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IZA DP No. 12257

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ABSTRACT

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

This paper uses the quantitative spatial model with heterogeneous locations linked by costly goods trade, migration and commuting developed in Monte et al. (2018) to address the workings of local labor markets in Germany. One key contribution concerns the analysis of the role of the expenditure share of housing in the economy. We provide arguments that, in accordance with Rognlie (2015), for an economy-wide quantitative exercise, this share should be chosen lower than stipulated in much of the extant research. Our analyses show that the local general equilibrium employment and resident elasticities with respect to local productivity shocks are significantly higher with a lower housing share. Moreover, simple ex-ante observable commuting measures have very little predictive power for these general equilibrium elasticities when the housing share is small. The size of the housing share turns out to play no crucial role for two further results, however. First, employment and resident elasticities are very heterogeneous across German local labor markets, irrespective of the housing share. Second, the housing share has only little influence on the welfare effects and location patterns of counterfactual commuting cost reductions.

JEL Classification: F12, F14, R13, R23

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

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1 Introduction

What once fired the imaginations of 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 budget on traveling from residences to workplaces and these shares have steadily risen in the last decades.[1] The decision of where to live and where to work involves tradeoffs between wages, living costs, amenities, and idiosyncratic factors, such as family ties, networks and personal tastes. These tradeoffs are affected by transport, commuting and migration costs. In a seminal article, Monte et al. (2018) develop a general equilibrium model which integrates these spatial linkages and which is amenable to analytic and quantitative investigation. They highlight the key role that *commuting across local labor markets* plays for the American economy. More specifically, they find that the employment responses to local productivity shocks (local employment elasticities) are large, very heterogeneous across local labor markets, and strongly driven by commuting.[2] This heterogeneity is of paramount importance for local and national policymakers who decide on infrastructure investments, taxes, subsidies and place-based policies.

This paper explores the spatial interactions of local labor markets in Germany, a particularly exciting scientific laboratory for two main reasons. First, improvements in its transport infrastructure are desperately needed. Branded the 'Teflon Teuton', the strongest economy in Europe for the last couple of years, faces potholed roads, rotten bridges and repair-prone railway tracks (Economist 2017). Second, exceptionally good data are available for Germany. Special mention must be made of a unique data set, the traffic forecast administered by the German Federal Ministry of Transport and Digital Infrastructure, which allows us to obtain a detailed portrait of bilateral trade of manufactured goods at the county level. Since such data are usually not available, the extant literature has been forced to impute regional trade shares (e.g. Monte et al. 2018). The backside of such pragmatic approaches is that the numbers may grossly deviate

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[1] Estimates of these costs put the mean round-trip at about 40 minutes and the mean household expenditure share devoted to transportation at 14.6% for a cross-section of advanced economies in recent years (Redding and Turner 2015). Monte et al. (2018) document the increasing prevalence and heterogeneity of commuting streams in the United States: whilst in 1960 the median US county had 91% of its residents working where they lived, this number is down to only 69% in 2000; there are now counties whose workforce consists of more than 80% commuters and still others where about the same share of residents flock to work elsewhere.

[2] The role of commuting follows from the observation that these local employment elasticities are much larger than the corresponding local resident elasticities (the responses of residences to the mentioned local productivity shocks). Monte et al. (2018) also advance independent empirical evidence which corroborates the importance of commuting. They show that the treatment effect of million dollar plants (as considered in Greenstone et al. 2010) is heterogeneously affected by locations' openness to commuting (worker paper versions of their paper also advanced evidence pertaining to the local effects of Chinese imports and to Bartik-shocks).

from the actual values. The traffic data are a big asset for the quality of our analyses of German local labor markets.

We use the quantitative spatial general equilibrium model by Monte et al. (2018) to address the following set of issues. First, how important is commuting for the adjustment of German local labor markets in response to local productivity shocks? Second, Monte et al. (2018) find that model-based, ex ante observable, commuting measures, are powerful predictors for the general equilibrium local employment and resident elasticities in the United States. Are these commuting measures similarly successful for Germany? Third, what are the effects of commuting cost reductions in Germany? Apart from being of supreme importance for Germany, results on these questions also allow us to put the findings of Monte et al. (2018) for the American economy into (an international) perspective.

A further, and critical, issue involves the role that the share of expenditures devoted to land (housing) plays for the findings concerning the first three questions. By addressing this methodological twist our analysis provides an important addition on previous research. To elaborate, since land is the only generically fixed and immobile resource, it is a key parameter for the dispersion of residences in any spatial model.[3] In new quantitative spatial models, the budget share devoted to land is one of the key structural parameters for which the researcher is assumed to have an a priori estimate.[4] The choice of this parameter is not trivial, however, and the values used in the extant literature differ widely, ranging from 10% to 40%. We provide strong arguments that this parameter should be chosen at the lower end (in the range of 10%) when the quantitative general equilibrium model is intended to portray the *aggregate economy*. Against the backdrop of previous research, we also consider possible rationalizations for higher values of this parameter, and we perform quantitative analyses in order to demonstrate where, and how, a difference to our preferred specification matters.

Our key findings are as follows. Regarding the first question we find that the responses of German local labor markets to local productivity shocks – a 5 % increase in local productivity – are very heterogeneous and commuting is key for this heterogeneity. At the level of counties, 90% of local employment elasticities are in the range from 2.83 to 4.17 and the same share of

[3] This holds true irrespective of whether the housing supply, as a short-cut, 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 in addition to other production factors to produce lots, e.g. Duranton and Puga (2015). Pflüger and Tabuchi (2010) highlight the role of land as ultimately the only immobile resource in a new economic geography framework.

[4] In models based on product differentiation (such as the one we use), the other key parameter is the elasticity of substitution between varieties, see Redding and Rossi-Hansberg (2017) for a lucid characterization of this approach.

local resident elasticities are in the range from 1.07 to 2.77, when the budget share spent on land is at 10%. When this share is at 40% these values are much lower. 90% of employment elasticities are then in a range from 1.67 to 2.93 and resident elasticities range from 0.38 to 0.78. The effect of different values for the housing parameter is even more dramatic for commuting zones, in particular for resident elasticities. Intuitively, with a smaller expenditure share on housing, the role of housing as a congestion force is very strongly diminished, implying that more workers will choose to shift their residences (i.e. migrate) instead of commute to the treated labor market. These findings lead to three conclusions. First, the housing share matters strongly for the quantitative effect of local productivity shocks, a low share implies (much) higher employment and resident elasticities. Second, irrespective of the housing share, commuting is very important for labor market adjustment in Germany. In fact, it is a key mechanism which renders German local labor markets flexible to local shocks. Third, and again irrespective of the housing share, heterogeneity is strong, similarly to the findings recorded for the United States.[5] This implies that seriously wrong conclusions would be drawn if some average elasticity across local labor markets was applied by policymakers and local planners.

Concerning the second issue, the predictive power of simple ex-ante commuting-based measures, the size of the housing parameter turns out to be of paramount importance. Applying a housing share of 0.4 as in Monte et al. (2018), we obtain very similar results for Germany as they do for the United States. A location's own commuting share – the share of residents working at their residence –, turns out to be a powerful inverse indicator for the general equilibrium local employment elasticities on the county level implied by the quantitative model, outperforming standard local labor market controls (e.g. wages, employment, housing) by far. The finding also largely carries over when we look at commuting zones rather than administrative counties, except that then the predictive power of the simple measures is lower. A key finding of our analysis is that the results are altogether different, however, when we apply our preferred housing share of 0.1. In this case the simple own commuting share loses almost all explanatory power for the heterogeneity of employment elasticities, both across counties and across commuting zones.[6] This very important finding can be rationalized by noting that general equilibrium repercussions are only imperfectly captured by simple (partial equilibrium-

[5] The quantitative numbers are larger than what is found for the United States when the budget share is at 40% as assumed in Monte et al. (2018). There is, of course, an issue of comparability between Germany counties and the counties in the United States. The same holds true for local labor markets even *within* Germany and *within* the United States as there is typically much stronger commuting activity *within* big cities which are classified as counties (e.g. Berlin) than in more rural counties.

[6] We have focused here just on the finding for the own commuting share, the most simple measure. Our analysis below shows that these findings carry over to other model-based commuting measures.

based) measures and this holds true a fortiori, the lower is the housing share. This is intuitive because a reduction of the housing share weakens a key congestion force in the model.

We consider a corridor of symmetric reductions in commuting costs between all counties in Germany to address the third question. These reductions range from 1% up to 20%. Our general finding is that the resulting welfare and location effects are not strongly affected by the housing share. Focusing on the results with a housing share of 10%, on average, a one percentage point decrease in commuting costs raises welfare by about half a percentage point. The welfare gain amounts to about 4.5 percent as commuting costs are brought down to 0.90, for example. Such a 10% reduction of commuting costs reduces the total share of non-commuters in the German population from 63.1% to 52.4%. As to the location consequences, two types of effects are visible. At a local level, reducing commuting costs increases the number of resident workers in urban counties relative to those in surrounding locations. At the macro level, the reduction in commuting costs also increases agglomeration.

Previous research. Our paper is related to various strands of previous research. Theoretical literature addressing a separation of the location of production from the location of residences is sparse. One exception is Borck et al. (2010), who set up a new economic geography model with two locations, goods trade and commuting, which exhibits demand and supply linkages as agglomeration forces and crowding in goods markets and congestion in housing markets as dispersion forces. Their analysis predicts that a simultaneous fall in distance-related frictions pertaining to trade and commuting leads to an increased spatial concentration of production and a decreased concentration of residences. Hence, an increasing role for commuting is predicted. The model is too stylized for quantitative analysis, however.

Quantification has become the focus of recent research which incorporates an arbitrary number of locations with heterogeneous geography, productivities, amenities, and local factors, as well as trade and commuting costs into the models. This new quantitative spatial economics builds on the new economic geography (or isomorphic models) and derives its thrust from restraining the agglomeration forces 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 meaningfully addressed as outlined in the recent survey by Redding and Rossi-Hansberg (2017). A milestone in this research is the model developed by Redding (2016) which integrates the regional model of Helpman (1998) with 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 to the framework developed in Monte et al (2018), who extend the quantitative spatial model developed by Redding (2016) to include commuting between local labor markets, and who perform a quantitative analysis of local labor market shocks for the United States.

The structure of the remainder of the paper is as follows. Section 2 provides descriptive evidence on German local labor markets. Section 3 introduces the model. Section 4 provides an overview of our data, an extensive discussion of the choice of the housing parameter, and a description of the quantification of the model and the derivation of model-consistent trade costs and local productivities. Sections 5 and 6 cover the quantitative analysis of the network of German local labor markets. Section 5 derives and analyzes the local employment and resident elasticities associated with counterfactual local productivity shocks both on the county level and on the level of commuting zones. Section 6 addresses the effects of a reduction of commuting costs. Section 7 provides concluding remarks.

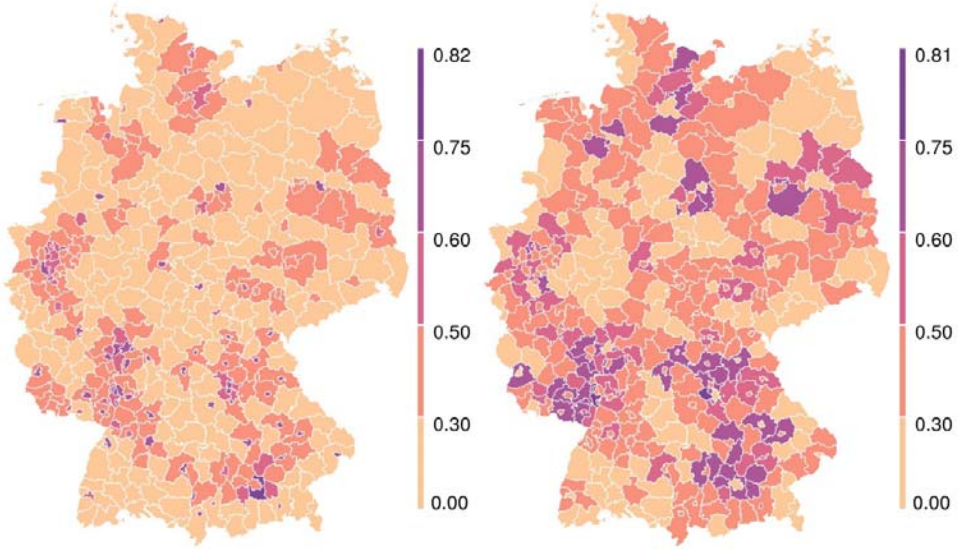
2 Descriptive Evidence

Commuting across local labor markets 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).

Commuter shares. To give a perspective on German local labor markets, the left panel of figure 1 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 Ludwigshafen (county), Fürth (county) and Schweinfurt (county).[7] A visual inspection of the two maps immediately reveals that the intensity of outflows exceeds the intensity of inflows.[8]

[7] The largest nominal inflows can be found in Frankfurt, Munich, Hamburg and Berlin, the largest nominal outflows in Berlin, Munich, Rhein-Sieg-Kreis and Rhein-Neckar-Kreis.
[8] Repeating this exercise for the 141 German commuting zones almost halves the numbers, but leaves the general pattern documented in figure 1 intact.

Distribution of commuters. To bring out this point more clearly, and to have a basis for a casual comparison with the United States, table 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.



(a) commuter share in total workers (b) commuter share in total residents

Figure 1: Share of total workers who commute into counties (panel a) and share of residents who commute out of counties (panel b). See section 4 for the data.

Table 1: Unweighted average commuting statistics across German counties and commuting zones. See section 4 for the data.

	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	1.79	3.59	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	0.06	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	1.16	0.95

The message conveyed by table 1 is reinforced by the kernel densities of the share of non-commuters in residents depicted in figure 2. 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).

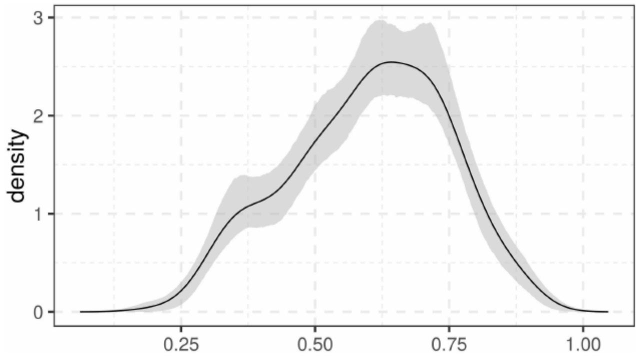
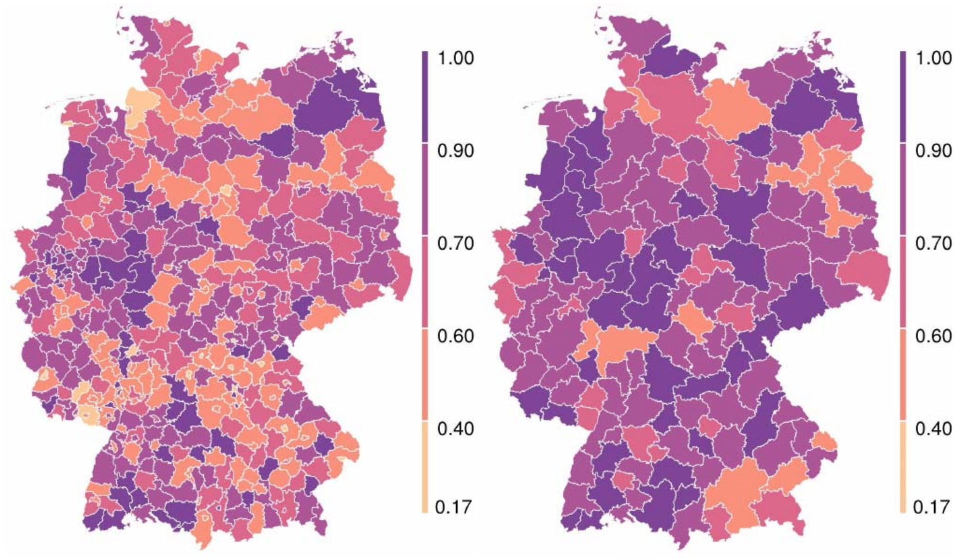


Figure 2: Kernel densities for the share of non-commuters in residents, German counties. 95% confidence interval shaded. See section 4 for the data.

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 3.[9] Panel (a) depicts this index for administrative local labor markets and panel (b) for commuting zones. Panel (a) 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 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 panel (a), 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 panel (b) in figure 3. Yet the overall heterogeneity remains strong with values ranging from 0.45 to just below 1.

[9] 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.



(a) Counties (b) Commuting Zones

Figure 3: Grubel-Lloyd indices for commuting in and out of German local labor markets, panel (a) for counties, panel (b) for commuting zones. See section 4 for the data.

Table 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
Counties	0.18	0.43	0.48	0.57	0.69	0.83	0.92	0.957	0.997
CZ	0.45	0.58	0.61	0.70	0.82	0.91	0.97	0.986	0.996

3 The Model

The Setup. We consider a version of the multi-location spatial general equilibrium model developed by Monte et al. (2018) as an extension of Redding (2016) who builds on Helpman (1998), in turn. Locations are linked in goods markets through trade and in factor markets through migration and commuting. Households consume land and a compound good which consists of a basket of differentiated varieties. Production of any variety takes place under increasing returns and with labor as the only factor. 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 H_n which is owned by local immobile landlords who earn rents from the residential use of land by consumers. To allow for external and internal geographies we assume that the set of locations $\Omega = \{1,..,N\}$ is exhaustively divided into disjoint subsets (territorial entities) $\Omega_g \subseteq \Omega$. 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 these subsets but not across them.

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 final goods basket $C_{ni\omega}$ and land $H_{ni\omega}$,

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

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 amenity pair and $\epsilon > 1$ parameterizes the dispersion of these amenities.

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

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

where $c_{ni\omega}(j)$ is consumption of a specific variety j, M_i is the mass of varieties, and σ is the constant elasticity of substitution between any two varieties. The price indices dual to (1) and (3) are respectively given by

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

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

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

and 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 $\Phi_{ni} = B_{ni} \left(\frac{e_{ni}}{\kappa_{ni} P_n}\right)^{\epsilon}$.

Production. Producers in each location i produce varieties 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 of variety j, F_i is a location-specific fixed input of labor, A_i is the location-specific productivity level and w_i is the location-specific wage.

Profit maximization implies that prices are constant markups on marginal cost. Consumers in location n pay $p_{ni}(j) = p_{ni} = d_{ni} \left(\frac{\sigma}{\sigma-1}\right) \frac{w_i}{A_i}$ for any variety j produced in location i, with $d_{ni} \geq$

1 denoting iceberg type transport costs for shipments from i to n. Profit maximization and zero-profits imply the break-even output $y_i(j) = y_i = A_i(\sigma - 1)\, F_i$ for any firm. Total costs can then be rewritten as $\Upsilon_i(j) = \Upsilon_i = \sigma\, F_i\, w_i$. Labor demand can be recovered from the cost function by application of Shepard's lemma. The aggregate use of labor in location i, L_i, can then be used to express the equilibrium number of firms as:

$$M_i = \frac{w_i L_i}{\Upsilon_i} \tag{6}$$

Goods trade and price indices. Goods trade between any two locations is characterized by a gravity equation in this model. Using the CES-structure of demand on the part of consumers 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:

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

Making use of optimal pricing, the firm number (6), and assuming $d_{nn} = 1$ price indices can be calculated as:

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

Market clearing. In each location i it must hold true that total sales equal the 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 local landlords spend all their rental income on goods and that they also bear their location's trade deficit D_n. Location n's total spending on goods, X_n, is then given by:

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

The expression combines the expenses of consumers in n 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 in location n.

In the housing market land is used for consumption by residents with an associated spending of $(1-\alpha)\bar{w}_n R_n$. Housing market clearing in location n thus commands:

$$q_n H_n = (1-\alpha)\,\bar{w}_n R_n \tag{11}$$

Labor mobility and commuting. Each worker chooses the commute from the subset of locations available to her that offers her the highest utility taking into account her idiosyncratic preferences (5). 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 that under the assumptions that we have imposed, $e_{ni} = w_i$):

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

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

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

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

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

The expected wage conditional on living in location n equals the wages that can be obtained in all possible workplaces weighted with the probabilities of commuting to those workplaces from location n, hence:

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

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. The general equilibrium system involves the set w_n, π_{ni}, X_n, $\bar{w}_n$, L_n, q_n, R_n, p_n of endogenous variables which are simultaneously determined by the set of equations (7), (8), (9), (10), (11), (14), (15) and (16) after substitution of $\lambda_{ni}|_{\Omega_g}$.

4 Data and Measurement

In this chapter we first describe the data sources and the initial data preparation (subsection 4.1). We then turn to the calibration of the model in subsection 4.2. A key part concerns the choice of the expenditure share devoted to land (housing) which plays a critical role in the quantitative analysis. We explain in detail, why this parameter should be chosen in the range of 10% when the quantitative model is intended to cover the aggregate economy. Subsection 4.3 applies model inversion to derive model consistent structural fundamentals.

4.1 Data Sources

Commuting data. Our commuting data stem from the German Federal Employment Agency (‘Pendlerstatistik’). 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.[10] We complement this data 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. Both data sets are based on social security accounts which exclude self-employed workers and other workers without social security.

Preparing the final commuting data on which the figures and tables in section 3 and the quantitative analyses performed below 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 exhibit commuting distances that are implausibly long for a daily commute. We take this as indicative of misreporting which, then, of course, also concerns the data for plausible commutes. Indeed, such misreporting is quite likely because the data are based on the accounts of companies which may report the wrong workplace of a worker (by mixing their headquarter or main plant with the actual plant, where the worker is employed) and/or a wrong residence address of the worker (because workers in Germany may be registered as residents at a main address (‘Hauptwohnsitz‘) and a secondary address (‘Nebenwohnsitz’)). We mend these problems of censoring and misreporting with the help of further, aggregate data, and with the help of gravity estimates, as we explain in section D of the appendix. 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.

[10] In 2011 an administrative reform reduced the number of counties in Germany to 402. Since some data sets are only available for this specification we work with it below.

Trade data. Our 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.[11] An in-depth description and analysis of this data set as well as a detailed picture of the implied German interregional trade and production network is provided by Krebs (2018). More specifically, he derives 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 data from the World Input Output Database (WIOD).[12] We use this interregional input-output table which is strongly rooted in observable data and which provides us a detailed portrait of bilateral trade of goods between German counties.

Further Data. Total wage sums ('totales Arbeitnehmerentgelt') for German counties as well as the number of flats by county, which we use as a control in our empirical section, are available from the Regional and Federal Statistical Offices ('Statistische Ämter des Bundes und der Länder').

4.2 Calibration

Strategy. In order to calibrate the model we need estimates of three exogenous parameters, the share of expenditures devoted to housing (α), the elasticity of substitution in consumer's preferences (σ), and the commuting elasticity (ϵ), as well as initial values of wages at the country 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, as well as the average wage (income) on the county level ($\bar{w}_n$). It is important to stress at the outset that taking the model to the data requires a number of choices as any model involves simplifications and, possibly even more critical, as the available data are typically not comprehensive.

[11] Air transport is not included in the data set. However, air transport 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').

[12] See appendix C for a summary of the approach used in Krebs (2018).

The key aim of this paper is to obtain a detailed picture of the workings of the network of German local markets. In addition, we view it as desirable to gain a perspective on the findings concerning American local labor markets provided by Monte et al. (2018). Hence, to ease the comparison, we keep many of our choices in line with that study. One issue involves the non-availability of original data on service trade at the local level which is the case both in Germany and the United States. Faced with the choices to assume that all services are non-tradable, to impute service trade, or to ignore the production of services altogether, we follow Monte et al. (2018) and adopt this final option.[13]

Initial values of endogenous variables. Using our final set of commuting flows we can immediately calculate all $\lambda_{ni|\Omega_g}$ and aggregate flows to find total labor available in Germany ($\bar{L}_g$). It should be remembered that this number is based on social security data and thus excludes any self-employed workers and workers without social security. Wages at the county level w_n are obtained by dividing county level total wage bills ('totales Arbeitnehmerentgelt') as reported by the German Federal and Regional Statistical Offices ('Statistische Ämter des Bundes und der Länder') 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 $\bar{w}_n = \left(\sum_{\mathrm{i} \in \Omega_\mathrm{g}} \lambda_{ni|\Omega_g} \bar{L}_g w_i\right) / R_n$.

We derive the exogenous deficit transfers D_n and the trade shares π_{ni} from the interregional input table provided by Krebs (2018) by aggregating trade flows across all manufacturing sectors and across all foreign countries and scaling all values such that German county level production equals county level wage sums.[14] Specifically, deficit transfers are obtained as $D_n = \sum_{i \in N} \pi_{ni} X_n - R_n \bar{w}_n$.[15] Having calculated trade deficits we obtain total expenditure X_n in n as $R_n \bar{w}_n + D_n$ and we can calculate import shares π_{ni} from trade flows $\pi_{ni} X_n$.

Exogenous parameters. We follow Monte et al. (2018) in choosing a substitution elasticity for the CES goods bundle of $\sigma = 4$. Our estimate of the commuting elasticity is based on the

[13] The interregional input-output table provided in Krebs (2018) includes both goods trade and service trade. Unlike the bilateral shares in goods trade which are rooted in observable data, the bilateral trade shares in service trade provided in Krebs (2018) are imputed based on a gravity estimate.

[14] Monte et al. (2018) scale trade values from the Commodity Flow Survey to match the total wage bill in each county. We follow them as close as possible and therefore also use the total wage bill despite the fact that this sum includes the service sector whereas trade flows from the Commodity Flow Survey and our shipment data do not.

[15] Note that due to commuting the value of total sales $w_n L_n$ in n differs from total income $R_n \bar{w}_n$. Therefore, deficit transfers can differ (in absolute terms) from trade imbalances $\sum_{i \in N} \pi_{in} X_i - \sum_{i \in N} \pi_{ni} X_n$.

probability $\lambda_{ni}|_{\Omega_g}$. We follow the approach laid out by Monte et al. (2018) to arrive at a regression which we estimate with a 2SLS approach to account for endogeneity of wages and commuting as explained in appendix D. We obtain a highly significant coefficient $\epsilon = 4.24$ which exceeds the estimate obtained for the United States. This is in line with our observation of stronger commuting flows in Germany.

Housing share. As pointed out in the introduction, the choice of the budget share devoted to land (housing) is far from trivial. The values selected in the extant literature exhibit a wide variation, differing by a factor of 4. The considerations behind these divergent choices are usually not made explicit. Closer inspection reveals that they reflect different stances on two issues. The first is whether the quantitative model is meant to involve only a segment or the whole of an economy, the second concerns what to count as expenditures on 'land/housing'.

One prominent estimate reflects the share of housing by renting households relative to their wage and salary income, as calculated from microeconomic census data such as the Decennial Census of Housing files (Davis and Ortalo-Magné 2011). This yields a median budget share of 24% and is used by Redding (2016), for example.[16] However, Davis and Ortalo-Magné (2014) also report, that the housing share comes down to 18% when only the pure contract rent is counted, the other 6% reflect the expenditure share for utilities. Furthermore, they report that these shares come further down to 15% and 3%, respectively, when macroeconomic data from national accounting are used. These numbers reflect shares in gross consumer income.

Larger values for the housing share are obtained when housing expenditures are related to household's net income and also when broader measures for housing expenditures are used. The typical value drawn from the Consumer Expenditure Survey released by the BLS amounts to roughly 1/3 (Duranton and Puga 2014; BLS 2017). Monte et al. (2018) come up with an even higher value of 40% with reference to data from the Bureau of Economic Analysis. A close inspection of that data reveals that in order to arrive at such a high value, not only a very broad concept of housing expenditures (including utilities) must be applied, but also further expenses would need to be included.[17]

[16] Davis and Ortalo-Magné (2011) also document strong empirical evidence in favor of a constant expenditure share. This justifies the Cobb-Douglas utility typically used in new quantitative models.

[17] For the year 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% including utilities, which should not be included in spending on the non-traded factor housing or land for housing. 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%. In the tables released by the BLS the category 'housing' includes further expenses such as, for example, 'laundry and cleaning supplies', 'postage', 'furniture' or 'household textiles'.

It should be noted that the values discussed so far are based on concepts that reflect a segment of the economy only, not the whole aggregate economy, and that very wide concepts of housing expenditure are used which include utilities and other expenditure items. Unsurprisingly, housing shares take on large values, if a small denominator (gross consumer income; household net income) and a large numerator (a very broad measure of housing expenditures) is chosen.

From the viewpoint of the whole (aggregate) economy, total final expenditure is relevant. This comprehends spending by the government and investments in addition to spending by consumers (gross consumer income and household net income reflect only consumers/households). A quantitative analysis which is targeted at the whole economy should therefore draw on total final expenditure. Furthermore, it is important to note that the conceptual role that land plays as dispersion force in the model of section 3, and that is captured by the share parameter α, could in general not be achieved by the broader concept of non-traded goods, because land is the only ultimately fixed and immobile resource.[18] For this reason a narrow concept of land/housing expenditures is warranted. Building on information from the World Input Output Database (WIOD) with its Socioeconomic Accounts (SEA's) and on EU-KLEMS data, Krebs and Pflüger (2018) arrive at economy-wide expenditure shares for land of around 10% both for Germany and for the United States.[19] Importantly, this value is strongly supported by the well-known study by Rognlie (2015) which addresses the evolution of the net capital share in national income of which housing income is a part. Rognlie reports a share of housing in net value added at factor cost of around 10% for the United States which supports the estimated 10% in Krebs and Pflüger (2018) from the factor cost side. It should also be noted that this (low) value is also in the ballpark of the numbers reported by Ortalo-Magné (2014), and would be even more so if the denominator was broadened from gross consumer income to net value added.

Since our goal is to portray the aggregate economy with our quantitative analysis, these arguments lead us to use an estimate of 10% for the housing share. However, it is instructive to check how the results are affected when this share is chosen at 40% as assumed in Monte et al. (2018) and we also report the results for an intermediate value of 25% (see appendices E and F).

[18] 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.
[19] See Timmer et al. (2015) on the WIOD and on its SEA's and O'Mahony and Timmer (2009) on EU-KLEMS.

4.3 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 as we now show in turn. 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

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

Together with a simple parameterization of trade barriers given by $d_{ni} = dist_{ni}^{\psi} \, \tilde{e}_{ni}$, where $dist_{ni}$ is the physical distance between locations n and i, and $\tilde{e}_{ni}$ a stochastic error term, this equation can be estimated, controlling for labor and wages with exporter fixed effects, and for the denominator and expenditure with importer fixed effects (see appendix C). Using a Poisson Pseudo Maximum Likelihood (PPML) estimator, we obtain a composite parameter $\psi(1-\sigma) = -1.56$.[20] Making use of our assumption that $\sigma = 4$ yields $\psi = 0.52$ and trade barriers can now directly be calculated using our parameterization. Once we have identified these bilateral trade barriers, the county level technology parameters A_i can also be recovered up to a proportionality factor from the ratio of bilateral trade shares and own share, $\frac{\pi_{ni}}{\pi_{nn}} = \frac{L_i w_i^{1-\sigma} \left(\frac{d_{ni}}{A_i}\right)^{1-\sigma}}{L_n w_n^{1-\sigma} \left(\frac{1}{A_n}\right)^{1-\sigma}}$. After imposing the normalization $A_n = 1$, we obtain productivities of any location i relative to location n as $A_i = \frac{d_{ni} \, w_i}{w_n} \left(\frac{\pi_{nn} \, L_i}{\pi_{ni} \, L_n}\right)^{\frac{1}{1-\sigma}}$.

Bilateral trade barriers. Figure 4 displays the relationship between our calculated barriers and observable distances between counties. We expect distance to be strongly correlated with our measure of iceberg trading costs and indeed this is what figure 4 shows.

We can also look at county level barriers with respect to a specific location. The left-hand panel of figure 5 depicts the implied barriers between all German counties exporting to Hamburg relative to barriers in Hamburg's trade with itself. It is seen that trade barriers increase with distance to Hamburg, in general. However, barriers between far-away locations may effectively be low when locations are connected by railway lines or waterways or when there are

[20] Using OLS instead of PPML and estimating our regression in log-linear form after dropping zero trade flows leads to a much higher coefficient of -2.04. This estimate, however, is biased in the presence of heteroskedasticity and zero trade flows. Moreover, it is also substantially larger than what is generally found in the literature. For this reason we deviate from Monte et al. (2018) and rely on PPML (rather than OLS) estimates in the following.

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 feature 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.

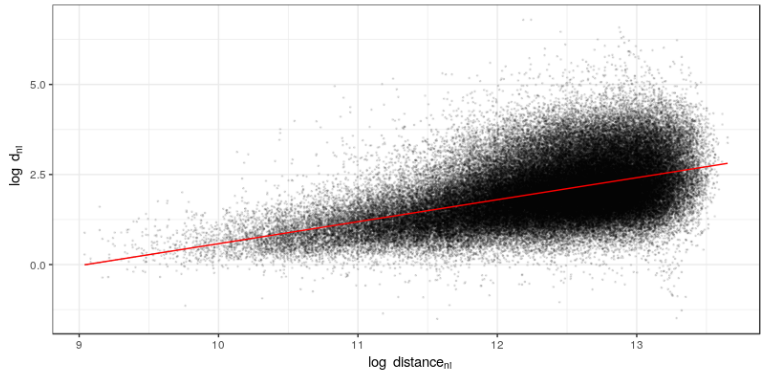
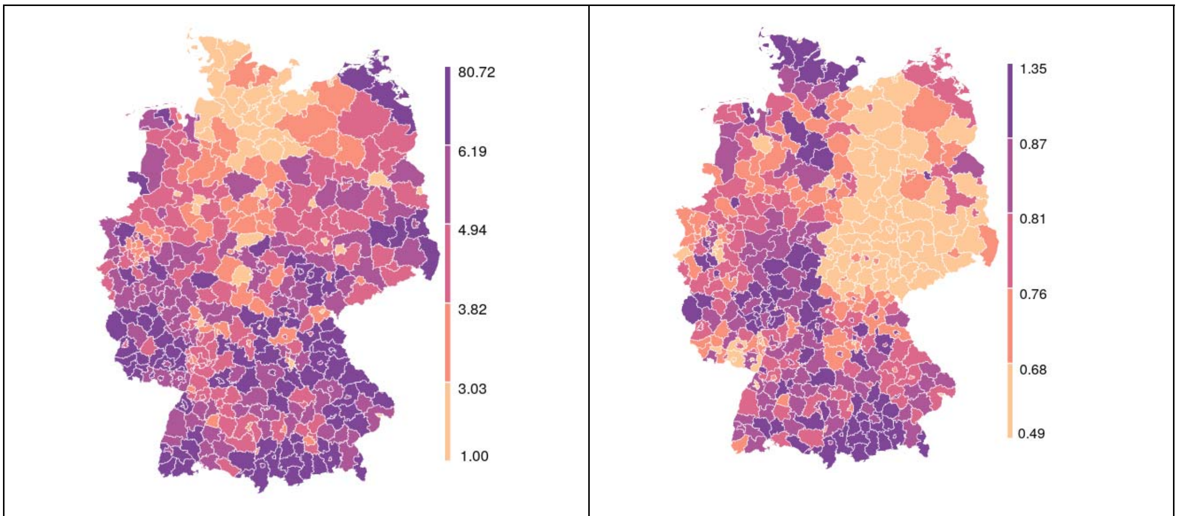


Figure 4: Model consistent trade barriers and distance

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 5. Strikingly, with 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 5: Model consistent trade costs and technologies relative to Hamburg

5 Productivity Shocks and Local Employment Elasticities

We now explore the workings of the German network of local labor markets by exposing the general equilibrium system to counterfactual local productivity shocks. We use the 'exact hat'-algebra popularized by Dekle et al. (2007).[21]

5.1 County level analysis

General equilibrium elasticities. We calculate 402 counterfactual equilibria, each representing a 5% productivity shock in one of the 402 German counties. Figure 6 shows the kernel densities of the resulting general equilibrium employment and resident elasticities in the counterfactually treated counties, with the 95% confidence intervals given by the shaded areas.[22] The darker curves in the foreground show the results for a housing share of 10%; the lighter curves in the background show the results for a housing share of 40%.

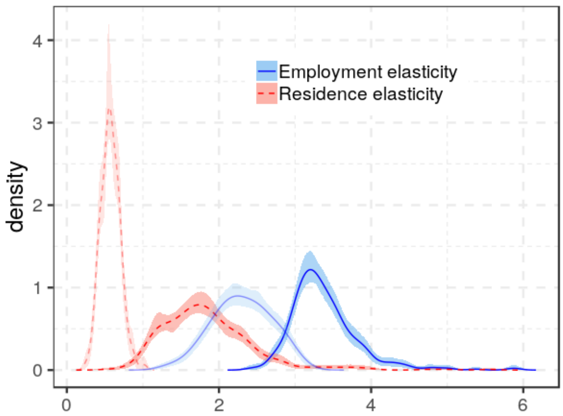


Figure 6: Kernel densities of general equilibrium elasticities of employment and residents; the darker curves and confidence bands show the results for a housing share of 10%; the lighter curves in the background show the results for a housing share of 40%.

An inspection of figure 6 shows that the general equilibrium employment elasticities across German counties are very heterogeneous, irrespective of the value of the budget share for land. Whilst 90% of employment elasticities are in a range from 1.67 to 2.93 when the housing share is at 0.4, the main range of this elasticities dramatically shifts up to 2.83 to 4.17 when the

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

[22] Given our counterfactual equilibrium these model consistent general equilibrium elasticities can be 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 general equilibrium elasticities follow in a deterministic manner from the model, the depicted confidence bands relate to the estimation of the kernel density.

housing share is at 10%, our preferred parameter choice as we explained in section 4.2.[23] Figure 6 also shows that resident elasticities are higher with a lower housing share. 90% of the density mass lies in the range from 1.07 to 2.77 when the housing share is at 10% compared to a range from 0.37 to 0.78 for a housing share of 40%. These higher local employment and resident elasticities are in line with the intuition that the dispersion force in the model is much weaker with a lower housing share. A second finding is that, using a housing share of 40% for comparison with the United States, we find that almost no county in Germany has an employment elasticity below 1, in contrast to Monte et al. (2018). This points towards much stronger home market and commuting effects in Germany. Third, irrespective of the budget share devoted to housing, local employment and resident elasticities exhibit a very strong heterogeneity in Germany (similarly to the United States). This implies that seriously wrong conclusions would be drawn if some average elasticity across local labor markets were to be applied by (local) planners and policymakers.

Explaining the general equilibrium elasticities. Obviously, differences in the elasticities of employment and residents can only stem from commuting. In the general equilibrium several mechanisms simultaneously drive the reaction of workers. Firstly, workers are attracted to the location that experiences a positive productivity shock because of the implied higher wages. When changing their workplace decision some workers, depending on their bilateral amenity draws, will prefer to move to the new location whereas others will commute to it. Secondly, lower prices due to the increased productivity will attract additional residents, some of which will also change their workplace whereas others, based on their amenity draws, will prefer to commute outwards. Thirdly, an increased number of residents drives up housing costs, a congestion effect. Fourthly, the general equilibrium is driven by spillover effects through commuting, that is, through changes in the number of workers and residents in untreated counties, and through trade linkages with untreated counties.

We now enquire whether the employment and resident elasticities which reflect these complex general equilibrium repercussions can be predicted by the ex-ante observable measures that are suggested in Monte et al. (2018) and that work so powerfully in their analysis of the American economy. Table 3 presents the results of our regressions when the housing share is at 0.4 and table 4 reports the results when this share is at our preferred value of 0.1. The structure of the two tables is the same to ease comparison.

[23] The average employment elasticity of 2.30 for a housing share of 0.4 is much above the average employment elasticity across US counties of 1.52 reported in Monte et al. (2018).

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, as a measure of the local housing stock, H_i, the number of flats in the county. 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. For a housing share of 0.4, these standard controls explain up to 35% of the variation of employment elasticities, as indicated by the values of the R-squared in table 3. Table 4 shows that the explanatory power of these standard controls only reaches about 8% when the housing parameter is at 0.1.

The regressions reported in columns (5), (6) and (7) turn to explanatory variables which are model-based. Column (5) considers the share of a county's residents that also work in that county, $\lambda_{ii|i}^R$, as a baseline measure for commuting suggested by the model, where the definition $\lambda_{ni|n}^R \equiv \frac{\lambda_{ni|\Omega_g}}{\lambda_n^R}$ is used. The lower the own share $\lambda_{ii|i}^R$, the more open is a local labor market to commuting, hence, the higher is the expected elasticity of employment. Table 3 shows that this variable alone – along with the constant – explains over 87.9% of the variation in employment elasticities. An inspection of column 5 in table 4 shows that this inverse measure of commuting loses its explanatory power almost entirely when the housing share is at 0.1, however.

Column 6 includes measures which build on three partial equilibrium elasticities of the model, the partial equilibrium elasticities of employment and residents with respect to wages, and the partial equilibrium elasticity of wages with respect to productivity.[24] These partial equilibrium elasticities imply a measure of commuting linkages, $\sum_{n\in N}\left(1-\lambda_{ni|n}^R\right)\vartheta_{ni}$, where $\vartheta_{ni} \equiv \lambda_{ni|n}^R R_n/L_i$ indicates the fraction of the workforce in location i that resides in n and commutes to work in i, a measure of migration linkages $\vartheta_{ii}\left(\frac{\lambda_{ii|\Omega_g}}{\lambda_i^R}-\lambda_i^L\right)$, and as a measure of what Monte et al. (2018) call 'trade linkages', the partial equilibrium elasticity of wages with respect to productivity, $\frac{\partial w_i}{\partial A_i}\frac{A_i}{w_i}$. In column 7 the three measures of linkages are interacted by multiplying the previous commuting and migration linkage with the partial equilibrium elasticity of wages with respect to productivity. The explanatory power of the three measures considered in column

[24] These partial equilibrium elasticities are derived from total differentiation of equations (9), (13) and (14) along with (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.

6 is similarly strong as the explanatory power of the own share $\lambda_{ii|i}^{R}$ when the housing share is at 0.4. Table 3 also shows that the explanatory power of the two combined measures in column 7 is lower compared to the three mentioned measures from which they were formed, but the explanatory power still by far exceeds that of standard controls. Strikingly, the explanatory power of the model-based simple measures considered in columns 6 and 7 is much reduced when the housing share is at our preferred value of 0.1 (see table 4). In fact these measures now perform only little better than the set of standard controls considered in regression 4 (cf. the R-squared of 0.08 compared to 0.25 in column 6).

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.191^{***}	-0.666^{***}	-0.690^{***}				-0.407^{***}	-0.518^{***}
		(0.027)	(0.069)	(0.069)				(0.025)	(0.049)
$\log(w_i)$			1.109^{***}	1.112^{***}				0.133^{***}	0.437^{***}
			(0.118)	(0.176)				(0.045)	(0.088)
$\log(H_i)$			0.436^{***}	0.417^{***}				0.388^{***}	0.417^{***}
			(0.070)	(0.068)				(0.025)	(0.048)
$\log(L_{-i})$				0.240^{***}					
				(0.039)					
$\log(w_{-i})$				-0.495^{**}					
				(0.242)					
$\lambda_{ii\|i}^{R}$					-2.518^{***}				
					(0.047)				
$\sum_{n\in N}\left(1-\lambda_{ni\|n}^{R}\right)\vartheta_{ni}$						0.151^{***}		0.110^{***}	
						(0.017)		(0.014)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda_i^R}-\lambda_i^L\right)$						-1.929^{***}		-1.975^{***}	
						(0.055)		(0.046)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.599^{***}		0.385^{***}	
						(0.048)		(0.040)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda_{ni\|n}^{R}\right)\vartheta_{ni}$							0.681^{***}		0.536^{***}
							(0.045)		(0.042)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda_i^R}-\lambda_i^L\right)$							-2.274^{***}		-2.237^{***}
							(0.137)		(0.134)
Constant	2.304^{***}	4.369^{***}	-7.574^{***}	-5.234^{***}	3.814^{***}	2.679^{***}	2.466^{***}	1.398^{***}	-1.388
	(0.020)	(0.292)	(1.257)	(1.675)	(0.029)	(0.038)	(0.031)	(0.485)	(0.930)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.111	0.290	0.352	0.879	0.858	0.570	0.916	0.672
Adjusted R^2	0.000	0.109	0.285	0.344	0.878	0.856	0.568	0.915	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. *p<0.1; **p<0.05; ***p<0.01

Table 3: Analysis of the general equilibrium local employment elasticities in response to 5 percent productivity shocks at the local level (counties) with an expenditure share of 40% for housing.

In columns 8 and 9 we combine the standard controls with the measures inspired by the model. With a housing share of 0.4 this does slightly improve the R-squared in both cases, but even the specification which performs best, (8), only marginally surpasses the simple measure of own commuting. The R-squared also increases when the housing share is at 0.1. Specifications (8) and (9) have the highest explanatory power, although the R-squared is only around 0.3.

The upshot of our analysis is that the housing share dramatically affects the results. When a very high housing share is chosen as in Monte et al. (2018), 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. When the housing share is at our preferred value of 0.1, the simplest measure, the own commuting share, loses its explanatory power, however. The simple model-based partial equilibrium measures retain some explanatory power, but it is much lower. The best performance is achieved when the model-based partial equilibrium elasticities are combined with standard labor market controls. These findings can be rationalized by noting that the general equilibrium repercussions are far stronger with a low housing share, because the congestion force in the model is then much weaker. Simple partial equilibrium-based measures, however, capture these general equilibrium repercussions only imperfectly. This explains why the simple ex-ante measures work so powerfully in Monte et al. (2018) and so poorly in our preferred model.

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		−0.006	−0.394***	−0.359***				−0.085	−0.226***
		(0.033)	(0.090)	(0.094)				(0.083)	(0.082)
$\log(w_i)$			0.355**	0.240				0.532***	0.766***
			(0.155)	(0.238)				(0.148)	(0.149)
$\log(H_i)$			0.412***	0.418***				0.174**	0.255***
			(0.092)	(0.092)				(0.081)	(0.082)
$\log(L_{-i})$				−0.188***					
				(0.053)					
$\log(w_{-i})$				0.576*					
				(0.328)					
$\lambda^R_{ii\|i}$					−0.345**				
					(0.152)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.142***		0.212***	
						(0.045)		(0.047)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						0.126		0.328**	
						(0.143)		(0.152)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						1.427***		1.548***	
						(0.125)		(0.131)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.501***		0.509***
							(0.069)		(0.071)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							1.572***		1.947***
							(0.212)		(0.228)
Constant	3.379***	3.444***	−0.898	−3.638	3.585***	2.596***	2.938***	−4.474***	−5.961***
	(0.022)	(0.353)	(1.656)	(2.272)	(0.094)	(0.100)	(0.048)	(1.585)	(1.578)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.0001	0.050	0.080	0.013	0.254	0.206	0.307	0.270
Adjusted R^2	0.000	−0.002	0.043	0.068	0.010	0.249	0.202	0.296	0.261

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. *p<0.1; **p<0.05; ***p<0.01

Table 4: Analysis of the general equilibrium local employment elasticities in response to 5% productivity shocks at the local level (counties) with an expenditure share of 10% for housing.

6.2 Commuting Zones

General equilibrium elasticities. We now turn to the analysis of local productivity shocks for the 141 German commuting zones. Figure 7 depicts the kernel densities of the general equilibrium elasticities of employment and residents for commuting zones. The darker curves in the foreground show the results for a housing share of 0.1, the lighter curves in the background show the results for a housing share of 0.4. Figure 7 reveals that, similarly to the results with counties, general equilibrium employment and resident elasticities are substantially higher, when the housing parameter is 10% rather than 40%. With the lower housing share, 90% of employment elasticities are in a range between 1.33 to 2.80, whereas this range is 1.30 to 1.64 with a housing share of 40%. The intuition is as before: with a smaller expenditure share for housing, the role of housing costs as a congestion force is strongly diminished, implying that more workers will choose to migrate instead of commute to the treated labor market.

A comparison of figure 6 for counties and figure 7 for commuting zones reveals that resident and employment elasticities are more similar for commuting zones. This captures the fact that commuting is more costly across commuting zones than across counties. Therefore, commuting to the treated location is more costly and fewer workers will choose to do so. Instead, when workers are attracted to the commuting zone which experiences a positive productivity shock they are more likely to completely relocate to the treated location instead of choosing to commute to it. Yet there still is a significant amount of commuting even across commuting zones, which explains the strong remaining heterogeneity in employment elasticities.

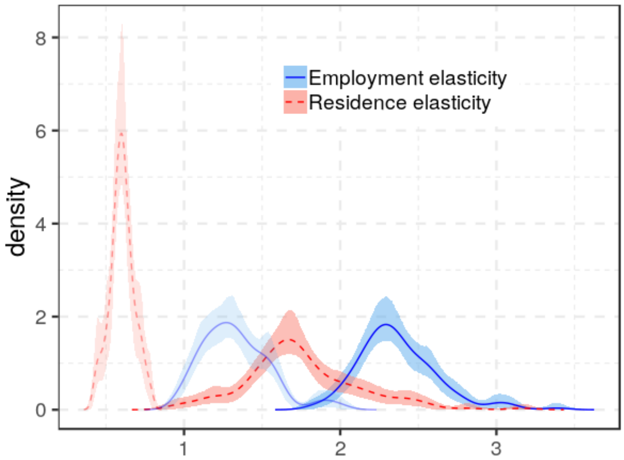


Figure 7: Kernel densities of general equilibrium elasticities of employment and residents (commuting zones): The darker curves and confidence bands show the results for a housing share of 10%; the lighter curves in the background show the results for a housing share of 40%.

Explaining general equilibrium elasticities. We now perform similar regressions for commuting zones as we did for counties in the previous sections. The results for a housing share of 0.4 are documented in table 5 in appendix E and table 6 in appendix E shows our regression results for a housing share of 0.1, our preferred value. Here we summarize our key findings. As with counties, when the housing share is at 0.4, standard controls perform much worse than the simple own commuting share or model based partial equilibrium elasticities. Furthermore, the best prediction of employment elasticities is still achieved by a combination of standard controls and model based partial equilibrium elasticities, although these outperform the simple own commuting share only marginally.

Central to our analysis, the lower housing share again has a dramatic effect on the explanatory power of different specifications. The simple measure of own commuting which alone explains 91% of the variation in employment elasticities with a high housing share now becomes an insignificant estimator altogether, with the R-squared marginally different from 0. Standard controls also perform extremely poorly and even the best specification, i.e. the combination of standard controls and partial equilibrium elasticities, can only explain slightly less than 40% of the observed variation in employment elasticities. Hence, while the effects of commuting are somewhat reduced in a scenario with commuting zones the central result remains unchanged: using our preferred specification of 0.1 for the housing share leads to stronger general equilibrium repercussions that are much more difficult to predict by ex-ante observable partial equilibrium estimators.

6 Commuting Cost Reduction

This section turns to an analysis of the economic effects of commuting cost reductions. For Germany, this is an important issue, because its transport infrastructure is in a miserable state, as we noted in the introduction. The counterfactual experiment that we pursue involves a corridor of symmetric reductions in commuting costs between all counties in Germany ranging from a reduction of 1% up to a reduction of 20%.[25] Technically speaking, we set the change in the commuting costs $\hat{\kappa}_{ni}$ equal to values from 0.99 to 0.8 for all pairs $n \neq i$.

[25] Of course, other types of community reductions, in particular asymmetric ones which focus on county pairs where deficiencies in the transport infrastructure are biggest, could be easily dealt with.
It should also be pointed out that we are unable to run the counterfactual highlighted in Monte et al. (2018), i.e. an analysis of the effects of empirically-observed reductions of commuting costs, since our commuting data do not have a time series dimension.

Figure 8 depicts the relative changes in expected welfare $\widehat{U}$ in Germany which result from this corridor of shocks. The red curve presents welfare gains for a housing share of 10%, the blue curve the respective gains for a housing share of 40%. The gains with a smaller housing share are larger but only modestly so. Focusing on the case with a housing share of 10%, it can be seen that, on average, a one percentage point decrease in commuting costs raises welfare by about half a percentage point. The welfare gain amounts to about 4.5 percent as commuting costs are brought down to 0.90, for example.

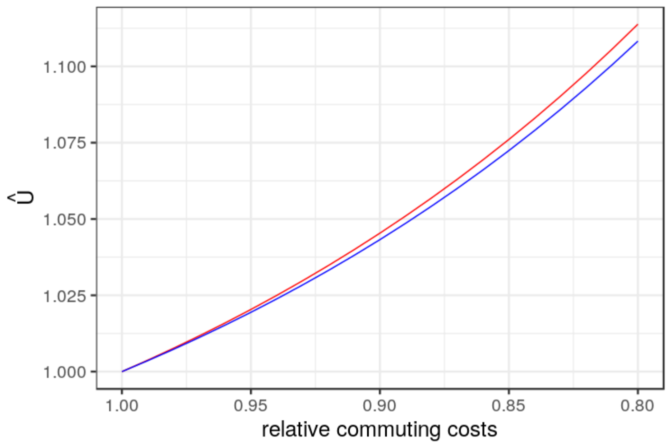


Figure 8: Welfare effects of a symmetric commuting cost reduction: red: 10% housing share, blue: 40% housing share.

Turning to the changes in commuting patterns induced by commuting cost reductions, we focus on the results for a 10% symmetric reduction in commuting costs. This change reduces the total share of non-commuters in the German population from 63.1% to 52.4% when the housing share is 10%, and to 53.1% when the housing share is 40%. Figure 9 depicts kernel densities for commuting distances before (black) and after the shock both with a housing share of 10% (red scenario) and a housing share in the blue scenario of 40%, where the area under the curves equals the share of commuters in all workers in each scenario. As expected the share of long commutes increases slightly while that of shorter commutes is reduced.

Figure 10 focuses on the location effects of a symmetrical 10% reduction in commuting costs. The left panel depicts the relative change in employment, $\hat{L}_n$, and the right panel the relative changes in residencies, $\hat{R}_n$, in each county. Two types of effects are visible. At a local level, the left-hand panel shows that the reduced commuting costs increase the number of workers in urban counties relative to those in surrounding locations because the reduction in commuting costs makes it cheaper to benefit from high wages due to agglomeration effects in cities while also profiting from lower housing costs in suburban locations.

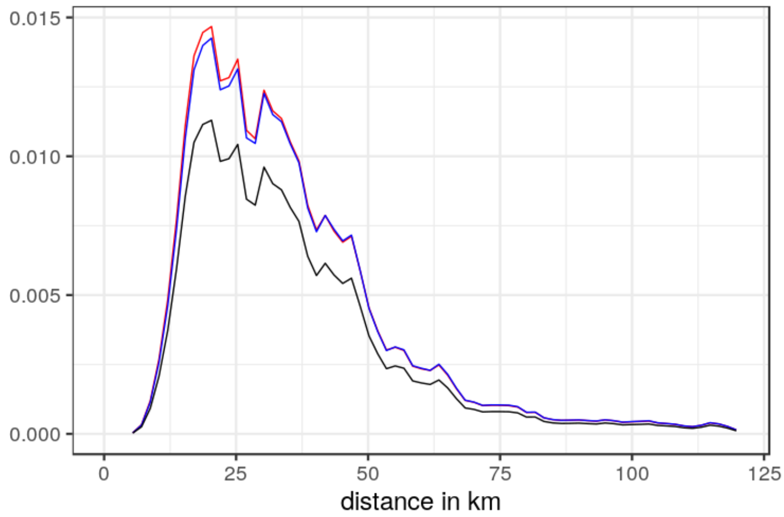
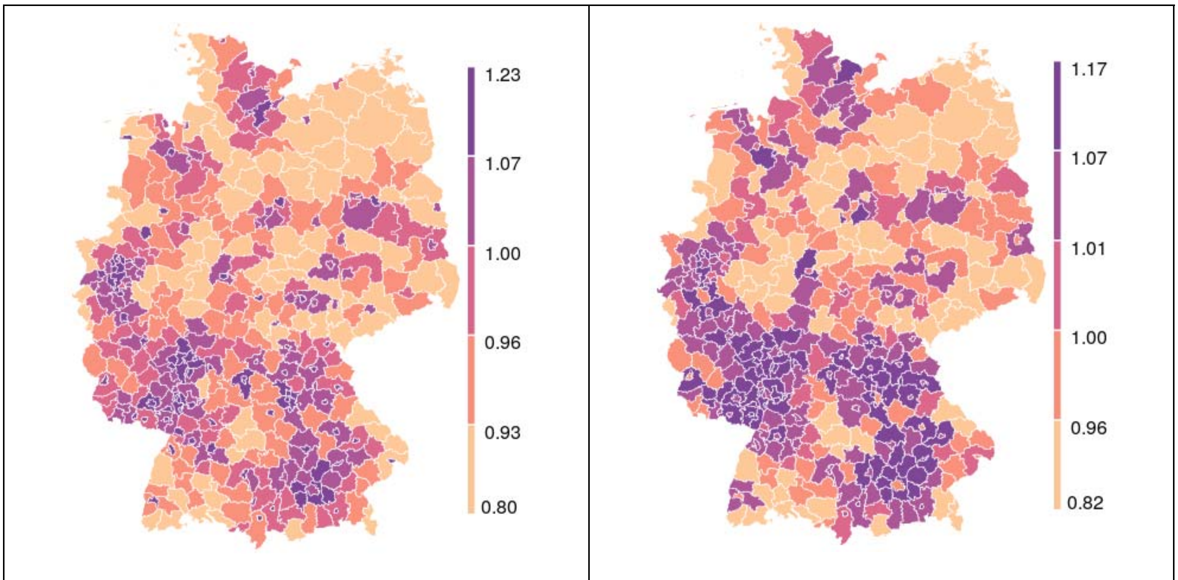


Figure 9: Kernel densities for commuting distances before (black) and after a 10% reduction in costs with a housing share of 10% (red curve) or a housing share of 40% (blue curve).

At the macro level, the reduction in commuting costs also increases agglomeration of workers and residents. It is seen that several clustered groups of counties experience increases in both workers and residents (e.g. the wider area of Munich in South-Germany; the wider area of Frankfurt in the middle west part of Germany) while other such spatial groups see population outflows (e.g. the North-East). Intuitively, these patterns accord with our finding that agglomeration forces in Germany are quite strong because, under these circumstances, already large locations gain despite the fact that commuting costs are reduced in a symmetric fashion in our counterfactual.



Relative change in workers, $\hat{L}_n$	Relative change in residents, $\hat{R}_n$

Figure 10: Effects of a 10% symmetric reduction of between county commuting costs, housing share 0.1.

7 Conclusion

This paper uses a quantitative spatial model with heterogeneous locations linked by costly goods trade, migration and commuting to shed light on the spatial fabrics and interactions of local labor markets in Germany. Unique data, a traffic forecast, 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.

One key contribution of this paper concerns the analysis of the role of the expenditure share of housing. We provide arguments that, for an economy-wide quantitative analysis, this share should be chosen lower than stipulated in much of the extant research.

Our quantitative and empirical analyses show that the local employment and resident elasticities with respect to local productivity shocks are significantly higher, with a low housing share. This corresponds to the intuition, that under these circumstances, dispersion forces are much weaker. Moreover, simple ex-ante observable commuting measures turn out to have very little predictive power for these general equilibrium elasticities when the housing share is low. Quite intuitively, simple partial equilibrium based measures fail to capture the full general equilibrium effects that become stronger as the congestion force in the model becomes weaker.

The housing share, in contrast, has little effect on the strong heterogeneity of employment and resident elasticities in response to local productivity shocks that we find for German local labor markets. Given this strong heterogeneity, seriously wrong conclusions would be drawn if some average elasticity across local labor markets were to be applied by policymakers and local planners. The housing share plays little role for the welfare and location effects of the counterfactual commuting cost reductions that we undertake for the German economy. Counterfactually reducing commuting costs our quantitative model predicts an increase in the number of resident workers in urban counties relative to those in surrounding locations and, at the macro level, increasing agglomeration.

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Appendix

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

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

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

(10)' $\quad \hat{X}_n X_n = \hat{\overline{w}}_n\,\hat{R}_n\,\overline{w}_n\,R_n + D_n\hat{D}_n$

(11)' $\quad \hat{q}_n = \hat{\overline{w}}_n\,\hat{R}_n$

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

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

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

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

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

B 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 $\overline{w}_n$, 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 $\hat{\overline{w}}_n$ 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 $\hat{w}_i + \zeta\left(\hat{w}_i^{tmp} - \hat{w}_i\right)$ 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.[26]

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.

C 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 (2018) 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

[26] 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.

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 the approach of Krebs (2018). Specifically, this paper 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 (2018) 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.[27] This input output table replicates observed 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. Hence, we make use of the regional input output table from Krebs (2018) but drop all service sector trade data before

[27] 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 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.

aggregating trade flows to a single sector and all foreign countries to a single artificial rest of the world (ROW).

Trade elasticity. Our county level shipment data allow us to directly calibrate our model instead of relying on estimates based on distance. In order to compare differences in the connection between trade barriers and distance in Germany with the US case studied in Monte et al. (2018) we do follow their analysis here and estimate the correlation based on our gravity equation. 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 bilateral barriers. Parameterizing trade barriers by $d_{ni} = dist_{ni}^{\psi} \tilde{e}_{ni}$, where $dist_{ni}$ is the physical distance between locations n and i, $\psi > 0$ a parameter and $\tilde{e}_{ni}$ a stochastic error term, we can write the above equation in its stochastic version as

$$\pi_{ni} X_n = S_i M_n dist_{ni}^{(1-\sigma)\psi} e_{ni} \, ,$$

where M_n and S_i are importer and exporter fixed effects capturing their respective variables and $e_{ni} \equiv \tilde{e}_{ni}^{(1-\sigma)}$ is the adapted multiplicative error term. In figure C.1 we depict the conditional relationship between log trade flows and log distance, i.e. the correlation after cleaning importer fixed effects M_n and exporter fixed effects S_i from both variables.[28]

Log linearizing the gravity equation to estimate via OLS commands that we have to drop all observations with zero trade flows biasing the results. Moreover, the figure indicates heteroscedasticity in the data leading to OLS becoming a biased estimator for our sought distance elasticity. While we report the results of this OLS estimation we therefore prefer to keep the gravity equation in its multiplicative form using PPML (see Santos Silva and Tenreyro 2006 for a discussion of the problem and the PPML method) to estimate $(1 - \sigma)\psi$.

[28] Specifically, for this figure we separately regress $\log \pi_{ni} X_n$ and $\log dist_{ni}$ on importer and exporter dummies using OLS and dropping observations with 0 trade flows and then regress the residuals of the first regression on those of the latter.

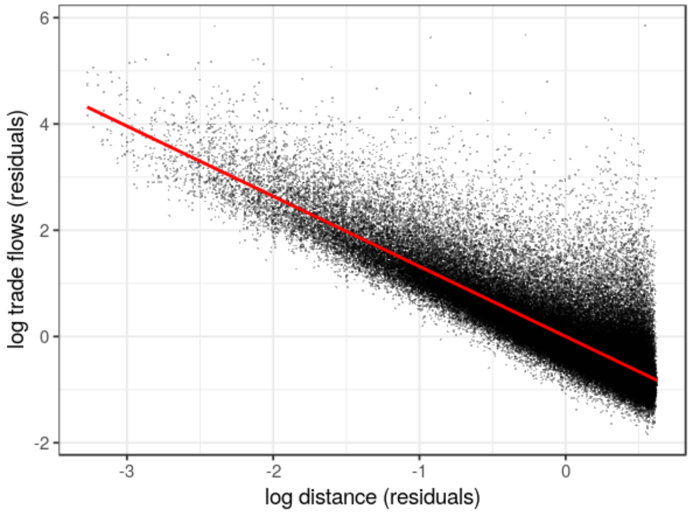

Figure C.1: (Log) relationship between trade flows and distance after removing importer and exporter fixed effects.

The table shown below demonstrates that with $(1-\sigma)\psi = -1.56$, in absolute terms, we obtain a slightly larger elasticity of trade flows with respect to barriers in Germany compared to the US. Given our assumption of $\sigma = 4$ the effect of distance on barriers measured by ψ is equal to 0.52 and thus slightly larger than in the US.

	OLS	PPML
log distance	-2.041	-1.560
robust s.e.	0.278	0.015
Observations	122064	161604
(Pseudo) R2	0.46	0.97

D Commuting

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 D.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.[29] The OLS regression lines for all commuting flows below and above 120 km respectively have slopes of -2.89 and -0.07 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.

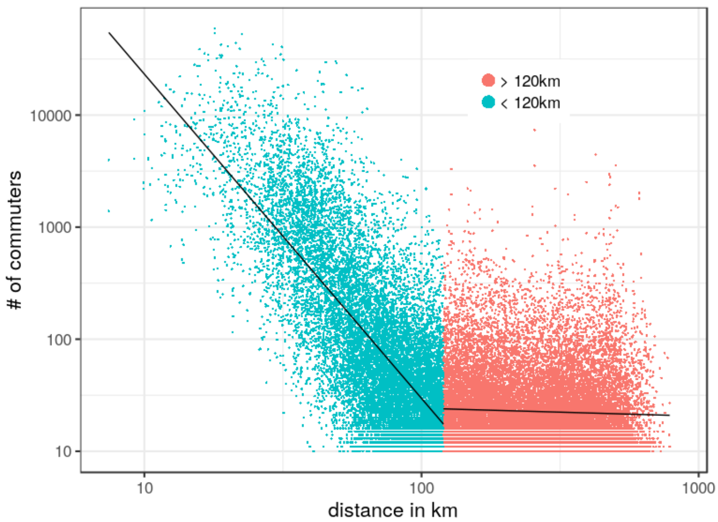

Figure D.1: Commuting flows and distance between counties in the raw commuting data (log scale).

[29] The easiest way to measure the distance between two counties is to take the great circle distance of their geometric centroids. This is problematic for German counties which often consist of a free city (‘Kreisfreie Stadt’) which is a county of its own, surrounded by a (roughly) ring shaped county. In this case the centroids of both counties can fall extremly close together leading to a misrepresentation of the average distance that commuters between those two locations face. For this reason we establish the bilateral distance between locations by calculating the mean of 10,000 pairwise distances between 100 random points in each of the counties.

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.[30]

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

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 D.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 D.2 reports the resulting coefficients β_{near} and β_{far} as well as their difference for threshold values ranging from 60 to 250 km (in steps of 5km). 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 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.

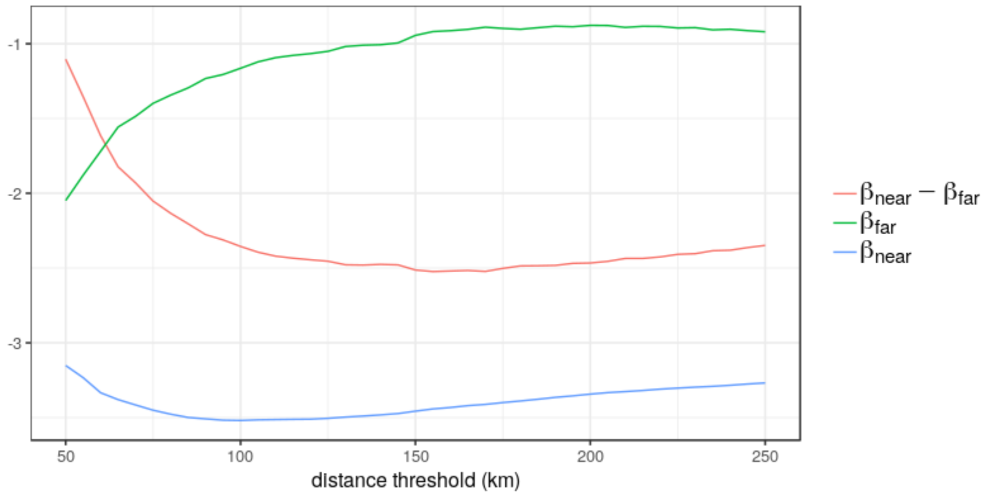

Figure D.2: Coefficients for different commuting thresholds

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

[30] 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.

county level. These aggregate inflows allow us to calculate that for 2.78% 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 (24% 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 D.1. In particular, we begin by calculating fitted values $\hat{\hat{\lambda}}_{ni}$ 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[31]

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

Figure D.3 again depicts the relationship between log commuters and log distances including our imputed values for censored flows.[32]

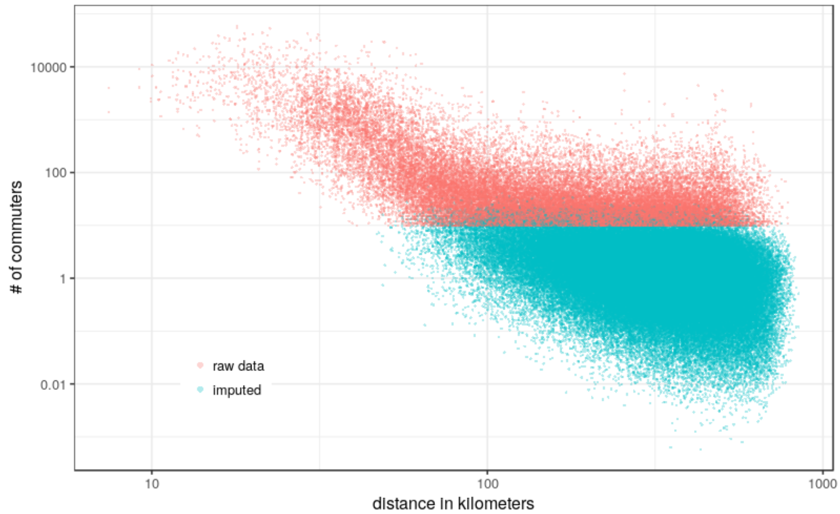

Figure D.3: (Log) relationship between commuters and distance with imputed data for censored flows.

[31] We ignore integer constraints for commuters in this procedure.
[32] 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.

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 noncommuters 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 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

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

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 (D.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 D.3 depicts the tight (log) relationship between commuters and distance in our final cleaned commuting data after removing residence and workplace fixed effects.

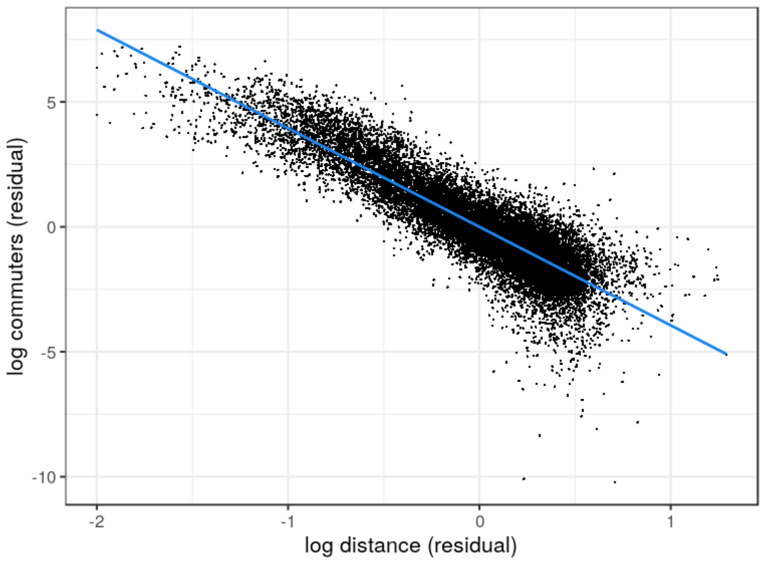

Figure D.3: Log commuting and log distance (residuals after removing county fixed effects) final data

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. We follow Monte et al. (2018) in defining the composite parameter $\mathcal{B}_{ni} \equiv B_{ni} \kappa_{ni}^{-\epsilon}$ as a measure for the ease and average attractivity of commuting between locations n and i and in assuming that, for the purpose of estimation, $\mathcal{B}_{ni}$ can be decomposed in the following way: $\mathcal{B}_{ni} = \mathbb{B}_n \mathbb{B}_i dist_{ni}^{\psi_\lambda} \mathbb{B}_{ni}$. The first and second term on the right hand side of this equation capture residence and workplace fixed effects respectively, distance is used to parameterize bilateral effects and $\mathbb{B}_{ni}$ captures the residual. Taken together we can rewrite the gravity equation for commuting flows in its stochastic version as

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

where $S_{\lambda,i}$ and $M_{\lambda,n}$ capture all residence (exporter) and workplace (importer) specific effects. Log linearizing this specification, dropping observations with 0 commuters and estimating with OLS yields a coefficient of $\psi_\lambda = -3.86$. However, both, dropping zeros and potential heteroscedasticity in the data, can bias the OLS results. In contrast to goods trade there is no clear indication of heteroscedasticity in the data and the 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 -3.69.

Finally we can extract the commuting elasticity ϵ by using the fact that from equation (12) residence fixed effects are given by $S_{\lambda,i} = \epsilon \log w_i$. Fixing the estimate of $\psi_\lambda = -3.69$ we rerun our gravity in commuting equation, explicity specifiying the residence fixed effect this time. To further account for the potential endogeneity problem between wages and commuting inflows 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 for our specific problem and we therefore feel confident in following Monte et al. (2018) in the estimation of the following log linearized version of our gravity equation with 2SLS after dropping observations with zero commuters.

$$\log \lambda_{ni}|_{\Omega_g} = \epsilon \log w_i + \log M_{\lambda,n} + \psi_\lambda \log dist_{ni} + \log \mathbb{B}_{ni}$$

Our highly significant 2SLS estimate for ϵ is 4.24 with a clustered standard error of 0.224.[33] 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.

[33]The validity of the instrument is underscored by an F-statistic of 358.5 in the first stage.

E Additional Tables

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.115^{***}	-0.532^{***}	-0.632^{***}				-0.086^{**}	-0.090
		(0.018)	(0.116)	(0.106)				(0.035)	(0.094)
$\log(w_i)$			0.388^{***}	0.463^{***}				0.048	0.116
			(0.121)	(0.159)				(0.036)	(0.099)
$\log(H_i)$			0.410^{***}	0.465^{***}				0.063^{*}	0.065
			(0.118)	(0.109)				(0.034)	(0.092)
$\log(L_{-i})$				0.206^{***}					
				(0.035)					
$\log(w_{-i})$				-0.501^{**}					
				(0.231)					
$\lambda^R_{ii\vert i}$					-2.000^{***}				
					(0.053)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\vert n}\right)\vartheta_{ni}$						0.039^{***}		0.020^{*}	
						(0.009)		(0.010)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-1.580^{***}		-1.578^{***}	
						(0.055)		(0.055)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.345^{***}		0.345^{***}	
						(0.040)		(0.040)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\vert n}\right)\vartheta_{ni}$							0.431^{***}		0.405^{***}
							(0.035)		(0.042)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-0.649^{***}		-0.551^{***}
							(0.130)		(0.147)
Constant	1.330^{***}	2.677^{***}	-1.681	0.428	2.899^{***}	2.170^{***}	1.387^{***}	1.892^{***}	0.354
	(0.018)	(0.207)	(1.271)	(1.749)	(0.042)	(0.046)	(0.043)	(0.395)	(1.037)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.234	0.318	0.459	0.912	0.946	0.635	0.952	0.642
Adjusted R^2	0.000	0.229	0.303	0.439	0.911	0.944	0.630	0.950	0.629

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. *p<0.1; **p<0.05; ***p<0.01

Table 5: Analysis of the general equilibrium local employment elasticities in response to 5 percent productivity shocks at the local level (commuting zones) with an expenditure share of 40% for housing.

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		0.051**	−0.269*	−0.221				−0.332**	−0.421***
		(0.023)	(0.159)	(0.163)				(0.144)	(0.145)
$\log(w_i)$			0.008	0.130				0.418***	0.497***
			(0.166)	(0.244)				(0.150)	(0.152)
$\log(H_i)$			0.342**	0.297*				0.386***	0.455***
			(0.163)	(0.167)				(0.141)	(0.142)
$\log(L_{-i})$				−0.066					
				(0.054)					
$\log(w_{-i})$				−0.120					
				(0.355)					
$\lambda^R_{ii\|i}$					0.089				
					(0.209)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.030		0.088**	
						(0.037)		(0.041)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						0.155		0.381*	
						(0.233)		(0.229)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						1.261***		1.428***	
						(0.168)		(0.167)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.201***		0.246***
							(0.058)		(0.064)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							1.558***		1.803***
							(0.215)		(0.226)
Constant	2.367***	1.766***	1.266	2.234	2.297***	1.694***	1.867***	−3.957**	−4.263***
	(0.021)	(0.274)	(1.749)	(2.682)	(0.165)	(0.194)	(0.071)	(1.644)	(1.594)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.034	0.067	0.080	0.001	0.295	0.281	0.396	0.388
Adjusted R^2	0.000	0.027	0.046	0.046	−0.006	0.280	0.271	0.369	0.366

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. *p<0.1; **p<0.05; ***p<0.01

Table 6: Analysis of the general equilibrium local employment elasticities in response to 5% productivity shocks at the local level (commuting zones) with an expenditure share of 10% for housing.

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.150^{***}	-0.588^{***}	-0.596^{***}				-0.326^{***}	-0.440^{***}
		(0.023)	(0.058)	(0.060)				(0.032)	(0.048)
$\log(w_i)$			0.890^{***}	0.849^{***}				0.226^{***}	0.502^{***}
			(0.100)	(0.153)				(0.058)	(0.087)
$\log(H_i)$			0.416^{***}	0.401^{***}				0.323^{***}	0.364^{***}
			(0.059)	(0.059)				(0.032)	(0.048)
$\log(L_{-i})$				0.140^{***}					
				(0.034)					
$\log(w_{-i})$				-0.220					
				(0.210)					
$\lambda^R_{ii\|i}$					-1.932^{***}				
					(0.059)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.147^{***}		0.128^{***}	
						(0.019)		(0.018)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-1.369^{***}		-1.354^{***}	
						(0.061)		(0.060)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.794^{***}		0.657^{***}	
						(0.054)		(0.052)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.622^{***}		0.512^{***}
							(0.043)		(0.041)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-1.267^{***}		-1.150^{***}
							(0.131)		(0.132)
Constant	2.625^{***}	4.245^{***}	-5.461^{***}	-4.430^{***}	3.783^{***}	2.699^{***}	2.633^{***}	0.172	-2.204^{**}
	(0.017)	(0.248)	(1.068)	(1.457)	(0.036)	(0.043)	(0.030)	(0.623)	(0.918)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.097	0.276	0.306	0.731	0.750	0.442	0.803	0.548
Adjusted R^2	0.000	0.095	0.271	0.298	0.730	0.749	0.439	0.800	0.542

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. *p<0.1; **p<0.05; ***p<0.01

Table 7: Analysis of the general equilibrium local employment elasticities in response to 5% productivity shocks at the local level (counties) with an expenditure share of 25% for housing.

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.069^{***}	-0.435^{***}	-0.495^{***}				-0.148^{**}	-0.173^{*}
		(0.015)	(0.101)	(0.098)				(0.058)	(0.091)
$\log(w_i)$			0.277^{***}	0.345^{**}				0.153^{**}	0.223^{**}
			(0.105)	(0.147)				(0.061)	(0.096)
$\log(H_i)$			0.365^{***}	0.395^{***}				0.141^{**}	0.160^{*}
			(0.103)	(0.101)				(0.057)	(0.089)
$\log(L_{-i})$				0.129^{***}					
				(0.032)					
$\log(w_{-i})$				-0.356^{*}					
				(0.213)					
$\lambda^R_{ii\|i}$					-1.379^{***}				
					(0.084)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.033^{**}		0.032^{*}	
						(0.014)		(0.017)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-1.070^{***}		-1.008^{***}	
						(0.091)		(0.093)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.584^{***}		0.629^{***}	
						(0.065)		(0.068)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.355^{***}		0.344^{***}
							(0.034)		(0.040)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-0.032		0.114
							(0.128)		(0.142)
Constant	1.673^{***}	2.485^{***}	-0.708	0.859	2.754^{***}	2.083^{***}	1.577^{***}	0.370	-0.820
	(0.015)	(0.179)	(1.107)	(1.613)	(0.067)	(0.076)	(0.042)	(0.669)	(1.002)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.129	0.215	0.300	0.657	0.776	0.468	0.790	0.492
Adjusted R^2	0.000	0.123	0.198	0.275	0.655	0.771	0.460	0.781	0.473

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. *p<0.1; **p<0.05; ***p<0.01

Table 8: Analysis of the general equilibrium local employment elasticities in response to 5% productivity shocks at the local level (commuting zones) with an expenditure share of 25% for housing.

F Additional Figures

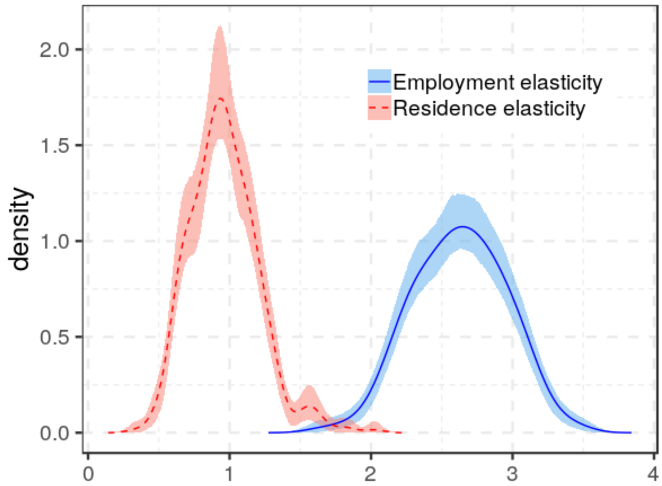

Figure F.1: Kernel densities of general equilibrium elasticities of employment and residents (counties) for a housing share of 25%

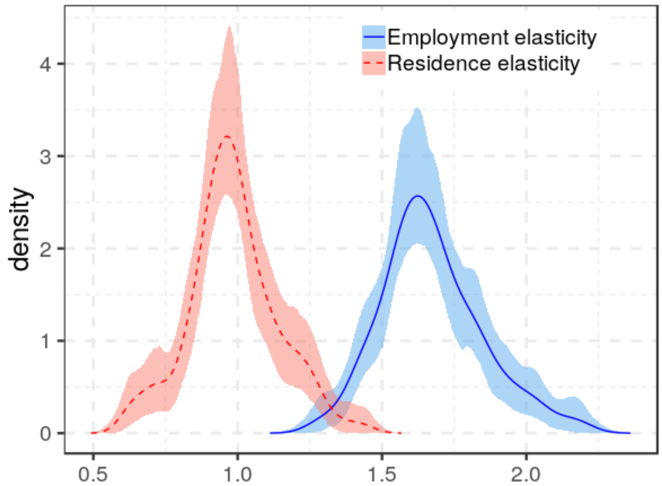

Figure F.2: Kernel densities of general equilibrium elasticities of employment and residents (commuting zones) for a housing share of 25%.