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Shocking Germany – A spatial analysis of German regional labor markets

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Shocking Germany - A spatial analysis of German regional labor markets*

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Abstract

This paper quantifies the surprisingly large heterogeneity of real income and employment effects across German counties in response to local productivity shocks. Using a quantitative model with imperfect mobility and sector-specific labor market frictions together with an outstanding data set of county level goods shipments, I identify the sources of the heterogeneity in Germany's complex interregional linkages. I find that population mobility reduces the magnitude of local employment rate responses by a striking 70 percent on average. In all but a few counties, changes in the sectoral composition of production have a much milder effect on employment elasticities. National employment rates are less dependent on mobility with worker in- and outflows in individual counties partially cancelling out effects. For productivity shocks affecting individual sectors across all regions the composition effect is substantially magnified, the mobility effect reduced. In line with recent real world observations I find that real income and employment effects, while correlated, do not need to be of the same sign. Finally, the spatial propagation of real income effects closely follows trade linkages whereas employment effects are more complex to predict.

JEL-Classification: F16, F17, R13, R23

Keywords: Quantitative spatial analysis, unemployment, migration, search and matching, labor market frictions

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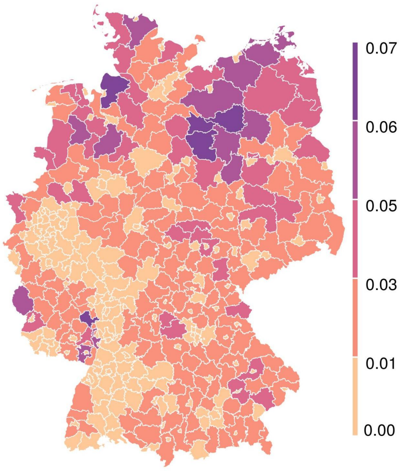
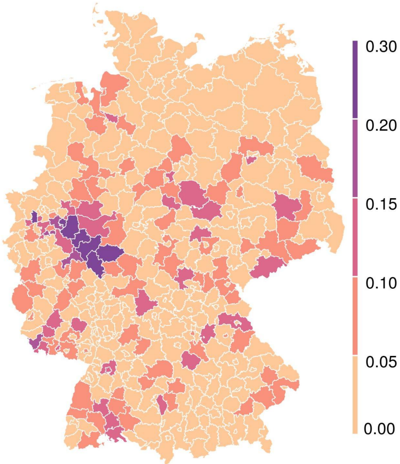
1 Introduction

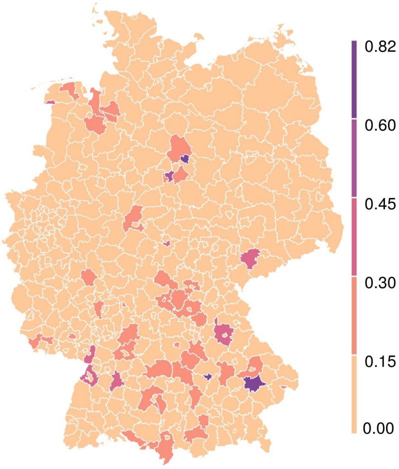
Economic activity is very unevenly distributed across German counties. The revenue generated in Berlin, for example, is about 100 times larger than that of the smallest German county. Similarly, the industries that counties depend on vary profoundly. Figure 1 exemplifies this by showing the share of three sample industries in each county's total revenue. Agriculture is more important in counties in the northeast of Germany than in the rest of the economy, the heavy industry (metal) is the economic base in the Ruhr area and transport equipment is of enormous importance for a handful of locations which host production plants of major car manufacturers (VW in the north, Audi and BMW in the southeast and Mercedes in the southwest). The arrangement of clusters differ as well. The metal industry is agglomerated in a single region but car manufacturing clusters are spread out across Germany.[1]



(a) Agriculture



(b) Metal



(c) Transport Equipment

Figure 1: Sectoral shares in total county revenue

Plausibly, this uneven distribution of economic activity implies that regional markets will respond differently to local and sectoral shocks and policies. A new technology in the automotive industry will affect regions differently than a new communications technology and a bankruptcy in Berlin will result in different effects than one in Munich. In fact, most economic shocks or policies possess a sectoral (e.g. industry innovations, product standards) or regional component (e.g. natural disasters, local policies, bankruptcies) and even a seemingly aggregate shock, such as a rise in import competition, translates into different regional shocks depending on the strength of foreign trade linkages with each county.

The goal of this paper is not to analyse a specific such event. Instead, in line with recent

[1]This is, of course, only a crude look at the production structure and agglomeration in Germany. Krebs (2018) provides a complete analysis of both the German production structure and interregional trade network, something that is beyond the scope of this paper.

research (see Caliendo et al. 2018; Monte et al. 2018; Krebs and Pflüger 2018a), I quantify the heterogeneity of responses to standardized local productivity shocks in a general equilibrium framework and, crucially, identify the drivers of the resulting differences. I am the first to do so for German counties in a general equilibrium model. The resulting heterogeneity of effects is surprisingly large. The local employment elasticities vary by a factor of 3.6 and real income elasticities by a factor of 2.3 depending on where a productivity shock takes place geographically. This quantification is vital for regional policy makers to project the impact that policies or productivity shocks, such as investments or bankruptcies, will have in a specific location. Moreover, these results are also informative in light of the growing body of empirical literature in the wake of Autor et al. (2013) that is concerned with analysing local labor market responses to aggregate shocks and that only derives single average elasticities of employment across regions.[2]

Importantly, I find that the heterogeneity of effects from regional productivity shocks persists with respect to resulting effects at the national level. Specifically, even after controlling for the size of the treated county, that is, looking at regional productivity shocks that are indistinguishable in the aggregate national data, national German welfare elasticities vary by a factor of 3.7 and national employment rate elasticities by a factor of 5.6 depending on where the shock occurs geographically. Clearly this implies that any analysis of national productivity shocks that ignores the underlying geography can be extremely misleading.

Moreover, the result that some local shocks have large aggregate consequences while others do not is in line with a sizable literature that explains how disaggregate shocks can be of aggregate importance. Long and Plosser (1983) and Horvath (1998, 2000), for example, show that sectoral shocks can magnify substantially through input-output networks in the real business cycle context. Similarly, Acemoglu et al. (2012) use network theory to show conditions under which "cascade effects" can lead from small disturbances in a production network to large aggregate effects. Gabaix (2011) demonstrate that even firm level shocks can magnify to important magnitudes if the size distribution of firms is sufficiently fat-tailed. Yet, all of these studies abstract from the geographical component of disaggregate shocks that this paper focuses on. One reason for this is that data on regional production and trade linkages between regions is rarely available at the necessary level of detail. At the heart of this paper, however, is a unique data set on shipments by truck, train or waterway among German counties and between counties and third countries that allows me to model Germany's complex sectoral and geographical input-output network. Based on this outstanding data I simulate how local productivity shocks ripple through the economy's network, po-

[2]Autor et al. (2013) analyse the effects of the rise in Chinese import competition on U.S. local labor markets. Further recent examples of this literature include Dauth et al. (2014) who perform a similar analysis for the German economy or Acemoglu and Restrepo (2017) and Dauth et al. (2018) who analyse the effect of robotization on U.S. and German local labor markets, respectively.

tentially multiply and affect the national German economy. In particular, I construct an Eaton and Kortum (2002) type spatial quantitative international and interregional trade model with multiple sectors and input-output relations as in Caliendo and Parro (2015) and with a geographically disaggregated Germany.[3] Moreover, in a regional context population movements are arguably also important linkages between locations and I therefore extend the model with imperfect labor mobility between German counties in the style of Redding (2016). In this setting workers have individual preferences for living in a particular region. Consequently, they will accept a lower real income to live in a location for which they have a strong preference and vice versa. Thus, in contrast to models with perfect mobility these models can replicate observed real income differentials across space in equilibrium if calibrated accordingly. The introduction of land and structures as a fixed factor in production similar to Krebs and Pflüger (2018b) serves as an exogenous factor determining agglomeration sizes. A large endowment of land ceteris paribus implies lower land prices and thus lower production costs and a more attractive location for firms.[4]

Finally, one of the key variables of interest regarding both local and national outcome is unemployment. Nevertheless, unemployment is often absent from trade models following the idea that any shock that raises real income, will in the presence of labor market frictions also lead to a higher employment rate and that both are thus simply two sides of the same coin. This notion, however, has come under heavy debate in the past years, as rising employment rates in the United States and European Union have gone hand in hand with stagnating real wages (The Economist 2018b). In line with this idea I find that for regional shocks aggregate welfare and employment effects are correlated but this correlation is far from perfect with a rank correlation of 0.61. Thus productivity increases in regions that have a large effect on national average or expected welfare need not have a large effect on the national employment rate and vice versa. It has been pointed out that the decoupling of the real income from the employment rate is in part due to an increase in jobs in low paying sectors with "The Economist" (2018a) poignantly noting that the number of hairdressers in the UK has increased by 50 percent since 2010.

To model how the growth and decline of specific sectors can influence the employment rate I

[3]Spatial quantitative models as surveyed by Redding and Rossi-Hansberg (2017) allow for a range of underlying trade structure. Using an Eaton-Kortum type model comes with two advantages. Firstly, it keeps my modelling approach closely related to Caliendo et al. (2018) who perform a similar study for the U.S., allowing me to compare my results with theirs. Secondly, sectoral size adjustments due to changes in comparative advantage match with the idea that different sectoral matching frictions drive unemployment effects as discussed below.

[4]As explained above, my modelling of trade follows Caetal2015 and is, thus not based on monopolistic competition and increasing returns to scale. Models of this type (see, for example, Krebs and Pflüger 2018a) feature an additional agglomeration force. However, in quantitative analysis parameters are usually chosen to restrict this force thus that circular effects, endogenous agglomeration and, subsequently, multiple equilibria can not arise (see Redding and Sturm 2008). Any agglomeration is, in both models, therefore exogenously determined by the initial calibration and choice of parameters.

follow Carrère et al. (2015) and incorporate industry-specific Diamond-Mortensen-Pissarides search and matching frictions into the model. In this setting firms can not directly hire new workers but instead open vacancies that lead to a successful match with a rate dependent on the number of job seekers and vacancies in the market. The sector specificity of frictions implies that given the same number of job seekers and vacancies in two different sectors vacancies will always be filled less likely in the one with the higher frictions. Carrère et al. (2015) and Carrère et al. (2014) demonstrate such differences in sectoral frictions using time series data for 25 OECD countries. To provide independent evidence for Germany I rely on time series data from the federal institute of employment research (IAB) containing information on job vacancies, unemployed (job seekers) and the average number of days that a job vacancy remains open beyond a company's preferred hire date. The data is on a yearly bases from 2012 to 2017 for the 16 German states and for 37 fields of occupation.[5] I use the log of the vacancy duration as a measure of labor market frictions and regress it on fixed effects of occupational fields, state-time fixed effects and the log of the number of unemployed per vacancy. Figure 2 depicts the deviation of fixed effects of occupational fields from their mean. Thus, for a given ratio of vacancies to job seekers filling a new vacancy takes about 32 percent longer than average in "security services" and 57 percent less time in "law and administration". Moreover, it is clear to see from the depicted 95 percent confidence intervals that in almost all cases these deviations are highly significant. A Wald test for a common fixed effects across occupational fields, that is, a common matching friction, is strongly rejected with an F-Value of 133.8.

Including such sector-specific frictions into the model has a central implication in line with the real world feature discussed above: changes in the employment rate no longer only depend on changes in the real wage. Instead, the employment effect can be decomposed into three separate channels. First, the initial productivity shock leads to an "expansion effect" that transmits through the trade network via terms of trade effects and induces firms to adapt the number of vacancies they open to hire workers. The change in the number of vacancies per job seeker then implies a change in the number of successful matches and the local employment rates. Secondly, shifts in comparative advantage in the trade network lead to structural transformation in each county. This "composition effect" shifts workers between sectors with different matching frictions and thereby influences the employment rate. Lastly, changes in the real income in each county lead to migration. An increase in the population size implies a larger number of job seekers per vacancy and vice versa for a decreasing population. This "mobility effect" consequently changes the number of successful matches per person and hence the employment rate in each county.[6]

[5] Cf. "Engpassanalyse" in "Berichte: Analyse Arbeitsmarkt" (2017) by the German institute for employment research.

[6] This is, in essence, the effect first described by Harris and Todaro (1970).

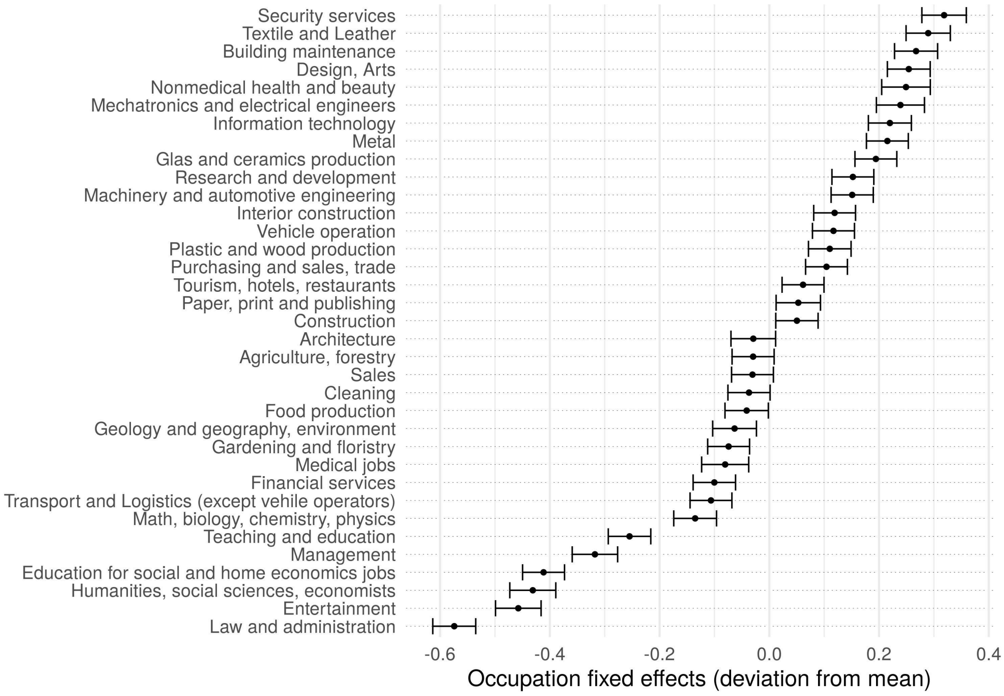


Figure 2: Matching frictions across occupational fields in Germany

A further key contribution of this paper is to quantify the role of these three effects in determining the overall local and national employment elasticities with respect to regional productivity shocks. Population inflow in response to a local productivity shock reduces the local employment elasticity by a striking 70 percent on average. Interestingly, the average influence of mobility on the national employment elasticity is much milder with only 3.64 percent as the employment effects of in- and outflows across counties mostly cancel each other out. The composition effect in contrast plays a much lower role on average. For shocks in some specific regions, however, it can reduce or increase local employment elasticities by up to -13 and 21 percent respectively and influence national employment elasticities by -9 to 13 percent. Moreover, looking at the detailed regional effects of local productivity shocks I find many regions that experience real income and employment effects of opposite signs in line with recent observations discussed above.

A final important result concerns the predictability of effects across locations. For real income gains the geographic dissipation of effects closely follows the treated county's trade network. The strength and sign of employment effects across counties, however, exhibits a more complex pattern depending not only on the trade network but also on population elasticities that are in turn influenced by individual preferences and locations' endowment with land.

Previous literature. In the broader context, this paper belongs to a branch of literature relying on (spatial) quantitative trade models that connect theory with numbers to quantify theoretical effects. Redding and Rossi-Hansberg (2017) provide a lucid survey of this literature that shows how quantitative models can be combined from a range of possible components. The specification of the model in this essay particularly relies on the seminal work by Caliendo and Parro (2015), providing a multisector specification of quantitative models, and Redding (2016) who introduces (imperfect) worker mobility. My work also builds on the recent literature that introduces the static Helpman and Itskhoki (2010) version of search and matching frictions into gravity type models. Felbermayr et al. (2013) and Heid and Larch (2016) build an Armington-type model with such frictions.[7] However, their model features no geographical disaggregation or population mobility and is constructed around one sector economies, which can not feature the sectoral reallocation effect on employment discussed in this paper. Carrère et al. (2015) instead build an Eaton-Kortum type multisector model with sector-specific search and matching frictions. They show that such a sectoral disaggregation implies that the real wage and employment rate are no longer perfectly correlated, as shocks to an economy induce shifts of workers between high and low friction industries. Yet, their model does not incorporate intermediates, which Caliendo et al. (2018) show to be crucial in the propagation of local shocks, nor do they include multiple production factors, or a regional context. Moreover, in contrast to their setting I also introduce population mobility which turns out to be crucial for quantitative effects.

My analysis is closely related to Caliendo et al. (2018) who study welfare and population elasticities of regional shocks in U.S. counties. Differences in modelling notwithstanding the magnitude of the heterogeneity of welfare elasticities in Germany that I find in this paper is similar to what Caliendo et al. (2018) find for U.S. counties. However, apart from studying a different country and using imperfect instead of perfect labor mobility, the superior data available for Germany allows me to model German counties integrated into the world economy whereas Caliendo et al. (2018) abstract from any international trade relations due to a lack of data. More importantly, however, their study rests on a full employment model and thus can not differentiate between employment and population elasticities. In contrast I explicitly model the strain that population inflows exert on local labor markets and find a strikingly large influence of mobility on employment rates. My study is also related to Monte et al. (2018) and Krebs and Pflüger (2018a) who use the same methodology to study the effects of commuting on local labor markets in the U.S. and Germany respectively albeit also using full employment models. Krebs and Pflüger (2018b) study the effects of a specific shock, the transatlantic trade and investment partnership (TTIP), at the German county level using a full employment model and constructing interregional trade flows based on proportionality assumptions. In contrast to their study, however, I can make use of a far superior data set to derive the subnational trade and production structure in Germany.

[7]Anderson and Van Wincoop (2003) for the Armingtons specification in gravity type models.

The remainder of the paper is structured as follows. Section 2 develops the theoretical model. Section 3 explains my empirical strategy and the calibration of the model, including the data sets used. Section 4 presents my results beginning with the aggregate, national effects of both regional and sectoral shocks and then turning to the disaggregated effects.

2 The model

Setup. I assume that the world economy consists of N locations, indexed by n or i. A subset $N^G \subset N$ of these locations represents German counties, the remainder are other countries and a modeled rest of the world (henceforth: ROW). Each location is endowed with an exogenous quality-adjusted amount of structures $\bar{S}_n$. The number of consumers in location n, denoted L_n, is exogenously given for countries but emerges endogenously in the case of German counties. Thus, the assumption is that the exogenous measure of German consumers $\bar{L}^G$, who supply 1 unit of labor each, are (imperfectly) mobile within Germany but not across countries. Land and labor are used to produce a continuum of differentiated goods in each of K sectors, indexed by k or j. Each of these sectors is subject to search and matching frictions between workers and firms that result in equilibrium unemployment. Workers will be perfectly mobile between sectors ex-ante but bound to their decision once they learn whether or not they will be unemployed. Hence, while the model features heterogeneous wages and unemployment rates across sectors a common ex-ante expected (or per capita) wage w_n across sectors emerges at each location. All locations can trade all varieties with each other subject to iceberg trade costs so that $d_{nik} \geq 1$ units of a good produced in industry k in location i have to be shipped in order for one unit of the good to arrive at location n. I assume that goods trade within a location is costless, $d_{nnk} = 1$. For each industry in each location another group of firms, operating under perfect competition and without adding value, sources all varieties from the cheapest supplier after trade costs to produce an industry aggregate. This compound good is non-traded and used either for consumption or as an input in the production process of varieties.

2.1 Consumers

Preferences. The preferences of a consumer Ω in location n are defined over the consumption of a goods bundle $C_n(\Omega)$ as follows:

$$U_n(\Omega) = a_n(\Omega)\, C_n(\Omega)\,, \tag{1}$$

where $a_n(\Omega)$ is a consumer specific amenity for living in location n discussed below. The consumption aggregate $C_n(\Omega)$ is defined over the consumption $C_{nk}(\Omega)$ of compound goods from each of K industries in a Cobb-Douglas fashion. Specifically,

$$C_n(\Omega) = \prod_{k=1}^{K} (C_{nk}(\Omega))^{\delta_{nC,k}}, \tag{2}$$

where $\delta_{nC,k}$ are the constant and location specific shares in consumption spending on industry k, with $0 \leq \delta_{nC,k} \leq 1$ and $\sum_{k=1}^{K} \delta_{nC,k} = 1$. The Cobb-Douglas price index for the consumption bundle is then

$$P_n = \prod_{k=1}^{K} P_{nk}^{\delta_{nC,k}}, \tag{3}$$

where P_{nk} denotes the price of the compound good of industry k in location n.

Mobility. I follow Redding (2016) and Tabuchi and Thisse (2002) in assuming that the location and consumer specific amenity $a_n(\Omega)$ is drawn independently by all consumers from location dependent distributions. As in Redding (2016) this distribution is of the Fréchet type with cumulative density functions given by

$$G_n(a) = e^{-A_n a^{-\epsilon}}. \tag{4}$$

Here A_n is a measure of average preference for location n and ϵ an inverse measure of the dispersion of amenities across workers. I assume that workers make their location decision after the amenity draw but before deciding on the sector in which to search for a job and before they know whether or not they will be unemployed. Hence, they will base their decision where to locate on their expected (indirect) utility from living in location n, which for risk neutral agents is given by

$$\mathcal{V}_n(\Omega) = a_n(\Omega) \frac{v_n}{P_n},$$

with v_n denoting the expected income of a consumer in location n. Since the right hand side fraction is independent of the individual worker Ω the expected indirect utility is also distributed Fréchet with the distribution function

$$G_n(\mathcal{V}) = e^{-A_n \left(\frac{v_n}{P_n}\right)^{\epsilon} \mathcal{V}^{-\epsilon}}.$$

Workers are mobile across German counties $N^G \subset N$ and move to the location that offers the highest level of utility ex-ante. With labor being infinitely divisible the share $L_n/\bar{L}^G$ of German workers living in a county $n \in N^G$ is equal to the probability that a German worker chooses to live in that county. Using the properties of the Fréchet distribution, the share of population λ_n that a location n has in its country's population is thus

$$\lambda_n = \begin{cases} \frac{A_n\left(\frac{v_n}{P_n}\right)^{\epsilon}}{\sum_{i\in N^G} A_i\left(\frac{v_i}{P_i}\right)^{\epsilon}} & \text{if } n \in N^G, \\ 1 & \text{otherwise.} \end{cases} \tag{5}$$

2.2 Production with search and matching

In any industry k at any location n a perfectly elastic supply of firms can produce each variety ω with constant returns to scale by combining labor, structures and potentially each industry's compound good. Locations and industries differ in terms of their input mix and firms in their productivities $z_{nk}(\omega)$. I follow Eaton and Kortum (2002) and Caliendo and Parro (2015) in assuming that the latter are drawn independently from location and industry specific Fréchet distributions with cumulative density functions given by

$$F_{nk}(z) = e^{-z^{-\theta_k}}$$

where θ_k is the shape parameter that controls the dispersion of productivities across varieties within each sector k, with a bigger θ_k implying less variability. As in Caliendo et al. (2018) I set the scale parameter of the Fréchet distribution to 1 and instead model differences in the average productivity between locations and sectors through the introduction of a second, non-random but factor augmenting technology parameter T_{nk} directly into the following production function,

$$q_{nk}(\omega) = z_{nk}(\omega)\, T_{nk}^{1-\beta_{nk}^M} \left(H_{nk}(\omega)\right)^{\beta_{nk}^H} \left(S_{nk}(\omega)\right)^{\beta_{nk}^S} \left(M_{nk}(\omega)\right)^{\beta_{nk}^M}. \tag{6}$$

Here $q_{nk}(\omega)$ is the quantity of variety ω produced in location n and industry k, $H_{nk}(\omega)$ and $S_{nk}(\omega)$ are the amounts of labor and structures used in production, $M_{nk}(\omega)$ is a Cobb-Douglas aggregate of compound goods from potentially all K industries and β_{nk}^H, β_{nk}^S and β_{nk}^M , with $\beta_{nk}^H+\beta_{nk}^S+\beta_{nk}^M = 1$, control the cost shares of labor, structures and intermediates in the production process. Of course, the specification of technology is analytically equivalent to setting the scale parameter of the distribution function equal to $T_{nk}^{1-\beta_{nk}^M}$. However, as Caliendo et al. (2018, p. 2052) argue, it ensures that technological shocks do not generate output increases in sectors which merely process intermediates ($1-\beta_{nk}^M = 0$) and thus prevents overproportional real GDP effects in the quantitative analysis below.

I assume that the labor market in each location and industry is subject to Diamond-Mortensen-Pissarides search and matching frictions.[8] Hence, firms can not employ workers

[8] See Pissarides (2000).

directly but instead need to open vacancies $V_{nk}(\omega)$. These result in successful matches depending on the total number of open vacancies (V_{nk}) and total number of workers searching for jobs (L_{nk}) in the respective industry and location according to the matching function

$$H_{nk} = \mu_{nk} V_{nk}^{\iota} L_{nk}^{1-\iota}, \tag{7}$$

where H_{nk} is the total number of successful matches in location n and industry k, $\mu_{nk} > 0$ is a measure of the matching efficiency and $0 \leq \iota \leq 1$ a parameter denoting the vacancy share in the matching process. Since each individual variety has zero weight in the industry no single firm can influence the matching rate through the number of vacancies $V_{nk}(\omega)$ it opens. Hence, this decision is made knowing that the firm needs to open V_{nk}/H_{nk} vacancies for each worker it wants to hire. I assume that the opening of vacancies comes at a cost ν_{nk} that has to be paid in terms of the final consumption bundle. Therefore, the cost b_{nk} of hiring per worker for a firm in location n and industry k is given by

$$b_{nk} = P_n \nu_{nk} \frac{V_{nk}}{H_{nk}}. \tag{8}$$

Wage bargaining. Following Helpman and Itskhoki (2010) the matching process is modeled as a one shot game, i.e. if a worker is unmatched he will be unemployed and receive no wage.[9] Likewise, if a matched worker or firm breaks the match the output generated by the additional worker is considered lost and there is no possibility to search for a replacement match. Hence, once a firm is matched with a worker the successful match creates a rent over which workers and firms bargain. I assume that bargaining takes the form of a Stole and Zwiebel (1996a,b) bargaining game which extends Nash bargaining to the case of multiple workers. More specifically, the assumption is that firms can negotiate with each worker individually and simultaneously without dependency on the outcome of other negotiations. Hence, the rent that workers and firms split is the marginal profit created by a worker acknowledging the marginal worker's influence on the negotiated wage for all workers. As in Nash bargaining the split occurs according to the bargaining weights $0 \leq \varphi_{nk} \leq 1$ for workers and $1 - \varphi_{nk}$ for firms. Thus,

$$\varphi_{nk} \frac{\partial \left(R_{nk}(\omega) - H_{nk}(\omega) w_{nk}(H_{nk}(\omega)) \right)}{\partial H_{nk}(\omega)} = (1 - \varphi_{nk}) w_{nk}(H_{nk}(\omega)),$$

where $R_{nk}(\omega) = p_{nk}(\omega) q_{nk}(\omega)$ is the firm's revenue, $p_{nk}(\omega)$ the variety's mill price, and $w_{nk}(H_{nk}(\omega))$ the negotiated wage in the production of variety ω in location n and industry

[9]While it is possible to introduce unemployment benefits into the framework I abstract from it here.

k. The solution to the above differential equation is

$$w_{nk}\left(H_{nk}\left(\omega\right)\right) = \frac{\varphi_{nk}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}\frac{\partial R_{nk}\left(\omega\right)}{\partial H_{nk}\left(\omega\right)} \tag{9}$$

Intuitively, for a given number of workers the higher their negotiation power the higher their wage. On the other hand a higher β_{nk}^{H} reduces the relative effect of a marginal worker leaving the match on the marginal revenue and hence decreases the share of marginal revenue they can obtain in the wage negotiations. However, as can immediately be seen by substituting $\frac{\partial R_{nk}(\omega)}{\partial H_{nk}(\omega)} = \beta_{nk}^{H}\frac{R_{nk}(\omega)}{H_{nk}(\omega)}$, at a given H_{nk} a larger β_{nk}^{H} also raises the level of marginal revenue. Since the latter effect dominates an increase in β_{nk}^{H} also increases the wage. Moreover, given the nature of the constant returns to scale production function this result implies that the negotiated wage is independent of firm size.

Optimal employment and input bundle costs. Using the negotiated wage rate (9) firm profits $\Pi_{nk}\left(\omega\right)$ can be written as

$$\Pi_{nk}\left(\omega\right) = \frac{1-\varphi_{nk}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}R_{nk}\left(\omega\right) - b_{nk}H_{nk}\left(\omega\right) - r_{n}S_{nk}\left(\omega\right) - \rho_{nk}M_{nk}\left(\omega\right) \tag{10}$$

where r_n denotes the rent for structures in location n and ρ_{nk} is the price index for an intermediate bundle used by producers in industry k in location n given by

$$\rho_{nk} = \prod_{j=1}^{K} P_{nj}^{\delta_{nk,j}} \tag{11}$$

with $0 \leq \delta_{nk,j} \leq 1$ being the share of industry j compound good in the intermediate input mix of firms in industry k and location n, for which $\sum_{j=1}^{K}\delta_{nk,j} = 1$. Solving the firm's profit maximization problem then leads to the optimal employment condition for workers:

$$w_{nk}\left(H_{nk}\left(\omega\right)\right) = \frac{\varphi_{nk}}{1-\varphi_{nk}}b_{nk} \tag{12}$$

Thus, firms employ workers until the negotiated wage is equal to the hiring costs multiplied with the relative negotiation power of workers. Intuitively, the perfectly elastic supply of competitors ensures that vacancies are opened until the expected profits of a vacancy are driven down to zero. Since, hiring costs depend only on location and industry but not on the produced variety, all firms in location n and industry k will pay the same wage despite having heterogeneous productivity levels $z_{nk}\left(\omega\right)$.

Deriving the remaining optimal input conditions, combining them with the negotiated wage rate (9) and defining the constant shares $\tilde{\beta}_{nk}^{H} \equiv \frac{\varphi_{nk}\beta_{nk}^{H}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}$, $\tilde{\beta}_{nk}^{S} \equiv \frac{(1-\varphi_{nk})\beta_{nk}^{S}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}$ and $\tilde{\beta}_{nk}^{M} \equiv$

$\frac{(1-\varphi_{nk})\beta_{nk}^M}{1-\varphi_{nk}\left(1-\beta_{nk}^H\right)}$ the industry wide factor payments and vacancy costs can be calculated as

$$\begin{aligned} H_{nk}w_{nk} &= \tilde{\beta}_{nk}^H R_{nk} \quad S_{nk}r_n = \tilde{\beta}_{nk}^S R_{nk} \\ M_{nk}\rho_{nk} &= \tilde{\beta}_{nk}^M R_{nk} \quad H_{nk}b_{nk} = \left(1-\tilde{\beta}_{nk}^H-\tilde{\beta}_{nk}^S-\tilde{\beta}_{nk}^M\right) R_{nk} \end{aligned} \tag{13}$$

where, with a slight abuse of notation, I denote industry aggregates by dropping the dependency on ω. Using optimal inputs in the cost function the implied cost of an input bundle is

$$c_{nk} = \zeta_{nk} w_{nk}^{\beta_{nk}^H} r_n^{\beta_{nk}^S} \rho_{nk}^{\beta_{nk}^M}, \tag{14}$$

where ζ_{nk} is defined as the constant $\zeta_{nk} \equiv \left(\beta_{nk}^H\right)^{-\beta_{nk}^H} \left(\beta_{nk}^S\right)^{-\beta_{nk}^S} \left(\beta_{nk}^M\right)^{-\beta_{nk}^M} \frac{1-\varphi_{nk}\left(1-\beta_{nk}^H\right)}{(\varphi_{nk})^{\beta_{nk}^H}(1-\varphi_{nk})^{1-\beta_{nk}^H}}$.

Trade shares and prices With perfect competition firms face mill prices equal to unit costs, which can be calculated by dividing the input bundle cost by the industry specific and randomly distributed variety specific parts of productivity. The price $p_{nik}(\omega)$ in location n of buying one unit of ω in sector k from a producer in location i also depends on the iceberg trade costs $d_{nik} \geq 1$ between the two locations, resulting in

$$p_{nik}(\omega) = \frac{d_{nik}c_{ik}}{z_{ik}(\omega) T_{ik}^{1-\beta_{ik}^M}}.$$

Perfectly competitive compound good producers in each location and industry costlessly combine all of the industry's varieties into an industry aggregate good. They treat varieties across locations as homogeneous and consequently source each variety from the location that provides it at the lowest price. Hence the price paid in location n for a variety ω from industry k is given by $p_{nk}(\omega) = \min\{p_{nik}(\omega); i = 1...N\}$ and, using the properties of the Fréchet distribution as in Eaton and Kortum (2002), the share of location n's expenditure in industry k on varieties produced in i becomes

$$\pi_{nik} = \frac{\left(d_{nik}c_{ik}T_{ik}^{1-\beta_{ik}^M}\right)^{-\theta_k}}{\sum_{s=1}^N \left(d_{nsk}c_{sk}T_{sk}^{1-\beta_{sk}^M}\right)^{-\theta_k}}, \tag{15}$$

where by construction $\sum_{i=1}^N \pi_{nik} = 1$.

Compound goods producers in each location and industry have a CES-type production function given by

$$Q_{nk} = \left(\int_0^1 q_{nk}^D(\omega)^{\frac{\sigma_k-1}{\sigma_k}} d\omega\right)^{\frac{\sigma_k}{\sigma_k-1}},$$

where Q_{nk} is the quantity of industry k's compound good produced in location n, $q_{nk}^D(\omega)$ is location n's use of variety ω and $\sigma_k > 1$ denotes the (constant) within-industry elasticity of substitution between any two varieties. Profit maximization of compound good producers then results in

$$q_{nk}^{D}(\omega) = \left(\frac{p_{nk}(\omega)}{P_{nk}}\right)^{-\sigma_k} Q_{nk},$$

where P_{nk} is the implied perfect CES price index for industry aggregates, i.e. the price of a compound good from industry k in location n. Given the properties of the Fréchet distribution this price index can be calculated as

$$P_{nk} = \gamma_k \left[\sum_{i=1}^{N} \left(d_{nik} c_{ik} T_{ik}^{1-\beta_{ik}^{M}}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}}, \tag{16}$$

where $\gamma_k \equiv \left[\Gamma\left(\frac{\theta_k+1-\sigma_k}{\theta_k}\right)\right]^{\frac{1}{1-\sigma_k}}$, $\Gamma(\cdot)$ denotes the gamma function and I assume that $1+\theta_k > \sigma_k$.

2.3 Unemployment

Due to labor market frictions, as long as $H_{nk} < L_{nk}$, there will be unemployment. By (7) the probability χ_{nk} of a worker finding a job in sector k in location n conditional on searching in this sector is[10]

$$\chi_{nk} \equiv \frac{H_{nk}}{L_{nk}} = \mu_{nk}\left(\frac{V_{nk}}{L_{nk}}\right)^{\iota}.$$

As explained above, I assume that workers can freely choose in which sector to work before the matching process. Hence, with risk neutral agents, in equilibrium a common ex-ante expected wage or wage per capita $w_n = \chi_{nk} w_{nk}$ for workers in location n emerges across all sectors. Using the optimal employment condition (12) and cost of opening vacancies (8) for any industry k in location n this wage is given by

$$w_n = \frac{\varphi_{nk}}{1-\varphi_{nk}} P_n \nu_{nk} \mu_{nk}^{-\frac{1}{\iota}} \chi_{nk}^{\frac{1}{\iota}} \tag{17}$$

Defining an inverse measure of the frictions in each labor market $\tilde{\mu}_{nk} \equiv \frac{\mu_{nk}}{\nu_{nk}^{\iota}}\left(\frac{1-\varphi_{nk}}{\varphi_{nk}}\right)^{\iota}$ that consists of a combination of the matching efficiency, the relative bargaining power of workers and the cost of opening vacancies, the employment rate χ_{nk} in sector k in location n can be written as

$$\chi_{nk} = \tilde{\mu}_{nk}\left(\frac{w_n}{P_n}\right)^{\iota}. \tag{18}$$

[10]It is easier for expositional purposes to work with the employment rate χ_{nk} but, of course, this immediately delivers the unemployment rate as $1-\chi_{nk}$.

Consequently, the sector specific employment rates are proportional to the inverse measure $\tilde{\mu}_{nk}$ with the common multiplicator being an increasing function of the real wage. However, as each location's total employment rate $\chi_n \equiv \frac{\sum_{k=1}^{K} H_{nk}}{L_n}$ can be obtained by summing over sectoral rates χ_{nk} weighted by industry size in terms of potential workers, policies that are real wage augmenting must not necessarily increase a location's overall employment rate. More specifically, while they do increase the region's sectoral employment rates via the real wage, the change in the overall regional employment rate also depends on the policy induced shift of workers between sectors. This can be seen by using sectoral employment rates (18) and sectoral wage sums (13) to write location n's total employment rate as

$$\chi_n = \frac{\sum_{k=1}^{K} L_{nk}\chi_{nk}}{L_n} = \left(\frac{w_n}{P_n}\right)^{\iota} \frac{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R_{nk} \tilde{\mu}_{nk}}{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R_{nk}}, \tag{19}$$

where the second term captures the sectoral composition of production.

2.4 Equilibrium

Wages and rents. The sector specific equilibrium wages can be calculated by combining per capita wages (17) with the employment rate (18), resulting in

$$w_{nk} = \frac{w_n^{1-\iota} P_n^{\iota}}{\tilde{\mu}_{nk}}. \tag{20}$$

Moreover, for any location n land market clearing requires that total rent income must equal total spending on land and structures. Using the factor payment shares (13),

$$r_n \bar{S}_n = \sum_{k=1}^{K} \tilde{\beta}_{nk}^{S} R_{nk},$$

where $\bar{S}_n$ is region n's endowment with land and structures. This immediately gives the local rent level r_n as

$$r_n = \frac{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{S} R_{nk}}{\bar{S}_n}. \tag{21}$$

Deficits. Traditionally, trade theory has emphasized the role of intertemporal consumption and saving decisions in the origin of the observed trade imbalances. In quantitative applications of static models trade imbalances are, thus, usually accounted for by exogenous (monetary) transfers. However, trade imbalances also emerge in a static context through foreign ownership of factors.[11] Value generated in one location is spend by the owner of

[11] From an accounting perspective the standard approach balances current accounts by setting direct transfers equal to the observed trade imbalances but with opposite sign, essentially ignoring net income.

this factor who lives in a different location. Arguably, the latter plays a larger role in the regional than in the international context, especially at the high level of regional disaggregation applied here, that is, owners of land would have to live in the same county where they possess land for this effect not to matter. For this reason I adopt a twin strategy with regards to the observed trade imbalances. Firstly, at the international level I model trade deficits through exogenous transfers D_n (negative for trade surpluses) in line with the idea that international trade deficits are mainly driven by differences in national savings rate. This trade deficit is borne on a per capita basis via the mechanism explained below. Secondly, at the level of German counties I follow Caliendo et al. (2018) in assuming that a share $0 \leq (1 - \Psi_n) \leq 1$ of each county's land rents is equally divided among its inhabitants via a lump sum transfer, while the remaining share Ψ_n is payed into a national portfolio. The (negative) *national* German deficit transfer D^G is added to this portfolio before it is redistributed across all counties on a per capita basis.[12] The portfolio shares Ψ_n can then be calibrated such that the remittances from and payments to the portfolio account for the *interregional* trade imbalances, representing the foreign ownership of land. The total deficit transfer D_n^{tot} then is

$$D_n^{tot} = \begin{cases} \lambda_n \left(\sum_{i \in N^G} \Psi_i \sum_{k=1}^{K} \tilde{\beta}_{ik}^S R_{ik} + D^G \right) - \Psi_n \sum_{k=1}^{K} \tilde{\beta}_{nk}^S R_{nk} + D_n^{reg} & \text{if } n \in N^G \\ D_n & \text{otherwise,} \end{cases} \tag{22}$$

where D_n^{reg} is an additional exogenous transfer accounting for cases in which the observed interregional trade deficits can not be explained even by remitting all ($\Psi_n = 1$) or none ($\Psi_n = 0$) of the land rents to the national portfolio.

Income. The total income $Y_n \equiv v_n L_n$ of all inhabitants of region n in equilibrium must be equal to locally generated factor income plus the (partly) endogenous deficit transfer. Using the factor payment shares in industry revenue (13) this total income can be expressed as

$$Y_n = \sum_{k=1}^{K} \left(\tilde{\beta}_{nk}^H + \tilde{\beta}_{nk}^S \right) R_{nk} + D_n^{tot}. \tag{23}$$

Goods market clearing. Market clearing in the non-traded compound goods sectors implies that the value of production $P_{nk}Q_{nk}$ equals expenditure for local consumption, local intermediate use and local vacancy costs. Formally,

$$P_{nk}Q_{nk} = \delta_{nC,k} Y_n + \sum_{j=1}^{K} \delta_{nj,k} M_{nj} \rho_{nj} + \sum_{j=1}^{K} \delta_{nC,k} b_{nj} H_{nj}. \tag{24}$$

[12] Caliendo et al. (2018) analyse regional trade between US states abstracting from foreign relations and hence international trade imbalances.

For variety producers market clearing entails that the value of production in industry k in location n must be equal to world expenditure for varieties from this industry. Since individual varieties are only directly demanded by compound good producers I make use of (13), (23) and (24) to write goods market clearing as

$$R_{nk} = \sum_{i=1}^{N} \pi_{ink} \left\{ \delta_{iC,k} D_i^{tot} + \sum_{j=1}^{K} \left[\delta_{ij,k} \tilde{\beta}_{ij}^{M} + \delta_{iC,k} \left(1 - \tilde{\beta}_{ij}^{M} \right) \right] R_{ij} \right\}. \tag{25}$$

Equilibrium. The equilibrium of the model consists of a set of industry location specific price indices P_{nk} and revenues R_{nk}, industry specific bilateral trade shares π_{nik}, and population shares λ_n that solve the equations for population mobility (5), expenditure shares (15), price indices (16) and market clearing (25) given by

$$\lambda_n = \begin{cases} \frac{A_n \left(\frac{v_n}{P_n} \right)^{\epsilon}}{\sum_{i \in N^G} A_i \left(\frac{v_i}{P_i} \right)^{\epsilon}} & \text{if } n \in N^G \\ 1 & \text{otherwise,} \end{cases}$$

$$\pi_{nik} = \frac{\left(d_{nik} c_{ik} T_{ik}^{1-\beta_{ik}^{M}} \right)^{-\theta_k}}{\sum_{s=1}^{N} \left(d_{nsk} c_{sk} T_{sk}^{1-\beta_{sk}^{M}} \right)^{-\theta_k}}$$

$$P_{nk} = \gamma_k \left[\sum_{i=1}^{N} \left(d_{nik} c_{ik} T_{ik}^{1-\beta_{ik}^{M}} \right)^{-\theta_k} \right]^{-\frac{1}{\theta_k}}$$

$$R_{nk} = \sum_{i=1}^{N} \pi_{ink} \left\{ \delta_{iC,k} D_i^{tot} + \sum_{j=1}^{K} \left[\delta_{ij,k} \tilde{\beta}_{ij}^{M} + \delta_{iC,k} \left(1 - \tilde{\beta}_{ij}^{M} \right) \right] R_{ij} \right\},$$

where the input bundle costs c_{nk} are given by (14), the expenditure per capita v_n by (23), the rental rate of structures r_n by (21) the price index for intermediates ρ_{nk} by (11) and the sectoral wages are calculated by combining (20) with (13) and (3).

3 Empirical strategy

3.1 The model in changes

The goal of this paper is to quantify the economic responses to local productivity shocks that can be interpreted as standardized labor demand shocks. Their heterogeneity thus translates to other events that create local labor demand shocks. However, solving the above equilibrium for any counterfactual scenario requires specifying the new *levels* of the shocked variables and identifying a vast number of variables that are not directly observable from the data, including any unchanged sectoral bilateral trade costs d_{nik} or productivities T_{nk}, substitution elasticities σ_{nk}, quality-adjusted housing stocks $\bar{S}_n$, and regional preference parameters A_n. To avoid these problematic tasks I turn to the method introduced by Dekle et al. (2007), which was applied to the multisector setting by Caliendo and Parro (2015) and to a setting with imperfect mobility by Redding (2016), and rewrite the model in terms of changes.

To this end, I denote all variables x in the counterfactual equilibrium, i.e. after the shock, with a prime and relative changes from the old to the new equilibrium with a hat, such that $\hat{x} = x'/x$. The four counterfactual equilibrium equations can then be rewritten in terms of $\hat{P}_{nk}$, R'_{nk}, π'_{nik}, and $\hat{\lambda}_n$ as follows:

$$\hat{\lambda}_n = \begin{cases} \dfrac{\left(\frac{\hat{Y}_n}{\hat{\lambda}_n \hat{P}_n}\right)^{\epsilon}}{\sum_{i \in N^G} \lambda_i \left(\frac{\hat{Y}_i}{\hat{\lambda}_i \hat{P}_i}\right)^{\epsilon}} & \text{if } n \in N^G \\ 1 & \text{otherwise} \end{cases} \tag{26}$$

$$\pi'_{nik} = \frac{\pi_{nik}\left(\hat{d}_{nik}\hat{c}_{ik}\hat{T}_{ik}^{1-\beta_{ik}^M}\right)^{-\theta_k}}{\sum_{s=1}^{N} \pi_{nsk}\left(\hat{d}_{nsk}\hat{c}_{sk}\hat{T}_{sk}^{1-\beta_{sk}^M}\right)^{-\theta_k}} \tag{27}$$

$$\hat{P}_{nk} = \left[\sum_{i=1}^{N} \pi_{nik}\left(\hat{d}_{nik}\hat{c}_{ik}\hat{T}_{ik}^{1-\beta_{ik}^M}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}} \tag{28}$$

$$R'_{nk} = \sum_{i=1}^{N} \pi'_{ink}\left\{\delta_{iC,k} D_i^{tot\prime} + \sum_{j=1}^{K}\left[\delta_{ij}^{k}\tilde{\beta}_{ij}^{M} + \delta_{iC,k}\left(1-\tilde{\beta}_{ij}^{M}\right)\right] R'_{ij}\right\}, \tag{29}$$

where

$$\hat{Y}_n = \frac{\sum_{k=1}^{K}\left(\tilde{\beta}_{nk}^{H}+\tilde{\beta}_{nk}^{S}\right) R'_{nk} + D_n^{tot\prime}}{\sum_{k=1}^{K}\left(\tilde{\beta}_{nk}^{H}+\tilde{\beta}_{nk}^{S}\right) R_{nk} + D_n^{tot}}, \quad \hat{c}_{nk} = \hat{r}_n^{\beta_{nk}^S}\hat{\rho}_{nk}^{\beta_{nk}^M}\hat{w}_{nk}^{\beta_{nk}^H}, \quad \hat{r}_n = \frac{\sum_{k=1}^{K}\tilde{\beta}_{nk}^{S} R'_{nk}}{\sum_{k=1}^{K}\tilde{\beta}_{nk}^{S} R_{nk}},$$

$$\hat{\rho}_{nk} = \prod_{j=1}^{K}\hat{P}_{nj}^{\delta_{nk,j}}, \qquad \hat{w}_{nk} = \left(\frac{\sum_k \tilde{\beta}_{nk}^{H} R'_{nk}}{\sum_k \tilde{\beta}_{nk}^{H} R_{nk}}\right)^{1-\iota}\hat{\lambda}_n^{-(1-\iota)}\left(\prod_{k=1}^{K}\hat{P}_{nk}^{\delta_{nC,k}}\right)^{\iota},$$

and

$$D_n^{tot\prime} = \begin{cases} \lambda_n\left(\sum_{i\in N^G}\Psi_i\sum_{k=1}^{K}\tilde{\beta}_{ik}^{S}R'_{ik} + D'_n\right) - \Psi_n\sum_{k=1}^{K}\tilde{\beta}_{nk}^{S}R'_{nk} + D_n^{reg\prime} & \text{if } n \in N^G \\ D'_n & \text{otherwise.} \end{cases}$$

This "equilibrium in changes" no longer depends on any of the parameters that were deemed difficult to observe above. In fact, the only two parameters that can not be directly observed in the data are the Fréchet shape parameters for firm specific productivities θ_k and for consumer specific regional amenities ϵ. I will return to these two parameters in the data subsection below.

Unemployment. Similar to Carrère et al. (2015) the method of Dekle et al. (2007) can also be applied to the employment rates defined in (19). Rewriting this equation in terms of changes yields:

$$\hat{\chi}_n = \left(\frac{\hat{w}_n}{\hat{P}_n}\right)^{\iota} \left(\frac{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R_{nk}}{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R_{nk} \tilde{\mu}_{nk}} / \frac{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R'_{nk}}{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R'_{nk} \tilde{\mu}_{nk}} \right) \tag{30}$$

The first term shows the positive correlation between real wages and employment rates. The second terms gives effect of shifts in the sectoral specialization pattern on employment. To see this consider an increase in the revenue of an industry with high frictions (low $\tilde{\mu}_{nk}$) that is (in terms of the wage sum) exactly offset by a decrease in revenue of an industry with low frictions (high $\tilde{\mu}_{nk}$): the numerator of both fractions in the second term then remains the same but the denominator is larger for the second lowering the overall employment rate. Hence, as stated by Carrère et al. (2015) the conventional wisdom that real wages and employment always move in the same direction is only partially true.

Finally, the change in the total German employment rate $\hat{\chi}^G$ can be calculated by weighing county employment rates with the population share both in the ex-ante and the counterfactual scenario:

$$\hat{\chi}^G = \frac{\sum_{n \in N^G} \chi_n \hat{\chi}_n \lambda_n \hat{\lambda}_n}{\sum_{n \in N^G} \chi_n \lambda_n}$$

Welfare. Turning to welfare I follow Redding (2016) and note that through the properties of the Fréchet distribution the expected (or average) utility U^G of a German worker conditional on living in location $n \in N^G$ is equal across all locations and for Germany as a whole.[13] Defining $\xi \equiv \Gamma\left((\epsilon - 1)/\epsilon\right)$ the common expected utility can be written as

$$U^G = \xi \left[\sum_{i \in N^G} A_i \left(\frac{v_i}{P_i}\right)^{\epsilon} \right]^{\frac{1}{\epsilon}} = \xi \left[\frac{A_n \left(\frac{v_n}{P_n}\right)^{\epsilon}}{\lambda_n} \right]^{\frac{1}{\epsilon}},$$

where the second equality makes use of equation 5 and holds for any n. However, this does not imply that individual consumers have the same utility everywhere, nor that the real income will be equalized across regions. Instead the interpretation is that in regions with low real per capita income only consumers with high amenity draws for that region remain (low λ), keeping the average utility up. In contrast rich regions will attract even people with lower amenity draws for that region (high λ), thus arriving at the same expected utility level. Rewriting the average utility in terms of changes to a counterfactual scenario immediately

[13] This is the consumer equivalent to the result of Eaton and Kortum (2002) that sectoral and regional price indices are the same conditioning on the source and for the importing country as a whole.

yields

$$\hat{U} = \hat{\lambda}_n^{-\frac{1}{\epsilon}} \frac{\hat{v}_n}{\hat{P}_n}. \tag{31}$$

The relative change in a county's expected real income directly increases the average utility of its consumers. Yet, when the higher expected income attracts additional workers, who on average have a lower amenity draw for the county than the workers already living there, the increase in λ dampens the utility gains. Conversely, counties that are the source for migrating workers lose population that has, on average, a lower amenity draw than the workers remaining in the county leading to a higher average welfare even if the average real income and the individual utility level of consumers remaining in the location was unchanged.

3.2 Data

My analysis relies on three main data sources. Firstly, country production data, international trade data, input-output structure and consumption structure for countries are taken from the World Input Output Database (WIOD). Secondly, county level sectoral revenue and unemployment data relies on publications by the German federal and regional statistical offices ("Statistische Ämter des Bundes und der Länder"). Finally, trade data at the German county level is derived using a recent data set containing information on shipments by truck, train or ship that start or end in one of the 402 German counties. I discuss all three data sources and the final calibration of the model in the following.

Country level data. My main data source for country level data is the world input-output database (WIOD).[14] It provides a time-series of world input-output tables compiled on the basis of officially published input-output tables in combination with national accounts and international trade statistics. The tables cover data from 56 industries in 44 countries, including one artificial "rest of the world" (ROW) country. The countries include all current members of the European Union, Switzerland and Norway, as well as most non-European major German trade partners. The complete list is provided in table A.1 in the appendix. In order to match the information with my other data sources I rely on the year 2010 and aggregate the 56 industries into 17 as given in table A.2 in the appendix.[15] I use the resulting input-output table to derive the sectoral consumption and intermediate good shares ($\delta_{nC,k}$ and $\delta_{nj,k}$), the share of value added ($1 - \tilde{\beta}^M_{nk}$) and the bilateral industry trade shares (π_{nik}) at the country level. Appendix D.1 explains this derivation in detail.

[14]See Timmer et al. (2015) for an introduction to the WIOD.

[15]The full matching between sectors of all classifications used by the different data sources to the final 17 sectors can be found in a supplementary appendix available online.

County level data. Sectorally disaggregated revenue data for Germany is, unfortunately, only published at the state and not at the county level. Therefore, in the mining and manufacturing sectors, where such information is available, I rely on sectoral county level employment data from the German federal and regional statistical offices to split sectoral state revenues across individual counties based on each county's share in its state's total sector employment. In instances where employment data is unavailable I instead rely on firm number shares. Final county production values are then calculated by scaling the sector totals to match with the German sectoral revenues from the WIOD. In the agriculture, construction and service sectors I proxy for county shares in the German total revenue with value added shares for which disaggregated data is available. A detailed description of the process can be found in section D.2 in the appendix.

An important problem for regional analysis in Germany is that data on interregional trade flows is usually unavailable. Therefore researchers have to rely on some kind of proportionality assumption or simple gravity equations to model linkages within Germany.[16] Such approaches are, however, unable to correctly capture trade driven by a rich structure of underlying motives like the connections with subsidiaries, the availability of highly specialized components or trust in long term relationships. In contrast in this paper I rely on an outstanding data set of county level trade in the mining and manufacturing sectors provided by Schubert et al. (2014) as part of the official "Forecast of nationwide transport relations in Germany 2030" on behalf of the German ministry of transport and digital infrastructure ("Bundesministerium für Verkehr und digitale Infrastruktur"). The data set gives the total shipments in tons by water, train or truck for 2010 (which explains my choice of base year) between German counties and their partners, disaggregated along 25 product categories. The trade partner can be either a further German county (including the county itself), one of 32 third countries (of which 25 are also in the WIOD Database), or a major German or international port. The latter two appear as origin or destination whenever the actual origin or final destination is unknown or not in the explicit country sample, for example shipments to and from Japan. I use this data to calculate the share of exports to each partner in the production of each county and sector, including own trade. Subsequently, I combine this information with the county revenues from above to obtain the bilateral industry trade and import shares π_{nik} at the county level. Again the details of these calculations are provided in section D.3 in the appendix. This section also explains how I disaggregate German WIOD trade flows in the utilities, construction and service sectors for which there is no shipment data available.

The final result of the above calculations is a data set containing information on revenues,

[16] See, for example, Krebs and Pflüger (2018b) who analyse county level effects of the transatlantic trade and investment partnership (TTIP) deriving trade shares based on regional sectoral production and demand shares.

value added and trade among 442 locations (402 German counties, 39 other countries and a modeled ROW) in 17 sectors for the year 2010. Overall, the shipment data set allows me to capture a much more accurate picture of interregional trade in Germany. Known trade connections between parent companies and subsidiaries or other suppliers are clearly visible in the data. While in itself highly informative, a detailed descriptive analysis of the German subnational trade and production network at this level of regional and sectoral disaggregation is beyond the scope of this paper. Krebs (2018) provides a thorough analysis of the structure.

Calibration. In calibrating the model I need to choose values for some of the remaining parameters. Specifically, I set ι, the weight of labor in the matching process, to 0.6, the central value of estimates in Petrongolo and Pissarides (2001). Further, I calculate the split of value added between labor and structures based on estimates of factor income for the U.S. economy by Valentinyi and Herrendorf (2008). In particular I set the share of land and structures in value added to 33.86%, 13.24%, 15.13%, and 19.95% in agricultural, manufacturing, construction and service sectors, respectively.[17]

The value for the Fréchet distribution shape parameter of consumer amenities, $\epsilon = 3.3$, is taken from the estimates in Monte et al. (2018). The sectoral Fréchet distribution shape parameters of productivities, θ_k, can be estimated from between country trade flows and observed trade barriers using equation (15).[18] I rely on the values calculated for the same country level trade flows in Krebs and Pflüger (2018b). Similarly, sectoral labor market frictions are taken from Carrère et al. (2015) who estimate them for 35 sectors based on time series employment data from a sample of 25 OECD countries.

Finally, as explained above, in some instances the observed interregional trade imbalances can not be fully explained even by remitting all ($\Psi_n = 1$) or none ($\Psi_n = 0$) of the locally created rents to the national portfolio and in these cases an exogenous transfer D_n^{reg} is used to fit the model to the data. However, with labor mobility, this implies that a reduction in a county's population, while increasing the productivity and subsequently wages of the remaining workers can actually leave them worse off, as the exogenous transfer is split over a smaller number of workers and thus trigger even more workers to leave the county. To avoid this problem, I again follow Caliendo et al. (2018) and solve for a base scenario in which the exogenous parts of interregional deficit transfers are set to 0. All counterfactual scenarios below are calculated starting from this base scenario. Moreover, while the model

[17]In particular I use the income shares of labor, land and intermediates from their table 6 to calculate the shares of capital and labor in value added of the four sectors. I multiply these results with the shares of land and structures in capital from their table 2 under the assumption that these values remain the same with intermediates.

[18]Head and Mayer (2014) provide an excellent overview over different techniques for estimating the trade elasticities.

and calculations include international trade and third countries my motivation is to study disaggregate geographical effects and I hence mostly limit the presentation of my results to effects in Germany.

4 Results

4.1 National effects

Benchmark scenario. Before turning to the effects of shocks to individual regions or sectors I establish a benchmark case to compare these results to. This benchmark represents a homogeneous productivity shock affecting all counties in Germany equally. Such a shock is modeled by a uniform increase in T_{nk} in all industries k in all German counties $n \in N^G$. The resulting, national welfare and employment effects are presented in terms of elasticities calculated by dividing the change in the respective variable by the relative size of the shock. Throughout the paper all effects are calculated based on 10 percent shocks, that is by setting the respective $\hat{T}_{nk}$ to 1.1.[19] This magnitude is close to observed annual changes of the technology parameter in US states and sectors over a 5 year period.[20]

The resulting national German welfare and employment elasticities are

$$\frac{\hat{U}^G - 1}{0.1} = 1.24 \quad \text{and} \quad \frac{\hat{\chi}^G - 1}{0.1} = 0.32.$$

Thus, a uniform increase in the German productivity level of 1% increases average welfare by 1.24% and the national employment rate by 0.32% or by 0.3 percentage points based on the initial German employment rate. The results of this aggregate shock, however, mask a vast heterogeneity of effects when actual shocks occur in a sectorally or regionally disaggregated manner. Of course, when one looks at regional German productivity shocks affecting all sectors in one county, sectoral shocks affecting one industry in all counties or region and sector specific shocks one would naturally expect the response of *national* variables to vary substantially due to the different sizes of the shocked sectors and counties.[21] Berlin, for example, as the largest German county is about 100 times larger in terms of population than

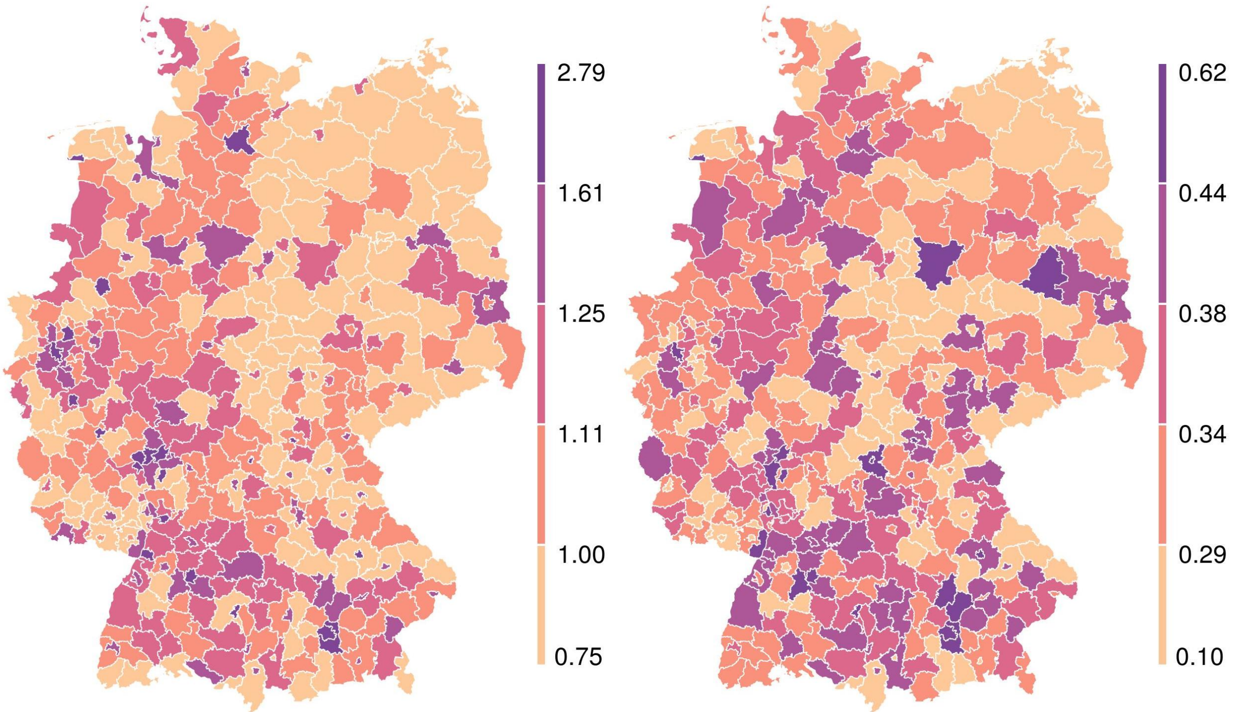
[19] Of course, as the model accounts for all non-linear general equilibrium effects, the calculated elasticities vary with the size of the shock. However, this is not problematic as non-linearities are small at the size of shocks considered here.

[20] Caliendo et al. (2018) calculate the average annual growth of the productivity parameter across US sectors and regions at 10.9% over the period 2002-2007, and the median over the period 2002-2007 and 2007-2012 at 8.4%.

[21] Regional productivity shocks are modelled by increasing T_{nk} for all industries k of one particular county $n \in N^G$, sectoral German shocks by increasing all T_{nk} for one sector k in all German counties $n \in N^G$, and region and sector specific shocks by changing individual T_{nk}.

the smallest county and thus shocks to it would certainly have a larger effect on the German economy as a whole. Hence to make the effects of disaggregated shocks comparable across experiments and to the results from the aggregate shock presented above, I follow Caliendo et al. (2018) and calculate elasticities for constant national magnitude shocks. Specifically, I not only divide the national welfare and employment changes of subsequent shocks by the size of the shock (0.1 in all instances) but also by the share of the German population directly affected, that is λ_n in the case of regional shocks. Intuitively, this implies that all elasticities presented below originate from productivity shocks that would be indistinguishable to an observer that only possesses aggregate national data.

Disaggregate shocks. Turning to productivity shocks in individual regions a large heterogeneity of effects emerges. Figure 3 depicts this heterogeneity combining the results of 402 separate regional productivity shocks. Specifically, each county is colored according to the national German welfare or employment elasticity resulting from a productivity shock in that particular county. Hence, shocks in counties with a darker color have - accounting for county size - a large effect on national welfare and employment, respectively.



(a) welfare elasticity (b) employment elasticity

Figure 3: National welfare and employment elasticities of regional shocks

The magnitude of welfare elasticities is, differences in modelling notwithstanding, similar to the results for U.S. states in Caliendo et al. (2018) and differs substantially across counties with a range from 0.76 to 2.78. This implies that predicting the effects of regional shocks based upon average effects of changes in a Germany wide measure of productivity can be deeply misleading. In particular the map shows that productivity shocks in Germany have the strongest national welfare effect if they take place in and around cities in the south and west of the country, especially Munich, Stuttgart, Frankfurt and Düsseldorf and that shocks in counties in former East Germany, in contrast, have a much milder effect.[22] This result is not as intuitive as it might seem. As my model captures the complete input-output network in Germany, a productivity shock to a smaller intermediate producer could, for example, lead to a larger national effect than a shock to a city that produces and consumes final goods. Counties with strong welfare elasticities are thus not only very productive but must also generate large spillovers to other locations in Germany through trade linkages. Turning to aggregate employment elasticities the observed heterogeneity across counties is even stronger with a range from 0.11 to 0.62.

The same heterogeneity of effects also exists when shocks affect a single sector in all German counties. Figure 4 shows the results of such shocks, with welfare elasticities ranging from 0.26 for shocks in the textiles sector to 4.19 for shocks in mining and quarrying. Again, employment elasticities are smaller, but their relative spread larger, ranging from 0.04 to 2.94.

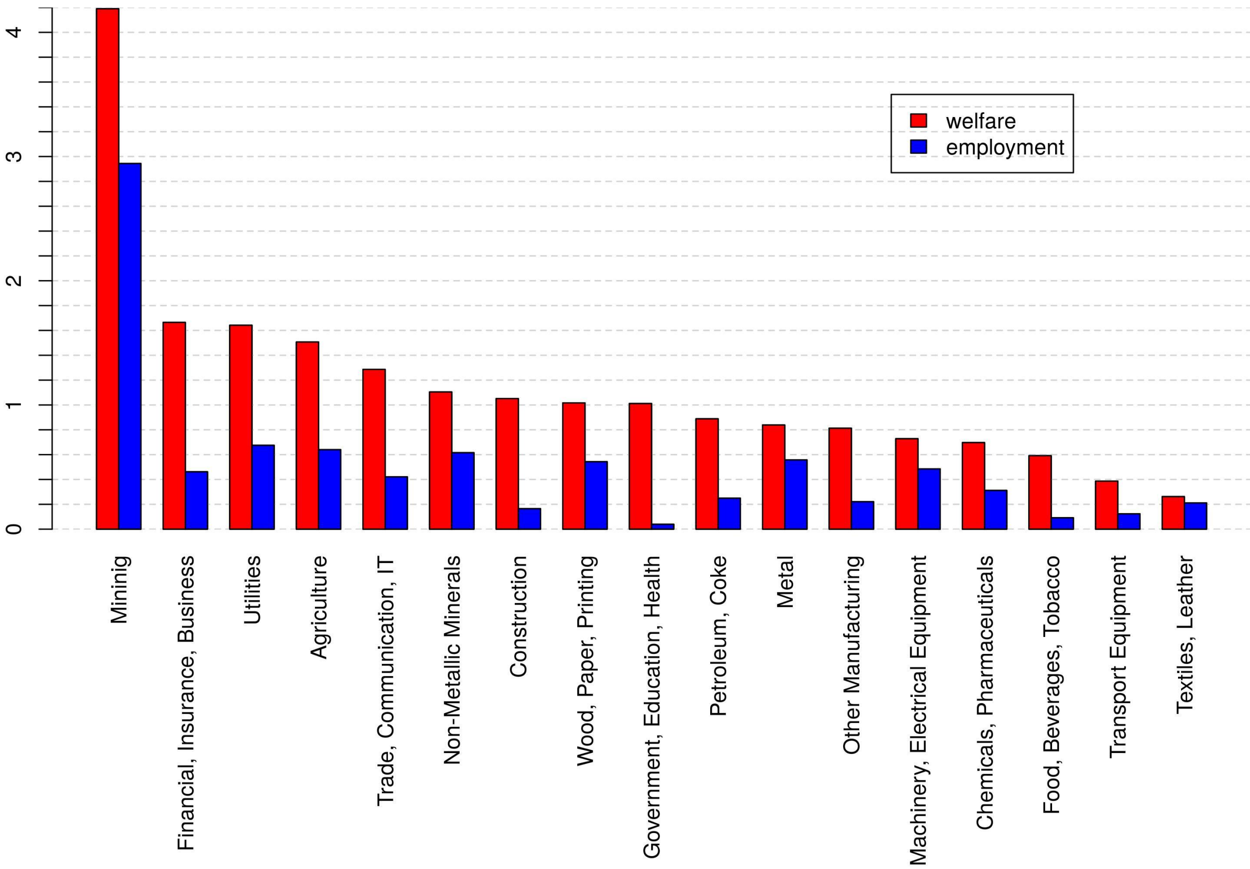


Figure 4: National welfare and employment elasticities of sectoral shocks

The results in figure 3 and 4 reveal a second important implication of my analysis. While

[22]The location of all counties referenced by name here can be found in figure B.1(a) in appendix B.

there is a correlation between national welfare and employment elasticities, this correlation is far from perfect with a Spearman's rank correlation coefficient of 0.61 for regional and 0.65 for sectoral shocks.[23] This is mirrored in the fact that figures 3(a) and (b) show both, counties in which a productivity shock has a strong effect on the average national welfare but not on national employment rates and vice versa. Importantly, and in contrast to Caliendo et al. (2018) my findings show that increasing average welfare and increasing the employment rate are not synonymous goals for policy makers.

4.2 Regional effects

Delving deeper. Having quantified the large differences in both national welfare and employment elasticities I now aim to identify the drivers of this heterogeneity in the complex interregional trade network and the strength of migration linkages. Before turning to the general results the interplay of effects is best explained by looking in detail at a single one of the 402 regional experiments that were summed up in figure 3 above.

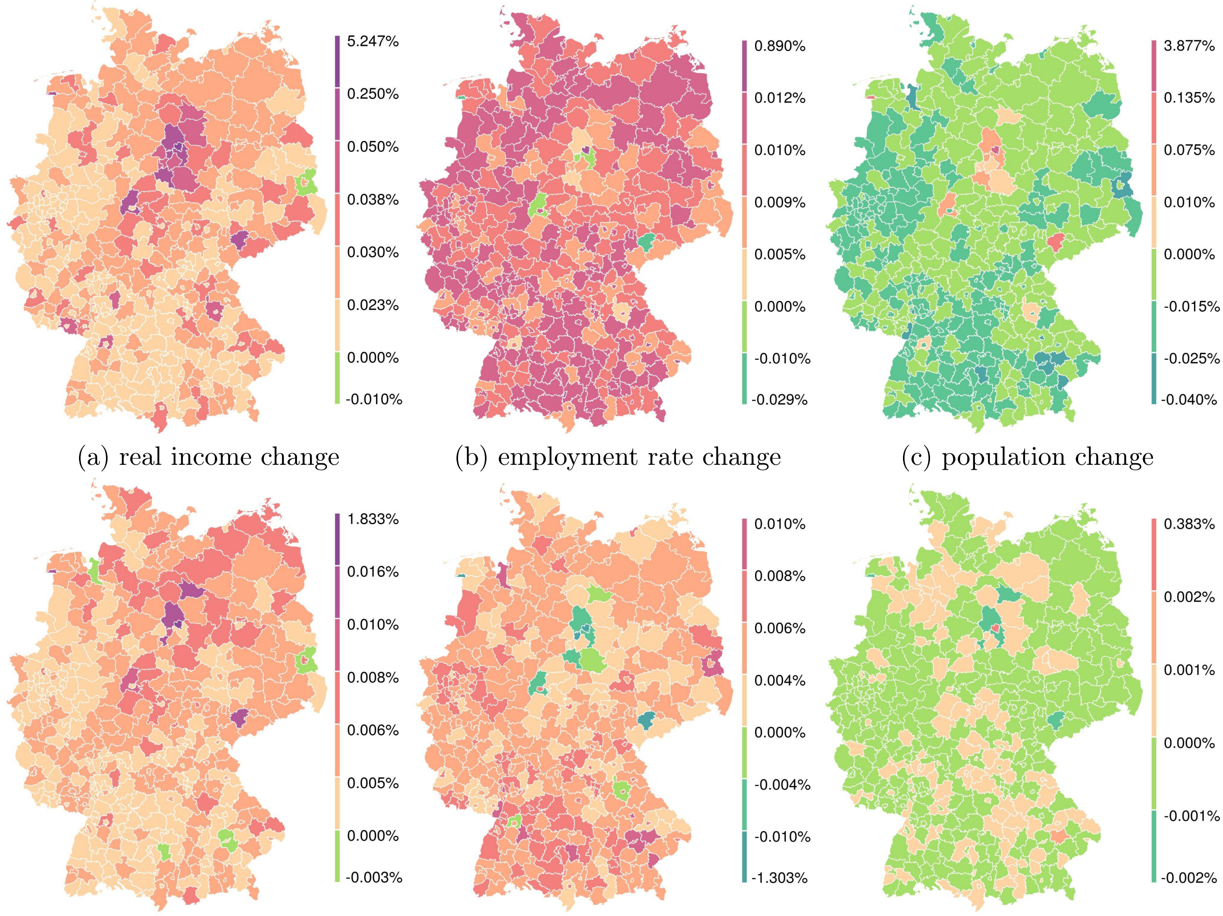
Figure 5, as an example, shows the effects of a 10 percent technology shock across all sectors in Wolfsburg, which has a relatively strong national welfare elasticity of 1.16 but a low national employment elasticity of 0.23 (cf. figure 3). Since the city is home to the car producer Volkswagen and therefore also hosts the by far largest single production plant in Germany with more than 50,000 workers, it is tightly integrated into the German production network and serves as an ideal laboratory.

The change in expected welfare ($\hat{U}_n - 1$) from the 10 percent shock is 0.043 percent. As explained above, population mobility and heterogeneous amenities ensure that this effect is equal across all German counties and for the country as a whole. However, expected or average real income changes ($\hat{v}_n/\hat{P}_n - 1$) vary substantially across counties as shown in figure 5(a). In fact, despite the intra-country viewpoint, the realized real income gains dissipate only very modestly throughout the economy with the second largest relative real income increase only about one twentieth of that in Wolfsburg.

The map also illustrates the great strength of the underlying data set which captures Wolfsburg's economic ties: counties that profit the strongest are either geographically close to Wolfsburg or have important supply and demand linkages. For example, the three strong beneficiaries Emden in the far northwest, county Kassel ("Landkreis Kassel") to the southwest and Zwickau to the southeast of Wolfsburg all host further large VW production plants.[24] Moreover, it can be clearly seen how the positive effects in these counties "spill over" to their

[23] I use rank correlations to account for the outlying result in the mining sector. Standard correlation coefficients are 0.62 and 0.93, respectively with the latter dropping to 0.62 when ignoring the mining sector.

[24] The location of all counties referenced by name here can be found in figure B.1(b) in appendix B.



(a) real income change (b) employment rate change (c) population change

(d) expansion effect (e) mobility effect (f) composition effect

Figure 5: Effects of regional shock in Wolfsburg

closest neighbors. Finally, counties with relatively strong increases in real income further to the south west and south are home to various automotive suppliers. Overall, this shows that the geographic dissipation of real income gains closely follows a counties trade linkages.

Interestingly, the changes in disaggregate employment rates ($\hat{\chi}_n - 1$) shown in 5(b) are more complex in nature. The employment rate in Wolfsburg increases by 0.89% but results in other counties are much milder ranging from -0.029% to 0.012%. Moreover, negative employment rate changes occur only in counties with close economic ties to Wolfsburg, despite these counties simultaneously winning both in terms of real income and average welfare. On the other hand, even some counties with hardly any real income gains, such as in the southwest of Germany, can increase their employment rates relatively strongly.

This pattern can in part be explained by population mobility. Importantly, real income increases do not necessarily imply an increase in population. Instead, Figure 5(c) shows that as implied by equilibrium condition (26) only counties in which expected real income increases faster than the national average see positive population changes ($\hat{\lambda}_n - 1$). In the case of Wolfsburg the 10% technology shock leads to a population gain of 3.88%. In accordance with the small real income changes only a handful of other counties experiences population gains of more than 0.01%. Similarly, losses are generally small in magnitude with only some larger changes occurring, for example, in the area northwest of Munich, where the VW competitor BMW has its headquarter.

The effect of worker mobility on employment rates stems from the induced shifts in *per capita* fixed factor endowments across counties and sets this model apart from previous quantitative studies. Specifically, a larger potential work force increases the likeliness of a match for each open vacancy and, thus, leads to a higher ratio of actual workers to land in the production process. In turn, the marginal production and hence value of each worker decreases and firms spend less on opening vacancies per worker, thereby decreasing the employment rate.

Employment change decomposition. I offer a unique strategy to derive the magnitude of this mobility effect on the employment rate. In particular, I decompose the employment rate given in equation (30) into

$$\hat{\chi}_n = \left(\frac{\hat{w}_n}{\hat{P}_n}|_{\hat{\lambda}=1}\right)^{\iota} \frac{\left(\frac{\hat{w}_n}{\hat{P}_n}\right)^{\iota}}{\left(\frac{\hat{w}_n}{\hat{P}_n}|_{\hat{\lambda}=1}\right)^{\iota}} \frac{\frac{\sum_{k=1}^{K}\tilde{\beta}^H_{nk}R_{nk}}{\sum_{k=1}^{K}\tilde{\beta}^H_{nk}R_{nk}\tilde{\mu}_{nk}}}{\frac{\sum_{k=1}^{K}\tilde{\beta}^H_{nk}R'_{nk}\tilde{\mu}_{nk}}{\sum_{k=1}^{K}\tilde{\beta}^H_{nk}R'_{nk}}},$$

where $|\hat{\lambda} = 1$ refers to changes in a counterfactual scenario in which the same shock occurs, but population is assumed to be immobile. In this paper, the use of a general equilibrium quantitative model comes with the great benefit that I can directly undertake this counterfactual. This is done by solving the equilibrium conditions (27) - (29) under the assumption that $\lambda_n = \lambda'_n$ and thus $\hat{\lambda}_n = 1$ for all n. The first term of the equation captures the effect of changes in productivity and economic expansion (or decline) on the employment rate that would have occurred under population immobility. The second term then measures further changes in the employment rate that stem from the movement of workers and the final term quantifies the effect of changes in the sectoral composition discussed above.

The bottom half of figure 5 shows this decomposition of the employment rate effect. Panels d, and e, reveal that in northern and eastern counties increases in the employment rate are mainly due to economic expansion, whereas in southern and eastern counties they are mostly driven by the mobility effect, that is by the increased scarcity of workers caused by migration. This effect is also the major explanation for the low gains or even losses of the counties with the closest economic ties to Wolfsburg. In Wolfsburg itself the expansion effect raises the employment rate by 1.83% and the population increase of 3.88% reduces it by -1.3%.

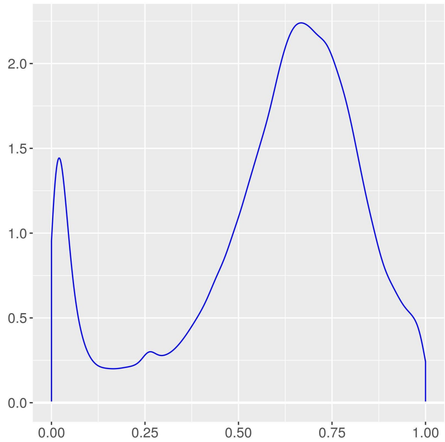
Finally, for the Wolfsburg shock the magnitude of the composition effect is much milder staying below an absolute 0.001% change in almost all counties. Nevertheless, in Wolfsburg itself it increases the employment rate by 0.38% and is thus responsible for more than one third of the total effect. The observed positive effect in Wolfsburg is inline with expectations: the high specialization on car manufacturing in Wolfsburg suggests that the county's firms have made productivity draws and face transport costs that allow them to outbid a large share of competitors in the transport equipment sector. This, however, also implies that for Wolfsburg the potential for further market gain from the increase in productivity through the shock is smaller in this sector compared to the others. Consequently, I observe that the *relative* share of transport equipment in the production of Wolfsburg is reduced by the shock. As transport equipment has the second lowest matching efficiency $\tilde{\mu}_{nk}$ the redistribution of workers between sectors explains the positive composition effect. Similarly, the only other positive composition effect above 0.001% is found in Dingolfing, which is home to the BMW headquarter. Here the increased productivity of the competitor VW decreases the relative focus of the county on the transport equipment sector exerting a positive force on the employment rate. In contrast the counties with suppliers and production plants connected to VW in Wolfsburg increase their share in this sector and thus experience losses from the composition effect.

Over all counties the average magnitudes of the mobility and composition effect relative to the average expansion effect are 0.89 and 0.13, respectively. This indicator for the importance of the three effects can also be calculated for their effect on the aggregate, national employment elasticities discussed in section 4.1. In case of the Wolfsburg shock this elasticity was 0.23 and it decomposes into an expansion effect of 0.17, a mobility effect of 0.03 and a composition effect of 0.02. As each increase in population must go along with a decrease somewhere else, the importance of the population effect for the national employment rate is reduced. In fact, the magnitude of the mobility effect relative to the expansion effect drops substantially to 0.17, whereas it remains about the same for the composition effect at 0.13. Despite the differences in their strength, all three effects clearly matter substantially in determining the effect of shocks on the German employment rate.

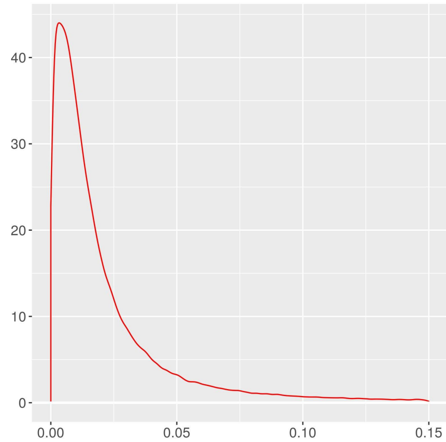
Regional shocks. The same decomposition of employment effects can be performed for all 402 different regional shocks. On average, for the national employment rate, the size of the mobility and composition effect is equal to 3.64% and 1.48% of the expansion effect with maxima across regional experiments of 50% and 12.61%, respectively.[25] I also perform the decomposition for local employment effects, that is for each of the 402 regional shocks I obtain 402 local employment effects and decompose them into the expansion, mobility and composition effect. To measure the importance of mobility and structural transformation on the employment rate I calculate the size of the (absolute) mobility effect and the (absolute) composition effect relative to all three effects combined. Figure 6 depicts the density distri-

[25] All 402 results are provided in a supplementary appendix available online.

butions of these two measures. Clearly, the role of the composition effect is minimal in most counties and for most shocks. Its size relative to the sum of employment effects is usually only a few percent. In contrast, population mobility matters greatly. It is responsible for around 70 percent of the total employment effects in a large share of counties for a large number of shocks. This points to a much more efficient adaptation of local labor markets to shocks than what is generally presumed for Germany.[26]



(a) Size of mobility effect relative to all effects



(b) Size of composition effect relative to all effects

Figure 6: Decomposition of employment effects of regional shocks

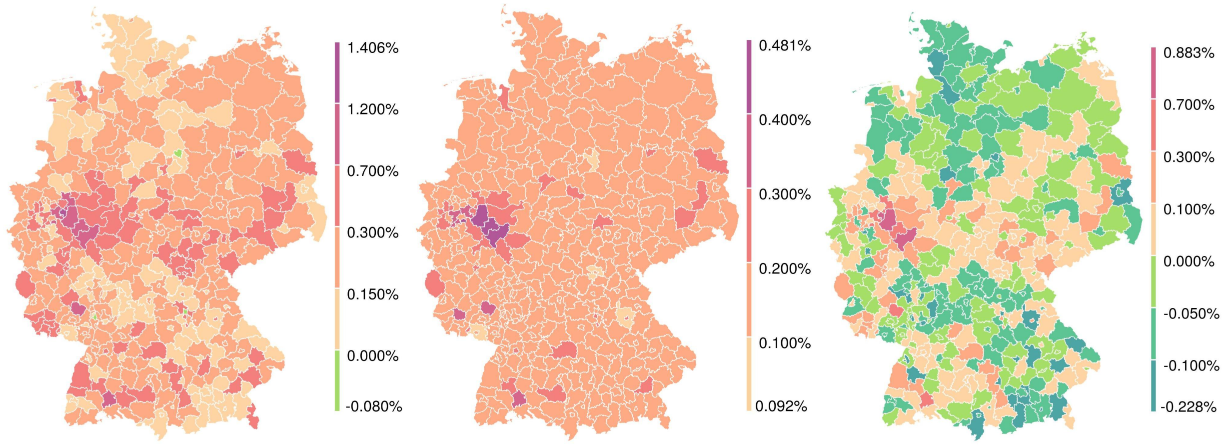
Interestingly, the relative size of the mobility effect exhibits a bi-modal distribution, that is, there is also a sizable fraction of counties that are affected relatively little by population mobility. The explanation for this lies with the structure of German counties that, in most cases, are either a single densely populated city or a less dense rural county. In the former locations the strain on the fixed factor is already high and additional population inflow quickly reduces the value of workers and their employment rate. In contrast even larger inflows to less densely populated locations with a high endowment with the fixed factor per capita will not influence the employment rate greatly.

In summary, whereas the dissipation of real income gains from a regional technological shock are strongly connected to the economic ties between counties, the employment effects are more difficult to predict. They depend, firstly, on these same economic ties but, secondly, also on the strength with which the ensuing migration influences worker productivity. This in turn hinges on fixed factor endowments. Thirdly, mobility effects are more important for regional employment changes than for national employment effects where positive and negative forces interact. Lastly, while the sectoral composition of each region's workforce plays a minor role in general, it is of greater importance in some select regions where shocks imply large structural transformation. However, this does not mean that the composition

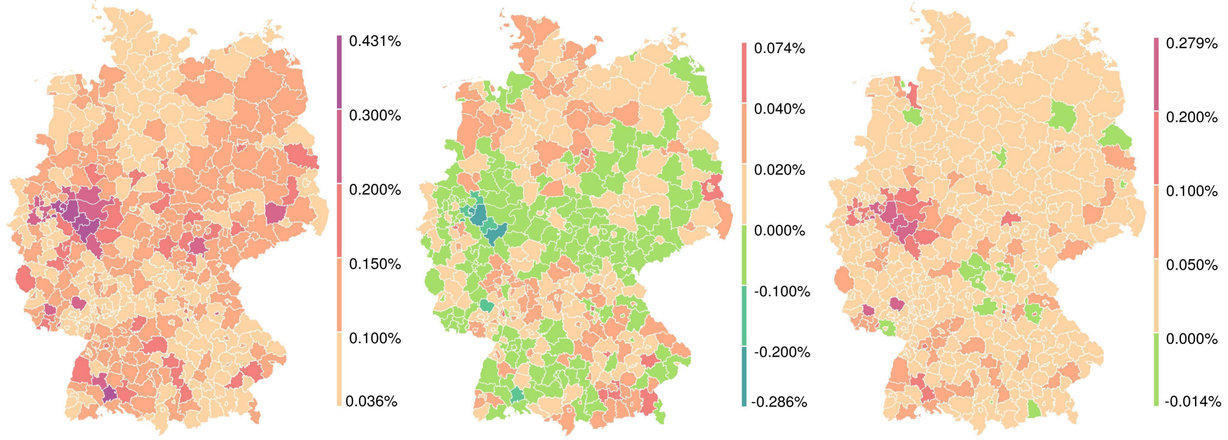
[26]This result is also obtained - albeit in a different model focusing on commuting - by Krebs and Pflüger (2018a).

effect can be neglected in general. Indeed, it can become more important when shocks favor one particular sector over the others. I turn to this type of sectoral shocks next.

Sectoral shocks. Instead of affecting a singular region, many types of productivity shocks affect a specific sector in the whole country. Recent examples for this in Germany include the emergence of electric cars, the regulatory end of nuclear power, or tighter emission standards for diesel cars. This section looks at these types of shocks and how the resulting effects differ from those of regional shocks. Again, it is helpful to begin with a specific shock as an example. In particular, figure 7 shows the disaggregate effects of a 10% technology shock in the German metal industry. Again, mobility ensures that the resulting welfare gain of 0.22% is identical across Germany. However, as before, real income gains are very heterogeneous. They are strongest in the Ruhr-area in the west of Germany where the metal industry is traditionally located and in some further clusters in the south west of the country. Employment rate changes are positive for all counties. In contrast, three counties ("Wolfsburg", "Ludwigshafen am Rhein", and "Erlangen") lose real income, albeit only slightly.



(a) real income change (b) employment rate change (c) population change



(d) expansion effect (e) mobility effect (f) composition effect

Figure 7: Effects of a nation wide shock in the metal sector

As all counties that produce in the metal industry see a direct positive effect from the technological shock, real income gains are regionally less concentrated than in the example of the cross-sector shock in Wolfsburg. Consequently, positive and negative population changes are more balanced, with 166 counties gaining and 236 losing population versus 14 and 388 in the previously considered case. Moreover, the relative spread of population changes is also smaller. As a result the importance of the mobility effect for regional employment rates drops. Across all counties the average magnitude of the mobility effect relative to the average magnitude of the expansion effect is now 0.22 compared to 0.89 in the Wolfsburg scenario.

At the same time, as the metal industry has the fourth highest matching efficiency, the technology shock is likely to lead to a positive composition effect. However, as can bee seen in figure 7(f) there can be exceptions. Firstly, a negative composition effect can occur if a county's production is in relative terms shifted away from industries with even higher matching efficiency. Secondly, indirect effects can, through terms of trade changes and factor movements, lead a county to focus its relative production away from the metal sector despite the technological improvement. Across all counties the average magnitude of the composition effects relative to the average magnitude of the expansion effect is now 0.26 and thus twice as high as in the Wolfsburg scenario.

Again, one can also assess the role of the three effects in forming the national employment elasticity. For the shock in the metal sector the latter is equal to 0.557, with an expansion effect of 0.446, a mobility effect of -0.002 and a composition effect of 0.079. Clearly, as positive and negative mobility effects are more balanced now, the influence of mobility on the national employment rate is reduced to almost 0. On the other hand, the composition effect is still about 17.8% as large as the expansion effect. Table A.3 in the appendix shows the same decomposition for all 17 possible sectoral shocks. On average across counterfactual scenarios the magnitude of the mobility effect is 1.14% that of the expansion effect. In contrast the composition effect influences the national employment rate change on average 11.23% as strongly as the expansion effect, with a maximum of 53.82% for a shock to the textiles and leather industry.

5 Conclusion

This paper quantified the surprisingly large heterogeneity of real income and employment effects across German counties in response to standardized local and sectoral productivity shocks. Local employment elasticities vary by a factor of 3.6 and real income elasticities by a factor of 2.3 depending on where a productivity shock takes place geographically. Using a quantitative model with imperfect mobility, land as a fixed factor and sector-specific labor market frictions, I identify the sources of this heterogeneity in Germany's complex interregional linkages. An outstanding data set of interregional shipments in Germany provides the unique opportunity to capture the true interregional trade structure. Based on this, I find that the spatial dissipation of real income effects in response to a local productivity shock closely follows the treated county's trade network.

In contrast, the heterogeneity of employment rate changes is driven by more complex effects. To see this, I make use of my quantitative modelling approach to decompose employment rate changes into an expansion effect directly resulting from increased productivity, a mobility effect driven by worker migration in and out of local labor markets, and a composition effect that captures the restructuring of county level productivity across sectors with varying labor market frictions that I prove to exist using unemployment and vacancy data from the German federal institute of employment research.

I find that population mobility reduces the magnitude of local employment rate responses to county level productivity shocks by a striking 70 percent on average. In contrast, the composition effect has a much milder influence on employment elasticities, except for in a handful of counties where it can reach a maximum magnitude of 20.9 percent compared to all employment effects combined. Responses in the national employment rates are shown to be less dependent on mobility, as the employment effect of worker in- and outflows in individual counties partially cancel out.

For productivity shocks affecting individual sectors across all regions the composition effect is substantially magnified as workers all across Germany are shifted into the treated sector implying a large restructuring. However, as all locations experience at least a small productivity boost from such a shock, the incentive to migrate and hence the strength of the mobility effect is reduced compared to the scenario of a productivity shock in a single region.

Moreover, I derive in line with recent real world observations that real income and employment effects, while correlated, do not move in unison. In fact, the combined mobility and composition effect can even be quantitatively large enough to overcome the expansion effect and thus lead to employment and real income effects of opposite sign. This is crucial for regional policymakers who have an interest in both outcome variables.

Finally, while I have focused on technology shocks and developments in Germany the model also delivers results for third countries and is apt to determine the effects of a range of further shocks such as reductions in trade barriers or changes in international and interregional deficit transfers. I leave such questions for future research.

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Appendix:
Shocking Germany - A spatial analysis of German regional labor markets

A Tables

Table A.1: Countries in the sample

ISO3	Name	ISO3	Name	ISO3	Name
AUS	Australia	FRA	France	MLT	Malta
AUT	Austria	GBR	Great Britain	NLD	Netherlands
BEL	Belgium	GRC	Greece	NOR	Norway
BGR	Bulgaria	HRV	Croatia	POL	Poland
BRA	Brazil	HUN	Hungary	PRT	Portugal
CAN	Canada	IDN	Indonesia	ROU	Roumania
CHE	Switzerland	IND	India	RUS	Russia
CHN	China	IRL	Ireland	SVK	Slovakia
CYP	Cyprus	ITA	Italy	SVN	Slovenia
CZE	Czech Republic	JPN	Japan	SWE	Sweden
DEU	Germany	KOR	Korea	TUR	Turkey
DNK	Denmark	LTU	Lithuania	TWN	Taiwan
ESP	Spain	LUX	Luxembourg	USA	United States
EST	Estonia	LVA	Latvia	ROW	Rest of World
FIN	Finland	MEX	Mexico		

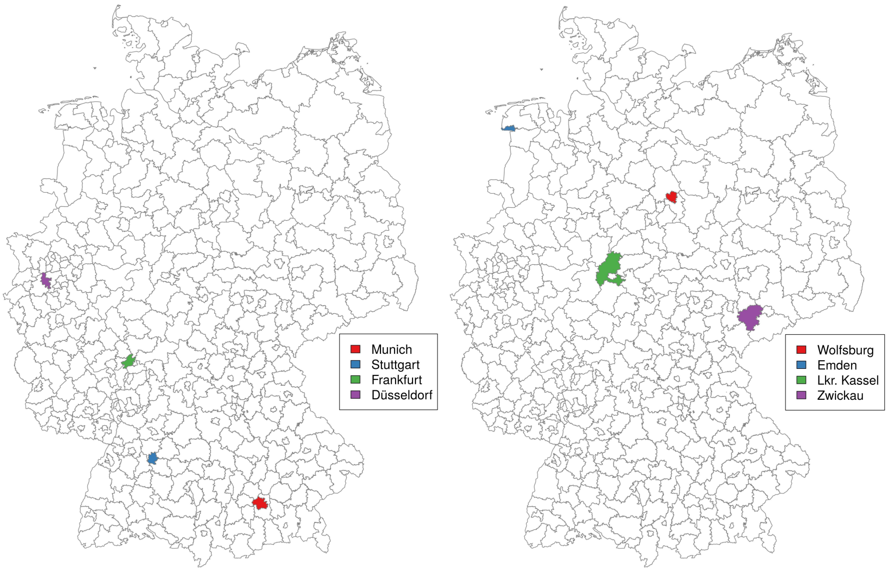
Table A.2: List of sectors

#	Description
1	Agriculture
2	Mininig
3	Food, Beverages, Tobacco
4	Textiles, Leather
5	Wood, Paper, Printing
6	Petroleum, Coke
7	Chemicals, Pharmaceuticals
8	Non-Metallic Minerals
9	Metal
10	Machinery, Electrical Equipment
11	Transport Equipment
12	Other Manufacturing
13	Utilities
14	Construction
15	Trade, Communication, IT
16	Financial, Insurance, Business
17	Government, Education, Health

Table A.3: Decomposition of national employment rate elasticities of sectoral shocks

	Total	Expansion	Mobility	Composition
Agriculture	0.640	0.721	-0.008	-0.039
Mininig	2.944	3.009	0.001	-0.017
Food, Beverages, Tobacco	0.091	0.104	-0.002	-0.009
Textiles, Leather	0.211	0.132	-0.001	0.071
Wood, Paper, Printing	0.543	0.425	-0.003	0.086
Petroleum, Coke	0.249	0.264	-0.002	-0.009
Chemicals, Pharmaceuticals	0.312	0.349	-0.001	-0.026
Non-Metallic Minerals	0.615	0.437	-0.002	0.127
Metal	0.557	0.446	-0.002	0.079
Machinery, Electrical Eq.	0.485	0.457	-0.000	0.019
Transport Equipment	0.123	0.146	-0.001	-0.019
Other Manufacturing	0.221	0.315	-0.002	-0.070
Utilities	0.675	0.662	0.001	0.007
Construction	0.165	0.163	0.002	-0.001
Trade, Communication, IT	0.421	0.437	-0.000	-0.010
Financial, Insurance, Business	0.462	0.466	0.000	-0.003
Government, Education, Health	0.039	0.036	0.004	0.000

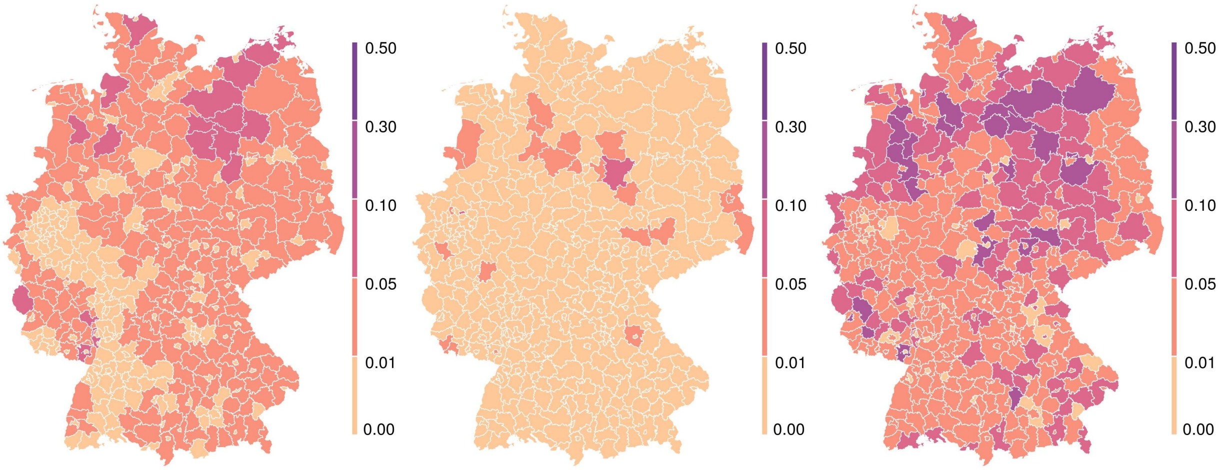
B County reference



(a) (b)

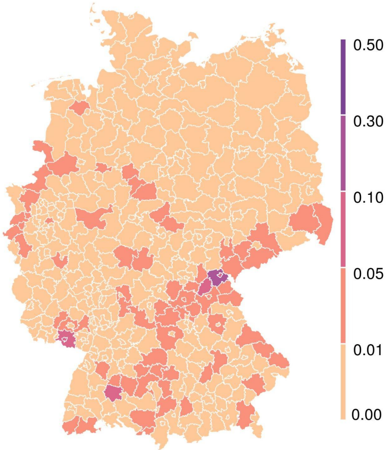
Figure B.1: County reference

C Initial production structure

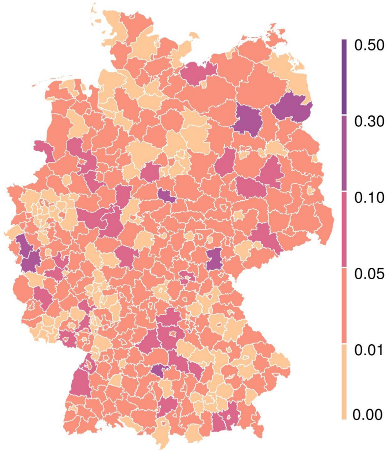


(a) Agriculture (b) Mininig (c) Food, Beverages, Tobacco

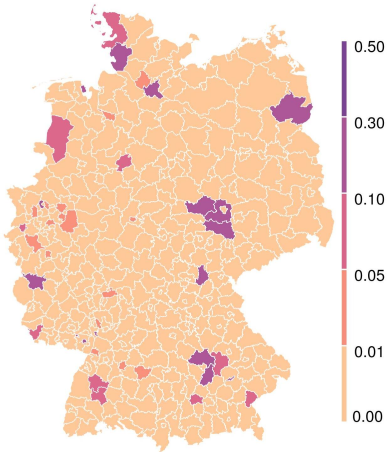
Figure C.1: Sectoral shares in county revenue (1)



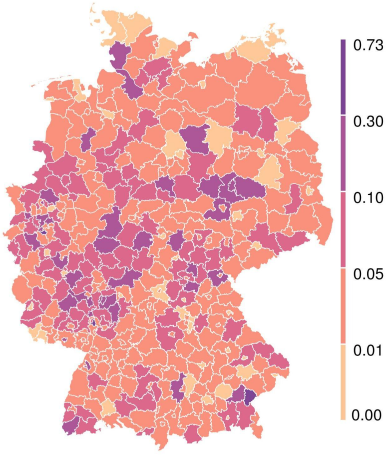
(a) Textiles, Leather



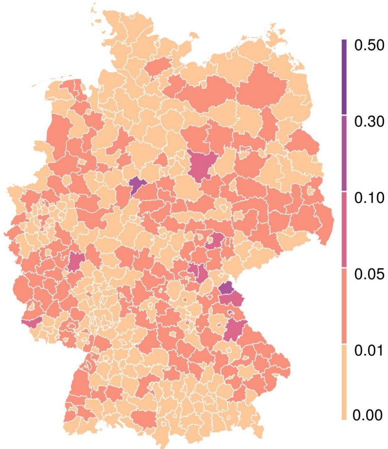
(b) Wood, Paper, Printing



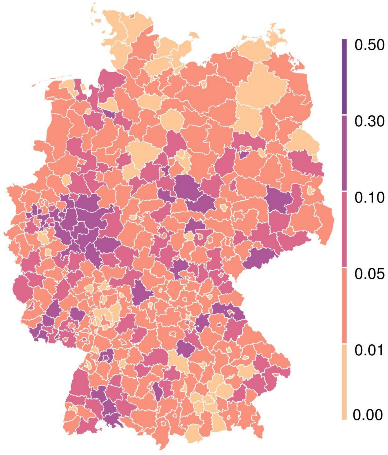
(c) Petroleum, Coke



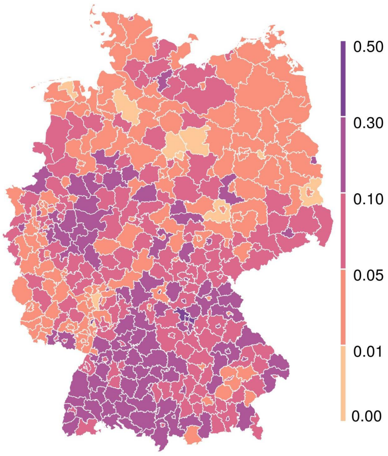
(d) Chemicals, Pharmaceuticals



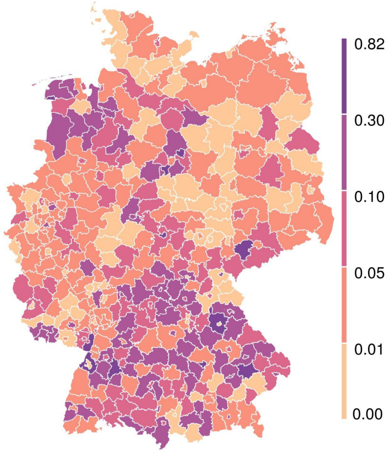
(e) Non-Metallic Minerals



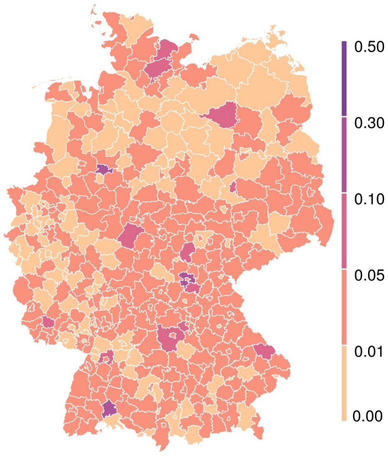
(f) Metal



(g) Machinery, Electrical Eq.

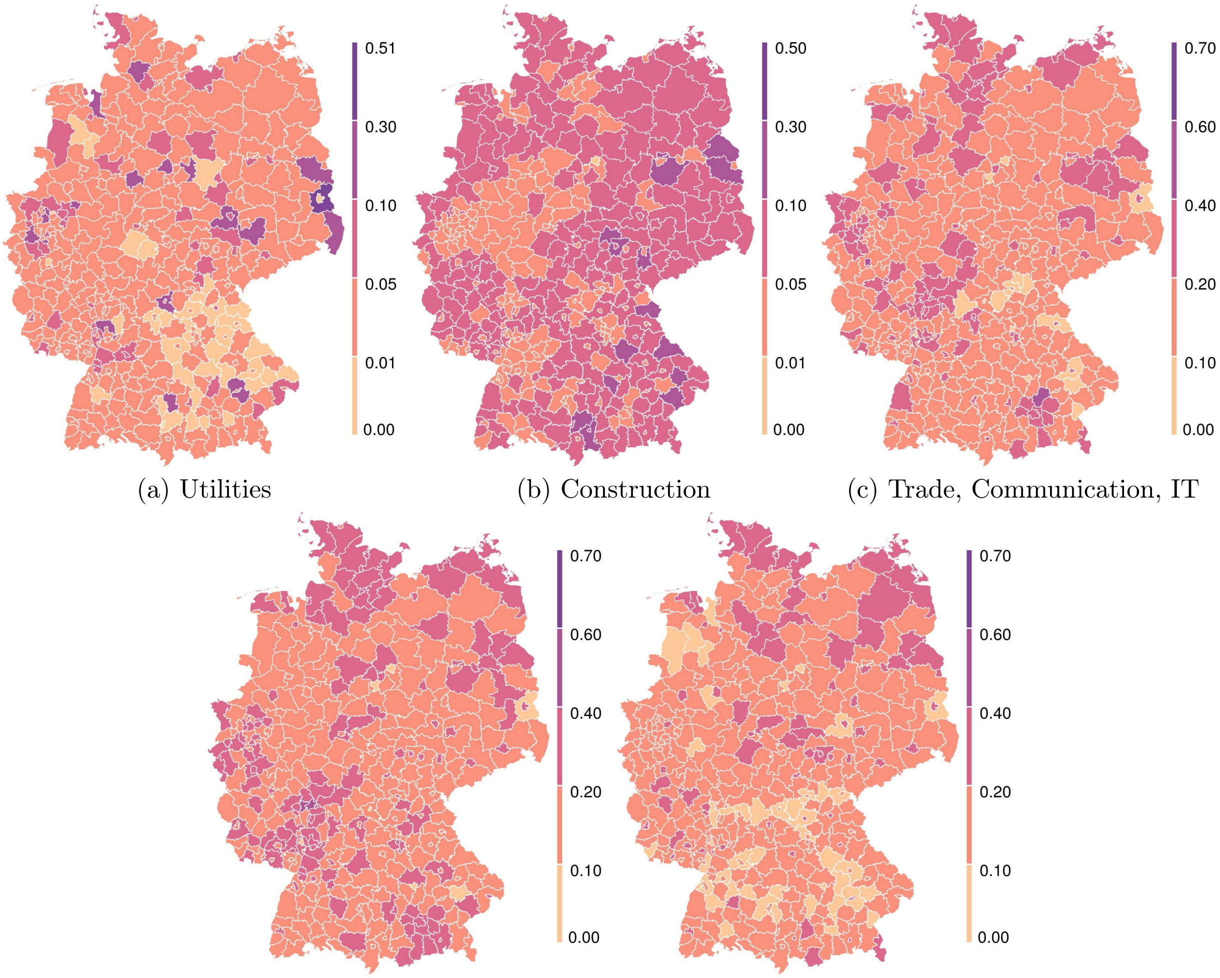


(h) Transport Equipment



(i) Other Manufacturing

Figure C.2: Sectoral shares in county revenue (2)



(a) Utilities (b) Construction (c) Trade, Communication, IT

(d) Financial, Insurance, Business (e) Government, Education, Health

Figure C.3: Sectoral shares in county revenue (3)

D Data

D.1 WIOD data

The raw WIOT-data. For each combination of countries and sectors the world input output table (WIOT) in the WIOD contains an entry $X_{ni,jk}$ for the value of flows from industry k in supplier country i to industry j in destination country n, including within country flows $X_{ii,jk}$. It also provides the values of flows from industry k in country i to country n that end up as final consumption by households $X_{ni,Ck}$, final consumption by non-profit organizations $X_{ni,Pk}$, government spending $X_{ni,Gk}$, investments $X_{ni,Ik}$ and inventory changes $X_{ni,Qk}$. All entries in these raw data (and in the following) are in value terms at current prices.

Inventory changes. Of course, inventory changes can be negative and sometimes they are significantly large. If final demand were simply calculated by summing over consumption, investment, government spending and inventory changes it would turn out to be negative in some cases. To reconcile the real world data with the static model that has no room for inventories I follow Costinot and Rodríguez-Clare (2014) and split the vector of inventory changes into a vector with all positive changes $X_{ni,Qk+}$ and one with all negative changes $X_{ni,Qk-}$ and treat them as follows. Positive inventory changes are directly included in final demand as are final consumption, government spending and investments, i.e. the build-up of inventory is treated as if it were consumed in the current period. Formally, final demand in country n for goods from industry k in country i, $X_{ni,Fk}$, is thus defined as $X_{ni,Fk} = X_{ni,Ck} + X_{ni,Pk} + X_{ni,Gk} + X_{ni,Ik} + X_{ni,Qk+}$. Negative inventory changes, in contrast, are treated as if they were produced (and consumed) in the current period. To do this, the output vector can not simply be increased by the respective (absolute) value of inventory changes because the production of the inventory in the last period also required intermediates and, thus, had a larger overall effect. To see how to calculate the necessary changes consider N countries and K sectors in matrix notation. X is the original $(N \cdot K) \times 1$-vector of total outputs, A the $(N \cdot K) \times (N \cdot K)$-matrix of input coefficients, F the $(N \cdot K) \times 1$-vector of final demand including positive inventory changes and Inv the $(N \cdot K) \times 1$-vector of negative inventory changes. Then the total output can be calculated as the sum of intermediate flows, final demand, and inventory changes as $X = AX + F + Inv$. The goal is to calculate the new level X_{new} for which the final demand vector is unchanged but inventory changes Inv are set to 0, i.e. the total output if the negative inventory changes had been produced in the current period. Rearranging terms gives $X_{new} = (E - A)^{-1}F$ where E is the unit matrix. The new input output matrix is obtained by combining intermediate good flows AX_{new} and the unchanged final demand vector F.

Consumption and intermediate goods shares. The final input-output table allows to derive two (country level) parameters of the model. Firstly, the share that industry k has in the consumption of country n can be calculated by dividing expenditures on industry k by total demand of country n to get $\delta^k_{nC} = \sum_i X_{ni,Fk} / \sum_k \sum_i X_{ni,Fk}$. Similarly, the share that industry k has in the intermediate demand of industry j in country n as $\delta^k_{nj} = \sum_i X_{ni,jk} / \sum_k \sum_i X_{ni,jk}$.

Bilateral trade flows. The adjusted input output matrix also serves to calculate for each industry k the trade flow X_{nik} between any supplying country i to any destination country n. These bilateral trade flows are obtained by summing over all uses of k (intermediate use in all industries and final demand) in its destination country, $X_{nik} = \sum_j X_{ni,jk} + X_{ni,Fk}$. When looking at the data, several of these bilateral trade flows are zero due to the high level of sectoral and geographical disaggregation. For trade between any two countries in any industry to become 0 in the Eaton-Kortum model trade costs between those two countries have to be infinitely high. This leads to two complications. Firstly, it can no longer hold true that direct trade between those countries is cheaper than trade via some partner country (with non-infinite trade costs) and I must, therefore, assume that such trade without modification is prohibited. Secondly, for any shock to trade barriers d_{nik} the relative change of the infinite trade barriers $\hat{d}_{nik}$ has to be defined as 1.

Country production and spending. The value of country i's total production in industry k, i.e. the revenue of firms in industry k, can be obtained by summing over all importing countries n, such that $X_{ik} = \sum_n X_{nik}$. The value of total production (revenue) in country i is then given by summing these across all industries, $R_i = \sum_k X_{ik}$. Summing across exporting countries i gives country n's total spending in industry k, $E_{nk} = \sum_i X_{nik}$. Then summing over the spending in each industry gives country n's total spending $E_n = \sum_k E_{nk}$.

Bilateral trade shares. The share π_{nik} that country i has in country n's spending in industry k can be calculated by dividing industry k flows from i to n, X_{nik}, by country n's total industry spending E_{nk}. Hence, these bilateral trade shares are, $\pi_{nik} = X_{nik}/E_{nk}$.

D.2 County revenue data

Sectorally disaggregated revenue data for Germany is, unfortunately, only published at the state and not at the county level. Therefore, in the mining and manufacturing sectors, where such information is available, I rely on sectoral county level employment data from the German federal and regional statistical offices to split sectoral state revenues across individual counties based on each county's share in its state's total sector employment. In a few cases with low firm numbers county sector level employment data is censored for anonymity reasons. In these cases I use the residual state sector revenues, that is, after subtracting calculated revenues from counties with employment data, and split them across the remaining counties with censored employment data according to firm numbers.[27]

In the agriculture, construction and service sectors no geographically disaggregated employment or firm data is available. In these sectors I proxy for county shares in the German total revenue with value added shares for which disaggregated data exists.[28] For the sector

[27] In this process I account for the employment in some very large or small firms via secondary sources (annual reports, etc.) to avoid larger distortions from the assumption of an average revenue per firm.

[28] German and state sectoral data for revenue, employment and firm number can be found in tables 42271-0002 and 42271-0011 from www-genesis.destatis.de. Regional data for employment and firm number is

"Utilities" value added data at the county level is only available as a total combined with the mining sector. To split the value added I begin by using the sectorally more disaggregated state data to calculate the state's share of value added in revenue in the mining sector.[29] Applying this state share to the county level mining revenue data derived above allows to approximate county level value added in the mining sector. Finally, subtracting this value from the aggregate utilities and mining value added from the data, gives the county level value added in the "Utilities" sector. I then proceed as with the other non-manufacturing sectors above and use the share of each counties sectoral value added in the national value added of the "Utilities" sector to proxy for the county's share in total German revenue in the "Utilities" sector.

Lastly, I scale sectoral revenues across all counties such that the resulting aggregate German sectoral revenues match the values reported in the WIOD.

D.3 County trade data

Raw Data. For county level trade in the mining and manufacturing sectors I rely on data provided by Schubert et al. (2014) as part of the official "Forecast of nationwide transport relations in Germany 2030" on behalf of the German ministry of transport and digital infrastructure ("Bundesministerium für Verkehr und digitale Infrastruktur"). The data set gives the total shipments in tons by water, train or truck for 2010 between German counties and their partners, disaggregated along 25 product categories.[30] The trade partner can be either a further German county (including the county itself), one of 32 third countries (of which 25 are also in the WIOD Database), or a major German or international port. The latter two appear as origin or destination whenever the actual origin or final destination is unknown or not in the explicit country sample, e.g. shipments to and from Japan. Moreover, the data thus differentiates between shipments to/from, e.g.Hamburg and Hamburg port.

The data on rail and river transport is based on data sets from the federal statistical office specially compiled to publicly unavailable levels of spatial and sectoral disaggregation. Data on truck shipments relies, firstly, on a similar special report at the county level prepared by the department of motor vehicles ("Kraftfahrtbundesamt") from a monthly .5% mandatory sample of German registered trucks with a gross vehicle weight rating above 3.5 tons and secondly, on complementary NUTS-3 level shipment data for foreign owned trucks from Eurostat.

available in table 001-51-4, and value added data in table 426-71-4-B from www.regionalstatistik.de.

[29] Sectorally disaggregated value added data at the state level is available in table 8211-0002 from www-genesis.destatis.de.

[30] The full matching between sectors of all classifications used by the different data sources to the final 17 sectors can be found in a supplementary appendix available online.

Of the 25 product categories 18 can be directly matched to my agriculture, mining and manufacturing industries 1 to 12.[31] Three categories have no match in my data ("mail", "moving items, not-for-market items", "Equipment and material for transportation, packaging") and are dropped. The remaining three categories refer to "mixed", "unknown" and "other" goods and I use those to scale trade in all other sectors for the respective pair of trade partners.[32] Finally, while the category "Secondary raw materials; municipal wastes and other wastes" would match to sector 13 ("Utilities") of this paper, it only makes up for a small share of trade in the sector. The much larger share of electricity, gas and steam supply, as well as water treatment, collection and supply is (mostly) not captured by the shipment data which does not contain information on pipeline or power line "transport". Consequently, I do not use the category to proxy for the geographical trade structure of the "Utilities" sector. Instead I drop the category from the shipment data set and treat the "Utilities" sector as the other service sectors below.

Value flows. I am interested in the sectoral trade values between German counties, and between German counties and third countries. Unfortunately, data is only available in terms of shipped tons and not value. I address this problem differently depending on the trade partners. For flows from foreign countries to German counties in the sectors with available shipment data (1 to 12) I calculate the counties share in the total sectoral weight exported from the third country to Germany. I then use these shares together with the value of the trade flow between the two countries as reported in the WIOD to calculate the value of the bilateral flow. Hence, the value flow X_{nik} from third country i to a German county n in sector k is given by $X_{nik} = (W_{nik}/\sum_{n \in N^G} W_{nik})X_{Gik}^{WIOD}$, where W_{nik} is the respective weight flow and X_{Gik} the value of total German imports from country i in sector k as calculated from the WIOD. If third country i is listed in the WIOD data but not explicitly listed in the shipment data I calculate weight shares by using the combined shipments that originate in one of the countries not in the WIOD or that appear in the data to originate in a major port.

There are two cases in which the WIOD reports flows from a foreign country to Germany despite zero flows in the shipment data. This is the case for exports from Ireland to Germany in industries 4 ("textiles and leather") and 8 ("metal") and I split these imports evenly across all German counties.

For German counties as exporters I proceed similarly: the data includes shipments within the county and hence the sum of all sectoral shipments originating in a German county represents total sectoral production weight of that county. Consequently, for exports from

[31] See the supplementary online appendix.

[32] Some select importer-exporter pairs only have shipments in the category "unknown". In these cases I assume that these shipments consist of the exporter's average export mix.

German counties to any partner I can use the share of the weight of the respective exports in total sectoral production weight to calculate the value of the flow from the sectoral county revenues. Mathematically, $X_{nik} = \frac{W_{nik} S_{nk}^{WIOD}}{\sum_n W_{nik} S_{nk}^{WIOD}} R_{ik}$, where R_{ik} is county i's revenue in sector k and S_{nk} a scale factor. The latter becomes necessary to ensure that the resulting aggregate flows from Germany to any third country as well as total inner German trade flows match the WIOD flows. In particular it scales relative export weights to each country-sector across all German counties until the aggregate German bilateral flow with the partner in each sector matches the value reported in the WIOD. Hence, for value flows X_{nik} from a German county i to a third country n in sector k the scale factor is chosen such that $X_{nGk}^{WIOD} = \sum_{i \in N^G} X_{nik}$, where X_{nGk}^{WIOD} is the WIOD trade flow from Germany to country n in sector k. Similarly, for value flows X_{nik} from a German county i to another county n in sector k the scale factor is chosen such that $X_{GGk}^{WIOD} = \sum_{i \in N^G} \sum_{n \in N^G} X_{nik}$, where X_{GGk}^{WIOD} is Germany's own trade in sector k as given by the WIOD.

For a few county-country trade partners and sectors there are weight flows in the shipment data despite the exporter having zero revenue in the respective industry, or weight flows between countries despite the WIOD reporting zero trade. These errors are likely to stem from classification and matching problems since shipment data is classified along product categories whereas WIOD and county revenue data is based on industry categories. This can, for example, lead to a situation where leather industry exports are coded as automotive products (leather car seats) and exports are measured in a sector in which nothing is produced according to the revenue data. In such cases, to remain matched to the WIOD, I rely on the revenue data and set shipment weights to zero.[33]

For utilities, construction and service sectors for which there is no shipment data, I obtain county exports to foreign countries by splitting the WIOD total German exports across counties according to each county's share in the respective sectors national revenue.

To obtain values for trade flows in the above sectors when a German county is an importer I must first calculate county sectoral demands (consumption and intermediate). To do so the sectoral German demand from the WIOD is split across counties according to their share in total German value added. The value added in turn is calculated in two separate groups. For agriculture, mining, utilities, construction and service sectors I use the sectoral German wide value added share from the WIOD to calculate county value added from county revenues. For the remaining sectors I rely on county level aggregate manufacturing value added from the data to first calculate an average value added share for the manufacturing sector as a whole in each county. I then scale the relative share of value added to remaining revenue across

[33]In four county-sectors the shipment data shows exports but no "own trade". This can not concur with the model assumptions and in these cases I set the share of own trade $\pi_n nk$ to 5%, which is at the lower end of all observed values in other county-sectors.

all German counties in each sector until the aggregate German value matches the sectoral value added share reported in the WIOD. Finally, sectoral German demand from the WIOD is split across counties according to the counties value added share in total German value added.

Intermediate demand at the county level can subsequently be calculated using the sectoral county revenues together with the derived value added shares and the national sectoral intermediate demand shares of each industry from the WIOD. Together with the consumption demand this allows to calculate county level demand for utilities, construction and service sectors. Trade flows between counties in these sectors are then calculated by assuming that this demand is satisfied across all counties according to their revenue share in the respective industry. Hence, for any pair of German counties n and i, $X_{nik} = \frac{R_{ik}}{\sum_{i \in N^G} R_{ik}} X_{GGk} \frac{X^D_{nk}}{\sum_{n \in N^G} X^D_{nk}}$, where X^D_{nk} is county n's total demand of industry k goods.

Having derived all bilateral trade flows and all sectoral county revenues I can calculate each county's trade deficit and supply with goods from each sector. Finally, I scale relative sectoral consumption and sectoral intermediate demand shares such that sectoral demand matches sectoral supply. This implies that in counties with a relatively high supply of e.g. "Transport Equipment" goods both relative intermediate usage and relative consumption of such goods will be larger.

The result is thus a data set containing information on revenues and trade among 442 locations (402 German counties, 39 other countries and a modeled ROW) in 17 sectors.