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Rush hours and urbanization[☆]

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ABSTRACT

We use a quantitative spatial general equilibrium model with potential commuting of workers to analyze the effects of rush hours on the spatial allocation of employment and population, the housing market, average labor productivity and welfare. We construct a measure of traffic congestion based on commuting time data for German districts in 2018 and use the model to quantify efficiency and welfare costs of rush hours. Reducing time lost in traffic by 50 percent raises the urbanization rate by 3.7 percentage points, average labor productivity by 0.8 percent and welfare by 3.5 percent. We also compare the role of commuting costs and housing markets as two major congestion forces with regard to urbanization, productivity, and welfare.

1. Introduction

The spatial economy is shaped by the interplay of agglomeration and congestion forces. While the housing market is an important limiting factor to urban growth, evidence suggests that traffic congestion is also quantitatively important in this regard (Ahlfeldt and Pietrostefani, 2019; Parry et al., 2007; Small and Verhoef, 2007). According to the INRIX Global Traffic Scorecard, traffic jams account for up to one third of commuting time. For example, commuters in Rome have lost 254 h in traffic in 2018, closely followed by Dublin (246), Paris (237) or London (227).[1]

While workers perceive commuting as a cost (Gottholmseder et al., 2009; Kahneman et al., 2004; Kuenn-Nelen, 2016), there is also a benefit as individuals can enjoy lower housing prices in less dense places and high-paid jobs in economic centers at the same time. If commuting costs fall short of the extra housing costs in cities and differences in amenities, this workplace-residence separation implies higher utility for the individual. Traffic jams during rush hours, however, distort the location decision. If commuting becomes more costly, it might be more beneficial to look for housing closer to work at the expense of higher prices. Alternatively, households might leave the area entirely and locate in other less congested regions of the economy.

In this paper, we aim to quantitatively evaluate the role of traffic congestion for the spatial economy. To this end, we develop a new measure of congestion at the local level by comparing bilateral commuting times with and without traffic delays and use a quantitative spatial general equilibrium model to run counterfactual analyses with hypothetical reductions of time lost in traffic. This exercise delivers a model-based estimate of efficiency costs of traffic congestion in terms of average productivity and insights into the effects on urbanization, the housing market, and welfare.

Our model builds on recent developments in the regional economics literature (Allen and Arkolakis, 2014; Redding, 2016; Monte et al., 2018) allowing for endogenous location and commuting decisions. Individuals consume a differentiated tradable good and housing that is supplied by immobile landlords. Rents adjust endogenously to changes in location-commuting decisions of workers and operate as a congestion force in the model. We parameterize commuting in time units as in

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[1] See www.inrix.com/scorecard for details.

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Ahlfeldt et al. (2015) with longer commuting times reducing welfare ceteris paribus. This allows us to use bilateral commuting time between locations when we confront the model with data and to back out a commuting elasticity that indicates how households value 1 min of additional commuting time in terms of utility. As in Allen and Arkolakis (2014), we assume that productivity in each location depends on exogenous factors and employment density, so changes in the spatial allocation of jobs affect location-specific and economy-wide productivity (Combes et al., 2012).

We quantify the model for 401 German districts in 2018 using bilateral commuting flows as well as information on employment and labor income. We retrieve bilateral commuting times between districts from a major web-mapping service with and without congestion and assume that workers commute to work at 8 a.m. and return at 5 p.m. on a workday. We interpret differences between both travel times as the time lost in traffic. In the counterfactual analysis, we reduce traffic congestion and solve the model for a new spatial equilibrium to receive answers to the above questions.

We find that reducing traffic congestion by 50 percent raises the urbanization rate of both residential population and employment by about 3.7 percentage points.[2] This outcome appears surprising at first sight as better accessibility of dense places should *reduce* urbanization. While this logic should be valid in a two location core-periphery setting, it does not necessarily carry over to a multi-location framework. We show that workers relocate to the vicinity of economic centers within broader urban areas from low-density peripheral regions which leads to an increase in overall urbanization. We further show that this spatial reallocation raises housing costs by up to 30 percent in locations with the highest traffic congestion and reduces them in low-density places facing net emigration. Higher agglomeration of employment leads to more pronounced differences in local labor productivity and an increase of average productivity by 0.8 percent in the baseline specification. As lower commuting times also exert a direct effect on utility, the model predicts a welfare increase of 3.5 percent.

We further relate housing markets and rush hours to shed light on the role of these two congestion forces for aggregate outcomes. Doubling the housing supply elasticity roughly doubles the increase in urbanization rates and labor productivity when time lost in traffic shrinks by 50 percent. For welfare, this factor is approximately one third. Importantly, these relationships are highly non-linear and depend on the level of change in commuting costs and housing supply elasticities.

As denser and more productive locations face more severe traffic congestion, our results suggest that investments in capacity-enhancing transport infrastructure generate a higher return in urban areas and their hinterland compared to the periphery. Although we know from the fundamental law of road congestion (Duranton and Turner, 2011) that additional road capacity has little impact on commuting times in equilibrium due to more driving and migration to this region, the higher capacity of traffic infrastructure allows more people to commute. Therefore, such investments promise average productivity gains due to higher economic density in line with our findings. However, we would expect these gains to be quantitatively smaller as the endogenous increase in traffic volume in those urban areas would act as a countervailing force. We therefore interpret our estimates as upper bounds.

Our paper relates to the regional economics literature on traffic and transport infrastructure using both structural partial equilibrium estimations (Duranton and Turner, 2011; Couture et al., 2018; Ahlfeldt and Feddersen, 2018) and theoretical partial and general equilibrium models (Rotemberg, 1985; Anas, 2012; Anas and Pines, 2013).[3] More recently, Fretz et al. (2019) show that the Swiss highway system raised the share of high-income taxpayers within 10 km and contributed to urban sprawl while Heblich et al. (2020) combine commuting decisions of households with the introduction of the steam railway in the mid-19th century in London to explain the growth in economic density in the city of London during that time. Paetzold (2019) and Fosgerau and Kim (2019) explore the role of subsidies and tolls for the pattern of commuting. Our paper contributes a new measure of traffic congestion for Germany to this literature and provides an estimate of efficiency losses based on a class of recently developed quantitative spatial general equilibrium models (Redding and Rossi-Hansberg, 2017; Behrens et al., 2017; Monte et al., 2018). As traffic congestion represents a friction for the spatial allocation of economic activity, our paper further connects with the misallocation literature (Hsieh and Klenow, 2009; Hsieh et al., 2019). In a recent paper, Hsieh and Moretti (2019) study the spatial consequences of housing regulation for the US. This paper undertakes a similar exercise for traffic congestion as another quantitatively important centrifugal force.

In the remainder of the paper, we start in Section 2 with a detailed exposition of the model, explain the quantification procedure in Section 3 and run the counterfactual exercise and discuss our findings in section 4.

2. Model

Consider an economy with $n, i \in N$ regions and L mobile workers. While each worker supplies one unit of labor inelastically, migration makes labor supply elastic from the perspective of regions. Importantly, workers are able to choose their locations of work and residence separately, so we distinguish between workers (L_n) and residents (R_n) in each location n. If the place of work differs from the place of residence, individuals need to commute. This comes at a cost (e.g. less leisure time) and reduces utility. Apart from labor mobility and commuting, regions are also connected via costly trade of differentiated varieties of a consumption good Q. Each region in the economy is further endowed with developable land for housing that is owned by immobile landlords who consume where they live. The market for land is perfectly competitive.

2.1. Workers

The utility of a worker ω living in region n and working in region i is given by

$$U_{ni\omega} = \frac{\hat{b}_{ni\omega}}{\kappa_{ni}} \left(\frac{Q_{n\omega}}{\alpha} \right)^{\alpha} \left(\frac{H_{n\omega}}{1-\alpha} \right)^{1-\alpha}, \tag{1}$$

where $Q_{n\omega}$ denotes the consumed quantity of a tradable differentiated good, $H_{n\omega}$ represents consumption of housing, κ_{ni} captures bilateral commuting costs and $b_{ni\omega}$ is a location-worker-specific amenity parameter, where $\hat{b}_{ni\omega} = \exp\left[b_{ni\omega}\right]$. The Cobb-Douglas parameter $0 < \alpha < 1$ governs the relative importance of the tradable good and housing in the utility function. The consumer good Q is composed of differentiated varieties according to a CES-aggregator of the form

$$Q_{n\omega} = \left[\sum_{i \in N} \int_0^{M_i} q_{ni}(j)^{\frac{\sigma-1}{\sigma}} dj \right]^{\frac{\sigma}{\sigma-1}},$$

where $q_{ni}(j)$ denotes the quantity of variety j that is produced in region i and consumed by a worker living in region n. M_i is the measure of firms located in region i. We assume that varieties are imperfect substitutes with a corresponding constant elasticity $\sigma > 1$.

Utility maximization implies that households dedicate fixed income shares α and $1-\alpha$ to the differentiated good and housing, respectively. Denoting by E_n aggregate expenditure in location n, we have

$$Q^*_{n\omega} = \frac{\alpha E_n}{P_{Q,n}} \quad \textit{and} \quad H^*_{n\omega} = \frac{(1-\alpha)E_n}{P_{H,n}},$$

[2] In a related paper, Takayama et al. (2020) develop a theoretical model with commuting costs within cities and show that lower commuting costs lead to fewer, but larger cities.

[3] Redding and Turner (2015) provide a recent survey of the literature on transportation in the spatial economy.

where $P_{Q,n}$ is the price index of the composite good and $P_{H,n}$ denotes the price per unit of housing in region n. Region $n's$ demand for a variety j imported from i is given by

$$q_{ni}(j) = \frac{p_{ni}(j)^{-\sigma}}{P_{Q,n}^{1-\sigma}} \alpha E_n, \tag{2}$$

with $p_{ni}(j)$ denoting the corresponding consumer price. Notice that landowners spend their entire income on consumption goods such that total expenditure on Q_n equals $P_{Q,n}Q_n = (\alpha\overline{v}_n + (1-\alpha)\overline{v}_n)R_n = \overline{v}_nR_n$ with $\overline{v}_n$ representing average per-capita labor income in n.

We follow Ahlfeldt et al. (2015) in modeling commuting costs as a function of bilateral commuting times. In particular, we impose $\kappa_{ni} = \tau_{ni}^{\mu}$, where τ_{ni} denotes bilateral commuting time and μ is a parameter describing the household's distaste for commuting. We will back out the value of this parameter from data in the empirical analysis below. The negative relation between commuting and utility can be motivated, for example, by the fact that commuting raises stress levels (Gottholmseder et al., 2009), deteriorates health conditions (Kuenn-Nelen, 2016) or that workers dislike traveling to work (Kahneman et al., 2004).

Finally, we assume that individuals have heterogeneous preferences for combinations of locations for work and living. The amenity value $b_{ni\omega}$ is drawn from an independent Type I extreme value (Gumbel) distribution with cdf $G_{ni}(b) = \exp\left(-B_{ni}\exp\left\{-\left[\epsilon b + \Gamma'(1)\right]\right\}\right)$, where $B_{ni} > 0$ is the scale parameter, $\epsilon > 0$ is the shape parameter and Γ' is the Euler – Mascheroni constant.[4] The scale parameter B_{ni} represents the average value of amenities from living in region n and working in region i. Higher values of ϵ imply a lower dispersion of the distribution. Indirect utility of worker ω living in n and earning her income in i then results as

$$U^*_{ni\omega} = \frac{\widehat{b}_{ni\omega} w_i}{\kappa_{ni} P_{Q,n}^{\alpha} P_{H,n}^{1-\alpha}}, \tag{3}$$

where w_i is labor income. Notice that indirect utility is a monotone transformation of the amenity parameter, so it is also Gumbel distributed with $G_{ni}(U) = \exp\left\{-\Phi_{ni}\exp\left\{-\left[\epsilon U + \Gamma'(1)\right]\right\}\right\}$ and $\Phi_{ni} = B_{ni}\left(\kappa_{ni} P_{Q,n}^{\alpha} P_{H,n}^{1-\alpha}\right)^{-\epsilon} w_i^{\epsilon}$.

We use the property that the maximum of repeated draws from the Gumbel distribution is also Gumbel distributed to write the probability that a worker chooses to live in location n and work in location i as

$$\lambda_{ni} = \frac{\Phi_{ni}}{\Phi} \tag{4}$$

with $\Phi = \sum_r \sum_s \Phi_{rs}$. By the law of large numbers, the probability of living in region n and working in region i should be equivalent to the share of workers living in n and working in i, so that $\lambda_{ni} = L_{ni}/L$. As workers are regionally mobile, expected utility needs to be equalized in equilibrium for all residence-workplace combinations. This means that

$$\overline{U} = \mathbb{E}[U_{ni\omega}] = \Phi^{1/\epsilon}. \tag{5}$$

We can write the probability that a worker commutes to region i given she lives in n as $\lambda_{ni|n} = \Phi_{ni}/\sum_s \Phi_{ns}$. Further notice that we can express the measure of workers employed in region i as $L_i = \sum_n L_{ni}$ and the measure of workers living in region n by $R_n = \sum_i L_{ni}$. Labor market clearing then implies that in every location i

$$L_i = \sum_n \lambda_{ni|n} R_n$$

must hold and the expected income conditional on living in location n is given by

$$\overline{v}_n = \sum_i \lambda_{ni|n} w_i. \tag{6}$$

2.2. Housing market

Land owners are immobile and supply housing according to the aggregate supply function

$$H_n^s = \overline{H}_n P_{H,n}^{\delta}, \tag{7}$$

where $\overline{H}_n$ captures region-specific housing fundamentals such as developable land, natural constraints or regulation, and δ denotes the housing supply elasticity (Saiz, 2010). From the household's optimal housing demand above we can derive the aggregate demand for housing in region n as

$$H_n^d = (1-\alpha)\frac{\overline{v}_n R_n}{P_{H,n}}. \tag{8}$$

Hence, housing market clearing requires that

$$P_{H,n} = \left[(1-\alpha)\frac{\overline{v}_n R_n}{\overline{H}_n}\right]^{\frac{1}{1+\delta}} \tag{9}$$

holds in equilibrium in every region.

2.3. Production and inter-regional trade

Firms employ labor as the only factor of production and operate under monopolistic competition and internal increasing returns to scale that stem from fixed costs fw_i. This implies decreasing average costs so every firm manufactures a unique variety j. To produce $q_i(j)$ units of variety j a firm needs to hire

$$l_i(j) = f + \frac{q_i(j)}{A_i(L_i)}$$

laborers, where $A_i(L_i) = \overline{A}_i L_i^{\nu}$ describes location-specific productivity, which is a function of the number of workers employed in that region. Therefore, density gives rise to an agglomeration force in our model (e.g. through knowledge spillovers) that is governed by the parameter ν (Combes and Gobillon, 2015).

Shipping goods between regions i and n requires iceberg trade costs $d_{ni} > 1$. The profit-maximizing price for every destination market results as a constant mark-up over marginal costs,

$$p_{ni}(j) = \frac{\sigma}{\sigma-1}\frac{d_{ni}w_i}{A_i(L_i)}.$$

Free entry of firms drives down profits to zero implying $l_i(j)^* = \sigma f$, so total employment in i, L_i, determines the number of operating firms, $M_i = L_i/(\sigma f)$, in this location.[5]

Against this background, we obtain the expenditure share spent on goods produced in region i as

$$\pi_{ni} \equiv \frac{M_i\, p_{ni}^{1-\sigma}}{\sum_k M_k\, p_{nk}^{1-\sigma}} = \frac{L_i^{1-(1-\sigma)\nu}\left(\frac{w_i d_{ni}}{\overline{A}_i}\right)^{1-\sigma}}{\sum_k L_k^{1-(1-\sigma)\nu}\left(\frac{w_k d_{nk}}{\overline{A}_k}\right)^{1-\sigma}}. \tag{10}$$

We observe from (10) that π_{ni} is increasing in the number of varieties produced in region i, M_i, and the corresponding local exogenous productivity, $\overline{A}_i$, and decreasing in trade costs between regions n and i,

[4] As the logarithmic transformations of a Type II extreme value random variable (Fréchet) follows a Gumbel distribution, our approach is analogous to the Fréchet assumption used in (among others) Eaton and Kortum (2002), McFadden (1974) and Monte et al. (2018). The advantage of the Gumbel distribution lies in its higher flexibility to empirical applications as the shape parameter is not constrained to be larger than one (as with Fréchet), but only needs to be larger than zero.

[5] We assume that firms are atomistic, i.e. they regard aggregate employment as given, ignoring the effect that their labor demand has on total employment and hence productivity in their region.

d_{ni}. This notation allows us to express region $n's$ price index for the composite good Q as

$$P_{Q,n} = \left[\sum_{i \in N} p_{ni}^{1-\sigma}\right]^{\frac{1}{1-\sigma}} = \frac{\sigma}{\sigma-1}\left(\frac{L_n^{1-(1-\sigma)\nu}}{\sigma f \pi_{nn}}\right)^{\frac{1}{1-\sigma}} \frac{w_n d_{nn}}{\overline{A}_n}. \tag{11}$$

2.4. Equilibrium

The equilibrium in this model is defined by a vector of six endogenous variables $\{w_n, \overline{v}_n, L_n, R_n, P_{H,n}, P_{Q,n}\}_{n=1}^N$ and a scalar $\overline{U}$ that solve the following equations: the price index (11), housing-market clearing (9), average income (6), the condition that income equals expenditure,

$$w_i L_i = \sum_{n \in N} \pi_{ni} \overline{v}_n R_n, \tag{12}$$

and aggregated probabilities of living and working in region n based on (4), that is $\lambda_n^R = \sum_i \lambda_{ni}$ and $\lambda_n^L = \sum_i \lambda_{in}$. Finally, the normalization of L determines the utility level $\overline{U}$ via the labor-market clearing condition $L = \sum_n L_n$.

3. Quantification

3.1. Data

We calibrate the model to the 401 German districts in 2018 using data on average monthly gross labor earnings by place of work and bilateral commuting from the German Federal Employment Agency for all German workers who are subject to social insurance contributions.[6] As the commuting data do not explicitly report the number of employees working and living in the same location, we use information on employment at the district level to fill this gap. As commuting is understood as a *daily* round-trip to work in this analysis, we include only district pairs with commutes of less than 3 h. The data reveal that about two thirds of employees work in the same district where they live. Of the remaining 30 percent, approximately 60 percent commute less than 50 km. Hence, truncating the commuting matrix affects only 7.2 percent of commuting flows that are most likely weekend rather than daily commutes.

One contribution of this paper is to develop a traffic congestion measure for German districts which we obtain as follows. We first define a residential and a commercial centroid for each district by using information on population density and commercial land use per square kilometer from the RWI-GEO-Grid dataset as weights and assume that workers commute from the residential to the commercial centroid. This allows us, in a second step, to retrieve bilateral commuting times, τ_{ni}, from a major web-mapping service that supplies both congested and uncongested travel times. We assume that workers start their commute at 8a.m. and return from work at 5p.m. For intra-district commuting times, we compute the average of 100 random trips within districts using population densities per square kilometer at the residential location as sampling weights.[7]

Our measure implies average commuting times of 38 min for a round trip which is in line with what Redding and Turner (2015) report for 17 countries in Europe and North America. To connect travel congestion with the spatial pattern of population density, Fig. 1 illustrates the time lost in traffic as a percentage of total average in-commuting times (panel a) and the classification of German districts according to the Federal Institute for Research on Building, Urban Affairs and Spatial Development in Germany (panel b). Cities with more than 100,000 inhabitants form an own category. “Mostly urban” refers to districts with population density of at least 150 inhabitants per square kilometer. “Mostly rural” regions have population densities between 100 and 150 inhabitants per square kilometer while “rural” districts are characterized by less than 100 inhabitants per square kilometer. Darker shading indicates higher population density. We observe that traffic congestion is highest in cities like Munich, Frankfurt or Dusseldorf. As detailed in Appendix A.1.2, there is also a positive relationship between employment and in-commuting times. Our data suggest that a one-percent increase in employment is associated with an increase in in-commuting time of about 0.1 percent.

Although our congestion measure reveals a plausible spatial pattern of traffic jams, it is limited in at least two regards. First, we only have access to aggregate commuter flows between districts impeding a higher precision in measuring congestion. It would clearly be desirable to use more granular data, ideally at the individual level. Second, we cannot distinguish commuting by mode of transport. While 92 percent of workers use their car to commute between districts, public transport arguably plays a larger role within dense locations. To shed light on the differential role of congestion within and between districts, we reduce observed traffic congestion in all locations as well as separately for inter- and intra-district commutes in the counterfactual below.

3.2. Model inversion

Although the model is fully quantifiable, we only need to uncover a subset of fundamentals to run counterfactual analyses. As we are interested in the effects of variation in traffic congestion and solve the model in changes, the levels of bilateral amenities, B_{ni}, or exogenous housing supply, $\overline{H}_n$, are not required. Instead, we set values for some exogenous parameters, estimate μ and ε from our commuting data and obtain the remaining unobservable primitives by inverting the model.

Residential population. We first derive location-specific employment and residential population from the commuting matrix based on the model's labor-market clearing conditions

$$L_n = \sum_{n \in N} \lambda_{ni} L \quad \text{and} \quad R_n = \sum_{i \in N} \lambda_{ni} L, \tag{13}$$

where we obtain total employment L as the sum of all elements of the commuting matrix and the unconditional commuting probabilities λ_{ni} as the ratio of bilateral commuters to L. Notice that we use equilibrium conditions from the model to determine R_n instead of using available data on residents to ensure consistency.

Residential wage income. Second, we combine conditional employment shares with observed wages by place of work, w_i, to determine average labor income in region n, $\overline{v}_n = \sum_i \lambda_{ni|n} w_i$.

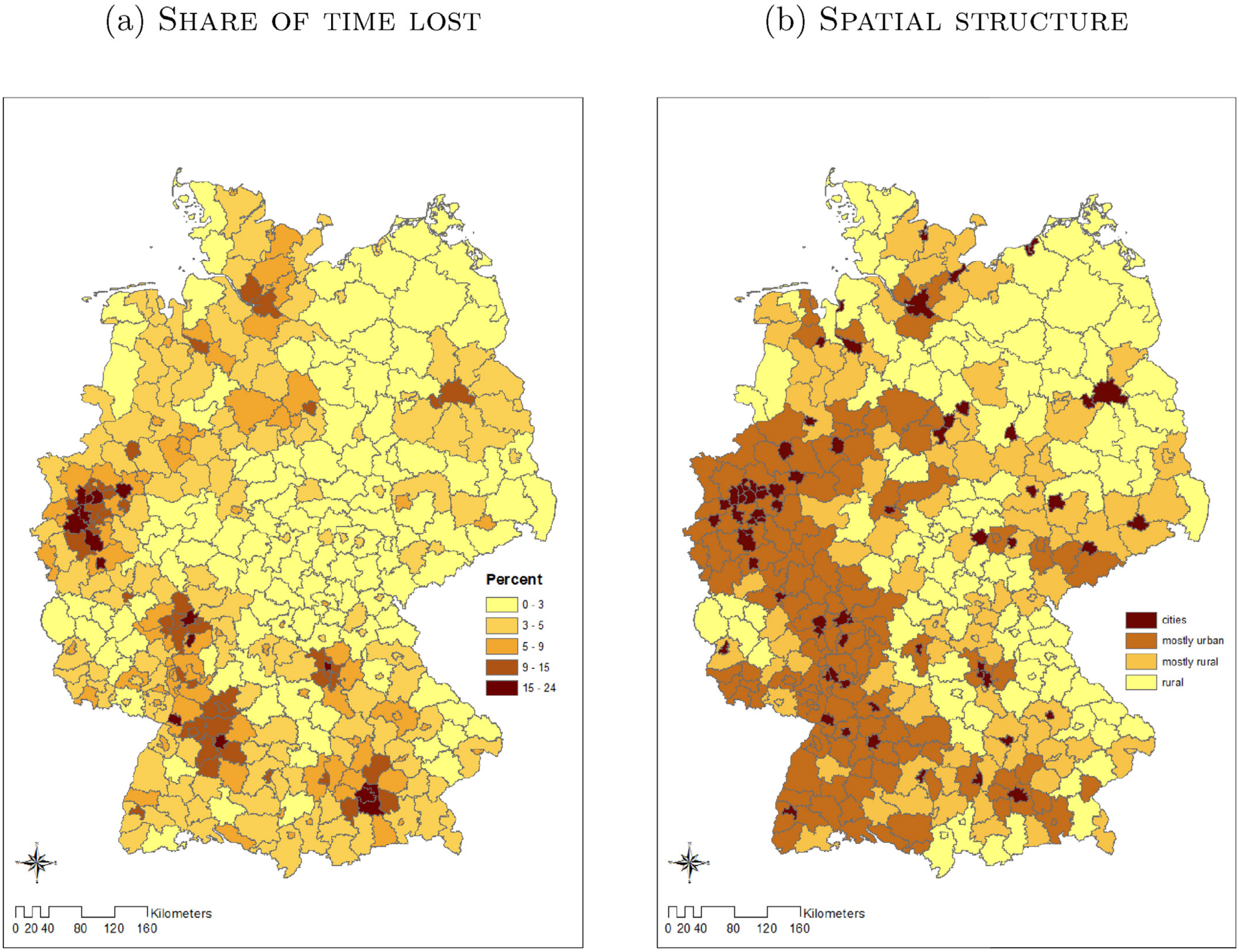
Fundamental productivity, $\overline{A}_n$. In a third step, we use the observed and derived values for R_n, L_n, w_n and $\overline{v}_n$ to uncover the region-specific productivity fundamentals based on Eqs. (10) and (12). One additional ingredient are bilateral trade frictions, d_{ni}, to determine bilateral expenditure shares, π_{ni}. We follow the trade gravity literature in assuming that trade costs are a function of bilateral distance, $d_{ni} = dist_{ni}^{\psi}$, where ψ determines how distance maps into trade frictions. The gravity model suggests a distance elasticity $\psi(\sigma - 1)$ which delivers an estimate for ψ if the elasticity of substitution is known. We use the estimate for the distance elasticity of 1.23 from Henkel et al. (2018) based on German inter-regional trade flows for the year 2010, the most recent year for which regional trade flows are available. This estimate is in line with average estimates in the literature (e.g. Head and Mayer, 2015). Setting $\sigma = 4$ as in Broda and Weinstein (2004) yields $\psi = 0.41$.

We are now equipped with the necessary information to back out location-specific productivity levels.[8] Substituting bilateral trade

[6] See Appendix A.1.1 for a detailed documentation of the data sources and definitions.

[7] Although desirable, restrictions in the downloadable data volume preclude a more extensive data set at finer grid cells, or sampling over various dates or times of day.

[8] See Monte et al. (2018) for a formal proof of existence and uniqueness of the solution.



Notes: Panel (a) plots the time lost in traffic as a share of total in-commuting times. Panel (b) documents the classification of German districts in 2018.

Fig. 1. Traffic congestion and spatial structure.

shares, (10), into the region-specific goods market clearing conditions, $w_i L_i = \sum_n \pi_{ni} \bar{v}_n R_n$, delivers a system of N equations which can be solved for a unique vector of $\overline{A}_n$, where we set the productivity elasticity of density to $\nu = 0.05$. This implies that productivity increases by 3.5 percent if population doubles – a value that is suggested in Rosenthal and Strange (2004). We illustrate the spatial pattern of $\overline{A}_n$ in Appendix A.1.3 and show that regional productivity fundamentals are positively and strongly correlated with wages and traffic congestion.

Commuting elasticity. Finally, we need to uncover parameters for the Gumbel shape parameter, ϵ, and the commuting distaste parameter μ. We start from the unconditional commuting probability

$$\lambda_{ni} = \frac{B_{ni}\left(\tau_{ni}^{\mu} P_{Q,n}^{\alpha} P_{H,n}^{1-\alpha}\right)^{-\epsilon} w_i^{\epsilon}}{\sum_r \sum_s B_{rs}\left(\tau_{rs}^{\mu} P_{Q,r}^{\alpha} P_{H,r}^{1-\alpha}\right)^{-\epsilon} w_s^{\epsilon}}$$

that gives rise to the estimation equation

$$(\log)\lambda_{ni} = g_0 + \eta_n + \zeta_i - \mu\epsilon \log \tau_{ni} + u_{ni}, \tag{14}$$

where g_0 is a constant term and η_n and ζ_i capture origin and destination fixed effects. We apply OLS, IV and PPML to obtain estimates for the commuting time elasticity $\mu\epsilon$. Table 1 reveals that the elasticity ranges between −2.16 (PPML) and −3.27 (IV) for commuting time and lower values for geographical distance. The IV-estimation uses geographical distance as an instrument for commuting time. The PPML-result matches the finding in Ahlfeldt and Wendland (2016) who estimate commuting time elasticities for 185 German municipalities around Frankfurt while the OLS-estimate is somewhat higher.

In order to disentangle the values of μ and ϵ, we substitute the destination fixed effect by wages at the workplace and estimate Eq. (14) again by OLS, PPML and IV. As the scale parameters B_{ni} that describe the average value households attach to living in n and working in i end up in the error term, we are confronted with a potential endogeneity problem since amenities and wages are likely correlated. While we use geographical distances again as an instrument for commuting time, we apply a shift share IV strategy following Bartik (1991) or Baum-Snow and Ferreira (2015) to instrument for wages. We construct our instrument as a region-specific average wage by fixing industry composition in terms of employment shares for the year 1999 (the earliest year for which we have data). Assuming that regional wages in each industry grow at the rate of the national industry average allows us to isolate shifts in local labor demand that come from national shocks in each sector of the economy. Variation across space arises because regions

Table 1
Commuting elasticity.

log(commuting shares)	*OLS* (1)	*OLS* (2)	*IV* (3)	*PPML* (4)	*PPML* (5)
log(dist)	−1.21***			−0.89***	
	(0.01)			(0.01)	
log(commuting time)		−3.27***	−3.15***		−2.16***
		(0.17)	(0.02)		(0.01)
Origin FE	Yes	Yes	Yes	Yes	Yes
Destination FE	Yes	Yes	Yes	Yes	Yes
(Pseudo) R^2	0.68	0.85	0.80	0.92	0.95
Observations	9894	9894	9894	9894	9894

Notes: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively. In column (3), commuting time is instrumented by distance.

Table 2
Commuting gravity estimation.

log(commuting shares)	*OLS* (1)	*PPML* (2)	*IV* (3)
log(wage)	3.98***	4.64***	4.55***
	(0.1)	(0.17)	(0.11)
log(commuting time)	−3.17***	−2.21***	−3.14***
	(0.02)	(0.01)	(0.02)
Origin FE	Yes	Yes	Yes
(Pseudo) R^2	0.73	0.91	0.71
Observations	9894	9894	9894

Notes: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively. In column (3), commuting time is instrumented by distance and wages by a Bartik instrument based on sectoral labor remuneration.

Table 3
Parameter values.

Parameter	Description	Value	Source
$1-\alpha$	Expenditure share housing	0.3	German Statistial Office
δ	Housing supply elasticity	0.38	Lerbs (2014)
ε	Gumbel shape parameter	4.6	own estimation
ν	Agglomeration elasticity	0.05	Rosenthal and Strange (2004)
μ	Commuting time distaste	0.47	own estimation
ψ	Trade gravity parameter	0.41	Henkel et al. (2018)
σ	Elasticity of substitution	4	Broda and Weinstein (2004)

differ in terms of their industry composition and the exclusion restriction is satisfied as long as national shocks and initial employment shares are uncorrelated with regional amenity levels.[9]

We observe from Table 2 that the estimates exhibit the expected signs: higher wages at the place of work lead to higher commuting shares while longer commutes reduce the fraction of commuters. In comparison to the literature, our estimate of ε is somewhat higher than related estimates in the empirical labor literature (Sokolova and Sorensen (2018), Gaigné et al. (2018) or Severen (2019) suggest values in the range of 1.8–2.7), but substantially smaller than within-city estimates as in Ahlfeldt et al. (2015) - 6.8 for Berlin - or in Kreindler and Miyauchi (2020) - 9.1 for Dhaka. Due to the identification challenges, we proceed by taking our estimates for German districts as parameter values for the baseline specification ($\varepsilon = 4.6$; $\mu = 0.47$) and undertake extensive robustness checks for the domain $\varepsilon \in [1,6]$ and $\mu \in [0.1,1]$ in section 4.3.

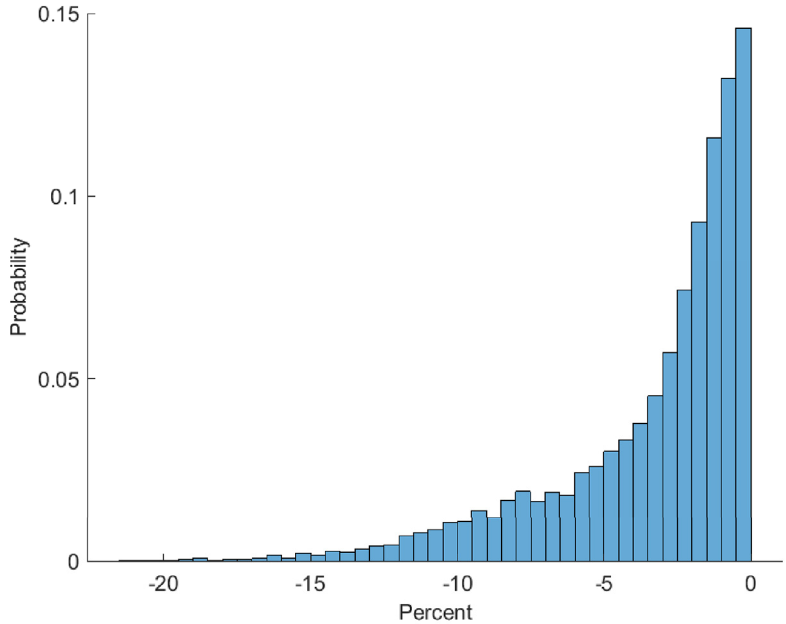
3.3. Solving the model in changes

To solve the model, we need to choose values for two additional parameters. The housing supply elasticity is assumed to be $\delta = 0.38$ as in Lerbs (2014). This value is at the lower end of suggested values in the literature, but to our knowledge the best available for Germany. Saiz (2010) finds a population-weighted average elasticity of 1.75 for metropolitan areas in the US with values below one for land-constrained large cities. Epple et al. (2010) estimate housing production functions for the US obtaining long-run elasticities in the vicinity of four. We start with $\delta = 0.38$ and interpret the model outcomes as rather short- to medium-run effects. Moreover, we explore higher values for the housing supply elasticity in section 4.2. The expenditure share of housing is set to 30 percent based on data from the German Statistical Office such that $\alpha = 0.7$. Table 3 summarizes all parameter values in our benchmark specification. Based on the model's parameters and hypothetical changes of commuting costs that are informed by changes of traffic congestion, $\hat{\kappa}_{ni}$, we use an iterative fixed point algorithm to determine changes in the endogenous variables (see Appendix A.2 for further details).

4. Counterfactual analysis

We now utilize the model for two main exercises. First, we explore the implications of a 50-percent reduction in traffic congestion for the spatial allocation of employment and population, commuting, the housing market, average productivity and welfare (section 4.1). As locations

[9] See Adão et al. (2019), Borusyak et al. (2019) and Goldsmith-Pinkham et al. (2020) for recent discussions about the appropriateness of Bartik-instruments. We thank Duncan Roth for providing us with the data.



Notes: The histogram shows travel time reductions across districts in percent if time lost in traffic during rush hours is reduced by 50 percent.

Fig. 2. Reduction of commuting times.

Table 4
Urbanization, wages and house prices.

	Baseline	All commutes	Only between	Only within
A. Population share				
Urban	67.8	71.5	69.1	70.4
Cities	28.9	32.4	29.2	32.5
B. Employment share				
Urban	71.3	75.1	72.8	73.8
Cities	36.4	41.0	37.8	40.0
C. Change in labor productivity				
Overall	–	0.78%	0.72%	0.02%
D. Change in house prices				
Overall	–	2.4%	0.6%	2.0%
Urban	–	6.7%	2.3%	5.3%
Rural	–	−8.4%	−3.2%	−5.9%
D. Welfare change				
Overall	–	3.5%	1.1%	2.5%

Notes: This table summarizes counterfactual outcomes for population shares, employment shares, nominal wage growth and house price growth when time lost in traffic is reduced by 50 percent. *All commutes* refers to a bilateral reduction for commutes between and within districts. Columns 3 and 4 report results if congestion is reduced only for commutes between or within districts separately. Urban regions include cities and locations with population density of more than 150 inhabitants per square kilometer. Cities are an own jurisdictional entity and accommodate at least 100,000 inhabitants. The classification is taken from the Federal Institute for Research on Building, Urban Affairs and Spatial Development.

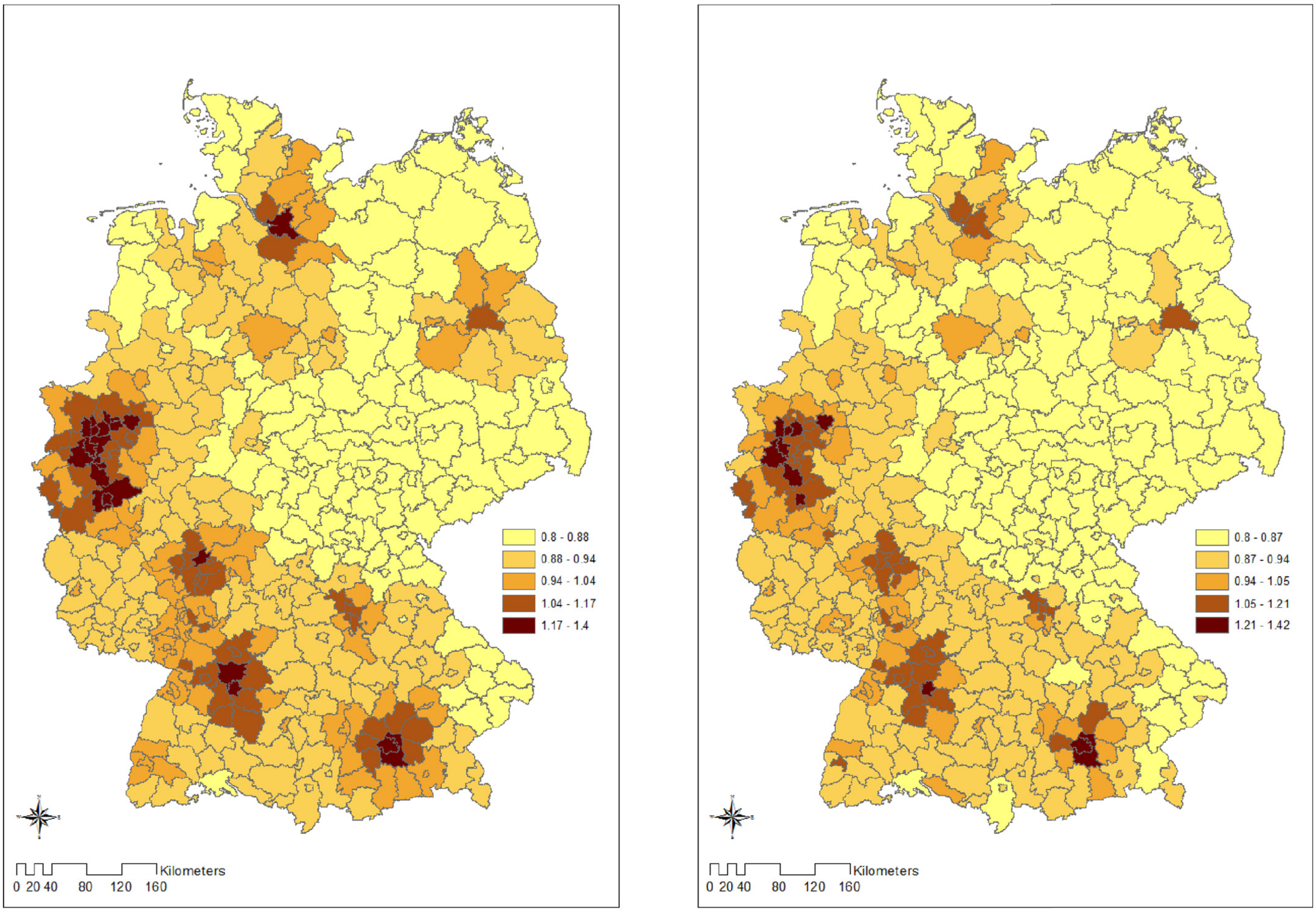
are affected by traffic jams to different extents (see Fig. 1), we expect heavily-congested areas to respond in a more pronounced way than less-congested areas with general equilibrium implications for all locations. To address the role of congestion within versus between districts, we reduce congestion (i) for all commutes, (ii) only for inter-district commutes and (iii) only for intra-district commutes.

Second, as our model contains congestion through traffic jams and the housing market, we compare these two important forces in a second exercise (section 4.2). We will explore the interaction between reductions in both congestion forces to learn about the relative importance for various outcomes.

4.1. Reducing traffic congestion

In the first exercise, we reduce traffic congestion by 50 percent. As our model does not feature infrastructure investment, it is silent about

(a) Residential population (b) Employment



Notes: The values correspond to the factor of change with unit values meaning no change.

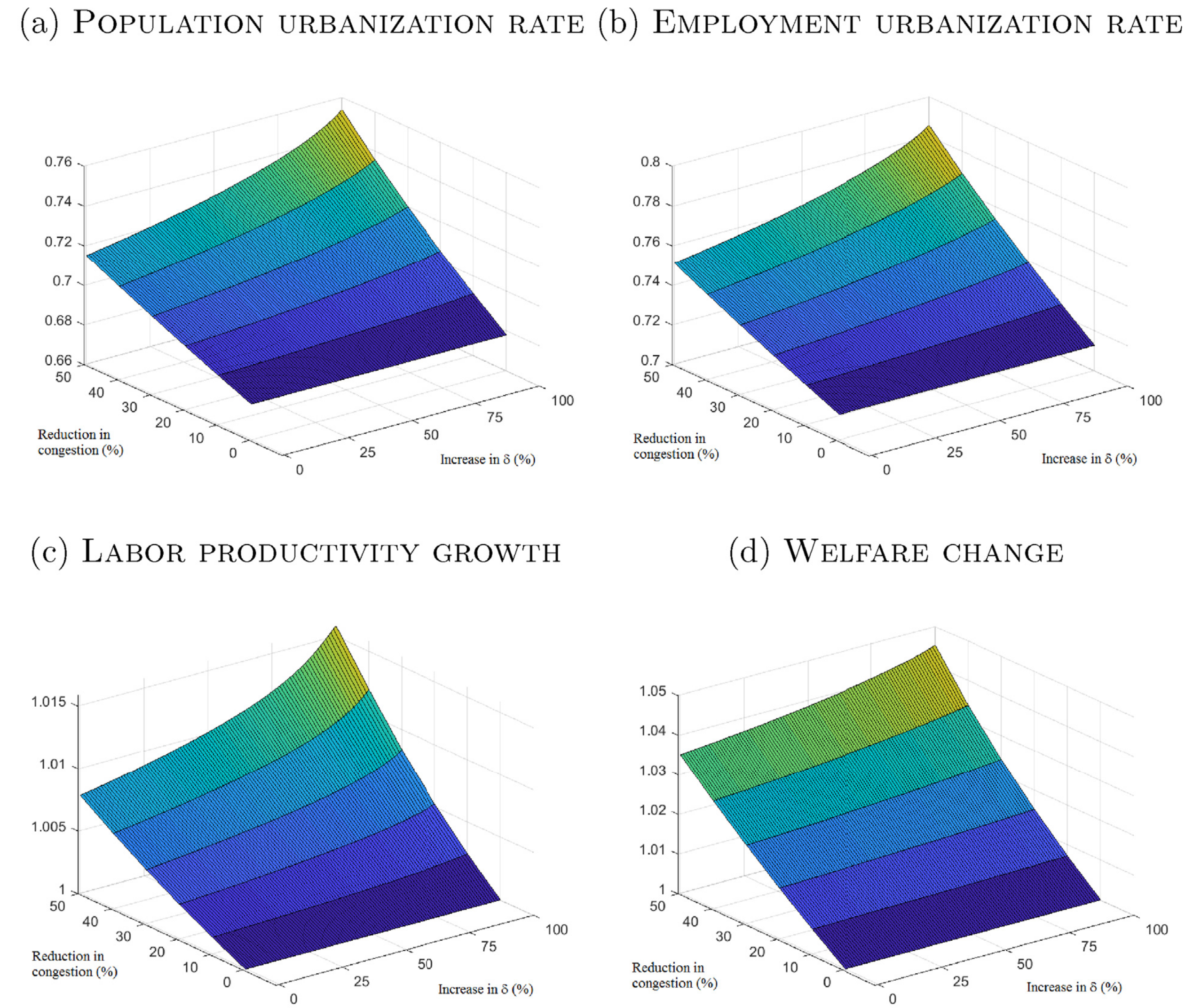
Fig. 3. Changes in spatial allocation.

the required volume to reach this reduction. Moreover, it is not straightforward to relate the reduction to a specific policy. This is particularly true against the background of the fundamental law of road congestion (Duranton and Turner, 2011), so we rather think about this counterfactual as a thought experiment that sheds light on the qualitative and quantitative spatial implications of traffic congestion in a multi-location general equilibrium setting and interpret the quantitative outcomes as upper bounds.

Fig. 2 illustrates the density of overall travel time reductions when time lost in traffic shrinks by 50 percent. As traffic jams account for different shares in bilateral trips, locations are affected by this uniform reduction to different extents. While commuting times between the majority of districts does not decline by more than 5 percent, in particular high-density and traffic-prone locations (classified as cities and mostly urban regions) become relatively more accessible. In some of these places, the reduction in traffic congestion leads to a decline in overall commuting times of more than 20 percent.

Table 4 summarizes counterfactual outcomes when we reduce road congestion for *all* commutes, only for commutes *between* districts and only for commutes *within* districts. *Urban* refers to “cities” and “mostly urban” districts while “rural” collects all remaining locations. Thereby, we can account for different definitions of urbanization. We observe that a uniform reduction of traffic jams by 50 percent for all commutes leads to higher urbanization rates of both employment and population. This applies to both definitions of urban locations. For the broader definition (“urban”), both outcomes increase by about the same percentage (about +3.7) while cities experience a strikingly higher growth rate of employment compared to residents (+4.6 vs + 3.5). This points to a reallocation of population and employment from peripheral areas to places with higher density and within the group of urban locations to a more pronounced clustering of employment in cities. Fig. 3 provides a geographical illustration. When we reduce congestion only for commutes between and within districts separately, the qualitative pattern is confirmed. However, lower commuting times between locations raises the population urbanization rate only by 0.3 percentage points while the share of employment goes up by 1.4 percentage points. Relieving traffic jams only within locations raises both population and employment shares by the same amount (e.g. +3.6 percentage points in cities). This implies a higher relative increase of population in cities compared to employment.

Intuitively, workers take advantage of lower commuting costs and choose locations with lower housing costs outside of cities while maintaining access to high-wage jobs in economic centers. However, the population urbanization rate does not decline, not even for the group of cities. This points to the more complex general equilibrium mechanisms in a multi-region framework. Although population grows most



Notes: The panels show model outcomes for combinations of housing supply elasticities δ and reductions in traffic congestion between 0-50 percent. Starting with the baseline housing supply elasticity $\delta = 0.38$, 100% refers to a value of 0.76.

Fig. 4. Traffic congestion versus housing market.

in urbanized regions outside of “cities”, overall urbanization increases due to immigration from low-density rural places. It is more surprising, however, that a reduction of commuting times only between locations leads to an increase in the population urbanization rate, albeit only marginally. One plausible explanation for this outcome relates to the particular geography of German cities. Inspection of Fig. 1 reveals that many cities are located fairly closely to each other, e.g. in the Rhine-Ruhr area in the western part of the country, such that moving to such a location makes neighboring cities more accessible, too. Further, higher employment density boosts labor productivity rendering these places also more attractive to reside in. It is a main message of this multi-region model that better access to dense places through lower commuting costs does not necessarily reduce population urbanization rates.

Looking at the commuting pattern, we find that the spatial reallocation lowers the share of workers living and working in the same district from 67.1 to 66.1 percent. The share of between-district commuters traveling less than 50 km to work increases from 19.0 to 20.3 percent rendering the share of commutes beyond 50 km essentially unchanged. Labor productivity is predicted to increase by 0.78% in response to higher agglomeration of employment. The low increase of only 0.02% for reductions in within-district commutes is primarily driven by the city of Wolfsburg (headquarter of Volkswagen) that is characterized by high wages and productivity, but low traffic congestion. Further, the reallocation of residents affects the housing market in the expected way. Urban districts experience house price increases of 6.7% while it becomes cheaper to live in rural locations (−8.4%). This implies an economy-wide average growth rate of 2.4%. Dusseldorf (+31.7%), Essen (+29.8%) and Stuttgart (+29%) experience the largest increases (see Appendix A.3.1 for further details). Finally, the model predicts a welfare gain of 3.5% as lower commuting costs also exert a positive direct effect on utility.

4.2. *Housing markets vs traffic congestion*

Our quantitative framework features both housing markets and traffic jams as two important congestion forces and allows us to explore the relative importance for the spatial economy. In particular, we study interaction effects of reducing traffic congestion and raising the housing supply elasticity. Panels (a)–(d) of Fig. 4 illustrate these interactions of population and employment urbanization rates, average labor

Table 5
Robustness of results.

	Urban population	Urban employment	Ø Productivity	Welfare
A: Reduction of traffic congestion				
0%	67.8%	71.3%	–	–
25%	69.6%	73.1%	0.35%	1.6%
50%	**71.5%**	**75.1%**	**0.78%**	**3.5%**
75%	73.6%	77.2%	1.32%	5.7%
100%	75.8%	79.5%	2.00%	8.3%
B: Housing expenditure share $1-\alpha$				
0.3	**71.5%**	**75.1%**	**0.78%**	**3.5%**
0.25	78.1%	80.8%	1.28%	5.5%

Notes: In all panels, the columns entitled "Urban population" and "Urban employment" denote the *share* of workers living and working in regions that are either cities with more than 100,000 inhabitants or population density larger than 150 inhabitants per square km. Columns (3) and (4) report the *percentage changes* in average labor productivity and welfare in the counterfactual. The results of the benchmark specification are marked in bold face.

productivity and welfare for combinations of housing supply elasticities and reductions in traffic congestion between 0 and 50 percent. Starting with the baseline housing supply elasticity of $\delta = 0.38$, a 100-percent increase implies an elasticity twice as high.

All subfigures show a positive interaction effect, but the gradients differ markedly with outcomes. Comparing population and employment urbanization rates the gradients look very similar, but with steeper increases for higher values of housing supply elasticities with regard to residents. This is intuitive because higher values of δ retard the increase in house prices in places that become more attractive, i.e. cities and urban districts, due to a larger increase in housing supply. A similar argument holds for the clustering of employment as workers leave the periphery to access urban job markets. A mitigation of house price increases contributes to the agglomeration of employment. Quantitatively, the difference in urbanization rates between a 50-percent and a 10-percent reduction is approximately 3 percentage points for $\delta = 0.38$ and reaches 6–6.5 percentage points for population and employment at a 100-percent higher elasticity value.

Panel (c) plots changes in labor productivity. Although a mirror image of employment density, it responds strikingly more elastically to reductions in traffic congestion at higher values of δ. Doubling the housing supply elasticity roughly doubles average labor productivity when time lost in traffic declines by 50 percent. The rise is driven by the fact that a few locations would experience very high growth rates of employment that boost overall labor productivity.

A different picture emerges with regard to welfare in panel (d). It is evident that changes in welfare are primarily driven by changes in commuting costs rather than from higher urbanization rates and higher labor productivity. Traffic congestion enters the utility function in a direct fashion and a 50-percent reduction leads to growth rates of average labor productivity between 0.8 and 1.6 percent.

4.3. Robustness

In this section, we explore the sensitivity of our results. First, we run the counterfactual analysis for alternative changes in traffic congestion. According to Panel A of Table 5, the share of urban population, the share of urban employment and changes in average labor productivity and welfare all increase with larger reductions of congestion which is in line with intuition. We observe that a full relief of traffic jams would lead to an urbanization rate of 75.8 percent (residential population) and 79.5 percent (employment), respectively. The efficiency gains as measured by average labor productivity reach 2.0 percent while welfare increases by 8.3 percent.

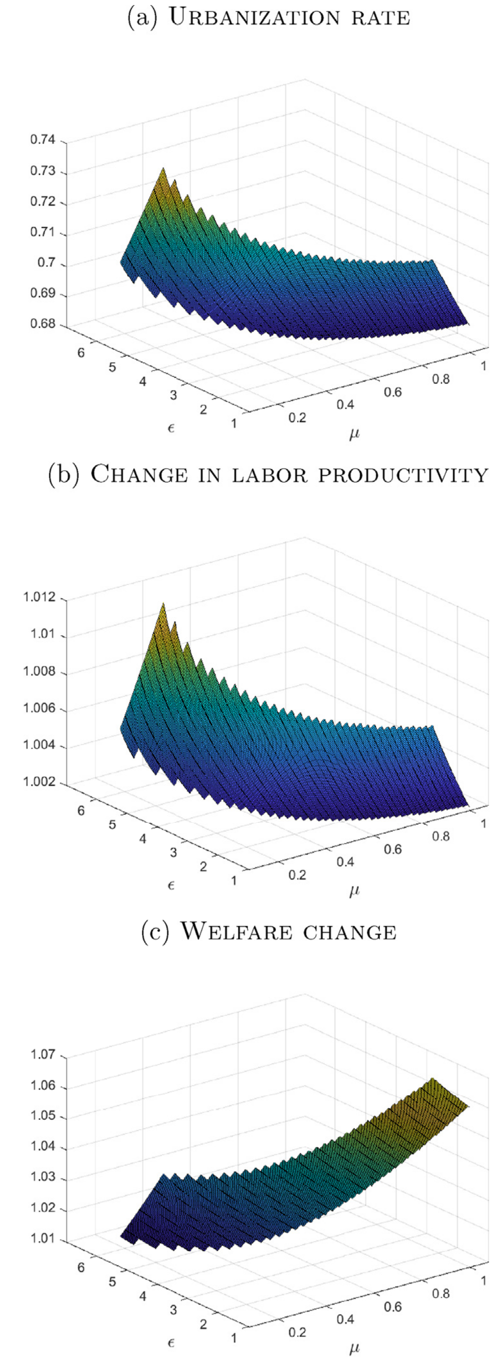
As a second robustness check, we reduce the expenditure share households dedicate to housing. In the baseline, we have used 30 percent which included utilities and other housing-related items whose prices are not necessarily location-specific. Notice that the expenditure share is an important determinant of the strength of the congestion force in the model, so reducing the share to 25 percent should favor agglomeration and thus higher productivity and welfare. This intuition is supported by Panel B. In fact, results turn out to be quite sensitive to the expenditure share parameter. A 50-percent reduction of traffic congestion would lead to urbanization rates that are around ten percentage points higher for population and employment compared to the baseline. Average labor productivity is predicted to rise by 1.28 percent. Due to larger increases of house prices in response to higher urbanization rates, welfare gains reach 5.5 percent.[10]

Finally, we explore the sensitivity of the labor supply elasticity parameter ε and the commuting distaste elasticity μ. As argued in Section 3.2, the literature suggests a wide range of estimates for ε. We therefore run the model for combinations of $\varepsilon \in [1, 6]$ and $\mu \in [0.1, 1]$ such that the commuting elasticity with respect to travel time $\mu\varepsilon \in [1, 2.1]$. Fig. 5 illustrates the counterfactual results for the population urbanization rate, labor productivity and welfare. We observe from Panel (a) that the urbanization rate is increasing in ε. As changes in commuting time have similar effects than changes in wages, a higher elasticity leads to a stronger response of workers with regard to their commuting probability. The higher employment density leads to higher labor productivity (see Panel (b)) which provides a second reason why this location becomes a more attractive place to live. The parameter μ governs to what extent changes in commuting time translate into utility. Panels (a) and (b) indicate, however, that results are not as sensitive in this dimension compared to ε. The picture changes when we look at welfare. Higher values of μ transform a given reduction in commuting time into higher utility gains, so the counterfactual results are more sensitive in this dimension compared to ε.

5. Conclusions

In this paper, we have explored the role of traffic congestion during rush hours for the spatial allocation of employment and population, the housing market, average labor productivity and welfare. Based on travel time information from a major web-mapping service, bilateral commuting and labor market data for German districts, we have computed a measure of bilateral traffic congestion and fed it into a quantitative spatial general equilibrium model to estimate aggregate efficiency costs. We find that a reduction of traffic congestion by 50 percent leads

[10] Notice, however, that changing the housing expenditure share affects structural residuals as the parameter α is crucial for the model inversion.



Notes: Panels (a) - (c) show counterfactual results of urbanization rate and changes in labor productivity and welfare for many combinations of μ and ε. The vertical axes indicate the share of residential population living in "urban" areas (Panel (a)) and changes in Panels (b) and (c) where a value one implies no change.

Fig. 5. Robustness with respect to ε and μ.

to more urbanization and an increase of average labor productivity by 0.8 percent. Welfare is predicted to increase by 3.5 percent as individuals do not only benefit from higher real output, but especially from lower commuting costs.

Traffic jams therefore affect the allocation of workers across space that is quantitatively important. The employment share in less-productive places is about 3.7 percentage points higher compared to a scenario with 50 percent lower traffic congestion. Our results indicate that capacity-enhancing infrastructure investments generate higher returns in urban locations compared to peripheral regions. The reason for this stems from households changing low-productivity jobs in low-density places for high-paid jobs in economic centers. We also related traffic jams to housing markets to learn about the relative importance of both congestion forces. It turned out that an increase in the housing supply elasticity has a relatively stronger effect on average labor productivity compared to welfare.

While this paper adds new insights to the role of traffic congestion in the spatial economy, it also has limitations that future research should remedy. First, it would be desirable to use more granular data, ideally at the individual level. Although the data requirements are ambitious, knowing individual commuting trips, commuting times and the share lost in traffic would deliver a superior congestion measure and better estimates of key parameters. Second, such an exercise should account for choices in mode of transport. Third, including transportation infrastructure investment would allow to relate costs to benefits which matters in particular for the measurement of welfare effects.

Declaration of competing interest

The authors declare that they have no relevant or material financial interests that relate to the research described in the paper.

Appendix.

A.1. Data

A.1.1. Data description

In this appendix, we list detailed sources for the data we have used in the empirical exercise:

Employment and commuting data. All data from the German Federal Employment Agency cover all employees in Germany that are employed in social security registered jobs. This includes regular full time employment, as well as apprenticeships, paid internships and student assistant jobs. It does not include part of state employees (Beamte) and self-employed workers. The exact datasets used are listed below. All data cover the year 2018, the dates mentioned in the detailed data description below indicate the date of the last official revision by the Federal Employment Agency.

- *Regional employment and population:* German Federal Employment Agency, Sozialversicherungspflichtig Beschäftigte nach ausgewählten Merkmalen, Nürnberg, June 2019. Employees' residential addresses are reported by employers, when registering a worker for social security with the Federal Employment Agency. Place of work is the location of the business unit within the company, where the employee actually works. Regional employment is the aggregate of registered workplaces over all districts. Regional population is the aggregate of registered residential addresses over all districts. The data are for 2018.
- *Commuting flows:* German Federal Employment Agency, Sozialversicherungspflichtig Beschäftigte - Pendler nach Kreisen, Nürnberg, Stichtag 30. Juni 2018. Commuting flows use the same social security filings as regional employment and population above, but are aggregated on bilateral pairs of workplace and residential districts instead. Bilateral pairs with less then 10 commuters in total are omitted and set to zero.

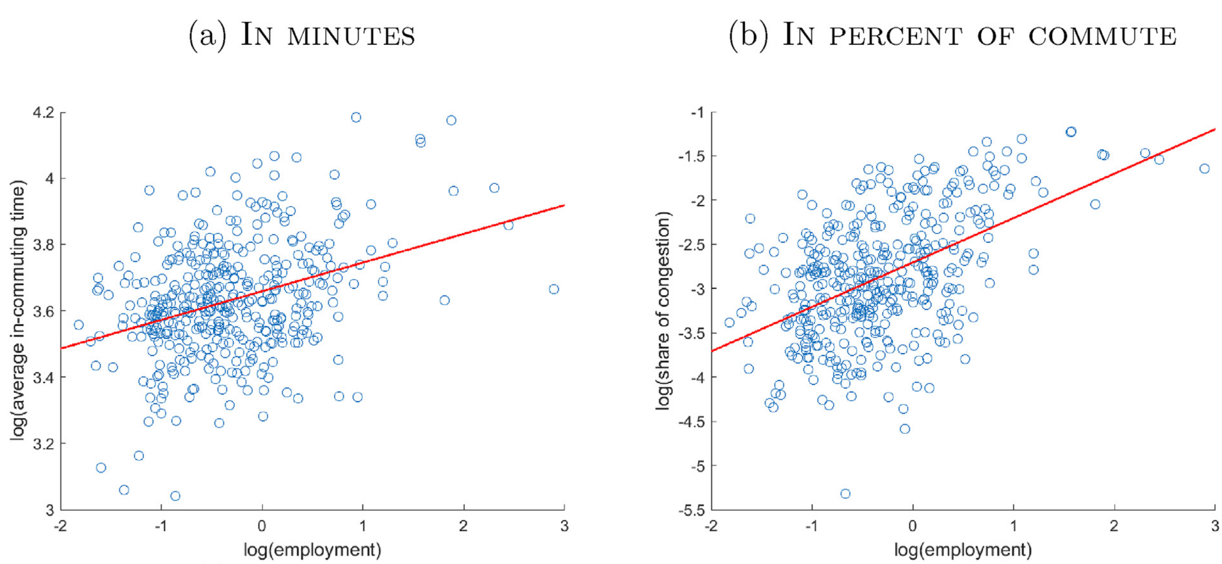
Earnings by place of work and residence: German Federal Employment Agency, Sozialversicherungspflichtige Bruttoarbeitsentgelte, Entgeltstatistik 2018. Reported wages are before deduction of taxes and all social security payments. Earnings by place of work are wages aggregate over regional employment defined as above. Earnings by residence are wages aggregate over regional population defined as above.

Geo-referenced data. We use information on population levels per square kilometer and the type of land use to construct population-weighted centroids and the commercial centroid for each district. The sources are as follows and can be obtained from the RWI webpage: http://fdz.rwi-essen.de/doi.html.

RWI; microm (2019): RWI-GEO-GRID: Socio-economic data on grid level- Scientific Use File (wave 8). Version: 1. RWI – Leibniz Institute for Economic Research. Dataset. http://doi.org/10.7807/microm:suf:V8.

Geographic information: German Federal Agency for Cartography and Geodesy, District definition for the year 2018. The German Federal Agency for Cartography and Geodesy provides shape files for all administrative units in Germany for different points in time. The file that we use uses a scale of 1:250. The employed projection is a Transverse Mercator projection (WGS 1984, UTM zone 32).

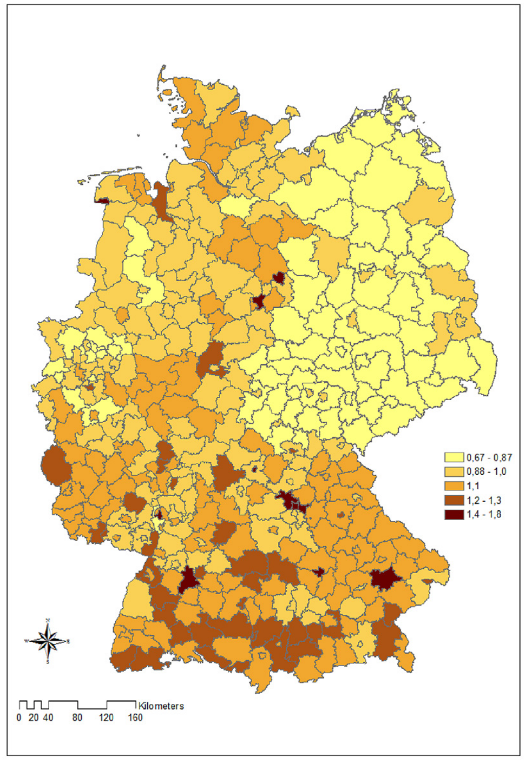
A.1.2. Location size and traffic congestion



Notes: Panel (a) relates the log of employment with the log of average in-commuting times per location. Panel (b) relates log employment with the log of commuting time shares lost in traffic. Employment is normalized to have a mean of one.

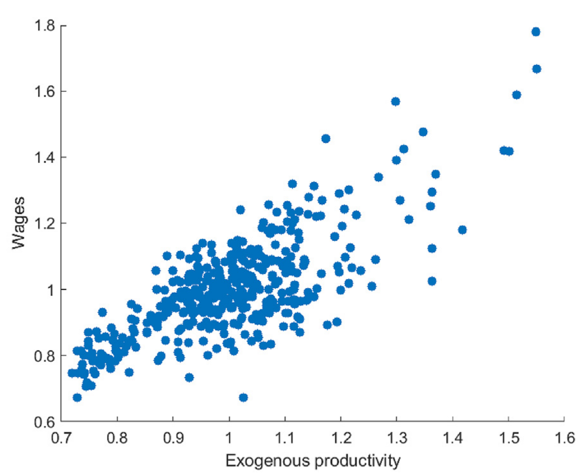
Fig. A.1 Correlation between location size and traffic congestion.

A.1.3. Exogenous productivity and wages



Notes: The figure shows the spatial distribution of the local productivity fundamentals $\bar{A}_n$ which is normalized to have a mean of one.

Fig. A.2 Exogenous productivity.



Notes: The figure shows the correlation between the local productivity fundamentals $\bar{A}_n$ and regional wages at the workplace w_i. Both productivity and wages are normalized to have mean of one.

Fig. A.3 Wages and productivity.

A.2. Solving the model in relative changes

This appendix sketches the solution algorithm we apply in the counterfactual analysis. Based on the model's parameters $\{\alpha, \delta, \varepsilon, \nu, \mu, \psi, \sigma\}$ and changes in commuting costs $\{\widehat{\kappa}_{ni}\}$, we solve for changes of the endogenous variables $\{\widehat{w}_n, \widehat{\overline{v}}_n, \widehat{L}_n, \widehat{R}_n, \widehat{\lambda}_{ni}, \widehat{P}_{Q,n}, \widehat{P}_{H,n}, \widehat{\pi}_{ni}\}$ according to the following set of equations and based on starting values for $\widehat{w}_n$ and $\widehat{\lambda}_{ni}$. The index t counts the number of iterations.

1. Based on guesses for $\widehat{w}_n$, compute

$$\widehat{\overline{v}}_n^{(t)} = \frac{1}{\overline{v}_n} \sum_{i \in N} \frac{\lambda_{ni} \left(\widehat{w}_i^{(t)} / \widehat{\kappa}_{ni} \right)^{\varepsilon}}{\sum_{s \in N} \lambda_{ns} \left(\widehat{w}_s^{(t)} / \widehat{\kappa}_{ns} \right)^{\varepsilon}} \widehat{w}_i^{(t)} w_i.$$

2. Use guesses for $\widehat{\lambda}_{ni}$ to calculate

$$\widehat{L}_i^{(t)} = \frac{\overline{L}}{L_i} \sum_{n \in N} \lambda_{ni} \widehat{\lambda}_{ni}^{(t)},$$

and

$$\widehat{R}_n^{(t)} = \frac{\overline{L}}{R_n} \sum_{i \in N} \lambda_{ni} \widehat{\lambda}_{ni}^{(t)},$$

3. Use these values to derive changes in house prices

$$\widehat{P}_{H,n}^{(t)} = \left(\widehat{\overline{v}}_n^{(t)} \widehat{R}_n^{(t)} \right)^{\frac{1}{1+\delta}}.$$

4. Bilateral expenditure shares can be obtained from

$$\widehat{\pi}_{ni}^{(t)} = \frac{\widehat{L}_i^{(t)1-(1-\sigma)\nu} \left(\widehat{w}_i^{(t)} / \widehat{\overline{A}}_i \right)^{1-\sigma}}{\sum_{k \in N} \pi_{nk} \widehat{L}_k^{(t)1-(1-\sigma)\nu} \left(\widehat{w}_k^{(t)} / \widehat{\overline{A}}_k \right)^{1-\sigma}}$$

5. We then use previous outcomes to determine

$$\widehat{P}_{Q,n}^{(t)} = \left(\frac{\widehat{L}_n^{(t)1-(1-\sigma)\nu}}{\widehat{\pi}_{nn}^{(t)}} \right)^{\frac{1}{1-\sigma}} \frac{\widehat{w}_n^{(t)}}{\widehat{\overline{A}}_n}$$

6. To obtain new values of the initial guesses for wages and unconditional commuting shares, we first calculate:

$$\widetilde{w}_i^{(t+1)} = \frac{1}{w_i L_i \widehat{L}_i^{(t)}} \sum_{n \in N} \pi_{ni} \widehat{\pi}_{ni}^{(t)} \overline{v}_n \widehat{\overline{v}}_n^{(t)} R_n \widehat{R}_n^{(t)}$$

$$\widetilde{\lambda}_{ni}^{(t+1)} = \frac{\left(\widehat{P}_{Q,n}^{(t)\alpha} \widehat{P}_{H,n}^{(t)1-\alpha} \right)^{-\varepsilon} \left(\widehat{w}_i^{(t)} / \widehat{\kappa}_{ni} \right)^{\varepsilon}}{\sum_{r \in N} \sum_{s \in N} \lambda_{rs} \left(\widehat{P}_{Q,r}^{(t)\alpha} \widehat{P}_{H,r}^{(t)1-\alpha} \right)^{-\varepsilon} \left(\widehat{w}_s^{(t)} / \widehat{\kappa}_{rs} \right)^{\varepsilon}}$$

7. Finally, we produce new starting values:

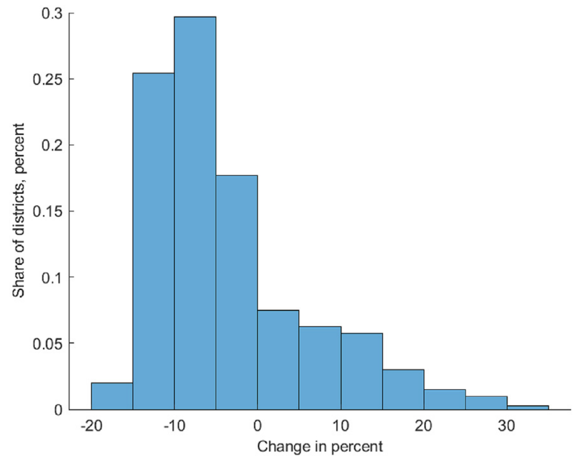
$$\widehat{w}_i^{(t+1)} = \zeta \widehat{w}_i^{(t)} + (1-\zeta) \widetilde{w}_i^{(t+1)}$$

$$\widehat{\lambda}_{ni}^{(t+1)} = \zeta \widehat{\lambda}_{ni}^{(t)} + (1-\zeta) \widetilde{\lambda}_{ni}^{(t+1)}$$

with $\zeta \in (0,1)$.

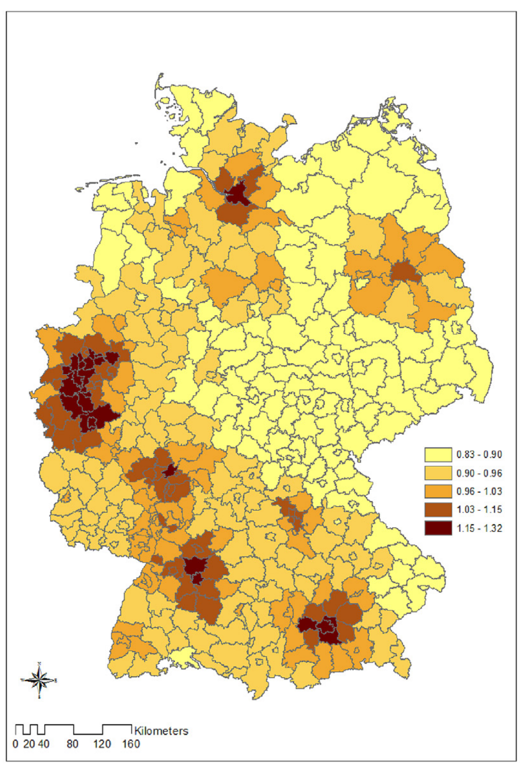
A.3. Counterfactual outcomes

A.3.1. Housing market



Notes: The figure shows the histogram of house price changes across districts in percent if time lost in traffic during rush hours was reduced by 50 percent.

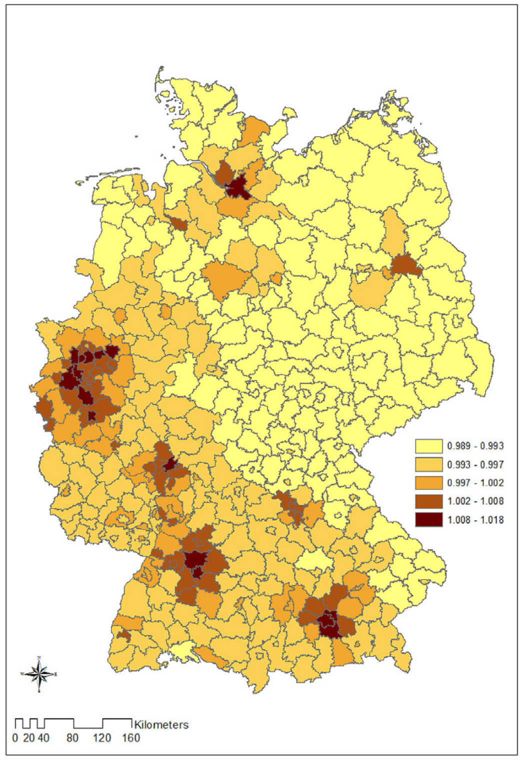
Fig. A.4 Change of house prices, in percent.



Notes: The figure shows the spatial distribution of house price changes. Values smaller than one indicate reductions in house prices while values above one indicate increases. A value of one means no change.

Fig. A.5 Spatial pattern of house price changes.

A.3.2. Labor productivity



Notes: The figure shows the spatial distribution of changes in labor productivity. Values smaller than one indicate reductions in house prices while values above one indicate increases. A value of one means no change.

Fig. A.6 Spatial pattern of changes in labor productivity.

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