National Industry Trade Shocks, Local Labor Markets, and Agglomeration Spillovers

Ines Helm

10th January 2019

Abstract

Using a broad set of national industry trade shocks, I employ a novel approach to estimate agglomeration effects by exploiting within industry variation in indirect exposure to the other local industries’ (national) trade shocks across local labor markets. This variation stems from differences in local industry composition and allows to test for the existence of heterogeneous agglomeration effects across industries. I find considerable employment spillovers from other tradable industries’ trade shocks and even stronger effects within the same broad sector. Spillovers are larger for industries employing similar workers and are triggered predominantly by shocks to high technology industries.

Keywords: Agglomeration, Local Labor Markets, Trade Shocks

JEL Classification: F16, J20, R11, R12

* I thank Uta Schönberg and Christian Dustmann for their guidance and support during the project. This paper has also benefited from discussions with Anna Bindler, Paula Bustos, Eric French, Christina Gathmann, Antonio Guarino, Brian Kovak, Stephen Machin, Markus Nagler, Diego Puga, Suphanit Piyapromdee, Jan Stuhler, Tanya Surovtseva, Antonella Trigari, Josef Zweimüller and seminar and workshop participants at CEMFI, Erasmus University Rotterdam, the IZA (Bonn), the IFN (Stockholm), Stockholm University, UCL, the University of St. Gallen, the University of Munich and in Piedmont. Financial support from the German National Academic Foundation, the Centre for Research and Analysis of Migration, and UCL is gratefully acknowledged. Finally, I thank Uta Schönberg and the Institute for Employment Research (IAB) for providing the anonymized data from German social security records on 3-digit x commuting zone level and Wolfgang Dauth for sharing code and correspondence tables.

† Stockholm University; Email: ines.helm@ne.su.se
1 Introduction

Economic activity is spatially concentrated in many countries. Well known examples of such concentration are the clustering of high-tech firms in Silicon Valley or the clustering of auto manufacturers and their suppliers in Detroit.

One explanation for the observed level of clustering is the existence of agglomeration economies, whereby firms benefit from productivity or cost advantages when they locate near other firms. Cost advantages can emerge from reductions in transport costs for firms with input-output linkages, while productivity advantages can arise from knowledge spillovers or an increase in matching quality in larger local labor markets (e.g. Marshall (1890)). In Silicon Valley, for example, the existence of many high-skilled workers potentially leads to an increase in knowledge exchange both at the workplace and across firms. The presence of many high-skilled workers might also attract new high-tech firms as the available labor pool is larger, and hence firms are likely to find better workers in the area. Car manufacturers and their suppliers likely cluster together as this reduces transport costs and simplifies communication amongst firms.

In this paper, I employ a novel approach to estimate agglomeration effects: I identify and estimate agglomeration externalities using a broad set of national industry shocks. I first document the existence of local spillovers from national industry shocks and that these spillovers magnify the direct local effects of these shocks. I then analyze heterogeneities in spillovers, focusing on three main questions: What role does economic proximity between industries play for the strength of spillovers? Which industries create spillovers? And which industries benefit from spillovers?

The national industry shocks exploited for identification are trade shocks to German industries stemming from two sources: trade integration of Eastern Europe after the fall of the iron curtain and that of China during the course of its WTO accession. These events led to gradual reductions in trade barriers between Germany and both Eastern Europe and China, and consequently to a substantial increase in import competition and export demand for many German industries producing tradable goods over time.1 These national industry trade shocks constituted shocks to local industry labor demand that were not correlated with other region-specific factors jointly affecting local industry labor demand in all industries in the region. They are thus well-suited to analyzing the existence of agglomeration spillovers. More specifically, I estimate agglomeration spillovers by relating changes in local industry employment to indirect exposure to the other local industries’ (national) trade shocks, exploiting within industry variation in exposure across local labor markets. This variation stems from initial differences in local industry structure within the tradable sector. Workers in the same industry but in regions with different local industry structures might hence be differentially affected by indirect exposure to the other local industries’ trade shocks.

What effects might arise from indirect exposure to other local industries’ national industry level shocks and more particularly from trade shocks? For tradable industries, indirect trade exposure potentially leads to two opposing effects at the regional level: reallocation effects and agglomeration

---

1 See Figure 1 for the evolution of German national imports and exports from and to China and Eastern Europe.
spillovers.\textsuperscript{2} If the other local industries are hit by a positive trade shock, they will in turn demand more labor, which, if workers are not perfectly mobile across regions, will lead to an increase in regional wages. The industry under observation will hence want to decrease employment - the reallocation effect. However, if the increase in labor demand of the other local industries is satisfied partly through workers moving into the region and consequently local labor market size increases, the industry under observation might benefit for at least two reasons from this growth in labor market size. First, the available labor pool increases which potentially results in better worker-firm matches. Second, the inflow of new human capital into the region and an increase in worker flows across local industries might lead to knowledge spillovers. Furthermore, the industry under observation might benefit if it shares input-output relations with the industries hit by the trade shock, as it can meet the increased demand for services and intermediate goods more cheaply and faster than suppliers in other regions. Consequently, indirect trade exposure might lead to positive spillovers, which, if the agglomeration economies are strong enough, can outweigh the reallocation effect.

To give an example, consider the German aircraft industry. Demand for airplanes in China rose considerably over the last decade. German airplane exports to China grew from around 80 million EUR in 1998 to around 1.61 billion at their peak in 2006. The aircraft industry is a highly clustered high technology industry employing overproportionally high-skilled workers. One of these clusters is located in Hamburg, where in 1998 about 21\% of all aircraft industry workers in Germany were employed. However, Hamburg is not only known as an aviation cluster, but more generally as a high-tech cluster. Indeed, the presence of the aircraft industry goes hand in hand with the existence of other high technology industries, such as the information technology industry. In the presence of agglomeration economies, an increase in demand for airplanes in China may consequently not only increase employment in the aircraft industry – and hence high-skilled employment in the region – but may potentially be beneficial for other high technology firms as well. These firms might, for example, benefit from a growing high-skilled labor market through thick market effects.\textsuperscript{3} Alternatively, the increase in high-skilled workers in the region might increase knowledge exchange between firms and workers. Furthermore, suppliers of aircraft manufacturers in Hamburg might benefit, as local demand for their goods and services increases.

I begin the analysis by providing a simple model of agglomeration economies. The model generates an equilibrium labor demand equation where local industry labor demand depends on the other local industries’ employment levels through productive benefits from co-locating. I then use the model to derive empirically testable predictions on how trade shocks can trigger employment spillovers in other local industries in the presence of agglomeration economies. First, trade shocks need to positively affect local employment of the industries directly affected by the shocks. Second, if local labor supply is less than infinitely elastic, trade shocks should increase local wages. Third,

\textsuperscript{2}Indirect trade exposure might also lead to national product demand shocks. I abstract from these here, as the focus of the analysis is on local spillovers. I also abstract from local multiplier effects on non-tradable industries, as the main focus here is on spillovers to tradable industries.

\textsuperscript{3}Note that the high-skilled employment share increased from 13 to 18\% between 1998 and 2006.
the overall indirect effect of trade shocks to the other local industries is ambiguous and depends on
the strength of agglomeration forces and the reallocation effect (i.e., endogenous wage adjustments),
which affect local industry employment in opposite directions.

For the empirical analysis I combine data from two sources. For local labor market outcomes, I
use administrative data from Germany, which contain the population of firms and workers covered
by the social security system. The UN Comtrade Database provides information on trade flows. I
estimate local spillovers from trade shocks controlling for the own industry trade shock and poten-
tial national indirect product demand spillovers. In particular, I relate changes in local industry
employment at the 3-digit industry x commuting zone level for three time periods between 1988 and
2008 to changes in indirect trade exposure, accounting for national industry time varying shocks and
local industry and regional characteristics potentially affecting local industry employment growth.
To account for the fact that changes in Chinese and Eastern European trade flows to and from
Germany might also be driven by German specific shocks, such as technology shocks to certain
industries, I follow Autor et al. (2013) and instrument changes in German trade flows by changes
in trade flows of other high income countries.

I first document that (positive) trade shocks positively affect employment in industries directly
affected by the trade shock, and that the joint regional trade shocks positively affect local em-
ployment. These results are a precondition for the existence of agglomeration spillovers, which
are assumed to work through the size of the local labor market, such as thick market effects and
knowledge spillovers working through increased worker mobility.

To then estimate spillover effects, I construct a measure of indirect trade exposure that quantifies
a local industry worker’s exposure to the joint trade shocks of the other tradable industries in the
region. I find considerable positive spillovers from other tradable industries’ net trade shocks and
even stronger effects within the same broad sector. These spillovers contribute about 38 percent
to the joint direct and indirect local employment effects of trade shocks. Further, based on the
simple model outlined above, these estimates imply an agglomeration elasticity of 0.22, an estimate
comparable to the elasticities reported by Gathmann et al. (2016) and Kline and Moretti (2014).

To investigate which of the sources of agglomeration economies is responsible for the observed
spillover effects in employment, I refine the measure of indirect trade exposure by rescaling the
strength of the other local industries’ trade shocks according to three measures of economic prox-
imity: share of inputs used from the industry under observation, share of outputs provided to the
industry under observation, and share of workers exchanged with the industry under observation.
I find that predominantly worker transitions between industries lead to employment spillovers, in-
dicating that knowledge spillovers or thick market effects are most important in creating spillovers.
In contrast, input-output relations do not seem to matter much.

I then analyze heterogeneities in spillovers across industries, focusing in particular on differences

4The broad sector definition differentiates between 17 broad sectors (6 within the tradable sector). For comparison,
there are 10 one-digit industries and 99 two-digit industries. The broad sector definition thus provides a bit finer
definition compared to that of the one-digit industry.
between high and low technology industries. I find that high technology industries benefit most from spillovers from trade shocks to other tradable industries in the region. While low technology industries do benefit, spillovers to high technology industries are about twice as large. To analyze heterogeneities in creating spillovers, I distinguish between the effects of indirect exposure to shocks to high technology industries versus indirect exposure to shocks to low technology industries. The results suggest that it is predominantly trade shocks to high technology industries that trigger spillovers in other industries, while those to low technology industries do not generate spillovers. The absence of spillover effects from shocks to low technology industries provides additional evidence that indirect product demand shocks to industries connected by input-output linkages may not be the main driver of spillover effects, as low technology industries are substantially linked by input-output relations and consequently shocks to low technology industries should lead to spillovers if input-output relations were an important source of agglomeration economies.

Overall, the findings indicate that national industry trade shocks lead to considerable agglomeration spillovers. The regional effects of national industry shocks are thus larger than would be expected if only taking into account the direct effects of national industry shocks. Spillovers are largely generated by high technology industries (or industries employing high-skilled workers) and act primarily between industries that share common worker requirements. These findings indicate that governments may want to take local industry structure into account when implementing place-based policies, as well as aim to attract high technology firms to increase the likelihood that such policies are successful. That said, to take a firmer stance regarding the consequences for place based policies, more direct research on place-based policies in relation to these findings is needed. If not regional policy is the primary interest of governments, but rather national welfare, the results further suggest that national governments should move subsidies away from low technology and towards high technology industries, as the latter are more likely to create additional employment through regional spillovers.

The paper is structured as follows. In Section 2 I relate my analysis to the existing literature. Section 3 presents the theoretical mechanisms through which trade shocks can lead to agglomeration spillovers. Section 4 introduces the empirical strategy used to assess the strength of agglomeration spillovers triggered by trade shocks. Section 5 describes the data and gives some descriptive statistics. Section 6 reports the main results and robustness checks. Finally, Section 7 discusses the implications of the analysis and concludes.

2 Related Literature and Contribution

This paper contributes to three strands of the literature: the literature analyzing the existence, strength and sources of agglomeration economies, the literature analyzing the effects of place based policies and the literature analyzing employment effects of globalization using trade shocks.

Recent advances in the literature analyzing the existence and strength of agglomeration economies
include the use of natural experiments.\footnote{There exists a large body of literature that examines the relationship between regional (or local industry) density and productivity to infer about the existence of agglomeration economies (see, for example, Ciccone and Hall (1996)'s seminal paper or Combes and Gobillon (2015) for an overview of the literature and the challenges in identifying agglomeration effects). An alternative and more indirect approach is the analysis of patterns of industry coagglomeration and its reasons (see e.g. Ellison and Glaeser (1999) or Ellison et al. (2010)).} Natural experiments can induce sizable shocks to local economies that are arguably not otherwise correlated with the outcome of interest. Greenstone et al. (2010), for example, analyze how large plant openings affect total factor productivity of incumbent plants located in the same region. For identification they exploit information about the runner-up locational choice, the region that just lost the competition to attract the plant. They find that five years after the opening of the plant, incumbent plants’ productivity is 12% higher in regions with plant openings compared to runner-up regions. Gathmann et al. (2016) analyze the inverse event, examining instead how large mass layoffs affect regional labor market outcomes. They find that local labor markets affected by mass layoffs lose many more workers than through the initial layoff. Kline and Moretti (2014) study how a place-based policy aimed at attracting manufacturing employment and providing investment in public infrastructure affects local employment over the long run. They find sizable long-term effects on manufacturing employment and explain these by the existence of agglomeration effects.

The use of natural experiments provides a plausible identification strategy for the analysis of the existence and strength of agglomeration economies. Yet these recent studies all exploit relatively specific events at the local level. I add to this literature by using a broader approach to identify agglomeration spillovers, which allows to convincingly control for region specific shocks. A major difference between the identification strategy in this paper and that applied in the recent studies mentioned above is that I fix the national industry shock per worker (every worker in a given industry is affected by the same national industry shock) and exploit differences in local industry structure, while Greenstone et al. (2010) and Gathmann et al. (2016), for example, fix local industry structure and exploit variation in per worker shocks across regions. In particular, I exploit a quasi experiment leading to a large set of national industry trade shocks. While there arguably still exist particularities when using national industry trade shocks to estimate agglomeration effects, I argue that this identification strategy can be applied to various other kinds of national industry shocks.

Moreover, to my knowledge, it has not to date been shown that national industry shocks can lead to this sort of regional spillovers.\footnote{Note, however, that Acemoglu et al. (2016) hint at this in analyzing how macroeconomic shocks propagate through the economy, pointing out the importance of national input-output networks and local networks of industry collocation.}

Furthermore, I can exploit variation in shocks both within and across industries, allowing me to

In addition, Beaudry et al. (2012) suggest a different source of potential spillover effects at the local industry level apart from agglomeration effects. They show that a change in industrial composition in a standard search and bargaining model of the labor market affects the bargaining position of workers by changing their outside options, which implies that local industry wages are higher in regions where the other industries are high-paying rather than low-paying. To rule out that my results are driven by these type of spillovers, in Appendix C.3 I compare and contrast the predictions of the model of agglomeration economies presented in this paper with those of Beaudry et al. (2012)'s search and bargaining model, and show that my results on employment cannot be explained by this model.
study heterogeneities across industries in greater detail than, for example, Greenstone et al. (2010) and Gathmann et al. (2016). This allows me to distinguish between spillovers triggered by shocks to high technology industries and those triggered by shocks to low technology industries. In this regard, I also add to the literature analyzing the effects of place-based policies (see for example Busso et al. (2013), or Becker et al. (2010)). Governments at least partially justify place-based policies by the existence of agglomeration spillovers (see for example Glaeser and Gottlieb (2008)). However, evidence on the effects of place based policies is mixed, likely because of heterogeneities in policies and the characteristics of the places at which they aim. Nevertheless, evidence on heterogeneous effects remains scarce. Notable exceptions include Briant et al. (2015), who detect heterogeneities in the effects of the French enterprise zone program and Becker et al. (2013), who analyze regional heterogeneities in the effects of the European Structural Funds. Results on heterogeneous effects may consequently provide an important indicator on which sort of firms governments may want to attract when implementing place-based policies and to which areas they should be attracted to and may spark more direct research on place-based policies that takes into account heterogeneities.

This study is also related to the literature examining employment effects of globalization using trade shocks.\footnote{In related work, Bloom et al. (2016) analyze the impact of Chinese import competition on broad measures of technical change, such as patenting, IT, and TFP, for several countries in Europe and find that trade induces technical change.} Autor et al. (2013) analyze the effects of rising Chinese import competition, due to China’s transition into a market oriented economy, on US local labor markets. They find that about 25% of the reduction in manufacturing employment in the US between 1990 and 2007 can be attributed to rising Chinese import competition. In a follow up paper, Acemoglu et al. (2015) additionally analyze the effects of rising import competition on employment in upstream and downstream industries on national industry level, hence accounting for indirect \textit{national} product demand spillovers. They find that these spillovers make up about 50% of the total national employment loss due to Chinese import competition. Dauth et al. (2014) conduct a similar study to that of Autor et al. (2013), but in the German context. To better accommodate the German setting, they additionally include trade shocks from Eastern European countries triggered by the fall of the iron curtain and analyze local employment effects of shocks to both export demand and import competition. While most of the literature studies medium-run effects, Dix-Carneiro and Kovak (2016) are able to study the evolution of the effects of trade liberalization on local labor markets in Brazil over time and can thus focus on adjustment processes.\footnote{Dix-Carneiro and Kovak (2016) analyze the local impact of changes in trade policy, exploiting differences in trade liberalization intensity across industries (see also, for example, Topalova (2010)). Kovak (2013) provides a theoretical foundation for this approach.}

I exploit the same type of shocks as Dauth et al. (2014). I add to the literature by giving additional insights into one particular aspect determining the local employment impact of trade shocks — the existence of agglomeration economies — that to my knowledge has been largely
I thus open up the “black box” of local employment effects estimated by Autor et al. (2013) and Dauth et al. (2014), and show that local employment effects are composed of both the direct effects of trade shocks and indirect effects through local employment spillovers.

3 Theoretical Framework

In this section, I begin by describing the sources of agglomeration economies that have been brought forward by the literature and describe how these sources can lead to spillovers following trade shocks. I then build a simple theoretical model incorporating agglomeration economies. From this model I derive empirically testable predictions on how trade shocks affect local industry employment in the presence of agglomeration economies.

3.1 Sources of Agglomeration Economies

As first hypothesized by Marshall (1890), there exist several reasons why industries may enjoy productivity or cost advantages from co-locating. Productivity advantages can arise through knowledge spillovers or thick labor market effects. A positive trade shock to one industry can lead to productivity spillovers through both of these mechanisms. More specifically, the trade shock leads to an increase in labor demand in the industry directly affected by the shock, causing the industry to increase its workforce and consequently local labor market size (as long as local labor supply is not completely inelastic). In a labor market with search frictions and heterogeneous firms and workers, this increase in local labor market size may make worker-firm matches of other local industries more productive, as now a greater number of firms offer jobs and more workers search for employment in the local labor market (see e.g. Helsley and Strange (1990)). Knowledge spillovers might take place, as the greater demand for labor of the local industry directly affected by the trade shock increases worker flows and hence mobility across local industries. In addition, the increase in local labor market size brings new human capital and consequently new knowledge into the region. Formal and informal interactions among these individuals may then bring about sharing of this knowledge, generating positive production externalities (see e.g. Lucas (1988); Glaeser (1999); Serafinelli (2016)).

Furthermore, positive trade shocks to one industry can lead to cost advantages for other local industries through input-output relations. Upstream suppliers located in the same region are likely

---

9A notable exception is Dix-Carneiro and Kovak (2016), who show that the observed local adjustment processes following trade liberalization are driven by slow capital adjustment and agglomeration economies and who apply the method I develop in this paper for the estimation of agglomeration economies.

10A larger labor market may, in addition, provide insurance against idiosyncratic shocks for both firms and workers (see, for example, Krugman (1991) or Overman and Puga (2010)). Following an increase in local labor market size due to a trade shock, the likelihood that a firm cannot fill a vacancy following an idiosyncratic labor supply shock or a worker cannot find another job when her employer is hit by an idiosyncratic negative demand shock may hence be reduced.

8
to benefit more from the resulting product demand shock than suppliers in other regions because they can meet the increased demand for services and intermediate goods faster and more cheaply.

In the modeling framework below, I capture agglomeration effects in a simple, reduced form way through a local industry specific productivity shifter, which is assumed to be a function of employment in all local industries in the region. This captures the idea that knowledge spillovers and thick market externalities (and also transport costs) depend on the size of the local labor market.

3.2 A Model of Agglomeration Economies

I now outline a simple theoretical model incorporating localized spillovers between industries. From this model, I derive predictions on how trade shocks affect local industry employment in the presence of agglomeration economies, basing the empirical strategy on a theoretical background.

Set-Up and Baseline Equilibrium

The model economy is assumed to consist of many regions $r$ and many industries $j$. Each industry produces an industry specific good whose price $p_j$ is determined internationally and is hence assumed to be exogenously given.

In each industry, output ($Y_{jr}$) is produced according to a Cobb-Douglas production function using labor ($L_{jr}$), capital ($K_{jr}$), and a non-tradable resource ($\bar{R}_{jr}$):

$$Y_{jr} = A_{jr} L_{jr}^\alpha K_{jr}^{(1-\alpha)\mu} \bar{R}_{jr}^{(1-\alpha)(1-\mu)}$$

(3.1)

Firms choose labor ($L_{jr}$), capital ($K_{jr}$), which is fully flexible and provided at an internationally determined price $i$, and the amount of resources ($\bar{R}_{jr}$) used in production to maximize profits, taking local industry specific productivity ($A_{jr}$), output prices ($p_j$), non-tradable resource prices ($q_{jr}$) and local wages ($w_r$) as given. The non-tradable resource ($\bar{R}_{jr}$) is assumed to be fixed at the local industry level. Assuming that local industry production includes a fixed resource ensures that regions can compete for multiple industries despite differences in local industry productivity and is common in spatial equilibrium models incorporating multiple local industries (see, for example, Kline and Moretti (2014) or Hanlon and Miscio (2016)). Such a fixed resource can be thought of as fixed industry specific capital or some natural resource input.

I further assume that local labor supply is exogenously given by

$$\ln (L_r) = \frac{1}{\eta} \ln (w_r),$$

(3.2)

where $\eta$ is the inverse local labor supply elasticity. This elasticity measures the local employment response to local wage changes. If $\eta \to 0$ local labor supply is perfectly elastic and hence individuals

\[11\] Note, for simplicity, I assume wages are determined locally, implying that workers are perfectly mobile across industries within a location.
do not have preferences for regions; if $\eta > 0$ individuals have preferences for regions (or face migration costs).\footnote{If $\eta \to 0$, the spatial equilibrium condition implies that the utility of all individuals is equalized across local labor markets, if $\eta > 0$, only utility for the marginal individual in the region needs to be equalized across local labor markets.}

Note that for simplicity I abstract from housing prices, which also influence individual location decisions. I do, however, present an extension of the model that includes housing prices in Appendix B.4, which does not change the model’s key predictions.

In Appendix B.1, I show that in this model, under perfect competition, cost minimization implies that changes in local industry labor demand are given by

$$
dlnL_{jr} = \frac{1}{(1 - \alpha)(1 - \mu)} dlnp_j + \frac{1}{(1 - \alpha)(1 - \mu)} dlnA_{jr} - \frac{1 - \mu(1 - \alpha)}{(1 - \alpha)(1 - \mu)} dlnw_r. \quad (3.3)
$$

Below, I will use the model to analyze the effects of national industry trade shocks on local industry labor demand and equilibrium employment in the presence of agglomeration economies.

**Agglomeration Forces and the Indirect Impact of National Industry Trade Shocks**

I assume that agglomeration forces and hence localized spillovers between industries are captured by the local industry specific productivity shifter $A_{jr}$ and work through the size of employment in all industries in the local labor market. Specifying that agglomeration spillovers work through regional (or local industries’) employment is common in the literature and captures the idea that knowledge spillovers and thick market externalities depend on the size of the local labor market.\footnote{See, for example, Moretti (2011) or Hanlon and Miscio (2016).}

In particular, the local industry specific productivity shifter $A_{jr}$ is assumed to depend on local employment in the following way:

$$
ln(A_{jr}) = \lambda lnL_r \quad (3.4)
$$

$\lambda$ represents the agglomeration elasticity ($\frac{\partial lnA_{jr}}{\partial lnL_r} = \lambda$). The elasticity should be thought of as a reduced form parameter reflecting all three sources of agglomeration spillovers discussed in Section 3.1: thick market effects, knowledge spillovers, and input-output relations. It measures how strongly an increase in local employment affects productivity in industry $j$. I assume a constant agglomeration elasticity in order to keep the model derivations simple and to be able to derive intuitive model predictions. I will however derive a version allowing for heterogeneous agglomeration economies that are allowed to vary across industries in Appendix B.3 and will come back to discussing heterogeneous agglomeration economies further below in this section.

How then do national industry trade shocks affect local industry employment (and local wages)? National industry trade shocks constitute shocks to industry product demand. These shocks can affect local industry employment in two ways: directly through the own industry trade shock and
indirectly through agglomeration spillovers. Within the model, the impact of such shocks can be understood by analyzing how changes in goods prices \( p_k \) affect local industry employment.\(^{14}\) In what follows I examine the indirect effects of trade shocks, as this is the main focus of the paper.

Before analyzing the effects of trade shocks on equilibrium local industry employment (and wages), it is instructive to study how a trade shock to industry \( k \) and hence a change in the price of the good produced by industry \( k \), \( p_k \), affects local industry labor demand in industry \( j \). The effect of such a price change can be analyzed by rewriting equation (3.3) as a total derivative with respect to \( p_k \):\(^{15}\)

\[
\frac{d\ln L_{jr}}{d\ln p_k} = \frac{\lambda}{(1-\alpha)(1-\mu)} \frac{d\ln L_r}{d\ln p_k} + \frac{1-\mu(1-\alpha)}{(1-\alpha)(1-\mu)} \frac{d\ln w_r}{d\ln p_k}
\]

(3.5)

Equation (3.5) shows that changes in the price of the good produced by industry \( k \) will affect labor demand in industry \( j \) through two opposing effects: agglomeration spillovers (first term) and reallocation effects, that is endogenous wage adjustments (second term). If there are no agglomeration forces at play, that is \( \lambda = 0 \), a price increase in industry \( k \) will reduce labor demand in industry \( j \), as the first term is equal to 0 and hence local industry employment in industry \( j \) is only affected because the price increase in industry \( k \) raises local wages (second term) - the reallocation effect. However, in the presence of agglomeration spillovers (i.e. \( \lambda > 0 \)), increases in \( p_k \) can positively affect labor demand in industry \( j \) through the effect of an increase in \( p_k \) on local employment (first term). Yet this is only the case if the shock to industry \( k \)'s labor demand actually increases local employment, that is only if \( \frac{d\ln L_r}{d\ln p_k} > 0 \).

By substituting the function defining agglomeration economies (equation (3.4)) and the local labor supply function (equation (3.2)) into the local industry labor demand equation (equation (3.3)), it is possible to go one step further and derive expressions for equilibrium local employment changes in industry \( j \) as well as local wage changes that depend only on exogenous parameters and changes in goods prices, \( d\ln p_k \) (see Appendix B.2 for the derivation).\(^ {16}\)

\(^{14}\)Alternatively, one could study how changes in national industry specific productivity affect local industry employment. Bustos (2011) and Lileeva and Trefler (2010) have, for example, shown that market size matters for innovation and hence for productivity. In this case, it would be necessary to define \( \ln(A_{jr}) = \lambda \ln L_r + \ln A_j \), where \( A_j \) is a national industry specific productivity shifter. The predictions from the model would, however, stay the same.

\(^{15}\)In the model it is assumed that \( \frac{d\ln p_j}{d\ln p_k} = 0 \) for all \( k \neq j \). That is, prices are assumed to be exogenous and hence there are no indirect product demand shocks affecting prices in industry \( j \) after a shock to prices of industry \( k \). Yet, if industry \( j \) and \( k \) are related through input-output linkages, it is possible that industry \( k \) increases its demand for goods produced by industry \( j \) in response to a positive labor demand shock, and hence the increase in demand of goods produced by industry \( j \) affects national prices in industry \( k \). Additionally, national prices could be affected if goods \( j \) and \( k \) are substitutes. In the empirical specification, national industry x period fixed effects will account for these national indirect product demand shocks.

\(^{16}\)\( s_{kr} \) is defined as the initial share of industry \( k \) employment in region \( r \), that is \( s_{kr} = \frac{L_{kr}}{L_r} \).
\[ \frac{d\ln L_{jr}}{dp_j} = \frac{1}{(1-\alpha)(1-\mu)} \frac{d\ln \eta}{d\ln p_j} + \frac{\lambda - [1 - \mu(1 - \alpha)] \eta}{(1-\alpha)(1-\mu)\eta - \lambda + [1 - \mu(1 - \alpha)] \eta} \sum_k s_{kr} d\ln p_k \]

\[ d\ln w_r = \frac{\eta}{(1-\alpha)(1-\mu) - \lambda + [1 - \mu(1 - \alpha)] \eta} \sum_k s_{kr} d\ln p_k. \]

Equation (3.6) reinforces the predictions made above. Holding constant an industry's own price change (first term), in the absence of agglomeration forces (\( \lambda = 0 \)), when other industries in the region face positive price shocks (i.e. \( d\ln p_k > 0 \)), the reallocation effect reduces local employment in industry \( j \) (as long as \( \eta > 0 \)). However, when agglomeration economies are present (that is \( \lambda > 0 \)) and if they are sufficiently strong (that is \( \lambda > [1 - \mu(1 - \alpha)] \eta \)), then positive shocks to other industries may lead to increases in equilibrium employment of industry \( j \).

Equations (3.6) and (3.7) further show that the inverse of the local labor supply elasticity (\( \eta \)) determines how price shocks affect local wages \( w_r \) and the strength of the reallocation effect. If local labor supply is fully flexible (i.e. \( \eta \to 0 \)), local industry labor demand shocks will not affect regional wages \( w_r \) and hence there are no reallocation effects affecting local industry employment. In this case, holding constant an industry’s own price change, changes in local industry employment fully reflect changes due to agglomeration spillovers. If individuals are, however, not perfectly mobile across regions (\( \eta > 0 \)), then a positive local industry labor demand shock will affect local wages and employment.

**Empirical Predictions**

The model consequently leads to three main empirical predictions:

1. For positive agglomeration spillovers to take place after a shock to the prices of goods in the other industries in the region, the effect of a price shock to industry \( k \) on local employment must be positive, that is \( \frac{d\ln L_{jr}}{dp_k} > 0 \) (see equation (3.5)). This implies that local labor supply cannot be fully inelastic (see equation (B.12) in Appendix B.2).

2. If local labor supply is less than infinitely elastic, local wages should increase following a price shock to a local industry, that is \( \frac{d\ln w_r}{dp_k} > 0 \) (see equation (3.7)).

3. The overall effect of shocks to goods produced by other industries is ambiguous and depends on the strength of agglomeration forces and that of the reallocation effects, which affect local employment in industry \( j \) in opposite directions. However, if \( \frac{d\ln L_{jr}}{dp_k} > 0 \) then agglomeration forces must outweigh reallocation effects (see equations (3.5) and (3.6)).
Connection to Trade Shocks and Empirics

In the model, changes in prices are used to analyze how product demand shocks triggered by national industry trade shocks affect local industry employment. In the empirical estimation I will however exploit national industry trade shocks directly, analyzing the effects of changes in quantities instead of changes in prices. This allows to jointly capture all margins of reductions in trade barriers following trade integration such as tariff reductions, better bilateral relations, or increases in trust but also, for example, the elimination of barriers to foreign investment.

To reflect this, one can rewrite equation (3.6) as

\[
d\ln L_{jr} = \theta_{dir} \left( \text{TrShock}_{j} + \beta_{\text{empl}}^{\text{dir}} \text{TrShockIndir}_{jr} \right) + \frac{\rho}{\sum_k \theta_{k} \text{dlnp}_{k}},
\]  

(3.8)

where \( \theta_{dir} = \frac{1}{(1-\alpha)(1-\mu)} \) and \( \beta_{\text{empl}}^{\text{dir}} = \frac{1}{(1-\alpha)(1-\mu)} \left( \frac{\lambda(1-\mu)}{(1-\alpha)(1-\mu)} - \frac{\lambda}{(1-\alpha)(1-\mu)} \right) \theta_{dir}. \) \( \rho \) should be thought of as a scaling factor that translates changes in quantities into changes in prices. I define \( \rho \) in more detail in Section 6.3 when using the structure of the model to derive an estimate of the agglomeration elasticity \( \lambda. \) \( \text{TrShock}_{j} \) represents direct national industry trade shocks to industry \( j, \) while \( \text{TrShockIndir}_{jr} \) represents indirect exposure to the other local industries’ trade shocks, defined in more detail in Section 4.2 (equation (4.1)). Using this equation, one can then derive the empirical specification described in Section 4.2 (equation (4.3)).

Heterogeneous Agglomeration Economies

The model thus far assumes constant agglomeration economies. It is, however, likely that agglomeration economies vary across industries, as agglomeration forces should be particularly strong in industries that are economically close to one another. For example, knowledge spillovers or thick market effects may be stronger between industries that exchange more workers with each other, while cost advantages between industries may be stronger for industries with stronger input-output relations. It is also possible that only certain industries are able to generate spillover effects while others are not. In this case, it is necessary to define an agglomeration elasticity that is allowed to vary across industries depending on which industry is shocked (industry \( k \)) and which industry is indirectly affected by the shock (industry \( j \)).

In particular, to account for heterogeneous agglomeration economies, the local industry specific productivity shifter \( A_{jr} \) can be defined as depending on local industry employment in the following way:

\[
ln \left( A_{jr} \right) = \sum_k \left[ \lambda_{jk} ln \left( L_{kr} \right) \right]
\]  

(3.9)

Now, \( \lambda_{jk} \) represents the agglomeration elasticity between industries \( j \) and \( k \) (\( \frac{\partial ln A_{jr}}{\partial ln L_{kr}} = \lambda_{jk} \)) and is allowed to vary across industries. To be more precise, the elasticity now measures how strongly
an employment increase in industry $k$ affects productivity in industry $j$ (and vice versa) and hence represents the strength of agglomerative forces between industry $j$ and industry $k$.

In Appendix B.3, I present a version of the model that allows to derive equilibrium local industry employment changes even if agglomeration economies are, as assumed here, heterogeneous across industries, and show how to connect the derived expressions to the empirics.

4 Empirical Framework and Identification

The key econometric challenge in estimating agglomeration effects is distinguishing spillover effects from other factors jointly affecting employment in all industries in the region. The solution proposed in this paper is to use observed national industry level shocks affecting local industry labor demand that are not correlated with other region specific shocks. In the next section, I argue that national industry level trade shocks affecting local industries constitute such shocks and describe the specific shocks I exploit. In Section 4.2, I then outline the empirical strategy, describing in greater detail how I exploit these shocks to estimate agglomeration effects and address some challenges for identification.

4.1 Trade Shocks

The national industry shocks I exploit to identify agglomeration spillovers are shocks reducing trade barriers between Germany and China and Germany and Eastern Europe, which led to substantial increases in import competition and export product demand for many German industries.\(^{17}\)

China’s transition to a market oriented economy is well-documented in the literature (see, for example, Naughton (2007)). As described by Autor et al. (2013), this transition has involved substantial rural-urban migration, access for Chinese industries to foreign technologies, capital goods and intermediate inputs, and the possibility for multinational firms to operate in China. These factors, together with China’s WTO accession in 2001, have led to a considerable increase in the competitiveness of Chinese industries and given rise to a substantial increase in imports of Chinese goods by high income countries. Further, the increase in competitiveness has heightened demand of Chinese firms and consumers for high income country products, leading to substantial increases in such exports to China. As can be seen in the left panel of Figure 1, this is especially true in the case of Germany, one of the world’s largest exporters. Both German imports from and exports to China rose substantially between 1988 and 2008 from about 3.2 to 55 billion EUR (or 1700%) and from about 3.5 to 32 billion EUR (or 900%) respectively.

In the aftermath of the fall of the iron curtain in 1989, most Eastern European countries intensified economic relations with the West. In 1995, the Czech Republic, Hungary, Poland, Slovakia, Bulgaria, and Romania joined the WTO. At the same time, bilateral agreements with other Eastern European countries and Russia were established. The process culminated in the European Union

\(^{17}\)I define Eastern Europe as Bulgaria, Czechoslovakia, Hungary, Poland, Romania, the USSR and its successor countries.
accession of the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, and Slovakia in 2004 and Bulgaria and Romania in 2007. Because of Germany’s proximity to Eastern Europe, these intensified relations brought about substantial increases in both German imports from and exports to Eastern Europe (see Figure 1, right panel).

Both China’s transition to a market-oriented economy and the fall of the iron curtain can hence be seen as quasi experiments leading to substantial import and export shocks exogenously affecting labor demand in many German industries. These shocks are well-suited to estimating agglomeration spillovers, as they should not be correlated with other region specific shocks jointly affecting local employment in all industries in the region.

4.2 Empirical Strategy

I estimate agglomeration spillovers by relating changes in local industry employment to indirect exposure to the other local industries’ trade shocks. In what follows, I first explain how I construct the indirect trade exposure measure used to estimate agglomeration effects and then describe the main empirical specification. In Appendix A, I provide an example to give some intuition for the identification strategy.

Measuring Local Indirect Trade Exposure

I measure local indirect trade exposure as an industry $j$ worker’s exposure to the other local industries’ trade shocks. The measure is constructed in three steps.

First, as I exploit information on trade flows at the national industry level, I use a Bartik type approach attributing industry $k'$s national trade flows ($TrShock_{kt}$) to regions according to the local industry’s share on national industry employment ($L_k t / L_k t$):

$$TrShock_{krt} = \frac{L_{krt}}{L_{kt}} TrShock_{kt}.$$  

Second, to obtain a measure of indirect per worker exposure of industry $j$ workers to the industry $k$ trade shock, I normalize the local industry $k$ trade shock by industry $j$ employment. The local indirect trade shock of industry $k$ to a worker in industry $j$ in region $r$ is then given by

$$TrShock_{krt}^j = \frac{1}{L_{jrt}} \left( \frac{L_{krt}}{L_{kt}} TrShock_{kt} \right).$$

Because the measure is normalized by industry $j$ employment it is comparable across industries and regions of different sizes. The final step in constructing the baseline measure of industry $j$ local indirect per worker trade exposure is then to sum the local indirect trade shocks up over the other

---

18In addition Cyprus, Malta and Slovenia joined the European Union in 2004.
19An important assumption for the identification of spillover effects is thus that the local industry structure in the tradable sector at time $t$ is not correlated with future trade shocks. Further, accruing trade flows to local industries according to their national employment shares avoids endogeneity problems that arise when observing actual local industry trade flows.
local industries in the tradable sector excluding the own industry trade shock, that is over industries \(k \neq j\), such that:

\[
TrShockIndir_{jrt} = \sum_{k \neq j} \frac{1}{L_{jrt}} \left( \frac{L_{krt}}{L_{kt}} TrShock_{kt} \right). \tag{4.1}
\]

In practice, the national industry trade shocks I exploit (i.e. \(TrShock_{kt}\)) are net trade shocks \((\Delta Net_{kt}^{GER})\) that stem from the trade integration of China and Eastern Europe. These net trade shocks are defined as the difference between changes in German exports to and imports from China and Eastern Europe (i.e. \(\Delta Net_{kt}^{GER} = \Delta Exp_{kt}^{GER} - \Delta Imp_{kt}^{GER}\)). The baseline measure of local indirect per worker trade exposure is then given by

\[
TrShockIndir_{jrt} = \Delta NetIndir_{jrt} = \sum_{k \neq j} \frac{1}{L_{jrt}} \left( \frac{L_{krt}}{L_{kt}} \Delta Net_{kt}^{GER} \right) \tag{4.2}
\]

and measures by how much a worker in industry \(j\) is affected by the net trade shocks to the other industries in the region.\(^{20}\)

A concern with this baseline measure of indirect trade exposure may be that the start of period local industry employment shares could be correlated with future trade shocks. In Appendix C.2, I provide a robustness check where employment levels used to distribute national industry trade flows to the local industries are the 1988 employment levels in all periods, and indirect trade exposure is normalized by the 1988 employment of the industry under observation to account for this concern. This has little impact on the findings.

**Empirical Specification**

To estimate agglomeration spillovers I then relate local industry employment in industry \(j\) and region \(r\) to the local indirect trade shock of industry \(j\) in region \(r\). The most parsimonious specification sticks closely to the equation that relates local industry equilibrium employment changes to national industry trade shocks derived in the model of agglomeration economies presented in Section 3.2 (equation (3.8)):

\[
\Delta \ln (L_{jrt}) \cdot 100 = \theta_{dir} TrShock_{jt}^{norm} + \beta_{indir} TrShockIndir_{jrt} + \nu_{jrt} \tag{4.3}
\]

\(\Delta \ln (L_{jrt})\) measures log changes in local industry employment from period \(t\) to \(t + 1\) (in practice \(t\) to \(t + 1\) will span a seven-year period). \(TrShock_{jt}^{norm}\) measures direct trade exposure per worker \((\frac{TrShock_{jt}}{L_{jlt}})\) and \(TrShockIndir_{jrt}\) measures indirect local industry trade exposure per worker as defined above. The parameter of interest is \(\beta_{indir}\). It measures the joint effect of agglomeration spillovers and reallocation effects. In the baseline specification, I only estimate a single parameter

\(^{20}\)I use indirect net trade exposure instead of indirect export and import exposure separately because these measures are highly correlated, with a correlation of about 0.94.
capturing average spillovers across industries. I relax this assumption in Section 6.2.2 when looking more closely at the mechanisms driving spillover effects, and in Section 6.2.3 when analyzing heterogeneities across industries.

Step by step, I then add further control variables, which may prove empirically necessary. First, I replace the \( \text{direct per worker trade exposure measure} (Tr\text{Shock}_{jt}^{norm}) \) with national industry x period fixed effects at the 3-digit industry level \( (\theta_{jt}) \). Hence, this specification exploits within industry variation in indirect trade exposure across regions. The national industry x period fixed effects now implicitly control for \text{direct per worker trade exposure}, but also for all other time varying national industry shocks such as, for example, indirect national product demand shocks to linked industries.

In the next step, I add both the initial share of tradable employment in the region \( \left( \frac{L_{Trad,rt}}{L_{rt}} \right) \) and the initial share of industry \( j \) employment \( \left( \frac{L_{jrt}}{L_{rt}} \right) \) as additional controls. These are necessary because the variation in the measure of indirect trade exposure can come from two sources: differences in the overall regional employment share of the other tradable sector industries (i.e. \( \frac{L_{Trad,Other,rt}}{L_{rt}} \)) and differences in initial local industry composition of the other industries within the tradable sector. Controlling for both the initial share of tradable employment and the initial share of industry \( j \) employment ensures that the within industry variation in indirect trade exposure across local labor markets that I exploit comes only from the initial industry composition of the other tradable sector industries in the region.\(^{21}\)

Lastly, I add an additional set of time varying local industry and regional characteristics \( X_{jrt} \), such as regional and local industry skill shares (low, medium, and high skilled), period x federal state fixed effects (10 federal states in West Germany), and the share of female and foreign workers in the region, such that

\[
\Delta \ln \left( L_{jrt} \right) \times 100 = \beta_{indir} Tr\text{Shock} Indir_{jrt} + \theta_{jt} + \pi_1 \frac{L_{Trad,rt}}{L_{rt}} + \pi_2 \frac{L_{jrt}}{L_{rt}} + \pi_3 X_{jrt} + \nu_{jrt}. \quad (4.4)
\]

This represents the main specification. It relates local industry employment in industry \( j \) and region \( r \) to the local indirect trade shock to industry \( j \) in region \( r \), keeping own industry and tradable sector size constant and exploiting within industry variation in indirect trade exposure across local labor markets.\(^{22}\)

**Estimation Method - Two Stage Least Squares**

A concern for identification is that it is not China and Eastern Europe specific factors that drive increases in trade flows between Germany and these countries, but unobserved factors within Ger-

\(^{21}\)A concern may be that the start of period employment shares are endogenous in the later periods. To account for this, I provide a robustness check in Appendix C.2 where I control instead for the 1988 shares in all periods. This has little impact on the effects.

\(^{22}\)The results are robust to controlling for commuting zone x period fixed effects instead of federal state x period fixed effects (see Appendix C.2).
many. A positive product demand shock for goods of a certain industry might, for example, be positively correlated with both increases in imports of the good from China and Eastern Europe, as with employment in that industry. This would understate the true impact of import shocks. Further, a positive technological shock to a certain German industry could increase demand for its goods in China and Eastern Europe. At the same time, industries with a strong export demand shock from China and Eastern Europe might be those doing less well otherwise. For instance, industries experiencing a decline in domestic (or world) product demand or reduced labor demand. While the former would overstate the effect, the latter would again lead to a downward bias. To account for these unobserved German specific factors, I follow Autor et al. (2013) and employ an instrumental variable strategy instrumenting German trade flows with trade flows of other high income countries with China and Eastern Europe:

\[
TrShockIndir_{jrt}^{IV} = \sum_{k \neq j} \frac{1}{L_{jr,t-1}} \left( \frac{L_{kr,t-1}}{L_{k,t-1}} TrShock_{kt}^{Other} \right)
\]

(4.5)

Note that I additionally use lagged employment instead of start of period employment when constructing the measure. This helps alleviate two further concerns. First, contemporaneous employment might already be affected by anticipated trade with China and Eastern Europe. Second, by shifting the normalization one period back, I avoid issues related to using start of period employment on both sides of the estimation equation in the second stage.

More particularly, indirect net trade exposure is instrumented using import and export shocks of other high income countries separately, where

\[
\Delta ExpIndir_{jrt}^{IV} = \sum_{k \neq j} \frac{1}{L_{jr,t-1}} \left( \frac{L_{kr,t-1}}{L_{k,t-1}} \Delta Exp_{kt}^{Other} \right)
\]

\[
\Delta ImpIndir_{jrt}^{IV} = \sum_{k \neq j} \frac{1}{L_{jr,t-1}} \left( \frac{L_{kr,t-1}}{L_{k,t-1}} \Delta Imp_{kt}^{Other} \right).
\]

(4.6)

Consequently, the first stage regression corresponding to the main specification (equation (4.4)) is

\[18\]

\[23\] This refers to unobserved factors correlated with the industry \( k \) direct trade shock and hence indirectly affecting industry \( j \). Correlation of the indirect trade shocks with unobserved factors affecting industry \( j \) employment would need to be within industry and across local labor markets. It is, however, unlikely that local industry region specific shocks are correlated with the indirect trade shocks created using the national industry direct trade shocks.

\[24\] I use the full set of high income countries used in Autor et al. (2013) and Dauth et al. (2014), excluding Japan. The countries are listed in Appendix Table C1. Dauth et al. (2014) exclude Denmark and Switzerland as they are neighboring countries, as well as Finland and Spain because they are in the Eurozone. I prefer to include these countries in the main specification as their trade exposure with respect to Eastern Europe should arguably be more similar to Germany than, for example, that of New Zealand or Singapore. Japan is, however, excluded as it would otherwise dominate the instrument and as Japanese industries are likely to be in high export competition with German industries. Consequently, the correlation in exports to China and Eastern Europe between Germany and Japan is likely to understate the true correlation and could lead to an underestimation of the spillover effect. I perform extensive robustness checks - excluding certain sets of instrument countries and including Japan - in Appendix C.2.
given by

\[ \text{TrShockIndir}_{jrt} = \beta_{\text{Exp}}^F S \Delta ExpIndir_{jrt}^{IV} + \beta_{\text{Imp}}^F S \Delta ImpIndir_{jrt}^{IV} + \theta_{jrt}^F S + \pi_1^F S \frac{L_{\text{Trad} jrt}}{L_{jrt}} + \pi_2^F S \frac{L_{jrt}}{L_{rt}} + \pi_3^F S X_{jrt} + \nu_{jrt}^F S \]  

(4.7)

where \( \text{TrShockIndir}_{jrt} \) is defined as in equation (4.2) as net indirect trade exposure (\( \Delta NetIndir_{jrt} \)).

I use the import and export shocks separately as instruments, as this is less restrictive and exploits more of the variation in the trade shocks than the net measure. These measures are, however, highly correlated, with a correlation of about 0.92 between \( \Delta ExpIndir_{jrt}^{IV} \) and \( \Delta ImpIndir_{jrt}^{IV} \) (0.94 between \( \Delta ExpIndir_{jrt} \) and \( \Delta ImpIndir_{jrt} \)), which is why I turn to using net indirect trade exposure in the second stage.

The instrumental variable strategy then identifies spillover effects due to Chinese and Eastern European specific factors, if the unobserved shocks are not correlated across high income countries due to, for example, a world trade demand shock. In Appendix C.2, I provide a robustness check controlling for changes in German world trade to control for potentially correlated shocks across high income countries. This has little impact on the results.

5 Data Sources and Descriptive Overview

5.1 Data Sources

For the empirical analysis I combine data from two sources: German social security records and the UN Comtrade database. Data from the social security records provides information on local labor market outcomes. In particular, I use aggregated data on 3-digit industry x commuting zone level for the years 1978 to 2008. The underlying data comprise the whole population of workers covered by the social security system in Germany.\(^{25}\) I reweight information on employment at the individual level into full-time equivalent units giving a weight of 0.6 (0.3) to part-time employed individuals that work 18 to 30 hours (less than 18 hours) and exclude marginal employment. Employment is measured at the 30th of June of each year. That is, I observe full-time equivalent employment aggregated on the 3-digit industry x commuting zone level as of the 30th of June of a given year. Furthermore, the data contains information on skill group shares (low-, medium-, high-skilled), age groups (16-25, 26-50, and 51-65), the share of female and foreign workers, and average wages in these cells. The underlying individual wage observation includes the average daily wage of the employment spell containing the 30th of June and is right censored at the social security limit. Before aggregating, wages are first deflated to 1995 prices. Right censored wages are then imputed assuming that the error term in the wage regression is normally distributed and allowing for separate variances by commuting zone, year, and gender. For data confidentiality reasons, I only observe

\(^{25}\)It does not, however, include the self-employed, civil servants, or military personnel. In 1995, 79.5% of workers in West Germany were covered by the social security system (according to the Federal Labor Office - Bundesagentur fuer Arbeit).
information on the 3-digit industry x commuting zone cells if these cells contain at least 20 individual observations, thus observing about 96.9 percent of total social security covered employment.

In addition, I merge information on land prices at the commuting zone level to the social security data. This data comes from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) and reflects purchase prices for building land.

Information on imports and exports comes from the UN Comtrade database, which records trade flows between countries for a very large number of reporter countries, amongst them all countries used in this analysis. The trade flow information is available on a detailed commodity level. I use the SITC3 classification at the 4-/5-digit level.\textsuperscript{26} The total number of commodities at the 4-digit level in the SITC3 classification that is either imported or exported by German industries is 1,031.

I merge the local industry labor market data to the trade flow data using correspondence tables between the SITC3 4-/5-digit commodity level and NACE1 3-digit industries.\textsuperscript{27} I drop all industries related to fuel, oil, and gas, as these have high price fluctuations. In what follows, the tradable sector is defined as all remaining 3-digit industries with world exports higher than 50 Million EUR in 1988. In total these are 102 industries. All other industries are defined as non-tradable.\textsuperscript{28} The main analysis is conducted with tradable industries only.

5.2 Estimation Sample and Descriptive Overview

In this section, I further describe how the estimation sample is constructed and provide some summary statistics describing the data.

As the fall of the iron curtain started in 1989 and China’s transition into a market-oriented economy started in the 1990s, I follow Dauth et al. (2014) and use observations from 1988 to 2008 such that the analysis period begins shortly before the fall of the iron curtain. I fit three 7-year equivalent periods into that time span: 1988 to 1995, 1995 to 2001, and 2001 to 2008.\textsuperscript{29} The first year of a period corresponds to $t$ and the last to $t + 1$. Lagged employment ($t − 1$), which is used for constructing the instrumental variables is 1981, 1988 and 1995 respectively.

The main part of the empirical analysis focuses on West Germany, as employment data for East Germany is only reliably available from 1993 onwards. Furthermore, I expect German national industry trade flows to better predict West German local trade flows as these make up more than 90\% of total German flows (German Federal Statistical Office (2014)). I examine spillover effects within commuting zones. Commuting zones are defined on the basis of commuter flows implying that

\textsuperscript{26} As SITC3 classification data for the US and Singapore is only available from 1989 onwards, I use the 1989 data for these two countries.

\textsuperscript{27} I use correspondence tables from the world bank. These are very similar to the tables used in Dauth et al. (2014) but additionally provide information on the 5-digit SITC level for a subset of commodities. I also reestimate the results using the correspondence tables from Dauth et al. (2014). These are very similar.

\textsuperscript{28} The non-tradable sector consequently also includes tradable services.

\textsuperscript{29} The results do not depend on the choice of periods and are very similar when fitting two 10-year periods as in Dauth et al. (2014). However, due to the fact that industries with high indirect trade exposure are rather negatively selected as shown below, I prefer fitting more periods as this controls more flexibly for other changes in regional and industry level characteristics.
at least 65% of individuals living in the commuting zone must be employed in the same commuting zone and travel times within the zone cannot exceed 45 minutes. There exist 204 commuting zones in West Germany, with an average employment level of about 95,000 in the data. As in some commuting zones employment in the tradable sector is dominated by a single industry (or firm), I drop the regions with the highest 3 percent share of a single industry on employment in the tradable sector in 1988. These are regions with a single industry accounting for more than 52% of local employment in the tradable sector. The sample consists of the remaining 198 commuting zones.

Summary statistics on local industry characteristics and indirect trade exposure measures are presented in Table 1. First, it should be highlighted that tradable employment in Germany decreased considerably in the period from 1988 to 2008. In each of the three 7-year periods, average local log industry employment in the tradable sector decreased by about 0.16 log points (see Table 1, Panel A). Furthermore, the employment share in the tradable sector declined over time, suggesting that some of the employment loss in the tradable sector is absorbed by the non-tradable sector and that the average local industry employment decline across all sectors is lower.

Panel B of Table 1 presents summary statistics on the measures of indirect per worker trade exposure. These are constructed as described in Section 4.2, equation (4.1), and measured in 1 million EUR per worker. Both indirect import and export exposure to trade shocks from Eastern Europe and China grow considerably over time, mirroring the picture of total national imports and exports in Figure 1. In the first two periods (1988 to 1995 and 1995 to 2001), indirect import and export exposure both grow at a similar level, implying that average indirect net trade exposure per worker is about 0. There is also, however, variation in net trade exposure in these two periods. In the last period from 2001 to 2008, indirect export trade shocks then outweigh indirect import trade shocks, leading to an indirect per worker net trade shock of about 0.25 per 1 million EUR. Furthermore, indirect trade exposure from trade shocks to other industries within the same sector amounts, on average, to about one third of the total tradable sector trade exposure. This is about the same proportion as the average share of same sector employment on employment in the other tradable industries in the region.

Figure 2 more closely examines variation in indirect per worker net trade exposure within 3-digit industries (and across commuting zones). The figure plots, for each 3-digit industry, the mean +/- the standard deviation of the residual of a regression of indirect per worker net trade exposure on period fixed effects and tradable and own industry employment shares. In this exercise, variation in indirect net trade exposure consequently comes only from differences in the local industry composition of the other tradable sector industries in the region. The figure shows considerable variation in

---

30 This drops commuting zones that include the district of Wolfsburg, where the car manufacturing industry makes up 86% of tradable employment, and that of Leverkusen, where the basic chemical manufacturing industry makes up 74% of tradable employment. This does not affect the spillover effects results presented in Section 6.2, but does affect the local employment effects estimated in Section 6.1. Dauth et al. (2014) instead control for the car manufacturing share in the region, which leads to similar results.

31 The average percentage employment decline is about 8%.
indirect per worker trade exposure across commuting zones for basically all of the 3-digit industries. This is important for the estimation of spillovers as identification in the main empirical specification (equation (4.4)) comes from within industry variation in indirect per worker trade exposure across commuting zones.

A concern with using within industry variation to identify spillover effects is that an industry (with a certain 3-digit code) located in a region with high indirect per worker net trade exposure might differ substantially in terms of its industry (and region) characteristics – for example in local skill structure or productivity – from an industry with the same 3-digit code located in a region with low indirect per worker net trade exposure. Consequently, this industry could potentially experience an employment increase due to some favorable local industry characteristics, and not because of agglomeration spillovers from trade shocks to other local industries. However, there are several points that alleviate this concern. First, the 3-digit industry level is a relatively detailed classification, such that it can be expected that these industries produce very similar goods. Second, to further dispel doubts that industry selection might cause local industry employment growth and not agglomeration spillovers, in Table 2 I present average industry characteristics for the whole sample, as well as for six further categories: industry observations with indirect net trade exposure below the 1st percentile, between the 1st and the 25th percentile, between the 25th and the 50th percentile, between the 50th and the 75th percentile, between the 75th and the 99th percentile, and above the 99th percentile. The percentile measures are constructed within 3-digit industries and period and are employment weighted; that is within percentile groups, the number of individuals employed is the same. Table 2 does not reveal a clear pattern in industry characteristics across percentile groups. Focusing on the groups between the 1st and the 99th percentile (columns (3) to (6)), industries with higher indirect trade exposure seem, if at all, to be negatively selected, as they have a lower average wage and a lower share of high-skilled workers. However, the differences in average wage and high-skill share are not statistically significant with respect to any of the other groups within the 1st and 99th percentile. The industry observations in the lowest and highest percentile of indirect trade exposure seem, however, to be negatively selected: their average wage and share of high-skilled workers is considerably lower than in the other groups. To account for this, in Appendix C.2 I provide a robustness check that estimates spillover effects excluding observations in the lowest and highest percentile of indirect net trade exposure. This robustness check leads to slightly increased, but generally similar, effects of indirect trade exposure on local industry employment.

\[32\] The instrumental variable strategy does not account for this kind of correlation. It only accounts for correlation of the direct shock with other German specific factors affecting industry employment in the industry affected by the direct shock and consequently indirectly affecting employment in the other local industries through spillovers.
6 Empirical Results

6.1 Direct and Local Employment Effects of Trade Shocks

I begin the empirical analysis by examining whether direct effects from trade shocks exist and whether the joint regional trade shocks affect local employment, wages, and land prices. Analyzing these effects is important, as both a positive impact of trade shocks on employment in the industry directly affected by the trade shock and on local employment are important preconditions for the observation of agglomeration effects following national industry trade shocks. This is because agglomeration spillovers due to thick market effects or increased knowledge exchange are expected to arise from increases in local labor market size due to the industry directly affected by the shock expanding employment (see Section 3.1 and Section 3.2).

The direct effects are estimated based on equation (4.4) (and using 2SLS), but replacing indirect net trade exposure by the direct national per worker trade shock of industry \( j \), \( \Delta Net^{GER}_{jt} / L_{jt} \) (measured in 1,000 EUR per worker).\(^{33}\) This measure does not vary within 3-digit industry and thus these regressions do not include national industry x period fixed effects. The results are shown in Table 3, columns (1) and (2). Column (1) reports the effects of the direct trade shock on local industry employment. An increase in the national direct per worker trade shock of 1,000 EUR increases local industry employment by 0.45 percentage points. Direct trade exposure did not, however, affect local industry wages (column (2)).

For the estimation of regional effects, I follow the literature estimating local employment effects of globalization using trade shocks, and construct the regional measure by summing up the local trade shocks across all local industries (including industry \( j \)), normalizing the measure by overall local employment \( L_{rt} \), that is \( \Delta Net^{GER}_{rt} = \sum_k L_{rt} / L_{kt} \Delta Net^{GER}_{kt} \) (measured in 1,000 EUR per worker). This measure consequently represents regional per worker trade exposure to the joint trade shocks of all local industries. The specification is otherwise the same as for the estimation of direct effects in columns (1) and (2), Table 3. That is, the estimation of local effects does not include national industry x period fixed effects. Column (3), Table 3, shows that a 1,000 EUR increase in the regional per worker trade shock leads to an increase in local industry employment of about 2.21 percentage points, but does not affect local wages or land prices.\(^{34}\)

Having established that (positive) trade shocks positively affect local industry employment in the industry directly affected by the trade shock and increase local labor market size, in the next section I analyze whether, as a consequence, agglomeration spillovers to other local industries in the region arise.

\(^{33}\)Direct effects of trade shocks on employment at the national industry level have previously been estimated by Acemoglu et al. (2015) and Pierce and Schott (2016). Both studies find significant direct effects of trade shocks on national industry level employment.

\(^{34}\)Both the direct effects estimates and the estimates of local employment effects are robust to the inclusion of sector x period fixed effects (distinguishing between 17 sectors).
6.2 Agglomeration Spillovers from Trade Shocks

In the following sections, I present evidence for the existence of agglomeration spillovers triggered by national industry trade shocks. I start by examining the effects of local indirect per worker trade shocks on tradable sector industries. I then further analyze how economic proximity affects the strength of spillovers between industries and analyze heterogeneities across industries.

6.2.1 Baseline Results

In this section, I show estimates of spillover effects from trade shocks based on variants of the two stage least squares model presented in Section 4.2, instrumenting trade exposure of German industries with that of other high income country industries. I start with the most parsimonious specification derived from the model of agglomeration economies presented in Section 3.2 and then go step by step adding control variables to gauge their impact. The sample consists of all tradable sector industries. Spillovers are assumed to be constant and symmetric across industry pairs, that is \( \lambda_{jk} = \lambda \forall j, k \).

The results are presented in Table 4. The specification in column (1) mirrors the specification derived from the model of agglomeration economies presented in Section 3.2. It includes the variable of interest, that is indirect net trade exposure \( (\Delta NetIndir_{jrt}) \), and the direct trade shock at the national industry level \( (TrShock_{jt}^{norm}) \) to account for the possibility that direct and indirect trade shocks may be correlated. The coefficient of 2.54 percentage points per 1 million EUR increase in indirect net trade exposure indicates a significant positive relationship between changes in local industry employment and indirect trade exposure, in line with the presence of agglomeration economies. Column (2) replaces the direct trade shock control by national industry x period fixed effects. This specification additionally controls for possible national indirect product demand shocks and other time varying national industry trends affecting local employment of industry \( j \) and hence identifies spillovers from within industry variation across local labor markets. This more than doubles the effect, which rises from 2.54 to 5.88 percentage points per 1 million EUR increase in indirect net trade exposure, indicating that (national) industries with on average higher indirect trade shocks faced negative employment trends and would have adjusted employment downwards if it had not been for the positive effects of the indirect trade shocks. Column (3) adds the tradable and own industry employment shares to ensure that variation in indirect trade exposure comes only from differences in the initial industry composition of the other tradable industries in the region and not from differences in the regional employment share of these industries. This only slightly increases the coefficient to 6.63 percentage points, which suggests that a large share of the variation in the indirect trade exposure measure stems from variation in initial industry composition. In column (4), results of the main baseline specification (equivalent to equation (4.4)) are presented. The specification adds further control variables, including federal state x period fixed effects, the local industry, and regional skill shares (low-, medium-, and high-skilled), as well as the share of female and foreign workers in the region to control for local characteristics that might be correlated
with indirect trade exposure and potentially affect employment growth. This slightly increases the coefficient to 7.75 percentage points per 1 million EUR increase in indirect net trade exposure, reinforcing the impression from Table 2 that local industries with higher indirect trade exposure are rather negatively selected. A coefficient of 7.75 implies that local industry employment increased on average by about 1.94 percentage points due to indirect trade exposure in the tradable sector in the period from 2001 to 2008 (indirect net trade exposure increased by 0.25 million EUR per worker in that period).

For comparison, the OLS results from estimating equation (4.4) without instrumenting indirect net trade exposure are presented in column (5). While the OLS results are still significantly positive, the coefficient is considerably smaller. One explanation for the difference between the OLS and 2SLS results is that positive technology shocks to German industries might increase demand for intermediate goods used as inputs by these industries, thus increasing imports from China and Eastern Europe independently of the increase in exposure to import competition from these countries. This would lead to downward biased OLS estimates. Secondly, industries that are more strongly affected by positive (net) trade shocks from China or Eastern Europe are industries that otherwise do less well due to, for example, a decline in domestic (or world) product demand. The substantial increase in the estimated effects when moving from the specification controlling for the direct trade shocks (column (1), Table 4) to the specification controlling for national industry x period fixed effects (column (2), Table 4) seem to confirm the existence of a strong negative correlation between the direct trade shocks and other factors affecting employment. Car manufacturing provides an example of an industry experiencing such negative demand conditions outside of China and Eastern Europe. The industry faced a decrease in domestic demand for cars, implying employment reductions, while at the same time the demand shock for German cars in China (and Eastern Europe) was one of the largest export demand shocks to a German industry stemming from the trade integration of China and Eastern Europe.\footnote{A further explanation for the difference in OLS and IV estimates may be that the impact of trade shocks on local industry employment is heterogeneous across industries. The fact that the IV results are estimated more precisely than the OLS results indicates that heterogeneous effects may be present in this setting.}

I demonstrate that the findings presented in this section are robust to adding commuting zone x period fixed effects, to adding controls for pre-trends in local industry employment or the change in net world trade, to normalizing indirect trade exposure by 1988 instead of start of period employment, and to trimming the top and bottom 1% of indirect trade exposure observations. I further show in Appendix C.3 that the results I find cannot be explained by a search and bargaining model as proposed in Beaudry et al. (2012).

What do we learn from the results presented here about the general application of the approach in other settings (i.e. when analyzing spillover effects of different types of national industry shocks)? I argue that researchers applying the approach provided here should proceed along similar lines, starting with the most parsimonious specification that only controls for direct trade shocks. However, they should then carefully gauge whether the inclusion of national industry x period fixed

\footnote{A further explanation for the difference in OLS and IV estimates may be that the impact of trade shocks on local industry employment is heterogeneous across industries. The fact that the IV results are estimated more precisely than the OLS results indicates that heterogeneous effects may be present in this setting.}
effects or other local or local industry-specific characteristics matter for the size of the effects. The results presented from the specific application used in this paper suggest that accounting for national industry time trends by including national industry x period fixed effects at the 3-digit industry level is of particular importance. Consequently, it is likely that in other settings as well the preferred approach will be to relate changes in local industry employment to indirect exposure to the other local industries’ (national) shocks exploiting within industry variation in indirect exposure across local labor markets.

6.2.2 Economic Proximity and Sources of Agglomeration Spillovers

The indirect trade exposure measure defined over all other tradable industries’ trade shocks is arguably a very coarse measure. This is especially true in light of the mechanisms leading to agglomeration spillovers described in Section 3.1, which indicate that economically close industries should be more greatly affected by indirect trade exposure, as spillovers between these industries are stronger. In this section, I analyze the importance of economic proximity between industries for the existence of agglomeration spillovers.

I start by decomposing the indirect trade exposure measure into indirect trade exposure from other industries in the same sector versus indirect trade exposure from industries in the other tradable sectors, distinguishing between 6 broad sectors within the tradable sector (that is $\Delta NetIndir_{jrt} = \Delta NetIndir^{Same}_{jrt} + \Delta NetIndir^{Other}_{jrt}$). This implies that I now allow the agglomeration elasticity to differ between industries in the same sector as industry $j$ and industries in other sectors, such that $\lambda_{jk} = \lambda_{., same}$ if industries $j$ and $k$ are in the same sector and $\lambda_{jk} = \lambda_{., other}$ if industries $j$ and $k$ are in different sectors. As industries in the same sector are likely to be economically closer to each other, one would expect that $\lambda_{., same} > \lambda_{., other}$. The results in Table 4 confirm this. Column (6) estimates the main specification including both regional controls and industry x period fixed effects (equivalent to the tradable sector specification in column (4)). The coefficient on the same sector measure indicates a positive employment spillover from indirect trade shocks to other industries in the same sector of 12.86 percentage points per 1 million EUR indirect per worker trade exposure. In contrast, spillovers from other tradable sector industries outside of the same sector are still positive, but with an employment increase of 5.08 percentage points per 1 million EUR indirect per worker trade exposure, about 2.5 times smaller than the spillovers from trade shocks in the same sector. This is a first indicator that economic proximity between industries is important for the existence of agglomeration spillovers between industries. But what are the mechanisms behind these spillovers? Do industries rather benefit from being located close to one another if they are connected through vertical linkages? Or do industries connected through the sharing of a common labor force benefit more, as they can benefit from better matches through thick labor market effects or from knowledge spillovers due to increased worker mobility across industries both within and across regions?

36More specifically, these six sectors are: the agricultural sector, the energy and mining sector, the food industry sector, and three manufacturing sectors (manufacturing of consumer products, manufacturing of producer goods, and manufacturing of investment goods and durables).
To investigate this question, I create three measures of economic proximity and use these measures to reweight the strength of trade shocks from other local industries. The first proximity measure is based on worker flows between industries and is calculated as the maximum of the share of workers leaving industry $j$ and moving to industry $k$ and the share of workers leaving industry $k$ and moving to industry $j$ over a 5-year window from $t - 5$ to $t$. This measure gives a higher weight to indirect shocks from industries with increased worker exchange or similar worker requirements as industry $j$ ($w_{jkt}^{\text{worker}}$). The other two measures reflect proximity through input-output linkages and are computed using German input-output tables from 1995, which are available at the 2-digit industry level. The first input-output measure is calculated as the share of goods produced in industry $k$ that is sold to industry $j$. It gives a higher weight to the indirect trade shock from industries that are upstream suppliers to industry $j$ ($w_{jk}^{\text{up}}$). The second input-output measure is calculated as the share of goods produced in industry $j$ that is sold to industry $k$. Consequently, this measure gives a higher weight to indirect trade shocks from industries that are downstream customers of industry $j$ ($w_{jk}^{\text{down}}$). The new rescaled indirect trade exposure measures accounting for economic proximity between industries are then given by

$$
\Delta \text{NetIndir}_{jrt}^{\text{prox}} = \sum_{k \neq j} \frac{1}{I_{jrt}} \left[ w_{jkt}^{\text{prox}} \left( \frac{L_{krt}}{I_{kt}} \Delta \text{TrShock}_{kt} \right) \right],
$$

(6.1)

where $w_{jkt}^{\text{prox}}$ represents the three rescaling measures $w_{jkt}^{\text{worker}}$, $w_{jk}^{\text{up}}$ and $w_{jk}^{\text{down}}$.\footnote{This implies that the agglomeration elasticity is now assumed to be given by $\lambda_{jk} = \lambda_{\text{prox}} w_{jk}^{\text{prox}}$, where prox represents the corresponding economic proximity measure.}

In Table 5, I present results from estimating equation (4.4), but adding the reweighted version of the respective proximity measures, $\Delta \text{NetIndir}_{jrt}^{\text{prox}}$, to the regression. These measures are standardized to have mean 0 and standard deviation 1.\footnote{In these regressions the baseline measure $\Delta \text{NetIndir}_{jrt}$ is also normalized to have mean 0 and standard deviation 1.} In columns (1) to (3), the effects of the rescaled indirect trade exposure measures are estimated one by one. In column (4), equation (4.4) is estimated including all three rescaled indirect trade exposure measures jointly, hence accounting for possible correlations across the three measures. The results indicate that agglomeration spillovers from trade shocks predominantly take place between industries that exchange more workers with one another (columns (1) and (4)), while input-output relations seem to matter less (columns (2), (3) and (4)).\footnote{It is unlikely that the slightly positive spillover effect triggered by trade shocks to upstream suppliers can be attributed to product demand shocks. Following an import shock to the upstream supplier, the industry under observation should rather benefit from reduced prices (see e.g. De Loecker et al. (2016) or Goldberg et al. (2010)), while an export shock to the upstream supplier potentially leads to an increase in the prices of the good the upstream supplier is producing and hence should reduce the industry’s demand for this good. Both mechanisms should negatively affect the coefficient of indirect net trade exposure to shocks from upstream suppliers.} When using 2-digit input-output tables to analyze the effects on vertically linked industries, part of the variation in input-output linkages might be missed. Unfortunately, in Germany input-output tables at a finer level do not exist. Instead, in Appendix C.4, I repeat the exercise using US input-output tables at the 3-digit industry level as a proxy. The estimated results are
very similar to those in Table 5.

The results in both Table 5 and Appendix Table C4 indicate that increased worker exchange between industries is important to create spillovers from trade shocks. This is particularly remarkable as the reallocation effect in response to a positive trade shock to an industry with similar worker requirements should also be stronger. It is, however, in line with the recent findings of Greenstone et al. (2010). Larger spillovers between industries with increased worker exchange on the one hand indicate that thick labor market effects are an important driver of spillover effects, as industries with increased worker exchange have similar worker requirements. Hence, an increase in the size of one industry due to a positive net trade shock positively affects the available labor pool for the other industry, potentially leading to an improvement in the quality of worker-firm matches. On the other hand, the inflow of new human capital into the region, and a higher level of worker mobility within the region as a consequence of the expansion of employment in the industry hit by the positive trade shock, can imply a higher level of knowledge exchange and increase productivity in industries exchanging workers with that industry.

6.2.3 Heterogeneities across Industries: High versus Low Technology Industries

In the previous two sections, I showed that national industry trade shocks can lead to local industry employment spillovers, and that these spillovers are stronger for industries that are economically close to the industry hit by the trade shock, most notably for industries with similar worker requirements. But are these effects the same across tradable sectors? Or do high technology industries benefit more from spillovers from trade shocks than low technology industries? Do trade shocks to all types of industries lead to spillovers or are predominantly high technology industries able to create spillovers as knowledge spillovers may be more likely to take place in high technology industries? This section investigates these questions.

To estimate differences in spillover effects between high and low technology industries I categorize industries following Grupp et al. (2000) who define high technology industries as those with R&D expenditure of at least 3.5% of overall production. To give a few examples, high technology industries include the aircraft industry and the pharmaceuticals industry, while low technology industries include the textile industry and the paper industry.40

Table 6, Panel A, columns (2) to (3), presents results from estimating spillover effects from indirect net trade exposure to the other tradable industries’ trade shocks separately for high versus low technology industries (estimation using equation (4.4)). Column (1) presents for comparison the baseline results using the full sample of all tradable sector industries. The results show that both high and low technology industries benefit from indirect net trade exposure to the other tradable industries’ trade shocks, however spillovers to high technology industries are twice as large as spillovers to low technology industries, with an effect of 13.94 percentage points per 1 million

---

40The measures in Grupp et al. (2000) are similar to those defined by the OECD, but account for differences in R&D intensity in Germany as compared to other OECD country industries.
EUR increase in indirect per worker net trade exposure compared to 6.26 percentage points for industries in the low technology sector.

Why do high technology industries benefit so much more from agglomeration spillovers than low technology industries? Are also predominantly shocks to high technology industries creating the spillovers? To investigate this question, in columns (4) to (6) of Panel A in Table 6, I additionally split the indirect net trade exposure measure up to distinguish between indirect exposure to trade shocks to high technology versus low technology industries, that is \( \Delta NetIndir_{jrt} = \Delta NetIndir^{\text{High}}_{jrt} + \Delta NetIndir^{\text{Low}}_{jrt} \). Column (1), Panel A, presents results for the full sample of tradable industries, while in columns (2) and (3) the sample is divided into high and low technology industries. The results are quite striking. Column (1) indicates that tradable industries only benefit from spillovers of trade shocks to high technology industries: While spillovers from shocks to high technology industries are strong with about 11 percentage points per 1 million indirect net trade exposure, the coefficient for spillovers from trade shocks to low technology industries is slightly negative and insignificant. This indicates that it is indeed predominantly shocks to high technology industries that trigger agglomeration spillovers, while shocks to low technology industries do not generate spillovers, or at least they are not strong enough to outweigh the reallocation effects. Furthermore, in line with the results in columns (2) and (3), high technology industries also benefit more from indirect exposure to the trade shocks of other high technology industries (19 percentage points), but low technology industries still benefit (8 percentage points).

In Panel B of Table 6, I divide (national) industries into classes according to the share of high-skilled workers employed in the industry, as an alternative to splitting industries into high and low technology according to their R&D expenditure. High-skilled industries are defined as the third of industries with the highest national share of high-skilled employment in 1988. These are industries with a high-skill share larger than 5.9 percent. The correlation between high-skilled and high technology industries is 0.5 and thus relatively high. However, there are still differences: high-skilled industries exist in all tradable sectors except agriculture, while high technology industries only exist in the manufacturing of consumer products and manufacturing of investment goods sectors, and about a third of industries that are high-skilled are not high technology and vice versa. Furthermore, low-skilled industries have a higher average indirect net trade exposure and a higher variation in indirect net trade exposure compared to low technology industries, which alleviates concerns that the results in Panel A are solely driven by the smaller variation in indirect net trade exposure in low technology industries. The results are fairly similar to those in Panel A: high skilled industries benefit more from spillover effects than low-skilled industries and are more strongly creating spillovers than low-skilled industries, although it seems that shocks to low-skilled industries can trigger spillovers to a certain extent.

Overall, the results in this section point to important heterogeneities in the existence of agglomeration economies across industries. They further reinforce the proximity results in Section 6.2.2,
as worker requirements between high technology industries should be more similar and hence thick labor market effects stronger amongst these industries. A further explanation for the pattern of results may be the existence of knowledge spillovers, which may take place both within the high technology sector, as between high and low technology industries. Moreover, the absence of positive spillovers from shocks to low technology industries provides additional evidence that input-output relations and hence local indirect product demand shocks may not be the main driver of spillover effects. Indeed, given that low technology industries are substantially linked by input-output relations, shocks to low technology industries should lead to positive spillovers if input-output relations were an important source of agglomeration economies.

The results also complement recent findings in the literature on local multipliers, knowledge spillovers, and place based policies. Moretti and Thulin (2013), for example, find that local multipliers are higher when triggered by additional high-skilled workers in the region or by additional jobs in the high technology sector. Serafinelli (2016) finds at least indicative evidence that workers in high-skilled occupations transfer more knowledge when moving firms, and Becker et al. (2013) discover that only regions with sufficient levels of human capital are benefiting from transfers of the European Union Structural Funds.

6.3 Magnitude of Effects - Comparison with Existing Estimates

How do the results of this study relate to both the existing literature on the local employment effects of globalization using trade shocks and the literature estimating agglomeration spillovers? To analyze this, I first quantify the contribution of spillover effects to the joint direct and indirect local employment effects of trade shocks. I then use the structure of the model to derive an estimate for the agglomeration elasticity.

Contribution to Local Employment Effects

I begin by analyzing the contribution of local industry spillovers to the overall (local) employment effects of trade shocks. To do so, I compare the spillover effects from indirect net trade exposure on local industry employment in both the tradable and non-tradable sector (7.60 percentage points per 1 million EUR increase in indirect trade exposure, see Table 7) to the sum of the spillover effects from indirect net trade exposure and the direct effects estimated in Section 6.1 (0.45 percentage points per one thousand EUR increase in direct trade exposure per worker, see Table 3, Column (1)). These two effects are not directly comparable as they are scaled differently. In order to make the estimates comparable, I compute the effects on local industry employment implied by the actual increase in net trade exposure, focusing on the period 2001 to 2008. Average direct net trade exposure in this period was equivalent to 4.67 thousand EUR per worker (see Table 1,

42 The estimate of the joint spillover effects in the tradable and non-tradable sector are only reported in Table 7. The specification is equivalent to the tradable sector results specification used in Table 4, Column (4).

43 I use this timeframe as import and export trade shocks in the two previous periods more or less average out, implying zero net exposure. However, a comparison of the effects over the full period leads to very similar results.
This suggests that local industry employment increased on average by 2.1 (\(= 0.45 \times 4.67\)) percentage points due to the effects on industries directly affected by increases in net trade with China and Eastern Europe. Indirect net trade exposure in the period 2001 to 2008 was 0.17 million EUR per worker (see Table 1, Panel B), indicating that agglomeration spillovers led to an increase in local industry employment of 1.29 (\(= 7.60 \times 0.17\)) percentage points. Consequently, local industry spillovers contributed 38 percent (\(= \frac{1.33}{2+1.3} \times 100\)) to the joint direct and indirect local employment effects of trade shocks and hence constitute a substantial share of the local employment effects of trade shocks.\(^{44}\)

**Quantifying the Agglomeration Elasticity**

To derive an estimate for the agglomeration elasticity, I use the structure of the model presented in Section 3.2 together with the reduced form effects estimated in Sections 6.1 and 6.2. Two difficulties arise when matching the empirics to the model that make it necessary to rescale the empirical estimates. First, in the empirics I analyze the consequences of shocks in trade quantities, while the model examines the consequences of price shocks. Therefore, in order to properly identify the agglomeration elasticity, it is in principle necessary to rescale the empirical estimates by the inverse of the elasticity of net trade with respect to (world) prices (defined as \(\rho\) in equation (3.8)).

The method I employ, allows however to estimate the agglomeration elasticity without making an assumption about \(\rho\), as I will show below. A second difficulty arises because I do not estimate an elasticity of employment changes with respect to trade shocks, but a semi-elasticity, as in this paper the trade shocks are defined as absolute changes per worker (see equation (4.2)). That said, one can easily calculate the elasticity at means by multiplying the coefficient estimates by the average of the trade shock per worker (\(\text{TrShockIndir}_{jrt}\) and \(\text{TrShockReg}_{rt}\) respectively, as defined in Sections 4.2 and 6.1) as \(\frac{df}{dx} = \frac{df}{dx} \times \frac{dx}{dx} = \frac{df}{dx} x\).

More specifically, I use the indirect employment estimates (corresponding to \(\beta_{\text{empl}}^{\text{indir}}\)) and the regional employment estimates (corresponding to \(\beta_{\text{empl}}^{\text{reg}}\)) to estimate the agglomeration elasticity. From equations (3.8) and (B.15) and accounting for the fact that I only estimate semi-elasticities empirically, we know that \(\beta_{\text{empl}}^{\text{indir}}\) and \(\beta_{\text{empl}}^{\text{reg}}\) rescaled by the respective average net trade shock identify\(^{45}\)

\[
\beta_{\text{empl}}^{\text{indir}} \cdot \text{TrShockIndir}_{jrt} = \frac{1}{\phi} \frac{\lambda - \gamma \eta}{\phi - \lambda + \gamma \eta} \rho \quad (6.2)
\]

\[
\beta_{\text{empl}}^{\text{reg}} \cdot \text{TrShockReg}_{rt} = \frac{1}{\phi} \frac{\lambda - \gamma \eta}{\phi - \lambda + \gamma \eta} \rho. \quad (6.3)
\]

These two equations can then be used to solve for the agglomeration elasticity. Under the assumption that trade shocks do not affect regional wages, given the evidence presented in Section 6.1 (i.e.

\(^{44}\)Alternatively, one can compare the spillover effects with the regional effects of trade shocks (see Table 3, column (3) for the regional effect estimates). The implied contribution of spillover effects to the overall local employment effects is then equal to 44 percent.

\(^{45}\)For simpler exposition I here define \(\phi = (1 - \alpha)(1 - \mu)\) and \(\gamma = 1 - \mu(1 - \alpha)\).
\[ dlnw_r = 0 \text{ and consequently } \eta = 0, \] the agglomeration elasticity then equals

\[ \lambda = \frac{\beta_{\text{empl}}^{\text{indir}} \cdot TrShockIndir_{jrt}}{\beta_{\text{empl}}^{\text{reg}} \cdot TrShockReg_{rt}} \phi. \]

Note that this equation no longer depends on the scaling parameter \( \rho \) and hence this method allows me to estimate the agglomeration elasticity without making an assumption about the elasticity of net trade shocks with respect to (world) prices. I then follow Kline and Moretti (2014) and set the share of the fixed resource \( \phi = (1 - \alpha)(1 - \mu) \) to 0.47.\(^{46}\) The coefficient estimate is reported in Table 7, along with the parameter estimates and calibrated parameter values used for the estimation. I estimate an elasticity of 0.220 (column (1.2)).

This estimate of 0.220 is similar to the elasticities estimated in recent studies by Kline and Moretti (2014) and Gathmann et al. (2016) of 0.22 and 0.19 respectively. It is, however, larger than those of earlier studies in the urban economics literature, such as that of Ciccone and Hall (1996) who report an elasticity of 0.04 estimated by instrumenting density differences in a cross section of US states with past determinants of population density. This difference may be explained by two reasons. First, earlier studies look at how differences in a cross section or changes over time in local employment (in the tradable and non-tradable sector) or population (density) affect local productivity. Here I study the impact of shocks to tradable sector industries and this is likely to lead to stronger agglomeration spillovers than shocks to non-tradable sector industries. Second, my results indicate that worker mobility across regions might be an important driver for agglomeration spillovers, as industries exchanging more workers are more strongly affected. Shocks to local industries are likely to (at least in the short term) induce increased mobility across industries both within and across regions. In contrast, by comparing productivity differences across localities with different size or density in a cross section, spillovers due to worker mobility will only be captured because of potential differences in general turnover between larger and smaller localities.\(^{47}\)

It is hence to be expected that agglomeration spillovers are larger following national industry trade shocks.

7 Conclusion

This paper shows that national industry shocks affecting local industries can have substantial indirect effects on employment in geographically close industries because of the existence of agglomeration economies. The specific national industry shocks exploited are trade shocks to German

\(^{46}\)Kline and Moretti (2014) assume that the labor demand elasticity \( \left( \frac{1-\mu(1-\alpha)}{1-\alpha(1-\mu)} \right) \), see equation (3.3) is equal to 1.5 and the share of capital in production \( ((1-\alpha)\mu) \) is equal to 0.3. From there it follows that the share of the fixed resource, \( (1-\alpha)(1-\mu) \) is equal to 0.47.

\(^{47}\)A similar argument can be made to explain the difference in estimates compared to studies estimating spatial wage disparities by following workers across regions over time, such as Combes et al. (2008) who estimate an elasticity with respect to density of 0.03.
industries stemming from trade integration of Eastern Europe after the fall of the iron curtain and that of China due to its transition to a market oriented economy. The findings suggest that these spillovers contribute about 38 percent to the joint direct and indirect local employment effects of trade shocks. Consequently, regional effects of national industry trade shocks are larger than would be expected if only taking into account the direct effects of these shocks. An important factor for the existence of these spillovers is economic proximity between industries: spillover effects from trade shocks are particularly large for industries producing in the same sector and those that share common worker requirements. In contrast, input-output relations seem to matter less. Interestingly, only trade shocks to high technology industries trigger spillovers to employment in other local industries, but both high and low technology industries benefit from these spillovers. Overall, these findings are consistent with the existence of thick market effects or knowledge spillovers that are transmitted through workers switching jobs and point to the existence of important heterogeneities in the existence of agglomeration economies across industries.

These findings indicate that governments may want to take local industry structure into account when implementing place-based policies, and aim to attract high technology firms in order to increase the likelihood that such policies are successful. That said, to take a firmer stance regarding the consequences for place based policies, more direct research on place-based policies in relation to the findings here is needed. Further, if it is not regional policy but rather national welfare that is the primary interest of governments, the results suggest that national governments should move subsidies away from low technology and towards high technology industries, as these are more likely to create additional employment through regional spillovers.

References


Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>sd</td>
<td>mean</td>
<td>sd</td>
</tr>
</tbody>
</table>

**Panel A: Local Industry Employment Characteristics**

- Log Employment Change ( Tradable Sector) (x100)  
  -16.91 40.97  
  -18.04 39.65  
  -15.58 44.75  
  -16.97 38.15
- Share Tradable Employment (x100)  
  34.79 9.29  
  38.24 9.04  
  33.68 8.55  
  31.79 9.04
- Share 3-digit Industry Employment (x100)  
  2.70 3.66  
  3.09 4.15  
  2.52 3.39  
  2.43 3.24

**Panel B.1: Indirect Trade Exposure Measures (in 1 Million EUR)**

- German Indirect Trade Exposure
  - Net Exposure (All Industries) 0.047 0.388 0.00 0.223 0.17 0.579
  - Net Exposure ( Tradable Sector) 0.062 0.528 -0.038 0.245 0.000 0.297 0.252 0.836
  - Net Exposure (same Sector) 0.025 0.254 -0.009 0.133 0.003 0.169 0.089 0.393
  - Net Exposure (other Tradable Sectors) 0.037 0.445 -0.029 0.218 -0.003 0.270 0.163 0.703
  - Import Exposure ( Tradable Sector) 0.388 1.147 0.200 0.533 0.453 1.294 0.547 1.452
  - Import Exposure (same Sector) 0.121 0.452 0.056 0.178 0.147 0.549 0.171 0.550
  - Import Exposure (other Tradable Sectors) 0.267 0.948 0.144 0.421 0.306 1.088 0.376 1.198
  - Export Exposure ( Tradable Sector) 0.450 1.407 0.162 0.479 0.452 1.222 0.799 2.102
  - Export Exposure (same Sector) 0.145 0.558 0.048 0.182 0.149 0.496 0.261 0.833
  - Export Exposure (other Tradable Sectors) 0.305 1.161 0.115 0.401 0.303 1.017 0.538 1.743
- Other High Income Countries Indirect Trade Exposure ( Instruments)
  - Import Exposure ( Tradable Sector) 0.587 1.988 0.120 0.382 0.672 2.053 1.063 2.795
  - Export Exposure ( Tradable Sector) 0.268 0.963 0.040 0.228 0.290 0.913 0.524 1.402

**Panel B.2: Direct and Regional Trade Exposure Measures (in 1000 EUR)**

- German Direct and Regional Trade Exposure
  - Net Direct Exposure ( All Industries) 0.385 7.157 -0.267 4.014 0.013 5.377 1.394 10.313
  - Net Direct Exposure ( Tradable Sector) 1.162 12.4 -0.717 6.560 0.040 9.455 4.668 18.464
  - Net Regional Exposure ( All Industries) 0.347 1.132 -0.259 0.582 -0.002 0.691 1.291 1.280
  - Net Regional Exposure ( Tradable Sector) 0.308 1.223 -0.310 0.630 -0.016 0.742 1.413 1.436

Notes: The table shows means and standard deviations of employment characteristics and trade exposure measures for the time periods shown in the top row. Observations are on the 3 digit industry x commuting zone level. Panel A shows employment characteristics of tradable industries. Panel B.1 shows the various indirect trade exposure measures as defined in equations (4.1) and (4.6) and Panel B.2 the direct and regional trade exposure measures as defined in Section 6.1. In Panel B, ( Tradable Sector) refers to exposure to the other local industries’ trade shocks within the tradable sector, ( same Sector) to exposure to the other local industries’ trade shocks within the same sector, and ( other Tradable Sectors) to exposure to the other local industries’ trade shocks in the tradable sectors outside the same sector. All observations are weighted by 3 digit industry x commuting zone employment.
Table 2: Descriptive Statistics by Percentiles of Net Indirect Trade Exposure (Tradables)

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>&lt;1st Percentile</th>
<th>&gt;1st Percentile &amp; &lt;25th Percentile</th>
<th>&gt;25th Percentile &amp; &lt;50th Percentile</th>
<th>&gt;50th Percentile &amp; &lt;75th Percentile</th>
<th>&gt;75th Percentile &amp; &lt;99th Percentile</th>
<th>&gt;99th Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indirect Net Trade Exposure</td>
<td>0.062</td>
<td>-0.829</td>
<td>-0.089</td>
<td>0.014</td>
<td>0.068</td>
<td>0.291</td>
<td>1.613</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.058)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.018)</td>
<td>(0.180)</td>
</tr>
<tr>
<td>Average Wage</td>
<td>83.26</td>
<td>75.74</td>
<td>83.52</td>
<td>83.76</td>
<td>84.53</td>
<td>81.94</td>
<td>71.45</td>
</tr>
<tr>
<td></td>
<td>(1.65)</td>
<td>(1.53)</td>
<td>(2.60)</td>
<td>(2.17)</td>
<td>(1.81)</td>
<td>(1.42)</td>
<td>(1.41)</td>
</tr>
<tr>
<td>Share Low Skilled (x100)</td>
<td>23.23</td>
<td>21.73</td>
<td>23.17</td>
<td>23.55</td>
<td>23.33</td>
<td>23.02</td>
<td>20.56</td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
<td>(0.86)</td>
<td>(0.58)</td>
<td>(0.71)</td>
<td>(0.74)</td>
<td>(0.79)</td>
<td>(0.76)</td>
</tr>
<tr>
<td>Share Medium Skilled (x100)</td>
<td>69.02</td>
<td>72.64</td>
<td>68.83</td>
<td>68.65</td>
<td>68.49</td>
<td>69.81</td>
<td>74.67</td>
</tr>
<tr>
<td></td>
<td>(0.49)</td>
<td>(0.80)</td>
<td>(0.61)</td>
<td>(0.65)</td>
<td>(0.56)</td>
<td>(0.73)</td>
<td>(0.65)</td>
</tr>
<tr>
<td>Share High Skilled (x100)</td>
<td>7.75</td>
<td>5.63</td>
<td>8.00</td>
<td>7.80</td>
<td>8.18</td>
<td>7.16</td>
<td>4.77</td>
</tr>
<tr>
<td></td>
<td>(0.66)</td>
<td>(0.52)</td>
<td>(0.90)</td>
<td>(0.94)</td>
<td>(0.81)</td>
<td>(0.43)</td>
<td>(0.27)</td>
</tr>
</tbody>
</table>

Notes: The table reports mean values and standard errors (in brackets) of the variables shown in the left column for observations at the 3-digit industry x commuting zone level by percentile groups of indirect net exposure to the other local industries’ trade shocks. Percentile groups are separated as shown in the top row. The percentile groups are calculated within 3-digit industry and period and are employment weighted. Low-skilled individuals are those without a high school or vocational degree, medium-skilled are those with a high school or vocational degree, and high-skilled are those with a college or university degree. Wages are average daily wages in EUR adjusted to 1995 prices. All observations are weighted by industry x commuting zone employment.
Table 3: Direct and Regional Effects

<table>
<thead>
<tr>
<th>Direct Effects</th>
<th>Regional Effects (all)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Employment (1)</td>
</tr>
<tr>
<td>Own Industry Net Exposure, 3 digit</td>
<td>0.447** (0.185)</td>
</tr>
<tr>
<td>Regional Net Exposure, Tradables</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table reports estimates of own industry and regional net trade exposure on local industry employment, wages, and land prices based on equation (4.4) including federal state x period fixed effects and regional and industry level controls. Observations are measured on the 3-digit industry x commuting zone level. All columns are estimated using two stage least squares instrumenting German trade exposure with other high income country trade exposure as explained in Section 4.2. In Columns (1) and (2) the variable of interest is own industry net trade exposure and in Columns (3) to (5) regional net trade exposure, as defined in Section 6.1. Both net trade exposure measures are measured in 1,000 EUR per worker (adjusted to 2005 prices). Reported first stage F-statistics are the Sanderson-Windmeijer F-Statistics. Standard errors are clustered at the commuting zone level. Significance levels 1%***, 5%**, 10%*. 
Table 4: Agglomeration Spillovers, Indirect Net Trade Exposure

<table>
<thead>
<tr>
<th></th>
<th>Net Exposure Tradables</th>
<th>Net Exposure Same/ Other Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2SLS</td>
<td>OLS</td>
</tr>
<tr>
<td></td>
<td>add Share</td>
<td>add further controls</td>
</tr>
<tr>
<td></td>
<td>direct net trade exposure</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>only</td>
<td>add 3 digit industry x period FE</td>
</tr>
<tr>
<td></td>
<td>Industry Control</td>
<td></td>
</tr>
<tr>
<td></td>
<td>period FE</td>
<td></td>
</tr>
<tr>
<td>N=25963</td>
<td>(1.237)</td>
<td>(1.592)</td>
</tr>
<tr>
<td>Indirect Net Exposure, Tradables</td>
<td>2.541** (1.237)</td>
<td>5.875*** (1.592)</td>
</tr>
<tr>
<td>Indirect Net Exposure, Same Sector</td>
<td>12.864** (3.211)</td>
<td>2.106** (0.933)</td>
</tr>
<tr>
<td>Indirect Net Exposure, Other Tradable Sectors</td>
<td>5.080*** (1.757)</td>
<td>0.839* (0.431)</td>
</tr>
<tr>
<td>Direct Net Trade Exposure, 3 digit</td>
<td>0.368*** (0.055)</td>
<td></td>
</tr>
<tr>
<td>Share Tradable Employment (x100)</td>
<td>0.411*** (0.105)</td>
<td>0.306*** (0.091)</td>
</tr>
<tr>
<td>Share 3-digit Industry Employment (x100)</td>
<td>-0.317 (0.225)</td>
<td>-0.433** (0.206)</td>
</tr>
<tr>
<td>Share Medium Skilled (in Industry, x100)</td>
<td>0.342*** (0.064)</td>
<td>0.346*** (0.065)</td>
</tr>
<tr>
<td>Share High Skilled (in Industry, x100)</td>
<td>-0.016 (0.122)</td>
<td>-0.06 (0.125)</td>
</tr>
<tr>
<td>Share Medium Skilled (in Region, x100)</td>
<td>-0.633* (0.259)</td>
<td>-0.669** (0.265)</td>
</tr>
<tr>
<td>Share High Skilled (in Region, x100)</td>
<td>-0.369 (0.306)</td>
<td>-0.23 (0.312)</td>
</tr>
<tr>
<td>Share Female Workers (in Region, x100)</td>
<td>0.317 (0.308)</td>
<td>0.245 (0.309)</td>
</tr>
<tr>
<td>Share Foreign Workers (in Region, x100)</td>
<td>-1.014*** (0.215)</td>
<td>-1.038*** (0.215)</td>
</tr>
<tr>
<td>Industry (3-digit) x Period FE</td>
<td>x x x x x x</td>
<td></td>
</tr>
<tr>
<td>Federal State x Period FE</td>
<td>x x x x x</td>
<td></td>
</tr>
<tr>
<td>First Stage Net Exposure</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Import Exposure IV, Tradables</td>
<td>-0.151*** (0.051)</td>
<td>-0.153*** (0.050)</td>
</tr>
<tr>
<td>Export Exposure IV, Tradables</td>
<td>0.550*** (0.109)</td>
<td>0.524*** (0.106)</td>
</tr>
<tr>
<td>Import Exposure IV, Same Sector</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Export Exposure IV, Same Sector</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Import Exposure IV, Other Tradable Sectors</td>
<td>0.008*** (0.009)</td>
<td>-0.148*** (0.051)</td>
</tr>
<tr>
<td>Export Exposure IV, Other Tradable Sectors</td>
<td>-0.002 (0.018)</td>
<td>0.537*** (0.119)</td>
</tr>
<tr>
<td>R2 (First Stage)</td>
<td>0.279</td>
<td>0.361</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>35.31</td>
<td>28.57</td>
</tr>
</tbody>
</table>

Notes: The table reports estimates of indirect net trade exposure on local industry employment based on variants of equation (4.4). Observations are measured on the 3-digit industry x commuting zone level. Columns (1) to (4) and column (6) are estimated using two stage least squares instrumenting German trade exposure with other high income country trade exposure as explained in Section 4.2, while Columns (5) and (7) estimate OLS regressions. Columns (1) to (5) estimate the effect of indirect exposure to other local tradable industries net trade shocks on employment. Column (1) only controls for national direct net trade exposure (measured in 1,000 EUR per worker) of the industry under observation. Column (2) instead adds national (3-digit) industry x period fixed effects, column (3) adds the tradable sector and own industry share on regional employment, and column (4) adds further regional and industry controls, as well as federal state x period fixed effects and estimates the equivalent to equation (4.4). Column (5) estimates the equivalent of column (4) but using OLS. Column (6) estimates the equivalent of column (4), but allowing for separate effects of indirect net trade exposure from industries within the same sector and from industries in other tradable sectors (6 broad sectors in tradables). Column (7) estimates the OLS equivalent to column (6). Indirect net trade exposure measures are measured in per 1 Million EUR per worker (adjusted to 2005 prices). Reported first stage F-statistics are the Sanderson-Windmeijer F-Statistics. Standard errors are clustered at the commuting zone level. Significance levels 1%***, 5%**, 10%*.
<table>
<thead>
<tr>
<th></th>
<th>Only Worker Transition Measure (1)</th>
<th>Only Upstream Measure (2)</th>
<th>Only Downstream Measure (3)</th>
<th>All Mechanisms (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indirect Net Exposure Worker Transitions</td>
<td>7.818** (3.425)</td>
<td>7.201** (2.819)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect Net Exposure Upstream</td>
<td>2.507*** (0.838)</td>
<td>1.988** (0.974)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect Net Exposure Downstream</td>
<td>0.302 (0.663)</td>
<td>-0.687 (0.690)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect Net Exposure (normalized)</td>
<td>-2.213 (1.995)</td>
<td>1.591*** (0.560)</td>
<td>2.700*** (0.517)</td>
<td>-2.723* (1.636)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>F-Statistic Worker Transitions 23.36</th>
<th>F-Statistic Upstream 32.01</th>
<th>F-Statistic Downstream 22.49</th>
<th>F-Statistic Indirect Net Exposure 26.568</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20.68</td>
<td>25.28</td>
<td>29.34</td>
<td>20.62</td>
</tr>
</tbody>
</table>

N | 25963 | 25963 | 25963 | 25963 |

Notes: The table investigates whether employment effects of local indirect net trade exposure vary by economic proximity. Estimates are from two stage least squares regressions based on equation (4.4) including federal state x period fixed effects, national industry x period fixed effects, and regional and industry level controls. Indirect net trade exposure is reweighted according to 3 measures of economic proximity (see equation (6.1)): the maximum of the share of workers leaving industry j and moving to industry k and the share of workers leaving industry k and moving to industry j over a 5-year window from t-5 to t (column (1)), the share of goods produced in industry k that is sold to industry j (column (2)), the share of goods produced in industry j that is sold to industry k (column (3)). In column (4), the 3 reweighted indirect net trade exposure measures are jointly included into the regression. All measures (including the baseline measure) are normalized to have mean 0 and standard deviation 1. Indirect net trade exposure is measured in per 1 Million EUR per worker (adjusted to 2005 prices). Reported first stage F-statistics are the Sanderson-Windmeijer F-Statistics. Standard errors are clustered at the commuting zone level. Significance levels 1%***, 5%**, 10%*. 
Table 6: Agglomeration Spillovers, High vs Low Technology and High vs Low Skilled Industries

### Panel A: High vs Low Technology Industries

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>High Technology (2)</th>
<th>Low Technology (3)</th>
<th>Baseline (4)</th>
<th>High Technology (5)</th>
<th>Low Technology (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indirect Net Exposure, Tradables</td>
<td>7.745***</td>
<td>13.935***</td>
<td>6.262***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Mean 0.062, SD 0.528)</td>
<td>(1.756)</td>
<td>(4.992)</td>
<td>(1.524)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect Net Exposure, Low Tech</td>
<td></td>
<td></td>
<td></td>
<td>-1.081</td>
<td>1.105</td>
<td>0.633</td>
</tr>
<tr>
<td>(Mean 0.000, SD 0.238)</td>
<td></td>
<td></td>
<td></td>
<td>(4.651)</td>
<td>(9.630)</td>
<td>(4.133)</td>
</tr>
<tr>
<td>Indirect Net Exposure, High Tech</td>
<td></td>
<td></td>
<td></td>
<td>10.763***</td>
<td>21.631***</td>
<td>7.250***</td>
</tr>
<tr>
<td>(Mean 0.062, SD 0.391)</td>
<td></td>
<td></td>
<td></td>
<td>(2.180)</td>
<td>(6.288)</td>
<td>(1.687)</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>27.99</td>
<td>9.11</td>
<td>35.29</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-Statistic, Low Tech</td>
<td></td>
<td></td>
<td></td>
<td>19.94</td>
<td>16.98</td>
<td>19.91</td>
</tr>
<tr>
<td>F-Statistic, High Tech</td>
<td></td>
<td></td>
<td></td>
<td>48.78</td>
<td>28.43</td>
<td>60.90</td>
</tr>
<tr>
<td>N</td>
<td>25963</td>
<td>6690</td>
<td>19273</td>
<td>25963</td>
<td>6690</td>
<td>19273</td>
</tr>
</tbody>
</table>

### Panel B: High vs Low Skilled Industries

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>High Skilled Industries (2)</th>
<th>Low Skilled Industries (3)</th>
<th>Baseline (4)</th>
<th>High Skilled Industries (5)</th>
<th>Low Skilled Industries (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indirect Net Exposure, Tradables</td>
<td>7.745***</td>
<td>18.822***</td>
<td>4.696***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Mean 0.062, SD 0.528)</td>
<td>(1.756)</td>
<td>(6.329)</td>
<td>(1.091)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect Net Exposure, Low Skilled</td>
<td></td>
<td></td>
<td></td>
<td>4.818**</td>
<td>12.738*</td>
<td>3.142**</td>
</tr>
<tr>
<td>(Mean 0.027, SD 0.451)</td>
<td></td>
<td></td>
<td></td>
<td>(1.891)</td>
<td>(6.687)</td>
<td>(1.272)</td>
</tr>
<tr>
<td>Indirect Net Exposure, High Skilled</td>
<td></td>
<td></td>
<td></td>
<td>11.053***</td>
<td>22.442***</td>
<td>6.685***</td>
</tr>
<tr>
<td>(Mean 0.034, SD 0.238)</td>
<td></td>
<td></td>
<td></td>
<td>(3.197)</td>
<td>(7.798)</td>
<td>(2.115)</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>27.99</td>
<td>8.46</td>
<td>42.66</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-Statistic, Low Skilled</td>
<td></td>
<td></td>
<td></td>
<td>20.67</td>
<td>5.45</td>
<td>33.43</td>
</tr>
<tr>
<td>F-Statistic, High Skilled</td>
<td></td>
<td></td>
<td></td>
<td>30.82</td>
<td>15.44</td>
<td>40.99</td>
</tr>
<tr>
<td>N</td>
<td>25963</td>
<td>7431</td>
<td>18532</td>
<td>25963</td>
<td>7431</td>
<td>18532</td>
</tr>
</tbody>
</table>

Notes: The table reports estimates of indirect net trade exposure on local industry employment. The estimates are from two stage least squares regressions based on equation (4.4) including federal state x period fixed effects, national industry x period fixed effects and regional and industry level controls. Observations are measured on 3-digit industry x commuting zone level. Panel A investigates whether employment effects of local indirect net trade exposure differ for high vs low technology industries (for definitions see Section 6.2.3). Columns (1) and (4) report results for the whole sample of tradable industries (column (1) is equivalent to Table 4, column (4)). Columns (2) and (5) report estimates for high technology industries only, while columns (3) and (6) report estimates for low technology industries. Panel B investigates whether employment effects of local indirect net trade exposure differ for high vs. low skilled industries (for definitions see Section 6.2.3). Columns (1) and (4) report results for the whole sample of tradable industries, while columns (2) and (5) reports estimates only for high-skilled industries and columns (3) and (6) report results only for low-skilled industries. Indirect net trade exposure is measured in per 1 Million EUR per worker (adjusted to 2005 prices). Reported first stage F-statistics are Sanderson-Windmeijer F-Statistics. Standard errors are clustered at the commuting zone level. Significance levels 1%***, 5%**, 10%*. 
Table 7: Estimation of the Agglomeration Elasticity

Panel A: The Agglomeration Elasticity

| Agglomeration Elasticity (\(\lambda\)) | \(\frac{\beta_{empl} \cdot \text{TrShockIndir}_{jrt}}{\beta_{reg} \cdot \text{TrShockReg}_{rt}}\) | 0.220*** | (0.080) |

Panel B: Calibrated Parameters, Scale Parameters, and Reduced Form Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of fixed resource in production</td>
<td>0.47</td>
<td>(\beta_{empl})</td>
<td>7.602***</td>
</tr>
<tr>
<td>((1 - \alpha)(1 - \mu))</td>
<td>(Kline and Moretti (2014))</td>
<td>(\beta_{indir})</td>
<td>(1.376)</td>
</tr>
<tr>
<td>(\text{TrShockIndir}_{jrt})</td>
<td>0.047</td>
<td>(\beta_{empl})</td>
<td>2.216**</td>
</tr>
<tr>
<td>(\text{TrShockReg}_{rt})</td>
<td>0.347</td>
<td>(\beta_{reg})</td>
<td>(0.878)</td>
</tr>
</tbody>
</table>

Notes: The table reports an estimate of the agglomeration elasticity in Panel A and the calibrated parameters and reduced form estimates used for the estimation of the agglomeration elasticity in Panel B. The values for the average indirect net trade shock \(\text{TrShockIndir}_{jrt}\) and the regional net trade shock \(\text{TrShockReg}_{rt}\) come from Table 1 and the parameter estimate for \(\beta_{reg}\) from Table 3, column (3). The parameter estimate for \(\beta_{indir}\) is not reported elsewhere. The specification is equivalent to the specification of the baseline results presented in Table 4, column (4), which is based on equation (4.3). However, all industries from both the tradable and the non-tradable sector are included in the regression, while in the baseline specification only observations from the tradable sector are included. Standard errors are clustered at the commuting zone level. Significance levels: 1% ***, 5% **, 10% *. 

43
Figure 1: Total Imports and Exports

Note: The Figure presents the total volume of German trade with China (Panel A) and Eastern Europe (Panel B) in Billion EUR (adjusted to 2005 prices) for the years 1978 to 2008 separately for Imports (solid line) and Exports (dashed line). The figure is equivalent to Figure 1 in Dauth et al. (2014), but derived from own calculations.

Figure 2: Within 3-digit Industry Variation in Indirect Net Trade Exposure (Tradeable Sector)

Notes: The figure presents for all 3-digit industries in the tradable sector means and standard deviations of indirect net trade exposure to trade shocks of other local tradable industries net of period fixed effects and effects due to differences in tradable and own industry employment share in the region.
Appendix

A  Example and Intuition for the Identification Strategy

Assume there are two regions (A and B) with the same size of the tradable sector, which is represented by the two pies in Figure A1. In each of these two regions 3 tradable industries are present: industry (1), (2), and (3). Assume also, that industry (1) is more prevalent in region A and that industry (2) is the same size in both regions. This implies that the joint size of industry (1) and industry (3) is the same in both regions and hence industry (3) must be more prevalent in region B. Now, for simplicity, let us assume that only industry (1) is hit by a positive national trade shock from China and Eastern Europe. Let us for now focus on what this implies for labor demand and changes in employment in industry (2). As shown theoretically in Section 3.2, equation (??), now two main mechanisms potentially affect employment in industry (2): the reallocation effect (endogenous wage adjustment) and agglomeration spillovers. First, because industry (1) is more prevalent in region A, this implies that industry (1) demands more additional workers in region A compared to region B, which as long as labor is not perfectly mobile, increases wages in region A by more than in region B and hence relatively seen industry (2) should want to reduce employment by more in region A than in region B. However, if at the same time industry (2) benefits from agglomeration spillovers because of the increase in labor market size due to the positive trade shock to industry (1) and hence an increase in the available labor pool potentially leading to better worker-firm matches and the inflow of new human capital into the region potentially increasing knowledge exchange, then these productivity spillovers will also be stronger in region A than in region B, because of the higher prevalence of industry (1) in region A.

The identification strategy exploits exactly this within industry variation in local industry structure of the other tradable industries (keeping the joint relative size of the other tradable industries constant) and hence in indirect exposure to the other local industries’ trade shocks. The estimates will be a composite of the reallocation effects and the agglomeration effects. However, as these effects go in different directions, when employment expands more in regions with higher indirect trade exposure, the agglomeration effects outweigh the reallocation effects.

Figure A.1: Example for the Intuition of the Identification Strategy

Notes: The figure corresponds to the example in Appendix A.1 provided to give an intuition of the identification strategy. Black numbers represent industries (industry 1, 2 and 3) and red numbers represent hypothetical employment sizes of these industries. Details of the example are explained in Appendix A.1.

---

In reality, it is likely that all three of the industries are hit by a trade shock, however in the empirical estimation I will control for the direct trade shock to industry (2) and analyze how the joint indirect trade shocks to the other tradable industries in the region affect local employment of industry (2).
B Theoretical Framework - Model Derivations

This section derives the equations for local industry labor demand changes (equations (3.3) and (3.5)) and equilibrium employment and wage changes (equations (3.6) and (3.7)) of the model presented in Section 3.2.49

As described in Section 3.2, the model economy is assumed to consist of many regions \( r \) and many industries \( j \). Each industry produces an industry specific good whose price \( p_j \) is determined nationally and is hence assumed to be exogenously given.

In each industry output \( (Y_{jr}) \) is produced according to a Cobb-Douglas production function using labor \( (L_{jr}) \), capital \( (K_{jr}) \), and a non-tradable resource \( (\bar{R}_{jr}) \):

\[
Y_{jr} = A_{jr}L_{jr}^\alpha K_{jr}^{(1-\alpha)\mu} \bar{R}_{jr}^{(1-\alpha)(1-\mu)} \tag{B.1}
\]

Firms choose labor \( (L_{jr}) \), capital \( (K_{jr}) \), which is fully flexible and provided at an internationally determined price \( i \), and the amount of resources \( (\bar{R}_{jr}) \) used in production to maximize profits, taking local industry specific productivity \( (A_{jr}) \), output prices \( (p_j) \), non-tradable resource prices \( (q_{jr}) \), and local wages \( (w_r) \) as given. The non-tradable resource \( (\bar{R}_{jr}) \) is assumed to be fixed at the local industry level.

B.1 Deriving an Expression for Changes in Local Industry Labor Demand

To derive an expression for changes in local industry labor demand, I start from the fact that perfect competition implies that revenue equals costs

\[
L_{jr}w + K_{jr}i + \bar{R}_{jr}q_{jr} = p_jY_{jr}. \tag{B.2}
\]

Totally differentiating this condition and using the first order conditions from cost minimization one can then show that:

\[
dln p_j + dln Y_{jr} = \alpha dln L_{jr} + (1-\alpha)\mu dln K_{jr} + \alpha dln w_r + (1-\alpha)(1-\mu)dln q_{jr}. \tag{B.3}
\]

We further know from cost minimization that

\[
dln Y_{jr} - dln A_{jr} = \alpha dln L_{jr} + (1-\alpha)\mu dln K_{jr}, \tag{B.4}
\]

which can be used to replace \( dln Y_{jr} \) in (B.3) such that:

\[
dln p_j + dln A_{jr} = \alpha dln w_r + (1-\alpha)(1-\mu)dln q_{jr}. \tag{B.5}
\]

One can then use equation (B.5) together with the fact that with a Cobb-Douglas production

49The derivations in Appendix B.1 and B.2 are similar to Dix-Carneiro and Kovak (2016).
function the elasticity of substitution between the input factors is equal to 1 (and the price of capital, $i$, is fixed), and hence

\[
\begin{align*}
\text{dln}L_{jr} - \text{dln}K_{jr} &= -\text{dln}w_r \\
\text{dln}K_{jr} &= \text{dln}q_{jr}
\end{align*}
\]  

(B.6)  

(B.7)

to express changes in local industry employment as a function of changes in wages

\[
\text{dln}L_{jr} = \frac{1}{(1-\alpha)(1-\mu)} \text{dln}p_j + \frac{1}{(1-\alpha)(1-\mu)} \text{dln}A_{jr} - \frac{1-\mu(1-\alpha)}{(1-\alpha)(1-\mu)} \text{dln}w_r
\]  

(B.8)

by plugging (B.7) into (B.6), solving for $\text{dln}q_{jr}$, using the resulting expression to replace $\text{dln}q_{jr}$ in (B.5) and finally solving for $\text{dln}L_{jr}$. Equation (B.8) is equivalent to equation (3.3) in the main text.

### B.2 Derivation of Equations (3.5) and (3.6): Agglomeration Economies

The last missing step is to incorporate agglomeration economies into the model and derive expressions for local industry labor demand changes (equation (3.5)) and changes in equilibrium local industry employment (equation (3.6)) that depend on the size of agglomeration economies. As mentioned in Section 3.2, agglomeration forces and hence localized spillovers between industries are captured by the local industry specific productivity shifter $A_{jr}$ and assumed to work through the size of employment in all industries in the local labor market. In particular, in the main part of the model, I assume a constant agglomeration elasticity such that $\ln(A_{jr}) = \lambda \ln L_r$. I will analyze a model with heterogeneous agglomeration economies in Appendix B.3.

The definition of agglomeration economies can be used to rewrite equation (B.8) to

\[
\text{dln}L_{jr} = \frac{1}{(1-\alpha)(1-\mu)} \text{dln}p_j + \frac{1}{(1-\alpha)(1-\mu)} \lambda \text{dln}L_r - \frac{1-\mu(1-\alpha)}{(1-\alpha)(1-\mu)} \text{dln}w_r
\]  

(B.9)

If instead expressing equation (B.9) as a total derivative with respect to $p_k$ and assuming $\frac{\text{dln}p_j}{\text{dln}p_k} = 0$ for all $k \neq j$ one can derive equation (3.5) from the main text:

\[
\frac{\text{dln}L_{jr}}{\text{dln}p_k} = \frac{\lambda}{(1-\alpha)(1-\mu)} \frac{\text{dln}L_r}{\text{dln}p_k} - \frac{1-\mu(1-\alpha)}{(1-\alpha)(1-\mu)} \frac{\text{dln}w_r}{\text{dln}p_k}.
\]  

(B.10)

The last step is then to derive expressions for equilibrium local industry employment changes and local wage changes that depend only on exogenous parameters. To do so, I first derive an expression for equilibrium employment changes in overall local employment.

This can be done by starting from the fact that factor market clearing implies that
\[ \sum L_{jr} = L_r. \]  

(B.11)

and hence

\[ \sum s_{jr} d\ln L_{jr} = d\ln L_r \]

where \( s_{jr} \) is the initial share of industry \( j \) employment in region \( r \), that is \( s_{jr} = \frac{L_{jr}}{L_r} \).

Summing up the expression for changes in local industry labor demand (equation (B.8)) across industries then implies that

\[ d\ln L_r = \sum s_{jr} d\ln L_{jr} = \frac{1}{(1-\alpha)(1-\mu)} \sum s_{jr} (d\ln p_j + d\ln A_{jr}) - \frac{1-\mu(1-\alpha)}{(1-\alpha)(1-\mu)} d\ln w_r. \]

Finally using the definition of agglomeration economies (\( d\ln A_{jr} = \lambda d\ln L_r \)) and the local labor supply condition (\( \ln (L_r) = \frac{1}{\eta} \ln (w_r) \), equation (3.7)), one can derive expressions for equilibrium employment changes in overall local employment and wages:

\[ d\ln L_r = \frac{1}{(1-\alpha)(1-\mu) - \lambda + [1-\mu(1-\alpha)]\eta} \sum s_{jr} d\ln p_j. \]

(B.12)

and

\[ d\ln w_r = \frac{\eta}{(1-\alpha)(1-\mu) - \lambda + [1-\mu(1-\alpha)]\eta} \sum s_{jr} d\ln p_j. \]

(B.13)

Equation (B.13) is equivalent to equation (3.7) in the main text. Lastly, to derive an expression for changes in equilibrium local industry employment that only depends on exogenous parameters, one needs to plug (B.12) and the local labor supply condition into equation (B.9) such that

\[ d\ln L_{jr} = \frac{1}{(1-\alpha)(1-\mu)} d\ln p_j + \frac{1}{(1-\alpha)(1-\mu)(1-\alpha)(1-\mu) - \lambda + [1-\mu(1-\alpha)]\eta} \sum s_{kr} d\ln p_k, \]

(B.14)

which is equivalent to equation (3.6) in the main text.

**Connection to Trade Shocks and Empirics**

In the model changes in prices are used to analyze how product demand shocks triggered by national industry trade shocks affect local industry employment. In the empirical estimation I however exploit national industry trade shocks directly, that is I analyze the effects of changes in quantities...
instead of changes in prices. To reflect this, one can rewrite equations (B.12), (B.13), and (B.14) as

\[
dlnL_r = \frac{\beta_{empl}}{r} TrShockReg_r, \quad \text{(B.15)}
\]

\[
dlnw_r = \frac{\beta_{wage}}{w} TrShockReg_r, \quad \text{(B.16)}
\]

\[
dlnL_{jr} = \frac{\theta}{(1-\alpha)(1-\mu)} TrShock_j + \frac{\beta_{empl}}{indir} TrShockIndir_{jr}, \quad \text{(B.17)}
\]

where \(\rho\) should be thought of as a scaling factor that translates changes in quantities into changes in prices. \(TrShock_j\) represents direct national industry trade shocks to industry \(j\), \(TrShockIndir_{jr}\) indirect exposure to the other local industries’ trade shocks and \(TrShockReg_r\) regional exposure to local industry trade shocks. These measures are defined in more detail in Section 4.2.
B.3 Allowing for Heterogeneous Agglomeration Economies

In this section, I incorporate heterogeneous agglomeration economies into the model presented in Section 3.2. The main difference to the model assuming constant agglomeration economies is that I now define the local industry specific productivity shifter as

\[ \ln(A_{jr}) = \sum_k \lambda_{jk} \ln(L_{kr}) \]

as in equation (3.9). To derive an expression for local industry equilibrium employment changes I start from the derived local labor demand function (equation (3.3) in the main text):

\[
\frac{d \ln L_{jr}}{d \ln L_{jr}} = \frac{1}{(1-\alpha)(1-\mu)} \frac{d \ln p_j}{d \ln p_j} + \frac{1}{(1-\alpha)(1-\mu)} \sum_k \lambda_{jk} \left( \frac{d \ln L_{kr}}{d \ln L_{kr}} \right) - \frac{1-\mu}{(1-\alpha)(1-\mu)} \frac{d \ln w_r}{d \ln w_r}
\]

For easier exposition I rewrite the function as

\[
\frac{d \ln L_{jr}}{d \ln L_{jr}} = \frac{1}{\phi} \frac{d \ln p_j}{d \ln p_j} + \frac{1}{\phi} \sum_k \lambda_{jk} \left( \frac{d \ln L_{kr}}{d \ln L_{kr}} \right) - \frac{\gamma}{\phi} \frac{d \ln w_r}{d \ln w_r}, \tag{B.18}
\]

where I define \( \phi \equiv (1-\alpha)(1-\mu) \) and \( \gamma \equiv 1-\mu(1-\alpha) \).

Analyzing the second term of equation (B.18) in more detail, one should notice that \( \sum_k \lambda_{jk} (d \ln L_{kr}) \) can be expressed as a series:

\[
\sum_k \lambda_{jk} (d \ln L_{kr}) = \sum_k \lambda_{jk} \left[ \frac{1}{\phi} d \ln p_k - \frac{\gamma}{\phi} d \ln w_r \right] + \frac{1}{\phi} \sum_k \lambda_{kl} \left[ \frac{1}{\beta} d \ln p_l - \frac{2}{\phi} d \ln w_r \right] + \frac{1}{\phi} \sum_m \lambda_{lm} \left[ \ldots \right]
\]

\[
\approx \left( \frac{1}{\phi} \right) \sum_k \lambda_{jk} d \ln p_k + \left( \frac{1}{\phi} \right) \sum_k \lambda_{jk} \left[ \frac{1}{\phi} \sum_l \lambda_{kl} d \ln p_l \right] + \left( \frac{1}{\phi} \right)^2 \sum_k \lambda_{jk} \left[ \sum_l \lambda_{kl} \sum_m \lambda_{lm} d \ln p_m \ldots \right]
\]

\[- \left( \frac{1}{\phi} \right) \gamma \left[ \sum_k \lambda_{jk} d \ln w_r + \left( \frac{1}{\phi} \right) \sum_k \lambda_{jk} \left[ \frac{1}{\phi} \sum_l \lambda_{kl} d \ln w_r \right] + \left( \frac{1}{\phi} \right)^2 \sum_k \lambda_{jk} \left[ \sum_l \lambda_{kl} \sum_m \lambda_{lm} d \ln w_r \ldots \right] \right]. \tag{B.19}
\]

Expressing \( \sum_k \lambda_{jk} (d \ln L_{kr}) \) in this way makes clear that agglomeration spillovers lead to additional agglomeration spillovers (line two of equation (B.19)) and through these to additional reallocation effects (line three of equation (B.19)). For easier exposition, in what follows, I proceed by ignoring the higher order effects and focus only on the first round of spillover and reallocation effects. That is, I assume:

\[
\sum_k \lambda_{jk} (d \ln L_{kr}) \approx \sum_k \lambda_{jk} \left[ \frac{1}{\phi} d \ln p_k - \frac{\gamma}{\phi} d \ln w_r \right] \tag{B.20}
\]

In that case equation (B.18) can be written as

\[
\frac{d \ln L_{jr}}{d \ln L_{jr}} = \frac{1}{\phi} d \ln p_j + \frac{1}{\phi} \sum_k \lambda_{jk} \left[ \frac{1}{\phi} d \ln p_k - \frac{\gamma}{\phi} d \ln w_r \right] - \frac{\gamma}{\phi} d \ln w_r \tag{B.21}
\]

Arguably, the bulk of the agglomeration response should be captured by the first round of spillovers.
and summing up across local industries $j$ leads to

$$
dlnL_j = \sum s_{jr} dlnL_{jr} = \frac{1}{\phi} \sum s_{jr} dlnp_j + \frac{1}{\phi^2} \sum s_{jr} \sum \lambda_{jk} dlnp_k - \frac{\gamma}{\phi^2} \sum s_{jr} \sum \lambda_{jk} dlnw_r - \frac{2}{\phi} dlnw_r.
$$

(B.22)

Using the fact that the local labour supply condition (equation (3.2)) implies that $\frac{1}{\eta} dlnw_r = dlnL_r$ and defining $\lambda_j \equiv \sum_k \lambda_{jk}$, one can use equation (B.22) to derive an expression for equilibrium changes in local wages only depending on exogenous parameters and price changes:

$$
dlnw_r = \frac{\eta}{\phi + \eta \frac{\gamma}{\phi^2} \sum_j s_{jr} \lambda_j} \left[ \sum s_{jr} dlnp_j + \frac{1}{\phi} \sum s_{jr} \sum \lambda_{jk} dlnp_k \right].
$$

(B.23)

Lastly, plugging equation (B.23) back into equation (B.21), one gets an expression of changes in local industry employment $dlnL_{jr}$ as a function of price changes $dlnp_k$ and exogenous parameters only, which again reflects the trade-off between agglomeration spillovers and endogenous wage reactions:

$$
dlnL_{jr} = \frac{1}{\phi} dlnp_j + \frac{1}{\phi^2} \sum_k \lambda_{jk} dlnp_k - \left( \frac{\lambda_j + \phi}{\phi^2} \right) \frac{\gamma}{\beta + \eta \frac{\gamma}{\phi^2} \sum_l s_{lr} \lambda_l + \eta \gamma} \left[ \sum s_{kr} dlnp_k + \frac{1}{\phi} \sum s_{lr} \sum \lambda_{lk} dlnp_k \right].
$$

(B.24)

Note that the strength of the endogenous wage adjustments does depend on the agglomeration elasticity $\lambda_{jk}$ as well, as first round agglomeration spillovers affect wages (see equation (B.20)).

Finally equation (B.24) can be rewritten as

$$
dlnL_{jr} = \frac{1}{\phi} dlnp_j + \frac{1}{\phi^2} \sum_k \left( \lambda_{jk} - \frac{(\lambda_j + \phi) \gamma}{\phi + \eta \frac{\gamma}{\phi^2} \sum_l s_{lr} \lambda_l + \eta \gamma} \left[ s_{kr} + \frac{1}{\phi} \sum s_{lr} \lambda_{lk} \right] \right) dlnp_k.
$$

(B.25)

acknowledging the fact that one cannot distinguish between endogenous wage adjustments and agglomeration spillovers empirically. Again, this equation shows that, holding constant an industry’s own price change (first term), in the absence of agglomeration forces ($\lambda = 0$), when other industries in the region face positive price shocks (i.e. $dlnp_k > 0$), the reallocation effect reduces local employment in industry $j$.\footnote{In that case equation (B.25) boils down to $dlnL_{jr} = \frac{1}{\phi} dlnp_j - \frac{\gamma}{\phi + \eta \frac{\gamma}{\phi^2} \sum_k s_{kr} dlnp_k}$, which is equivalent to the expression in the model presented in Section 3.2, when assuming $\lambda = 0$, see equation (3.6).} However, when agglomeration economies are present (that is $\lambda_{jk} > 0$ for some $j, k$) and if they are sufficiently strong, then positive shocks to other industries may lead to increases in the equilibrium employment of industry $j$.\footnote{In that case equation (B.25) boils down to $dlnL_{jr} = \frac{1}{\phi} dlnp_j - \frac{\gamma}{\phi + \eta \frac{\gamma}{\phi^2} \sum_k s_{kr} dlnp_k}$, which is equivalent to the expression in the model presented in Section 3.2, when assuming $\lambda = 0$, see equation (3.6).}
Connection to Empirics

Equation (B.25) allows to analyze the existence of heterogeneous agglomeration economies empirically. To do so, one can put more structure on the agglomeration elasticity. For example, to allow for the fact that spillovers should be particularly strong in industries that are economically close to each other, one can define measures of economic proximity \((w_{j\text{prox}}^{\text{prox}})\) such that the agglomeration elasticity can be expressed as \(\lambda_{jk} = \lambda_{\text{prox}}^{\text{prox}} w_{jk}^{\text{prox}}\). Assuming this structure of agglomeration economies implies the following expression for changes in local industry employment:

\[
\frac{d \ln L_{jr}}{\phi} + \frac{1}{\phi^2} \sum_k \left( \frac{\lambda_{jk} + \phi \gamma \eta}{\phi + \phi_\eta \sum_l s_{lr} \lambda_l + \eta \gamma} \left[ s_{kr} + \frac{1}{\phi} \sum_l s_{lr} (\gamma_1 \lambda_{\text{prox}}^{\text{prox}} w_{lk}^{\text{prox}}) \right] \right) d \ln p_k
\]

Alternatively one may want to analyze whether agglomeration effects vary by certain groups of industries. For example, one can divide industries into two groups \(G_1\) and \(G_2\). In this case the change in local industry employment can be expressed as

\[
\frac{d \ln L_{jr}}{\phi} + \frac{1}{\phi^2} \sum_k \left( \frac{\lambda_{jk} - (\lambda_j + \phi \gamma \eta)}{\phi + \phi_\eta \sum_l s_{lr} \lambda_l + \eta \gamma} \left[ s_{kr} + \frac{1}{\phi} \sum_l s_{lr} (\gamma_1 \lambda_{\text{prox}}^{\text{prox}} w_{lk}^{\text{prox}}) \right] \right) d \ln p_k + \\
+ \frac{1}{\phi^2} \sum_{k' \in G_2} \left( \frac{\lambda_{jk'}}{\phi + \phi_\eta \sum_l s_{lr} \lambda_l + \eta \gamma} \left[ s_{kr'} + \frac{1}{\phi} \sum_l s_{lr} \lambda_l \right] \right) d \ln p_{k'}
\]

If one further assumes that agglomeration economies are constant for all industries within \(G_i\), then the agglomeration elasticity can be expressed as \(\lambda_{jk} = \lambda_{\text{prox}} w_{jk}^{\text{prox}}\).

I investigate whether agglomeration economies are heterogeneous in Sections 6.2.2 and 6.2.3 by distinguishing between spillover effects from shocks to industries in the same broad sector as industry \(j\) (\(G_1\)) and industries in other broad sectors (\(G_2\), by creating 3 measures of economic proximity \(w_{jk}^{\text{prox}}\), and by analyzing whether spillovers between industries are stronger when trade shocks directly affect high technology industries (\(G_1\)) as opposed to low technology industries (\(G_2\)).

B.4 Model Extension: Housing

The model presented in Section 3.2 does abstract from housing and land markets. One can, however, relatively easily extend the model to include housing. To do so, I assume that workers inelastically demand one unit of housing \(H_r^{D}\), such that \(H_r^{D} = L_r\). For simplicity, I also assume that housing
supply $H^S_r$ is exogenously given and only depends on housing prices $r_r$ such that

$$\ln H^S_r = \frac{1}{\kappa} \ln r_r,$$

where $\kappa$ represents the inverse elasticity of housing supply. This elasticity measures the local housing supply response to local house price changes. Housing prices are determined by the housing market clearing condition, $H^S_r = H^D_r$ such that

$$\ln r_r = \kappa \ln L_r.$$

From there, one can derive the equilibrium expression for changes in housing prices by using the equilibrium expression for local employment changes (equation (B.12)) derived in Section B.2 such that now there are three equilibrium expressions, one for changes in local industry employment, one for local wages, and one for local housing prices:

$$d\ln L_{jr} = \frac{1}{(1-\alpha)(1-\mu)} d\ln p_j + \frac{1}{(1-\alpha)(1-\mu)} \frac{\lambda - [1 - \mu(1 - \alpha)]}{(1 - \alpha)(1 - \mu) - \lambda + [1 - \mu(1 - \alpha)]} \eta \sum_k s_{kr} d\ln p_k,$$

(B.27)

$$d\ln w_r = \eta \frac{(1-\alpha)(1-\mu) - \lambda + [1 - \mu(1 - \alpha)]}{\eta} \sum_k s_{kr} d\ln p_k,$$

(B.28)

and

$$d\ln r_r = \kappa \frac{(1-\alpha)(1-\mu) - \lambda + [1 - \mu(1 - \alpha)]}{\eta} \sum_k s_{kr} d\ln p_k.$$

(B.29)

The expression for equilibrium changes in local housing prices consequently leads to an additional prediction of the model: If local housing supply is less than infinitely elastic (i.e. $\kappa > 0$), local house prices should increase following a price shock to a local industry, that is $\frac{d\ln r_r}{d\ln p_k} > 0$.

The incorporation of housing prices also has implications for the interpretation of the local labour supply elasticity ($\frac{1}{\eta}$). It now represents the effective elasticity of labor supply that incorporates housing market feedback in the labor supply decision (see, for example, Suárez Serrato and Zidar (2016)). This implies that through the local labour supply, elasticity changes in housing prices will have an impact on local wages and hence reinforce the reallocation effect.
C Supplemental Empirical Results & Tables

C.1 Set of Instrument Countries

Table C1: Set of Instrument Countries

<table>
<thead>
<tr>
<th></th>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Australia</td>
</tr>
<tr>
<td>2</td>
<td>Canada</td>
</tr>
<tr>
<td>3</td>
<td>Denmark</td>
</tr>
<tr>
<td>4</td>
<td>Finland</td>
</tr>
<tr>
<td>5</td>
<td>New Zealand</td>
</tr>
<tr>
<td>6</td>
<td>Norway</td>
</tr>
<tr>
<td>7</td>
<td>Singapore</td>
</tr>
<tr>
<td>8</td>
<td>Spain</td>
</tr>
<tr>
<td>9</td>
<td>Sweden</td>
</tr>
<tr>
<td>10</td>
<td>Switzerland</td>
</tr>
<tr>
<td>11</td>
<td>United Kingdom</td>
</tr>
</tbody>
</table>

**Notes:** The table reports the set of high income countries used to instrument German trade exposure.

C.2 Robustness Analysis

The results presented in Section 6.2.1 are robust to a number of alternative specifications and choices of instrument countries. Table C2, Panel A presents the results of alternative specifications focusing on the effects of spillovers from other tradable industries’ trade shocks. For comparison, column (1) presents the baseline results (equivalent to Table 4, column (4)) estimated using equation (4.4), that is controlling for the tradable industry share in the region, the 3-digit industry share, further regional and industry characteristics, 3-digit industry x period fixed effects and federal state x period fixed effects. In column (2), the federal state x period fixed effects are replaced by commuting zone x period fixed effects. This specification implicitly controls for endogenous wage changes at the regional level, that is it controls for the part of the reallocation effect that is common to all local industries in the commuting zone.\(^{52}\) The estimated effect is very similar to the baseline estimate and is in line with the absence of local wage effects estimated in Section 6.1 (see also Table 3, column (2)). Column (3) instead controls for the change in indirect net exposure to world trade (excluding trade with China and Eastern Europe). This specification is aimed at alleviating concerns about high income countries being affected by common export or import demand shocks due to, for example, correlated technological shocks. The results are very similar to the baseline specification, indicating that the results are not driven by world demand shocks. A further concern is that local industry employment shares are correlated with future trade shocks, for instance because these shares are affected by past trade shocks and trade shocks might be correlated over time. To account for this, in column (4), instead of using start of period employment levels, 1988 levels are used in all periods.

---

\(^{52}\) In addition, this specification helps to alleviate concerns that the rise in employment following indirect trade shocks is driven by an increase in local amenities attracting more workers to the region rather than agglomeration spillovers.
(1981 levels for the instruments) to distribute national industry trade flows to the local industries, to normalize the indirect trade exposure measure, and to generate the share controls (see also equation (4.1)). The results do not change considerably. In column (5), local industries in the lowest and the highest percentile of indirect net trade exposure (within 3-digit category) are dropped from the sample. This accounts for the fact that industries with the lowest and highest levels of indirect net trade exposure (within 3-digit category) seem to be negatively selected (see Table 2). Excluding these observations increases the coefficient of indirect net trade exposure slightly. In column (6), I control for potential pre-shock trends in local industry employment growth that may be correlated with indirect net trade exposure by controlling for log employment growth from 1981 to 1988. Controlling for such pre-trends does not significantly change the estimated coefficients.

In Panel B of Table C2, I present results using alternative sets of instrument countries. Column (1) presents the baseline results for comparison (equivalent to Table 4, column (4) in B.1 and to Table 6, Panel B, column (1) in B.2). Column (2) adds Japan to the set of instrument countries. Column (3) instead adds the US while column (4) excludes the Eurozone countries Finland and Spain from the set of instrument countries and column (5) excludes the countries sharing a border with Germany (Switzerland and Denmark). The results in columns (2) to (5) are largely similar to the baseline results in column (1). The qualitative conclusions from the baseline results are consequently not driven by a specific choice of the set of instrument countries.

---

53 The only large difference is when including Japan in the set of instrument countries. The lower estimated effect can potentially be explained by the fact that Japanese industries are in high export competition with German industries. Consequently, the correlation in exports to China and Eastern Europe between Germany and Japan likely understates the true correlation between the German and Japanese export shocks. This might lead to a downward bias in the effects. Furthermore, the Japan coefficient increases to 5.27 percentage points when excluding industries below the 1st or above the 99th percentile of indirect net trade exposure.
Table C2: Agglomeration Spillovers, Robustness

<table>
<thead>
<tr>
<th>Panel A: Alternative Specifications</th>
<th>Panel B: Instrument Countries</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline (1)</td>
</tr>
<tr>
<td>Tradable Sector Measure</td>
<td>7.745*** (1.756)</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>27.99</td>
</tr>
<tr>
<td>N</td>
<td>25963</td>
</tr>
</tbody>
</table>

Panel B: Instrument Countries

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>+ Japan (2)</th>
<th>+ USA (3)</th>
<th>Exclude Eurozone Neighbours (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B.1 Baseline</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indirect Net Exposure, Tradables</td>
<td>7.745*** (1.756)</td>
<td>3.006*** (1.083)</td>
<td>6.199*** (1.727)</td>
<td>9.402*** (2.216)</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>27.99</td>
<td>39.038</td>
<td>30.899</td>
<td>20.161</td>
</tr>
</tbody>
</table>

B.2 High vs Low Skill Exposure

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>+ Japan (2)</th>
<th>+ USA (3)</th>
<th>Exclude Eurozone Neighbours (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indirect Net Exposure, Low Skilled</td>
<td>4.818** (1.891)</td>
<td>1.322</td>
<td>2.850* (1.213)</td>
<td>6.675*** (1.542)</td>
</tr>
<tr>
<td>Indirect Net Exposure, High Skilled</td>
<td>11.053*** (3.197)</td>
<td>7.155*** (2.612)</td>
<td>8.397*** (3.141)</td>
<td>11.735*** (3.614)</td>
</tr>
<tr>
<td>F-Statistic, Low Skilled</td>
<td>20.67</td>
<td>17.951</td>
<td>20.285</td>
<td>17.551</td>
</tr>
<tr>
<td>F-Statistic, High Skilled</td>
<td>30.82</td>
<td>47.806</td>
<td>39.718</td>
<td>21.377</td>
</tr>
</tbody>
</table>

| N                          | 25963 | 25963 | 25963 | 25963 | 25963 |

Notes: The table reports estimates of indirect net trade exposure on local industry employment. All estimates are from two stage least squares regressions based on equation (4.4) including federal state x period fixed effects, national industry x period fixed effects, and regional and industry level controls. Observations are measured on 3-digit industry x commuting zone level. Panel A, Column (1) shows the baseline specification results from Table 4, column (4). In column (2), federal state x period fixed effects are replaced by commuting zone x period fixed effects. Column (3) controls for the change in net world trade (total German net trade minus net trade with China and Eastern Europe). Column (4) uses 1988 employment instead of start of period employment for both accruing national trade flows to local industries and the normalization of the indirect trade exposure measure and weights regressions by 1988 employment. Column (5) excludes the industries with the lowest and the highest percentile of indirect net trade shocks and column (6) controls for pre-shock trends in local industry employment, by controlling for log industry employment growth from 1981 to 1988. N is measured on 3-digit industry x commuting zone level. Significance levels 1%***, 5%**, 10%*. Standard errors are clustered at the commuting zone level.
C.3 Comparison to Beaudry et al. (2012)

In this section, I compare and contrast the predictions from the Beaudry et al. (2012) search and bargaining model with those in the model of agglomeration economies presented in Section 3.2, and analyze what this implies for the interpretation of the empirical results presented in Section 6. Beaudry et al. (2012) examine whether the industrial composition of jobs in a region matters for observed local industry wage levels. The idea is that in a standard search and bargaining model of the labor market, a change in industrial composition affects the bargaining position of workers by changing their outside options, which implies that local industry wages are higher in regions where the other industries are high-paying rather than low-paying. This presents an additional source of potential spillovers in local labor markets, apart from spillovers stemming from agglomeration economies.

In terms of wages, the predictions of Beaudry et al.’s (2012) search and bargaining model are congruent with the predictions of the model of agglomeration spillovers presented here. Both spillovers from agglomeration and increased wage pressure through an increase in the outside option due to wage increases in other industries predict positive effects on wages. However, the predictions are not congruent in terms of employment. While Beaudry et al. (2012) focus on the effects of increased bargaining power due to changes in the industrial composition on wages, the effects on job creation (and hence employment) are analyzed more explicitly in a follow-up paper. In Beaudry et al. (2013), the authors predict that assuming free entry, an increase in wages in the region (or in the other industries in the region) must lead to a decline in the tightness of the labor market and hence a decline in the employment rate. This relationship between wages and the employment rate determines the job creation curve. The search and bargaining model by Beaudry et al. (2012, 2013) would consequently predict negative effects on employment and the employment rate. This stands in contrast to my model of agglomeration economies, which predicts that in the presence of agglomeration economies, indirect exposure to the local industry trade shocks of the other local industries in the region may lead to increases in local industry employment (and hence predict a tightening of the labor market). This indicates that the results presented here cannot be explained by the Beaudry et al. (2012) search and bargaining model, as I find strong positive spillover effects on employment and no increases in regional wages.

However, to relate my results better to the Beaudry et al. (2012, 2013) story, I present some additional results in Appendix Table C3. First, I explicitly estimate the effects of local industry trade shocks to the other local industries in the region on wages in the industry under observation using equation (4.4). These results do not indicate positive wage spillovers from local industry trade shocks, if anything it seems that wage spillovers may be negative (column (1)). That said, due to data restrictions these estimates do not account for potential composition effects, which could explain the negative effects (i.e. the newly hired workers could earn less because they are seen as relatively less able). Second, I estimate a version of employment rate spillovers from trade shocks, that is a model with the change in the (log) local industry employment rate as dependent
variable. This specification allows to analyze whether labor market tightness in the industry under observation increased following trade shocks to the other industries in the region, which would be predicted if agglomeration spillovers are at play, but not in the Beaudry et al. (2012, 2013) scenario. I find similarly strong effects on the employment rate, as on absolute employment, indicating that labor market tightness increases in response to indirect trade exposure (column (2)). Lastly, I estimate a version of equation (4.4) with log industry employment changes as dependent variable, where I explicitly control for indirect exposure to wage changes in the other local industries in the region in column (3), hence directly accounting for potential wage spillovers. Here I define indirect wage changes as in Beaudry et al. (2012) as $\sum s_{jr} w_{jr}$, where $s_{jr}$ is defined as the initial share of industry $j$ employment in region $r$. The coefficient is again very similar to the baseline coefficient (compare to Table 4, column (4)). These results jointly provide further evidence that the effects in this paper cannot be explained by the Beaudry et al. (2012) search and bargaining model, but are instead in line with the presence of agglomeration spillovers.

Table C3: Comparison to Beaudry et al. (2012)

<table>
<thead>
<tr>
<th></th>
<th>Wages (1)</th>
<th>Employment Rate (2)</th>
<th>Employment Employment (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indirect Net Exposure, Tradables</td>
<td>-0.822** (0.419)</td>
<td>7.506*** (1.719)</td>
<td>7.805*** (1.768)</td>
</tr>
<tr>
<td>Indirect Exposure to Wage Changes</td>
<td>-0.004 (0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-Statistic</td>
<td>27.99</td>
<td>27.99</td>
<td>27.92</td>
</tr>
<tr>
<td>N</td>
<td>25962</td>
<td>25963</td>
<td>25962</td>
</tr>
</tbody>
</table>

Notes: The table reports estimates of indirect net trade exposure on local industry employment and wages. The estimates are from two stage least squares regressions based on equation (4.4) including federal state x period fixed effects, national industry x period fixed effects, and regional and industry level controls. Observations are measured on the 3-digit industry x commuting zone level. The dependent variable in column (1) is the change in log wages (x100), the dependent variable in column (2) the log change in the employment rate (x100), and the dependent variable in column (3) the log change in local industry employment (x100). Column (3) controls additionally for indirect exposure to the wage changes of the other industries in the region. Indirect net trade exposure is measured in per 1 Million EUR per worker (adjusted to 2005 prices). Reported first stage F-statistics are Sanderson-Windmeijer F-Statistics. Standard errors are clustered at the commuting zone level. Significance levels 1%***, 5%**, 10%*.
C.4 US Input-Output Tables (3-digit level)

Table C4 investigates the impact of economic proximity on the strength of spillovers by using US input-output tables at the 3-digit industry level as a proxy for the German input-output relations, allowing to analyze the effects on vertically linked industries on a finer level than between 2-digit industries. I use the input-output tables from the 1997 Benchmark Input-Output Accounts published by the Bureau of Economic Analysis (BEA). The correlation between the upstream measures of indirect trade exposure at the 2-digit and the 3-digit industry level is 0.5 and the correlation between the two downstream measures of indirect trade exposure is 0.46. The estimated results are very similar to those in Table 5.

Table C4: Agglomeration Spillovers, Mechanisms (US Input-Output Tables (3-digit))

<table>
<thead>
<tr>
<th>Only Worker Transition Measure</th>
<th>Only Upstream Measure</th>
<th>Only Downstream Measure</th>
<th>All Mechanisms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Indirect Net Exposure Worker Transitions</td>
<td>7.818**</td>
<td>8.949**</td>
<td>3.425</td>
</tr>
<tr>
<td>Indirect Net Exposure Upstream</td>
<td>-0.381</td>
<td>-1.103</td>
<td>0.619</td>
</tr>
<tr>
<td>Indirect Net Exposure Downstream</td>
<td>-0.597</td>
<td>-1.416**</td>
<td>0.582</td>
</tr>
<tr>
<td>Indirect Net Exposure</td>
<td>-2.213</td>
<td>3.145***</td>
<td>3.197***</td>
</tr>
</tbody>
</table>

| F-Statistic Worker Transitions | 23.36 | 32.644 |
| F-Statistic Upstream | 26.55 | 33.106 |
| F-Statistic Downstream | 17.91 | 20.567 |
| F-Statistic Indirect Net Exposure | 26.568 | 19.717 | 35.264 | 26.477 |

| N | 25963 | 25963 | 25963 | 25963 |

Notes: The table investigates whether employment effects of local indirect net trade exposure vary by economic proximity. Estimates are from two stage least squares regressions based on equation (4.3) including federal state x period fixed effects, national industry x period fixed effects, and regional and industry level controls. The indirect net trade exposure is reweighted according to 3 measures of economic proximity (see equation 6.1): the maximum of the share of workers leaving industry j and moving to industry k and the share of workers leaving industry k and moving to industry j over a 5-year window from t-5 to t (column (1), equivalent to Table 4, column (1)), the share of goods produced in industry k that is sold to industry j (column (2)), and the share of goods produced in industry j that is sold to industry k (Column (3)). These measures are calculated using US input-output tables at the 3-digit industry level. In Column (4), the 3 reweighted indirect net trade exposure measures are jointly included into the regression. All measures (including the baseline measure) are normalized to have mean 0 and standard deviation 1. Indirect net trade exposure is measured in per 1 Million EUR per worker (adjusted to 2005 prices). Reported first stage F-statistics are the Sanderson-Windmeijer F-Statistics. Standard errors are clustered at the commuting zone level. Significance levels 1%***, 5%**, 10%*. **