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Rush hours and urbanization

Abstract

We use a spatial general equilibrium model with potential commuting of workers between their place of work and their place of residence to analyze the effects of rush hours on the spatial allocation of employment and population, average labor productivity and the housing market. Abolishing traffic congestion during rush hours leads to a more urbanized economy as households move from the low-density countryside to the commuter belts of cities rather than from the city centers to the periphery. Employment, however, becomes more agglomerated in high-density large cities. This adjustment implies an increase of average labor productivity of 7.2 percent and higher inequality of housing costs.

JEL-Codes: R120, R130, R410.

Keywords: urbanization, commuting, traffic, congestion, spatial general equilibrium.

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1 Introduction

Commuting to work during rush hours imposes a cost to workers. It does not only reduce leisure, but also raises the stress level of individuals (Gottholmseder et al. 2009) and deteriorates individual health conditions (e.g. Kuenn-Nelen 2016). Kahneman et al. (2004) shows that individuals rank commuting as the least satisfying activity of their daily routine. Redding and Turner (2015) documents for several developed countries that the average employee commutes approximately 40 minutes per day. Importantly, however, it is not only the distance between home and work, but also the amount of traffic that determines commuting times. According to the INRIX Global Traffic Scorecard, estimates indicate that traffic jams account for up to one third of commuting time. To provide a few examples, commuters in Rome lost 254 hours in traffic congestion in 2018. Dublin (246), Paris (237) or London (227) are further examples of urban areas in this ranking.[1]

While commuting is costly, it also offers employees the opportunity to separate their place of residence from their place of work. Thereby, households can enjoy lower housing costs in less dense places (e.g. in the countryside or the periphery of cities) 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 places of the economy.

To understand the economy-wide implications of rush hours, we use a spatial general equilibrium model that allows individuals to migrate across locations and separate their place of work from their place of residence. Individuals consume a differentiated tradable good and housing owned by immobile landlords. Rents adjust endogenously to changes in location-commuting decisions of workers and operate as a congestion force in the model. We are particularly interested in how reductions in commuting times affect the population and employment shares in urban versus rural areas, the average productivity of labor and housing prices. We build on Monte, Redding, and Rossi-Hansberg (2018), but extend their framework in two important ways. First, we model commuting in time units as in 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

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

commuting elasticity that indicates how households value one minute of additional commuting time in terms of utility. Second, we endogenize location-specific productivity as in Allen and Arkolakis (2014). Productivity in each location depends on exogenous factors and increases in employment density, so changes in the spatial allocation of jobs affects location-specific and economy-wide average productivity (Combes et al. 2012). The latter is affected via two channels. First, average productivity increases if workers substitute their job in a low-productivity region with one in a higher-productivity region. Second, productivity is positively associated with higher employment density.

We calibrate the model for 412 German districts in 2010 using bilateral trade and commuting flows as well as information on employment, population and house prices. In the baseline scenario, we retrieve bilateral commuting times between districts from google maps. We assume that the journey to work starts at 8 a.m. and that workers return at 5 p.m. In the counterfactual analysis, we eliminate traffic congestion by substituting the travel times during rush hours with those at 3 a.m. when there are hardly any cars on the roads. Solving the model for a new spatial equilibrium delivers answers to the above questions.

We find that the reduction in traffic congestion leads to a *higher* degree of overall urbanization in the economy – although commuting becomes relatively more attractive between urban centers and their less populated hinterland. The reason is that workers leave the countryside to move to the periphery of economic centers. It is the combination of living there and commuting to the city that becomes more appealing at the expense of low-density rural areas. While the city periphery experiences net immigration, employment clusters more intensively in high-productive economic centers. These adjustments map to changes in relative housing costs with highest increases in the commuter belts of cities and declines in remote places. The agglomeration of jobs in cities and the reallocation of jobs from low-productivity to high-productivity locations implies an increase of average labor productivity of 7.2 percent.

The policy implications of this quantitative framework 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 an additional congestion force.

Our paper relates to several strands of literature. First, there exists a regional economics literature on traffic and transport infrastructure using both structural partial equilibrium estimations (e.g. Duranton and Turner 2011, Couture, Duranton, and Turner 2018 and Ahlfeldt and Feddersen 2018) and theoretical partial and general equilibrium models (e.g. Rotemberg 1985, Anas 2012 and Anas and Pines 2013). Our model builds on a system of regions and sheds light on the productivity and allocation effects of rush hours. Second, we build our analysis on recent advancements in spatial general equilibrium theory (e.g. Allen and Arkolakis 2014, Allen and Arkolakis 2019, Redding 2016, Redding and Rossi-Hansberg 2017 and Behrens et al. 2017) where locations are connected via labor mobility and goods trade. For our research question, it is essential to allow for commuting and thus a possible separation of place of work and place of residence. We therefore combine Monte, Redding, and Rossi-Hansberg (2018) with Ahlfeldt et al. (2015) to model commuting in time units. Fretz, Parchet, and Robert-Nicoud (2017) use a similar model to estimate the effect of highway connections in Switzerland on local labor markets. Heblich, Redding, and Sturm (2018) 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.

Third, traffic congestion represents a friction for the spatial allocation of economic activity that leads to spatial misallocation of resources (Hsieh and Klenow 2009). Our results are qualitatively similar to Hsieh and Moretti (2018) showing that stringent housing supply regulation reduces growth as it restricts access to highly productive cities and Hsieh et al. (2018) analyzing the effect of skill mismatches.

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

2 Model

Consider an economy with regions $n, i \in N$ 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 the cost of less leisure time and reduces utility. Apart from labor mobility and commuting, regions are also connected via costly trade of varieties of a differentiated 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

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

where $Q_{n\omega}$ denotes the 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. The Cobb-Douglas parameter $0 < \alpha < 1$ governs the relative importance of the tradable good and housing for workers' utility. 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

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

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 $P_{Q,n}Q_n = (\alpha \bar{v}_n + (1-\alpha)\bar{v}_n)R_n = \bar{v}_n R_n$ with $\bar{v}_n$ representing average per-capita 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 (e.g. Gottholmseder et al. 2009), deteriorates health conditions (e.g. Kuenn-Nelen 2016) or that workers dislike traveling to work (e.g. Kahneman et al. 2004).

Finally, we assume that individuals have heterogeneous preferences for combinations of locations for work and living. We follow (among others) Eaton and Kortum (2002), McFadden (1974) and Monte, Redding, and Rossi-Hansberg (2018) in modeling amenities $b_{ni\omega}$ as random draws from a Fréchet distribution. Therefore, their cdf is given by $G_{ni}(b) = e^{-B_{ni}b^{-\epsilon}}$, where $B_{ni} > 0$ and $\epsilon > 1$. 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

$$U_{ni\omega}^{*} = \frac{b_{ni\omega} w_i}{\kappa_{ni} P_{Q,n}^{\alpha} P_{H,n}^{1-\alpha}}, \tag{3}$$

where w_i is her labor income. Notice that indirect utility is a monotone transformation of the amenity parameter, so it is also Fréchet distributed with $G_{ni}(U) = e^{-\Phi_{ni}U^{-\epsilon}}$ and $\Phi_{ni} = B_{ni}\left(\kappa_{ni} P_n^{\alpha} Q_n^{1-\alpha}\right)^{-\epsilon} w_i^{\epsilon}$.

We use the property that the maximum of repeated draws from the Fréchet distribution is also Fréchet 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 $\Phi = \sum\limits_r \sum\limits_s \Phi_{rs}$. 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

$$\bar{U} = \mathbb{E}[U_{ni\omega}] = \Phi^{1/\epsilon}\Gamma\left(\frac{\epsilon-1}{\epsilon}\right). \tag{5}$$

We can write the probability that a worker commutes to region i given she lives in n as $\lambda_{ni|n} = \Phi_{ni}/\sum\limits_s \Phi_{ns}$. Further notice that we can express the measure of workers employed in region i as $L_i = \sum\limits_n L_{ni}$ and the measure of workers living in region n by $R_n = \sum\limits_i L_{ni}$. 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

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

2.2 Housing market

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

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

where $\bar{H}_n$ 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

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

Hence, housing market clearing requires that

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

holds 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 $A_i(L_i) = \bar{A}_i L_i^{\nu}$ describes location-specific productivity, which is a function of the number of workers employed in that region. Therefore, productivity spillovers act as an agglomeration force in our model and the parameter ν governs the strength of these spillovers (see e.g. Behrens and Robert-Nicoud 2015).

Shipping goods between regions i and n implies iceberg trade costs $d_{ni} > 1$ while we normalize intra-regional trade costs to unity, $d_{nn} = 1$. 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.[2]

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

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

We observe from (10) that π_{ni} is increasing in the number of varieties produced in region i, M_i, and decreasing in trade costs between regions n and i, d_{ni}. This notation allows us to express region $n's$ price index for the composite good Q as

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

[2] 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.

2.4 Equilibrium

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

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

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 $\bar{U}$ via the labor-market clearing condition $L = \sum_n L_n$.

3 Data and calibration

3.1 Data

We calibrate the model to the German economy with its 412 districts using data on average monthly gross labor earnings by place of work and by residential location, regional employment and residential information from the German Federal Employment Agency for all German workers who are subject to social insurance contributions.[3] Bilateral in- and out-commuting flows between districts are available from the same source and for the same population of workers. Further, we use information on land prices from the Federal Institute for Research on Building, Urban Affairs and Spatial Development. Bilateral trade flows come from the Forecast of Nationwide Transport Relations in Germany (Verkehrsverflechtungsprognose 2030) provided by the Clearing House of Transport Data at the Institute of Transport Research of the German Aerospace Center. The data contain bilateral trade volumes in metric tons at the product level by transport mode (road, rail, water) between European regions, where one German region is either exporter, importer or part of the trade route. As the most recent year for these data is 2010, this constraint defines the year of the analysis. We relegate a more detailed description of these data sources to the appendix.

To get round trip commuting times τ_{ni}, we feed regions' centroids derived from GIS software into google maps and request two travel time matrices. For the baseline scenario, we assume that workers start their commute at eight o'clock in the morning

[3] Jurisdictions are equivalent to the EU's NUTS-3 classification (Kreise and Kreisfreie Städte).

and return from work at five o'clock in the afternoon to capture traffic-congested rush hours. To obtain congestion-free travel times, we repeat the same exercise for three o'clock in the morning. Our commuting data only include cross-border journeys where 92 percent of workers choose the car as the mode of transport. We therefore ignore public transport as a mode of commuting. A limitation of our dataset is that we only observe worker locations at the district level which does not allow us to infer intra-district commuting times. Rather than setting them to zero, we approximate these missing values by computing the weighted average of travel times from neighboring regions and take 20 percent of this value. If everybody was living on the region's border, the value would be around 50 percent. We show in the robustness section 4.4 below that our results are robust to alternative values between 0-40 percent.

Our data set contains a small number of workers who, if the data were taken literally, have round trip commuting times of over ten hours per day (see Figure 6 in the appendix). As we understand commuting as daily trips to work, we truncate the distribution by allowing only round trip commuting times of less than 3 hours and document in the robustness section 4.4 below that our findings are not sensitive to varying this threshold between 1-4 hours. Truncating at 3 hours includes 92.8 percent of all cross-district commutes in Germany.

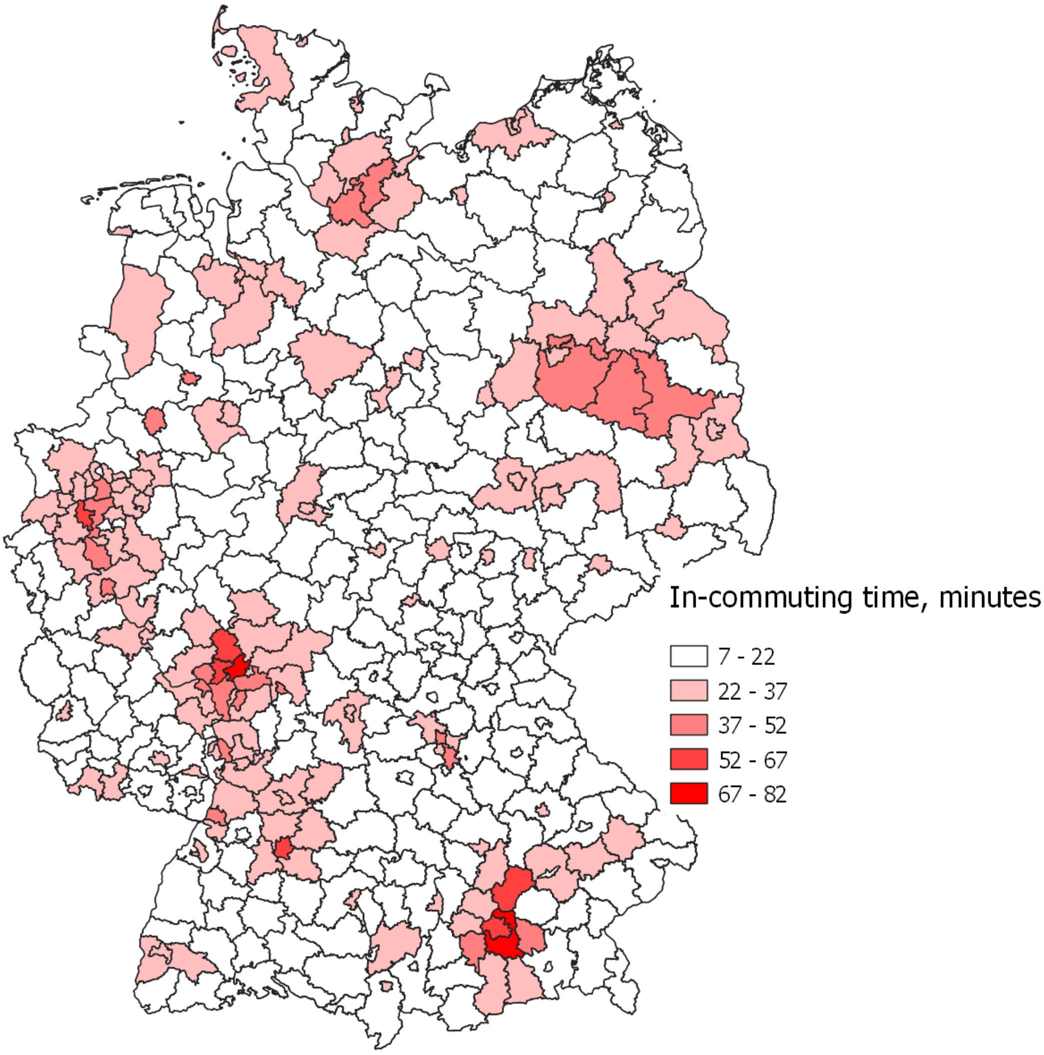
To develop an idea about the spatial commuting pattern, we plot average in-commuting times per district in Figure 1. Workers spend significantly less time on commuting in rural areas while economic centers like Munich, Stuttgart, Frankfurt or Cologne and Dusseldorf are characterized by average in-commuting times of up to 80 minutes. Table 1 underlines these regional disparities by reporting the top-5 and bottom-5 districts or cities ranked by the average in-commuting times. We further observe that high in-commuting is driven to a remarkable extent by higher traffic congestion. In the top-5 districts, commuters spend up to 38 percent of their time in traffic jams while in the bottom-5 districts this ratio ranges only between 12-17 percent.[4]

3.2 Calibration

We now bring the model to data. First, we use the commuting data to obtain bilateral commuting shares, λ_{ni}, and the conditional commuting share, $\lambda_{ni|n}$. Together with information on location-specific employment, L_i, labor-market clearing conditions $L_i = \sum_n \lambda_{ni|n} R_n$ allow us to back out the number of residents in region n.

[4]See also Figure 7 in the appendix.

Figure 1: Average in-commuting time per district



Notes: In-commuting times are weighted by the shares of in-commuters from other districts.

Notice that we use equilibrium conditions from the model to determine R_n instead of using available data on residents to ensure that the model is consistent. In a similar vein, we combine conditional employment shares with observed wages by place of work, w_i, to determine average labor income in region n, $\bar{v}_n = \sum_i \lambda_{ni|n} w_i$. Relating these model predictions for $\bar{v}_n$ and R_n to observed data in panels (a) and (b) of Figure 2 documents a good model fit. We observe that our predictions for local population are centered about the actual values and deviations are relatively small (within $\pm 6\%$). For average residential income, our model predicts slightly lower values, but the relationship still turns out strong. Overall, this is a first assurance that our model describes the spatial economy well.

Housing fundamentals, $\bar{H}_n$. We use data on land prices as a measure of housing

Table 1: Commuting times and time spent in traffic

	∅ in-commuting time, minutes	∅ time in traffic, minutes	∅ % in traffic
Top 5			
Munich (district)	82	25	30%
Frankfurt	67	23	34%
Main-Taunus-Kreis	66	16	25%
Dusseldorf	62	24	38%
Munich (City)	58	19	33%
Bottom 5			
Harz	9	1	14%
Erzgebirgskreis	9	1	15%
Southwest Palatinate	8	1	17%
Garmisch-Partenkirchen	8	1	12%
Goerlitz	7	1	13%

Notes: We sorted all districts in Germany by the average in-commuting time for workers. All numbers are rounded to the nearest integer.

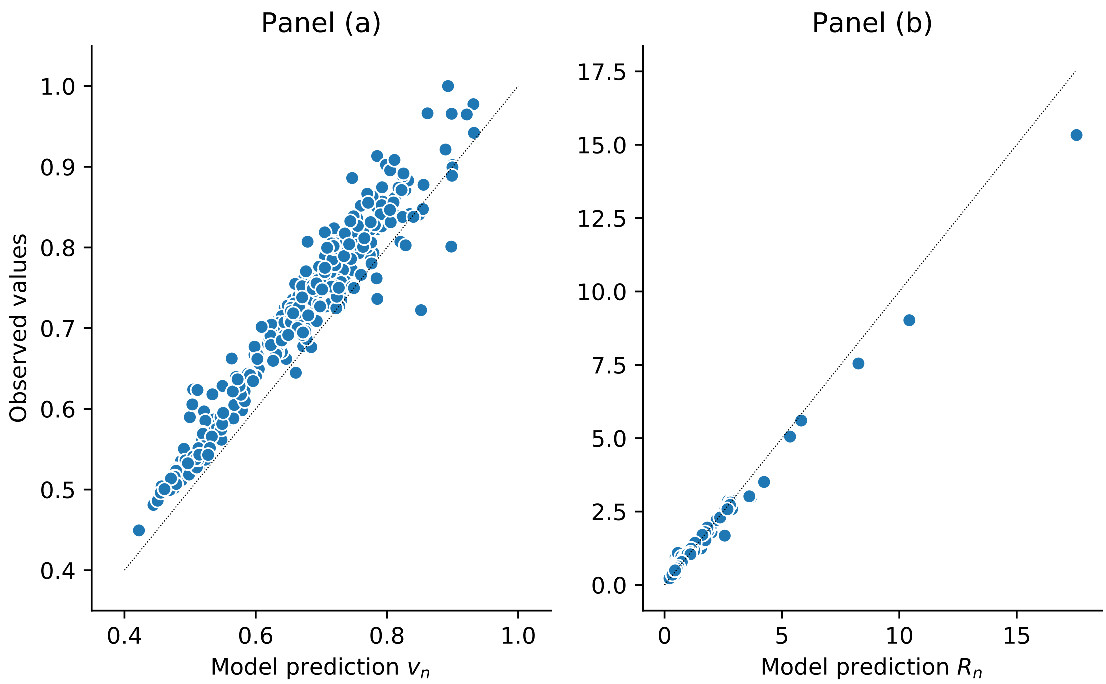
prices $P_{H,n}$ and determine region-specific housing fundamentals, $\bar{H}_n$, from (9). Based on the German Statistical Office (2015), households spend around one third of their disposable income on housing, so we set the expenditure share for consumption goods to $\alpha = 0.7$. As this expenditure includes energy and maintenance, we alternatively use a share of 20 percent in the robustness section 4.4 to show that the insights do not change qualitatively. Further, we follow Lerbs (2014) in choosing a value for the housing supply elasticity $\delta = 0.38$. Adding price data on developed land, $P_{H,n}$, yields $\bar{H}_n$.

Fundamental productivity, $\bar{A}_n$. To uncover the region-specific productivity fundamentals, we first need to obtain estimates for unobserved bilateral trade frictions, d_{ni}. We do so by deriving a gravity equation from the model,

$$Q_{ni} = \pi_{ni}\bar{v}_n R_n = \frac{\frac{L_i}{\sigma f}\left(\frac{\sigma}{\sigma-1}\frac{w_i d_{ni}}{A_i}\right)^{1-\sigma}}{\Omega_n}\frac{\bar{v}_n R_n}{P_{Q,n}},$$

where $\Omega_n \equiv \sum_k M_k \; p_{nk}^{1-\sigma}$ denotes a multilateral resistance term. Notice that the left-hand side captures quantities rather than values as bilateral regional trade data are only available in volumes. Taking logs on both sides delivers the estimation

Figure 2: Observed vs. predicted wages and employment



Notes: We have normalized wages to range between zero and one. Employment is normalized to have a mean of one.

equation

$$\log Q_{ni} = \log \left[\frac{L_i}{\sigma f} \left(\frac{w_i \ \sigma}{A_i \ (\sigma - 1)} \right)^{1-\sigma} \right] + \log \left(\frac{\bar{v}_n R_n}{\Omega_n P_{Q,n}} \right) + (1-\sigma) \log d_{ni}$$
$$= \chi_i + \xi_n - (\sigma - 1) \log d_{ni}, \tag{12}$$

where χ_i and ξ_n are exporter and importer fixed effects. To parameterize trade frictions, we follow the gravity literature (e.g. Head and Mayer 2015) in assuming that trade costs are a function of bilateral distance, a set of standard controls $\mathbb{C}$ and an error term,

$$d_{ni} = dist_{ni}^{\psi} \ e^{\gamma \mathbb{C}} \ \tilde{e}_{ni}. \tag{13}$$

Plugging this into (12) yields

$$\log Q_{ni} = \chi_i + \xi_n - (\sigma - 1) \ \psi \ \log dist_{ni} + (1-\sigma)\gamma\mathbb{C} + (1-\sigma) \ \log(\tilde{e}_{ni}). \tag{14}$$

Imposing a value for the elasticity of substitution of $\sigma = 4$ (Broda and Weinstein 2004), we are able to estimate ψ with ordinary least squares. The result delivers bilateral trade frictions according to (13).[5] Importantly, bilateral trade flows

[5]Note that the trade gravity can only be used to calibrate trade costs where $dist_{ni} > 0$, i.e.

are available at the sector level which allows us to capture the price dimension by including sector fixed effects. Transforming these volume data into values by using unit prices from COMTRADE delivers similar estimates of the trade elasticity (Henkel and Seidel 2019).

Table 2: Trade gravity estimation

log(Trade volume)	(1)	(2)
log(Distance)	-1.259^{***}	-0.977^{***}
	(0.002)	(0.004)
Dialect similarity		0.225^{***}
		(0.013)
Contiguity		0.524^{***}
		(0.009)
Same state		0.468^{***}
		(0.005)
Constant	3.035^{***}	3.039^{***}
	(0.063)	(0.063)
Sector dummies	Yes	Yes
Importer FE	Yes	Yes
Exporter FE	Yes	Yes
R^2	0.402	0.408
Observations	1,116,832	1,116,832

Notes: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively.

Table 2 summarizes the results of the trade gravity estimation. The estimated distance elasticities of -0.98 and -1.26 are in line with the values usually found in the gravity literature. Head and Mayer (2015) find trade elasticities to be consistently in the area of -1. Having set $\sigma = 4$ implies a parametrization for $\psi = 0.42$ if we build on column (2).

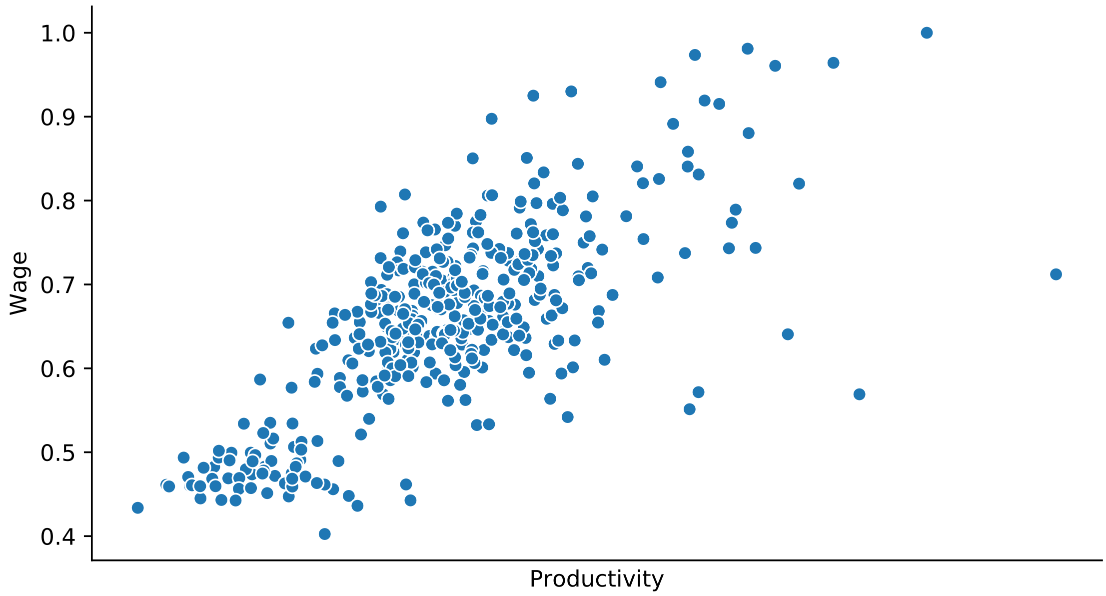
We are now equipped with the necessary information to back out location-specific productivity levels.[6] Substituting bilateral trade shares, (10), into the region-specific goods market clearing conditions, $w_i L_i = \sum_n \pi_{ni} \bar{v}_n R_n$, delivers a system of N equations which can be solved for a unique vector of $\bar{A}_n$, where we choose the parameter

$n \neq i$ and $Q_{ni} > 0$. As trade costs are assumed to be of the iceberg form, we already know that $dist_{ni} = 0 \implies d_{ni} = 1$. For the case where no bilateral trade is observed, i.e. $Q_{ni} = 0$, trade costs are assumed to be prohibitively high, i.e. $Q_{ni} = 0 \iff d_{ni} = \infty$.

[6] See Monte, Redding, and Rossi-Hansberg (2018) for a formal proof of existence and uniqueness of the solution.

value for the strength of productivity spillovers to $\nu = 0.05$. This implies that productivity increases by 3.5 percent if population doubles – a value that is in line with the findings in Rosenthal and Strange (2004). The obtained regional productivity fundamentals are positively and strongly correlated with wages according to Figure 3.

Figure 3: Wages and productivity



Notes: The figure shows correlation between the local productivity fundamentals $\bar{A}_n$ and regional wages at the workplace w_n. Note that productivity fundamentals are only determined up to scale, therefore we omit an explicit scale on the horizontal axis.

Price index, $P_{Q,n}$. Using the results from above in (11) and normalizing the fixed labor input requirement f to unity delivers values for local price indices.

Commuting cost parameter, μ. In a next step, we examine how workers value commuting to work. Our model helps us to answer this question. We start from the commuting share equation

$$\lambda_{ni} = \frac{B_{ni}\left(\tau_{ni}^{\mu} P_n^{\alpha} Q_n^{1-\alpha}\right)^{-\epsilon} w_i^{\epsilon}}{\sum_r \sum_s B_{rs}\left(\tau_{rs}^{\mu} P_r^{\alpha} Q_r^{1-\alpha}\right)^{-\epsilon} w_s^{\epsilon}}$$

and take logs on both sides to get

$$\log \lambda_{ni} = g_0 + \eta_n + \epsilon \log w_i - \mu\epsilon \log \tau_{ni} + u_{ni}, \qquad (15)$$

where g_0 is a constant term and η_n captures residence fixed effects. Notice that 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. Using round trip commuting times, τ_{ni},

Table 3: Commuting gravity estimation

log(commuting shares)	*OLS* (1)	*IV* (2)
log(wage)	4.474***	5.046***
	(0.125)	(0.137)
log(commuting time)	−3.756***	−4.579***
	(0.045)	(0.051)
Constant	−28.011***	−28.591***
	(1.107)	(1.197)
Residence FE	Yes	Yes
R^2	0.651	0.630
Observations	6,393	6,393

Notes: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively.

as derived from google maps, (15) delivers estimated values for the Fréchet shape parameter, ϵ, and the commuting cost elasticity, μ.

To obtain unbiased estimates, one needs to assume that B_{ni} is orthogonal to wages and bilateral commuting times. This, however, is inconsistent with the notion of a spatial model where location decisions of workers emerge endogenously based on amenities, wages, and commuting times. We therefore amend the naive OLS regression with an instrumental variables approach where we use Euclidian distances as instruments for commuting times τ_{ni}.[7] We further instrument for wages using a shift share IV strategy following Bartik (1991) or Baum-Snow and Ferreira (2015). 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 differ in terms of their industry composition and the exclusion restriction is satisfied as long as national shocks are uncorrelated with regional amenity levels.[8]

[7] We relegate results on the first stage to the appendix.

[8] We thank Duncan Roth for providing us with the data.

Table 3 reports the results of both estimation approaches. We observe that higher wages at the place of work lead to higher commuting shares while longer commutes reduce the fraction of commuters. In particular, a one percent increase in the wage rate raises the commuting share by 4.5 percent in the OLS specification while a one percent increase in commuting time reduces the commuting share by 3.8 percent. In the IV specification, the point estimates on wages and commuting time increase in absolute terms.

Amenities, B_{ni}. Finally, we use bilateral trade shares to obtain a $N \times N$ system of equations that solves for $N \times N$ values of B_{ni}.[9] This completes the calibration exercise.

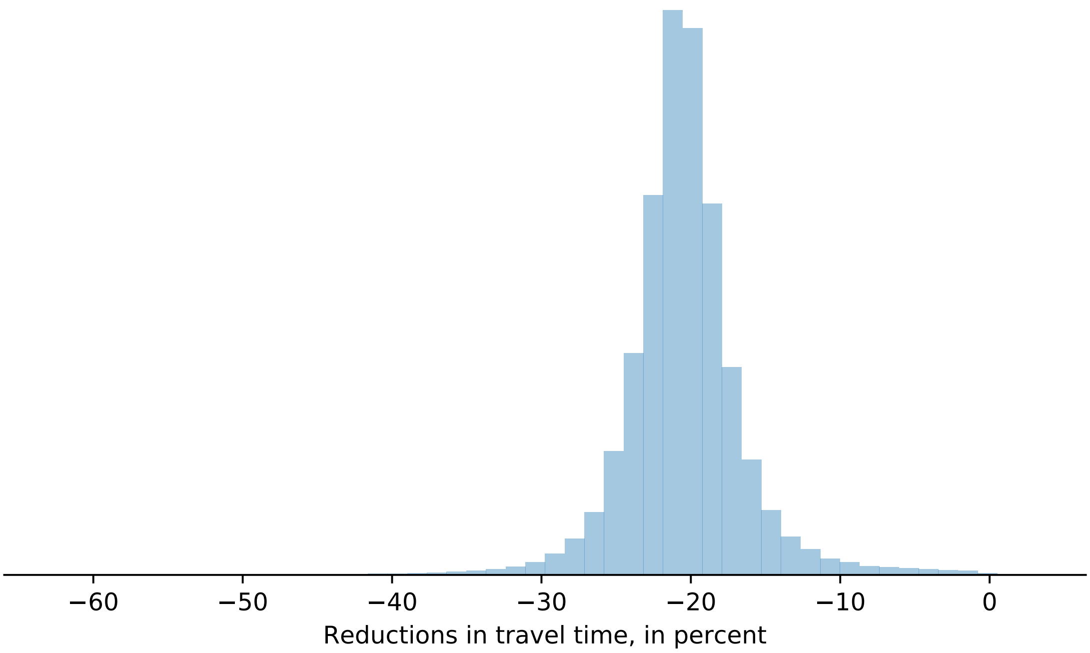
4 Eliminating traffic jams

We now utilize the model to understand the implications of rush hours for the spatial allocation of employment and population, average productivity and the housing market. Rather than haircutting bilateral commuting times by a certain share, we abolish location-specific traffic congestion by recomputing travel times between districts at 3 a.m. The idea is that traffic at that time is so low that even in the most traffic-prone locations there is no congestion. As locations are affected by traffic jams to different extents (see Table 1), we can expect heavily congested areas to respond in a more pronounced way than less congested areas with general equilibrium implications for all locations. For the counterfactual, we also impute intra-district commuting times without traffic congestion following the same procedure as in the baseline scenario. We compute for each region the average commuting time from all contiguous districts, weighted by the number of workers commuting into the district and take 20 percent of this value.

Figure 4 plots the distribution of travel times in a world without traffic jams (at 3a.m.) relative to the travel time in a world with traffic congestion during rush hours (at 8a.m. and 5p.m. during weekdays). We observe that the reduction centers at around -20% while there is quite a bit of heterogeneity across places. For the most traffic-prone regional commuting pairs an elimination of traffic jams reduces commuting times by more than 60%.

[9] See Figure 8 in the appendix for the geographical distribution of the calibrated amenities.

Figure 4: Reduction of commuting times



Notes: The figure shows the histogram of travel time reductions in percent if all traffic jams during rush hours were abolished.

4.1 Spatial allocation of population and employment

Abolishing traffic congestion makes it more appealing to choose a place of residence with low housing costs and a place of work offering high nominal income. In Table 4, we use the classification of the Federal Institute for Research on Building, Urban Affairs and Spatial Development in Germany to group districts according to population density and size. Large cities with more than 100,000 inhabitants form one group; three additional categories sort locations according to population density in "Mostly urban region", "Mostly rural region" and "Rural region".

We observe that locations in the two categories with the lowest density lose in terms of both population and employment. In contrast, the population share living in mostly urban regions and cities increases by 2.4 and 2.5 percentage points, respectively. The relative increase, though, is higher for mostly urban districts as their population shares are lower initially compared to cities. Employment, however, becomes more concentrated in large cities because their commuting belts grow in terms of population and workers get better access to these high-wage places through commuting. Taking the Gini-index as a measure of inequality, we find an increase with respect to population from 0.39 to 0.45 and a more pronounced increase with respect

Table 4: Rush hours and urbanization

	Population share		Employment share		Average productivity	
Region type	Baseline	Counterfactual	Baseline	Counterfactual	Baseline	Counterfactual
Large city	43.1	45.6	53.7	68.7	1.00	1.01
Mostly urban region	25.7	28.1	22.1	16.7	0.93	0.92
Mostly rural region	17.5	15.4	13.5	8.4	0.80	0.79
Rural region	13.7	10.9	10.6	6.2	0.76	0.74

Notes: We follow the type classification defined by the Federal Institute for Research on Building, Urban Affairs and Spatial Development. We classify regions consisting only of a city (kreisfreie Städte) and more than 100,000 inhabitants as "Large city". "Mostly urban region" denotes regions with a population density of more than 150 inhabitants per square km. "Mostly rural region" refers to regions with population densities between 100 and 150 inhabitants per square km. "Rural regions" are regions with less than 100 inhabitants per square km. Productivity is normalized to one in large cities in the baseline scenario, so that all productivity averages can be interpreted relative to large cities.

to employment from 0.44 to 0.58.[10] Although low-density districts with low housing costs become relatively more attractive places of residence when traffic jams are abolished, it is not rural areas but "mostly urban region" that experience net immigration. In sum, traffic congestion during rush hours reduces both the economy-wide degree of urbanization and the agglomeration of employment. Further, the share of cross-district commuters climbs from one third to 54 percent reflecting that traffic jams have a strong impact on the workplace-residence decision and operate as a significant friction in the spatial economy. It illustrates that commuting is an important factor to understand spatial general equilibrium effects.

4.2 Labor productivity

The reason why the population in cities grows as well as in primarily urban areas with lower housing costs roots in a combination of lower traffic congestion and higher productivity. The last two columns in Table 4 reveal that cities are the only type of regions that become more productive. We normalize productivity in large cities to unity and express productivity levels in all other categories relative to this value. As productivity changes are positively associated with employment changes, all types of locations experience a decline in productivity except for large cities. More productive workers earn higher wages making high housing costs in cities affordable for a larger fraction of households. Average productivity in cities

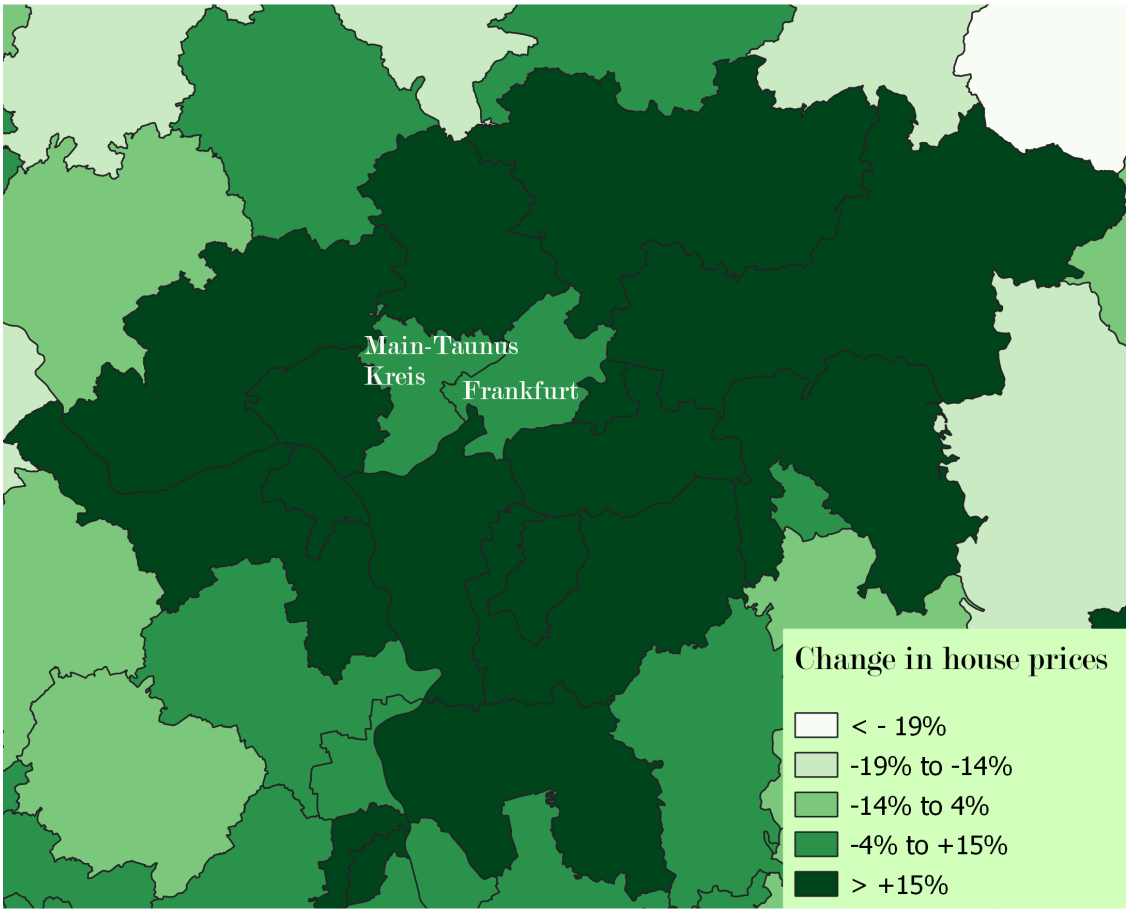
[10] Figures 9 and 10 in the appendix provide a graphical illustration of this finding.

grows by approximately 1 percent while it declines in the three remaining categories by 1-2 percentage points. Although productivity changes at the regional level are moderate, average productivity in the economy increases by 7.2 percent. This is primarily driven by the relocation of workers from less productive to more productive places.

4.3 Housing market

Adjustments in residence and workplace decisions of households change both housing demand and supply – the latter through changes in prices according to (7) – at the district level. The response of regional house prices is very heterogeneous across space. In districts experiencing net emigration, house prices are up to 27 percent lower in the new equilibrium. High-density locations, classified as "Large city" or "Mostly urban region" in Table 4 above, experience an average increase in housing costs of 11.4% and 5.7%, respectively. The growth in cities is almost entirely driven by the Ruhr Area – Europe's largest conglomerate of urbanized areas (Schmidheiny and Suedekum 2015) – in Germany's most populous state North Rhine-Westphalia that suffers heavily from traffic congestion. If we take out all districts in North Rhine-Westphalia, house prices in cities do not increase at all while mostly urban regions experience an increase of 6%. Low density locations, classified as "Mostly rural region" and "Rural region", see an average decrease in housing costs of 9.3% and 18.7%, respectively. These changes translate to larger inequality of housing prices across space: the population-weighted Gini-index goes up from 0.72 to 0.79.

Figure 5: THE HOUSING MARKET IN THE FRANKFURT REGION



Notes: The figure above depicts changes in house prices in our main specification of the counterfactual scenario around the city of Frankfurt. The color scheme is chosen, so that changes in house prices are grouped in quintiles over all districts in Germany.

In Figure 5, we take a closer look at the city of Frankfurt with its surrounding regions. We observe that, even though house prices might increase in the economic center when traffic congestion vanishes, the increase is much more pronounced in the commuting belt around the city. Looking at this pattern alone shows that lower commuting costs contribute to a convergence of house prices in this greater area because growth rates are higher in the commuting belt.

4.4 Robustness

To check the sensitivity of our conclusions with regard to the chosen parameter values in the empirical exercise above, we undertake three robustness checks. First, we vary the weight on intra-district versus cross-district commuting. In the baseline case, we have taken 20 percent of the weighted commuting times from neighboring districts as the measure for intra-district commuting time. We now vary this weight between 0-40 percent. This is an important exercise because it affects the relative attractiveness of places. For example, if we ignored intra-district commuting time altogether, we would make adjacent districts relatively more attractive in the counterfactual implying higher net immigration there. Panel A in Table 5 supports this intuition. Columns 1 and 2 report the counterfactual shares of population and employment in "Large cities" or "Mostly urban regions" according to the classification above. Column 3 informs about the economy-wide average productivity change. For the sake of convenience, we repeat counterfactual results with the baseline parameter values in bold. Reducing the weight to zero – implying no intra-district commuting time – leads to a slightly lower population share and a slightly higher employment share. The reason is that the counterfactual makes location in neighboring regions relatively more attractive because commuting costs cannot decline within districts by construction. Therefore, more workers locate outside of cities and commute to high-wage jobs. As an immediate implication, the employment share in urban regions increases which, in turn, translates into higher average productivity. The opposite qualitative results emerge if we raise the share from 20 percent. Importantly, counterfactual outcomes do not respond much despite large changes in parameter values.

As a second robustness check, we alter the truncation of travel times between districts. Compared to the baseline where we have included only round-trip travel times of up to three hours, truncating at 1 or 2 hours leads to lower productivity gains and lower agglomeration of employment and population. This is intuitive as households do not get the chance to commute longer distances by construction which rules out gains from separation of place of work and place of residence. If we raise the truncation to 4 hours, the results remain fairly stable.

Table 5: Robustness of results

Panel A: Within district commuting

	Urban population	Urban employment	∅ Productivity
0%	73.5%	85.6%	7.7%
10%	73.6%	85.5%	7.4%
20%	**73.7%**	**85.4%**	**7.2%**
30%	73.8%	85.3%	6.9%
40%	74.0%	85.2%	6.6%

Panel B: Truncation of travel times

	Urban population	Urban employment	∅ Productivity
1h	71.2%	81.9%	4.0%
2h	73.3%	84.9%	6.7%
3h	**73.7%**	**85.4%**	**7.2%**
4h	73.5%	85.2%	7.0%

Panel C: Share of consumption expenditure

	Urban population	Urban employment	∅ Productivity
$\boldsymbol{\alpha = 0.7}$	**73.7%**	**85.4%**	**7.2%**
$\alpha = 0.8$	76.0%	87.3%	9.1%

Notes: In all panels, the columns entitled "Urban population" and "Urban employment" denote the share of workers living and working in "Large cities" and "Mostly urban regions" in our counterfactual scenario. The third column denotes the increase in average productivity in the counterfactual. In our main specification, we use a value of 20 percent of the weighted bilateral commuting time of neighbouring districts for intra-district commuting, a 3-hour threshold for travel times, and a share of consumption expenditure of 0.7. In each panel, we deviate from the main specification only in the respective dimension.

Finally, 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 determines the strength of the congestion force in the model, so reducing the share to 20 percent should favor agglomeration and thus higher productivity. This intuition is supported by Panel C of Table 5. Average productivity goes up by approximately 2 percentage points, but the general insight that lower commuting times between districts raise economy-wide urbanization remains unaffected.

5 Conclusions

In this paper, we have explored the role of traffic congestion during rush hours for the spatial allocation of employment and population, average labor productivity and the housing market. Intuitively, longer commutes to high-density, high-wage locations make it more attractive to either move to cities at the expense of higher housing costs, or live and work in the countryside. Calibrating the model for Germany shows, however, that an abolishment of traffic congestion stimulates immigration to locations in the vicinity of economic centers that are within commuting distance to high-wage locations. Therefore, traffic congestion reduces the degree of overall urbanization. Although living and working in high-wage places becomes a more appealing option, congestion avoids urban sprawl in commuter belts.

Traffic jams therefore lead to a misallocation of workers across space as employment is higher in less-productive places than in the absence of traffic jams. The model suggests that average labor productivity would be 7.2 percent higher in the absence of traffic jams. The adjustment of workplace and residence choices also carries over to the housing market. While housing supply adjusts to price changes endogenously according to the housing supply elasticity, housing prices decline in districts experiencing net emigration while denser locations become more expensive places to live.

Our results indicate that capacity-enhancing infrastructure investments generate higher returns in cities and their commuter belts 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.

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Appendix

A Solving the model in relative changes

We can solve for the relative changes in our model by solving the following system of equations according to the iterative algorithm outlined in Monte, Redding, and Rossi-Hansberg (2018):

$$\begin{aligned}
\hat{Q}_n &= \left(\frac{\hat{\bar{v}}_n \hat{R}_n}{\hat{\bar{H}}_n}\right)^{\frac{1}{1+\delta}} \\
\hat{w}_i \hat{L}_i w_i L_i &= \sum_n \hat{\pi}_{ni} \pi_{ni} \hat{\bar{v}}_n \bar{v}_n \hat{R}_n R_n \\
\hat{P}_n &= \left(\frac{\hat{L}_n^{1-(1-\sigma)\nu}}{\hat{\pi}_{nn}}\right)^{\frac{1}{1-\sigma}} \frac{\hat{d}_{nn} \hat{w}_n}{\hat{\bar{A}}_n} \\
\hat{\lambda}_{ni} \lambda_{ni} &= \frac{\lambda_{ni} \hat{B}_{ni} \left(\hat{P}_n^{\alpha} \hat{Q}_n^{1-\alpha}\right)^{-\epsilon} \left(\hat{w}_i / \hat{\kappa}_{ni}\right)^{\epsilon}}{\sum\limits_r \sum\limits_s \lambda_{rs} \hat{B}_{rs} \left(\hat{P}_r^{\alpha} \hat{Q}_r^{1-\alpha}\right)^{-\epsilon} \left(\hat{w}_s / \hat{\kappa}_{rs}\right)^{\epsilon}} \\
\hat{\bar{v}}_n \bar{v}_n &= \sum_i \frac{\lambda_{ni} \hat{B}_{ni} \left(\hat{w}_i / \hat{\kappa}_{ni}\right)^{\epsilon}}{\sum\limits_s \lambda_{ns} \hat{B}_{ns} \left(\hat{w}_s / \hat{\kappa}_{ns}\right)^{\epsilon}} \hat{w}_i w_i \\
\hat{R}_n &= \frac{\bar{L}}{R_n} \sum_i \lambda_{ni} \hat{\lambda}_{ni} \\
\hat{L}_i &= \frac{\bar{L}}{L_i} \sum_n \lambda_{ni} \hat{\lambda}_{ni} \\
\hat{\pi}_{ni} \pi_{ni} &= \frac{\pi_{ni} \hat{L}_i^{1-(1-\sigma)\nu} \left(\hat{d}_{ni} \hat{w}_i / \hat{\bar{A}}_i\right)^{1-\sigma}}{\sum\limits_k \pi_{nk} \hat{L}_k^{1-(1-\sigma)\nu} \left(\hat{d}_{nk} \hat{w}_k / \hat{\bar{A}}_k\right)^{1-\sigma}}
\end{aligned}$$

The system of equations above maps the model parameters $\{\delta, \sigma, \alpha, \epsilon\}$, the changes in fundamentals $\{\hat{\bar{H}}_n, \hat{d}_{ni}, \hat{\kappa}_{ni}, \hat{B}_{ni}, \hat{A}_n\}$ and the observed current variables $\{w_n, L_n, \pi_{ni}, \bar{v}_n, R_n, \lambda_{ni}\}$ into the relative changes in all model variables. For our elimination of traffic jam we calculate $\hat{\kappa}_{ni} = (\tau'_{ni}/\tau_{ni})^{\mu}$, where τ'_{ni} denotes google's estimate of travel time between n and i in the absence of traffic. We assume that the remaining fundamentals do not change.

B First stage results

In this section, we present results of the first-stage regression of the IV-estimation of the distaste parameter for commuting, μ. Column (1) reports results for the predicted values of wages while column (2) refers to travel time. The results indicate that both instruments are valid.

Table 6: FIRST STAGE REGRESSIONS

Dependent variable	Wage	Travel time
	(1)	(2)
log(shift share wages)	0.563^{***}	0.035^{***}
	(0.007)	(0.013)
log(distance)	-0.000	0.607^{***}
	(0.002)	(0.004)
Constant	5.562^{***}	2.236^{***}
	(0.045)	(0.084)
Residence fixed effects	Yes	Yes
Observations	6,393	6,393
R^2	0.789	0.809
F Statistic (df = 413; 5979)	54.164^{***}	61.231^{***}

Notes: ***, **, * denote significance at the 1-, 5-, and 10-percent level, respectively.

C Data

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

- 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 2010, the dates mentioned in the detailed data description below indicates 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, Juni 2015.
  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.
- *Earnings by place of work and residence:* German Federal Employment Agency, Sozialversicherungspflichtige Bruttoarbeitsentgelte, Entgeltstatistik 2014.
  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.
- *Commuting flows:* German Federal Employment Agency, Sozialversicherungspflichtig Beschäftigte - Pendler nach Kreisen, Nürnberg, Stichtag 30. Juni 2014.
  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.

- *Regional land prices:* German Federal Statistical Office, Statistik der Kaufwerte für Bauland, EVAS-Nr.: 61511-01-03-4.
  Local tax offices collect information on all sales of undeveloped plots of land with a size of at least 100 m^2. The price per square meter is computed as the quotient of total sales price and and plot size.

- *Bilateral trade flows:* The trade flow matrix comes from the Forecast of Nationwide Transport Relations in Germany 2030 (VVP). It covers trade flows (in metric tons) that either have a German NUTS-3 region as origin or destination or serve as a transit region for intra-European trade of regions outside of Germany. The data distinguish between the mode of transport, namely road, rail, and water, and product groups according to NST2007. For rail and water, the data come from the German Federal Statistical Office and for road from the Federal Motor Transport Authority (Kraftfahrtbundesamt). Locations trade flows are reported at the NUTS-3 level. The data were collected in a project undertaken by Intraplan Consulting, Munich, in collaboration with BVU Consulting, Freiburg, for the Federal Ministry of Transport and Digital Infrastructure and is only available for 2010. The data are made available through the Institute for Transport Research of the German Aerospace Center.

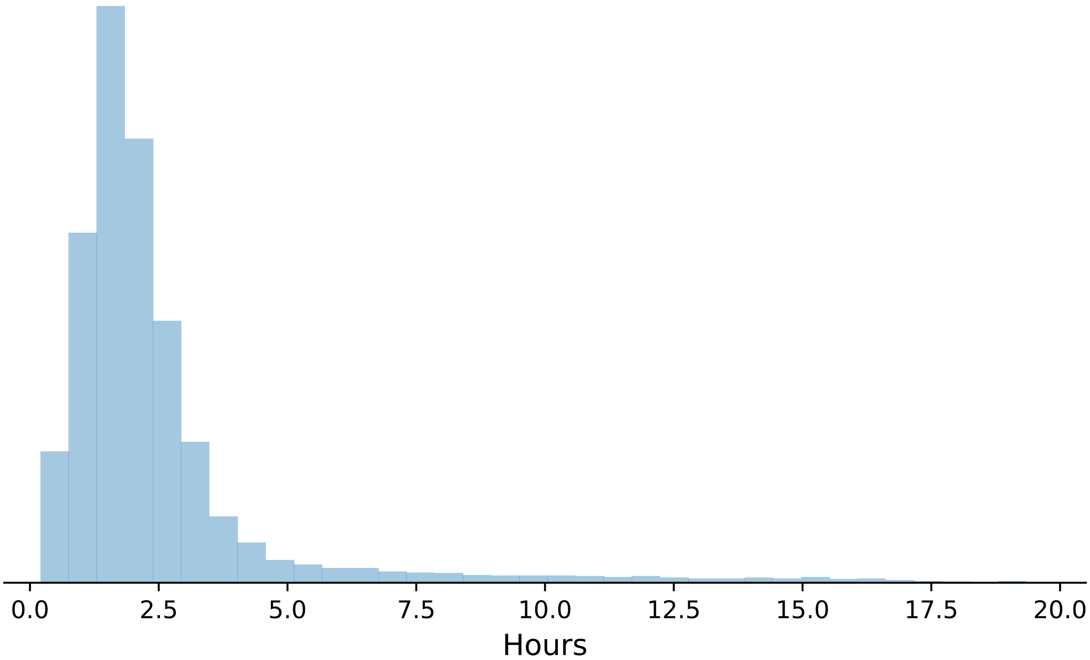
- *Language similarity:* We use the index of language similarity in Germany for all NUTS-3 regions constructed by Lameli et al. (2015). The index is based on a comprehensive language survey of more then 40,000 German schools in the late 19th century by the linguist Georg Wenker. A more detailed discussion of the survey can be found in Lameli (2013). The similarity index is constructed by comparison of 66 language characteristics between regions.

- *Geographic information:* German Federal Agency for Cartography and Geodesy, District definition for the year 2010. The German Federal Agency for Cartography and Geodesy provieds 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).

- *Classification of districts:* The definition follows Federal Institute for Research on Building, Urban Affairs and Spatial Development
`https://www.bbsr.bund.de/BBSR/DE/Raumbeobachtung/Raumabgrenzungen/Kreistypen4/kreistypen.html?nn=443270`
As the regional classification from the institute is not available for years prior to 2015 we use a similar method on our regions for the year 2010. We classify regions consisting only of a city (kreisfreie Städte) and more than 100,000 inhabitants as “Large city”. “Primarily urban” denotes regions with population density of more than 150 inhabitants per square km. “Primarily rural” refers to regions with population densities between 100 and 150 inhabitants per square km. “Rural regions” are regions with less than 100 inhabitants per square km.

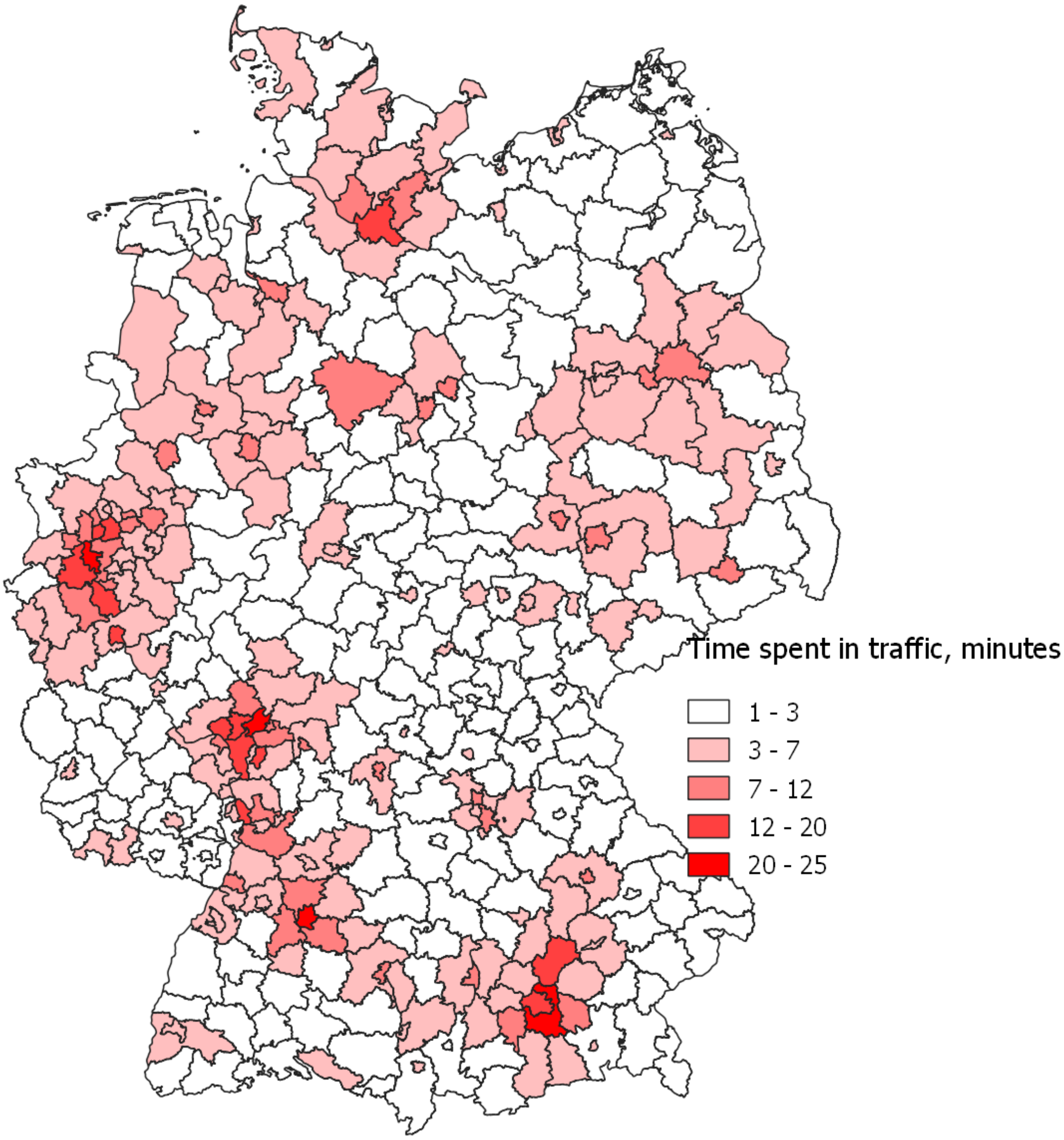
D Figures

Figure 6: Round-trip travel times between home and work



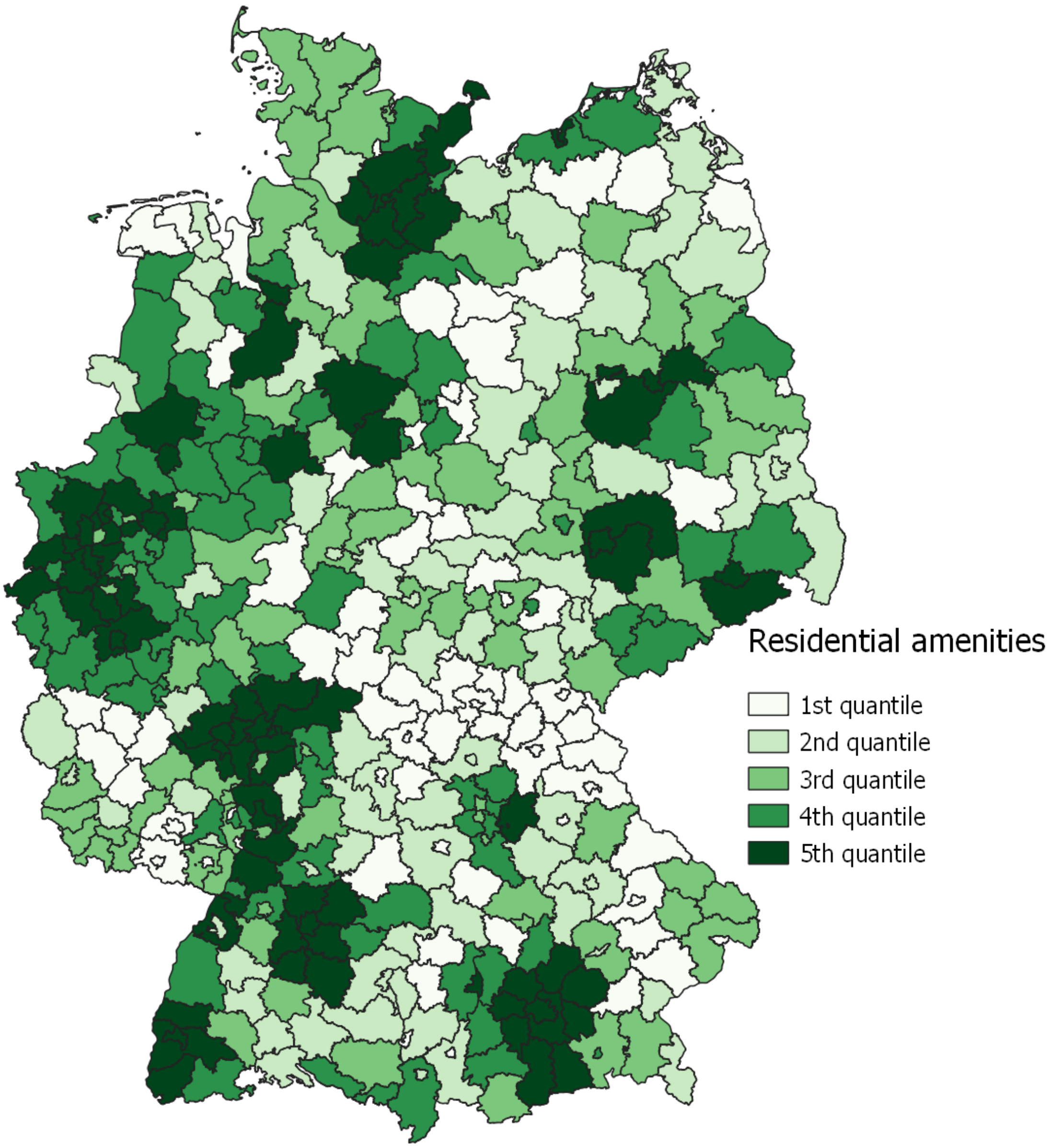
Notes: The figure shows round trip travel times for all combinations of districts by car. We take the centroid of each district and compute travel times at 8 a.m. and 5 p.m. from google maps.

Figure 7: Average absolute time spent in traffic



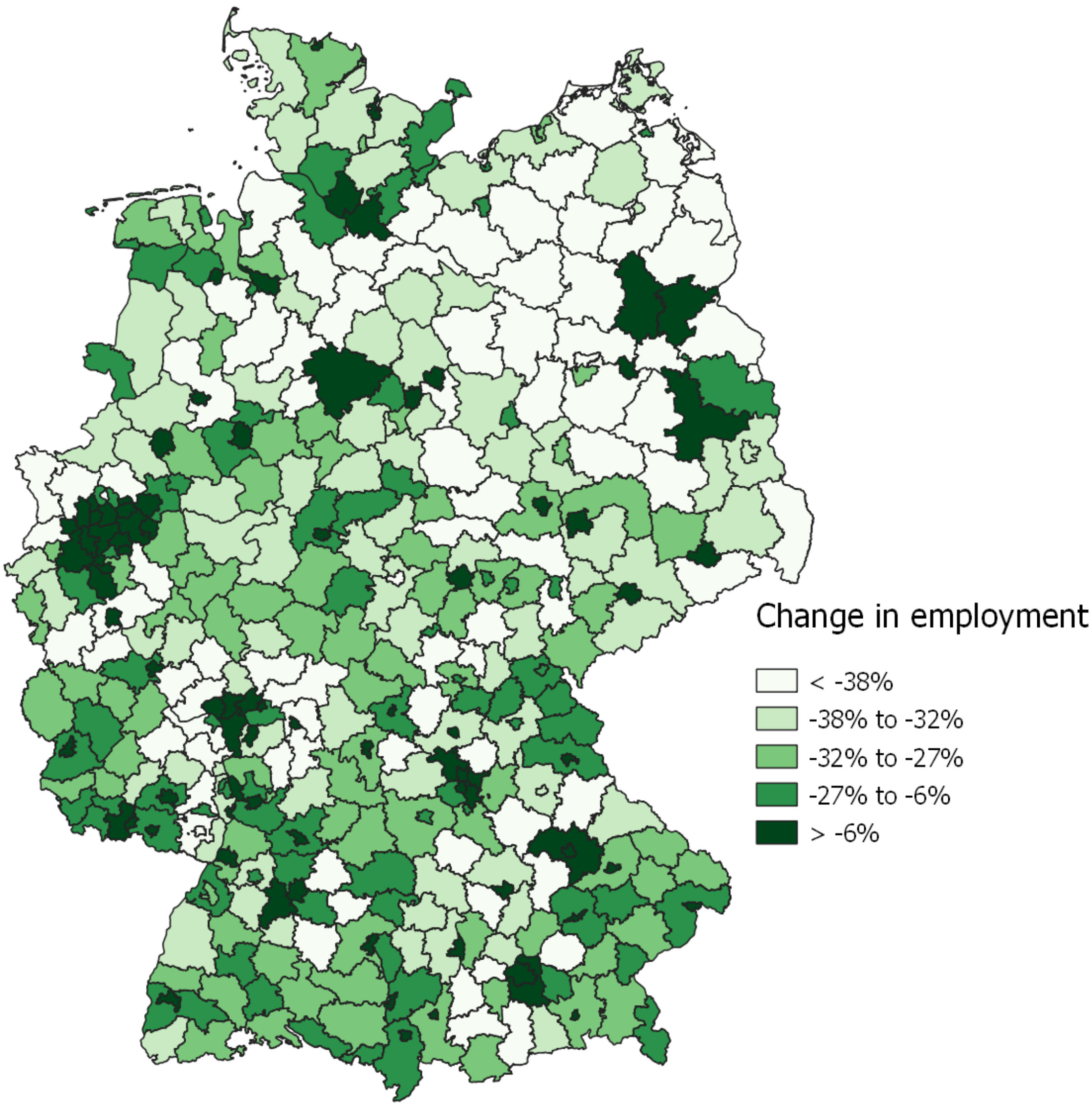
Note: Time spent in traffic is computed as the average difference between rush hour travel time and traffic free travel time, weighted by the number of workers commuting into a region.

Figure 8: Average Amenities in residential locations



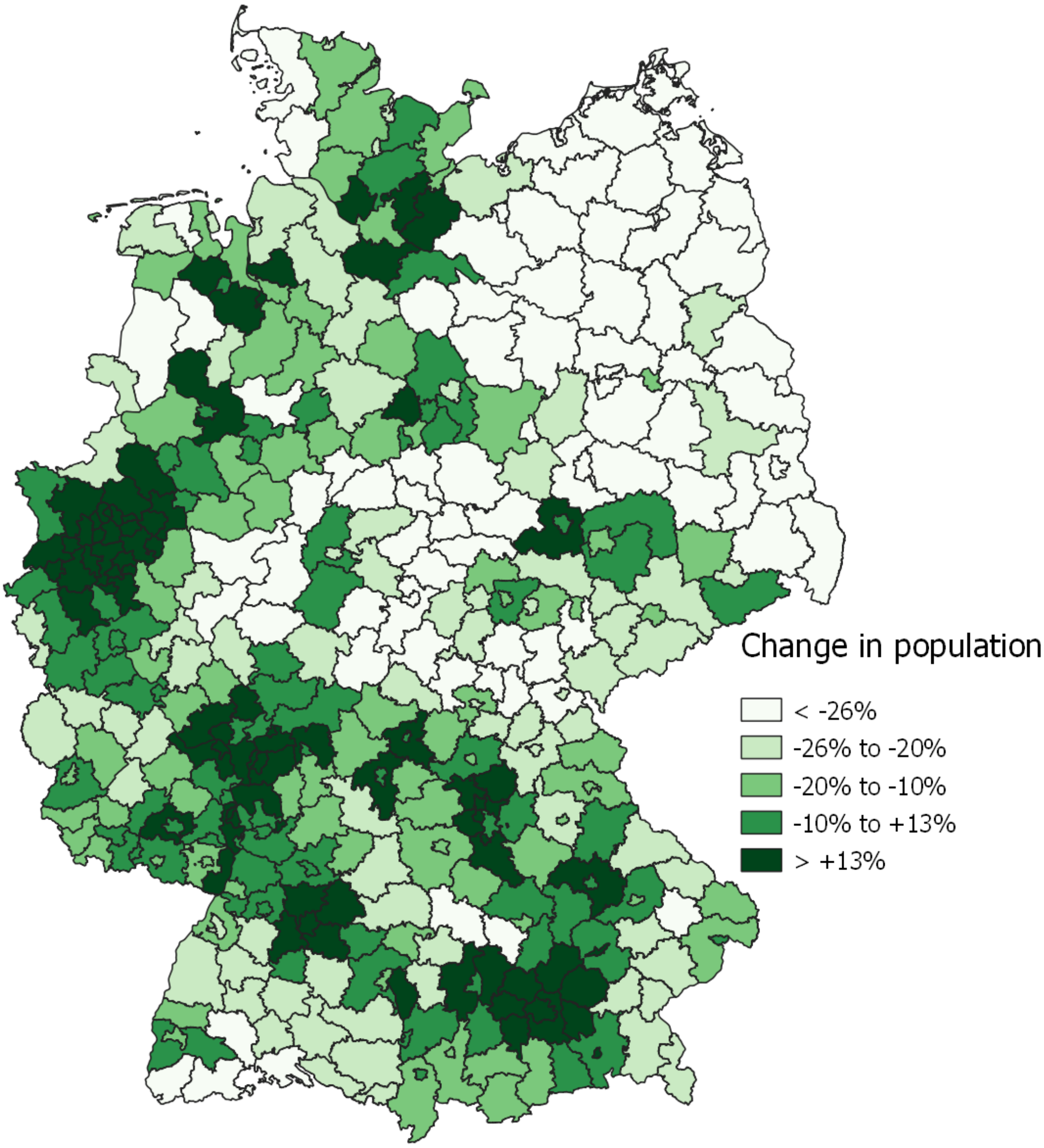
Notes: Residential amenities are computed as an employment weighted sum over all estimated bilateral amenities B_{ni}.

Figure 9: Regional changes in employment



Notes: Color scheme is ordered in quintiles of the distribution of relative employment changes.

Figure 10: Regional changes in population



Notes: Color scheme is ordered in quintiles of the distribution of relative population changes.