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On the Road (Again): Commuting and Local Employment Elasticities in Germany

Abstract

This paper develops a quantitative spatial general equilibrium model for the German economy to address two issues. First, we explore the role of commuting for local labor markets and their capacity to absorb productivity shocks. Second, we address the role of housing markets for quantitative analyses. Germany is an exciting laboratory because commuting across local labor markets is pervasive, unique data are available, and because Germany's high degree of trade openness poses a thrilling counterpoint to the United States. Our key findings for German counties are that the employment and resident elasticities associated with local productivity shocks are much above unity, yet disparate (the former larger than the latter), very heterogeneous, and only poorly predicted by simple labor market statistics. Allowing the supply of land/housing to be price elastic increases the elasticities and reinforces our conclusions. The regional heterogeneity of the land/housing shares in Germany turns out to be inessential for our findings, the level of the land/housing share plays an important role, however. We perform a plethora of robustness checks which allow us to gain perspective on extant findings for the United States.

JEL-Codes: F120, F140, R130, R230.

Keywords: quantitative spatial analysis, commuting, migration, employment and resident elasticities.

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1 Introduction

What once fired the imaginations of poets and musicians, Jack Kerouac, the Canned Heat and Willie Nelson has become dreary reality for zillions of workers today, albeit in an altogether different vein. The world is on the road (again). Workers spend substantial shares of their time and budgets on traveling between residences and workplaces and these shares have steadily risen in the last decades (Redding and Turner 2015). In deciding where to live and where to work households trade off living costs, access to consumption goods, amenities, and idiosyncratic factors, such as family ties, networks and personal tastes. Until recently, research on the implications of the separation of workplaces and residences has almost exclusively focused on the internal structure of cities and so on commuting *within* cities.[1] Novel research has shifted attention to regional economies and the importance of *commuting across local labor markets*.[2] This requires to address spatial linkages in goods and factor markets, trade, commuting and migration, and their respective costs. The seminal study by Monte et al. (2018) develops a quantitative spatial general equilibrium model which integrates these linkages and which corroborates the crucial role that commuting across local labor markets plays for the American economy. Research along this line is still very scant, however, and little systematic is known for other countries.[3]

This paper makes two contributions to this research line. First, we perform quantitative analyses to explore the role of commuting for local labor markets in Germany, an exciting scientific laboratory for a number of reasons. Commuting across local labor markets is pervasive. According to our data, on average only 60% of a county's residents work at the same place where they live. Figure 1 depicts the kernel densities of this 'own-commuting share'. It can be seen that the peak of the distribution is also at about 60% and that a large share of counties exhibits values (much) below one.[4] Moreover, we have exceptionally good data, notably a unique observation-based dataset for bilateral manufacturing trade at the county level, a decisive advantage over extant work which relies on imputations. A final reason is that, with its high degree of trade openness, Germany poses a thrilling counterpoint to the United States. The ambition of this paper goes much beyond replicating extant work for another country, however. Our second contribution is of methodological nature. We use the German case to address the role of housing markets for quantitative analysis. The key parameter on the demand

[1] See Duranton and Puga (2015) for a recent survey and Ahlfeldt et al. (2015) for a recent key contribution.
[2] This redirection is largely due to the work by Autor et al. (2013) whose empirical findings highlight the role and diversity of American local labor markets and their adjustment to the rise of China in world trade (Redding 2020).
[3] See Redding (2020), Redding and Rossi-Hansberg (2017) and our review of the literature below.
[4] See section 4 and appendix E for details.

side is the expenditure share devoted to land/housing.[5] Since widely differing numbers are used for this share in the extant literature, we carefully discuss its choice. Further, this share is taken to be uniform across local labor markets in the canonical model of spatial quantitative analysis (Redding 2016; Redding and Turner 2015; Redding and Rossi-Hansberg 2017; Redding 2020). German regional data show that the housing share varies markedly across counties, however. This inspires us to explore the implications of this local heterogeneity. We also scrutinize the key parameter on the supply side, the elasticity of housing supply, and we highlight its interplay with the housing share in shaping regional outcomes.

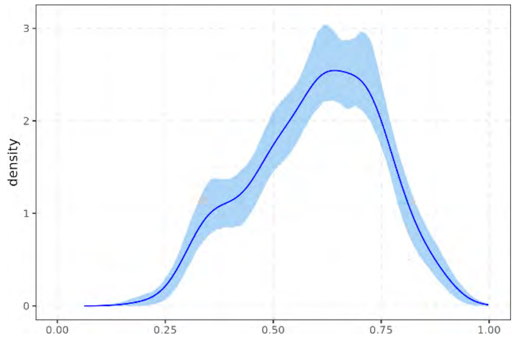

Figure 1: Kernel densities for the own-commuting share (share of non-commuters in residents of German counties), 95% confidence interval shaded. See section 4 and appendix E for the data and further details.

Both aims are addressed in the context of an analysis of the absorption of counterfactual local productivity shocks by German local markets. Specifically, we pose the following key questions. How is local production and employment affected by these treatments? How do local labor markets adjust? Specifically, how are the agents' choices of workplaces and residences affected by these shocks? In what ways do the results depend on the parameters in the housing market and further features of the model?

To explore these questions, we develop a quantitative spatial general equilibrium model with heterogeneous locations tailored to the German economy. We borrow the main model from Monte et al. (2018) who abstract from external trade in addressing the U.S. economy.[6] With export and import shares in GDP of about 45%, Germany can hardly be treated as a closed economy, however.[7] We therefore go beyond Monte et al. (2018) and consider Germany's internal *and* external trade relations. We explore the importance of trade openness in a robustness check which shuts down all international trade. In calibrating the model, we devote special attention to the housing market and we derive model-consistent technologies and trade costs as a check of the model's specification. We proceed in two steps. We first numerically

[5] Throughout this paper we use 'land' and 'housing' as synonymously referring to land and structures.
[6] This also holds true for Caliendo et al. (2018).
[7] See the German Statistical Office at https://www.destatis.de.

compute and analyze the general equilibrium local employment and resident elasticities in response to a treatment with productivity shocks. We then perform regressions to analyze how well the elasticities can be predicted with labor and commuting market statistics. This second part of our analysis is important because it provides a backdrop on the scope of reduced-form approaches to local labor markets, in particular on treatment effect heterogeneity, an issue which is also crucial for policymakers seeking guidance for their decisions on local infrastructure, taxes, subsidies, and place-based policies.[8]

Our thought experiment ('treatment') throughout is a counterfactual 5% productivity shock in each German local labor market, holding productivity at all other locations as well as all other exogenous parameters constant.[9] Our exploration is centered around a 'baseline scenario' which grounds on the observation-based bilateral trade data for internal and external trade, a uniform expenditure share of housing of 10% (our preferred value for the economy-wide application, as explained below), and inelastic housing supply. We focus on Germany's 402 counties, since our model explicitly deals with spatial linkages in goods and labor markets. This allows us to perform the analysis at a finer spatial scale than that of Germany's 141 commuting zones (which are simply aggregated up from counties). We perform extensive robustness checks which put the assumptions of this baseline under scrutiny.

Our key results are as follows. The general equilibrium local employment elasticities in the baseline scenario are all well above unity. This points to very strong home market effects. Resident elasticities are smaller but also typically exceed 1. Their (unweighted) mean (1.89) is half the one for employment elasticities (3.72). This divergence demonstrates the importance of commuting in Germany. Both types of elasticities are very heterogeneous across counties. Hence, seriously wrong conclusions would be drawn, if an average elasticity was applied in policy analysis. Our regression analyses show that ex-ante observable labor and commuting market statistics are poor predictors of the local employment elasticities. A regression focusing on the own-commuting share (depicted in Figure 1) is indicative of our findings: the regression R-squared is only 0.2.

Our robustness checks focusing on the size and heterogeneity of the housing shares yield remarkably different results. There are views – differing from our economy-wide approach – which put the level of the housing share at up to 40% (see below). Increasing the share from our preferred 10% to 40% has two consequences. First, whilst the employment elasticities

[8] Redding (2020, section 2) provides an in-depth discussion of the relationship between reduced-form empirical approaches such as Autor et al. (2013) and quantitative spatial models.
[9] We have also experimented with 1% and 10% shocks. This leaves the results virtually unchanged.

remain larger than the resident elasticities, and whilst both remain heterogeneous, the elasticities fall sharply. Second, the explanatory power of simple labor and commuting market statistics as predictors of the employment elasticities increases strongly. The R-squared of a regression focusing on the own-commuting share rises up to 0.89 with a housing share of 40%. Both findings are intuitive: increasing this share fosters the dispersive force of housing prices, which reduces the elasticities; the general equilibrium repercussions in the economy are also much weaker when a high share of expenditures is local, and this explains why simple (partial-equilibrium) statistics become better predictors. The heterogeneity of housing shares across German counties turns out to play only a negligible role, in contrast. We find that the distribution of employment and resident elasticities differs only marginally from those when a uniform housing share is imposed *at the same average level*, and our verdict with respect to the poor explanatory power of labor market statistics remains intact.

We address the supply side of the housing market by rerunning the treatments for a range of elasticities that we take from the extant literature (see section 3.2.3 for details). Employment and resident elasticities turn out to be larger and the predictive power of the own-commuting share falls sharply with larger supply elasticities. Both findings are intuitive and can be related to our results for the housing share. A larger supply elasticity reduces pressure on housing prices associated with the wage and mobility effect of positive local productivity shocks, similar as a smaller housing share does from the demand side. The key insight that we derive from this analysis is that small housing shares and positive supply elasticities wipe out the predictive power of simple labor and commuting market statistics and this holds true for a considerable share of ranges for the two parameters.

In further robustness analyses we run the treatments disregarding Germany's external trade, we look at commuting zones rather than counties, and we consider trade in services in addition to manufacturing (this forces us to use imputed data, see below). Whilst each of these extensions yields a number of specific results, our key results remain intact.

Previous research. Theoretical literature addressing the separation of workplaces and residences in regional analysis is sparse. One exception is Borck et al. (2010), who set up a two-region new economic geography model with commuting across regions which allows for demand and supply linkages, crowding in goods markets and congestion in housing markets, and multiple equilibria. A simultaneous reduction of trade and commuting costs fosters the spatial concentration of production and a dispersion of residences in the model, so that the importance of commuting rises. New quantitative spatial economics has turned away from such stylized settings to models with an arbitrary number of locations with heterogeneous geography, productivities, amenities, and local factors, as well as trade and commuting costs. This research derives its thrust from restraining the parameters so that multiple equilibria are excluded. The payoff is that combining, measuring and quantifying theoretical mechanisms and identifying key structural parameters becomes possible and that counterfactuals can be addressed (see Redding 2020, Redding and Rossi-Hansberg 2017). A milestone in this research is the model developed by Redding (2016) which generalizes Helpman's (1998) model to arbitrary many locations, and which builds a bridge to various trade models, such as the Armington model (Anderson 1979; Anderson van Wincoop 2003), the monopolistic competition model with homogeneous firms (Krugman 1980; Helpman and Krugman 1985), or heterogeneous firms (Melitz 2003), and the multi-region Ricardo model (Eaton and Kortum 2002). Our analysis is most closely related Monte et al (2018), who introduce commuting across locations in Redding's (2016) model and who perform quantitative analysis of local labor market shocks for the United States.[10] We highlight the relation of our analysis with this work, as we go along. The Monte et al. (2018) model is also used by Seidel and Wickerath (2020) to study rush hours congestion in Germany.[11]

The structure of our paper is as follows. Section 2 introduces the model. Section 3 characterizes the data, the calibration of the model, and the derivation of model-consistent trade costs and local productivities. Our quantitative analyses are performed in section 4 starting with the baseline scenario and moving on to extensive robustness checks. Section 5 concludes.

2 The Model

The Setup. We build on the spatial general equilibrium model developed by Monte et al. (2018). Locations are linked through trade, migration and commuting. Households consume land and a compound good which consists of differentiated varieties produced with labor under increasing returns. Space is divided into a set of locations $\Omega = \{1,..,N\}$ which serve as workplaces and residences. Each location $n \in \Omega$ is endowed with an exogenous supply of land/housing $\overline{H}_n$ owned by local immobile landlords who earn rents from the residential use by households. Monte et al. (2018) consider an economy with an internal geography only. Our adaptation of the model for Germany allows for external trade. We assume that the set of locations $\Omega = \{1,..,N\}$ is exhaustively divided into disjoint subsets (territorial entities), $\Omega_g \subseteq$

[10] Dingel and Tintelnot (2020) develop an extension with granular interactions.
[11] They use the same transport data as we do but arrive at different bilateral trade flows since they apply simple unit values for traded tons. See section 3.1.2 and appendix D.

Ω. Each subset is populated by an exogenous measure $\bar{L}_g$ of workers who supply 1 unit of labor each. Workers are mobile and can commute to work within subsets but not across them.[12] German local labor markets are one such subset in our analysis and Germany's external trading partners (countries) form the other subsets.

Preferences. A consumer ω who lives in location $n \in \Omega$ and works in location $i \in \Omega$ has preferences characterized by an upper-tier utility of the Cobb-Douglas-type over a basket of goods $C_{n\omega}$ and housing $H_{n\omega}$ with expenditure shares α and $1-\alpha$, respectively,[13]

$$U_{ni\omega} = \frac{b_{ni\omega}}{\kappa_{ni}} \left(\frac{C_{n\omega}}{\alpha}\right)^{\alpha} \left(\frac{H_{n\omega}}{1-\alpha}\right)^{1-\alpha}, \qquad 0 < \alpha < 1 \tag{1}$$

where $\kappa_{ni} \in [1, \infty)$ is a parameter of iceberg commuting costs in terms of utility and $b_{ni\omega}$ is a consumer-specific work-residence amenity pair drawn from the Fréchet-distribution:

$$G_{ni}(b) = e^{-B_{ni} b^{-\epsilon}}, \qquad B_{ni} > 0, \epsilon > 1 \tag{2}$$

The scale parameter B_{ni} indicates the average amenity level of the work-residence pair and $\epsilon > 1$ parameterizes the dispersion of these amenities.

The basket of goods is a CES-bundle of differentiated varieties j:

$$C_{n\omega} = \left[\sum_{i \in N} \int_0^{M_i} c_{ni\omega}(j)^{\frac{\sigma-1}{\sigma}} dj\right]^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1 \tag{3}$$

where $c_{ni\omega}(j)$ is consumption of variety j produced in i, M_i is the mass of varieties, and σ is the elasticity of substitution between any two varieties. Price indices dual to (1) and (3) are

$$P_n = p_n{}^{\alpha} q_n{}^{1-\alpha}, \quad \text{and} \quad p_n = \left[\sum_{i \in N} \int_0^{M_i} p_{ni}(j)^{1-\sigma} dj\right]^{\frac{1}{1-\sigma}}, \tag{4}$$

respectively, where q_n is the price of housing in n, $p_{ni}(j)$ the price of variety j produced in i paid by consumers in n, and consumer ω's indirect utility is

$$V_{ni\omega} = \frac{b_{ni\omega}}{\kappa_{ni}} \frac{e_{ni}}{P_n} \tag{5}$$

where e_{ni} denotes the total expenditure of any consumer choosing to commute from n to i. Since indirect utility is a monotonic function of the amenity draw $b_{ni\omega}$, it also follows a Fréchet-distribution, $\mathcal{G}_{ni}(U) = e^{-\Phi_{ni} U^{-\epsilon}}$, where $\Phi_{ni} = B_{ni} \left(\frac{e_{ni}}{\kappa_{ni} P_n}\right)^{\epsilon}$.

[12] We face similar data-limits as Monte et al. (2018) and we therefore abstract from international cross-border commuting, too.

[13] Following standard practice, we use the term ‚goods‘ to comprise services where appropriate. Davis and Ortalo-Magné (2011) provide empirical evidence in favor of constant expenditure shares. We allow this parameter to be heterogeneous across local labor markets in our robustness analysis.

Production. Producers in location i produce varieties j under increasing returns and monopolistic competition according to the total cost function $\Upsilon_i(j) = \left(F_i + \frac{y_i(j)}{A_i}\right) w_i$, where $y_i(j)$ is output, F_i and A_i are the location-specific fixed input of labor and productivity, respectively, and w_i is the location-specific wage. Symmetry allows us to suppress the index j, from now on. Profit maximization implies that prices are constant markups on marginal costs. Consumers in location n pay $p_{ni} = d_{ni}\left(\frac{\sigma}{\sigma-1}\right)\frac{w_i}{A_i}$ for any variety j produced in i, with $d_{ni} \geq 1$ denoting iceberg costs for shipments from i to n. Zero-profits then imply a firm's output $y_i = A_i(\sigma - 1)\, F_i$, its labor use $l_i = \sigma\, F_i$, and its total costs $\Upsilon_i = \sigma\, F_i\, w_i$. Labor market clearing in i commands that labor use $M_i l_i$ equals supply L_i so that the equilibrium number of firms is:

$$M_i = \frac{L_i}{\sigma\, F_i} \tag{6}$$

Trade and price indices. Goods trade between any two locations is characterized by a gravity equation. Using the CES-structure of demand as well as the pricing rule, the measure of firms (6), and total costs $\Upsilon_i = \sigma\, F_i\, w_i$, the share of location n's expenditure on varieties produced in i (relative to location n's total spending on goods) is derived as:

$$\pi_{ni} = \frac{M_i\, p_{ni}{}^{1-\sigma}}{\sum_{m\in N} M_m\, p_{nm}{}^{1-\sigma}} = \frac{\frac{L_i}{F_i}\left(\frac{d_{ni}}{A_i}\right)^{1-\sigma} w_i{}^{1-\sigma}}{\sum_{m\in N}\frac{L_m}{F_m}\left(\frac{d_{nm}}{A_m}\right)^{1-\sigma} w_m{}^{1-\sigma}} \tag{7}$$

Using optimal pricing along with eq. (6), the CES price indices (4) can be rewritten as:

$$p_n = \left(\frac{\sigma}{\sigma-1}\right)\left(\frac{w_n d_{nn}}{A_n}\right)\left(\frac{L_n}{\pi_{nn}\,\sigma\, F_n}\right)^{\frac{1}{1-\sigma}} \tag{8}$$

Market clearing. In each location i total sales equal production costs. Hence we can write:

$$\sum_{n\in N} \pi_{ni} X_n = w_i L_i \tag{9}$$

We follow Monte et al. (2018) in assuming that landlords spend all rental income on goods and that total regional spending X_n may differ from residential income $\bar{w}_n\, R_n$ by an exogenous trade deficit D_n (or surplus) which is borne by local landlords. Combining the expenses of consumers on goods, $\alpha\, \bar{w}_n\, R_n$, with the spending of local landlords, $(1-\alpha)\, \bar{w}_n\, R_n + D_n$, where $\bar{w}_n$ is the average wage in location n (characterized below) and R_n is the measure of residents, location n's total spending on goods (services) is thus:[14]

[14] A region's expenditure, X_n, may differ from the region's value of production $w_n\, L_n$ for two reasons. To see this, rewrite equation (10) as $X_n - w_n\, L_n = (\bar{w}_n R_n - w_n\, L_n) + D_n$. First, the production value and residential income may differ due to commuting, $(\bar{w}_n R_n - w_n\, L_n)$. Second, a region may run trade deficit (surplus) D_n.

$$X_n = \bar{w}_n R_n + D_n \tag{10}$$

In the housing market housing is consumed by residents with an associated spending of $(1-\alpha)\bar{w}_n R_n$. Following Saiz (2010) we assume that the housing supply H_n at each residence n depends on exogenous characteristics of the location $\bar{H}_n$ and on the price of housing q_n according to the specification $H_n = \bar{H}_n {q_n}^{\eta_n}$ where $\eta_n \geq 0$ is the price elasticity of the supply of developed land. The standard specification of a completely exogenous and perfectly inelastic supply ($H_n = \bar{H}_n$) is portrayed by $\eta_n = 0$. A perfectly elastic housing supply is depicted by the case $\eta_n \to \infty$. Housing market clearing in location n thus commands:

$${q_n}^{1+\eta_n} \bar{H}_n = (1-\alpha)\bar{w}_n R_n \tag{11}$$

Labor mobility and commuting. From the subset of available location pairs $m, l \in \Omega_g$ each worker chooses the commute that offers the highest utility taking her idiosyncratic preferences (5) into account. With the Fréchet distribution of indirect utility, the probability that a worker chooses to live in location n and to work in location i is (where we now use $e_{ni} = w_i$):

$$\lambda_{ni}|_{\Omega_g} = \frac{B_{ni}\left(\frac{w_i}{\kappa_{ni} P_n}\right)^{\epsilon}}{\sum_{m \in \Omega_g} \sum_{l \epsilon \Omega_g} B_{ml}\left(\frac{w_l}{\kappa_{ml} \mathrm{P_m}}\right)^{\epsilon}} \equiv \frac{\Phi_{ni}}{\Phi_g} \tag{12}$$

The share of workers employed by all firms in location n must match the overall probability that a worker chooses to work in this location:

$$\lambda_n^L \equiv \frac{L_n}{L_g} = \sum_{i \epsilon \Omega_g} \lambda_{in}|_{\Omega_g} \tag{13}$$

Moreover, the share of residents in location n must match the overall probability that a worker chooses to live in this location:

$$\lambda_n^R \equiv \frac{R_n}{L_g} = \sum_{i \epsilon \Omega_g} \lambda_{ni}|_{\Omega_g} \tag{14}$$

The expected wage conditional on living in location n equals the wages paid at all possible workplaces weighted with the probabilities of commuting to those workplaces from location n:

$$\bar{w}_n = \sum_{i \in \Omega_g} \frac{B_{ni} {\kappa_{ni}}^{-\epsilon} {w_i}^{\epsilon}}{\sum_{l \in \Omega_g} B_{nl} {\kappa_{nl}}^{-\epsilon} {w_l}^{\epsilon}} w_i \tag{15}$$

The expected utility of a worker is the same for all pairs of residence and workplace within the relevant subset of locations because of population mobility. It can be calculated as:

$$\bar{U} = \mathbb{E}[U_{ni\omega}] = \Gamma\left(\frac{\epsilon}{\epsilon-1}\right)\left[\sum_{m \in N} \sum_{l \in N} B_{ml}\left(\frac{w_m}{\kappa_{ml} P_l}\right)^{\epsilon}\right]^{\frac{1}{\epsilon}} \tag{16}$$

where $\mathbb{E}$ is the expectations operator and $\Gamma(\cdot)$ is the Gamma function.

General equilibrium and uniqueness. In the general equilibrium the set $\{w_n, \pi_{ni}, X_n, \bar{w}_n, L_n,\ q_n, R_n, p_n\}$ of endogenous variables is simultaneously determined by the set of equations (7), (8), (9), (10), (11), (14), (15) and (16) after the substitution of $\lambda_{ni}|_{\Omega_g}$. The techniques developed in Allen et al. (2020; 2016) imply the sufficient condition $(\sigma - 1)/\epsilon \geq 1$ for the general equilibrium to exist and to be up-to-scale unique (appendix A provides details). Hence, this condition requires the Fréchet parameter of idiosyncratic location preferences ϵ to be small relative to the elasticity of substitution σ.[15] Importantly, this condition does not involve the housing share $(1 - \alpha)$, a finding, which to the best of our knowledge, is novel and also intuitive. Whilst housing and idiosyncratic location preferences are dispersion forces, the respective parameters have distinct roles in a model *with commuting*. The Fréchet parameter ensures that all locations are residences *and* workplaces, a (positive) housing share only implies that all locations are residences.[16] Hence, in a model with commuting, the Fréchet parameter 'dominates' the housing share. That the housing supply elasticity does not enter this condition is also intuitive. Different supply elasticities relax or tighten price pressure in the housing market (just as housing shares do) and so only influence whether residences are non-empty. This is, however, already implied by a low enough Fréchet parameter.

3 Data and Model Inversion

Section 3.1 describes our data (details are provided in appendix D and E). Section 3.2 takes up the model calibration. Section 3.3 explores model consistent structural fundamentals.

3.1 Data Sources

3.1.1 Commuting. Our commuting data stem from the German Federal Employment Agency ('Pendlerstatistik'). They contain bilateral flows between all 412 German counties ('Kreisfreie Städte und Landkreise') in 2010 for all workers with social security whose workplace differs from the registered residence. In 2011 an administrative reform reduced the number of counties to 402. Since other data sets are only available for this classification we work with the latter. We complement this data with total local employment supplied by the German Institute for Labor Market Research (IAB) to derive the number of non-commuters (workers whose workplaces coincide with their residences) in each county. Both data sets are based on social security accounts which exclude self-employed workers and other workers without social

[15] This is intuitive since agglomeration forces in the Krugman-Dixit-Stiglitz model are weaker, the larger is σ (e.g. Fujita et al. 1999), whilst dispersion forces are stronger the smaller is the Fréchet location choice parameter ϵ.
[16] This difference is important as in models with trade and migration but *without* commuting (i.e. unlike ours), the dispersive forces of land/housing and the Frechet-parameter are isomorphic, see e.g. Allen and Arkolakis (2014).

security. Preparing the final commuting data, on which all figures, tables and quantitative analyses are based, we faced two challenges. First, in the raw data all bilateral commuting flows between two counties with less than 10 commuters are censored and, hence, indistinguishable from county pairs with no commuters. Second, the raw data contain commuting distances that are implausibly long for a daily commute. We take this as indicative of misreporting which is quite likely the case as the process of data collection is error-prone for two reasons. First, the data are based on the accounts of companies which may report the wrong workplace of a worker by muddling up the company's headquarter or main plant with the actual plant, where the worker is employed. Second, the residence address of the worker may be misreported because workers in Germany may be registered at a main address ('Hauptwohnsitz') and a secondary address ('Nebenwohnsitz'). Note that such possible misreporting concerns all our data, and so also the data for commutes with plausible distances. We mend the two problems of censoring and misreporting with the help of further, aggregate data, and with the help of gravity estimates, as we explain in appendix E. Our final data set contains commutes up to a threshold of 120 km and/or a travel time of less than 1:45 hours by train. The data show that commuting across local labor markets is pervasive in Germany as documented by the own-commuting shares in Figure 1. Across German counties, the unweighted average share of a county's residents that work at other locations is 40%, and that of a county's total workforce that lives in a different location is 36%. Appendix E provides more detailed information about commuting in Germany.

3.1.2 Trade. Our trade data are based on a unique data set, the traffic forecast ('Verkehrs-verflechtungsprognose 2030') administered by the German Federal Ministry of Transport and Digital Infrastructure.[17] These data contain the weight of goods shipped between German counties and their trade partners by ship, train or truck, disaggregated across 25 product categories. Sources for the data stem from the respective agencies for rail- and waterways and from a representative weekly sample of truck shipments in Germany.[18] Krebs (2018) uses these data to construct an interregional input output table at the level of 17 sectors for all German counties and 26 foreign countries which replicates observed German county level sectoral revenues, value added, and intermediate demand reported by the regional statistical offices, and whose aggregates for Germany are cell-by-cell compatible with the national and international

[17] See appendix D for further details on the following.

[18] Air transport is not included in the data. However, it only makes up about 0.1 percent of total transported weight in Germany (4.2 million tons compared to 3.7 billion tons, see Schubert et al. (2014)), and only about 1 percent of the value of total foreign trade (source: 'Bundesverband der Deutschen Luftverkehrswirtschaft').

data from the World Input Output Database (WIOD).[19] An important feature of the input-output table derived in Krebs (2020) is that, unlike in other works, the weight data are not mechanically transformed into value data on the basis of national unit values for sectoral outputs (cf. footnote 11). Rather, Krebs (2020) uses additional information about the counties' specific production structure before transforming weight data into value data. This is important because shipments within one and the same sector may include goods of entirely different nature and, hence, weight (e.g. car seats and car engines in the auto-industry), so that an application of national unit values would grossly misrepresent the regional production and trade structure. Being based on observable data, the interregional input-output table derived in Krebs (2020) thus allows us to obtain a detailed and reliable portrait of bilateral manufacturing trade between German counties as well as between German counties and foreign trade partners (countries). This is a key advantage over extant research where the entries for regional trade shares were imputed on the basis of regional production values, the regional workforce, and/or higher-level spatial aggregates (see e.g. Monte et al. 2018).

Monte et al. (2018) and Caliendo et al. (2018) focus on manufacturing in their analyses of US local labor markets. With our superior observation-based regional manufacturing trade data, such a focus is particularly justified in our case. Since the size of the service sector in Germany and the fact that a considerable and growing share of services is tradeable, we view it as desirable to challenge our baseline case with a robustness scenario which allows for trade in services in addition to manufactures, however. We borrow the respective data from Krebs (2020) who complemented the observation-based manufacturing data with regional trade data in service industries which he imputed on the basis of gravity estimates in establishing a full interregional input-output table for German counties and their international trading partners.

3.1.3 Further Data. Total wage sums ('totales Arbeitnehmerentgelt') for German counties, the size and number of flats by county (which we use as controls in our empirical section and also in our robustness check) are available from the Regional and Federal Statistical Offices ('Statistische Ämter des Bundes und der Länder'). Disaggregated (regional) rent data from the German Federal Office for Building and Regional Planning (BBSR) are key for our robustness check concerning the heterogeneity of housing shares.

[19] See Timmer et al. (2015) for the World Input Output Database (WIOD) and Table (WIOT). The 26 countries in our study are Austria, Belgium, Bulgaria, Switzerland, the Czech Republic, Denmark, Spain, Estonia, France, Great Britain, Croatia, Hungary, Italy, Lithuania, Latvia, Luxemburg, the Netherlands, Poland, Portugal, Rumania, Russia, Slovakia, Slovenia, Sweden, Turkey, all other trade partners are in the rest of the world (ROW).

3.2 Calibration

In order to calibrate the model we need estimates of four exogenous parameters, the share of expenditures devoted to housing $(1-\alpha)$, the price elasticity of the supply of developed land η, the elasticity of substitution in consumer's preferences σ, and the commuting elasticity ϵ, as well as initial values of wages at the county level w_n, bilateral trade shares π_{ni}, bilateral commuting shares $\lambda_{ni|\Omega_g}$, the number of residents R_n and workers L_n in each county, and the average wage (income) on the county level $\bar{w}_n$.

3.2.1 Initial values of endogenous variables. Using our final set of commuting flows we can calculate the location choice probabilities $\lambda_{ni|\Omega_g}$ and aggregate flows to obtain total labor in Germany $\bar{L}_g$. Recall that this number is based on social security data and thus excludes the self-employed and workers without social security. Wages at the county level w_n are obtained by dividing county level total wage bills ('totales Arbeitnehmerentgelt') reported by the German Federal and Regional Statistical Offices by the local working population. Using the values for $\bar{L}_g$, $\lambda_{ni|\Omega_g}$ and w_n, the total number of residents R_n and the total number of workers L_n can immediately be calculated from (13) and (14), respectively, and the average wage of residents follows as $\bar{w}_n = \left(\sum_{\mathrm{i} \in \Omega_\mathrm{g}} \lambda_{ni|\Omega_g} \bar{L}_g w_i\right)/R_n$. By making use of the interregional input-output table established by Krebs (2020), we derive the exogenous deficit transfers D_n and the trade shares π_{ni}. We proceed as follows. To arrive at total trade flows (X_{ni}) across German counties and foreign countries we aggregate the data from the IO-table across sectors and we scale values such that German county level production equals county level wage sums.[20] Aggregating the values for total imports (including own consumption) we arrive at a region's expenditure X_n, and we calculate import shares as $\pi_{ni} = X_{ni}/X_n$. With the data for X_n, R_n and $\bar{w}_n$, trade deficits can be calculated from (10), $D_n = X_n - R_n\bar{w}_n$.

3.2.2 Exogenous parameters. Our estimate of the commuting elasticity is based on the location choice probabilities $\lambda_{ni}|_{\Omega_g}$. We follow the approach taken by Monte et al. (2018) to arrive at a regression which we estimate using two-step least squares to account for the endogeneity of wages and commuting as we explain in appendix E. We instrument wages with the technology levels A_i that we recover as structural fundamentals from model inversion (see below). In the baseline with internal and external trade and our observation-based bilateral trade data our 2

[20] Monte et al. (2018, Online Appendix: p. 73) scale trade values from the Commodity Flow Survey to match the total wage bill in each county despite the fact that this bill also includes wages earned in the service sector, whereas trade flows from the Commodity Flow Survey do not comprise services. We follow their practice in our baseline scenario. We cover an extension where trade also encompasses services in section 4.7.

SLS-estimation yields a highly significant coefficient $\epsilon = 4.56$.[21] We choose a substitution elasticity for the CES-basket of $\sigma = 5.6$.[22]

3.2.3 Housing market. A key contribution of this paper is to address the role of housing markets for spatial quantitative analysis by putting the key factors on the demand and supply side, the expenditure share of housing and the supply elasticity under scrutiny.

Size of the housing share. The canonical model of new quantitative spatial economics stipulates a uniform housing share across local labor markets. Widely different numbers have been chosen for this parameter in taking the model to the data. The considerations behind these choices are usually not made explicit. A critical examination reveals different stances on two issues.[23] A first issue concerns the scope of the quantitative model. One notion is to think of the model as a representation of only a segment of the economy whose expenditure side consists strictly of the household sector, only. An alternative is to view the model as applying for the aggregate economy, which also comprises the government and firms as final users. In this second approach, households' expenditure patterns are assumed to *represent* aggregate expenditures and, hence, also those of firms and the government.[24] The macroeconomic perspective entails that housing expenditures are related to gross or net value added (the denominator in the calculation of the share) whilst from a pure household perspective gross or net household income or personal consumption expenditure are relevant. The second issue concerns what to count as 'land/housing' expenditures. A narrow concept focuses on rental payments (contract rent and imputed rent for owner occupied housing). A broader approach counts expenditures for utilities (electricity, gas, water), in addition. A yet much broader view includes further expenditures on items associated with 'living'.[25] A further approach moves away from a literal interpretation of 'land/housing' altogether and takes this label to stand for non-traded goods and factors that cannot adjust in the time horizon considered by the model.[26]

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[21] The vector of A_i's depends on the dataset (manufacturing trade or also service trade) and on whether the economy is open to international trade or not. Our 2 SLS estimates for the other scenarios are reported in sections 4.4 and 4.7. All estimates are highly significant.

[22] This ensures that the sufficient condition for existence and uniqueness (section 2) is fulfilled in all scenarios.

[23] See Davis and Ortalo-Magné (2011), Davis and Van Nieuwerburgh (2015), Monte et al. (2018), Piazzesi and Schneider (2016), Rognlie (2015), the US Bureau of Economic Analysis (BEA) at https://www.bea.gov/, and the further works referenced in this paragraph.

[24] The implicit assumption in this second interpretation is to take the model of section 3 as a short-cut such that households‘ preferences mimic the objective functions of governments and firms. This short-cut avoids the complication of explicitly introducing firms and the government into the model.

[25] Such a very broad approach is exemplified by the US Bureau of Labor Statistics (BLS 2018) whose aggregate 'housing' category comprises e.g. 'laundry and cleaning supplies', 'postage', 'furniture' or 'household textiles'.

[26] We have benefitted from communication with Esteban Rossi-Hansberg on this point.

Our choices are the following. We want our analysis to speak to the aggregate economy which is also what our trade and production data represents on the supply side. This economy-wide stance leads us to adopt the model interpretation where households' expenditures represent the economy's total final expenditures. Moreover, we adopt a narrow concept of 'land/housing' expenditures which focuses on (factual and imputed) rental payments by all economic agents (households, the government, firms) in the economy, for the following reasons. We do not include expenditures on utilities because these have become highly traded in supra-regional markets, rather than being tied to local markets and local land. Hence, they are a part of the basket of goods and services. The same reasoning applies to spending categories broadly related with 'living'. We view our static model as depicting a long-run equilibrium, since we allow for the relocation of firms and households, and since our counterfactual local productivity shock is thought to affect a location's fundamentals. We discard the interpretation of 'land/housing' as standing broadly for non-traded goods, because 'land/housing' is intended to serve as dispersion force in the model,[27] and this role cannot be taken on by non-traded goods.[28] Against the background of an economy-wide perspective and a narrow concept of 'land/housing' expenditures our preferred level for the housing share in Germany is 10% as derived in Krebs and Pflüger (2018) by relating census data for housing from the German Statistical Office to total final expenditure backed up by the WIOD. Note that a value in this range gets strong support from the macroeconomic factor shares documented in Rognlie (2015).[29] Since different stances can be taken with respect to the housing share, we view it to be desirable to check robustness, however. We do so and allow this parameter to be as large as in Monte et al. (2018:

[27] Land, the only generically fixed and immobile resource, is a key dispersion force in any spatial model. This holds true irrespective of whether housing is equated with land, as in Helpman (1998), or whether housing space is assumed to be provided by a competitive construction industry which uses land and other factors to produce lots (e.g. Duranton and Puga 2015). Pflüger and Tabuchi (2010) highlight this role of land in a new economic geography framework. Notice that land maintains this role as key dispersion force in the quantitative model with commuting, too, even though it is no longer essential for existence and uniqueness (cf. Section 2 and appendix A).

[28] The argument is the following. Unless non-traded goods are produced with decreasing returns, they cannot play a role as dispersion force. With constant returns, the supply of non-traded goods can be tuned up to any scale. With increasing returns, non-traded goods even become an agglomeration force as in the canonical model of Abdel-Rahman and Fujita (1990) which is heavily used in urban economics (e.g. Duranton and Puga 2014). If non-traded goods are produced with decreasing returns this necessitates a fixed factor, which, ultimately, must be land.

[29] Rognlie (2015) shows that the increase in the (average) capital share in the G7 economies in the last decades is largely due to housing's contribution to net capital income which expanded „…from roughly 3 percentage points in 1950 to nearly 10 percentage points today." Rognlie's (2015:14) numbers for Germany are even lower due to problems of recording imputed rent on self-owned housing. Note that our preferred value is in the range reported by Davis and Ortalo-Magné (2011), Davis and Van Nieuwerburgh (2015) and Piazzesi and Schneider (2015), once their denominator is broadened from personal consumption expenditures to net or gross household income.

3870) who opt for a level of 40%.[30] We also check the results for a level of 25%, as in Davis and Ortalo-Magné (2014) and Redding (2016).[31]

Local heterogeneity of the housing share. With our data on housing consumption and offer rents at the county level we can also challenge the assumption of uniformity of the housing share imposed in the canonical model. Together with the expenditure data at the county level, X_n, and after scaling, we obtain housing shares for German counties which at the national level correspond to the 10% expenditure share of our baseline scenario. These data reveal considerable heterogeneity: housing shares vary strongly across regions ranging from about 2.4% in Bremerhaven and 4.4% in Hof to levels of up to 16% for cities such as Munich, Frankfurt, and Tübingen. Rescaling of these shares allows us to study scenarios with national levels of 25% and 40% in our robustness checks.

Elasticity of housing supply. Whilst excellent data are available for most features of German local labor markets, this does not hold true for the supply side of local housing markets. To cope with this issue, we draw on two research lines, macroeconomic housing research and Saiz's (2010) regional analysis for the United States. The macroeconomic literature recognizes that empirical estimates of the price elasticity of housing supply vary widely, depending on data and methods. A recent study for the United States therefore uses a benchmark of 2.5 but considers a range between 0 and 6 (Floetotto et al. 2016).[32] Even though we have a housing supply elasticity of 0.428 for Germany from Caldera and Johansson (2013), the findings for the United States make us cautious. Saiz (2010) reports housing supply elasticities for US MSA's ranging from 0.60 to 5.45. In the light of these two sets of findings we challenge the assumption of an exogenous supply of housing supply in a robustness check, by considering a range from 0 to 5.45 for Germany and we apply these uniformly for all locations.

[30] They refer to data from Bureau of Economic Analysis. We have been unable to verify their „central value", however. For 2016 the BEA lists total personal consumption expenditure for the US at $12,816,386 million and personal consumption expenditure in the category 'housing and utilities', which includes imputed rents for owner occupied housing, at $2,331,526 million. These numbers imply a spending share of 18.2% when utilities are included. The corresponding values for 2010 are $10,196,850 million for personal consumption and $1,908,992 million for 'housing and utilities', resulting in a share of 18.7%. We acknowledge that, for methodological considerations, the choice of the parameter may abstract from a literal interpretation, cf. footnote 26.

[31] Such a level can be rationalized from a pure household perspective when expenditures on utilities are included. Davis and Ortalo-Magné (2011) use the Decennial Census of Housing files, to obtain a share of pure contract rent in household's wage and salary income of 18% which is scaled up by 6% if expenditures for utilities are added.

[32] For the United States, Caldera and Johansson (2013) report a housing supply elasticity of 2.0 whilst Sommer and Sullivan (2018) arrive at an estimate of 0.90.

3.3 Model Consistent Structural Fundamentals

Given the model and the German data, the general equilibrium can be inverted to identify model consistent values for bilateral trade costs and local productivities, which turn out to provide strong support for our model. We summarize the approach here and provide further details and results in appendix D. Assuming that the fixed input of labor is the same across locations ($F_i = F_m \; \forall \; i, m \; \in N$) and using equation (7) trade flows from location i to n can be written as

$$\pi_{ni} X_n = \frac{L_i w_i^{1-\sigma} \left(\frac{d_{ni}}{A_i}\right)^{1-\sigma}}{\sum_{m \in N} L_m w_m^{1-\sigma} \left(\frac{d_{nm}}{A_m}\right)^{1-\sigma}} \left(R_n \bar{w}_n + D_n\right).$$

We parameterize trade barriers as $d_{ni} = dist_{I,ni}^{\psi_I} \, dist_{R,ni}^{\psi_R} \, dist_{INT,ni}^{\psi_{INT}} \, \tilde{e}_{ni}$, where $dist_{I,ni}$ denotes intraregional distance (1 for $n \neq i$), $dist_{R,ni}$ interregional distance (taking a value different from one if both $n, i \in \Omega_g$), and $dist_{INT,ni}$ international distance (1 for either $n = i$ or both $n, i \in \Omega_g$) and where $\tilde{e}_{ni} = e_{ni}^{1/(1-\sigma)}$ is a transformed error term that captures any remaining unobserved bilateral characteristics. Together with exporter fixed effects S_i and importer fixed effects M_n our econometric representation of equation (7) becomes $\pi_{ni} X_n = S_i M_n dist_{I,ni}^{(1-\sigma)\psi_I} \, dist_{R,ni}^{(1-\sigma)\psi_R} \, dist_{INT,ni}^{(1-\sigma)\psi_{INT}} \, e_{ni}$. Relying on a Poisson Pseudo Maximum Likelihood (PPML) estimator (we discuss this choice and alternatives in appendix D) we obtain highly significant composite parameters $\psi_I(1-\sigma) = -0.842$, $\psi_R(1-\sigma) = -1.183$, and $\psi_{INT}(1-\sigma) = -1.153$ in our baseline scenario. Making use of our assumption that $\sigma = 5.6$ yields coefficients $\psi_I = 0.150, \psi_I = 0.211$, $\psi_I = 0.206$. Given the parameterization of trade barriers the resulting exporter fixed effects S_i are up-to-scale equivalent to $L_i w_i^{1-\sigma} A_i^{1-\sigma}$ and can be used together with our data on wages and employment to directly recover the unobserved technology levels A_i after normalization.[33]

Bilateral trade barriers. Our specification of d_{ni} which includes the error term yields model consistent trade barriers, that is, trade barriers which under the structure of the model reproduce the observed trade flows. Figure 2 displays their relationship with observable distances. The clear log-linear relationship for all three types of barriers makes us confident in our parameterization of iceberg trading costs.

We can also look at county level barriers with respect to a specific location. The left-hand panel of Figure 3 depicts the implied barriers between all German counties exporting to Hamburg

[33] Note that while the joint variability of exporter fixed effects and bilateral terms is determined by the model we need to parameterize trade barriers to separate the two. Specifically, without our assumption on trade barriers the exporter fixed effects would contain any exporter specific parts of d_{ni}.

relative to Hamburg's internal trade barriers. As shown, trade barriers increase with distance to Hamburg, in general. However, barriers to far-away locations may effectively be low when there are particularly favorable railway lines or waterways or when there are established personal, firm or cultural ties. The figure shows that there are some cities in the Middle and South of Germany – Nuremberg, the bright small spot in the Southeast is a case in point – that have very low trade frictions with Hamburg despite their considerable distance. Moreover, barriers with respect to cities are typically lower than with respect to rural areas.

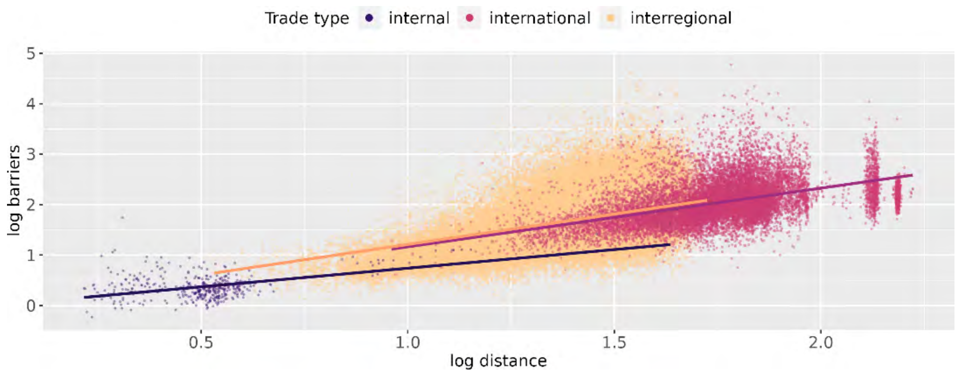
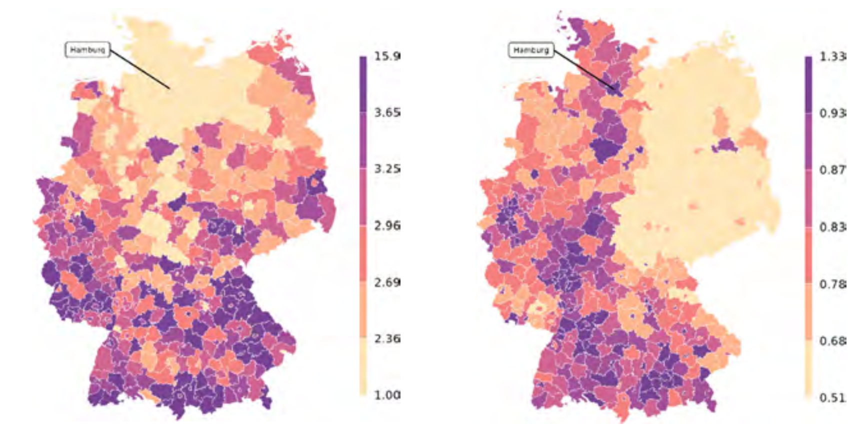


Figure 2: Model consistent trade barriers and distance

Local productivities. To look at the technology levels implied by the model we normalize productivity in Hamburg at 1 and depict all productivities relative to that in Hamburg in the right-hand panel of Figure 3. The figure visualizes the well-known 'German problem' that, with the data from 2010 and thus almost 20 years after reunification, productivity levels in the East of Germany are – with the exception of some emerging cities – still considerably lower than in the rest of the country. In line with expectations, given observable trade flows, our model implies that cities in the south and west of Germany, as well as their surrounding areas are the most productive locations in the country.



Trade barriers with respect to Hamburg Technologies with respect to Hamburg

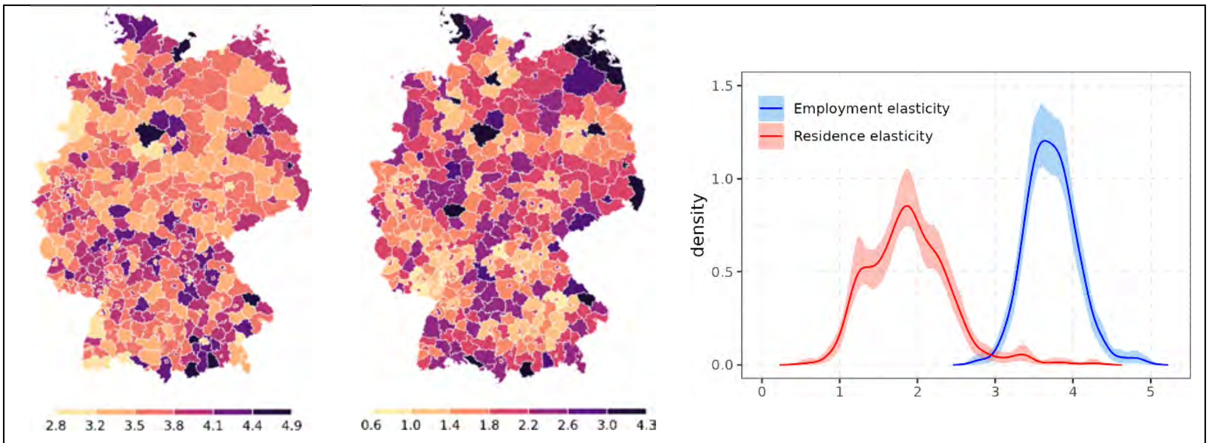
Figure 3: Model consistent trade costs and technologies relative to Hamburg

4 Productivity Shocks, Employment and Resident Elasticities

We now use the calibrated model to explore the functioning of local labor markets in Germany. Our ‘treatment’ throughout is a counterfactual 5% productivity shock at one location, holding productivity at all other locations and all other exogenous parameters of the general equilibrium system constant. We use the ‘exact hat’-algebra popularized by Dekle et al. (2007)[34]. Sections 4.1 and 4.2 start with our ‘baseline scenario’. Sections 4.3 to 4.7 cover various extensions and section 4.8 compares our results with the extant findings for the US.

4.1 General equilibrium elasticities

Baseline scenario. The baseline scenario assumes that the housing share is equal across counties at our preferred level of 10%, the supply of housing is inelastic, there is trade between German counties and between these counties and Germany’s international trade partners, and this trade is backed-up by our unique observation-based regional trade data. Panels A and B of figure 4 display the results of 402 separate treatments, depicting for each case respectively the general equilibrium employment and resident elasticities in the treated German county. Panel C condenses this information by showing the kernel densities of employment elasticities (blue) and of resident elasticities (red) in the treated counties, with the 95% confidence intervals given by the shaded areas.[35]



Panel A: Employment elasticities

Panel B: Resident elasticities

Panel C: Kernel densities

Figure 4: General equilibrium employment elasticities (panel A) and resident elasticities (panel B) in treated counties in response to counterfactual 5% productivity shocks. Panel C depicts the associated kernel densities of employment elasticities (blue) and resident elasticities (red). Shaded areas depict 95% confidence bands.

[34] Appendices B and C document the equilibrium system in changes as well as the algorithm we use to obtain counterfactual equilibrium values.

[35] Model consistent general equilibrium elasticities are calculated as $(\hat{L}_i - 1)/(\hat{A}_i - 1)$ and $(\hat{R}_i - 1)/(\hat{A}_i - 1)$, respectively, where the relative change of a variable is denoted by a hat, $\hat{x} \equiv x'/x$, and x' is the value of a variable in the counterfactual equilibrium. Note that these counterfactual elasticities follow deterministically from the model, the depicted confidence bands relate to the estimation of the kernel density.

Three results emerge from Figure 4. First, employment elasticities exceed a value of 1 by far in all treated counties, with a minimum at about 2.8 and a maximum at about 4.9. The average (unweighted) employment elasticity across counties is at 3.72. Resident elasticities, though smaller than the employment elasticities, also take on values that typically exceed a level of 1, with an unweighted mean of 1.88. This points to strong home market effects associated with local productivity shocks which most strongly show up in the employment responses. Second, the difference between employment and resident elasticities is typically very large. This points to the paramount importance of commuting for local labor markets in Germany. Third, both the employment and the resident elasticities are very heterogeneous and this holds true even more so for the latter. The difference between the maximum and minimum elasticities is about 2.2 for employment elasticities but 3.7 for the resident elasticities. Resident elasticities exhibit a variance of 0.27, the variance of employment elasticities is 0.10. This heterogeneity implies that seriously wrong conclusions would be drawn, if policymakers acted on the presumption that some "average" elasticity applied for all locations.

The housing share. We made a strong case that our aggregate perspective implies a choice of the housing share of (about) 10% for Germany. However, we also pointed out, that other perspectives can be taken, so it is important to explore the implications of alternative levels for this parameter.[36] Figure 5 depicts the kernel densities for employment and resident elasticities arising from 14 x 402 simulations of counterfactual 5% productivity shocks for seven levels of the housing share (from 10% up to a maximum of 40% that we have recorded in the literature).

It is immediately seen that the qualitative results that we have found for our preferred specification of 10% carries over for larger levels of the housing share. Employment elasticities are always much larger than resident elasticities and both elasticities are very heterogeneous. The distinct difference is that both types of general equilibrium elasticities fall sharply as the housing share is successively increased. In fact, the mean employment elasticity falls from 3.61 (at 10%) to 2.99 (at 25%) and 2.67 (at 40%) and the mean resident elasticity falls from 1.88 (at 10%) to 1.01 (at 25%) and to 0.61 (at 40%). Hence, the home market effect becomes successively weaker but it is still strongly borne out in the employment elasticities. What is the reason for this evolution of employment and resident elasticities? Intuitively, the successive increase of the housing share strongly enhances the role of housing as a congestion force in the

[36] Our analytical calculations (linearizing the system by total differentiation) turned out to be unrevealing because of the many simultaneous interactions involved.

model, implying that less and less workers will choose to shift their residences (i.e. migrate) instead of commute to the treated labor market.

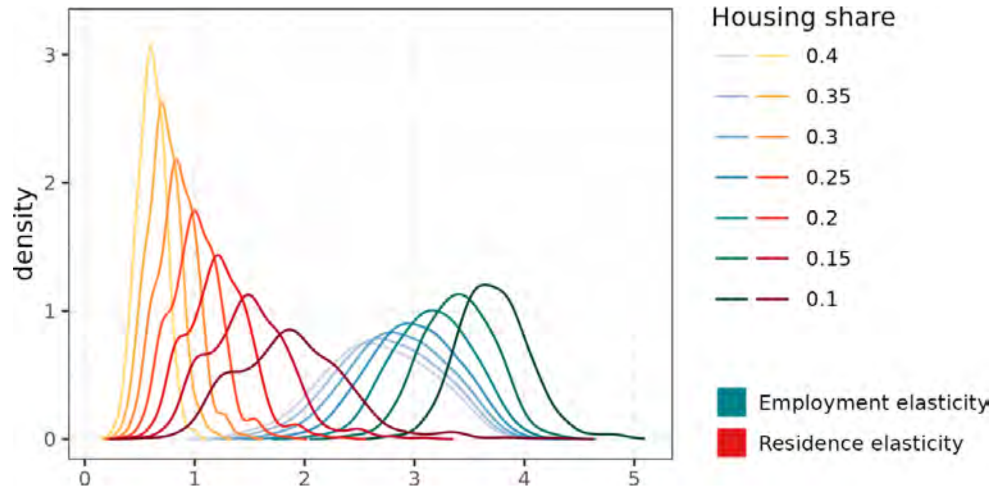


Figure 5: Kernel densities for employment elasticities (light to dark blue) and residence elasticities (yellow to red) for housing shares from 10% to 40%.

4.2 Explaining the general equilibrium elasticities

The location choices of workers faced with local productivity shocks is simultaneously driven by several mechanisms in our general equilibrium model. Workers are attracted to the location that experiences a positive productivity shock because of the implied higher wages and lower goods prices. Housing costs are driven up when the number of residents increases at a location. Whether a worker remains at her residence or relocates to or near to her workplace also depends on personal idiosyncrasies. Moreover, the general equilibrium responses are driven more broadly by spillover effects through commuting (through changes in the number of workers and residents in untreated counties), and through trade linkages with untreated counties. We now enquire whether the elasticities which reflect these general equilibrium repercussions can be explained by ex-ante available labor and commuting market statistics, focusing on employment elasticities and the selection of explanatory variables highlighted by Monte et al. (2018). This analysis is important as a backdrop on reduced-form approaches to local labor markets, as stressed by Redding (2020), and it is also of practical importance for policymakers.

Analysis of the baseline. Table 1 presents the results of our regressions for the employment elasticities which emerge in the baseline scenario for a housing share of 10%.[37] Column 1 regresses the employment elasticities on a constant capturing the mean across the 402 German counties. Column 2 uses the log of the location's employment as a measure for the size of the local labor market, in addition. Column 3 further adds the local wage and the number of flats

[37] To facilitate comparison, we maintain the structure of this table in all our analyses.

in the county, as a measure of the local housing stock, H_i. Column 4 complements these standard controls by adding the total workforce and the average wage which prevails in surrounding labor markets. We define these surrounding labor markets following Monte et al. (2018) as all counties with a distance of less than 120km from the county that is exposed to the productivity shock. These standard controls explain only about one tenth of the variation of employment elasticities, as indicated by the values of the R-squared.

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.081^{***}	-0.452^{***}	-0.440^{***}				-0.191^{***}	-0.312^{***}
		(0.023)	(0.062)	(0.065)				(0.053)	(0.058)
$\log(w_i)$			0.505^{***}	0.441^{***}				0.375^{***}	0.583^{***}
			(0.107)	(0.169)				(0.095)	(0.107)
$\log(H_i)$			0.377^{***}	0.377^{***}				0.219^{***}	0.282^{***}
			(0.063)	(0.064)				(0.052)	(0.058)
$\log(L_{-i})$				-0.040					
				(0.038)					
$\log(w_{-i})$				0.183					
				(0.230)					
$\lambda^R_{ii\|i}$					-0.998^{***}				
					(0.098)				
$\sum_{n \in N} \left(1 - \lambda^R_{ni\|n}\right) \vartheta_{ni}$						0.139^{***}		0.160^{***}	
						(0.029)		(0.030)	
$\vartheta_{ii} \left(\frac{\lambda_{ii}}{\lambda^R_i} - \lambda^L_i\right)$						-0.526^{***}		-0.412^{***}	
						(0.091)		(0.097)	
$\frac{\partial w_i}{\partial A_i} \frac{w_i}{A_i}$						1.057^{***}		1.062^{***}	
						(0.077)		(0.081)	
$\frac{\partial w_i}{\partial A_i} \frac{w_i}{A_i} \cdot \sum_{n \in N} \left(1 - \lambda^R_{ni\|n}\right) \vartheta_{ni}$							0.462^{***}		0.424^{***}
							(0.044)		(0.045)
$\frac{\partial w_i}{\partial A_i} \frac{w_i}{A_i} \cdot \vartheta_{ii} \left(\frac{\lambda_{ii}}{\lambda^R_i} - \lambda^L_i\right)$							0.260^{*}		0.479^{***}
							(0.132)		(0.144)
Constant	3.720^{***}	4.597^{***}	-1.051	-1.882	4.319^{***}	3.266^{***}	3.480^{***}	-1.220	-2.605^{**}
	(0.016)	(0.250)	(1.114)	(1.538)	(0.061)	(0.067)	(0.037)	(0.998)	(1.107)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.030	0.127	0.130	0.206	0.409	0.217	0.451	0.294
Adjusted R^2	0.000	0.028	0.121	0.119	0.204	0.404	0.213	0.443	0.285

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 1: Analysis of the general equilibrium local employment elasticities in response to 5 percent productivity shocks at the county level with a housing share of 10%

The regressions reported in columns (5), (6) and (7) turn to model-based explanatory variables which are easy to observe ex-ante. Column (5) considers the own-commuting share $\lambda^R_{ii|i}$ portrayed in Figure 1.[38] The lower this share, the more open is a local market to commuting, hence, the higher is the expected elasticity of employment. When this variable is used (along with a constant) the R-squared rises to 20%. Column 6 includes measures which build on three model-based partial equilibrium elasticities, the partial equilibrium elasticities of employment and of residents with respect to wages, and the partial equilibrium elasticity of wages with

[38] This uses the definition $\lambda^R_{ni|n} \equiv \lambda_{ni}|_{\Omega_g} / \lambda^R_n$.

respect to productivity.[39] These partial equilibrium elasticities imply a measure of commuting linkages, $\sum_{n\in N}\left(1-\lambda^R_{ni|n}\right)\vartheta_{ni}$, where $\vartheta_{ni} \equiv \lambda^R_{ni|n} R_n / L_i$ indicates the fraction of the workforce in location i that resides in n and commutes to work in i, a measure of migration linkages $\vartheta_{ii}\left[\left(\lambda_{ii|\Omega_g}/\lambda^R_i\right)-\lambda^L_i\right]$, and, as a measure of what Monte et al. (2018) call 'trade linkages', the partial equilibrium elasticity of wages with respect to productivity, $\frac{\partial w_i}{\partial A_i}\frac{A_i}{w_i}$. The explanatory power of the three measures considered in column 6 is nearly double that of the own share $\lambda^R_{ii|i}$. Column 7 shows that, interacting the two measures of migration and commuting linkages with the partial equilibrium elasticity of wages with respect to productivity, brings the R-squared down to little more than one fifth. The specification that performs best combines standard labor market controls with the three measures of linkages: this brings the R-squared up to more than 45%, see column (8). Keeping the standard controls and interacting the linkages with the partial equilibrium elasticity of wages, see column (9), brings the R-squared down, similar as in column (7). Overall, these results indicate that simple labor and commuting market statistics are poor predictors of the general equilibrium employment elasticities. Interestingly, this also holds true for the own-commuting share that works so well in the analysis of Monte et al. (2018) for the US. One key difference across the two studies concerns the choice of the housing share, which we now put under scrutiny (see also section 4.8).

The housing share. The analysis in section 4.1 shows that the general equilibrium elasticities are very sensitive to the size of the housing share. To see whether and how this parameter affects our ability to explain the general equilibrium elasticities of the quantitative model, we have rerun the regressions of table 2 with housing shares of 25 % and of 40%, respectively (appendix F provides the full regression tables). Our key finding is that the size of the housing share dramatically affects the results. With a high housing share, model-based partial equilibrium measures, the simple inverse measure of openness, $\lambda^R_{ii|i}$, in particular, perform very well in explaining the heterogeneity of employment elasticities across counties, and these measures outperform standard controls by far. Figure 6 summarizes this key result by graphing the R-squared of regressions containing the own-commuting share and a constant as explanatory variables for seven values of the housing share. We with our preferred 10% housing share which we then increase in steps of 5 percentage points up to 40% interpolating intermediate values. For now, we focus on the red curve which applies to our baseline scenario (with manufacturing

[39] These partial equilibrium elasticities are derived from total differentiation of equations (9), (13), (14) and (7) and evaluating the result for a productivity change in one county. The values of all other endogenous variables, including productivities in other counties, are held constant.

trade) and a uniform housing share across all locations. The curve shows that the regression R-squared rises steadily from 0.206 with a housing share of 10% (column 5 in table 1) to a value of almost 0.9 with a housing share of 40% (appendix F, table F2, column 5). This finding is intuitive. The general equilibrium repercussions are far stronger with a low housing share, because the associated congestion force is then much weaker. Simple partial equilibrium-based measures, such as the own-commuting share (but also other statistics, cf. table 2 and appendix F), capture these general equilibrium repercussions only imperfectly.

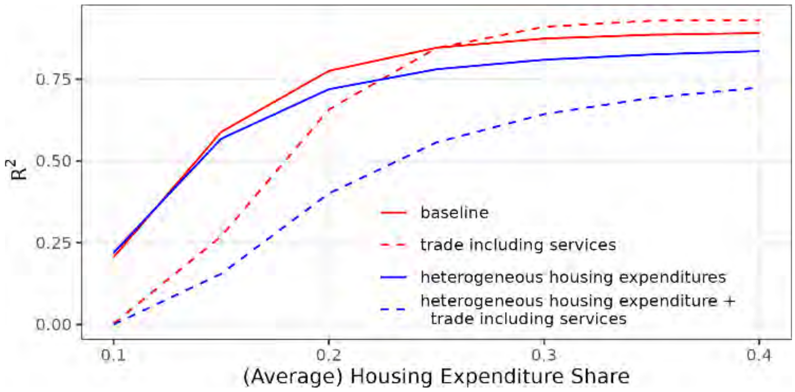


Figure 6: R-squared for a regression of the employment elasticities on the own-commuting shares and a constant.

4.3 Accounting for the regional heterogeneity of housing shares

The canonical model of new quantitative spatial analysis assumes a uniform housing share for all locations and we have so far adapted this assumption. Our data for German regions reveal considerable heterogeneity as we documented in section 3.2.3, however.

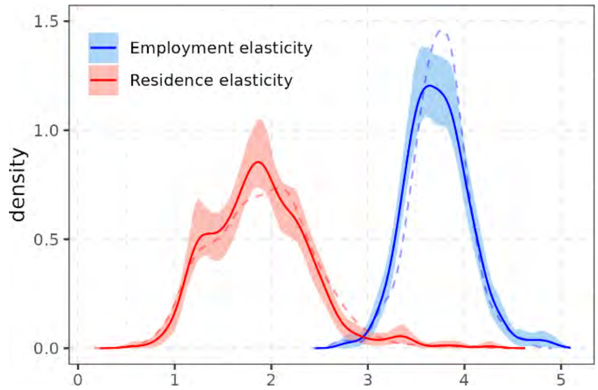


Figure 7: Kernel densities for employment elasticities (blue) and resident elasticities (red) with heterogeneous housing shares. Average housing share is 10. Shaded areas show the 95% confidence bands. Dashed curves depict the baseline with uniform housing shares, only.

Possibly surprising, we find that the distributions of employment and resident elasticities associated with our treatment hardly change relative to the baseline which assumes a *uniform* housing share of 10%. Figure 7 depicts the essence of this result: the kernel densities for the employment and resident elasticities with heterogeneous shares (the dark blue and red curves) are strikingly similar to the kernel densities for the baseline scenario (the dashed blue and red curves also depicted in Figure 6 panel C).[40] Table 2 shows that the (unweighted) means of average employment and resident elasticities are virtually the same: for a heterogeneous housing share of on average 10% the mean employment elasticity is 3.73 rather than 3.72 with a uniform share of 10% and the mean resident elasticity is 1.91 rather than 1.89, respectively. The finding that the elasticities are very similar as in the baseline which stipulates uniform shares also carries over to scenarios where the heterogeneous shares are at average values of 25% and of 40%. This is seen in table 2 by comparing column (3) with (1) for the mean employment elasticities and column (4) with (2) for the mean resident elasticities.

	Uniform housing share in all counties		**Heterogeneous housing share**	
Housing share	**(1) Mean employment elasticity**	**(2) Mean resident elasticity**	**(3) Mean employment elasticity**	**(4) Mean resident elasticity**
10%	3.72	1.89	3.73	1.91
25%	2.99	1.01	3.01	1.04
40%	2.66	0.61	2.69	0.64

Table 2: Mean employment and resident elasticities resulting from 5% productivity treatment; baseline shaded.

Turning to the explanatory power of labor and commuting market statistics in predicting the general equilibrium elasticities, we still find that these have little explanatory power for an average housing share of 10% but become more powerful at high housing shares. The solid blue curve in Figure 6 depicts the evolution of the explanatory power of the own commuting share with heterogeneous housing shares. It can be seen that the R-squared increases with successively higher average housing shares, but less so than with uniform shares.

To summarize, we obtain the interesting result that neither the general equilibrium elasticities nor our ability to predict these elasticities with simple labor market statistics are much affected by the substantial heterogeneity of housing shares that prevails across German regions. What greatly matters is the level of the housing share, however.[41]

4.4 Elastic supply of housing

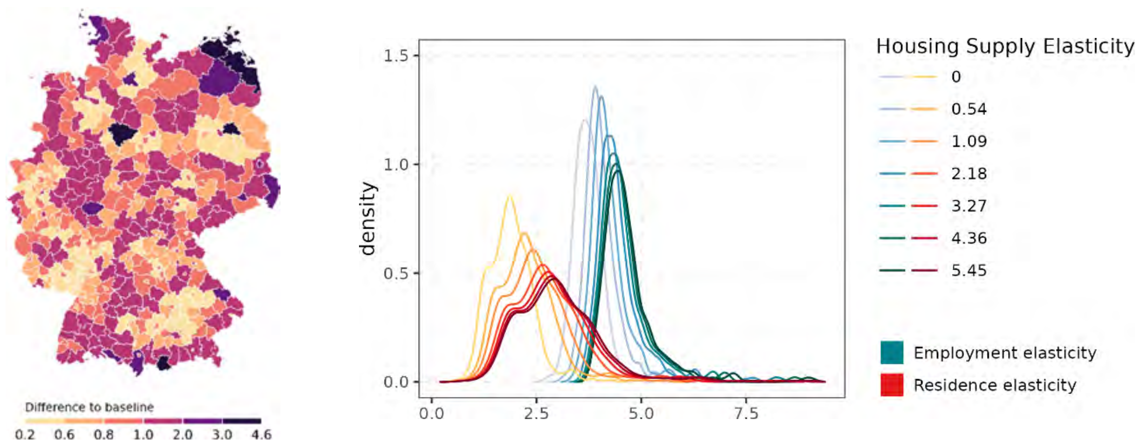
The elasticity housing supply in local labor markets has attracted a lot of attention in recent research (e.g. Hsieh and Moretti 2019; Duranton and Puga 2019). The housing supply elasticities for US counties supplied by Saiz (2010) on the basis of geographical data and local

[40] Figures H11 and H12 in the appendix provide the detailed results for all individual counties.

[41] It should also be noted that our housing shares are averages across local units, which wash out differences between e.g. low- and high-income earners which are a subject of the current public discourse (e.g. Economist 2018) and of academic research (e.g. Dustmann et al. 2018).

regulations are pivotal for this research.[42] Unfortunately, such information is not available for Germany. Since the supply elasticity is an important feature of local labor markets, however, we perform quantitative analyses assuming that the supply elasticity is positive and uniform across German counties. We hasten to add that this is surely a first approximation only (but so is the assumption of inelastic housing). To check robustness, we consider the range of supply elasticities documented by Saiz (2010), cf. section 3.2.3.

Figure 8 depicts the results of our standard treatment (5% local productivity shocks) when supply elasticities differ from nil. Specifically, panel A shows how the employment elasticities change when the supply elasticity is at the maximal value of $\eta = 5.45$ found in Saiz (2010) compared to $\eta = 0$ in our baseline. The key result is that this change is always positive, hence employment elasticities are unambiguously larger for a larger elasticity of housing supply. Panel A also shows that the increase of the supply elasticities is especially large in border areas and in large cities like Hamburg, Munich, and Berlin. We caution that the latter result should not be overstressed in view of the assumption of uniform supply elasticities.



Panel A: Change of the employment elasticities when switching from $\eta = 0$ to $\eta = 5.45$.

Panel B: Evolution of kernel densities for employment elasticities (blue) and resident elasticities (yellow to red) when the housing supply elasticity is raised in steps from $\eta = 0$ to $\eta = 5.45$.

Figure 8: Treatment effects, baseline scenario, alternative housing supply elasticities

Panel B complements this analysis by allowing the housing supply elasticity to change in six steps from the level of nil to the mentioned maximum and by depicting the kernel densities for the local general equilibrium employment elasticities (blue) and also the resident elasticities (yellow to red). The pattern is clear. Employment and resident elasticities are larger, the larger is the housing supply elasticity. This finding conforms to the intuition that the pressure on land prices associated with the wage and mobility effect of positive local productivity shocks is

[42] Monte et al. (2018) use these data in an extension of their analysis. We come back to this in section 5.8.

lower, when the housing supply elasticity is larger, so that the real income and, hence, location choice responses are stronger. Moreover, this qualitative pattern also corresponds to the effect of a low housing share which similarly implies smaller price pressure on local land markets in response to local productivity shocks, see eq. (11).

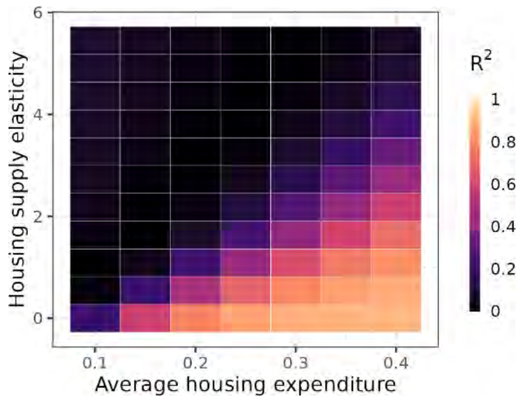


Figure 9: The map considers 7 values for the housing expenditure share and 11 values for the housing supply elasticity. The map reports the R-squared for the associated 7 x 11 local general equilibrium employment elasticity regressions.

What are the consequences of a positive housing supply elasticity for our ability to predict the employment elasticities with simple ex-ante observable statistics and how do the results compare to the effects of different levels of the housing share on the demand side? Our focus is again on the regression specification drawing on the own-commuting share. Figure 9 depicts the R-squared of the employment elasticity regressions for alternative combinations of the elasticity of the housing supply and the economy's expenditure share devoted to housing. Several important results emerge from this map. Broadly speaking, the explanatory power of the own-commuting share is the larger, the lower is the elasticity of the supply and the larger is the housing share, as already acknowledged.[43] The map also reveals more subtle and nuanced results. First, the dominant number of parameter combinations shown in the map yield an R-Squared of 0.2 or below. Second, there is an important asymmetry. With a housing share of 10%, the preferred value for the economy-wide analysis, the R-squared is almost nil for all values of the housing supply elasticity (i.e. even when housing is supplied completely inelastic). When a very large housing share of 40% is chosen, there is at least a range of *small* housing supply elasticities where the R-squared is larger than 50%, in contrast.

The key conclusion from this section is that~~,~~ simple labor and commuting market statistics already have little capacity to predict the strongly heterogeneous local general equilibrium

[43] The results of section 4.2 (Figure 6, solid red curve) are represented at the bottom of the map where the housing supply is inelastic. The explanatory power of the own-commuting share is almost nil when the housing share is 10% (bottom left corner) but increases strongly when this share is 40% (bottom right corner).

employment elasticities when an economy-wide perspective is taken, and that this insight gets further backing when positive supply elasticities are taken into account in addition. Together, this yields the two warnings not to base policy prescriptions on average statistics and not to rely on such statistics as controls in reduced-form policy analysis.

4.5 Disregarding international trade

Germany is deeply embedded in world trade. Our bilateral trade data allowed us to track the internal trade between German local labor markets as well as their external trade with Germany's foreign trading partners. What are the consequences for the analysis if this embedment cannot be tracked, a situation with which extant work for the United States is faced?[44] To explore this question, we now consider a counterfactual situation where trade only takes place between Germany's counties. We subject local labor markets to the productivity shock treatment as before and compare the outcomes with our previous results for the open economy. To start, we adjust the regional trade matrix to the counterfactual initial state without external trade before the treatment. Simply applying the definition of trade shares it is readily derived theoretically that the trade shares between German counties are larger *on average*, when international trade is disregarded in calibration. Individual trade shares may be smaller, however. This also conforms with intuition, as bilateral trade that would be classified as international is now channeled to trade between counties. Our model inversion implies a new set of technology levels A_i and our 2SLS estimate for the commuting elasticity now yields $\epsilon = 4.49$, hardly a change from the baseline (where $\epsilon = 4.56$). We keep all other parameters at their previous levels. To tie up our analysis with our baseline scenario we focus on a housing share of 10% and we assume that the supply of housing is completely inelastic, $\eta = 0$. The key change vis-à-vis the open-economy baseline-scenario is that the local employment and resident elasticities are now larger, and the kernel densities are shifted to the right as can be seen in Figure 10.[45] Rerunning the treatment with heterogeneous housing shares which average out at the 10% level yields almost the same picture as Figure 10 and we therefore omit it here. The mean employment elasticities associated with the treatment are 3.87 with a uniform housing share and 3.89 with heterogeneous shares and the respective numbers are 2.09 and 2.12 for the mean resident elasticities.

[44] The Commodity Flow Survey, which is commonly used to capture internal US trade flows, does not track sources or destinations outside the USA. Instead, international flows are treated as if they started or ended in the administrative region that was the entry point into or exit point out of the US.

[45] Detailed results for the local employment and resident elasticities are provided in appendix J1 and J2.

We have also run a full set of regressions to check how well the model-implied local general equilibrium employment elasticities can be explained with simple labor-market and commuting statistics. Regression table J4 provided in the appendix is indicative of our findings. The own-commuting share, although significant as before, turns out to be a very poor predictor, the regression R-squared is down at a meager 0.006. The intuition for this result parallels our explanation for the low explanatory power of this statistic when the housing share is low and/or the housing supply elasticity is large. In each of these three cases, the general equilibrium repercussions are strong, so that the general equilibrium elasticities become larger, which makes them harder to predict with partial equilibrium statistics.

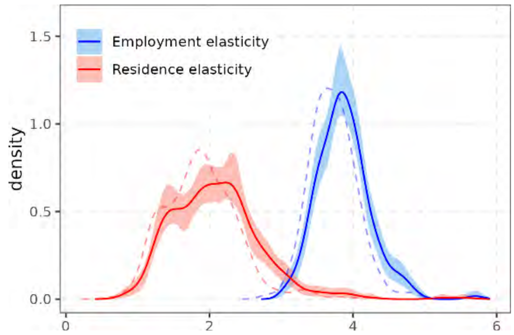


Figure 10: Kernel densities for local employment and resident elasticities, closed economy; dashed curves depict the open-economy-baseline (as in Figure 4, panel C).

4.6 Commuting Zones

Our motivation to focus on the 402 German counties was that our underlying framework explicitly deals with the spatial linkages involved in trade and commuting, so that we could conduct the analysis at a finer spatial scale than that with the 141 German commuting zones which result from aggregation of counties. To check the robustness of our results we have rerun the numerical simulations of the 5% productivity shock treatment and we have also redone the regression analysis at the level of commuting zones for a large variety of scenarios. The essence of our findings can be summarized as follows.[46] First, compared with the elasticities at the county level, resident and employment elasticities are more similar for commuting zones as is most easily seen by comparing the respective kernel densities (see appendix K1). This captures the fact that commuting is less commonly observed and thus implicitly more costly across commuting zones than across counties. Hence, commuting to a treated location is more costly and fewer workers will choose to do so. When workers are attracted to a commuting zone which experiences a positive productivity shock they are more likely to relocate to that location instead of choosing to commute to it. The mentioned kernel densities show that both elasticities are

[46] Detailed results are presented in appendix K.

very heterogeneous across locations. Second, similar to the results for counties, general equilibrium employment and resident elasticities fall substantially, when the housing share is raised from our preferred level of 10% to levels of 25% or 40%. The intuition is as before. With a larger expenditure share, the importance of housing costs as a congestion force rises strongly. Third, as with counties, general equilibrium elasticities are only poorly predicted by labor and commuting market statistics, when the housing share is at our preferred level of 10%. Again, the predictive power of the own-commuting share increases strongly when we allow for larger housing shares. Fourth, all mentioned results still hold when the factual heterogeneity of housing shares is taken into account. As with counties, these heterogeneities matter only marginally. Finally, the qualitative results that we found when disregarding Germany's trade openness also still hold.

4.7 Service trade in addition to manufacturing trade ('all trade')

All results derived so far are grounded on unique observation-based regional trade data, a decisive advantage over the extant literature which had to draw on imputed data. Once we are willing to allow for gravity imputed trade data, we have the advantage to be able to tap the interregional input-output table that Krebs (2020) established for Germany which also comprehends imputed service trade. Hence, we can perform analyses with the aggregate trade flows in manufactures and services, a setting that we term "all trade". Because of these data imputations, our explorations and results should be taken with more caution than our results in previous sections. The new setting commands that we adjust the regional trade matrix to the additional trade in services.[47] Model inversion then delivers a new vector of technology levels A_i and our 2SLS estimate of the commuting elasticity is now at 4.19, down from 4.56 with manufacturing trade only (cf. section 3.2.2).

We start by considering a scenario which follows our baseline with a housing share of 10% but where we now consider all trade. Our key result is that the employment and resident elasticities associated with counterfactual productivity shocks of 5% at each location are now significantly higher than in the baseline with manufacturing trade only (see appendix G, figures G1). The essence of this finding is transparently documented by the kernel densities for the employment and resident elasticities shown in Figure 11, which have shifted to the right compared to the kernel densities for the baseline scenario (as already shown in Figure 3 panel C). The

[47] Note that our calibration ties down production at locations to match the local wage bill. Hence, production values carry over from the baseline scenario. The bulk of services originates in (big) cities in Germany, however (see Krebs 2020), and this causes regional trade shares to change as we now shift to 'all trade'.

(unweighted) average employment elasticity rises from 3.72 to 4.27 and the average resident elasticity rises from 1.89 to 2.74 (cf. appendix table H3 which lists these means for various scenarios).

Redoing this simulation exercise for all trade with housing shares of 25% and of 40% delivers the insight that, in line with our earlier finding and intuition (cf. section 4.1), the general equilibrium elasticities fall strongly with higher housing shares. The (unweighted) mean employment elasticity falls from 4.27 to 2.52 and the (unweighted) mean resident elasticity falls from 2.74 to 0.78 when the housing share is at 40% rather than at 10%.[48]

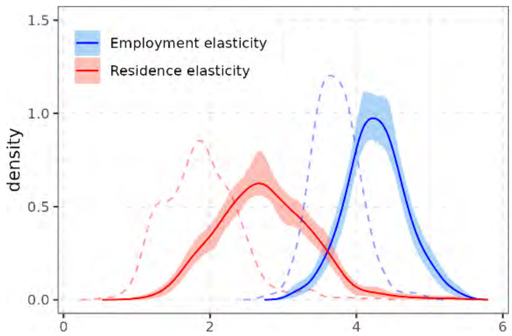


Figure 11: Kernel densities for employment elasticities and resident elasticities, all trade. Housing share is 10%. Shaded areas show the 95% confidence bands. Dashed curves depict the baseline with manufacturing trade, only.

What can be said about the explanatory power of simple labor market and commuting statistics in predicting the general equilibrium elasticities? The full results of our regressions are provided in appendix G. Figure 6 visualizes the key finding: similarly to the scenario with manufacturing trade only, the own-commuting share has almost no explanatory power for our preferred housing share of 10% but becomes very powerful with a high housing share (see the red broken line) and the intuition for this evolution carries over from section 4.2.

Further robustness checks for ‘all trade’ yield the following. First, the general equilibrium elasticities that we obtain when the local heterogeneity of housing is taken into account differ only marginally from those for uniform shares (see appendix H3) and the explanatory power of the own-commuting share develops similarly under heterogeneity and uniformity when housing shares are raised (see Figure 6). Second, positive housing supply elasticities yield larger employment and resident elasticities and reduce the explanatory power of simple labor and commuting market statistics. Alternative combinations of the housing supply elasticity and housing shares have a strikingly similar impact on this explanatory power as in the case when

[48] Appendix G2 shows the evolution of the kernel densities for all trade as the housing share is successively increased from 10% to 40% (this parallels figure 5).

trade is confined to manufacturing (as is seen by comparing appendix I with Figure 9) and for the same reason as discussed in section 4.4. Third, we have also analyzed a shutdown of international trade with the all trade data. The 2SLS estimate for the commuting elasticity ϵ falls to 3.36, a much more dramatic fall relative to the open economy case compared to the respective elasticities with manufacturing trade, only. We find that the kernel densities for employment and resident elasticities are shifted to the left (see appendix J3) in accordance with this strong fall in the commuting elasticity.

To sum up, the quantitative outcomes of our treatments differ when we adjust trade to include services (as we would expect), but the key qualitative conclusions that we established with our observation-based manufacturing regional trade data carry over to the 'all trade' scenario.

4.8 Comparison to the United States

Our key findings in a nutshell are that – based on our preferred calibration with a housing share of 10% -, the employment and resident elasticities associated with the local productivity are much above unity, yet disparate (the former larger than the latter), very heterogeneous, and only poorly predicted by simple labor and commuter market statistics. Whilst some of our findings parallel those of Monte et al. (2018) for the United States at least qualitatively – in particular the key role of commuting as a shock absorber, and the heterogeneity of the elasticities -, other findings pose a striking contrast. First, employment elasticities for Germany are quantitatively way above those for the United States, the mean employment elasticity in Germany is 3.72 (cf. table 3) whilst it is 1.52 in the US for the respective preferred settings. Second, simple labor and commuting market statistics, notably the own-commuting share, have strong explanatory power for these elasticities in Monte et al. (2018), in stark contrast to our finding for Germany. Taking these differences at face value would be comparing apples with pears, however. To arrive at a sensible evaluation, we stress four key elements which differ across the two studies, geographies, the trade regimes, the data, and the parameter choices.

The geographies differ strongly. The United States has 25fold the area of Germany, long distances and geographic barriers between its centers in the East, West, around the Great Lakes and in the South, much in contrast to Germany. At the same time, population is only 4fold that of Germany, implying a population density of about 36 persons/km^2 compared to 226 persons/km^2 for Germany. The average size of the 3111 counties in the United States is about 1.5 times larger than that of the 402 counties in Germany. For these reasons alone, it is unsurprising that commuting activity across counties is much stronger in Germany: the unweighted average share of a county's residents that work at other locations is 40%, and that of a county's total workforce that lives in a different location is 36 % in Germany, numbers that are almost twice those reported for the US (cf. Table 1 and Monte et al. 2018). The stronger commuting linkages in Germany are also manifested by our estimate of the commuting elasticity of $\epsilon = 4.56$ which exceeds the value for the United States ($\epsilon = 3.3$ estimated in Monte et al. 2018).

A second difference (associated with geography) is that Germany is so deeply embedded in international trade that we could not abstract from its external trade in our baseline, in contrast to what Monte et al. (2018) and also Caliendo et al. (2018) are forced to do for the United States. Neglecting the external trade of the United States altogether is clearly at odds with the facts, however (e.g. Costinot and Rodriguez-Claré 2014), and hence the source of a bias, if only because external and internal trade are then confounded (see our discussion in section 4.5). Our counterfactual scenario for Germany where international trade is disregarded shows that this biases the local general equilibrium elasticities upwards. On the basis of our findings, the elasticities found in Monte et al. (2018) potentially are too large because of the inability to account for the trade openness of the US.

A third difference concerns the availability and quality of the data. For one (and related to the previous issue), a decisive advantage of our observation-based manufacturing trade data is that they give us a reliable portrait of internal *and* external trade which we can take into account in our analyses. Hence, we avoid a bias which would result if we counterfactually took Germany to be a closed economy. For another, the imputation performed by Monte et al. (2018) to arrive from their bilateral trade data for the 123 CFS (Commodity Flow Survey) regions at bilateral trade for the 3111 counties, clean as it is from a pure technical viewpoint, leads to numbers which have to be taken with a grain of salt. The direction of the bias associated with this imputation is not clear, however. Finally, we pointed out that our analyses for 'all trade' which are based on gravity-imputed service trade data in addition to the observation-based manufacturing trade data, have to be taken with caution, too. This notwithstanding, our analysis teaches that, accounting for service trade, general equilibrium elasticities would be driven up and this would make it harder to predict the employment elasticities with simple statistics.

The fourth and key difference between our study and Monte et al. (2018) concerns the choice of the housing share parameter. Our economy-wide approach, backed by macroeconomic data, implies a share of 10 % whereas Monte et al. (2018) move away from a literal interpretation of this parameter and work with a share of 40%. Our robustness check for Germany teaches us, what to expect if we stipulated a similarly large share. This would substantially lower the general equilibrium elasticities, which would still stay significantly larger than those for the US (cf. table 3) – possibly for the mentioned reasons of geography. Moreover, the explanatory power of simple labor market statistics – notably the own-commuting share - would also improve considerably. Our extensive robustness checks with positive housing supply elasticities for Germany revealed that the predictive power of this simple statistic quickly vanishes with higher supply elasticities and lower housing shares (cf. Figure 9), which reinforces the key result that we spelled out at the start of this section.

5 Conclusion

This paper develops a quantitative spatial model with heterogeneous locations linked by costly goods trade, migration and commuting to shed light on the functioning of local labor markets in Germany and to explore the role of housing markets for quantitative analyses. Unique data, a traffic study, in particular, allow us to put our analyses on a much more solid footing than extant work which had to impute bilateral trade shares among locations.

Our key findings are that the employment and resident elasticities associated with local productivity shocks are much above unity, yet disparate (the former larger than the latter), very heterogeneous, and only poorly predicted by simple labor and commuter market statistics, in our preferred calibration which stipulates a housing share of about ten percent. Allowing the housing supply to be price elastic increases the employment and resident elasticities and reinforces these conclusions. The marked regional heterogeneity of the housing shares in Germany turns out to be inessential for this finding, but their level does not. When housing shares are very large (and supply elasticities very low), the dispersion force of scarce housing become very strong and the general equilibrium repercussions induced by local productivity shocks become weak. The much smaller employment and resident elasticities can then be predicted much easier with ex-ante observable labor market measures. We also consider a Germany which is, counterfactually, shut down to external trade. This exercise teaches us that international trade works like a buffer which absorbs part of the effects of productivity shocks which reduces the general equilibrium repercussions for the local economy (much like high housing share and small housing supply elasticities).

Whilst some of our findings parallel those of Monte et al. (2018) for the United States – the key role of commuting as a shock absorber, and the heterogeneity of the elasticities -, other findings pose a striking contrast. First, the quantitative numbers for the employment and resident elasticities in Germany are way above those for the United States. Second, simple labor and commuting market statistics, notably the own-commuting share, have strong explanatory for these elasticities in Monte et al. (2018), in stark contrast to our findings for Germany. Our extensive robustness analyses for Germany allow us to rationalize these differences by referring to the varying geographies and trade regimes of the two countries and the data and parameter choices used in the studies.

We see at least two fruitful avenues for future research. One involves an extension of the analysis to account for vertical linkages in production. The second involves a disaggregation of labor along skill groups and/or task groups to study the distributional consequences of local labor market shocks.

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Online Appendix

On the Road (Again): Commuting and Local Employment Elasticities in Germany

by Oliver Krebs and Michael Pflüger

A Existence and Uniqueness

We use the methods and theorems developed in Arkolakis et al. (2020; 2016) to establish a sufficient condition for the existence and uniqueness of the model. We follow Monte et al. (2018) in abstracting from trade deficits but generalize their derivation by allowing for positive land supply elasticities. Using equations (12), (13) and (15) allows us to derive the income of commuters from residence n to workplace i as:

$$w_i \lambda_{ni} \bar{L} = \left(\frac{\bar{U}}{\delta}\right)^{-\epsilon} \bar{L} B_{ni} \kappa_{ni}{}^{-\epsilon} (P_n^{\alpha}\ Q_n^{1-\alpha})^{-\epsilon} w_i{}^{1+\epsilon} \tag{A.1}$$

Total workplace income in location i (obtained by summing (A.1) across residences n) is then

$$Y_i = \sum_{n\in N} w_i \lambda_{ni} \bar{L} = \left(\frac{\bar{U}}{\delta}\right)^{-\epsilon} \bar{L}\, w_i^{1+\epsilon} \sum_{n\in N} B_{ni} \kappa_{ni}{}^{-\epsilon} (P_n^{\alpha}\ Q_n^{1-\alpha})^{-\epsilon}, \tag{A.2}$$

and total residential income in location n (obtained by summing (A.1) across workplaces i) is:

$$X_n = \sum_{i\in N} w_i \lambda_{ni} \bar{L} = \left(\frac{\bar{U}}{\delta}\right)^{-\epsilon} \bar{L}\, (P_n^{\alpha}\ Q_n^{1-\alpha})^{-\epsilon} \sum_{i\in N} B_{ni} \kappa_{ni}{}^{-\epsilon}\, w_i^{1+\epsilon} \tag{A.3}$$

Using (10) and abstracting from trade imbalances, land market clearing (11) can be written as

$$Q_n = \left[\frac{(1-\alpha)X_n}{\bar{H}_n}\right]^{\frac{1}{1+\eta_n}}, \tag{A.4}$$

so that total workplace income in location i (A.2) can be rewritten as

$$Y_i = \left(\frac{\bar{U}}{\delta}\right)^{-\epsilon} \bar{L}\, (1-\alpha)^{\frac{-(1-\alpha)\epsilon}{1+\eta_n}} w_i^{1+\epsilon} \sum_{n\in N} B_{ni} \kappa_{ni}{}^{-\epsilon} P_n^{-\alpha\epsilon} X_n{}^{\frac{-(1-\alpha)\epsilon}{1+\eta_n}}\, \bar{H}_n{}^{\frac{(1-\alpha)\epsilon}{1+\eta_n}} \tag{A.5}$$

and total residential income in location n (A.3) can be rewritten as

$$X_n = \left(\frac{\bar{U}}{\delta}\right)^{-\epsilon} \bar{L}(1-\alpha)^{\frac{-(1-\alpha)\epsilon}{1+\eta_n}}\, \bar{H}_n{}^{\frac{(1-\alpha)\epsilon}{1+\eta_n}}\, P_n^{-\alpha\epsilon} X_n{}^{\frac{-(1-\alpha)\epsilon}{1+\eta_n}} \sum_{i\in N} B_{ni} \kappa_{ni}{}^{-\epsilon}\, w_i^{1+\epsilon} \tag{A.6}$$

The price index (8) can be re-written using $Y_i = w_i L_i$

$$P_n{}^{1-\sigma} = \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \frac{1}{\sigma F} \left[\sum_{i\in N} Y_i \left(\frac{d_{ni}}{A_i}\right)^{1-\sigma} w_i{}^{-\sigma}\right] \tag{A.7}$$

Using $Y_i = w_i L_i$ and $X_n = \bar{v}_n R_n$ and the trade shares (7) the goods market clearing condition (9) can be written as

$$w_i{}^{\sigma} = \sum_{n\in N} \frac{1}{\sigma F} \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \left(\frac{d_{ni}}{A_i}\right)^{1-\sigma} P_n{}^{\sigma-1} X_n \tag{A.8}$$

The system of equations for workplace income (A.2), residence income (A.3), the price index (A.7) and goods market clearing (A.8) can then be rearranged as follows

$$P_n{}^{1-\sigma} = \xi^P \sum_{i\in N} \kappa_{ni}^P Y_i w_i{}^{-\sigma} \quad \text{where} \quad \xi^P \equiv \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \frac{1}{\sigma F}, \quad \kappa_{ni}^P \equiv \left(\frac{d_{ni}}{A_i}\right)^{1-\sigma} \tag{A.9}$$

$$w_n{}^{\sigma} = \xi^w \sum_{i\in N} \kappa_{ni}^w\, P_i{}^{\sigma-1} X_i \quad \text{where} \quad \xi^w \equiv \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \frac{1}{\sigma F}, \quad \kappa_{ni}^w \equiv \left(\frac{d_{ni}}{A_i}\right)^{1-\sigma} \tag{A.10}$$

$$Y_n w_n^{-(1+\epsilon)} = \xi^Y \sum_{i\in N} \kappa_{ni}^Y P_i^{-\alpha\epsilon} X_i{}^{\frac{-(1-\alpha)\epsilon}{1+\eta_n}} \tag{A.11}$$

$$\text{where} \quad \xi^Y \equiv \left(\frac{\bar{U}}{\delta}\right)^{-\epsilon} \bar{L}\, (1-\alpha)^{-\frac{(1-\alpha)\epsilon}{1+\eta_n}}, \qquad \kappa_{ni}^Y \equiv B_{ni} \kappa_{ni}{}^{-\epsilon} \bar{H}_n{}^{\frac{(1-\alpha)\epsilon}{1+\eta_n}}$$

$$X_n{}^{1+\frac{(1-\alpha)\epsilon}{1+\eta_n}}\, P_n^{\alpha\epsilon} = \xi^X \sum_{i\in N} \kappa_{ni}^X\, w_i^{1+\epsilon} \tag{A.12}$$

$$\text{where} \quad \xi^X \equiv \left(\frac{\bar{U}}{\delta}\right)^{-\epsilon} \bar{L}(1-\alpha)^{(1-\alpha)^{-\frac{(1-\alpha)\epsilon}{1+\eta_n}}}, \quad \kappa_{ni}^X \equiv B_{ni} \kappa_{ni}{}^{-\epsilon} \bar{H}_n{}^{\frac{(1-\alpha)\epsilon}{1+\eta_n}}$$

These equations are of the form considered by Allen, Arkolakis and Li (2016; 2020, cf. Remarks 2 and 3) and the corresponding matrices involving the exponents of P_n, w_n, Y_n, X_n are given by:

$$B = \begin{bmatrix} 1-\sigma & 0 & 0 & 0 \\ 0 & \sigma & 0 & 0 \\ 0 & -(1+\epsilon) & 1 & 0 \\ \alpha\epsilon & 0 & 0 & 1+\frac{(1-\alpha)\epsilon}{1+\eta_n} \end{bmatrix} \quad \Gamma = \begin{bmatrix} 0 & -\sigma & 1 & 0 \\ \sigma-1 & 0 & 0 & 1 \\ -\alpha\epsilon & 0 & 0 & \frac{-(1-\alpha)\epsilon}{1+\eta_n} \\ 0 & 1+\epsilon & 0 & 0 \end{bmatrix}$$

and $$A = \Gamma\, B^{-1} = \begin{bmatrix} 0 & \frac{\epsilon+1}{\sigma}-1 & 1 & 0 \\ \frac{\alpha\,\epsilon\,(1+\eta_n)}{(\sigma-1)[\epsilon(1-\alpha)+(1+\eta_n)]}-1 & 0 & 0 & \frac{1+\eta_n}{\epsilon(1-\alpha)+(1+\eta_n)} \\ \frac{\alpha\,\epsilon\,(1+\eta_n)}{(\sigma-1)[\epsilon(1-\alpha)+(1+\eta_n)]} & 0 & 0 & \frac{1+\eta_n}{\epsilon(1-\alpha)+(1+\eta_n)}-1 \\ 0 & \frac{\epsilon+1}{\sigma} & 0 & 0 \end{bmatrix}$$

from which we can derive the matrix A^p which reformulates matrix A such that all of its entries appear in absolute terms, $(A^p)_{kh} = |(A)_{kh}|$:

$$A^P = \begin{bmatrix} 0 & \left|\frac{\epsilon+1}{\sigma}-1\right| & 1 & 0 \\ \left|\frac{\alpha\,\epsilon\,(1+\eta_n)}{(\sigma-1)[\epsilon(1-\alpha)+(1+\eta_n)]}-1\right| & 0 & 0 & \frac{1+\eta_n}{\epsilon(1-\alpha)+(1+\eta_n)} \\ \frac{\alpha\,\epsilon\,(1+\eta_n)}{(\sigma-1)[\epsilon(1-\alpha)+(1+\eta_n)]} & 0 & 0 & 1-\frac{1+\eta_n}{\epsilon(1-\alpha)+(1+\eta_n)} \\ 0 & \frac{\epsilon+1}{\sigma} & 0 & 0 \end{bmatrix}$$

Theorem 1 in Allen et al. (2020) states sufficient conditions for existence and uniqueness of a general equilibrium solution in this class of models which depend on the largest eigenvalue $\rho(A^p)$ of matrix A^p being smaller or equal to one, $\rho(A^p) \leq 1$. Remark (5) in Allen et al. (2020) then invokes the Collatz–Wielandt formula which shows that the largest eigenvalue or spectral radius $\rho(A^p)$ of matrix A^p is bounded by the smallest and largest summation of each column (or row) of A^P. While columns 3 and 4 trivially sum to 1, the same is true for the other two columns under the parameter conditions, $\frac{(\sigma-1)}{\epsilon} \geq \frac{\alpha\ (1+\eta_n)}{\epsilon(1-\alpha)+(1+\eta_n)}$ and $\frac{(\sigma-1)}{\epsilon} \geq 1$. An inspection immediately reveals that the second condition is stronger. Hence, the crucial condition is:

$$\frac{(\sigma-1)}{\epsilon} \geq 1$$

Notice moreover, that if this condition holds, *all* columns sum to 1 and thus the spectral radius is bound from below and above by 1, implying $\rho(A^p) = 1$ (this is to be expected in an equilibrium defined nominally, cf. Allen et al. 2020). Under this condition Theorem 1, ii, b in Allen et al. (2020) guarantees the up-to-scale, i.e. up to normalization, uniqueness of the equilibrium.[49] We can thus conclude that only two parameters, the Fréchet parameter of idiosyncratic preferences ϵ and the preference parameter σ, are crucial for uniqueness and existence, but not the housing share $(1-\alpha)$. Intuition is provided in the body of the paper.

This result, to the best of our knowledge, has not been stated in the extant literature. Monte et al. (2018, online appendix B3) just state the matrix A^p (they address the case $\eta_n = 0$), noting that its largest eigenvalue needs to be smaller or equal to one. However, it is easily seen that their parameters *violate* the condition $(\sigma-1)/\epsilon \geq 1$.

[49] Theorem 1, iii, further shows that there exists in fact some combination of trade and commuting barrier shocks that would lead to the existence of multiple equilibria if our condition is violated.

B Equilibrium in changes

We rewrite our equilibrium system in terms of changes. Following the literature, we use a prime to denote variables from a counterfactual scenario and a hat to denote the relative change of a variable, i.e. $\hat{x} = \frac{x'}{x}$. The equilibrium system of equations (7) through (15), together with the price index of consumption and commuting shares thus becomes:

(7)’ $$\hat{\pi}_{ni} = \frac{\frac{\hat{L}_i}{\hat{F}_i}\left(\frac{\hat{d}_{ni}}{\hat{A}_i}\right)^{1-\sigma} \hat{w}_i^{1-\sigma}}{\sum_{m\in N} \pi_{nm}\frac{\hat{L}_m}{\hat{F}_m}\left(\frac{\hat{d}_{nm}}{\hat{A}_m}\right)^{1-\sigma} w_m^{1-\sigma}}$$

(8)’ $$\hat{p}_n = \frac{\hat{w}_n}{\hat{A}_n}\left[\frac{\hat{L}_n}{\hat{\pi}_{nn}\,\hat{F}_n}\right]^{\frac{1}{1-\sigma}}$$

(9)’ $$\sum_{n\in N} \hat{\pi}_{ni}\, \pi_{ni}\, \hat{X}_n X_n = \hat{w}_i\, \hat{L}_i w_i L_i$$

(10)’ $$\hat{X}_n X_n = \hat{\bar{w}}_n\, \hat{R}_n\, \bar{w}_n\, R_n + D_n \hat{D}_n$$

(11)’ $$\hat{q}_n = \hat{\bar{w}}_n\, \hat{R}_n$$

(12)’ $$\hat{\lambda}_{ni}\big|_{\Omega_g} = \frac{\hat{B}_{ni}\,\hat{\mathrm{P}}_{\mathrm{n}}^{-\epsilon}\,\hat{\kappa}_{ni}^{-\epsilon}\hat{w}_i^{\epsilon}}{\sum_{m\in\Omega_g}\sum_{l\epsilon\Omega_g}\lambda_{ml}|_{\Omega_g}\hat{B}_{ml}\,\hat{\mathrm{P}}_{\mathrm{m}}^{-\epsilon}\,\hat{\kappa}_{ml}^{-\epsilon}\hat{w}_l^{\epsilon}}$$

(13)’ $$\frac{\hat{L}_n\, L_n}{\bar{L}_g} = \sum_{i\epsilon\Omega_g} \hat{\lambda}_{in}|_{\Omega_g}\lambda_{in}|_{\Omega_g}$$

(14)’ $$\frac{\hat{R}_n\, R_n}{\bar{L}_g} = \sum_{i\epsilon\Omega_g} \hat{\lambda}_{ni}|_{\Omega_g}\lambda_{ni}|_{\Omega_g}$$

(15)’ $$\hat{\bar{w}}_n \bar{w}_n = \sum_{i\epsilon\Omega_g} \frac{\hat{B}_{ni}\hat{\kappa}_{ni}^{-\epsilon}\hat{w}_i^{\epsilon}\lambda_{ni}|_{\Omega_g}}{\sum_{m\epsilon\Omega_g}\hat{B}_{nm}\hat{\kappa}_{nm}^{-\epsilon}\hat{w}_m^{\epsilon}\lambda_{nm}|_{\Omega_g}} \cdot \hat{w}_i \cdot w_i$$

where $\hat{\mathrm{P}}_n = \hat{p}_n^{\alpha}\hat{q}_n^{1-\alpha}$

C Algorithm

For any shock defined by $\hat{B}_{ni}$, $\hat{\kappa}_{ni}$, $\hat{F}_n$, $\hat{A}_n$, $\hat{d}_{ni}$ for all n, i, and initial guesses for $\hat{w}_i$ and $\hat{\lambda}_{ni|\Omega_g}$ we use our data for $\bar{w}_n$, w_n, L_n, R_n, π_{ni} and $\lambda_{ni|\Omega_g}$ to solve the equilibrium in changes using the following algorithm.

Step 1: We calculate new values for $\hat{L}_n$, $\hat{R}_n$ and $\hat{\bar{w}}_n$ using equations (13)' through (15)'.

Step 2: Using the obtained values we derive changes in housing costs as $\hat{q}_n = \hat{R}_n \hat{\bar{w}}_n$ via equation (11)' and in trade shares as $\hat{\pi}_{ni} = \frac{\frac{\hat{L}_i}{\hat{F}_i}\left(\frac{\hat{d}_{ni}}{\hat{A}_i}\hat{w}_i\right)^{1-\sigma}}{\sum_{m \in \Omega_g} \pi_{nm} \frac{\hat{L}_m}{\hat{F}_m}\left(\frac{\hat{d}_{nm}}{\hat{A}_m}\hat{w}_m\right)^{1-\sigma}}$.

Step 3: Given the changes in trade shares we solve for changes in the consumer goods price index via $\hat{p}_n = \frac{\hat{w}_n}{\hat{A}_n}\left[\frac{\hat{L}_n}{\hat{\pi}_{nn}\hat{F}_n}\right]^{\frac{1}{1-\sigma}}$.

Step 4: Given all new variables we solve for temporary values of $\hat{w}_i^{tmp}$ and $\hat{\lambda}_{ni}^{tmp}$ using equations (9)' and (10)' in combined form, i.e. $\hat{w}_i = \frac{1}{\hat{L}_i} \sum_{n \in N} \pi_{ni} \hat{\pi}_{ni} (R_n \hat{R}_n \bar{w}_n \hat{\bar{w}}_n + D_n \hat{D}_n)$ as well as equation (12)'.

Step 5: We update our guess for $\hat{w}_i$ to $\hat{w}_i + \zeta(\hat{w}_i^{tmp} - \hat{w}_i)$ and our guess for $\hat{\lambda}_{ni|\Omega_g}$ to $\hat{\lambda}_{ni|\Omega_g} + \zeta\left(\hat{\lambda}_{ni|\Omega_g}^{tmp} - \hat{\lambda}_{ni|\Omega_g}\right)$ where $0 < \zeta < 1$ represents a dampening factor.[50]

We repeat these steps until the equilibrium is reached with a sufficiently small tolerance, that is, until $\hat{w}_i^{tmp} - \hat{w}_i$ and $\hat{\lambda}_{ni|\Omega_g}^{tmp} - \hat{\lambda}_{ni|\Omega_g}$ converge to 0.

[50] Throughout a broad range of counterfactuals $\zeta = 0.3$ has proven to be an acceptable compromise between speed of convergence and preventing and overshooting of the algorithm.

D Goods Trade

Trade data. Trade data are based on a unique data set, the traffic forecast ('Verkehrsverflechtungsprognose 2030') administered by the German Federal Ministry of Transport and Digital Infrastructure. They contain the weight of goods shipped between German counties and their trade partners by ship, train or truck disaggregated across 25 product categories. Sources for the construction of the data set stem mainly from the respective agencies for rail- and waterways and from a representative weekly sample of truck shipments in Germany. Krebs (2020) provides an in-depth analysis of this data set, as well as the implied German interregional trade and production network.

The main challenge in the initial data preparation is to move from shipments in terms of weight to trade in terms of value. The traditional approach to this type of problem uses unit values for shipped tons. At the broad level of product categories for which shipment data is available this implies, for example, that a ton of 'transport equipment' exports from a county that hosts car seat manufactures would be valued at the same price as exports from a county with engine producers. Hence, this assumption implies trade flow values that do not make sense to someone who is familiar with the German regional production structure.

To avoid this problem, we follow Krebs (2020) who uses further regional revenue data from the regional statistical offices and county sector level employment data from the Federal Institute of Labor Market Research (IAB) to calculate county sector level production values. 18 of the 25 product categories in the shipment data can be directly matched to the 12 agriculture, mining and manufacturing sectors for which county level revenue data can be calculated. Weight flows are then used to derive export shares at the county sector level and multiplied with the county sector revenues to derive trade values. To integrate world trade, all trade flows are rescaled to match the aggregate German exports to foreign locations given in the WIOD. Compared to the mentioned traditional approach of using national unit values to translate weight flows into value flows, this method has the key advantage that it accounts for the fact that goods in the same sector but from different counties can have very different values per ton.

Krebs (2020) uses this trade matrix as a constraint in a multidimensional extension of the iterative proportionate fitting (also known as RAS) method and imputes service sector trade by gravity estimation to derive at a full interregional input output table at the level of 17 sectors for all German counties and 26 foreign countries.[51] This input output table replicates observed

[51] Given an initial matrix, the RAS method finds a new matrix that, according to a valuation function, deviates as little as possible from the original matrix while satisfying given target values for row and column sums (see

German county level sectoral revenues, value added, and intermediate demand reported by the regional statistical offices and its aggregates for Germany are cell-by-cell compatible with the national and international data from the World Input Output Database (WIOD). It is hence strongly rooted in observable data and simultaneously allows us to obtain a detailed portrait of bilateral trade of goods between German counties.

To ease the comparison with the study by Monte et al. (2018) we follow their specifications as closely as possible. Faced with the choice to include the imputed service trade flows into total trade values, to assume that all services are non-tradable, or to ignore the production of services altogether, we follow Monte et al. (2018) and adopt this final option as our baseline scenario. Hence, in the baseline we make use of the regional input output table from Krebs (2020) but drop all service sector trade data before aggregating trade flows to a single sector.

Technologies. Our county level shipment data allow us to directly calibrate our model instead of relying on estimated trade flows based on distance. However, we do follow the analysis of Monte et al. (2018) here and estimate the correlation based on our gravity equation for two reasons. First, as a means to compare the results for Germany with the US case and, second, to infer technology levels A_i that we use an instrument in the estimation of commuting elasticities ϵ in appendix E. Assuming that the fixed input of labor is the same across locations ($F_i = F_m$ $\forall\, i, m \in N$) equation (7) becomes $\pi_{ni} = \frac{L_i w_i^{1-\sigma} (d_{ni}/A_i)^{1-\sigma}}{\sum_{m \in N} L_m w_m^{1-\sigma} (d_{nm}/A_m)^{1-\sigma}}$, so that trade flows from location i to n can be written as

$$\pi_{ni} X_n = \frac{L_i w_i^{1-\sigma} \left(\frac{d_{ni}}{A_i}\right)^{1-\sigma}}{\sum_{m \in N} L_m w_m^{1-\sigma} \left(\frac{d_{nm}}{A_m}\right)^{1-\sigma}} (R_n \bar{w}_n + D_n)\,,$$

which in turn can be decomposed into exporter and importer specific effects as well as bilateral barriers. We parameterize trade barriers dependent on distance, allowing for coefficients to differ between intraregional ($dist_{I,ni}$, 1 for $n \neq i$) and interregional distances ($dist_{R,ni}$, 1 for $n = i$), as well as, in scenarios with international trade, international distances ($dist_{INT,ni}$, 1 for either $n, i \in \Omega_g$ or $n = i$). Thus we specify $d_{ni} = dist_{I,ni}^{\psi_I}\, dist_{R,ni}^{\psi_R}\, dist_{INT,ni}^{\psi_{INT}}\, \tilde{e}_{ni}$, with $\tilde{e}_{ni}$ denoting an error term that captures any remaining unobserved bilateral characteristics. Together with exporter fixed effects S_i and importer fixed effects M_n our econometric representation of equation (7) becomes $\pi_{ni} X_n = S_i M_n dist_{I,ni}^{\psi_I}\, dist_{R,ni}^{\psi_R}\, dist_{INT,ni}^{\psi_{INT}}\, \tilde{e}_{ni}$.

Bacharach (1970) for a detailed description). The multidimensional version extends this approach to multidimensional arrays while also allowing for more complex constraints on the target array.

Estimating the log-linearized version of this equation with OLS commands that all observations with zero trade flows have to be dropped. Moreover, the residual plot in figure D.1 indicates heteroscedasticity in the data.[52] Both imply that estimation with OLS in the log-linearized form would lead to biased results. Hence, while we report the results of this OLS estimation, we prefer to keep the gravity equation in its multiplicative form using a Poisson Pseudo Maximum Likelihood (PPML) estimator (see Santos Silva and Tenreyro 2006 for a discussion of the problem and the PPML method).

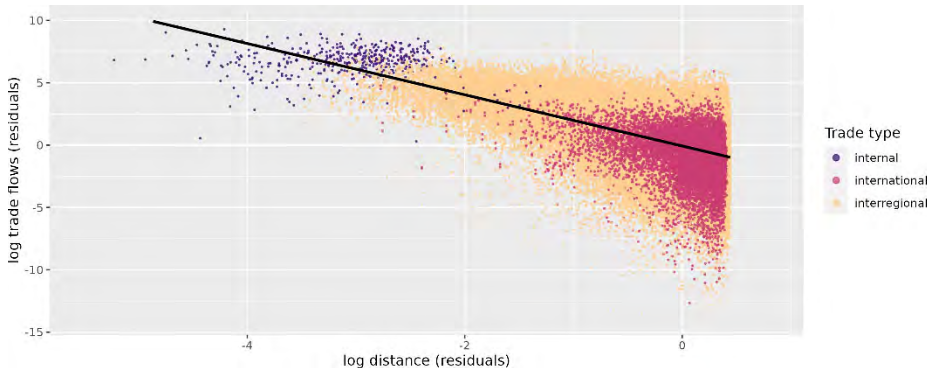


Figure D.1: (Log) relationship between trade flows and distance after removing importer and exporter fixed effects.

Relying on this estimator we obtain highly significant composite parameters $\psi_I(1-\sigma) = -0.842$, $\psi_R(1-\sigma) = -1.183$, and $\psi_{INT}(1-\sigma) = -1.153$ in our baseline scenario (Table D.1 provides results for our alternative scenarios and for estimation with OLS). Making use of our assumption that $\sigma = 5.5$ yields $\psi_I = 0.150, \psi_I = 0.211$, $\psi_I = 0.206$, which are all significantly smaller then Monte et al. (2018)'s US result of a common distance elasticity of 0.43 with respect to trade costs.

Table D.1: Gravity Estimation Results.

	OLS			PPML		
Dependent var:	$\log \pi_{ni} X_n$			$\pi_{ni} X_n$		
$\log dist_{I,ni}$	-1.752 (0.041)	-0.394 (0.036)	-1.779 (0.042)	-0.842 (0.107)	-1.165 (0.071)	-1.093 (0.053)
$\log dist_{R,ni}$	-2.018 (0.028)	-1.321 (0.009)	-2.031 (0.028)	-1.183 (0.093)	-1.670 (0.055)	-1.372 (0.032)
$\log dist_{INT,ni}$	-1.969 (0.036)	-1.527 (0.018)		-1.153 (0.098)	-1.582 (0.075)	

[52] Specifically, for this figure we separately regress trade flows $\pi_{ni} X_n$ and $dist_{ni}$ on importer and exporter dummies using PPML and then regress for all non-zero trade flows the logged multiplicative residuals of the first regression on those of the latter.

Exporter FE	x	x	x	x	x	x
Importer FE	x	x	x	x	x	x
Internatl. Trade	x	x		x	x	
Services		x			x	
Observations	142,653	183,184	122,064	183,184	183,184	161,604

Given the parameterization of trade barriers the resulting exporter fixed effects S_i are up-to-scale equivalent to $L_i w_i^{1-\sigma} A_i^{1-\sigma}$ and can be used together with our data on wages and employment to directly recover the unobserved technology levels A_i, which we depict in Figure 3 in the main text.

E Commuting

Commuting data. Our commuting data stem from the German Federal Employment Agency (‘Pendlerstatistik’) and are based on social security data. They contain bilateral flows between all 412 German counties in existence in 2010 of all workers with social security whose workplace differs from the registered residence. The commuting data excludes any self-employed workers or other workers without social security.

Initial data preparation faces two challenges. Firstly, all commuting flows between two counties with less than 10 commuters are censored and indistinguishable from county pairs with no commuters, an issue that we tackle by imputing censored flows based on gravity estimates as explained below. Secondly, the raw data set is generated based on company reports of each worker's registered residence address as well as the county of the plant where she is employed. This process is prone to reporting errors. Firms may wrongly report their headquarter or main plant instead of the actual plant of the worker's employment. Moreover, workers can be registered as residents at a main (‘Haupt-‘) and a secondary (‘Nebenwohnsitz’) address potentially introducing "fake" commuters to the data. Together, these issues lead to implausibly long commutes in the data and introduce systematic error. In response to this problem we assume that (very) long distance commutes in the data must consist exclusively of misreported values and use the information contained in the size of these flows to clean our data from misreporting as we explain below.

Distance Threshold. Figure E.1 depicts the relationship between the log of uncensored commuting flows and the log of distance in the raw commuting data, where all flows are larger or equal to 10 and where implausible flows are reported for very long distances (for a commute on a daily basis). There is a strong sign of discontinuity at a commuting distance of 120 km, similar to the one found in Monte et al. (2018), which we interpret as a threshold for possible daily commutes. The OLS regression lines for all commuting flows below and above 120 km respectively have slopes of -2.58 and -0.08 and we take the low dependence on distance above 120km as a sign of the data being (mostly) driven by misreporting instead of true commutes.

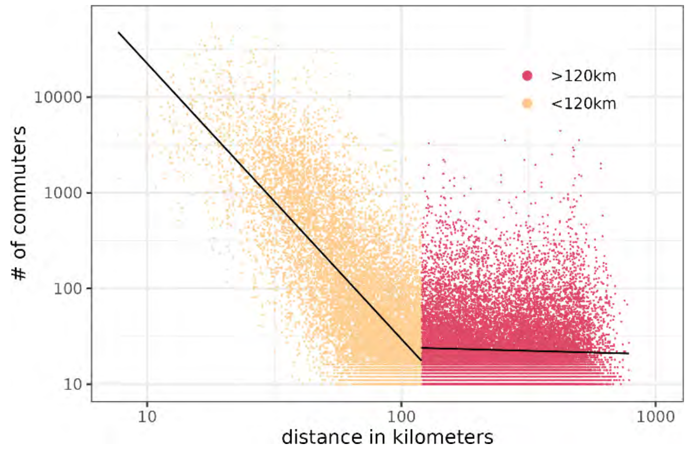


Figure E.1: Commuting flows and distance between counties in the raw commuting data (log scale).

We verify that this change in the slope of the regression persists after controlling for county size and further workplace and residence specific effects using origin and destination county fixed effects and we substantiate the threshold of 120 kilometers by running the following gravity specification for close and far commutes.[53]

$$\tilde{\lambda}_{ni} = \left[I_{near}\left(S_{i,near}M_{n,near}dist^{\beta_{near}}\right) + (1 - I_{near})\left(S_{i,far}M_{n,far}dist^{\beta_{far}}\right)\right] e_{ni} \quad \text{(E.1)}$$

where $\tilde{\lambda}_{ni}$ is the flow of commuters who work in i and live in n in the raw data, S_i and M_n are workplace and residence fixed effects and e_{ni} is a multiplicative error term. I_{near} is an indicator variable that takes the value 1 if the distance $dist_{ni}$ between the two counties is smaller than some threshold. We estimate specification E.1 in its multiplicative form using PPML to account for a potential bias from heteroscedasticity (see Santos Silva and Tenreyro 2006 for a discussion of the problem and the PPML method). Figure E.2 reports the resulting coefficients β_{near} and β_{far} as well as their difference for threshold values ranging from 60 to 240 km (in steps of 1km). For very low threshold values both coefficients are strongly negative but with a rising threshold $\beta_{far}$is quickly reduced in magnitude whereas β_{near} remains large and negative. For

[53] We also experiment with including quadratic logarithmic terms in this estimation to allow for a nonlinear effects of log distance. While we find significant coefficients for these terms, fitted values remain almost linear over the range in question and very little explanatory power is gained.

a threshold above 120km the difference remains relatively constant as both β_{far} and β_{near} shrink slightly in magnitude reassuring our choice of 120km as kink point.

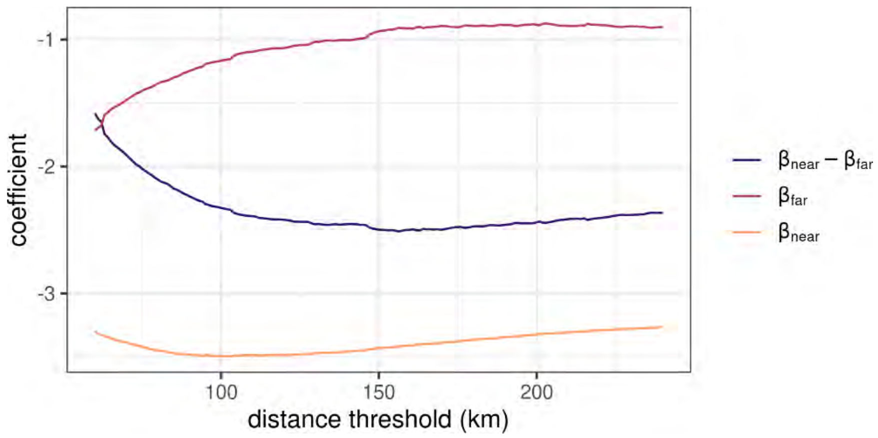


Figure E.2: Coefficients for different commuting thresholds

Censored Data. Next to commuting flows equal to or larger than 10 commuters our data set also provides aggregate commuter inflows to each workplace county originating in larger administrative areas ('Regierungsbezirke') or states that include flows censored on a county by county level. These aggregate inflows allow us to calculate that for 2.68% of all commuters the residence county is censored in the data. However, while the number of affected commuters is small a large share of county pairs is affected. Specifically, 78% of all county pairs (25% of all county pairs with a distance of less than 120km) list no commuting flows in the data, implying that the flow is either truly 0 or censored for being below 10. Simply setting all unknown flows to 0, counting censored commuters as non-commuters or dropping them from the total number of workers, would thus vastly overstate the role of zero trade flows in our gravity estimations. Instead, for each workplace, we split the aggregate worker inflow with censored residence county contained in inflows from larger administrative areas across potential residence counties relying on the estimates from regression E.1. In particular, we begin by calculating fitted values $\hat{\tilde{\lambda}}_{ni}$ for commuting flows between censored county pairs based on our two part estimation from above. As explained, the data set also allows to derive $\sum_{i \in m} \tilde{\lambda}_{ni}$, the aggregate commuters to a destination county n from a group m of censored counties and we scale our fitted values to match these observations setting[54]

$$\tilde{\lambda}_{ni|i \in m} = \frac{\hat{\lambda}_{ni}}{\sum_{i \in m} \hat{\lambda}_{ni}} \sum_{i \in m} \tilde{\lambda}_{ni}$$

[54] We ignore integer constraints for commuters in this procedure.

Figure E.3 again depicts the relationship between log commuters and log distances including our imputed values for censored flows.[55]

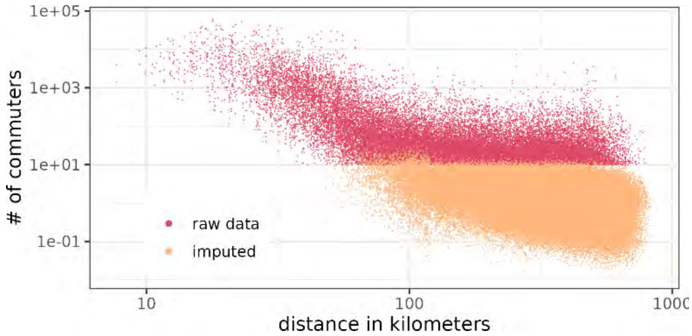


Figure E.3: (Log) relationship between commuters and distance with imputed data for censored flows.

Having derived all commuting flows, we combine our data set with information on total local employment from the German Institute for Labor Market Research (IAB) to derive the number of non-commuters in each county as the difference between local employment and total commuter inflow.

Misreporting. As explained above, one interpretation of the observed discontinuity is that commuting flows above 120km are unlikely to be true commuting flows but instead originate from misreporting. Misreporting is independent from distance and hence the slope of the regression line beyond 120km is strongly reduced in magnitude. However, misreporting is not random, as, for example, counties that have many headquarters such as Munich or Berlin will more likely be wrongly attributed to commuters as workplace. While any such county specific effects are unproblematic for the estimation of a distance coefficient in our gravity equation with county fixed effects they do matter for the calibration of the model that takes commuting flows as inputs. Since misreporting also occurs for commutes below 120km distance, we make use of the information contained in misreported long distance commutes to clean the raw commuting data. Specifically, we split the raw data, as well as imputed flows into commutable and non-commutable county pairs. To that end, we assume that commuting can only occur for distances below 120km or if there exists a public transportation connection with less than 1 hour and 45 minutes travel time between the largest cities in the two counties. Our main reason for including the latter criterion is that several important commutes between large cities occur via Germany's high speed rail network that often connects specific locations much faster than the highway system. A case in point is the commute between Germany's largest cities Hamburg

[55] Despite using fitted values from our initial estimations, flows for large distances lie on average far below the average of uncensored values. This can occur - and indeed is the main reason for – our rescaling to observed aggregate inflows.

and Berlin with a distance of about 290km and a road travel time of more than three hours but with a regular high speed train connection that only takes 1 hour and 45 minutes. We chose the travel time threshold such that this commute is still included also because it is similar to the expected road travel time for 120kms.

Further, we assume that an equal share ζ of all true commuting flows λ_{ni} is being misreported and that all flows among non-commutable county pairs consist purely of misreported commuters that are driven only by county specific factors such as the number of firm headquarters in the county.

Our observed number of commuters in the raw data $\tilde{\lambda}_{ni}$ can hence be decomposed as

$$\tilde{\lambda}_{ni} = I_{comm}(\lambda_{ni} - \zeta\lambda_{ni}) + \widetilde{M}_n \tilde{S}_i \tilde{e}_{ni}\,, \tag{E.2}$$

where I_{comm} is a dummy that takes the value 1 if a flow is commutable and 0 otherwise, $\widetilde{M}_n$ and $\tilde{S}_i$ are the origin and destination county specific effects determining the size of misreporting and $\tilde{e}_{ni}$ is a multiplicative error term. The first term on the left hand side is the number of true commuters reduced by the share ζ that is wrongly attributed to some different county pair. The second term then adds commuters wrongly attributed to the county pair ni from somewhere else.

We make use of the assumption that non-commutable flows consist only of misreporting to estimate

$$\tilde{\lambda}_{ni|noncommutable} = \widetilde{M}_n \tilde{S}_i \tilde{e}_{ni}$$

on the subsample of non-commutable flows, determining which counties are more likely to be miss specified as residence $\widetilde{M}_n$ or workplace $\tilde{S}_i$ of a commuter. We can then calculate estimated (fitted) sizes of misreporting for commutable flows as $\hat{\widetilde{M}}_n \hat{\tilde{S}}_i$ and derive the "true" commuting flows from equation (E.2) as

$$\lambda_{ni} = \frac{\tilde{\lambda}_{ni|commutable} - \widetilde{M}_n \tilde{S}_i \tilde{e}_{ni}}{1 - \zeta}\,,$$

where $\zeta = \frac{\sum_{n,i} \widetilde{M}_n \tilde{S}_i \tilde{e}_{ni}}{\sum_{n,i} \tilde{\lambda}_{ni}}$ is directly obtained as the share of all misreported flows in all observed flows and where we use the estimate of misreported flows $\hat{\widetilde{M}}_n \hat{\tilde{S}}_i$ instead of $\widetilde{M}_n \tilde{S}_i \tilde{e}_{ni}$ for all commutable county pairs.

Figure E.4 depicts the tight (log) relationship between commuters and distance in our final cleaned commuting data after removing residence and workplace fixed effects.

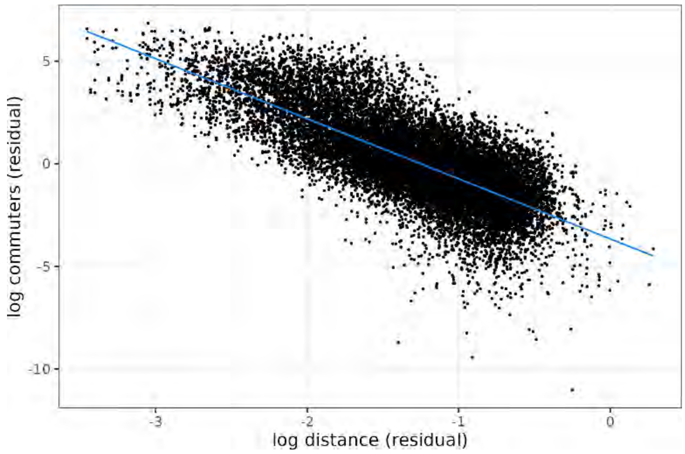


Figure E.4: Log commuting and log distance (residuals after removing county fixed effects) final data

Descriptive Evidence on Commuting. Commuting is pervasive in Germany, irrespective of whether we look at the administrative classification which divides Germany into 402 counties (Kreisfreie Städte and Landkreise), or at the 141 commuting zones which are aggregated up from the 402 counties (Kosfeld and Werner 2012; Eckey, Kosfeld and Türck 2006).

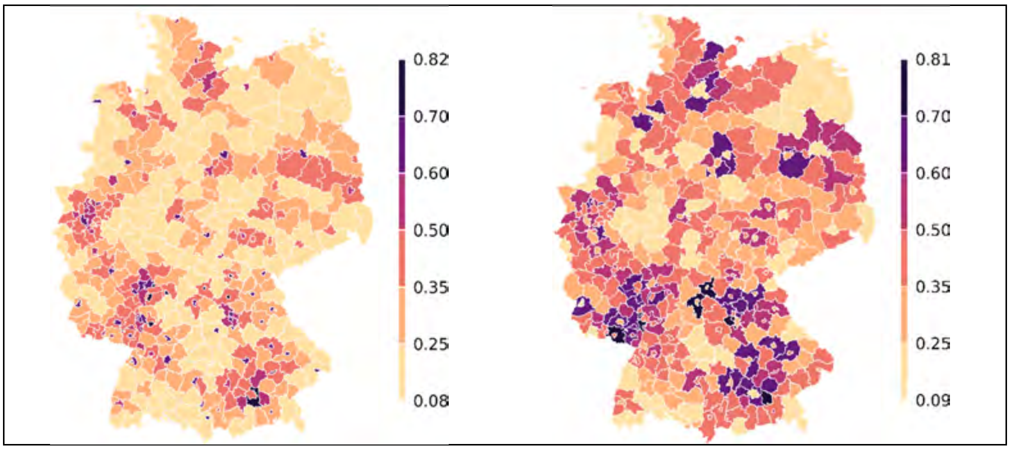


Figure E.5: Share of total workers who commute into counties (left panel) and share of residents who commute out of counties (right panel).

Commuter shares. To give a perspective on German local labor markets, the left panel of figure E.5 shows the share of total workers that commute to work in German counties whilst the right panel shows the share of residents that commute to other workplaces. The counties with the largest shares of inflows of workers are Schweinfurt (city), Munich (county) and Aschaffenburg, the ones with the largest shares of outflows of workers are Rhein-Pfalz-Kreis (county), Fürth (county) and Schweinfurt (county).[56] A visual comparison of the two panels of

[56] The largest nominal inflows can be found in Frankfurt, Munich, and Hamburg and Berlin, the largest nominal outflows in Munich, Rhein-Sieg-Kreis and Rhein-Neckar-Kreis.

figure E.5 immediately reveals that the intensity of inflows exceeds the intensity of outflows in cities and vice versa for the surrounding counties.[57]

Distribution of commuters. To bring out this point more clearly, and to have a basis for a casual comparison with the United States, table E.1 documents statistics for the distribution of commuters. Across German counties, the unweighted average share of a county's residents that work at other locations is 40% and that of a county's total workforce that lives in a different location is 36%. These numbers are almost twice the numbers reported by Monte et al. (2018) for the 3111 counties in the United States. When commuting zones rather than (administrative) counties are looked at, the numbers are less than half (such a halving is also reported by Monte et al. 2018). Table 1 also provides the ratio between workers and residents at various percentiles. As one would expect from the construction of commuting zones, the comparison of the numbers for counties with the numbers for commuting zones reveals that the latter are very much stronger centered around 1.

Table E.1: Unweighted average commuting statistics across German counties and commuting zones.

	min	p5	p10	p25	p50	p75	p90	p95	max	mean
	County Level (Kreise)									
commuter outflow/residents	0.09	0.19	0.22	0.29	0.38	0.50	0.62	0.66	0.81	0.40
commuter inflow/workers	0.08	0.15	0.18	0.23	0.33	0.46	0.62	0.66	0.82	0.36
workers/residents	0.40	0.58	0.66	0.77	0.89	1.07	1.53	1.80	3.60	1.00
	Commuting Zones									
commuter outflow/residents	0.04	0.09	0.11	0.14	0.19	0.28	0.32	0.40	0.57	0.22
commuter inflow/workers	0.07	0.09	0.10	0.13	0.16	0.21	0.27	0.29	0.39	0.18
workers/residents	0.64	0.81	0.84	0.90	0.96	1.00	1.06	1.10	1.17	0.95

The message conveyed by table E.1 is reinforced by the kernel densities of the share of non-commuters in residents depicted in figure E.6 (which is reproduced in the body of the paper as figure 1). This figure reveals that the peak of the distribution is at a share of non-commuters in residents of slightly higher than 60% which is comparable in range to what has been established for the United States (see Monte et al. 2018).

[57] Repeating this exercise for the 141 German commuting zones almost halves the numbers, but leaves the general pattern documented in figure 1 intact.

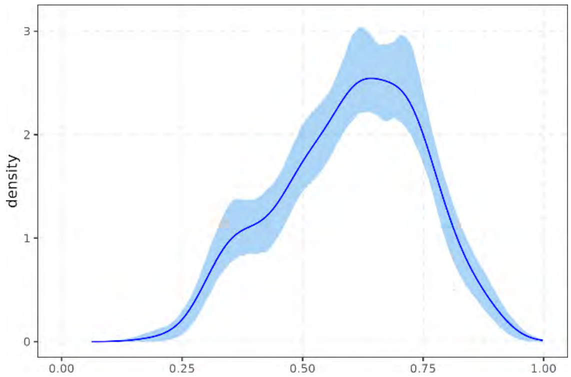


Figure E.6: Kernel densities for the share of non-commuters in residents, German counties. 95% confidence interval shaded. See section 4 for the data.

Two-way commuting. Grubel-Lloyd indices for two-way commuting in and out of German local labor markets provide another piece of evidence, see Figure E.7.[58] The left panel depicts this index for administrative local labor markets and the right panel for commuting zones. The left panel reveals that two-way commuting is pervasive in Germany and strongest in large cities and regions in the West and Southwest. The mean and median of the GL-index at the county level are both at 0.69. The distribution of the Grubel-Lloyd index shown in table E.2 is similar to what is found for the United States (cf. Monte et al. 2018). It should be noted that Germany also has a number of counties where one-way commuting is extremely strong. These are visualized by the few bright areas in the left panel, the most prominent one is Wolfsburg, home to the largest VW production plant, followed by Frankfurt, Germany's financial center, and a number of mid-size Bavarian cities such as Regensburg, where BMW has a large plant, Bamberg, Erlangen, Schweinfurt and their surrounding counties. With commuting zones, two-way commuting is more prominent as they combine counties with strong worker inflows with counties with strong worker outflows, see the right panel in Figure E7. Yet the overall heterogeneity remains strong with values ranging from 0.45 to just below 1.

[58] Following the use in international trade, these indices are defined as $GL_i = 1 - \frac{|\sum_{n\neq i} L_i^n - \sum_{n\neq i} L_n^i|}{\sum_{n\neq i} L_i^n + \sum_{n\neq i} L_n^i}$. The subscript indicates the place of residence and the superscript the workplace, so that $\sum_{n\neq i} L_i^n$ are location i's total 'exports' of commuters and $\sum_{n\neq i} L_n^i$ are location i's total 'imports' of commuters from other residences. The index takes on values between $GL_i = 0$ if there is only one way commuting and $GL_i = 1$ if there is perfect two-way commuting.

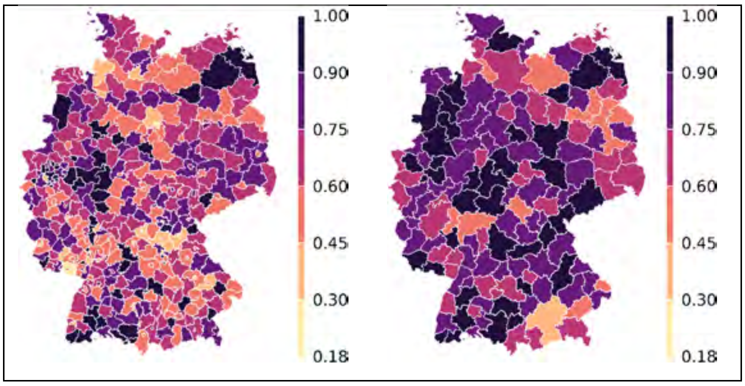


Figure E.7: Grubel-Lloyd indices for commuting in and out of German local labor markets, left panel for counties, right panel for commuting zones. See section 4 for the data.

Table E.2: Percentiles of the distribution of the Grubel-Lloyd index. See section 4 for the data.

	min	p5	p10	p25	p50	p75	p90	p95	max	mean
Counties	0.18	0.43	0.48	0.57	0.69	0.83	0.92	0.955	0.998	0.69
Commuting Zones	0.45	0.58	0.61	0.70	0.82	0.90	0.97	0.986	0.996	0.80

Commuting elasticity. Similar to the gravity estimation of goods trade above, we can use the commuting equation (12) to derive a gravity equation of commuter flows. Note first that (12), after substituting the overall price index P_n from (4), the goods price index p_n from (8) and land prices q_n from (11) is a system of $N \cdot N$ equations in the $N \cdot N$ "ease of commuting parameters" $\mathcal{B}_{ni} \equiv B_{ni}\kappa_{ni}^{-\epsilon}$. Given the data on $w_i, L_i, \pi_{ii}, \bar{w}_i, R_i, \bar{H}_i$ and $\lambda_{ni}|_{\Omega_g}$ as well as the technology parameters A_i (which we have obtained from model inversion) and given the parameters α, σ, η_n and ϵ, these $N \cdot N$ equations have an up-to-normalization unique solution in the "ease of commuting parameters" $\mathcal{B}_{ni}$ (Proposition 2, MRRH 2018, online appendix). We follow Monte et al. (2018) in modelling $\mathcal{B}_{ni}$ in the following way, $\mathcal{B}_{ni} = \mathbb{B}_n\mathbb{B}_i dist_{ni}^{\psi_\lambda}\mathbb{B}_{ni}$, where $\mathbb{B}_n$ is a residence component, $\mathbb{B}_i$ is a workplace component, $dist_{ni}^{\psi_\lambda}$ is a distance component and $\mathbb{B}_{ni}$ is the orthogonal error. Inserting this in (12) yields $\lambda_{ni}|_{\Omega_g} = \mathbb{B}_n\mathbb{B}_i dist_{ni}^{\psi_\lambda}\mathbb{B}_{ni}\, \mathcal{P}_{\mathrm{n}}{}^{-\epsilon} w_i{}^{\epsilon} / \sum_{m\in\Omega_g}\sum_{l\epsilon\Omega_g} B_{ml}\left(\frac{w_l}{\kappa_{ml}\mathcal{P}_{\mathrm{m}}}\right)^{\epsilon}$ which, after taking the logarithm, can be rewritten as

$$\ln\lambda_{ni}|_{\Omega_g} = g_0 + S_{\lambda,i} + M_{\lambda,n} + \psi_\lambda \ln dist_{ni} + \ln \mathbb{B}_{ni}$$

where $S_{\lambda,i} \equiv \ln[\mathbb{B}_i w_i{}^{\epsilon}]$ captures the workplace fixed effect, $M_{\lambda,n} \equiv \ln[\mathbb{B}_n\, \mathcal{P}_{\mathrm{n}}{}^{-\epsilon}]$ is the residence fixed effect, $g_0 \equiv \ln\left[1/\sum_{m\in\Omega_g}\sum_{l\epsilon\Omega_g} B_{ml}\left(\frac{w_l}{\kappa_{ml}\mathcal{P}_{\mathrm{m}}}\right)^{\epsilon}\right]$ is a constant and $\ln \mathbb{B}_{ni}$ is, by construction, orthogonal to log distance. After dropping observations with zero commuters ordinary least squares (OLS) estimation yields a coefficient of $\psi_\lambda = -3.92$. Dropping zeros and heteroscedasticity may potentially bias the OLS results. However, in contrast to goods trade (see appendix D) there is no clear indication of heteroscedasticity in the data, and any bias from estimation via OLS turns out to be small as estimating the gravity in commuting equation in its multiplicative form using PPML leads to a similar coefficient of -3.67.

The commuting elasticity ϵ can finally be extracted by using the fact that workplace fixed effects are given by $S_{\lambda,i} \equiv \ln[\mathbb{B}_i {w_i}^{\epsilon}]$. Fixing the estimate of $\psi_\lambda = -3.67$ we rerun the estimation of the commuting gravity equation, now using the mentioned definition of the workplace fixed effect, $\ln\lambda_{ni}|_{\Omega_g} = g_0 + M_{\lambda,n} + \epsilon \ln w_i + \psi_\lambda \ln dist_{ni} + \ln u_{ni}$ where $\ln u_{ni} \equiv \ln B_i + \ln \mathbb{B}_{ni}$. To account for the potential endogeneity between wages and commuting inflows (workplace wages depend on the supply of commuters and this supply depends on amenities appearing in the error term $\ln u_{ni}$) we follow Monte et al. (2018) and instrument wages w_i with the technology levels A_i obtained from our model inversion in section 5. Unfortunately, there is currently no consistent estimator that allows to estimate the gravity equation with an instrument variable specification and using fixed effects. However, our previous results showed that the bias introduced from the OLS estimator is small and we therefore feel confident in following Monte et al. (2018) in the estimation of the mentioned linearized version of our gravity equation with 2SLS after dropping observations with zero commuters. Our highly significant 2SLS estimate for ϵ is 4.56 with a clustered standard error of 0.148.[59] The fact that our estimate is substantially larger than for the US case is in line with our observation of stronger commuting flows in Germany.

[59]As in Monte et al. (2018) we find a p-value of the F-statistic of numerically 0 in the first stage, underscoring the validity of the instrument. However, in contrast to their work we find the results from a direct estimation via OLS ($\epsilon = 4.51$) or PPML ($\epsilon = 4.80$) to show only a small bias.

F Regression results: Baseline scenario with other housing shares

F1 Regression results for employment elasticities, housing share 25%

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.192^{***}	-0.682^{***}	-0.694^{***}				-0.406^{***}	-0.520^{***}
		(0.027)	(0.069)	(0.070)				(0.029)	(0.050)
$\log(w_i)$			1.087^{***}	1.103^{***}				0.181^{***}	0.415^{***}
			(0.118)	(0.181)				(0.052)	(0.091)
$\log(H_i)$			0.455^{***}	0.428^{***}				0.389^{***}	0.430^{***}
			(0.070)	(0.069)				(0.028)	(0.049)
$\log(L_{-i})$				0.206^{***}					
				(0.041)					
$\log(w_{-i})$				-0.438^{*}					
				(0.247)					
$\lambda^R_{ii\|i}$					-2.476^{***}				
					(0.053)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.165^{***}		0.128^{***}	
						(0.019)		(0.016)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-1.869^{***}		-1.889^{***}	
						(0.059)		(0.053)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.684^{***}		0.495^{***}	
						(0.050)		(0.044)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.601^{***}		0.478^{***}
							(0.041)		(0.038)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-1.840^{***}		-1.820^{***}
							(0.122)		(0.122)
Constant	2.992^{***}	5.067^{***}	-6.416^{***}	-4.469^{***}	4.477^{***}	3.238^{***}	3.129^{***}	1.445^{***}	-0.497
	(0.020)	(0.292)	(1.229)	(1.648)	(0.033)	(0.043)	(0.034)	(0.543)	(0.945)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.112	0.289	0.333	0.846	0.834	0.557	0.892	0.657
Adjusted R^2	0.000	0.110	0.284	0.324	0.846	0.833	0.554	0.890	0.652

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

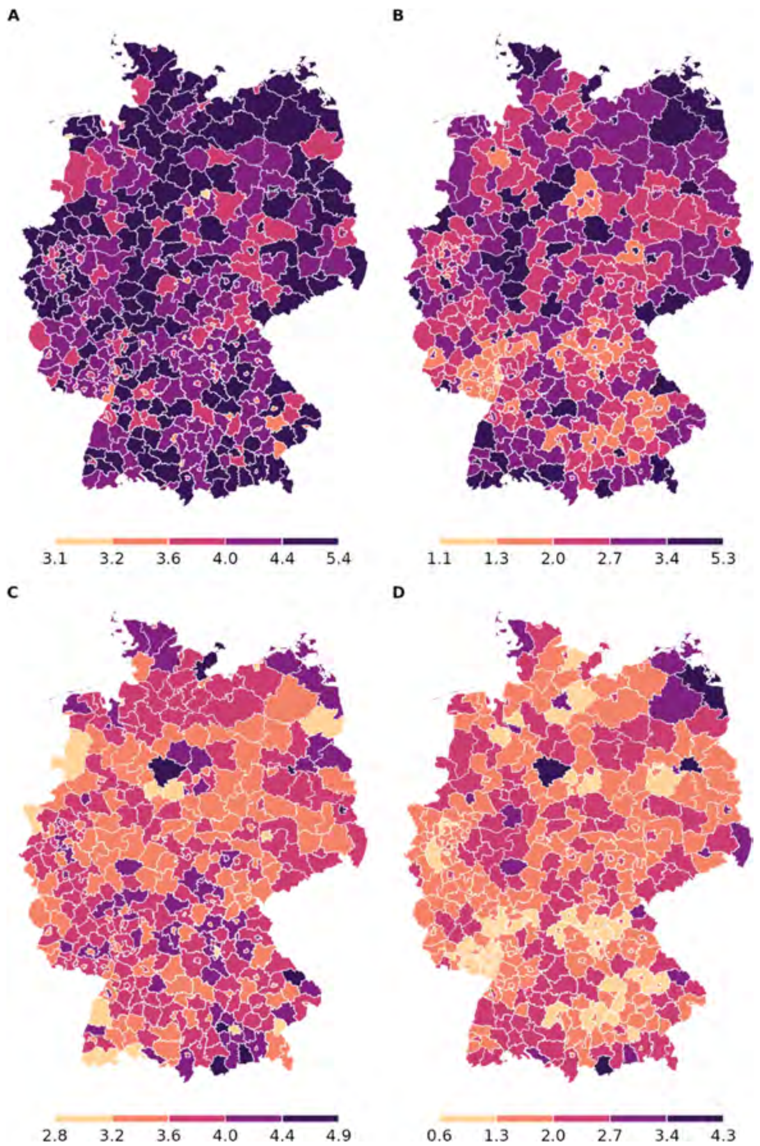
F2 Regression results for employment elasticities, housing share 40%

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.232^{***}	-0.780^{***}	-0.803^{***}				-0.489^{***}	-0.605^{***}
		(0.033)	(0.084)	(0.084)				(0.027)	(0.054)
$\log(w_i)$			1.338^{***}	1.398^{***}				0.114^{**}	0.369^{***}
			(0.144)	(0.218)				(0.049)	(0.099)
$\log(H_i)$			0.497^{***}	0.461^{***}				0.462^{***}	0.496^{***}
			(0.085)	(0.083)				(0.027)	(0.054)
$\log(L_{-i})$				0.294^{***}					
				(0.049)					
$\log(w_{-i})$				-0.686^{**}					
				(0.297)					
$\lambda^R_{ii\|i}$					-3.084^{***}				
					(0.054)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.176^{***}		0.121^{***}	
						(0.020)		(0.016)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-2.428^{***}		-2.497^{***}	
						(0.063)		(0.050)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.562^{***}		0.304^{***}	
						(0.053)		(0.042)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.666^{***}		0.513^{***}
							(0.045)		(0.042)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-2.672^{***}		-2.722^{***}
							(0.135)		(0.133)
Constant	2.665^{***}	5.172^{***}	-8.839^{***}	-5.782^{***}	4.516^{***}	3.185^{***}	2.948^{***}	2.246^{***}	0.013
	(0.024)	(0.355)	(1.499)	(1.985)	(0.033)	(0.046)	(0.038)	(0.517)	(1.026)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.111	0.283	0.343	0.891	0.875	0.631	0.933	0.725
Adjusted R^2	0.000	0.109	0.278	0.335	0.891	0.874	0.629	0.932	0.722

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

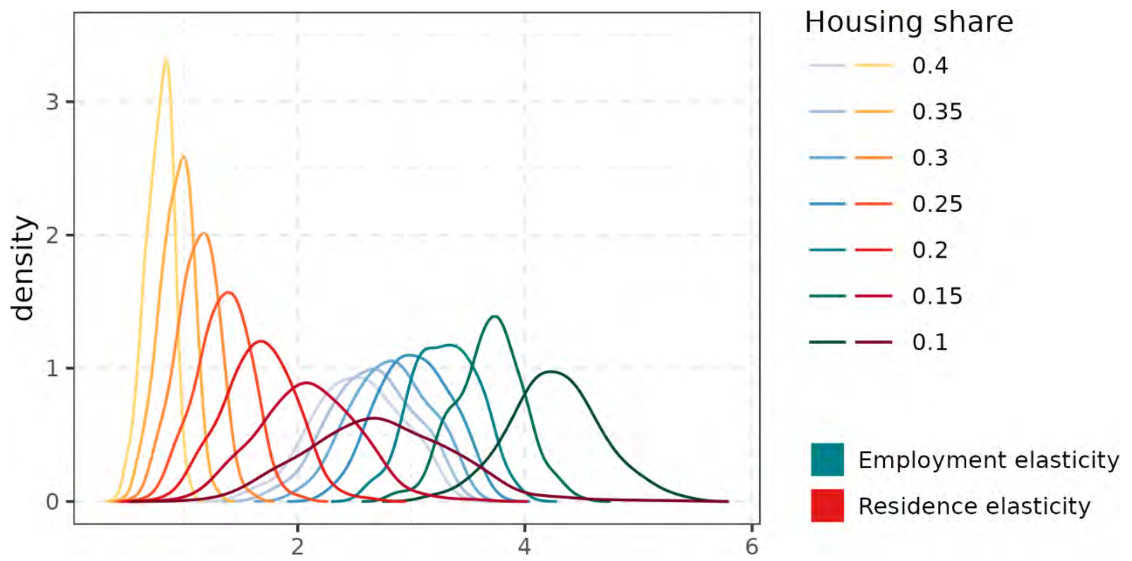
G Results for all trade with uniform housing share

G1 Employment and Resident elasticities: Baseline, housing share 10%, all trade



Note: For ease of comparison the results with all trade for employment elasticities (panel A) and resident elasticities (B) are contrasted with the respective results with manufacturing trade only, panels C and D (which replicate Figure 6)

G2 Kernel densities for employment and resident elasticities for alternative housing shares



G3 Regression results for employment elasticities, housing share 10%

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		0.065**	−0.832***	−0.761***				−0.325***	−0.525***
		(0.030)	(0.064)	(0.064)				(0.064)	(0.060)
$\log(w_i)$			−0.055	−0.467***				0.305***	0.367***
			(0.109)	(0.165)				(0.095)	(0.098)
$\log(H_i)$			1.043***	1.036***				0.588***	0.762***
			(0.064)	(0.063)				(0.061)	(0.057)
$\log(L_{-i})$				−0.196***					
				(0.037)					
$\log(w_{-i})$				1.062***					
				(0.225)					
$\lambda^R_{ii\|i}$					−0.139				
					(0.139)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.309***		0.403***	
						(0.038)		(0.036)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						1.006***		1.012***	
						(0.114)		(0.098)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						2.126***		2.021***	
						(0.144)		(0.152)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.683***		0.687***
							(0.070)		(0.068)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							2.243***		1.981***
							(0.154)		(0.141)
Constant	4.266***	3.567***	2.101*	−2.737*	4.349***	2.240***	3.346***	−4.149***	−3.423***
	(0.020)	(0.319)	(1.135)	(1.504)	(0.086)	(0.123)	(0.067)	(1.003)	(1.018)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.012	0.435	0.482	0.002	0.428	0.356	0.656	0.628
Adjusted R^2	0.000	0.009	0.431	0.476	−0.00002	0.424	0.353	0.650	0.623

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

G4 Regression results for employment elasticities, housing share 25%

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.156^{***}	-0.778^{***}	-0.763^{***}				-0.419^{***}	-0.621^{***}
		(0.020)	(0.046)	(0.046)				(0.030)	(0.036)
$\log(w_i)$			0.697^{***}	0.516^{***}				0.142^{***}	0.228^{***}
			(0.079)	(0.117)				(0.044)	(0.060)
$\log(H_i)$			0.648^{***}	0.616^{***}				0.444^{***}	0.611^{***}
			(0.046)	(0.045)				(0.028)	(0.035)
$\log(L_{-i})$				0.161^{***}					
				(0.026)					
$\log(w_{-i})$				-0.041					
				(0.158)					
$\lambda^R_{ii\|i}$					-1.841^{***}				
					(0.041)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.264^{***}		0.197^{***}	
						(0.017)		(0.016)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-0.963^{***}		-1.023^{***}	
						(0.052)		(0.045)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						1.520^{***}		0.950^{***}	
						(0.067)		(0.071)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.684^{***}		0.373^{***}
							(0.044)		(0.041)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-0.440^{***}		-0.935^{***}
							(0.097)		(0.087)
Constant	2.932^{***}	4.614^{***}	-3.430^{***}	-3.245^{***}	4.036^{***}	2.112^{***}	2.707^{***}	0.558	0.383
	(0.015)	(0.216)	(0.819)	(1.074)	(0.025)	(0.057)	(0.042)	(0.461)	(0.622)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.132	0.437	0.493	0.836	0.769	0.522	0.861	0.733
Adjusted R^2	0.000	0.129	0.433	0.486	0.835	0.767	0.520	0.858	0.730

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01

G5 Regression results for employment elasticities, housing share 40%

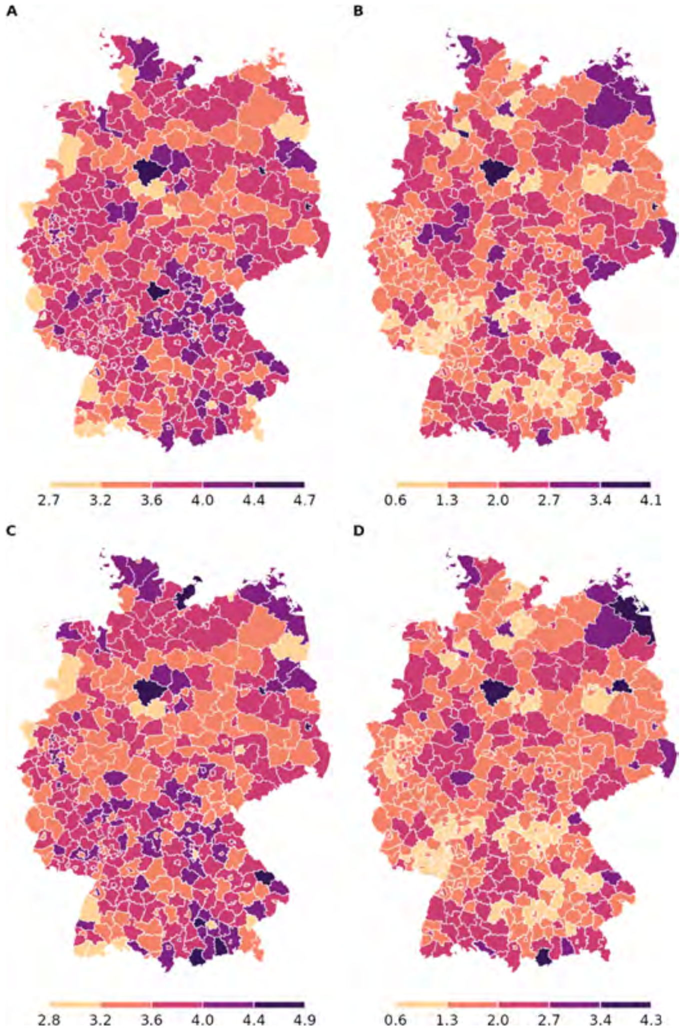
	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.229^{***}	-0.790^{***}	-0.790^{***}				-0.463^{***}	-0.677^{***}
		(0.025)	(0.064)	(0.062)				(0.032)	(0.041)
$\log(w_i)$			1.010^{***}	0.917^{***}				0.093^{**}	0.195^{***}
			(0.109)	(0.161)				(0.046)	(0.067)
$\log(H_i)$			0.546^{***}	0.501^{***}				0.420^{***}	0.592^{***}
			(0.064)	(0.061)				(0.030)	(0.039)
$\log(L_{-i})$				0.272^{***}					
				(0.036)					
$\log(w_{-i})$				-0.395^{*}					
				(0.220)					
$\lambda^R_{ii\|i}$					-2.530^{***}				
					(0.034)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.255^{***}		0.137^{***}	
						(0.018)		(0.017)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-1.731^{***}		-1.814^{***}	
						(0.054)		(0.048)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						1.335^{***}		0.610^{***}	
						(0.069)		(0.075)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.704^{***}		0.284^{***}
							(0.048)		(0.046)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-1.438^{***}		-2.020^{***}
							(0.105)		(0.097)
Constant	2.522^{***}	4.996^{***}	-5.907^{***}	-4.188^{***}	4.040^{***}	2.128^{***}	2.546^{***}	2.003^{***}	1.461^{**}
	(0.019)	(0.276)	(1.136)	(1.467)	(0.021)	(0.059)	(0.045)	(0.492)	(0.696)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.168	0.360	0.443	0.931	0.853	0.662	0.906	0.803
Adjusted R^2	0.000	0.166	0.356	0.436	0.931	0.852	0.661	0.905	0.801

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01

H Results for heterogeneous housing shares

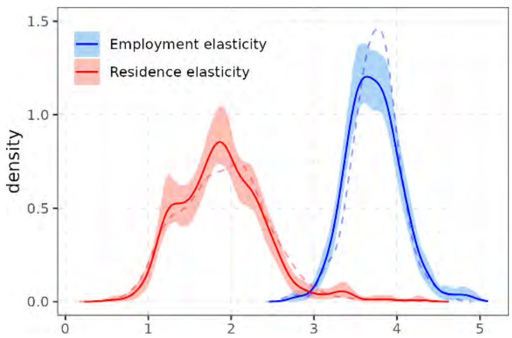
H1 Baseline scenario with manufacturing trade and average housing share of 10%

H11 Employment and resident elasticities



Note: For ease of comparison the results with heterogeneous housing expenditure shares for employment elasticities (panel A) and resident elasticities (B) are contrasted with the respective results with homogeneous housing expenditure shares, panels C and D (which replicate Figure 6)

H12 Kernel densities



Kernel densities for employment elasticities (blue) and resident elasticities (red) with heterogeneous housing shares. Average housing share is 10%. Dashed curves depict the baseline with uniform housing shares, only. Shaded areas show the 95% confidence bands. This is Figure 7 in the main text.

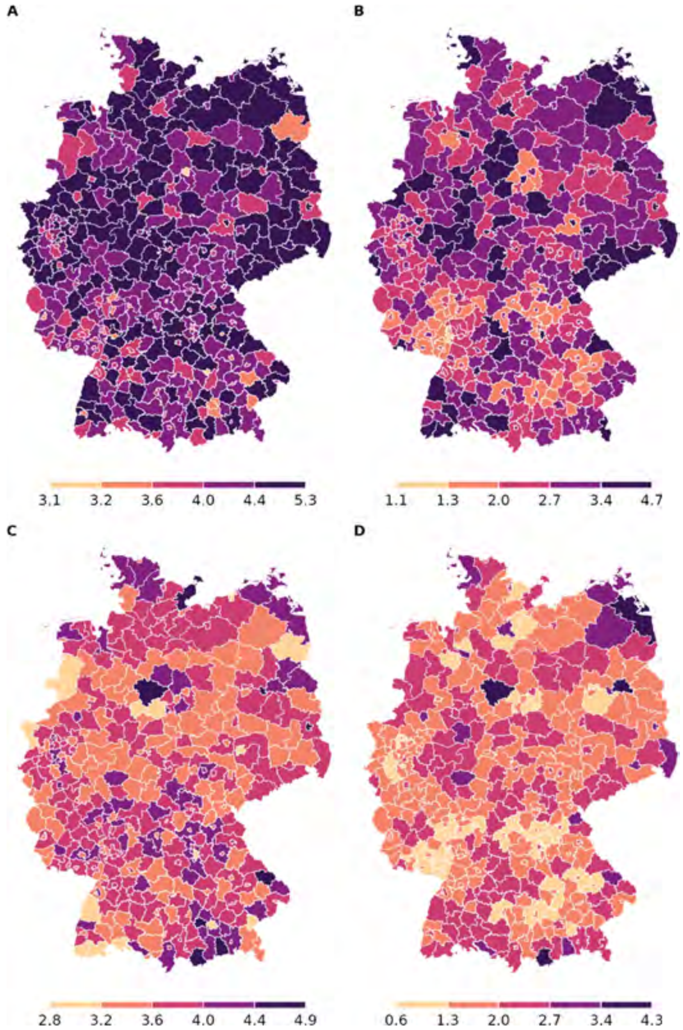
H13 Regression results

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.101^{***}	-0.317^{***}	-0.319^{***}				-0.089^{*}	-0.200^{***}
		(0.021)	(0.058)	(0.060)				(0.049)	(0.055)
$\log(w_i)$			0.181^{*}	0.160				-0.014	0.180^{*}
			(0.099)	(0.155)				(0.089)	(0.101)
$\log(H_i)$			0.232^{***}	0.218^{***}				0.102^{**}	0.160^{***}
			(0.058)	(0.059)				(0.049)	(0.055)
$\log(L_{-i})$				0.084^{**}					
				(0.035)					
$\log(w_{-i})$				-0.135					
				(0.212)					
$\lambda^R_{ii\|i}$					-0.935^{***}				
					(0.088)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.123^{***}		0.118^{***}	
						(0.026)		(0.028)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-0.515^{***}		-0.546^{***}	
						(0.083)		(0.091)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.932^{***}		0.884^{***}	
						(0.070)		(0.076)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.403^{***}		0.354^{***}
							(0.041)		(0.043)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							0.170		0.193
							(0.122)		(0.136)
Constant	3.736^{***}	4.826^{***}	2.613^{**}	3.203^{**}	4.297^{***}	3.356^{***}	3.538^{***}	3.370^{***}	1.987^{*}
	(0.015)	(0.223)	(1.030)	(1.414)	(0.054)	(0.061)	(0.034)	(0.937)	(1.051)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.056	0.093	0.107	0.220	0.405	0.199	0.413	0.227
Adjusted R^2	0.000	0.054	0.086	0.095	0.218	0.401	0.195	0.404	0.217

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

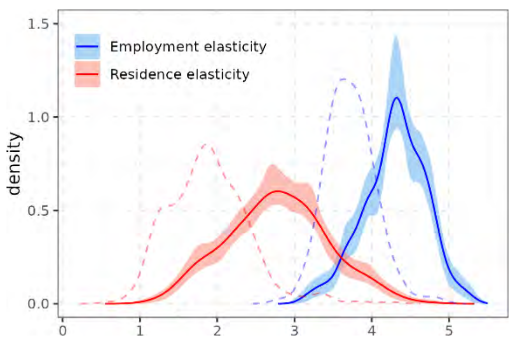
H2 All trade (service and manufacturing) and average housing share of 10%

H21 Employment and resident elasticities



Note: For ease of comparison the results with heterogeneous housing expenditure shares and all trade for employment elasticities (panel A) and resident elasticities (B) are contrasted with the respective results with homogeneous housing expenditure shares and manufacturing trade only, panels C and D (which replicate Figure 6)

H22 Kernel densities



Kernel densities for employment elasticities (blue) and resident elasticities (red) with heterogeneous housing expenditure shares and all trade. Average housing share is 10%. Dashed curves depict the baseline with uniform housing shares and manufacturing trade only. Shaded areas show the 95% confidence bands.

H23 Regression results

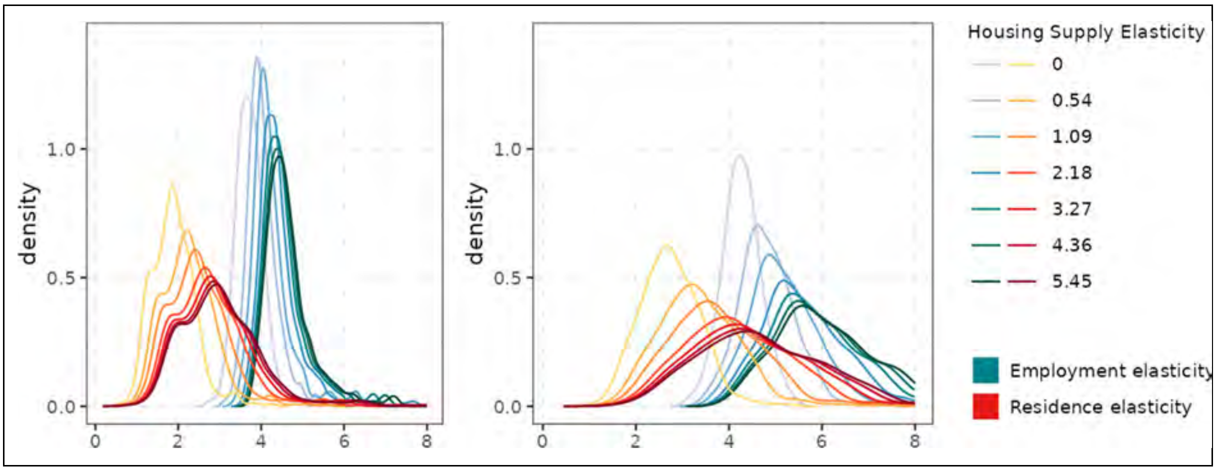
	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		0.034	-0.595^{***}	-0.541^{***}				-0.071	-0.310^{***}
		(0.029)	(0.065)	(0.068)				(0.068)	(0.064)
$\log(w_i)$			-0.667^{***}	-1.034^{***}				-0.351^{***}	-0.274^{***}
			(0.112)	(0.175)				(0.100)	(0.105)
$\log(H_i)$			0.794^{***}	0.762^{***}				0.327^{***}	0.534^{***}
			(0.066)	(0.067)				(0.064)	(0.061)
$\log(L_{-i})$				0.018					
				(0.039)					
$\log(w_{-i})$				0.561^{**}					
				(0.238)					
$\lambda^R_{ii\|i}$					0.014				
					(0.137)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.303^{***}		0.378^{***}	
						(0.036)		(0.037)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						1.102^{***}		0.880^{***}	
						(0.109)		(0.103)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						2.110^{***}		2.087^{***}	
						(0.138)		(0.160)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.648^{***}		0.637^{***}
							(0.067)		(0.072)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							2.347^{***}		1.841^{***}
							(0.148)		(0.151)
Constant	4.297^{***}	3.935^{***}	8.918^{***}	6.313^{***}	4.288^{***}	2.248^{***}	3.367^{***}	3.130^{***}	3.778^{***}
	(0.020)	(0.316)	(1.162)	(1.592)	(0.085)	(0.118)	(0.064)	(1.056)	(1.088)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.003	0.390	0.402	0.00003	0.463	0.393	0.607	0.561
Adjusted R^2	0.000	0.001	0.386	0.395	-0.002	0.459	0.389	0.601	0.556

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01

H3 Overview table

	Uniform housing share in all counties		Heterogeneous housing share	
Mean employment elasticity	**(1) Manufacturing trade**	**(2) All trade**	**(3) Manufacturing trade**	**(4) All trade**
Housing share 10%	3.72	4.27	3.74	4.30
Housing share 25%	2.99	3.02	3.02	3.06
Housing share 40%	2.66	2.52	2.69	2.56
Mean resident elasticity				
Housing share 10%	1.89	2.74	1.91	2.78
Housing share 25%	1.01	1.35	1.04	1.40
Housing share 40%	0.61	0.78	0.64	0.83

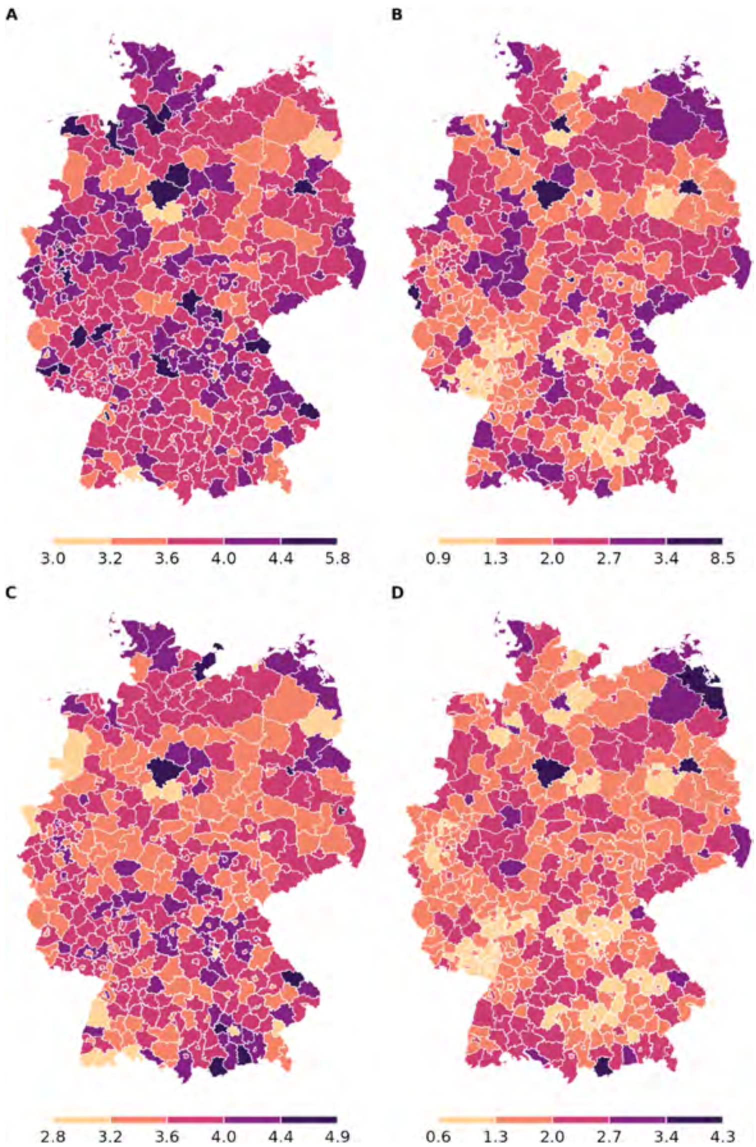
I Results with positive housing supply elasticities



Evolution of kernel densities for employment elasticities (blue) and resident elasticities (yellow to red) when the housing supply elasticity is raised in steps from $\eta = 0$ to $\eta = 5.45$. Left panel: baseline, manufacturing trade only; Right panel: all trade;

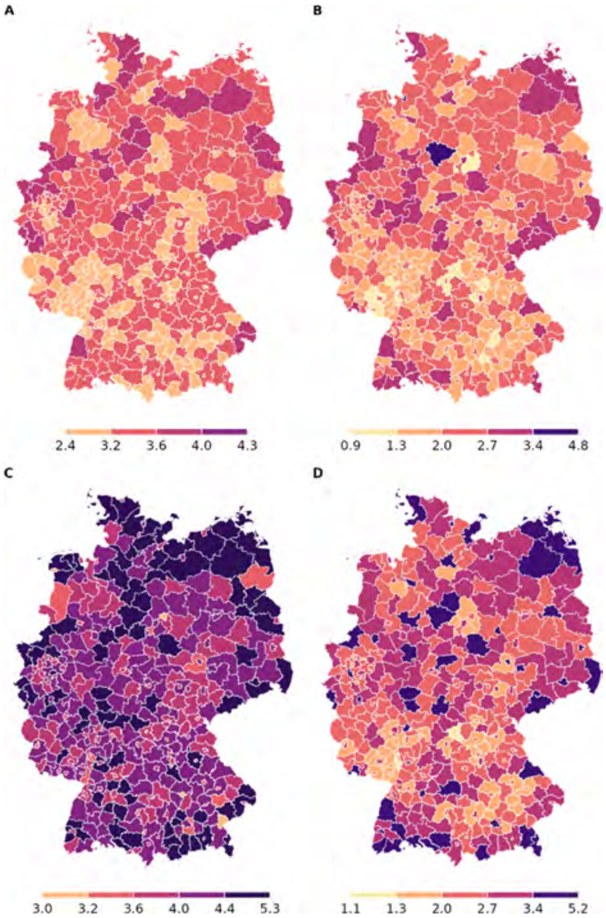
J Results when international trade is shut down

J1 Employment and resident elasticities, manufacturing, closed economy



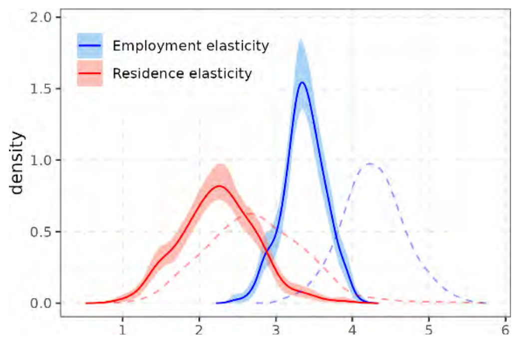
Note: For ease of comparison the results for the (internationally) closed economy for employment elasticities (panel A) and resident elasticities (B) are contrasted with the respective results with international trade, panels C and D (which replicate Figure 6)

J2 Employment and resident elasticities, all trade, closed economy



Note: For ease of comparison the results for the (internationally) closed economy for employment elasticities (panel A) and resident elasticities (B) with all (regional) trade are contrasted with the respective results with international trade, panels C and D.

J3 Kernel densities for employment and resident elasticities, all trade, closed economy



Kernel densities for employment elasticities (blue) and resident elasticities (red) in the (internationally) closed economy with all (regional) trade. Average housing share is 10%. Dashed curves depict the open economy with all trade (manufacturing and services). Shaded areas show the 95% confidence bands.

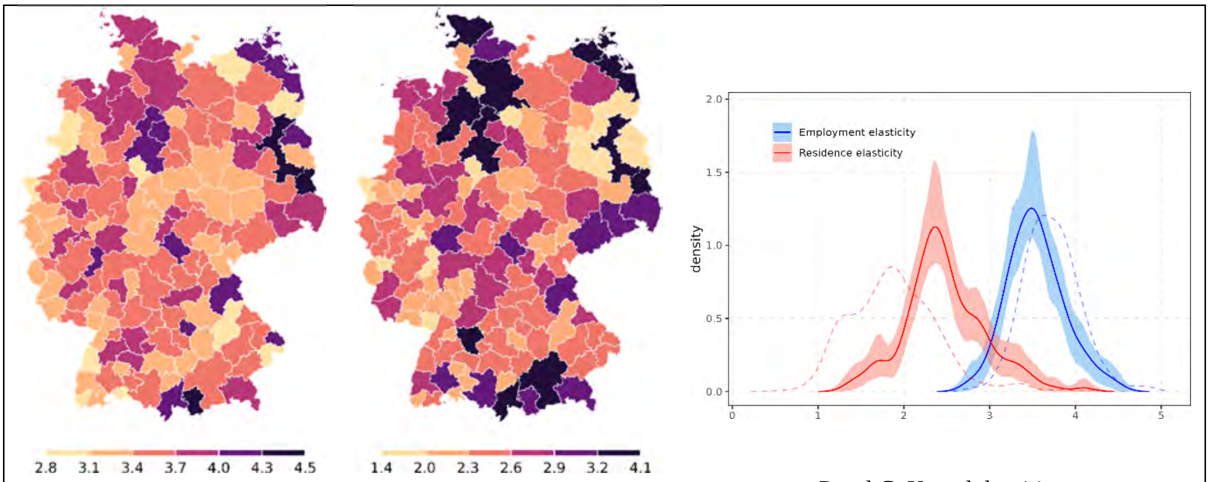
J4 Regression results for employment elasticities, all trade, closed economy

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		0.035^{*}	-0.566^{***}	-0.496^{***}				-0.415^{***}	-0.489^{***}
		(0.020)	(0.041)	(0.040)				(0.047)	(0.036)
$\log(w_i)$			-0.175^{**}	-0.593^{***}				0.163^{***}	0.170^{***}
			(0.071)	(0.103)				(0.062)	(0.062)
$\log(H_i)$			0.713^{***}	0.702^{***}				0.565^{***}	0.627^{***}
			(0.042)	(0.039)				(0.041)	(0.034)
$\log(L_{-i})$				-0.164^{***}					
				(0.023)					
$\log(w_{-i})$				1.008^{***}					
				(0.140)					
$\lambda^R_{ii\|i}$					0.147				
					(0.094)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.149^{***}		0.167^{***}	
						(0.026)		(0.024)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						0.913^{***}		0.871^{***}	
						(0.079)		(0.064)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						1.178^{***}		0.831^{***}	
						(0.122)		(0.141)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.229^{***}		0.200^{***}
							(0.040)		(0.034)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							1.356^{***}		1.146^{***}
							(0.094)		(0.077)
Constant	3.364^{***}	2.986^{***}	3.329^{***}	-1.269	3.276^{***}	1.984^{***}	2.815^{***}	-1.381^{**}	-0.696
	(0.014)	(0.216)	(0.736)	(0.936)	(0.058)	(0.106)	(0.047)	(0.653)	(0.644)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.008	0.480	0.561	0.006	0.408	0.350	0.680	0.672
Adjusted R^2	0.000	0.005	0.476	0.556	0.004	0.403	0.346	0.675	0.668

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

K Results for Commuting Zones

K1 Employment and resident elasticities, kernel densities, uniform housing share 10%



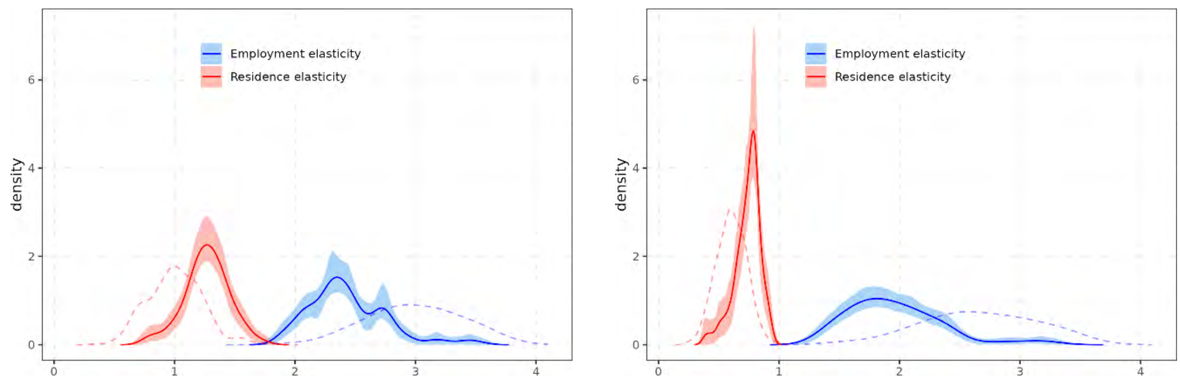
Panel A:
Employment elasticities

Panel B:
Resident elasticities

Panel C: Kernel densities

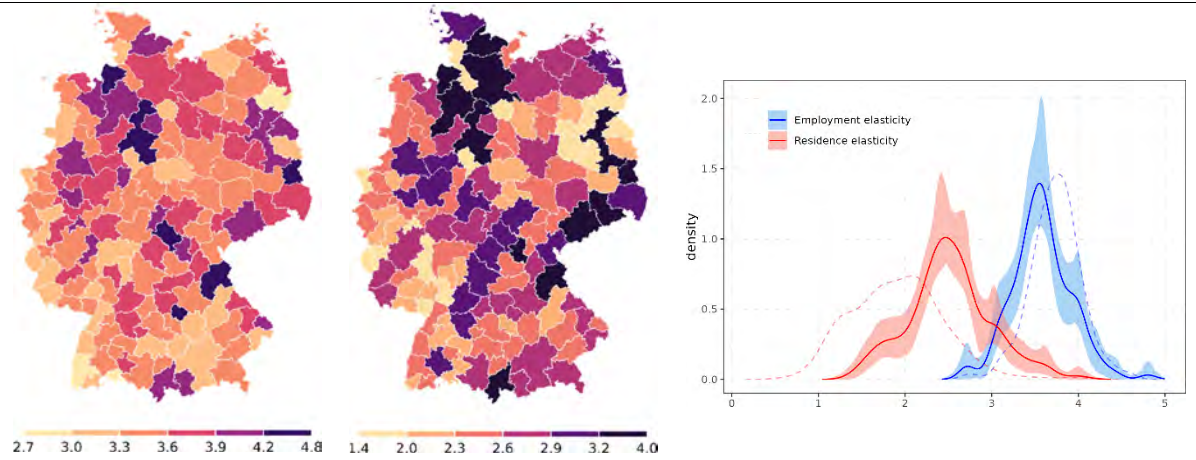
General equilibrium employment elasticities (panel A) and resident elasticities (panel B) in treated CZs in response to counterfactual 5% productivity shocks. Panel C depicts the associated kernel densities for employment elasticities (blue) and resident elasticities (red). Dashed curves represent results from the same scenario at the county level. Shaded areas depict 95% confidence bands.

K2 Kernel densities of employment and resident elasticities, uniform housing shares of 25% and 40%



Kernel densities for employment elasticities (blue) and resident elasticities (red) at the level of CZs with uniform housing shares of 25% (left panel) and 40% (right panel). Dashed curves represent results from the same scenarios at the county level. Shaded areas depict 95% confidence bands.

K3 Employment and resident elasticities, kernel densities, heterogeneous housing share at average level of 10%



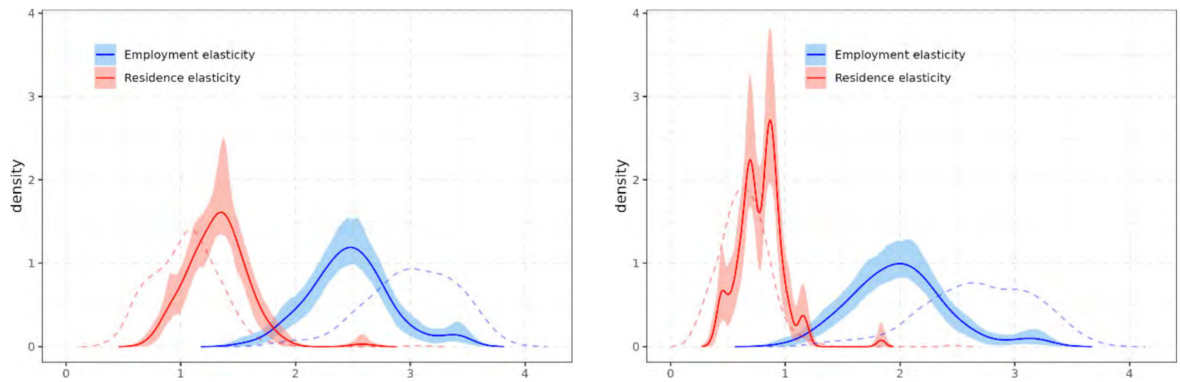
Panel A: Employment elasticities

Panel B: Resident elasticities

Panel C: Kernel densities

General equilibrium employment elasticities (panel A) and resident elasticities (panel B) in treated CZs in response to counterfactual 5% productivity shocks with heterogeneous housing/land shares. Panel C depicts the associated kernel densities for employment elasticities (blue) and resident elasticities (red). Dashed curves represent results from the same scenario at the county level. Shaded areas depict 95% confidence bands.

K4 Kernel densities of employment and resident elasticities, heterogeneous housing share at average levels of 25% and 40%



Kernel densities for employment elasticities (blue) and resident elasticities (red) at the level of CZs with heterogeneous housing shares with average levels of 25% (left panel) and 40% (right panel). Dashed curves represent results from the same scenarios at the county level. Shaded areas depict 95% confidence bands.

K5 Regression results for employment regressions, uniform housing share of 10%

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		0.0002	-0.557^{***}	-0.531^{**}				-0.477^{***}	-0.596^{***}
		(0.031)	(0.208)	(0.213)				(0.178)	(0.192)
$\log(w_i)$			0.145	0.431				0.572^{***}	0.719^{***}
			(0.217)	(0.325)				(0.188)	(0.206)
$\log(H_i)$			0.583^{***}	0.535^{**}				0.505^{***}	0.597^{***}
			(0.213)	(0.219)				(0.174)	(0.189)
$\log(L_{-i})$				0.006					
				(0.068)					
$\log(w_{-i})$				-0.545					
				(0.466)					
$\lambda^R_{ii\|i}$					-0.796^{***}				
					(0.262)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.030		0.073	
						(0.045)		(0.051)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-0.666^{**}		-0.400	
						(0.282)		(0.282)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						1.500^{***}		1.687^{***}	
						(0.178)		(0.183)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.370^{***}		0.383^{***}
							(0.067)		(0.075)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							1.405^{***}		1.781^{***}
							(0.245)		(0.267)
Constant	3.541^{***}	3.538^{***}	1.423	4.441	4.165^{***}	3.224^{***}	2.982^{***}	-3.730^{*}	-5.101^{**}
	(0.028)	(0.361)	(2.230)	(3.387)	(0.207)	(0.232)	(0.089)	(2.010)	(2.104)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.00000	0.052	0.062	0.062	0.379	0.263	0.451	0.352
Adjusted R^2	0.000	-0.007	0.031	0.027	0.055	0.366	0.252	0.426	0.328

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

K6 Regression results for employment regressions heterogeneous housing share, average 10%

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.023	-0.263	-0.328				-0.186	-0.279
		(0.032)	(0.218)	(0.219)				(0.199)	(0.216)
$\log(w_i)$			-0.292	-0.115				0.023	0.183
			(0.227)	(0.334)				(0.211)	(0.231)
$\log(H_i)$			0.285	0.306				0.210	0.283
			(0.223)	(0.225)				(0.195)	(0.212)
$\log(L_{-i})$				0.156^{**}					
				(0.070)					
$\log(w_{-i})$				-0.611					
				(0.480)					
$\lambda^R_{ii\|i}$					-0.835^{***}				
					(0.272)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.011		0.011	
						(0.047)		(0.057)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-0.766^{**}		-0.759^{**}	
						(0.298)		(0.315)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						1.491^{***}		1.484^{***}	
						(0.188)		(0.205)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.352^{***}		0.339^{***}
							(0.071)		(0.084)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							1.390^{***}		1.489^{***}
							(0.260)		(0.299)
Constant	3.578^{***}	3.843^{***}	6.319^{***}	9.141^{***}	4.232^{***}	3.343^{***}	3.028^{***}	2.724	0.869
	(0.029)	(0.374)	(2.330)	(3.487)	(0.215)	(0.245)	(0.094)	(2.248)	(2.361)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.004	0.038	0.076	0.064	0.354	0.231	0.362	0.242
Adjusted R^2	0.000	-0.004	0.017	0.042	0.057	0.340	0.219	0.333	0.214

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

K7 Regression results for employment regressions, uniform housing share of 25 %

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.150^{***}	-0.821^{***}	-0.942^{***}				-0.217^{***}	-0.249
		(0.028)	(0.182)	(0.170)				(0.074)	(0.160)
$\log(w_i)$			0.609^{***}	0.850^{***}				0.195^{**}	0.317^{*}
			(0.190)	(0.259)				(0.079)	(0.172)
$\log(H_i)$			0.661^{***}	0.711^{***}				0.186^{**}	0.213
			(0.186)	(0.175)				(0.073)	(0.157)
$\log(L_{-i})$				0.276^{***}					
				(0.054)					
$\log(w_{-i})$				-0.943^{**}					
				(0.372)					
$\lambda^R_{ii\|i}$					-2.894^{***}				
					(0.109)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.014		-0.006	
						(0.018)		(0.021)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-2.525^{***}		-2.464^{***}	
						(0.116)		(0.118)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.605^{***}		0.648^{***}	
						(0.073)		(0.077)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.549^{***}		0.521^{***}
							(0.053)		(0.062)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-0.674^{***}		-0.463^{**}
							(0.194)		(0.222)
Constant	2.436^{***}	4.198^{***}	-2.501	1.722	4.704^{***}	3.761^{***}	2.468^{***}	1.913^{**}	-0.659
	(0.027)	(0.325)	(1.944)	(2.704)	(0.086)	(0.095)	(0.070)	(0.843)	(1.754)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.175	0.268	0.393	0.835	0.893	0.528	0.902	0.542
Adjusted R^2	0.000	0.169	0.252	0.370	0.834	0.891	0.521	0.897	0.525

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

K8 Regression results for employment regressions heterogeneous housing share, average 25%

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.168^{***}	-0.556^{***}	-0.751^{***}				0.043	0.032
		(0.031)	(0.212)	(0.188)				(0.137)	(0.203)
$\log(w_i)$			0.202	0.382				-0.306^{**}	-0.171
			(0.221)	(0.287)				(0.146)	(0.218)
$\log(H_i)$			0.397^{*}	0.500^{**}				-0.074	-0.061
			(0.217)	(0.193)				(0.135)	(0.199)
$\log(L_{-i})$				0.404^{***}					
				(0.060)					
$\log(w_{-i})$				-1.058^{**}					
				(0.412)					
$\lambda^R_{ii\|i}$					-2.894^{***}				
					(0.172)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						-0.003		-0.060	
						(0.034)		(0.039)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-2.586^{***}		-2.760^{***}	
						(0.213)		(0.218)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.603^{***}		0.469^{***}	
						(0.135)		(0.142)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.529^{***}		0.480^{***}
							(0.067)		(0.079)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-0.663^{***}		-0.709^{**}
							(0.245)		(0.282)
Constant	2.479^{***}	4.445^{***}	2.002	6.388^{**}	4.748^{***}	3.857^{***}	2.515^{***}	7.737^{***}	4.746^{**}
	(0.031)	(0.362)	(2.271)	(2.990)	(0.136)	(0.175)	(0.089)	(1.556)	(2.223)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.176	0.196	0.402	0.672	0.710	0.397	0.731	0.409
Adjusted R^2	0.000	0.170	0.178	0.380	0.670	0.703	0.389	0.719	0.387

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

K9 Regression results for employment regressions, uniform housing share of 40 %

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.200^{***}	-0.954^{***}	-1.121^{***}				-0.142^{**}	-0.154
		(0.033)	(0.214)	(0.196)				(0.059)	(0.176)
$\log(w_i)$			0.776^{***}	1.041^{***}				0.070	0.189
			(0.224)	(0.298)				(0.063)	(0.189)
$\log(H_i)$			0.734^{***}	0.811^{***}				0.102^{*}	0.114
			(0.219)	(0.201)				(0.058)	(0.173)
$\log(L_{-i})$				0.368^{***}					
				(0.062)					
$\log(w_{-i})$				-1.153^{***}					
				(0.428)					
$\lambda^R_{ii\|i}$					-3.671^{***}				
					(0.091)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.011		-0.024	
						(0.015)		(0.017)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-3.213^{***}		-3.215^{***}	
						(0.094)		(0.093)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.342^{***}		0.339^{***}	
						(0.059)		(0.061)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.628^{***}		0.593^{***}
							(0.058)		(0.068)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-1.364^{***}		-1.215^{***}
							(0.212)		(0.245)
Constant	1.956^{***}	4.293^{***}	-4.110^{*}	0.938	4.833^{***}	3.853^{***}	2.179^{***}	3.561^{***}	0.539
	(0.033)	(0.384)	(2.296)	(3.108)	(0.072)	(0.077)	(0.077)	(0.667)	(1.930)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.211	0.300	0.450	0.921	0.952	0.615	0.958	0.620
Adjusted R^2	0.000	0.206	0.285	0.430	0.920	0.951	0.609	0.956	0.606

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01

K10 Regression results for employment regressions heterogeneous housing share, average 40 %

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.213^{***}	-0.734^{***}	-0.960^{***}				0.072	0.078
		(0.035)	(0.237)	(0.207)				(0.118)	(0.209)
$\log(w_i)$			0.437^{*}	0.662^{**}				-0.346^{***}	-0.218
			(0.248)	(0.315)				(0.126)	(0.224)
$\log(H_i)$			0.516^{**}	0.635^{***}				-0.111	-0.112
			(0.243)	(0.212)				(0.116)	(0.205)
$\log(L_{-i})$				0.473^{***}					
				(0.066)					
$\log(w_{-i})$				-1.266^{***}					
				(0.452)					
$\lambda^R_{ii\|i}$					-3.663^{***}				
					(0.151)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						-0.003		-0.068^{**}	
						(0.030)		(0.034)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-3.257^{***}		-3.454^{***}	
						(0.189)		(0.188)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.340^{***}		0.190	
						(0.119)		(0.122)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.611^{***}		0.558^{***}
							(0.069)		(0.081)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-1.351^{***}		-1.416^{***}
							(0.253)		(0.290)
Constant	1.996^{***}	4.493^{***}	-0.361	4.924	4.867^{***}	3.932^{***}	2.220^{***}	8.391^{***}	5.027^{**}
	(0.035)	(0.409)	(2.540)	(3.288)	(0.120)	(0.155)	(0.092)	(1.339)	(2.285)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.213	0.245	0.457	0.809	0.829	0.519	0.850	0.530
Adjusted R^2	0.000	0.207	0.228	0.437	0.807	0.825	0.512	0.844	0.513

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. Standard errors in parenthesis.
*p<0.1; **p<0.05; ***p<0.01