.19)	(0.15)	(0.16)
Individual controls	–	Yes	Yes	–	Yes	Yes
Federal state dummies	Yes	Yes	–	Yes	Yes	–
Time dummy	Yes	Yes	–	Yes	Yes	–
State and time interaction	–	–	Yes	–	–	Yes
R-square	0.572	0.698	0.726	0.425	0.593	0.419
First stage (KP)				18.184	14.742	16.818
p Hansen				0.059	0.045	0.065

Observations: 259. Standard errors clustered by administrative districts and years in parentheses.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: BHP and UN comtrade.

Table C.10: Robustness checks: Labor market regions (China results)

	Dependent variable: 10-year change manufacturing employment/working age pop. in %-points					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ import exposure	0.076	0.079	0.064	0.110	0.086	0.059
	(0.11)	(0.07)	(0.08)	(0.10)	(0.08)	(0.09)
Δ export exposure	1.838***	1.846***	1.706***	1.505***	1.671***	1.508***
	(0.26)	(0.25)	(0.30)	(0.26)	(0.22)	(0.26)
Individual controls	–	Yes	Yes	–	Yes	Yes
Federal state dummies	Yes	Yes	–	Yes	Yes	–
Time dummy	Yes	Yes	–	Yes	Yes	–
State and time interaction	–	–	Yes	–	–	Yes
R-square	0.638	0.758	0.768	0.525	0.684	0.524
First stage (KP)				43.881	48.328	82.638
p Hansen				0.207	0.681	0.578

Observations: 259. Standard errors clustered by administrative districts and years in parentheses.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: BHP and UN comtrade.

Table C.11: Wage inequality according to occupational status

	Dependent variables: 10-year change in ln daily wage differentials			
	Eastern Europe trade		China trade	
	Blue collar	White collar	Blue collar	White collar
	50/15 quantile range			
Δ import exposure	1.088***	1.121***	0.064	0.216
	(0.34)	(0.31)	(0.08)	(0.14)
Δ export exposure	−0.667**	−0.620***	−0.925**	−1.363***
	(0.29)	(0.23)	(0.38)	(0.40)
	85/50 quantile range			
Δ import exposure	0.310	−0.983***	0.048	−0.163
	(0.29)	(0.28)	(0.15)	(0.11)
Δ export exposure	−0.553***	0.233	−0.878**	−0.756**
	(0.15)	(0.17)	(0.35)	(0.35)
	85/15 quantile range			
Δ import exposure	1.398***	0.137	0.111	0.054
	(0.45)	(0.32)	(0.20)	(0.17)
Δ export exposure	−1.220***	−0.388	−1.803***	−2.119***
	(0.31)	(0.27)	(0.53)	(0.52)

Observations: 739. Standard errors clustered by administrative districts and years in parentheses.
IV estimates, including federal state and time interactions and all controls described in Section 4.3.2.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: Statistics Department of the German Federal Employment Agency, BHP, and UN comtrade.

Table C.12: Wage inequality in the non-manufacturing sector and trade exposure

	Dependent variables: 10-year change in ln daily wage differentials					
	Eastern Europe trade			China trade		
Quantile spread	**50/15**	**85/50**	**85/15**	**50/15**	**85/50**	**85/15**
Δ import exposure	1.060***	0.038	1.098***	0.066	0.035	0.101
	(0.37)	(0.21)	(0.42)	(0.16)	(0.12)	(0.19)
Δ export exposure	-0.444*	0.076	-0.368	-0.342	0.103	-0.239
	(0.25)	(0.14)	(0.28)	(0.53)	(0.38)	(0.50)
R-square	0.345	0.058	0.194	0.328	0.059	0.186
First stage (KP)	23.757	23.757	23.757	21.187	21.187	21.187
p Hansen	0.383	0.447	0.503	0.171	0.178	0.080

Observations: 739. Standard errors clustered by administrative districts and years in parentheses.
Coefficients and standard errors multiplied times 100. IV estimates, including federal state and time interactions and all controls described in Section 4.3.2.
Levels of significance: *** 1 %, ** 5 %, * 10 %.
Source: Statistics Department of the German Federal Employment Agency, BHP, and UN comtrade.

Abstract

Disparities in regional economic outcomes within Germany are almost as pronounced as disparities between countries of the European Union. This book investigates how disparities in the industrial structure can influence the development of regional employment. The main part of this book consists of three independent studies. The first two focus on the economics of agglomeration, that is, the geographical concentration of plants from the same or similar industries.

While the existence of agglomeration externalities is well accepted in both the empirical and theoretical literature, there is only consensus as far as they foster productivity. The evidence on employment effects is ambiguous. The first study tries to fill this gap by analyzing the inertia of employment growth in both agglomerations and non-agglomerated local industries. The main result is that positive employment shocks are more persistent in industrial agglomerations and increase employment in the long run, which is evidence for the existence of agglomeration externalities.

However, as long as only spillovers within local industries are considered, the mechanisms causing these externalities remain hidden. The second study sheds light on these mechanisms by analyzing spillovers between different, but kindred industries. Adopting methods of spatial econometrics, it is possible to discriminate between forward-backward linkages, labor market pooling, and knowledge spillovers. The main result implies that spillovers between industries are also an important aspect of agglomeration externalities and that labor market pooling is of particular importance.

The last study shifts its focus on how regions are exposed to the effects of international trade due to the structure of resident industries. There is evidence that the exceptional rise of China and Eastern Europe on the global market has in fact been favorable for Germany. For the average region, export opportunities in these countries had positive effects on manufacturing employment. These effects have more than compensated the decline of industries that faced increasing competition by imports from the East.

Kurzfassung

Regionale Unterschiede ökonomischer Größen sind innerhalb Deutschlands ähnlich stark ausgeprägt wie zwischen den verschiedenen Ländern der Europäischen Union. Dieses Buch untersucht wie sich Unterschiede in der Branchenstruktur auf die regionale Beschäftigungsentwicklung auswirken. Der Hauptteil des Buches besteht aus drei eigenständigen Studien. Die ersten beiden konzentrieren sich auf die Ökonomie der Agglomeration, also der geographischen Konzentration gleicher oder verwandter Branchen.

Während es in der empirischen und theoretischen Literatur allgemein anerkannt ist, dass es Agglomerationsvorteile gibt, herrscht nur Einigkeit darüber, dass sie sich positiv auf die Produktivität auswirken. Die Evidenz zu Beschäftigungseffekten ist dagegen nicht eindeutig. Die erste Studie versucht, diese Lücke zu schließen. Dazu wird die Trägheit des Beschäftigungswachstums in agglomerierten und nicht-agglomerierten lokalen Branchen verglichen. Das zentrale Ergebnis ist, dass positive Beschäftigungsschocks in industriellen Agglomerationen nachhaltiger sind und langfristig zu stärkerem Beschäftigungswachstum führen. Dies belegt die Existenz von Agglomerationsvorteilen.

Solange jedoch nur Wechselwirkungen innerhalb lokaler Branchen betrachtet werden, bleiben die Mechanismen, die diese Effekte erklären, verborgen. Die zweite Studie gibt Aufschluss über jene Mechanismen, indem Wechselwirkungen zwischen unterschiedlichen aber verwandten Branchen betrachtet werden. Die Anpassung von Methoden der räumlichen Ökonometrie ermöglicht es, zwischen Lieferbeziehungen, gemeinsamen Arbeitsmärkten und der Übertragung von Ideen zu unterscheiden. Die Ergebnisse zeigen, dass Wechselwirkungen zwischen verschiedenen Branchen ein wichtiger Bestandteil von Agglomerationsvorteilen sind und dass gemeinsame Arbeitsmärkte eine besonders große Rolle spielen.

Die letzte Studie verlagert den Fokus darauf, wie stark Regionen aufgrund ihrer Branchenstruktur den Auswirkungen des internationalen Handels ausgesetzt sind. Die Ergebnisse deuten darauf hin, dass der außerordentlich starke wirtschaftliche Aufstieg Chinas und Osteuropas auf den Weltmärkten eine günstige Wirkung auf Deutschland hatte. Für die durchschnittliche Region hatten die neuen Exportmöglichkeiten in diese Länder positive Effekte auf die Beschäftigung im verarbeitenden Gewerbe. Diese Effekte haben sogar den Abschwung jener Industrien überkompensiert, welche sich einer gestiegenen Konkurrenz durch Importe aus dem Osten gegenübersahen.