Cities, Aggregate Welfare, and Growth♣

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February 25, 2025

ABSTRACT

This paper explores the macroeconomic consequences of regulatory barriers in housing markets. We take a European perspective, allowing us to offer novel facts, theory, and methodology. Our focus is on Germany, a compelling case exemplifying key characteristics unique to European city systems. To take our model to the data, we estimate its structural equations for the population elasticities of urban benefits and costs using rich micro-data. The quantified model receives strong support from several sources of independent evidence. We study the effects of a counterfactual reduction of land-use regulations on aggregate welfare and evaluate the effect of cities on growth.

JEL-Classification: C52, R12, D24

Keywords: city systems, urban growth, urban benefits and costs, land-use regulations, amenities, location fundamentals

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♣ This paper is a major revision of IZA-DP 16127 which appeared under a different title. We are particularly indebted to Gilles Duranton for very valuable comments and discussion. We acknowledge helpful comments from and discussion with Treb Allen, Gadi Barlevy, Nathanial Baum-Snow, Rainald Borck, Wolfgang Dauth, Toker Doganoglu, Maximilian von Ehrlich, Jason Faberman, Oliver Falck, Fernando Ferreira, Ruben Gaetano, Jessie Handbury, Dan Hartley, Stephan Heblich, Thomas Klier, Hans Koster, Marianna Magagnoli, Dennis Novy, Holger Sieg, Kurt Schmidheiny, Will Strange, Daniel Velásquez, Felix Weinhardt, Maisy Wong, Matthias Wrede, and audiences at conferences and research seminars in Bern (CRED), Chicago (Federal Reserve Bank), Copenhagen (UEA), Freiburg, Essen, Karlsruhe, Montreal, Munich, Nuremberg, Passau, Philadelphia (Wharton), Toronto (Rotman, UEA), Regensburg (VfS) and Würzburg. We thank Tobias Seidel, Marcel Henkel and Jens Suedekum for providing us their German tax-transfer data.

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1 Introduction

Cities, celebrated as humanity's greatest invention, are a focal point of public debate today (Glaeser 2011; 2020). Societal perception is shifting to the downsides of urban living, in particular escalating housing costs and shortages of affordable housing in desirable places.[1] Recent research converges on the idea that these housing market pressures stem not solely from the interplay of demand and supply but are significantly influenced by regulatory measures. These include a range of constraints from land-use regulations and urban containment policies to zoning laws and fiscal externalities, often enacted by local policymakers to protect the interests of current residents ('city insiders') at the expense of potential new residents, the 'city outsiders' (Glaeser 2014; Glaeser and Cutler 2021; Glaeser and Gyourko 2018).

This paper explores the macroeconomic consequences of these regulatory barriers, focusing on how urban development affects aggregate welfare and national growth. We address these issues from a European perspective, allowing us to offer novel facts, theory, and methodology.[2] Major progress has been made recently by establishing an aggregate urban growth model which, using minimalist elements – essentially two pillars, heterogeneous natural productivity advantages of locations, and political economy driven land-use regulations –, depicts the US city system extremely well (Duranton and Puga 2023; henceforth DP 2023). Urban systems in Europe differ from the US in important ways, however. To rationalize the observed sizes of European cities we develop a parsimonious extension which brings amenities – a diverse set of consumption benefits that render places attractive – into focus.

We develop this European perspective by focusing on Germany, a compelling case that parallels the US in some aspects, but also exemplifies key characteristics unique to European city systems. First, reports of high rents and NIMBY policies in Germany's 'Top 7' metropolises (Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Duesseldorf) and other popular cities underscore the impact of political economy-driven land-use regulations.[3] Second, high-quality microdata on workers, rents, and travel to work speed enable our quantitative analysis. Third, and crucial, the German urban system provides an intriguing counterpoint to the US. Fig.1 illustrates this important difference in the German urban system that is representative for

[1] The propensity of cities to foster welfare and growth is a classic theme (Marshall 1890, Jacobs 1969, Lucas 1988, Duranton and Puga 2004). Duranton and Puga (2020) survey the research on benefits and costs of cities.
[2] Extant work is focused on the United States, much inspired by Hsieh and Moretti (2019).
[3] See The Economist (2015), FAZNET (2021), the annual report of Germany's Council of Economic Experts (2024) and Thomsen et al. (2020) for accounts of housing shortages and NIMBY policies in Germany. Besides the 'Top 7', the real estate industry highlights a '2nd tier' (Hanover, Dresden, Leipzig, Nuremberg, Essen, Dortmund), and attractive small cities like Freiburg (PricewaterhouseCoopers 2019; Postbank 2022).

other European cities. Panel A shows mean annual earnings and panel B mean rents. As in the US, mean annual earnings and mean rents are positively correlated with city size. The striking difference to the US-city system is that the relationship between city population and rents is much tighter than that between population and earnings. In fact, the unconditional size elasticity of mean annual earnings with respect to city population (0.077) is only about half the unconditional elasticity of rents with respect to population (0.144). This differs substantially from the US, where the difference between the two is statistically indistinguishable, as emphasized by Behrens and Robert-Nicoud (2015:176ff.). Moreover, panel A shows substantial dispersion around the regression line with a number of small cities offering very high earnings, whereas low incomes are earned in some very large cities.[4] From an aggregate perspective, these observations suggest that location fundamentals *must* play a key role. For firms, high wages must be mandated by a location's fundamental productivity. For workers, low wages must be compensated by consumption benefits to make city life attractive.

Panel A: Mean annual earnings 2017 Panel B: Rents per sqm 2017

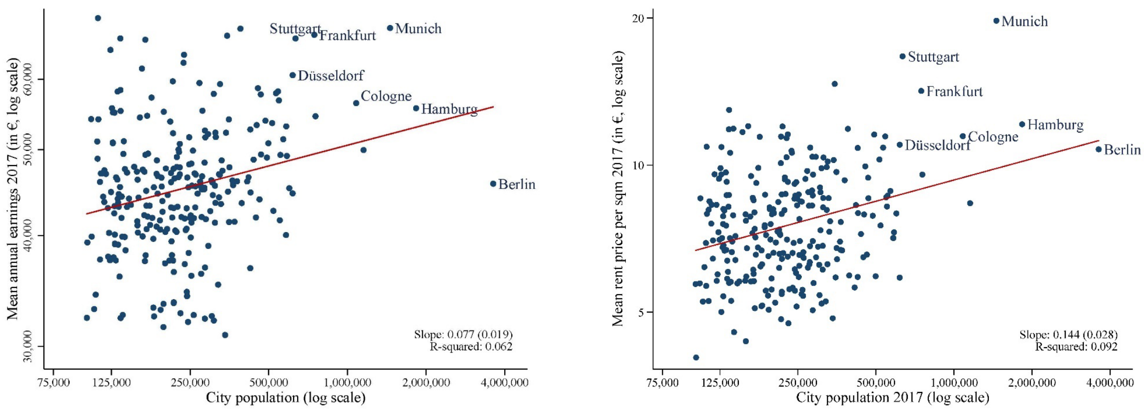

Figure 1: Mean annual earnings and rents per sqm 2017 in German Cities.

Notes: Panel A links mean annual earnings to city population in 2017. Panel B plots the relationship between the mean rent price per sqm in a city and its city population in 2017. Cities are defined as in appendix B1. Our data comprise 264 cities, the Top 7 are highlighted by name. See section 3.1 and Appendix B for details of the data.

Our key methodological innovation is to incorporate amenities in an urban growth model to accurately represent German cities. In our model, amenities influence the locally optimal city sizes, which are set by local governments in the form of land-use regulations that keep out city

[4] With a city population of only 110,000, Erlangen pays the highest mean annual earnings in Germany. Ingolstadt (135,000) and Ludwigshafen (168,00) have also top-ranked earnings. Berlin, with 3.6 million citizens, by far the largest city, has mean earnings that are 18%-30% lower than in Hamburg (1.8 million), Munich (1.46 million), Frankfurt (747,000), and many smaller-sized cities. This inspired former mayor Klaus Wowereit to coin the famous words, "Berlin is poor, but sexy" (Economist 2017). Leipzig ranks 14 in the distribution of city population but only 210 in earnings, Dresden, another famous cultural center ranks 17 and 189, respectively (cf. footnote 3). Freiburg, an intellectual center in the Southwest ranks 21 and 71.

outsiders for the benefit of city incumbents. This generalization and a novel calibration strategy turn out to be a minimalist extension that allows us to depict the German city system extremely successfully, whilst maintaining the macroeconomic spirit of DP (2023).[5]

We proceed as follows to take the model to the data. First, we estimate the model's structural equations for the population elasticities of urban benefits and costs using our rich German micro-data. Next, we calibrate the model. We use the theoretical wage equation along with data on wages and city sizes to back out cities' fundamental productivities – in sharp contrast to DP (2023) who infer these productivities from the model-implied equation for city sizes. We then invert the theoretical city-size equation and use factual city sizes, and the productivities obtained in the first step, to recover the cities' amenities.[6] With these two types of location fundamentals, the estimated elasticities, and armed with a parameter for rural income that we take from extant research, we obtain a utility-based ordering by which sites in Germany are developed.

The utility-based ranking of cities that we develop for Germany presents a decisive difference to the productivity-based ordering of US cities offered by DP (2023). Their analysis assumes that New York, the largest city, has the highest fundamental productivity, and thus provides the highest welfare level, followed by Los Angeles, the second largest agglomeration with second highest welfare, and so on. Whilst this procedure works well for the US, it produces implausible results for Germany, as it would e.g. put Berlin at the top, despite its meager average productivity and incomes, and it would position very productive yet smaller cities (e.g. Erlangen) at low ranks.[7] Our utility-based ranking implies a much more nuanced picture to fit the European city context. Major cities like Munich, Frankfurt, and Stuttgart rank high in our attractivity index, but smaller yet fundamentally productive locations also occupy top positions. Cities rich in amenities, such as Berlin (which scores second in our amenity ranking) or Bamberg, Dresden, Freiburg, Leipzig, Osnabrück, Trier and Würzburg, achieve positions that surpass what their relatively modest average incomes might imply, highlighting the significant role of amenities for their attractiveness.

[5] Our model follows DP (2023) in abstracting from sectoral specialization, the relative geographical position of cities, sorting by skills or occupations, and idiosyncratic location costs. We deviate from DP (2023) by using different micro-foundations for agglomeration economies and for human capital accumulation, see section 3.1.
[6] Our calibration is also informed by geographical constraints that we pioneer for Germany's cities following Saiz (2010). We also take the fiscal equalization system in Germany into account (see below).
[7] See table D3 in appendix D.5 for a ranking of cities along our extension and along the implausible classification obtained by mechanically following the procedure that DP (2023) use for the US.

To assess the validity and quality of our quantified model and our utility-based ranking we confront it with several sources of independent data. The model turns out to be remarkably successful in rationalizing this evidence. First, the amenities that we back out from the model correlate strongly with empirically observed indicators of quality of life. Second, the model-implied attractivity (utility) ranking of Germany's cities is validated by a striking correlation with an independent measure of real income based on different data. Third, land-use regulations implied by the political-economy mechanism of the model are highly correlated with the wedge between housing prices and replacement costs, which we use as an empirical proxy for land-use regulations. Fourth, rent gradients, rents at the city center, and, notably, rents at the edges of German cities, accord with the model's land-use regulations (as we explain below).

We view this very strong external validation as a key strength of our minimalist macroeconomic model. Focusing on three key pillars – fundamental productivities, amenities, local political-economy determined city sizes –, allows us to represent German cities extremely well. We thus extend the analysis of DP (2023) who showed that two of these pillars sufficed to successfully characterize the US-economy. It is worth stressing that in this aggregate approach, by conception, and much in the spirit of Solow (1956), factors excluded from the model (cf. footnote 5) are captured through these pillars. We elaborate on this below.

Backed by the external support and the characterisation of the model's social optimum that we establish, we evaluate the aggregate effect of cities in Germany. Our key counterfactual is a proportionate increase of the population in the Top 7 by 10% each, which we implement by corresponding reductions in land-use regulations. Pushing cities beyond their local optima involves a welfare loss for city incumbents, which turns out to be very mild, however. City newcomers, movers to the Top 7, and rural settlers, experience a strong welfare increase, in contrast. Averaging gains and losses we find a strong increase of average real incomes. Hence, urban containment policies in Germany have significant societal costs. We also quantify the impact of agglomeration economies – which work through city growth and human capital accumulation in our model -, for national growth. The positive growth effect that we find appears modest, at first sight. However, our numbers are in the ballpark of extant results, once the time frame of our analysis dictated by the German reunification, is taken into consideration.

Related Research. Our paper is most closely related to DP (2023), which builds on Albouy et al. (2019), who extended the static city system model of Henderson (1974) to account for heterogenous production fundamentals, and on the urban growth models of Black and Henderson (1999) and others (Rossi-Hansberg and Wright 2007; Duranton 2007). Our key contribution relative to these works is to incorporate amenities in the model. Moreover, through our modelling and calibration, location fundamentals are given a stronger role, more generally.

Amenities have, of course, been highlighted in spatial equilibrium analysis for long (Roback 1982; Albouy 2016). Their fundamental role for the inner structure of European cities has been worked out from the classic analysis of Brueckner et al. (1999) up to the recent work of Ahlfeldt et al. (2015), a milestone for new quantitative spatial modelling (see also Allen and Arkolakis 2014; Redding and Rossi-Hansberg 2017; Redding 2022). However, neither of these works features a local political economy mechanism, nor do these models address long-run growth effects of cities, the issues to which we contribute.

Our paper is also related to various empirical literatures. First is the research addressing urban containment policies focusing on the US-economy. The very influential study by Hsieh and Moretti (2019) uses a framework that differs from ours – a Rosen-Roback-spatial equilibrium model with a fixed number of cities and a free migration equilibrium (rather than local political-economy determined city sizes). They find that such regulations have substantial quantitative effects (recently put into question by Greaney (no date)). Key further works are Davis et al. (2014), Desmet and Rossi-Hansberg (2013), Fajgelbaum et al. (2019), Fajgelbaum and Gaubert (2020) and Turner et al. (2014).[8] Second is research concerned with the estimation of the costs and benefits of cities (e.g. Ahlfeldt and Pietrostefani 2019; Combes and Gobillon 2015; Combes et al. 2011; Combes et al. 2019; and the survey by Duranton and Puga 2020). In the German context, agglomeration economies have recently been estimated by Peters (2020), Grujovic (2021) and Dauth et al. (2022) yielding similar results as ours. We contribute the first estimate of congestion elasticities in cities for Germany. Finally, there is research addressing local price level indices and real wage inequality across locations (e.g. Moretti 2013; Diamond 2016; Diamond and Moretti 2022; Diamond and Gaubert 2022; Dustmann et al. 2022; Weinand and von Auer 2020). These works focus on skill group differences whilst we highlight real incomes of city incumbents and outsiders.

The structure of our paper is as follows. Section 2 presents the model, derives the general equilibrium under local governments, and establishes the social optimum. Section 3 discusses our data, provides context for the German economy, and takes up the estimation of population elasticities of urban benefits and costs, and the quantification of the model. Section 4 presents external support in favor of the model, takes up policy counterfactuals and our analysis of the growth effect of cities, and broadens our amenity spillovers. Section 5 concludes.

[8] Henkel et al. (2021) is an exception which focuses on Germany.

2 The model

2.1 Economic environment

Our theoretical framework draws on the urban growth model developed by DP (2023), which we generalize by incorporating amenities and by building on different micro-foundations for agglomeration economies and human capital accumulation.

Space and population. The model is set in discrete time t. There is a fixed amount of land which can be occupied by cities (i) or used as rural area (r) for rural production. We follow DP (2023) in assuming that land sites are heterogeneous in terms of their time-varying productivities A_{it}^{p} and in terms of their time-invariant geographical constraints to city development. We additionally assume that land sites differ in terms of time-invariant amenities A_{i}^{c}. The economy hosts an exogenously evolving population N_t which resides in cities and the rural area. Both the extensive margin of urban development (the sites to be developed as cities) and the intensive margin (the population in each city N_{it} and the rural area N_{rt}) are determined endogenously. The allocation is governed by local city governments which perform three actions. First, they rent land at its alternative cost and sublease plots for one period to the highest bidder at each location. Second, they redistribute the resulting differential land rent among the local populations. Third, and crucially, they set the outer size of the city (the 'housing stock') to maximize the welfare of city residents and control the locally optimal sizes by imposing land-use regulations on would-be city entrants.

The economy has a simple overlapping generations structure. Each person lives for two periods, a childhood (first period), where she is assumed to live with their parents, and an adulthood (second period). The population is replaced each period: at the end of a period, each adult has one offspring and then dies. Her offspring 'inherits' the parent's location and the economy's average education level through compulsory schooling. Productivities in each site are governed by a multiplicative process involving non-negative shocks g_{it} which are independently drawn from a common distribution with support $(1, \infty)$, such that $A_{it}^{p} = g_{it} A_{it-1}^{p}$ as in Gabaix (1999). Faced with the updated productivity, individuals decide whether to stay at the inherited location or to move elsewhere, facing the respective land rents and regulations.

The economy produces one homogeneous final output with one production factor, educated labor ('human capital'), both in the cities (Y_{it}), and in the rural area (Y_{rt}). This output is the numéraire and assumed to be tradeable at no cost across cities. Individuals' utility increases in the consumption of the numéraire. Each individual supplies 1 unit of labor without loss of utility. A city dweller incurs urban costs for commuting to the workplace at the central business district (CBD) and because of the housing costs for 1 unit of land/floorspace which she inelastically demands. Individuals in the rural area are assumed to face no urban costs.

Human capital formation. Human capital H_{it} in a city is related to its workforce L_{it} through the identity $H_{it} = h_{it}\, L_{it}$, where h_{it} is the level of human capital per worker. The accumulation of human capital is specified by $h_{it} = h_t \cdot {N_{it}}^{\beta}$. The first component, $h_t = e^{\psi\, l_{ht}}$, $\psi > 1$, is a Mincer-learning-process as in Jones (2002; 2005), where $0 < l_{ht} < 1$ denotes the share of each individual's adult life (normalized at unity) devoted to schooling.[9] The second component, ${N_{it}}^{\beta}$, $\beta > 0$, is a city-specific learning effect which is the stronger, the bigger the city, in accordance with empirical findings (De la Roca and Puga 2017). The local workforce is then $L_{it} = (1 - l_{ht})N_{it}$ and a city's human capital is $H_{it} = B(l_{ht})\, {N_{it}}^{1+\beta}$, where $B(l_{ht}) \equiv e^{\psi\, l_{ht}}(1 - l_{ht})$. We note that $B(0) = 1$ and $B'(l_{ht}) > 0$.

Production in cities. Production of the numéraire in city i is modelled as in Duranton and Puga (2004; 2014), so that urban agglomeration economies are based on input sharing associated with the monopolistically competitive local supply of intermediates produced under increasing returns.[10] The final good is produced by combining an (endogenous) mass m_{it} of symmetric intermediate goods ω with quantities $q_{it}(\omega)$ according to a CES production function $Y_{it} = A_{it}^{p} \left\{\int_0^{m_{it}} q_{it}(\omega)^{\frac{1}{1+\sigma}}\, d\,\omega\right\}^{1+\sigma}$, where $0 < \sigma < 1$. The elasticity of substitution between any two intermediates is $\varepsilon \equiv (1+\sigma)/\sigma$ and A_{it}^{p} represents local productivity. Intermediates are non-tradable and produced under increasing returns and monopolistic competition with educated labor $h_{it}(\omega)$ according to $h_{it}(\omega) = \frac{\alpha}{\rho} + \frac{q_{it}(\omega)}{\rho}$ which exhibits a fixed and a variable (output-related) component. Applying standard calculations, invoking symmetry and a convenient normalization, final output in city i can be derived as $Y_{it} = A_{it}^{p}\, {H_{it}}^{1+\sigma}$ (see appendix A.1). Combining this with the city's human capital, H_{it}, we have $Y_{it} = A_{it}^{p}\, B(l_{ht})^{1+\sigma}\, {N_{it}}^{(1+\beta)(1+\sigma)}$. Educated workers are compensated with their average product:

$$w_{it} = \frac{Y_{it}}{N_{it}} = A_{it}^{p}\, B(l_{ht})^{1+\sigma}\, {N_{it}}^{\sigma+\eta}, \quad \eta \equiv \beta(1+\sigma) \tag{1}$$

[9] The exponential formulation is possibly the simplest and most straightforward way to incorporate human capital such that it accords with the research on schooling and wages (see Jones 2002 and also Bils and Klenow 2000).
[10] This differs from DP (2023) who assume input sharing under competitive suppliers and human capital spillovers with partial compensation. Our specification is helpful to establish the social optimum (section 2.3) and to relate our results to research on semi-endogenous economic growth (Jones 2022; 2005).

where w_{it} denotes the wage paid per unit of educated labor. Eq. (1) shows that wages grow with city size and the premium associated with larger cities has two sources. The parameter σ implies a static earnings premium which stems from the productive advantages of sharing local intermediates. The parameter η captures a dynamic earnings premium associated with (the parameter of) learning in cities β which interacts with the static agglomeration externality.[11]

Production and utility in the rural area. Production of the numéraire in the rural area takes place with a decreasing marginal product of labor, so that workers earn the wage $w_{rt} = A_{rt}\, {N_{rt}}^{-\lambda}$, where $0 < \lambda < 1$, and where all location attributes are captured in A_{rt}.[12] Since the marginal product goes to infinity as rural employment N_{rt} approaches nil, rural production is always active in the economy. Individuals in the rural area are assumed to face no urban costs.

Our quantitative analysis takes into account that Germany has a complicated, yet powerful, system of redistributive regional fiscal transfers (φ_i), which sum up to zero across sites (Henkel et al. 2021). We incorporate fiscal transfers as an exogenous part of the model to neutralize their effect on the location fundamentals that we back out in our quantitative analysis below. The utility of rural workers is then given by,

$$v_{rt} = w_{rt} + \kappa_r = A_{rt}\, {N_{rt}}^{-\lambda} + \kappa_r \qquad (2)$$

where κ_r is the transfer per person in the rural area (implied by the transfer sum across cities).

Indirect utility in cities. Indirect utility in a city (v_{it}) is positively affected by the wage w_{it}, negatively affected by net urban costs nuc_{it} (specified below), and positively affected by amenities A_i^c.[13]

$$v_{it}(w_{it}, nuc_{it}, A_i^c) = w_{it} - \frac{(1-\varphi_i)}{A_i^c}\, nuc_{it} \qquad (3)$$

Amenities are compensating factors as in Roback (1982). Crucially, the specification keeps up the gist and tractability of the political-economy augmented framework of DP (2023) that we

[11] This differs from DP (2023) where the dynamic component is represented by the exponent β. The reason for this difference is not the different micro-foundation of agglomeration economies. Rather, it is DP's (2023) assumption of an asymmetry between the supply of local human capital available for production (where learning in cities is taken into account) and the supply of local human capital in idea generation (where the effect of learning in the city is ignored), see DP (2023, FN 9). If the effect of learning in cities was accounted for in both, the dynamic component in DP (2023) would also be given by $\eta \equiv \beta(1+\sigma)$.

[12] To keep the model simple and tractable we follow DP's (2023) implicit assumption that education does not raise a worker's marginal product in rural production.

[13] Methodologically, our approach is inspired by Epple and Sieg (1999: 651f.), and as in their analysis, there is no closed-form direct utility function that yields this indirect utility. Strong separability assumptions are also imposed in related work (e.g. Diamond and Gaubert 2022; Gyourko et al. 2013; Kline and Moretti 2014; Moretti 2011).

follow, which assumes that city sizes are determined by local governments (not by free migration). As shown below, amenities appreciated by citizens then have a positive effect on city size (and so do positive fiscal transfers φ_i).[14] Note that city size would be unaffected under local governments if amenities were included as multiplicative shifters of per capita income net of urban costs.[15] Since all location factors are incurred in the numéraire, indirect utility expressed in eq. (3) can also be understood as net-consumption or real income in terms of the final good. We will use these terms interchangeably from now on.

Internal structure of cities. Cities are monocentric, linear one-sided, and stretch from the CBD at $x = 0$ to the city border x_b. Due to time-invariant geographical constraints only the share $0 < \Lambda_i < 1$ of the raw land of a site can be developed (as in Brueckner 1987 and Saiz 2010). Each worker consumes 1 unit of land/floor-space and, hence, $1/\Lambda_i$ units of raw land.[16] The city border is then at $x_b = N_{it}/\Lambda_i$. Commuting costs in the city are formalized by $T_{it}(x) = \tau_t\, {N_{it}}^{\theta} x^{\gamma}$, where x^{γ} is the length of the commute which is assumed to increase with elasticity $\gamma > 0$ with distance x from the CBD as in DP (2023). The term $\tau_t\, {N_{it}}^{\theta}$ formalizes the cost per unit distance, where τ_t is a parameter for the commuting technology, and ${N_{it}}^{\theta}$ stands for congestion in commuting in the city which relates to city size N_{it} with elasticity $\theta > 0$. Spatial equilibrium in the city commands that urban costs (which comprise rents and commuting costs) are equalized across all locations x so that,

$$T_{it}(x) + P_{it}(x) = P_{it}(0) = T_{it}(N_{it}/\Lambda_i) \tag{4}$$

where $P_{it}(x) \equiv R_{it}(x)/\Lambda_i$ is defined as the (quality-transfer) unadjusted price of a dwelling at distance x from the CBD and $R_{it}(x)$ is the bid rent per unit of raw land at location x.[17] Eq. (4) implies that in a spatial equilibrium in the city, an increase in commuting costs associated with a longer commute must be compensated by a corresponding fall in land rents, $d\,P_{it}(x)/dx = -\,d\,T_{it}(x)/dx$, the familiar Alonso-Muth condition. Assuming that total differential land rents in the city are rebated to citizens on a per capita basis and performing the standard calculations net urban costs per capita in the city are derived as (see appendix A.2):

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[14] Fiscal transfers are included in (3) in a way inspired by Albouy et al. (2019).

[15] These considerations command the modelling of commuting costs in terms of local output rather than in terms of time, as city size is unaffected by productivity under the latter (Duranton and Puga 2004; Albouy et al. 2019). We point out in this context that an indirect utility specification of the form $v_{it} = A_i^c(1 - \mathrm{t}_i)w_{it} - nuc_{it}$, where t_i are net taxes, is isomorphic to eq. (3), i.e. it results in the same city sizes and other equilibrium values.

[16] We follow DP (2023) in abstracting from a competitive construction industry. Hence, there are no other costs than land to provide ("build") new homes, and we can therefore equate the terms land and floorspace.

[17] In view of eq. (3), the spatial equilibrium condition (4) could also be written by multiplying each term with the factor $(1 - \varphi_i)/A_i^c$. This quality-transfer adjustment is inessential for the trade-off between rents and commuting costs within a city. However, it is relevant when taking the model to the data.

$$nuc_{it} = [T_{it}(x) + P_{it}(x)] - \frac{TLR_{it}}{N_{it}} = \frac{\tau_t}{(1+\gamma)\Lambda_i{}^{\gamma}} N_{it}{}^{\gamma+\theta} \tag{5}$$

Using eqs. (1) and (5) in eq. (3) indirect utility can be written as:

$$v_{it} = A_{it}^{p}\, B(l_{ht})^{1+\sigma}\, N_{it}{}^{\sigma+\eta} - \frac{(1-\varphi_i)}{A_i^c \Lambda_i{}^{\gamma}} \frac{\tau_t}{(1+\gamma)} N_{it}{}^{\gamma+\theta} \tag{6}$$

2.2 Equilibrium allocation with local governments

Human capital investment. Citizens choose the time they devote to learning, l_{ht}, to maximize indirect utility which by (1) and (6) boils down to maximize the wage through $B(l_{ht}) = e^{\psi\, l_{ht}}(1 - l_{ht})$. We use an asterisk (*) to characterize the local government solution from now on. The solution is $l_{ht}^{*} = 1 - 1/\psi$ (as in Jones 2005). We define $B(l_{ht}^{*}) = e^{\psi\, l_{ht}^{*}}(1 - l_{ht}^{*}) = e^{\psi - 1}/\psi \equiv B(\psi)$.

Determination of city size by incumbents. City size is determined by incumbent residents maximizing their indirect utility. Using $B(\psi)$ in eq. (6) indirect utility can be written as:

$$v_{it} = A_{it}^{p}\, B(\psi)^{1+\sigma}\, N_{it}{}^{\sigma+\eta} - \frac{(1-\varphi_i)}{A_i^c \Lambda_i{}^{\gamma}} \frac{\tau_t}{(1+\gamma)} N_{it}{}^{\gamma+\theta} \tag{7}$$

'Locally optimal' city sizes and the associated indirect utility levels are then[18]

$$N_{it}^{*} = \left(\frac{(\sigma+\eta)(1+\gamma)}{(\gamma+\theta)} \frac{B(\psi)^{1+\sigma}}{\tau_t} \frac{A_{it}^{p}\, A_i^c\, \Lambda_i{}^{\gamma}}{(1-\varphi_i)} \right)^{\frac{1}{(\gamma+\theta)-(\sigma+\eta)}} \tag{8}$$

$$v_{it}^{*} = \frac{(\gamma+\theta) - (\sigma+\eta)}{(\sigma+\eta)(1+\gamma)} \frac{\tau_t\, (1-\varphi_i)}{A_i^c\, \Lambda_i{}^{\gamma}} N_{it}^{*}{}^{\gamma+\theta} \qquad \eta \equiv \beta(1+\sigma) \tag{9}$$

Eq. (8) reflects the "fundamental trade-off" between agglomeration and congestion forces in cities (Fujita and Thisse 2013) which are balanced at the peak of the hump-shaped real income curves implied by eq. (7). As in DP (2023), city sizes are positively related to productivity A_{it}^{p} and the share of locally developable land Λ_i, and also positively affected by human capital accumulation which positively responds to the return to education. Importantly, city sizes are positively affected by the level of amenities A_i^c, and positively (negatively) affected by fiscal transfers φ_i if positive (negative).[19] This is a key difference to DP (2023) who abstract from amenities and fiscal factors, so that $A_{it}^{p}\, A_i^c/(1 - \varphi_i)$ is absorbed by fundamental productivity A_{it}^{p}. Eq. (9) shows that (locally optimal) real income v_{it}^{*} rises in (locally optimal) city size N_{it}^{*} with elasticity $\gamma + \theta$. By implication, land sites are occupied by cities in descending order of

[18] The second-order condition is $\gamma + \theta > \sigma + \eta$. Positive city sizes require agglomeration economies, $\sigma + \eta > 0$.
[19] Section 4.4 generalizes this specification to $A_i^c = \bar{A}_i^c N_{it}{}^{-\xi}$, where $\bar{A}_i^c > 0$.

the location-specific composite factor $\Omega_{it} \equiv A_{it}^{p\,\frac{\gamma+\theta}{(\gamma+\theta)-(\sigma+\eta)}} \left(\frac{A_i^c\,\Lambda_i{}^{\gamma}}{(1-\varphi_i)}\right)^{\frac{\sigma+\eta}{(\gamma+\theta)-(\sigma+\eta)}}$, from the highest to successively lower ones.

Note that, using $P_{it}(0) = \frac{\tau_t}{\Lambda_i{}^{\gamma}}\, N_{it}{}^{\gamma+\theta}$, we can rewrite eq. (9) as:

$$v_{it}^* = \frac{(\gamma+\theta)-(\sigma+\eta)}{(\sigma+\eta)(1+\gamma)} \frac{(1-\varphi_i)}{A_i^c}\, P_{it}(0) \tag{10}$$

This reveals that the (quality-transfer) adjusted price of housing in the city center, $\frac{(1-\varphi_i)}{A_i^c}\, P_{it}(0)$, is a sufficient statistic for the attractiveness of a site (cf. footnote 17). Hence, our model extension exhibits the property that the maximization of the value of individual homes, Fischel's (2001) homevoter hypothesis, is equivalent to the maximization of v_{it}. DP (2023) term this the "golden rule of planning regulation". This theoretical implication is strongly supported by the German data, as we show below. We follow DP (2023) in assuming that these real income differences across locations are shored up by land-use regulations p_{it} which are imposed by city incumbents on (potential) city newcomers to make them indifferent between living in a city and living in the rural area where the lowest level of real income $v_{rt}^* = w_{rt} + \kappa_r$ is realized in this economy. The level of land-use regulations that newcomers face in city i is thus given by

$$p_{it}^* = v_{it}^* - v_{rt}^*. \tag{11}$$

The city system in general equilibrium. The general equilibrium of the city system is characterized by (locally optimal) city sizes (8), real income levels in cities (9), real income in the rural area given by $v_{rt}^* = A_{rt}\, N_{rt}^{*}{}^{-\lambda} + \kappa_r$, and by local land-use regulations (11). The model is closed by two conditions. First, real income in the marginally populated city (characterized by an underline) just equals the real income in the rural sector, $\underline{v}_{it}^* = v_{rt}^*$, so that this marginal city does not have to impose land-regulations, i.e. $\underline{p}_{it}^* = 0$. Second, the population in the cities and in the rural area must add up to the total population N_t.

City growth and the size distribution of cities. We now turn to the determinants of city growth and the city size distribution. Log-differencing eq. (8) yields a decomposition of the factors that determine the growth of a city i over two consecutive points in time $t-1$ and t:

$$\Delta \ln N_{it} \equiv \ln N_{it} - \ln N_{it-1} = \frac{1}{(\gamma+\theta)-(\sigma+\eta)} \left[\Delta \ln A_{it}^p + (1+\sigma)\Delta \ln B(\psi) - \Delta \ln \tau\right] \tag{12}$$

Starting from the right end of eq. (12), a first systematic component of city growth is given by the evolution of the common commuting technology $\Delta \ln \tau$. A second systematic component arises from human capital accumulation through time spent learning which enhances human capital. This component exerts a positive influence on city sizes if the return to education increases. The third component, $\Delta \ln A_{it}^{p}$, is used by DP (2023) to connect this city systems model with random growth models (see Gabaix 1999, Eeckhout 2004; Duranton and Puga 2014). Under the assumption that local productivities accumulate through non-negative random multiplicative shocks g_{it} which are identically and independently distributed across locations, $\Delta \ln A_{it}^{p} = \ln g_{it}$, it follows from eq. (12) that cities have a common growth trend in expectation, but they also experience idiosyncratic ups and downs relative to this trend. The growth process described in eq. (12) thus follows Gibrat's law so that (under some further conditions spelled out in DP 2023), the steady-state city size distribution implied by the model approximates Zipf's law, a key feature of the DP (2023) model in view of the empirics observed worldwide.[20]

2.3 The social optimum

The socially optimal allocation maximizes aggregate utility. Under the assumptions, this is equivalent to the maximization of aggregate net consumption of the numéraire subject to the population constraint (as in Albouy et al. 2019). Since our focus is not on the optimality of the German fiscal transfer system, we treat them as exogenously given. In this sense, the social optimum characterized in the following is a constrained one.[21] We defer the formal derivation of the choice of $\{l_{ht}, N_{it}, N_{rt}, \underline{A}_{it}^{p}\}$, i.e. the time devoted to learning, city populations, the rural population, the productivity of the marginal city, to the appendix (A.3), and focus on the results, their intuition, and relation to extant research. In fact, the technical program of the social planner in our model nests the choice the optimal level of human capital in the analysis of growth in Jones (2005) and the choice of city sizes and the extensive margin between cities and the rural area in Albouy et al. (2019).

Start with the socially optimal share of time to education. This turns out to be identical to the human capital investment chosen by citizens, $l_{ht}^{opt} = l_{ht}^{*}$ as in Jones (2005), since citizens and the social planner face the same problem, as the wage (the private return) equals the average product of labor (the return taken into account by the social planner). Our model does not

[20] Duranton and Puga (2014) survey empirical studies and argue forcefully that looking at city-size distributions through the lens of Zipf's law is useful, despite the finding that a (truncated) log normal or a double Pareto log normal distribution provides yet a better fit for some countries, see e.g. Eeckhout (2004) and Giesen et al. (2010).
[21] Henkel et al. (2021) focus fully on the German fiscal transfer system, in contrast. However, even their analysis of optimal transfers targets only a constrained social optimum since they take local taxes as exogenously given.

involve an external effect of human capital on production, so the individual choice of the time devoted to education is undistorted (Lucas 1988).

Turning to the social planner's choices with respect to the city system, these mirror the results of Albouy et al. (2019).[22] The social planner's extensive margin condition for urban development commands that the shadow price of any further worker in the city system equals the marginal product of labor (plus the fiscal balance) in the rural area. The social planner's intensive margin condition requires that the net marginal benefit of residing in any city is equalized across all cities which are inhabited. Finally, the utility level in the least developed city must be the same as the utility from living and working in the rural area. Since these conditions coincide with those in Albouy et al. (2019, Prop. 1), their proof can be invoked to show that, except for the marginal city, which is to be developed at its locally efficient scale, socially optimal city sizes (for populated sites) have larger population than cities under local governments, $N_{it}^{opt} > N_{it}^{*}$, and that fewer cities are inhabited in the social optimum. Intuitively, city sizes are too small and cities too numerous under local governments, since these ignore the extensive margin of urban development. This causes an inefficiency when sites are heterogeneous: diminishing returns from lower site qualities at the system level, which are taken into account by the social planner, are ignored by local governments (Albouy et al. 2019). This result is important as a backbone for the counterfactuals that we perform below.

3 Quantification

3.1 Data

The quantification of the model for the German economy necessitates that we estimate two pairs of key parameters for urban benefits (σ and η) and urban costs (γ and θ). To do so we follow DP (2023) and draw on structural relationships implied by the theoretical model. We start by characterizing our delineation of spatial units and by providing an overview over the three sets of microdata which inform us about individual earnings, rent prices and commuting behavior in German cities as well as complementary data-sources. Detailed characterizations of the data and definitions are relegated to appendix B. We focus on the time span between 1995 and 2017, i.e. the developments after German unification until the most recent year (2017) for which we can connect the various data to maintain consistency across our estimations.

[22] It is key here that our micro-foundations of agglomeration economies involve no net inefficiency (an assumption implicitly maintained in Albouy et al. 2019), see appendix A1.

Definition of cities. To accord with our labor market data, our definition of cities draws on the well-established classification of district regions by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). This results in 315 district regions with a minimum population of 100,000 inhabitants. The BBSR categorizes each district region as either urban or rural. We take the 264 urban district regions as corresponding to cities in the model. The remaining 51 rural district regions comprise the rural area. Our population data for 2017 are taken from 'Regionaldatenbank Deutschland' by the Federal Statistical Office for Germany, the population data for 1995 come from 'Laufende Raumbeobachtung des BBSR' provided by the BBSR. The resulting dataset ensures a time consistent definition of the territorial boundaries of district regions – as on December 31, 2017 – allowing for a direct comparison of population data between 1995 and 2017 (appendix B.1 provides details).

SIAB-R. Our estimates of the benefits of urban agglomeration – the static and the dynamic wage premium captured by the parameters σ and η –, draw on the SIAB-R dataset (Sample of Integrated Labour Market Biographies Regional File; see Antoni et al. 2019). This panel dataset provides a 2% random sample of administrative social security records, which comprise employees subject to social security contributions and marginal part-time employment. It includes workers' employment histories across locations, which allows us to control for unobservable individual heterogeneity in human capital. Since wages above the upper earnings limit for statutory pension insurance are top-censored and set equal to the upper earnings limit, we impute these observations following Dustmann et al. (2009) and Card et al. (2013). We restrict our sample to full-time workers liable to social security with workplace in urban areas and the time period from 1993 to 2017. Further, only individuals of German nationality that are at least 18 years old are included. Our final sample has 1,530,393 observations (see appendix B.2 for further details).

RWI-GEO-RED. To estimate the urban costs parameter γ, we use the RWI-GEO-RED data provided by the Research Data Centre Ruhr at RWI (RWI 2019; Schaffner 2019). This dataset is based on real estate advertisements from the internet platform ImmobilienScout24. It includes detailed information on prices and characteristics of apartments and houses for sale and rent for the years 2007 to 2020. The data allows for small scale analysis, as property locations are observed at a grid of 1-square-kilometer cells. We focus only on apartments for rent and on the year 2017 for the mentioned reasons. We restrict the sample to apartments located in urban areas and to apartments with a living area between 50 and 400 square meters and rents between 50€ and 5,000€ (i.e., we exclude unusually cheap and luxurious objects). Using information on living area and rent price, we calculate the rent per square meter, which serves as the dependent variable in our regression analysis. The final sample comprises 906,315 observations (further details are provided in appendix B.3).

Mobility in Germany. Our estimate of the congestion parameter, θ, draws on the dataset 'Mobilität in Deutschland (MiD)' instructed by the Federal Ministry of Transport and Digital Infrastructure in Germany (BMVI 2017). This is a nationwide survey of households on their sociodemographic background and on their everyday travel behavior in 2017. Randomly selected households are asked about their travel behavior and distances travelled on a given reference date. The place of residence of each household is observed on a grid of 1-square-kilometer cells, that are mapped to the district regions in Germany. We prepare the dataset as follows. To capture congestion arising from traffic, we restrict the sample to commuting trips by private car. Further, we include only individuals who personally drove the car and were in their usual environment on the reference date, ensuring that commuting trips are correctly assigned to district regions based on the individual's place of residence. Finally, the sample is restricted to individuals residing in urban areas. This yields a sample of 57,034 individuals from 48,161 households with a total of 187,435 commuting trips (see appendix B.4 for details).

Figure 2: Geographical constraints

Notes: The map visualizes the spatial distribution of geographical constraints in Germany. Darker areas indicate district regions with a higher share of geographically constrained land, brighter areas indicate less geographically constrained regions.

Geographically constrained land. To quantify the share of developable land Λ_i, we follow Saiz (2010) and calculate for each city the share of geographically unconstrained land within the city's 30-km radius of the city center. An area is considered geographically constrained if it is covered by water and wetlands, slopes steeper than 15%, nature reserves or if it belongs to a foreign country (see appendix B.5 for further details). The spatial distribution of these geographical constraints is illustrated by fig. 2.

3.2 The German city system in context

We now provide some context for the German city system to explain where and why we follow or deviate from choices that DP (2023) found suitable for the US.

Start with consumption amenities and the fiscal system. These are abstracted from in DP (2023) even though these factors have been identified as important drivers for the US-city system in recent research (e.g. Fajgelbaum et al. 2019; Albouy et al. 2016; Diamond 2016). Using the terminology of Behrens and Robert-Nicoud (2015), DP (2023) allow for only one fundamental "cause" of cities' attractiveness, their fundamental (heterogeneous) productivity. These productivities (A_{it}^{p}, in eq. (8)) then necessarily capture the joint effect of productivities, amenities, and fiscal transfers (the term $A_{it}^{p}\,A_{i}^{c}/(1-\varphi_{i})$ in eq. (8)), as our different modeling makes clear. It is a strength of DP's (2023) minimalist aggregate approach to characterize the US-city system not only parsimoniously but also remarkably well. The same does not hold true in our European context (see section 1). Rather, it is essential to bring in consumption amenities, our key methodological innovation. Note that we could have followed DP (2023) in abstracting from regional fiscal transfers. Their effect on cities would then be captured by the consumption amenities in our model (cf. eq. (3) and the discussion below). Given its importance, and the availability of data, we opted to include the German fiscal transfer system (Henkel et al. 2021).

Second, concerning housing costs – a key component of urban costs – the OECD affordable housing database shows that in Germany, roughly 53-55% are tenant households and 41-43% are owner-occupiers. In contrast, in the US, 62-65% of households are owner-occupiers. Moreover, according to the 2022 Census, homeownership rates in Germany are particularly low in large cities with homeowners primarily concentrated in rural areas and smaller cities. Using rents as indicator of housing costs (rather than house prices), a choice made in DP (2023), is thus even more appropriate for Germany.

Third, turn to the travel to work mode. Our analysis of congestion costs/travel speed focuses on automobile travel and not mass transit, and so for good reasons. Even though the US is more car centric compared to Europe, almost 70% of workers in Germany use the car to commute to work, and this number is stable for more than two decades (https://www.destatis.de), so it clearly is the dominant travel to work mode. It must be acknowledged that mass transit is much more important in the largest agglomerations than in small places in Germany, but this discrepancy appears to be even stronger in the US city system.

Fourth, the quantitative analysis that we develop in section 4 will assume that the model equilibrium represents the factual situation in the economy, following standard practice in quantitative spatial research.[23] Clearly, any economy is confronted with shocks that induce population adjustments which take time (e.g. the southward migration in the US induced by the invention of air conditioning), and so the presumption of a spatial equilibrium can only be an approximation. The developments in Germany – the reunification in 1990 – necessitate particular care. First, the events and the associated data break force us to confine our long-run analysis to the period after reunification. Second, we consider the factual situation of Germany in 2017 as the starting point for our counterfactuals, because the massive East-West migration induced by Germany's unification took place mainly in the 1990s and faded out thereafter. This underlies our assumption of an equilibrium in that year.

3.3 Population elasticity of urban benefits

Our strategy for the estimation of the two parameters of the benefits of agglomeration – the static and the dynamic earnings premium from working in a bigger city, σ and η, that are contained in the city wage equation (1) – draws on the two-step methodology performed by De la Roca and Puga (2017). The estimation is enabled by the longitudinal worker-level information provided in the SIAB-R panel database. The regression framework consists of three equations:

$$ln\, y_{it}^{j} = a_i + a_j + a_t + \sum_i \; b_i\, e_{it}^{j} + X_t^{j} b + \epsilon_{it}^{j} \tag{13}$$

$$\hat{a}_i = \sigma \;\ln N_i + \epsilon_i \tag{14}$$

$$\hat{a}_i + \hat{b}_i \bar{e} = (\sigma + \eta)\;\ln N_i + \epsilon_i. \tag{15}$$

Eq. (13) is a worker-level earnings regression which features log earnings of worker j in city i at time t as dependent variable. The independent variables consist of a city fixed effect a_i, a worker fixed effect a_j, a time fixed effect a_t, the experience e_{it}^{j} acquired by worker j in city i up until time t, a vector of time-varying individual and job characteristics X_t^{j}, and an error term ϵ_{it}^{j}. The scalars b_i and the vector b are parameters. The worker fixed effect in the regression

[23] This holds true irrespective of whether the model is a Rosen-Roback spatial equilibrium model (e.g. Diamond 2016; Moretti 2013), a new quantitative spatial model (e.g. Ahlfeldt et al. 2015; Allen and Arkolakis 2024; Redding and Rossi-Hansberg 2017), or a city system model such as DP (2023).

controls for unobservable time-invariant characteristics of workers and the time fixed effect accounts for common factors that affect wages over time (e.g. inflation and technological progress). This first-step regression allows for a static earnings premium if the city fixed effect a_i is positively correlated with city size. This is analyzed with the second-step eq. (14) which regresses the estimated city fixed effects ($\hat{a}_i$) from the first-step regression on city size N_i, to obtain an estimate of σ. The first-step regression also allows for learning effects from working in big cities. An estimate of the dynamic earnings premium associated with learning (together with the static premium) is obtained from eq. (15). This is a further second-step regression, which regresses the estimated value of the experience accumulated in (bigger) cities $\hat{b}_i$ evaluated at the average local experience $\bar{e}$ along with the estimated city fixed effects from the first-step regression on city size N_i to obtain an estimate of $\sigma + \eta$. With the definition $\eta = \beta(1 + \sigma)$, the learning effect β is backed-out from the regression results, eq. (14) and eq. (15).

Three remarks are in order before we proceed to the regressions and their results. First, it should be noted that the city fixed effects, which are crucial in this strategy, are only estimated from workers who change location between two dates, i.e., from 'movers'. If all workers stayed at the same workplace, it would not be possible to separately identify city fixed effects from worker fixed effects. This raises the issue that the estimate may be based on a possibly highly selected set of individuals (see Combes et al. 2011). Second, in taking the model to the data we face the decision of whether to base the estimates on city population or on population density (see Duranton and Puga 2020 for a discussion). Practical arguments associated with German district regions on which our city classification is based speak in favor of the use of city population data which we therefore use in the body of the paper (as explained in appendix C.1). However, in the appendix we also provide a robustness check based on population densities, which indicates that the results are very much in line with our specification in the body of the paper. Third, the experience variable needs to be operationalized, leaving much room for choice. We have opted to follow De la Roca and Puga (2017) in focusing on the experience in the 5 largest cities in terms of population in Germany which are Berlin, Hamburg, Munich, Hannover and Cologne (and we focus on the year 2017 which yields $\bar{e} = 6.5$ years) in our data. We also consider the experience accumulated in German cities with a population of more than 500,000 excluding the mentioned five biggest cities in our regression.

Our regression results are shown in table 1. Column (1) presents the results of a one-step estimation of the parameter σ to which we turn later. The results of our focused two-step estimation are shown in columns (2) through (4). Column (2) provides the results of the first step regression eq. (13). It is seen that experience is more valuable when it is accumulated in bigger cities. The estimated coefficients for experience in the five biggest cities and in cities with a population exceeding 500,000 without the five biggest cities are both positive and significant, but the former (0.020) is stronger than the latter (0.016). Columns (3) and (4) display the results of the second step regression eqs. (14) and (15). Column (3) shows an estimated elasticity of the static earnings premium with respect to city size of 0.018. This suggests that moving to a city of double the initial size increases earnings by 1.8%. Column (4) shows an estimated elasticity of the medium-term earnings premium with respect to city size of 0.049. Two-fifths of the medium-term premium are due to static benefits and three-fifths due to dynamic benefits of agglomeration. With an estimated value for σ of 0.018, parameter η is estimated at 0.031. This yields an estimate for the learning effect in cities β of 0.030.

Table 1: Estimation of population elasticities of urban benefits

	(1)	(2)	(3)	(4)
Dependent variable:	Ln earnings		Static premium (city indicators column (2))	Medium-term premium (static + 6.5 years local experience)
Ln city size	0.0178^{***} (0.0011)		0.0181^{**} (0.0078)	0.0487^{***} (0.0092)
City indicators		Yes		
Worker fixed effects	Yes	Yes		
Experience in five biggest cities	0.0199^{***} (0.0008)	0.0197^{***} (0.0008)		
Experience in five biggest cities x exp.	-0.0008^{***} (0.0001)	-0.0008^{***} (0.0001)		
Experience in cities > 500,000 (without five biggest)	0.0159^{***} (0.0008)	0.0153^{***} (0.0008)		
Experience in cities > 500,000 (without five biggest) x exp.	-0.0006^{***} (0.0001)	-0.0005^{***} (0.0001)		
Experience	0.0477^{***} (0.0008)	0.0471^{***} (0.0008)		
Experience^2	-0.0015^{***} (0.0001)	-0.0015^{***} (0.0001)		
Observations	1,530,393	1,530,393	264	264
R^2	0.4857	0.4925	0.0161	0.0961

Notes: All regressions include a constant term. Columns (1) and (2) include firm tenure and its square, year indicators, 4 occupational skill indicators, 14 sector indicators, and 120 occupation indicators. Column (2) in addition includes 264 city indicators. Worker values of experience and tenure are calculated on the basis of actual days worked and expressed in years. Coefficients are reported with robust standard errors in parenthesis, which are clustered by worker in columns (1) and (2). ***, **, and * indicate significance at the 1, 5, and 10 percent levels. The R^2 reported in columns (1) and (2) is within workers.

Our estimates of the two agglomeration parameters for Germany are quantitatively in line with results from similar regressions in the literature (see the survey by Combes and Gobillon 2015). Germany is also addressed in recent work by Peters (2020), Grujovic (2021) and Dauth et al. (2022) who also use SIAB-data but different city samples and/or geographical units. Grujovic (2021) and Dauth et al. (2022) find very similar static premia, Peters (2020) finds a slightly higher dynamic premium. De la Roca and Puga's (2017:120) estimates for Spain are also in the same ballpark. In their study for the United States DP (2023:24) obtain a significantly higher estimate of 0.045 for σ, and a similar estimate of 0.031 for β.

Column (1) of table 1 presents the results of a one-step estimation of the parameter σ which draws on regression eq. (13) but replaces the city fixed effect with (the log of) population size, $\ln N_i$. This regression gives an alternative estimate for σ of 0.018 which is quite similar to the estimate that is obtained from the two-step procedure. To address potential endogeneity concerns in estimating eqs. (14) and (15), we instrument for current city size with historical population density in 1871 and 1910. The results are shown in appendix C2. The point estimates are close to our baseline estimates of table 1 which is line with results from the literature (e.g., Dauth et al. 2022). Based on these findings, we work with the results from columns (3) and (4).

3.4 Population elasticity of urban costs

Urban costs are represented by the two elasticity parameters of eq. (5) of the model, the elasticity of commuting costs (distance travelled) with respect to distance from the CBD, γ, and the elasticity of congestion costs/travel speed with respect to the city population, θ. We now address the estimation of these two parameters in turn.

Elasticity of commuting costs (distance travelled). Our strategy to estimate the elasticity of commuting costs (distance travelled) with respect to the distance from the CBD follows DP (2023) and draws on eq. (4) which, along the lines of Alonso-Muth, implies:

$$\frac{d \ln\ [P_{it}(x) - P_{it}(0)]}{d \ln x} = -\frac{d \ln T_{it}(x)}{d \ln x} = -\gamma. \tag{16}$$

Eq. (16) shows that moving away from CBD, (quality-transfer) unadjusted housing costs must fall in the same proportion as commuting costs rise, and that this proportionate change is given by the parameter γ. Hence, with data on rents across locations within a city this parameter can be estimated by the following regression

$$\ln P_{il}^{j} = a_i - \gamma \ln x_{il}^{j} + X_l^{j} b + \epsilon_{il}^{j} \tag{17}$$

where $\ln P_{il}^{j}$ is the log rent/m^2 for renter-occupied apartment l in grid cell (block) j, $\ln x_i^j$ is the log of distance between the place of residence and the city-center, a_i is a city fixed effect and X_l^j is a vector of dwelling and neighborhood characteristics, b is a parameter vector and ϵ_{il}^{j} is an error term.

Table 2: Estimation of elasticities of urban costs

	(1)	(2)
Dependent variable:	Ln rent price per square meter	Ln estimated city travel speed
Ln distance to city center	-0.0708*** (0.0003)	
Ln city size		-0.0680*** (0.0062)
City indicators	Yes	
Controls	Grid cell & dwelling characteristics	
Observations	485,980	264
R^2	0.7440	0.2794

Notes: All regressions include a constant term. Column (1) includes city indicators and, as grid cell controls, indicators for riverfront and oceanfront location, and average unemployment rate and purchasing power per household. Average unemployment rate and purchasing power are centered at the city mean. Dwelling controls comprise living area, indicators for the number of rooms, object category, and construction decade. In column (2), the dependent variable is the log of city travel speed estimated in a previous step by regressing travel speed for individual trips by private car on city indicators, including the same grid cell controls as in column (1) in addition to driver and trip controls. We use this to predict for each city the speed of a 15km commuting trip on a Tuesday at 8AM by a driver with average characteristics. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

We use the RWI-GEO-RED data (RWI 2019; Schaffner 2020) and proceed as follows. The distance of an apartment to the center of its district region is calculated as the haversine distance between the midpoint of the grid cell in which an apartment is located and the center of the district region which we define as the place indicated by Google Maps for the core of the main city of the district region. The dwelling characteristics that we include as controls comprise the living area, indicators for the number of rooms, object category, and the construction decade. Table B4 in appendix B.3 provides descriptive statistics on these dwelling characteristics as well as on the rent per square meter, the dependent variable in regression eq. (17). The neighborhood characteristics that we take into account are the average unemployment rate and the purchasing power per household in a grid cell[24] - both centered at the city mean -, as well

[24] The data for both come from RWI and microm (2017a) and (2017b) provided by the Research Data Centre Ruhr at RWI. The riverfront location is defined as the location of a grid cell at a large river, whereby large rivers have a catchment area larger than 50,000 km^2 or other rivers and tributaries that have a catchment area larger than 5,000

as indicators for oceanfront and riverfront location. The city fixed effect a_i absorbs $\ln P_{it}(0)$, the natural log of the rent per square meter of a national-reference apartment at the center of its district region for city-average grid cell characteristics in eq. (17) whilst $\ln P_{il}^j$ corresponds to $\ln P_{it}(x)$. Column (1) of table 2 shows our regression results. We find an estimate of 0.071 for the parameter γ in Germany. Hence, rent prices per square meter in an urban district region decline by 7.1% when the distance to the city center of the region is doubled. Duranton and Puga (2019:25) obtain a similar estimate (0.0734) for the United States.[25]

Elasticity of congestion/travel speed. Our estimation strategy for the elasticity of congestion costs/travel speed with respect to the city population θ is inspired by DP (2023). Recall that the cost per unit commuting distance in the model (which can be thought of as time loss in commuting) is given by $\tau_{it} = \tau_t \, {N_{it}}^{\theta}$, or, rewritten in logarithmic form, $\ln \tau_{it} = \ln \tau_t + \theta \ln N_{it}$. To a first approximation τ_{it} can be taken to be inversely proportional to the travel speed $\hat{\tau}_i$ in the city, i.e., $\tau_{it} \sim 1/\hat{\tau}_i$. This then inspires the regression:

$$\ln \hat{\tau}_i = b + \theta \ln N_i + \varepsilon_i \tag{18}$$

where b is a constant, ε_i is an error term, and θ is the key parameter which can be estimated with data on travel speed in cities (and city population). The survey of household traffic behavior, Mobility in Germany (BMVI 2019), allows us to perform this exercise.

We proceed in two steps. First, we estimate the travel speed in each city specified as the speed of a 15km commuting trip on a Tuesday at 08:00AM by a driver with average characteristics,

$$\ln \tau_{ik}^j = a_i + X_{ik}^j b + \varepsilon_{ik}^j \tag{19}$$

where τ_{ik}^j is the travel speed of driver j for the commuting trip k in city i, a_i is a city fixed effect, X_{ik}^j is a vector of grid cell, driver and trip characteristics, b is a vector of parameters and ε_{ik}^j is an error term. We use the following controls for grid cells: water and riverfront location, the unemployment rate, and the purchasing power of a household. Trip characteristics contain the natural logarithm of the trip distance, indicators for the day of week and departure time in 30-minute intervals, and the trip purpose. Driver characteristics comprise indicators for age groups, single-person household, retires, the driver being male, household structure, the number

km^2. The corresponding shapefile is from the European Environmental Agency (Permalink: D7925F3C-AFF7-4256-8162-513A2C1C69E3), as is the shapefile for the construction of the indicator for oceanfront location (Permalink: 88055d120fd54c82a3606b97502d21c1).

[25] Note that we purposefully report the estimate stated in the predecessor version of DP (2023) since our estimation strategy follows this earlier work. Using a related but slightly different approach DP (2023) find a value of 0.0769.

of drivers in the household, and the driver's distance to the city center (see table B5 in appendix B.4 for descriptive statistics of these control variables). Based on the estimated parameter vector $\hat{b}$ and the estimated city fixed effects $\hat{a}_i$, we calculate the speed of a 15km commuting trip on a Tuesday at 08:00AM by a driver with average characteristics for each city i, $\hat{\tau}_{ik}^{j}$.

In the second step, we use this estimate as dependent variable and regress it on a constant and the city population N_i as in eq. (18) where we use $\hat{\tau}_{ik}^{j}$ for $\hat{\tau}_i$. Our results are shown in column (2) of table 2. We obtain a highly significant estimate of 0.068 for θ (a standard error of 0.0062) and a regression R-squared of 0.279 for Germany. This implies that with a doubling of the city population the travel speed in the city falls by 6.8%. Our results compare with an estimated value of the elasticity of travel speed of 0.0388 for the United States (DP 2023:20).

3.5 Population elasticity of rural income

A further important parameter is the population elasticity of rural income which plays a key role for the rural wage in eq. (2). Since we lack data for the estimation of this parameter, we take it from the study of factor shares for the United States by Valentinyi and Herrendorf (2008). They find a value of $\lambda = 0.18$, which we adopt for our model calibration and counterfactuals. To check robustness, we have scaled this parameter up and down around this value. None of our results is crucially affected by these variations.

4 The German City System and the Aggregate Economy

4.1 The German city system through the lens of the model

Calibration. We now analyze the German city system through the lens of the model focusing on the situation in 2017. We assume that the factual Germany city sizes are indeed a general equilibrium of the model under local governments, i.e., factual city sizes in 2017 correspond to N_{it}^{*} as specified by equation (8). In the spirit of DP (2023) we assume that the cities' incumbents are represented by the city populations in the initial year of our analysis (the year 1995) and we take the citizens entering cities from 1995 to 2017 to be the newcomers (if positive). We use the following approximations for our estimated parameters, $\sigma = 0.018, \eta = 0.031, \gamma = 0.071$ and $\theta = 0.068$, and we assume $\lambda = 0.18$.

The model postulates that cities are populated in descending order of real incomes v_{it}^{*}. To quantify real incomes, we start by backing out productivities A_{it}^{p} from the wage equation (1) using the observed wages and city sizes. We scale the value of fiscal transfers across cities from the various German fiscal equalization schemes (Henkel et al. 2021) by net urban costs (5) and observed city sizes to obtain the fiscal transfer rates φ_i.[26] With this information at hand, we filter out amenities A_i^c from the equation for optimal city sizes (8).[27] This allows us to calculate v_{it}^* from (9).[28] The productivity parameter in the rural area is calculated from the condition that the real income in the marginal city has to be equal to the real income in the rural area, $\underline{v}_{it}^* = v_{rt}^*$, which can be rearranged to yield $A_{rt} = \left(\underline{v}_{it}^* - \kappa_r\right) {N_{rt}^*}^{\lambda}$.

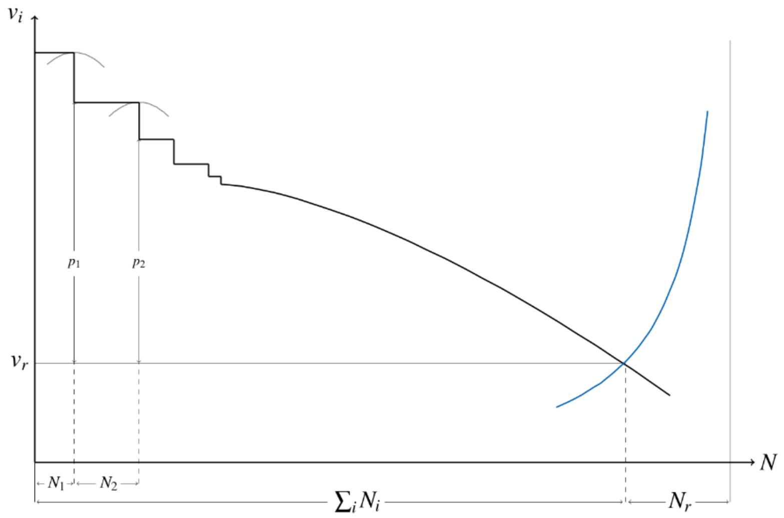


Figure 3: The German city system in 2017

Notes: The figure illustrates the allocation of population across German urban and rural areas in 2017 as the equilibrium of the model under local governments. The vertical axis depicts real incomes, and the length of the horizontal axis is total population in Germany with part of the population living in cities $\sum_i N_i$ and part living in the rural area N_r. Real income in the rural area as a function of the rural population is represented by the blue curve depicted from the right to the left. The thick horizontal segments give the equilibrium real income for incumbents in each city and the length of the segments is the population of the corresponding city. Equilibrium real incomes result from the maximization of real income with respect to city population by local governments represented by the thin gray curves. German cities are plotted in descending order of real incomes. The spatial equilibrium of the model is determined by the intersection of the black downward-sloping curve (locally optimal real income peaks) with the blue curve (real income in the rural area).

Fig. 3 portrays the German city system in 2017. The total population of 82,52 million in 2017 is depicted on the horizontal axis.[29] German cities (urban district regions) are listed in

[26] Henkel et al. (2021) describe the institutional background of the German fiscal transfer system, a complicated set of rules comprising various fiscal equalization schemes, and they meticulously work out local tax revenues before and after redistribution, and so the net transfers across locations. We are very grateful to these authors for generously providing us these data which allowed us to calculate the fiscal transfer rates for our analysis.
[27] Appendix D.1 provides details and results for productivities, consumption amenities and the fiscal transfer rates. Note that the effect of fiscal transfers would be "loaded" unto consumption amenities if the system of fiscal equalization was left out of the model (cf. section 3.2).
[28] Our quantification yields real income levels relative to the normalized commuting cost factor τ_t which prevails in all cities and which we assume to be 10,000.
[29] Germany has experienced only small population growth in the time span considered, so the general equilibrium for 1995 (where German population was at 81,45 million) looks much the same.

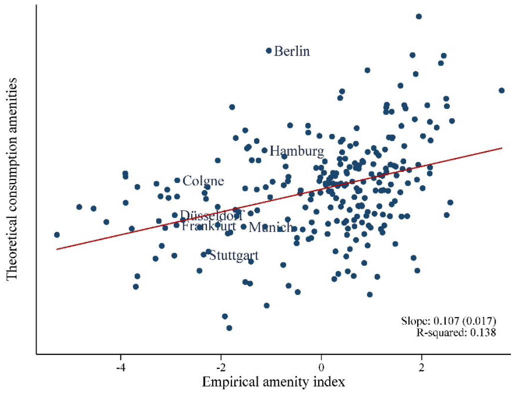
descending order of real incomes. The city with the highest real income, Erlangen, is depicted as city 1 with $N_1 = 100{,}857$. Munich comes second with a population of $N_2 = 1{,}232{,}755$, and so on for all 264 urban district regions. Hamburg is at position 28, Berlin at position 123. The total urban population, $\sum_i N_i$, can be read off the intersection of the black downward-sloping curve connecting locally optimal real income peaks with the blue curve which shows the declining marginal product of labor in the rural area (plus the fiscal balance term) from right to left. The rural population amounts to $N_r = 9$ million. Also shown are the land-use regulations p_{it}^* that are assumed to be levied by city incumbents on city newcomers. The highest level of these land-use regulations p_{1t}^* is imposed by the most attractive German city, Erlangen, followed by Munich, whose citizens impose land-use regulation amounting to p_{2t}^* in terms of output. The marginal urban district region, Erzgebirgskreis, imposes no land-use regulations, $p_{264t}^* = 0$ (see table D3 in appendix D.5 for information on all urban district regions).

Empirical support. Several independent pieces of evidence provide strong empirical support for our theoretical model and calibration. Our model innovations, notably the incorporation of consumption amenities, are key for the capacity of the model and calibration to accord with facts that prevail in Germany as we now show. These facts make us confident about our model innovations and calibration.

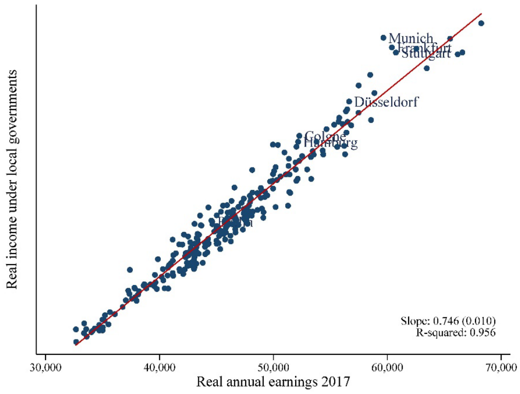
An important first piece of evidence is shown in panel A of fig. 4, the consumption amenities that we back out of the model receive strong support from independently observed consumption amenities. We use fifteen different data sources on location attractiveness that can be grouped into seven categories: nature, overnight stays, cultural institutions, crime, pollution, education quality, and quality of the health system.[30] We integrate these into a single index using principal component analysis (PCA) and we depict the first principle component on the horizontal axis. It is seen that this empirical index correlates strongly with the backed-out amenities plotted on the vertical axis (appendix D.2 provides further details).

[30] The category nature comprises forest area, water area, and sunshine duration. Overnight stays are defined as the number of overnight stays in tourist facilities. Cultural institutions encompass the number of libraries and cinemas. Crime is measured by the number of violent and street crimes. Pollution is assessed using fine dust and nitrogen dioxide pollution. Education quality comprises accessibility of educational institutions and share of children in day care facilities. Quality of the health system includes number of hospital beds, family doctors, and nursing home places.

Panel A: Consumption amenities



Panel B: City ranking – Real incomes



Panel C: Price–cost wedge and regulations

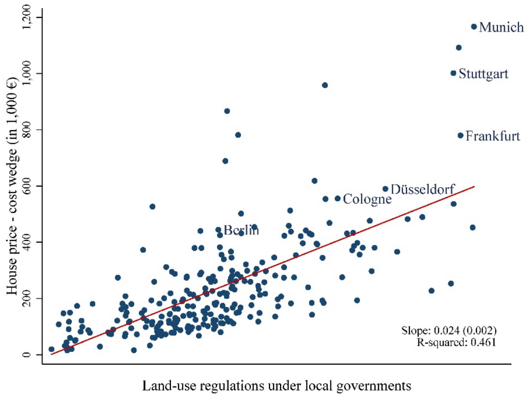


Figure 4: Consumption amenities, real incomes, and land-use regulations

Notes: Panel A plots the model-implied consumption amenities on the vertical axis and our empirical amenity index on the horizontal axis (appendix D.2 provides details). Panel B plots real incomes under the local government allocation of our model (vertical axis) against an independent measure of real income (horizontal axis) which uses the regional price indices recently established by Weinand and Von Auer (2020) based on micro-price consumer data collected for German counties by the Federal Statistical Office and the Statistical Offices of the Länder as deflators for average wages in cities. The bridge from counties to district regions is explained in Appendix B1. Panel C plots an independent measure for the house price- cost wedge in cities against the model-implied land-use regulations under local governments. The measure for the house price – cost wedge is taken from Braun and Lee (2021) who decompose the price of a single-/double-family, owner-occupied residential house into its replacement cost and land value at the German county-level. The replacement cost is based on an estimate for county-specific construction costs. We take their estimated land values for the year 2017 as a measure for the house price – cost wedge of cities.

A crucial second piece of evidence externally validates the model-implied real income (indirect utility) ranking of Germany's cities depicted in fig. 3. Panel B of fig. 4 shows the very close correlation between our measure of real income based on the local government allocation with our model and data (vertical axis) and an independent measure of real income (horizontal axis). This independent measure uses the regional price indices recently established by Weinand and Von Auer (2020) on the basis of micro-price consumer data collected for German counties by the Federal Statistical Office and the Statistical Offices of the Länder as deflators for the average earnings in cities. The correlation coefficient between the two measures exceeds 0.9. The positioning of individual cities in the implied city ranking is also very similar, as illustrated by Berlin which – pushed by its consumption amenities - comes at position 123 in our ranking and at position 149 in the alternative ranking.[31]

Third, the political-economy mechanism developed by DP (2023) implies that, in equilibrium, land-use regulations equal the price of housing at the city periphery, as our model abstracts from construction costs. This allows us to empirically approximate land-use regulations using the wedge between the price of housing and its replacement cost. To measure this house price-cost wedge, we rely on Braun and Lee (2021), who decompose the price of a single-/double-family, owner-occupied residential house into its replacement cost and land value at the German county-level. We take their estimated land values for the year 2017 as a measure for the house-price cost wedge of cities. Panel C of fig. 4 shows that the model-implied land-use regulations under local governments are positively correlated with the independent measure for the house price-cost wedge in cities.[32]

Panel A: Rents at the city periphery

Panel B: Rent gradients

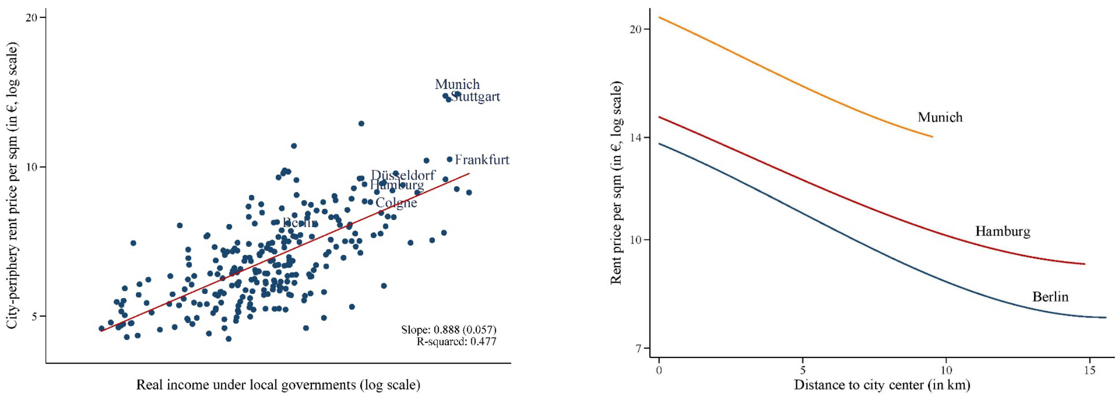


Figure 5: Rents at the city periphery and rent gradients

Notes: Panel A plots city-periphery rent prices per sqm in 2017 against real income under local governments. The city periphery is defined as the 95th percentile of dwelling distances from the CBD. The rents at the city periphery are estimated from a regression of the log rent per sqm on a third-degree polynomial of distance to the CBD allowing the coefficients of the polynomial to be city specific. The regression includes the same controls as column (1) of table 2. Panel B depicts the rent price per sqm as a function of distance to the CBD for the three cities Berlin, Hamburg, and Munich. The rent gradients are obtained from the regression used to establish panel A. City-periphery rents (panel A) and rent gradients (panel B) are plotted for a dwelling with average national characteristics in a neighborhood with average city characteristics using the RWI-GEO-RED data.

[31] To establish the figure shown in fig. 4 panel B, we adjust the regional classification (from counties to district regions) as explained in Appendix B1. Note that the alternative measure does not take consumption amenities and fiscal transfers into account (which shifts the city Berlin up in our ranking, for example).

[32] Further model implications could be confronted with the data, if systematic information on land-use regulations, similar to the Wharton Residential Land Use Regulatory Index (Gyourko, Saiz and Summers 2008; Gyourko, Hartley and Krimmel 2021) was available for Germany, which unfortunately is not the case.

Fourth, the political-economy mechanism of city-size determination comes with the novel implication that, due to the land-use regulations imposed by incumbents on city newcomers, house prices at the edges of cities are not equated, in contrast to the standard monocentric city model.[33] Rather, there are discrete differences, and these are systematically higher, the more attractive the city (cf. eqs. 10 and 11).[34] The scatterplot of periphery rents for all urban district regions in our database presented in panel A of fig. 5 shows that this implication accords well with the German facts.

Fifth, panel B in fig. 5 presents the evolution of housing rents over the extension of cities for a convenient selection of cities, Berlin, Hamburg, and Munich, to exemplify important further points. First, the gradient of housing rents is falling which accords with the predictions of the standard monocentric city model, the backbone of our urban model (cf. section 2.1). More importantly, it is also seen that the rents at the city edge in Munich, exceed those at the city edge of Hamburg, and that Berlin, the much-featured biggest German city which has yet a lower real income (attractivity) than the previous two, exhibits yet lower periphery rents, reiterating the point we made in our discussion of panel A.[35] Panel B shows another important finding. Our model predicts that the (quality-transfer) adjusted house prices in the city center are a sufficient statistic for the attractiveness of a city. These adjusted prices are the relevant model predictors for the empirically observed house prices at the city centers. The data shown in panel B accord with this implication. Munich exhibits the highest factual rents in the city center, followed by Hamburg. Berlin, the other city in our selection, has the lowest city center rents.

4.2 Cities and aggregate income in Germany

Expansion of the Top Seven. Our theoretical analysis of the welfare properties of the model shows that existing cities are undersized under local governments (cf. section 2.3). This conforms with the public perception that housing in Germany's most attractive cities, notably the Top Seven Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Duesseldorf is dramatically short of demand (cf. section 1). We therefore now consider a counterfactual expansion of the city populations in these cities. We assume a proportionate increase of each

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[33] See DP (2023) for an extended comparison of their model with the standard monocentric city model.

[34] Our modification of the DP (2023) model plays out here. Abstracting from land constraints there is a 1:1 relation between city size, city productivity and city attractiveness (real income), in DP (2023) so that they can largely focus on the relationship between periphery prices and city size. In our modification of the model, amenities and fiscal transfers are further determinants of a city's attractiveness which explains why we focus on attractivity (not city population) in figure 5, panel A.

[35] It should be noted that, due to the different components of a city's attractiveness in our modification of the model alluded to in the previous footnote, there is no 1:1 relationship between the ranking of housing prices and the extension of cities which is determined by the city population, in contrast to DP (2023).

city by 10%, so that $\widehat{N}_{it} = 1.1\, N_{it}$, where we us a hat ($\widehat{\ }$) to indicate counterfactual values. Given the factual (baseline) population in these cities in 2017, this implies that Berlin expands by 360,000 citizens, Hamburg by 180,000, Munich by 150,000, Cologne by 110,000, Frankfurt by 75,000, Stuttgart by 63,000 and Düsseldorf by 62,000, so that a total of 1 million people become new citizens in these locations. This counterfactual command that land-use regulations are reduced. Given the long-run nature of the model this can be understood as an increase of the housing supply in the Top Seven.[36] We assume that all migrants to these cities become newcomers in their destinations. Remember at the outset of the following analysis that, in the initial equilibrium, the real incomes of city incumbents v_{it}^{*} exceed the real income of city newcomers $v_{it}^{*} - p_{it}^{*} = v_{rt}^{*}$, which coincide with real incomes of workers in rural areas $v_{rt}^{*} = A_{rt}\, N_{rt}^{*}{}^{-\lambda} + \kappa_{r}$.

To analyze the consequences of this counterfactual we start by providing a qualitative description of the implied population reallocation. The algorithm that we use to implement this counterfactual is outlined in appendix D.3. Note that incumbents in cities other than the Top Seven have no incentive to change their city sizes because they remain locally optimal. Hence, encouraged by the lower land-use regulations, the first migrants to the Top Seven must come from the rural area. This fall in the rural population raises the marginal product of labor and so the real income in the rural area which now starts to exceed the (initial) real income of incumbents in the least productive cities. Consequently, the cities with the lowest real income will successively be vacated and their former residents migrate along with rural workers to Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart and Duesseldorf. This process continues until the population of the Top Seven has increased by 10% and the spatial equilibrium condition is restored. In this new equilibrium the real income of rural workers and citizens in the new marginal city are again equalized. Note that incumbent residents in cities other than the Top Seven, even though they maintain their city sizes, will adjust (lower) their land-use regulations to correspond with the new (and higher) threshold of real income. The described reallocations and the new equilibrium can be imagined by reference to fig. 3. The counterfactual shifts the black downward-sloping 'ladder'-curve rightwards, so that at the new intersection, i.e. equilibrium, the total urban population increases, the rural population shrinks

[36] This counterfactual is, grosso modo, in the ballpark of the 'housing shortage' that is currently diagnosed in a study commanded by various German Associations, including the Labor Union IGBAU, the Tenants' Association (Deutscher Mieterbund) and Caritas (Pestel-Institut 2023). To put our counterfactual into the perspective it is also instructive to note that the current German government plans to expand the housing supply by 400,000 housing units per year for "some years", but the current record falls dramatically short of this, FAZnet, January 12, 2023 (https://www.faz.net/aktuell/politik/studie-zum-wohnungsmangel-700-000-wohnungen-fehlen-18598219.html).

and the now higher real income in the rural area, $\hat{v}_{rt}$, defines the new utility threshold for the development of the (new) marginal city which is also the new real income of city newcomers. Our calculations show that the population in the rural area falls from initially 9 million to 8.3 million and that one city (Erzgebirgskreis) would be vacated, so that 263 cities remain.

The implied consequences for real incomes vary across groups of citizens. Incumbents in the Top Seven see their real incomes fall because their cities are now expanded beyond the locally optimal sizes. We calculate that their real income falls by 0.003%. The intuition for this mild real income loss is that the ∩-shaped real income curve is flat near the optimum, where agglomeration benefits and costs are balanced from the perspective of local governments. Incumbents in the 256 remaining cities other than the Top Seven where city sizes are unchanged maintain their real incomes, as already mentioned. All other groups gain in the counterfactual scenario, and they do so in a substantial way. Residents remaining in the rural area gain because of the increase in the marginal product of labor and so do newcomers in all cities because of the implied reduction in land-use regulations. This common real income gain amounts to 1.25%. The real income gain for former incumbents moving from the vacated city to the Top Seven also amounts to 1.25%. Note that these gains are constrained by the fact that land-use regulations in the new equilibrium are still substantial, which itself is a consequence of the mentioned flatness of real income curves near the optimum: incumbents in the Top Seven have to adjust the land-use regulations only by a small amount to accommodate their city expansions. Weighting all gains and losses with the respective population share we derive the aggregate consequences for real income in Germany for this counterfactual: average real income per person increases by 1.11%. The analysis thus substantiates the notion that the urban containment policies of incumbents in the Top 7 in Germany have significant societal costs.
To put our results into perspective we note that large population movements and welfare effects in the ballpark of ours have also been found in related research addressing the US city system exploring similar counterfactuals with different models.[37] We are not aware of a study performing a similar analysis for Germany, however.

Counterfactual shift to the social optimum. We have established the social optimum in section 2.3 to assure ourselves of the distortions and the directions of these distortions under local governments, of which there are potentially several in the model. As shown and discussed, the only (net) distortion arising under our chosen micro-foundations of agglomeration

[37] See DP (2023), Desmet and Rossi-Hansberg (2013) and Davis et al. (2014). Substantially larger welfare effects associated with the reduction of various land-use regulations are reported by Turner et al. (2014) and, notably, by Hsieh and Moretti (2019), numbers that merit further scrutiny (Proost and Thisse 2019; Greaney, no date).

economies concerns city sizes which are too small under local governments, since they ignore the extensive margin of development, which leads to the mentioned inefficiency when sites are heterogeneous. This motivated us to explore the expansion of a set of most attractive cities. One may also wonder about the effects of a complete switch from the status quo local government allocation to the social optimum. Such a counterfactual would be extreme, however, commanding a dramatic lowering of land-use regulations of 95.5% on average, and it would imply a hefty fall of the rural population down to 132,00 people and the vacation of 253 cities, as our calculations show.[38] These findings do not come as a surprise, however, as similarly strong results are also reported by DP (2023) and the preceding version Duranton and Puga (2019), and even more dramatic ones by Hsieh and Moretti (2019), for counterfactuals that are (partly) much less comprehensive than a shift to the social optimum. We take these extreme findings as suggestive of the need to explore the makings of the land-use regulations and the role of idiosyncratic preferences as mobility brakes more closely in future work.

4.3 The Contribution of Cities and Agglomeration Economies to Growth in Germany

We now turn to the implications of urban growth for aggregate growth in Germany. Taking the log-difference of the expected value of income per person across two points in time, one obtains from eq. (1):

$$\mathbb{E}(\Delta \ln w_{it}) = \mathbb{E}\left(\Delta \ln A_{it}^{p}\right) + (1+\sigma)\, \Delta \ln B(\psi) + (\sigma+\eta)\, \mathbb{E}(\Delta \ln N_{it}) \tag{20}$$

The first component on the right-hand side of eq. (20) captures the growth of productivities. Crucial for our analysis are the second and third term. The static agglomeration parameter σ magnifies the impact of human capital accumulation on per person income growth from 1 to $(1+\sigma)$. Moreover, with $\sigma+\eta>0$, city population growth directly contributes to income growth. Expected city growth can similarly be derived from log-differencing eq. (8):

$$\mathbb{E}(\Delta \ln N_{it}) = \frac{1}{(\gamma+\theta)-(\sigma+\eta)} \left[\mathbb{E}\left(\Delta \ln A_{it}^{p}\right) + (1+\sigma)\Delta \ln B(\psi) - \Delta \ln \tau_t\right] \tag{21}$$

This shows that expected city growth is affected by the development of travel costs, human capital accumulation, and productivities, and crucially so by the agglomeration parameters $\sigma+\eta$ whose size is key for the 'multiplier' that scales the impact of these drivers.

[38] This extreme scenario would also imply a substantial rise of average real income per person by 46.90%. Incumbents in the remaining 11 cities experience real income losses per person between 0.86% and 6.99% which are mild relative to the big real income gains of newcomers and the rural population (+102.67%), and incumbents of vacated cities (+1.51% to 102.67%). Appendix D.4 provides further details.

Eq. (20) can be brought to the data to gauge the impact of cities and agglomeration economies on growth in Germany. For this, we need data on average income growth per capita, growth in human capital accumulation and average city growth. We have the following information. In the time span from 1995 to 2017, average growth in income per person is 1.4% (Destatis 2021:21), so $\mathbb{E}(\Delta \ln w_{it}) = \ln(1.014)$, average city population growth is 0.2% per year (see appendix B.1), so $\mathbb{E}(\Delta \ln N_{it}) = \ln(1.002)$, and human capital grew by 0.2 % per year (Penn World Tables PWT 10.0), hence $\Delta \ln B(\psi) = \ln(1.002)$.[39]

Our counterfactual is to decrease agglomeration economies until they are eliminated. Start with the role of human capital formation. With static agglomeration represented through $\sigma = 0.018$, $\Delta \ln B(\psi)$ is multiplied by 1.018, so that the contribution from human capital formation to the annual growth rate of income per person is magnified from 0.2 to 0.204 percentage points. Hence, static agglomeration benefits raise the impact of human capital accumulation on growth in income per person by 0.004 percentage points. With urban agglomeration economies acting through static and dynamic benefits $\sigma + \eta = 0.049$, city population growth contributes $(\sigma + \eta)\ \mathbb{E}(\Delta \ln N_{it}) = 0.010$ annual percentage points to per capita income growth per year.[40] The overall effect of agglomeration economies on per capita growth is obtained by adding up the 0.004 percentage points from the magnification of human capital formation and the 0.010 percentage points contributed by city growth to yield additional 0.014 percentage points of income growth per person. Hence, agglomeration economies and cities resulted in a 0.31% higher output in the 22 years from 1995 to 2017, one quarter of which is due to their impact on human capital accumulation and three quarters of which are due to city population growth acting through static and dynamic benefits.

The growth effect of urban agglomeration economies for Germany appears very moderate, notably in perspective to the much larger number reported in the study of DP (2023) for the United States. It is instructive to understand why. First, note that our estimates of static and dynamic agglomeration economies which act as 'multipliers' in eq. (20) are only little more than half those reported by DP (2023). However, our numbers are in line with other estimates for Germany (cf. section 3.2) and also in the ballpark of the estimates reported in Combes and Gobillon (2015) and notably also the numbers and recommendations stated in Ahlfeldt and Pietrostefani (2019). The recent estimates of these parameters in DP (2023) lean strongly

[39] With these data, we can also back out the growth rate of productivity from eq. (20) as 1.2% per year, i.e. $\mathbb{E}(\Delta \ln A_{it}^{p}) = \ln(1.012)$. The growth rate of travel costs from eq. (21) is 1.4% per year, i.e. $\Delta \ln \tau_t = \ln(1.014)$.
[40] We also note that as $\sigma + \eta$ approaches nil in eq. (21), city population growth is reduced from the observed 0.2% to 0.1% per year.

towards the high end of prevalent findings, in contrast. Second, the different time frame is a further crucial factor. Germany's reunification and the issue of data compatibility confine the period that we can meaningfully address to the 22 years between 1995 and 2017, whilst DP (2023) look at the six decades after World War II (1950-2010). Much of the education expansion in both countries has taken place in the decades after 1950 that are included in DP (2023) but not in our study (Penn World Tables PWT 10.0). This rationalizes that human capital accumulation in our study is only one third of that in the US for 1950-2020. Moreover, population growth, a key driver behind city growth, is in our study only about one eighth of that in DP (2023). Taking these factors into account, we conclude that the effect of cities on national economic growth in Germany is weaker but not in an exceptional dimension compared to extant findings for the United States.[41]

4.4 Generalizing amenity spillovers

We have so far largely highlighted the role of exogenous consumption amenities. Yet, due to the micro-foundation of the internal structure of cities, our model comprises important city size dependent forces – housing costs, commuting costs and congestion costs – which canonical models of the new quantitative spatial literature appeal to as key examples of amenity spillovers (Allen and Arkolakis 2014; 2024). The typical black-box specification in these quantitative models takes amenities u_i to be iso-elastic in city-size, $u_i = \bar{u}_i {N_i}^{-\alpha}$, where $\bar{u}_i$ formalizes exogenous amenities, and where the parameter α is interpreted as a compound measure of amenity spillovers which represents various isomorphisms. It may formalize endogenous effects working through housing or other urban costs, idiosyncratic location preferences, the crowding of public goods or public amenities, rendering this parameter negative. It also stands for the endogenous creation of amenities through a skill-composition effect as cities become larger (e.g. Diamond 2016), working in the other direction. In our analysis, the amenity spillover parameter α is so far represented by $\gamma + \theta$, the population elasticities of urban costs and congestion costs.

Our model is easily broadened to capture the congestion of public amenities and goods more generally and/or to cover positive endogenous supply effects by assuming that consumption amenities enter our specification of indirect utility, eq. (3), as $A_i^c = \bar{A}_i^c {N_{it}}^{-\xi}$, where $\bar{A}_i^c > 0$. Indirect utility, eq. (7), then generalizes to $v_{it} = A_{it}^p B(l_{ht})^{1+\sigma} {N_{it}}^{\sigma+\eta} - \frac{(1-\varphi_i)}{\bar{A}_i^c {\Lambda_i}^{\gamma}} \frac{\tau_t}{(1+\gamma)} {N_{it}}^{\gamma+\eta+\xi}$.

[41] Our analysis neglects that cities also foster innovation which would raise agglomeration economies, the same is true for DP (2023:36), however, so the country difference must have other sources.

Locally optimal city sizes, by eq. (8), become $N_{it}{}^{*} = \left(\frac{(\sigma+\eta)(1+\gamma)}{(\gamma+\theta+\xi)} \frac{B(\psi)^{1+\sigma}}{\tau_t} \frac{A_{it}^{p} \bar{A}_i^{c} \Lambda_i{}^{\gamma}}{(1-\varphi_i)}\right)^{\frac{1}{(\gamma+\theta+\xi)-(\sigma+\eta)}}$, and the associated indirect utility in eq. (9) changes accordingly. The compound amenity spillover parameter α is represented by $\gamma + \theta + \xi$ in this more general framework. A downside of this generalization is that we do not have the data to identify the parameter ξ in similar ways that we used to estimate γ and θ. We can nonetheless challenge the robustness of our findings by borrowing the compound amenity spillover parameter from the extant literature. We focus on three sources. The canonical study of Allen and Arkolakis (2014) appeals to the expenditure share of housing in the US and uses a preferred value of $\alpha = 0.3$, implying an additional amenity spillover of $\xi = \alpha - (\gamma + \theta) = 0.16$ in our framework. For their study of the fiscal transfers in Germany, Henkel et al. (2021) suggest a preferred value of $\alpha = 0.66$ which they base on the expenditure share of housing in Germany and on idiosyncratic location tastes. This raises the additional parameter up to $\xi = 0.52$. Fajgelbaum and Gaubert (2020, online appendix) allow for positive supply effects building on the empirical amenity index in Diamond (2016). The compound amenity parameter then becomes $\alpha = 0.19$, so that $\xi = 0.05$ is implied.

How are our results affected by this generalization? First, our qualitative representation of the German city system (section 4.1) is not affected by this generalization. Amenity spillovers have no effect on the wage equation (1), so that the backed out fundamental productivities remain the same. Amenity spillovers affect the locally optimal city size, the modified eq. (8), but the qualitative ordering of cities' consumption amenities (A_i^c) is not affected by a change in the value of the compound amenity spillover elasticity. Hence, the key conclusion that our quantitative model is remarkably successful in representing German cities remains intact.

Turn to our counterfactuals. After quantifying both the exogenous and endogenous part of amenities, we rerun our main counterfactual, a population increase of 10% in each of the Top 7 cities. The results are summarized in table 3. With broadened amenity spillovers, the real income loss of incumbents in the Top 7 becomes slightly larger due to increased congestion from newcomers moving to the Top 7. Conversely, the real income gains for the other groups – movers to the Top 7, newcomers across all cities, and rural workers – are also slightly higher compared to the baseline counterfactual. Overall, the real income gain per person rises successively from +1.11% when $\xi = 0$ up to +1.14% for $\xi = 0.52$, but these effects remain clearly in the same ballpark.

Table 3: Robustness - Expansion of the Top 7 cities with endogenous amenities

	Exogenous amenities	Endogenous amenities		
	$\xi = 0$	$\xi = 0.051$	$\xi = 0.161$	$\xi = 0.521$
Panel A: New distribution of population				
Δ Top 7	Increase population by 10% in each of the Top 7 cities			
Δ Rural population	-7.332%	-7.332%	-7.332%	-7.332%
Number of vacated cities	1	1	1	1
Panel B: Real income changes				
Incumbents of Top 7	-0.003%	-0.004%	-0.007%	-0.015%
Movers to Top 7	+1.245%	+1.263%	+1.276%	+1.286%
Newcomers in all cities	+1.245%	+1.263%	+1.276%	+1.286%
Rural population	+1.245%	+1.263%	+1.276%	+1.286%
Average change	+1.108%	+1.123%	+1.135%	+1.144%

Finally, turn to the contribution of cities and agglomerations to economic growth. Here we can also conclude that our results remain intact when amenity spillovers are broadened. The reason is that the key equation (20) is unaffected by such a broadening. There is only an indirect effect working through city population growth, eq. (21), as the "multiplier" in front of the square bracket changes from $\frac{1}{(\gamma+\theta)-(\sigma+\eta)}$ to $\frac{1}{(\gamma+\theta+\xi)-(\sigma+\eta)}$, but due to the balancing of urban benefits and costs, the effect of this change is (again) minimal.

Summarizing the results in this section we can state: since our baseline analysis comprises key amenity spillovers captured in urban costs and congestion costs already, a broadening of these spillovers and an application of elasticities applied in extant research leaves all of our key results and key conclusions intact.

5 Conclusions

Escalating housing costs and a lack of affordable housing in desirable places have brought cities in the focus of public and political debate, in recent years. Current research converges on the idea that these housing market pressures stem not only from the interplay of demand and supply but are significantly influenced by regulatory measures, enacted by local policymakers to protect the interests of city incumbents ('city insiders') at the expense of 'city outsiders'. Recent research has started to explore the macroeconomic consequences of these regulatory barriers, focusing on how urban development affects aggregate welfare and aggregate growth in the US.

This paper contributes a European perspective where urban systems differ from the US in important ways. Our analysis focuses on Germany which constitutes an exciting laboratory as reports about high rents and NIMBY-policies abound, and as high-quality microdata are available. Most importantly, Germany provides an intriguing counterpoint to the US, in that location fundamentals, notably amenities, are of paramount importance. To develop this perspective, we generalize a novel urban growth model which embeds political-economy driven land-use regulations to target the US. Our key methodological innovations are to model amenities to rationalize the observed sizes of German cities. To bring the model to the data, we estimate the models' structural equations for the population elasticities of urban benefits and costs using our rich German micro-data, and we develop a novel strategy to back out the location fundamentals. We assess the quantified model using several sources of independent evidence and find that is remarkably successful rationalizing this evidence. Our key policy counterfactual involves a reduction of land-use regulations in Germany's Top 7 such that the population in each grows by 10%. This yields an overall welfare benefit of 1.11% per person, but only mild losses for city incumbents, which indicates that urban containment policies in Germany have significant societal costs. We then gauge the impact of cities and agglomeration economies for aggregate growth in Germany. We obtain a positive, yet moderate number, which is not exceptionally different from extant findings for the US, once the time frame of our analysis is put under close scrutiny. These results are robust to generalizing amenity spillovers of larger city populations from congestion in housing markets and local travel in our baseline specification to further effects concerning public goods and amenities.

We see several avenues for future work. One concerns the inclusion of idiosyncratic location preferences into the theoretical framework and the empirical analysis. A second concerns the integration of more detailed aspects of the supply side of housing markets. A third promising avenue is an extension to different skill groups to enable the study of welfare differentials across qualifications.

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Appendix: Cities, Aggregate Welfare, and Growth

by Katja Gehr and Michael Pflüger, February 25, 2025

A Theory Appendix

A.1 Micro-foundations of static agglomeration economies: production in cities

A.2 Micro-foundations of urban costs: internal structure of cities

A.3 Social optimum and comparison with the allocation under local governments

B Data Appendix

B.1 BBSR-urban district regions

B.2 Sample of Integrated Labour Market Biographies (SIAB-R)

B.3 Real-estate data (RWI-GEO-RED)

B.4 Mobility in Germany (MiD)

B.5 Geographical constraints

C Robustness checks

C.1 Population density

C.2 IV estimation

D Quantification and algorithms for the counterfactuals

D.1 Quantification

D.2 Consumption amenities

D.3 Counterfactual: Expansion of the Top Seven

D.4 Counterfactual: Social optimum

D.5 Ranking of cities

A Theory Appendix

A.1 Micro-foundations of static agglomeration economies: production in cities

We borrow the micro-foundations of static agglomeration economies from Duranton and Puga (2004; 2014) and adapt them to our context.[42] Production of the numéraire in city i takes place by combining an (endogenous) mass m_{it} of symmetric intermediate goods ω with quantities $q_{it}(\omega)$ according to a CES production function $Y_{it} = A_{it}^{p} \left\{\int_0^{m_{it}} q_{it}(\omega)^{\frac{1}{1+\sigma}}\, d\,\omega\right\}^{1+\sigma}$, where $0 < \sigma < 1$. The elasticity of substitution between any two intermediates is $\varepsilon \equiv (1+\sigma)/\sigma$ and A_{it}^{p} represents the local productivity. Intermediates are non-tradable and produced under increasing returns and monopolistic competition with educated labor $h_{it}(\omega)$ according to the function $h_{it}(\omega) = \frac{\alpha}{\rho} + \frac{q_{it}(\omega)}{\rho}$ which exhibits a fixed and a variable (output-related) component. The quantities of intermediates are chosen to minimize the costs to produce final output. Conditional input demand is $q_{it}(\omega) = \frac{[z_{it}(\omega)]^{-(1+\sigma)/\sigma}}{\left\{\int_0^{m_i}[z_{it}(\omega')]^{-1/\sigma} d\omega'\right\}^{1+\sigma}} \frac{Y_{it}}{A_{it}^{p}}$, where $z_{it}(\omega)$ denotes the price of intermediate ω. This implies that firm ω faces an own-price demand elasticity of $-(1+\sigma)/\sigma$. Its profit-maximizing price is a constant mark-up on marginal costs, $z_{it}(\omega) = (1+\sigma)\, w_{it}$, where w_{it} is the wage paid per unit of educated labor. Symmetry allows us to drop the index ω. Free entry drives intermediates' profits to zero, $\pi_{it} = z_{it}q_{it} - w_{it}h_{it} = 0$. A firm's break-even output is then $q_{it} = \frac{\alpha}{\sigma}$, and its demand for educated labor is $h_{it} = \frac{\alpha(1+\sigma)}{\rho\sigma}$. Labor market clearing implies that the mass of intermediates is $m_{it} = \frac{H_{it}}{h_{it}} = \frac{\rho\sigma}{\alpha(1+\sigma)} H_{it}$, where H_{it} denotes the city's human capital. Invoking these results and symmetry, final output in city i is $Y_{it} = A_{it}^{p}\, {H_{it}}^{1+\sigma}$, where setting $\rho = (1+\sigma)(\alpha/\sigma)^{\frac{\sigma}{1+\sigma}}$ normalizes units of intermediates (as in Duranton and Puga 2014). Combining this with human capital in the city, $H_{it} = B(l_{ht})\, {N_{it}}^{1+\beta}$, we have $Y_{it} = A_{it}^{p}\, B(l_{ht})^{1+\sigma}\, {N_{it}}^{(1+\beta)(1+\sigma)}$. Educated workers are paid their average product:

$$w_{it} = \frac{Y_{it}}{N_{it}} = A_{it}^{p}\, B(l_{ht})^{1+\sigma}\, {N_{it}}^{\sigma+\eta}, \quad \eta \equiv \beta(1+\sigma) \tag{A1}$$

Eq. (A1) enters the main text as eq. (1).

[42] The micro-foundations of agglomeration economies in Duranton and Puga (2014; 2004) draw on Ethier (1982) and Abdel-Rahman and Fujita (1990) but, unlike the latter, abstain from assuming that labor is needed in addition to intermediates in the final production stage. Under the assumption that the total differential land rent is proportionally rebated to citizens (an assumption we impose, see A.2), agglomeration economies exhibit no net inefficiency, because the prices of all inputs reflect an identical mark-up on marginal costs (in contrast to the Abdel-Rahman and Fujita (1989) model which features a distortion), see Duranton and Puga (2004, section 2.24) and Pflüger (2021).

A.2 Micro-foundations of urban costs: internal structure of cities

We assume monocentric, linear one-sided cities, that extend from the CBD at $x = 0$ to the city border x_b. We abstract from a competitive construction industry so that we can equate the terms land and floor-space. Due to time-invariant geographical constraints only the share $0 < \Lambda_i < 1$ of the raw land of a site can be developed (as in Brueckner 1987 and Saiz 2010). Each worker consumes 1 unit of floor-space and, hence, $1/\Lambda_i$ units of raw land. The city border is then at $x_b = N_{it}/\Lambda_i$. Commuting costs in the city are formalized by $T_{it}(x) = \tau_t \, {N_{it}}^{\theta} x^{\gamma}$, where x^{γ} is the length of the commute which is assumed to increase with elasticity $\gamma > 0$ with distance x from the CBD. This specification is used for empirical reasons (the estimation of urban costs, in section 3.4) and to include secondary employment centers and other features that the monocentric city model abstracts from, as in DP (2023:9). The term $\tau_t \, {N_{it}}^{\theta}$ formalizes the cost per unit distance, where τ_t is a parameter for the commuting technology, and ${N_{it}}^{\theta}$ stands for congestion in commuting in the city which relates to city size N_{it} with elasticity $\theta > 0$. Spatial equilibrium in the city commands that urban costs (which comprise rents and commuting costs) are equalized across all locations x so that,

$$T_{it}(x) + P_{it}(x) = P_{it}(0) = T_{it}(N_{it}/\Lambda_i) \tag{A2}$$

where $P_{it}(x) \equiv R_{it}(x)/\Lambda_i$ is defined as the (quality-transfer) unadjusted price of a dwelling at distance x from the CBD and where $R_{it}(x)$ is the bid rent per unit of raw land at location x. This equation, which appears as eq. (4) in the main text, implies that in a spatial equilibrium in the city, an increase in commuting costs associated with a longer commute must be compensated by a corresponding fall in land rents, $d\,P_{it}(x)/dx = -\,d\,T_{it}(x)/dx$, the Alonso-Muth condition. Using the formula for commuting costs, $T_{it}(x) = \tau_t \, {N_{it}}^{\theta} x^{\gamma}$, bid rents for raw land at x implied by eq. (4) are calculated as $R_{it}(x) = \Lambda_i \, \tau_t \, {N_{it}}^{\theta}((N_{it}/\Lambda_i)^{\gamma} - x^{\gamma})$. Total differential land rents in the city, $TLR_{it} = \int_0^{x_b} R_{it}(x)\, dx = {N_{it}}^{\gamma+\theta+1} \tau_t \, \gamma/(1+\gamma){\Lambda_i}^{\gamma}$, are assumed to be rebated to citizens on a per capita basis.

Net urban costs per capita in the city are then given by

$$nuc_{it} = \left[T_{it}(x) + \frac{1}{\Lambda_i} \, R_{it}(x)\right] - \frac{TLR_{it}}{N_{it}} = \frac{\tau_t}{(1+\gamma){\Lambda_i}^{\gamma}} {N_{it}}^{\gamma+\theta} \tag{A3}$$

which appears as eq. (5) in the main text.

A.3 Social optimum and comparison with the allocation under local governments

The social optimal allocation maximizes aggregate utility. Under our assumptions this is equivalent to the maximization of aggregate net consumption of the numéraire subject to the population constraint (as in Albouy et al. 2019).[43] Since our focus is not on the normative issue of the optimality of the German fiscal transfer system, we only include transfers for their positive effects and treat them as exogenously given. The social optimum characterized in the following is a constrained one. Formally, the program is to choose $\{l_{ht}, N_{it}, N_{rt}, \underline{A}_{it}^{p}\}$, i.e. the time devoted to learning, city populations, the rural population, the productivity of the marginal city, to maximize:

$$Y_{rt}(N_{rt}) + \int_{A_{min}^{p}}^{\infty} N_{it}\, v_{it}\, dG(A_{it}^{p}) \tag{A4}$$

$$\text{s.t.} \qquad N_{rt} + \int_{A_{min}^{p}}^{\infty} N_{it}\, dG(A_{it}^{p}) = N_t \tag{A5}$$

where $Y_{rt}(N_{rt}) = \frac{A_{rt}}{1-\lambda} {N_{rt}}^{1-\lambda} + \kappa_r N_{rt}$ is rural real income, v_{it} is real income in cities as specified in eq. (7) in the main text, and where $G(A_{it}^{p})$ is the cumulative density of the productivity in the economy with support $[A_{min}^{p}, \infty]$. Using μ to denote the Lagrange-Parameter associated with the population constraint (A5) and the index 'opt' to characterize the social optimum, the first order conditions of this program imply:

$$l_{ht}^{opt} = 1 - \frac{1}{\psi_t} \tag{A6}$$

$$\mu = {Y_{rt}}'(N_{rt}^{opt}) = A_{rt} N_{rt}^{opt^{-\lambda}} + \kappa_r \tag{A7}$$

$$\mu = (1 + \sigma + \eta)\, A_{it}^{p} \cdot B(\psi)^{1+\sigma} \cdot N_{it}^{opt^{\sigma+\eta}} - (1 + \gamma + \theta)\, \frac{(1-\varphi_i)}{A_i^c {\Lambda_i}^{\gamma}} \frac{\tau_t}{(1+\gamma)}\, N_{it}^{opt^{\gamma+\theta}} \tag{A8}$$

$$\mu = \underline{A}_{it}^{p\ opt}\, B(\psi)^{1+\sigma}\, \underline{N}_{it}^{opt^{\sigma+\eta}} - \frac{(1-\varphi_i)}{A_i^c {\Lambda_i}^{\gamma}} \frac{\tau_t}{(1+\gamma)}\, \underline{N}_{it}^{opt^{\gamma+\theta}} \tag{A9}$$

together with the population constraint (A5).

Eq. (A6) gives the socially optimal share of time devoted to education. This choice is undistorted and so the resulting optimal level coincides with the privately optimal level derived in the previous section (as in Jones 2005).

Results (A7), (A8) and (A9) mirror the results of Albouy et al. (2019). Eq. (A7) is the extensive margin condition for urban development which states that the shadow price of any further worker in the city system corresponds to the marginal product of labor (plus the fiscal balance)

[43] It is important to note here that our micro-foundations of agglomeration economies exhibit no inefficiency, on net, cf. appendix A.1. This property is implicitly maintained by Albouy et al. (2019:104).

in the rural area. Eq. (A8) is the intensive margin condition which expresses that the net marginal benefit of residing in any city has to be equal across all cities which are inhabited. Condition (A9) states that the utility level in the least developed city must be the same as the utility of living and working in the rural area.

Since eq. (A8) must also hold for the least developed city with productivity $\underline{A}_{it}^{p\,opt}$ we can use eqs. (A8) and (A9) to solve for this city's population level and then the Lagrange parameter:

$$\underline{N}_{it}^{opt} = \left(\frac{(\sigma+\eta)(1+\gamma)}{(\gamma+\theta)} \frac{B(\psi)^{1+\sigma}}{\tau_t} \frac{\underline{A}_{it}^{p\,opt}\, A_i^c\, \Lambda_i{}^{\gamma}}{(1-\varphi_i)} \right)^{\frac{1}{(\gamma+\theta)-(\sigma+\eta)}} \tag{A10}$$

$$\mu = \frac{(\gamma+\theta)-(\sigma+\eta)}{(\sigma+\eta)(1+\gamma)} \frac{\tau_t\,(1-\varphi_i)}{A_i^c\, \Lambda_t{}^{\gamma}}\, \underline{N}_{it}^{opt\,\gamma+\theta} \tag{A11}$$

Comparing eqs. (A10) and (A11) with eqs. (8) and (9) in the main text reveals that the least site to be populated in the social optimum is developed at its locally efficient scale, $\underline{N}_{it}^{opt} = N_{it}^{*}\left(\underline{A}_{it}^{p\,opt}\right)$ and that $\mu = v_{it}^{*}\left(\underline{N}_{it}^{opt}\right)$. Given the Lagrange parameter, eq. (A11), the rural population follows from eq. (A7), $N_{rt}^{opt} = \left(\frac{A_{rt}}{\mu-\kappa_r}\right)^{\frac{1}{\lambda}}$, and the total city population is $N_t - N_{rt}^{opt}$. Socially optimal city sizes N_{it}^{opt} are implicitly determined by eq. (A8) after using μ from eq. (A11). Since eqs. (A7), (A8) and (A9) are analogous to the system in Albouy et al. (2019, Proposition 1), their proof can be invoked to show that, except for the mentioned marginal city, socially optimal city sizes (for populated sites) have larger population than cities under local governments, $N_{it}^{opt} > N_{it}^{*}$, and that fewer cities are inhabited in the social optimum.

Note that the social optimum exhibits 'implicit land-use regulations': the equation of net marginal benefits across cities in the social optimum implies that cities with successively lower hump-shaped real income curves exhibit not only successively smaller population levels, but also successively lower different real incomes, and hence, successively smaller implicit 'land-use regulations' which only vanish for the last city.

B Data Appendix

B.1 BBSR-urban district regions

Definition of district regions. To ensure consistency with our labor market data taken from the SIAB-R dataset (Sample of Integrated Labour Market Biographies, Regional File), our definition of cities draws on the classification of district regions by the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR) at the territorial allocation as on December 31, 2017. The district regions are constructed from the autonomous municipal authorities (*kreisfreie Städte*) and administrative districts (*Kreise*) of Germany such that each district region has a population above 100,000 inhabitants in the reference year 2017. This yields in total 328 district regions (Antoni et al., 2019: 24). We further aggregate district regions whenever a city is completely enclosed by its surrounding county and, therefore, the city constitutes the center of the county.[44] This results in 315 aggregated district regions that are displayed in panel A of fig. B1.

Panel A: Territorial boundaries

Panel B: Urban and rural areas

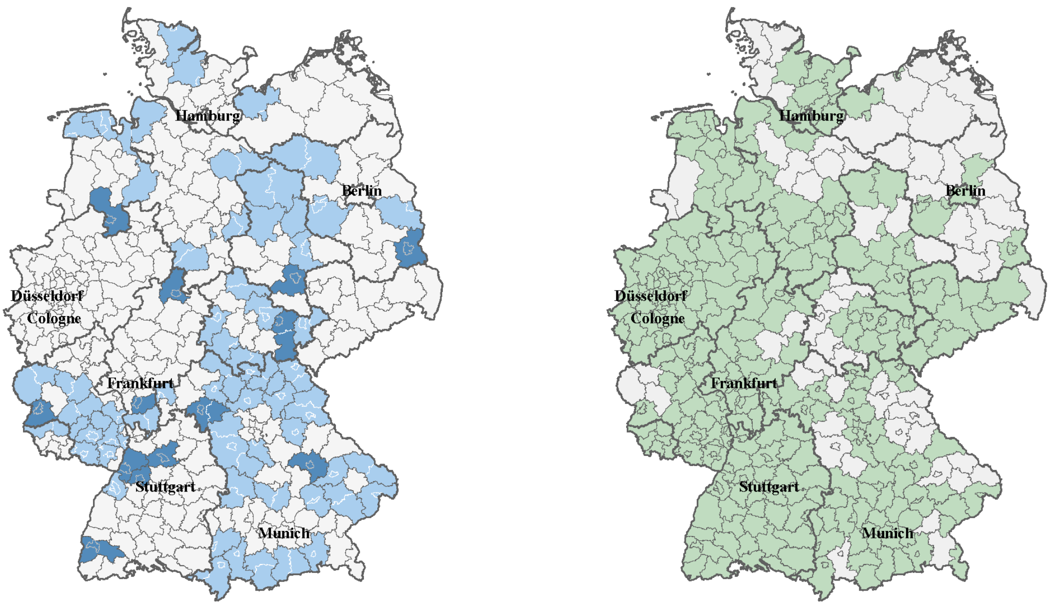

Figure B1: Aggregated district regions

Notes: Panel A visualizes the aggregation of German autonomous municipal authorities and administrative districts to district regions. Light blue areas indicate districts that are summarized to district regions such that each region has a population above 100,000 inhabitants. Dark blue areas indicate the further aggregation of district regions whenever a city is surrounded by its county. Panel B shows the spatial distribution of urban and rural areas. Green/gray areas indicate district regions classified as urban/rural.

[44] Precisely, this applies to the following district regions: Darmstadt and Darmstadt-Dieburg, Spree-Neiße and Cottbus, Saalekreis and Halle (Saale), Freiburg im Breisgau and Breisgau-Hochschwarzwald, Heilbronn and the city of Heilbronn, Trier-Saarburg and Trier, Regensburg and the city of Regensburg, the city of Würzburg and Würzburg/Kitzingen, Enzkreis and Pforzheim, Karlsruhe and the city of Karlsruhe, Osnabrück and the city of Osnabrück, Kassel and the city of Kassel, Jena and Saale-Holzland-Kreis/Saale-Orla-Kreis.

Definition of cities. The aggregated district regions are assigned to urban and rural areas by the classification of the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR), see BBSR (2012). This classification defines four district types and three region types by their degree of urbanization. The district types are constructed on the following criteria: share of population in large and medium-sized cities, population density, and population density without taking large and medium-sized cities into account. The region types are based on the criteria: share of population in large and medium-sized cities, presence and size of a large city, population density, and population density without taking large cities into account. Detailed descriptions of the district and region types, along with their differentiation criteria, are provided in Tables B1 and B2.

We classify aggregated district regions, that are assigned to sparsely populated rural districts in rural regions by the BBSR, as rural areas. The remaining aggregated district regions are classified as urban areas, and we take them as corresponding to the cities in the model. Therefore, we classify 264 out of the 315 aggregated district regions as urban. This yields a share of population living in urban areas in 2017 of 89.17% and a share of territorial area declared urban of 69.79%. The assignment of aggregated district regions to urban and rural areas is illustrated in panel B of fig. B1.

Table B1: Differentiation criteria for district types

District-free cities	- district-free cities with at least 100,00 inhabitants
Urban districts	- districts with a population share in large and medium-sized cities of at least 50% and a population density of at least 150 inhabitants per km^2 - districts with a population density outside large and medium-sized cities of at least 150 inhabitants per km^2
Rural districts with beginning agglomeration	- districts with a population share in large and medium-sized cities of at least 50%, but a population density of less than 150 inhabitants per km^2 - districts with a population share in large and medium-sized cities of less than 50% and a population density outside large and medium-sized cities of at least 100 inhabitants per km^2
Sparsely populated rural districts	- districts with a population share in large and medium-sized cities below 50% and a population density outside large and medium-sized cities of less than 100 inhabitants per km^2

Table B2: Differentiation criteria for region types

Urban regions	- regions with at least 50% of the population living in large and medium-sized cities and with a large city of at least 500,000 inhabitants - regions with a population density outside large cities of at least 300 inhabitants per km^2
Regions with inter-mediate urbanization	- regions with at least 33% of the population living in large and medium-sized cities and with a population density between 150 and 300 inhabitants per km^2 - regions with at least one large city and a population density outside large cities of at least 100 inhabitants per km^2
Rural regions	- regions with less than 33% of the population living in large and medium-sized cities and a population density of less than 150 inhabitants per km^2 - regions with a large city, but a population density outside large cities of less than 100 inhabitants per km^2

Definition of city centers. Following the approach of Duranton and Puga (2023), we define the city center of a district region as the location indicated by Google Maps for the core of the main city of the district region. We then calculate the distance to the city center as the haversine distance, which takes the curvature of the earth's surface into account, between the midpoint of each grid cell and the center of the district region.

Population data for 1995 and 2017. Our population data for the administrative districts in Germany for the year 2017 are taken from 'Regionaldatenbank Deutschland' provided by the Federal Statistical Office of Germany. The population levels are in consistency with the territorial boundaries of the administrative districts on 31 December 2017. The population data is then aggregated to district regions.

Due to several district reforms in Germany between 1995 and 2017, the territorial boundaries of district regions in 1995 were substantially different from the boundaries in 2017. Hence, data for the population of the district regions in 1995 with the territorial boundaries as on 31 December 2017 is required for comparability between the years 1995 and 2017. As the population dataset from 'Regionaldatenbank Deutschland' for the year 1995 corresponds to the territorial boundaries of the administrative districts on 31 December 1995, this data source is not suitable for our analysis. Instead, population data from 'Laufende Raumbeobachtung des BBSR' provided by the BBSR is used. As described in BBSR (2010), the territorial boundaries of the administrative districts are assigned to the status as on 31 December 2017. Moreover, the dataset is adjusted for the census of 2011 (BBSR, 2016). The resulting population dataset provides a time consistent definition for the territorial boundaries of the German districts such that the population of district regions in 1995 and 2017 can directly be compared.

B.2 Sample of Integrated Labour Market Biographies (SIAB-R)

Our estimation of the benefits of urban agglomeration is based on the factually anonymous Sample of Integrated Labour Market Biographies (SIAB) of the Institute for Employment Research (IAB) (version 1975 – 2017). The regional file of the SIAB is provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the IAB. The dataset contains a 2% random sample of the administrative social security records from 1975 to 2017 including employees subject to social security contributions and marginal part-time employment. Hereby, the information on employment histories comes from the Employee History (Beschäftigtenhistorik - BeH). The SIAB dataset comprises employment biographies for 1,827,903 individuals with a total of 62,340,521 observations (Antoni et al., 2019: 6). Because of anonymization, the regional file of the SIAB dataset includes 47,536 individuals less than the original SIAB dataset such that 2.5% of the individuals are not contained in the regional file (Antoni et al., 2019: 25). The dataset is in spell format where the unit of observation is any change in the employment status of an individual. The workplace of an individual is observable at the level of district regions. District regions are constructed from the administrative districts of Germany by aggregation to at least 100,000 inhabitants per district region. This gives in total 328 district regions (Antoni et al., 2019: 24). Further details on the district regions can be found in appendix B.1.

Following Dauth and Eppelsheimer (2020), we first convert the dataset into a yearly panel with June 30 as the cut-off date. This date is chosen as the variables on establishments from the Establishment-History-Panel (Betriebs-Historik-Panel - BHP) are not spell data but are only exact on 30 June each year. Fig. B2 plots the distribution of wages for the year 2017 in SIAB-R dataset. As can be seen in the figure, the bar furthest to the right is exceptionally high. This corresponds to the top-censoring of wages above the upper earnings limit for statutory pension insurance in the dataset. The wages that exceed this upper earnings limit are set equal to the upper earnings limit (Antoni et al, 2019: 42). This yields the high bar at the furthest right of fig. B2. Since the top censoring of wages would bias our estimation, we impute wages above the censoring threshold following the procedure in Dustmann et al. (2009) and Card et al. (2013). Therefore, we run a series of tobit imputations for each year, East-West Germany, and three education groups, separately. In each tobit estimation, we predict censored wages employing controls for age, gender, part-time employment, experience, and city size. Furthermore, we include the individuals' mean wage in other years, the fraction of top-censored wages in other years, and a dummy if the individual is observed only once in the sample as in Card et al. (2013). Under the assumption that wages are log-normally distributed, we impute censored log wages as follows: $X\beta + \sigma\Phi^{-1}[k + u(1-k)]$, where $u \sim U[0,1]$, $k = \Phi[(c - X\beta)/\sigma]$, s is the censoring limit, and σ is the standard deviation of the residual. The distribution of imputed wages is shown in fig. B2.[45]

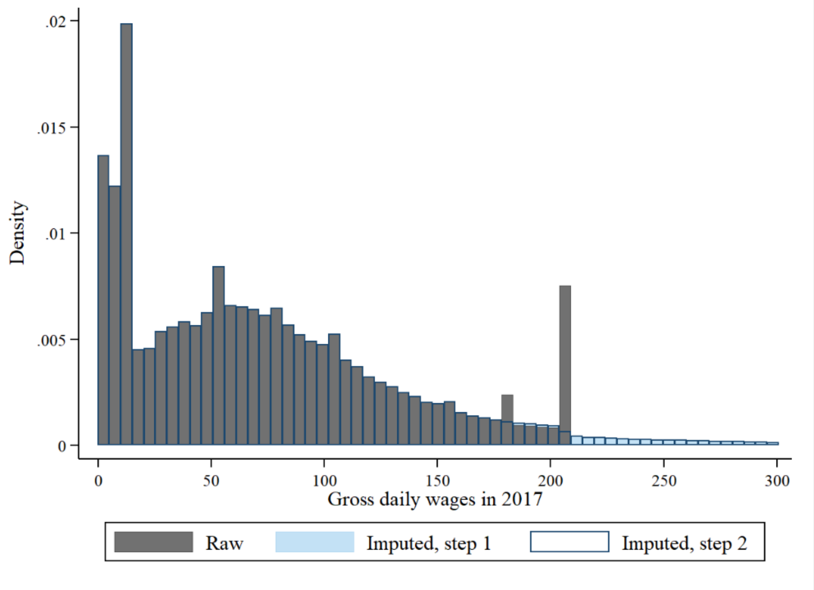

Figure B2: Distribution of wages in 2017

Notes: This figure reports the distribution of the censored daily wage and the imputed daily wage after the first and second imputation steps for the year 2017 using the SIAB-R data.

Moreover, we restrict the dataset to the time period from 1993 to 2017 since the social security notifications in East Germany are only complete from 1993 on because of the German reunification in 1990 (Antoni et al., 2019: 21). We also constrain the sample to full-time employees liable to social security because only the daily wage but not the underlying hours worked are observed for part-time workers. Hence, it is not feasible to control for changes in part-time workers' wages due to changes in the underlying hours worked. As marginal employments are only included since 2011 in the dataset, we also exclude these observations from the sample. Further, we only include workers of German nationality since the full labor market histories cannot be observed for foreign born workers. To constrain the sample to workers at least 18 years old for whom the full labor market histories are observable, we restrict

[45] When we re-run our estimations for the urban benefits from section 3.2 excluding top-coded wages, we find that our results are very much in line with the results based on imputed wages.

the year of birth to years between 1975 and 1999. Finally, we drop all observations for which no workplace location is observed from the sample and restrict the dataset to urban areas as defined in appendix B.1. This yields a final sample of 1,530,393 observations.

The variables work experience and firm tenure, included as controls in our estimation of the urban benefits, are constructed following Eberle and Schmucker (2019). The variable firm tenure measures the number of days an individual was employed in an establishment expressed in years. Training periods in the establishment are included in our measure of firm tenure. The variable work experience counts the number of days an individual has been employed up to the current point in time and is measured in years. Training periods are excluded from our measure of work experience. Descriptive statistics on the variables used in the estimation of the urban benefits can be found in table B3.

Table B3: Descriptive statistics on the SIAB-R data

Variable	Mean	St. Error	1st decile	Median	9th decile
Gross daily wage (in €)	91.57	53.96	45.00	81.00	146.00
Work experience	6.38	4.46	1.20	5.53	12.87
Firm tenure	3.96	3.85	0.33	2.82	9.37
Experience in five biggest cities	0.78	2.30	0.00	0.00	2.75
Experience in cities >500,000 (without five biggest)	0.81	2.33	0.00	0.00	2.88
Very-high-skilled occupations	0.12	0.33	0.00	0.00	1.00
High-skilled-occupations	0.11	0.31	0.00	0.00	1.00
Medium-skilled occupations	0.71	0.46	0.00	1.00	1.00
Low-skilled occupations	0.06	0.24	0.00	0.00	1.00

B.3 Real-estate data (RWI-GEO-RED)

Our estimation of the urban cost parameter, γ, uses rent prices for Germany coming from the real-estate RWI-GEO-RED data provided by the Research Data Centre Ruhr at RWI (RWI 2019). The dataset is based on real estate advertisements from the largest German listing platform ImmobilienScout24. It includes information on prices and various further characteristics of apartments as well as houses for sale and for rent. These further characteristics cover size, facilities and equipment, additional costs, and power consumption of a real estate. As the advertised price of an object is not binding, the prices in the dataset correspond to offering prices at which an owner is willing to sell or rent an object. The dataset is provided on a monthly basis for the years 2007 to 2020. The location of a real estate is provided on a grid of 1-square-kilometre raster cells covering whole Germany. The projection on the 1-square-kilometre grid raster follows the European standard ETRS89-LAEA according to the INSPIRE guidelines. Each grid cell is assigned to an administrative district in the dataset (Schaffner, 2020).

We prepare the dataset as follows for our analysis. We restrict the dataset to apartments for rent advertised in the year 2017. The year 2017 is chosen to keep consistency with the datasets on commuting behavior (MiD 2017) and on labor market histories (SIAB-R). Since the territorial status assigned to the administrative districts is as on 31 December 2015, we reassign grid cells to administrative districts based on territorial definitions on 31 December 2017. Then, we aggregate the administrative districts to district regions as described in appendix B.1 and restrict the dataset to apartments located in district regions classified as urban. In the dataset, the problem arises that some advertisement identifiers are not unique as described in Schaffner (2020). This can occur for the following main two reasons. First, an advertisement was not concluded at the time of data delivery and, therefore, is also included in the next data delivery. The advertisement is then included twice in the dataset. Second, an old advertisement is used as a template for a new advertisement. Then, the same advertisement identifier corresponds to different objects. Following the guideline of Schaffner (2020), we drop apartments from the data if objects with the same identifier are classified as similar based on their observed characteristics and if in addition, the gap between the advertisements is not larger than six months. Following Klick and Schaffner (2019), we drop apartments with a rent above 5,000€ or a living area exceeding 400 square meters from the sample as these apartments are very luxurious and not representative for the German real estate market. Furthermore, we exclude apartments with a rent below 50€ or a living area smaller than 50 square meters from the sample. These advertisements mainly correspond to parking spaces, cellar compartments, and workrooms and, hence, do not belong to rental apartments in a narrow sense. We construct the variable rent per square meter used in our estimation by dividing the exclusive rent of an apartment by its living area.

After our outlined data preparation steps, a final sample with 936,814 observations is obtained. The sample covers all 264 urban district regions with an average of 166 grid cells per district region. This yields, on average, 3549 observations per urban district region. The mean rent in the sample is 8.64€ with a mean dwelling area of 71.31 sqm. Further descriptive statistics on the main variables in the dataset can be found in table B4.

Table B4: Descriptive statistics on the RIW-GEO-RED data

Variable	Mean	St. Error	1st decile	Median	9th decile
Rent (€ per m²)	8.64	4.06	5.00	7.63	13.29
Dwelling area (€ per m²)	71.31	29.25	40.00	66.00	107.00
Number of rooms	2.51	0.95	1.00	2.00	4.00
Construction decade	1963	40.96	1900	1970	2010
Object categories					
top floor apartment	0.17	0.38	0.00	0.00	1.00
apartment	0.66	0.47	0.00	1.00	0.00
mezzanine	0.03	0.17	0.00	0.00	1.00
maisonette	0.01	0.07	0.00	0.00	0.00
penthouse	0.05	0.22	0.00	0.00	0.00
basement	0.01	0.12	0.00	0.00	0.00
terrace apartment	0.05	0.22	0.00	0.00	0.00
other	0.01	0.11	0.00	0.00	0.00
Distance from grid cell to city center (in km)	7.50	8.30	1.03	4.44	18.43
Number of grid cells per urban area	166.13	90.80	68	153	273
Number of observations per urban area	3549	6270	696	1847	6783

B.4 Mobility in Germany (MiD)

Our estimation of the elasticity of congestions costs draws on the dataset 'Mobilität in Deutschland (MiD)' which is a nationwide survey instructed by the Federal Ministry of Transport and Digital Infrastructure in Germany (BMVI) provided by the infas Institute for Applied Social Sciences (BMVI, 2017). The survey is conducted in the year 2017. Households are selected randomly and questioned on their socio demographic background and their travel behavior on a given reference date. On the household level, the dataset contains information on the household size, age structure, economic status, place of residence, and endowment with means of transport. Age, sex, common use of transport, and the possession of a driver's license are included on the individual level in the dataset. For the travel behavior on the survey day, departure and arrival time, commuting distance, trip purpose, use of transport, and the travel speed are most importantly reported for our analysis. The place of residence of an individual is observed on a grid of 1-square-kilometre raster cells covering all parts of Germany. The projection on the 1-square-kilometre raster grid follows the European standard ETRS89-LAEA according to INSPIRE. As grid cells are not assigned to German administrative districts in the dataset, this is done as part of the data preparation. We allocate each grid cell to a district region according to the largest share of surface area of a district region that is included in a grid cell (Follmer and Gruschwitz, 2019).

Table B5: Descriptive statistics on the MiD 2017 data

Variable	Mean	St. Error	1st decile	Median	9th decile
Travel speed (in km/h)	27.72	17.97	9.50	22.80	51.36
Travel distance (in km)	10.83	20.53	1.31	5.51	23.75
Retire	0.30	0.46	0.00	0.00	1.00
Age groups					
18 – 29 years	0.07	0.25	0.00	0.00	0.00
30 – 39 years	0.10	0.30	0.00	0.00	0.00
40 – 49 years	0.18	0.38	0.00	0.00	1.00
50 – 59 years	0.26	0.44	0.00	0.00	1.00
60 – 69 years	0.21	0.41	0.00	0.00	1.00
70 – 79 years	0.15	0.35	0.00	0.00	1.00
80 years and older	0.04	0.19	0.00	0.00	0.00
Trip purpose					
Commute to workplace	0.17	0.38	0.00	0.00	1.00
On business	0.13	0.34	0.00	0.00	1.00
Commute to education place	0.01	0.08	0.00	0.00	0.00
Errands	0.22	0.41	0.00	0.00	1.00
Grocery shopping	0.17	0.38	0.00	0.00	1.00
Leisure	0.21	0.41	0.00	0.00	1.00
Distance from grid cell to city center (in km)	9.71	8.45	1.66	7.29	20.86
Number of observations per urban area	709	955	95	442	1428

The dataset contains a total sample of 316,361 individuals from 156,420 households with 960,619 reported commuting trips. We restrict the sample to commuting trips by private car in order to estimate the urban cost parameter, θ, only through congestion that arises from traffic jams. Further, an interviewed person is only included if the person drove herself. Otherwise, the possibility arises that an individual is passenger in another trip reported, for example, by a household member of the interviewed person. Then the trip would be included twice in the sample: once for the driver and once for the passenger of the same trip. Moreover, a trip is only included in the sample if the interviewed person is in her usual environment on the reference date such that the commuting tip is assigned to the correct district region of the driver's place of residence. Finally, the sample is restricted to drivers whose place of residence is located in an urban area to keep consistency with the theoretical model. This yields a sample of 57,034 individuals from 48,161 households with a total of 187,176 commuting trips. Descriptive statistics on the main variables in the dataset are contained in table B5.

B.5 Geographical constraints

To quantify the share of developable land Λ_i, we follow Saiz (2010) and calculate for each city the share of geographically unconstrained land within the city's 30-km radius of the city center. Hereby, an area is classified as geographically constrained if it is covered by water and wetlands, slopes steeper than 15%, nature reserves or if it belongs to a foreign country.

The slope is calculated using the EU Digital Elevation Model at its 25-meter resolution from the Copernicus Land Monitoring Service. All areas with slopes steeper than 15% are classified as geographically constrained. Data on water and wetlands including seas, lakes, rivers, and other internal water bodies comes from the CORINE Land Cover 5 ha CLC5 for the year 2018. Nature reserves are identified with OpenStreetMapData and foreign land is identified from the official boundary files of the Federal Agency for Cartography and Geodesy.

C Robustness checks

C.1 Population density

To estimate the urban benefits and costs, it is crucial to determine whether city population or density should be used in regressions as a measure of city size. On the one hand side, cities with high population density but small population size are unlikely to exhibit strong agglomeration economies. On the other hand side, workers at the outskirts of large cities where population density is low are unlikely to fully benefit from agglomeration economies. Hence, neither population size nor density alone can adequately capture agglomeration effects in these cases. Empirically, a positive correlation between city density and population can be found such that both measurements used in regression analyses should result up to a certain point in similar results (Duranton and Puga, 2020: 7).

Table C1: 20 largest cities by population and density

Rank	City	Population
1.	Berlin	3,613,495
2.	Hamburg	1,830,584
3.	Munich	1,456,039
4.	Region of Hannover	1,152,675
5.	Cologne	1,080,394
6.	Karlsruhe	754,592
7.	Frankfurt am Main	746,878
8.	Stuttgart	632,743
9.	Düsseldorf	617,280
10.	Recklinghausen	616,824
11.	Rhein-Sieg-Kreis	599,056
12.	Dortmund	586,600
13.	Essen	583,393
14.	Leipzig	581,980
15.	Bremen	568,006
16.	Region of Aachen	554,068
17.	Dresden	551,072
18.	Rhein-Neckar-Kreis	546,745
19.	Ludwigsburg	546,745
20.	Esslingen	532,447

Rank	City	Density
1.	Munich	4686
2.	Berlin	4055
3.	Stuttgart	3052
4.	Herne	3043
5.	Frankfurt am Main	3008
6.	Düsseldorf	2839
7.	Offenbach am Main	2822
8.	Essen	2774
9.	Nuremberg	2763
10.	Oberhausen	2743
11.	Cologne	2668
12.	Bochum	2509
13.	Gelsenkirchen	2481
14.	Hamburg	2424
15.	Bonn	2307
16.	Mainz	2201
17.	Ludwigshafen am Rhein	2176
18.	Duisburg	2140
19.	Mannheim	2125
20.	Wuppertal	2100

However, not only theoretical aspects should be considered but also practical concerns. Table C1 presents the twenty largest district regions in Germany, ranked by population size and density. Density is calculated by dividing a district region's population by its area. Since district regions are taken as the geographical unit of analysis, distortions arise in the ranking of their size. Table C1 shows that some district regions with relatively low expected agglomeration economies are ranked as having a large population size. For example, Recklinghausen and

Rhein-Sieg-Kreis have a large aggregate population but consist of many small cities and lack a major city with strong agglomeration effects. Similarly, distortions occur with density as a measure for city size, such as for the district regions of Herne and Oberhausen. In these cases, the boundaries of the district regions are drawn relatively close to the city limits, excluding surrounding countryside. In contrast, other district regions include surrounding countryside, which results in an overestimation of density for some district regions. As the described distortions seem to be stronger when considering density, we decide to use the district region's population as the measurement of its size in our baseline specification. However, alternative regression results based on city density are also provided in table C2 for estimating the elasticity of urban benefits and in table C3 for estimating the elasticity of congestion.

Table C2: Estimation of elasticities of urban benefits based on density

	(1)	(2)	(3)	(4)
Dependent variable:	Ln earnings		Static premium (city indicators column (2))	Medium-term premium (static + 6.5 years local experience)
Ln city density	0.0214*** (0.0008)		0.0288*** (0.0043)	0.0391*** (0.0048)
City indicators		Yes		
Worker fixed effects	Yes	Yes		
Experience in five biggest cities	0.0195*** (0.0008)	0.0197*** (0.0008)		
Experience in five biggest cities x exp.	-0.0008*** (0.0001)	-0.0008*** (0.0001)		
Experience in cities > 500,000 (without five biggest)	0.0152*** (0.0008)	0.0153*** (0.0008)		
Experience in cities > 500,000 (without five biggest) x exp.	-0.0005*** (0.0001)	-0.0005*** (0.0001)		
Experience	0.0478*** (0.0008)	0.0471*** (0.0008)		
Experience^2	-0.0015*** (0.0001)	-0.0015*** (0.0001)		
Observations	1,530,393	1,530,393	264	264
R^2	0.4866	0.4925	0.1453	0.2211

Notes: All regressions include a constant term. Columns (1) and (2) include firm tenure and its square, year indicators, 4 occupational skill indicators, 14 sector indicators, and 120 occupation indicators. Column (2) in addition includes 264 city indicators. Worker values of experience and tenure are calculated on the basis of actual days worked and expressed in years. Coefficients are reported with robust standard errors in parenthesis, which are clustered by worker in columns (1) and (2). ***, **, and * indicate significance at the 1, 5, and 10 percent levels. The R^2 reported in columns (1) and (2) is within workers.

Table C3: Estimation of elasticity of congestion costs/travel speed based on density

Dependent variable:	Ln estimated city travel speed
Ln density	-0.0394*** (0.0038)
Observations	264
R^2	0.3343

Notes: The regression includes a constant term. City travel speed is estimated in a previous step by regressing travel speed for individual trips by private car on city indicators, including grid cell, driver and trip controls. We use this to predict for each city the speed of a 15km commuting trip on a Tuesday at 8AM by a driver with average characteristics. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent levels.

C.2 IV estimation

To address potential endogeneity concerns in estimating the elasticities of urban benefits, we instrument for current city size with historical population density in 1871 and 1910. These instruments are relevant due to the persistence of spatial patterns in population and economic activity, while the significantly different drivers of high productivity today help satisfy the exclusion restriction. Our historical population data is sourced from the German Local Population Database (GPOP), which provides population figures for German municipalities, districts and states for several years between 1871 and 2019 (Roesel 2022, 2023). The second step regression results are shown in table C4.

Table C4: IV estimation of population elasticities of urban benefits

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Static premium	Medium-t. premium	Static premium	Medium-t. premium	Static premium	Medium-t. premium
Instrumented ln city size	0.0102 (0.0217)	0.0544** (0.0238)	0.0127 (0.0196)	0.0559** (0.0219)	0.0135 (0.0191)	0.0564*** (0.0214)
First-stage statistic	24.5616	24.5616	27.8912	27.8912	13.7382	13.7382
Overid. p-value	-	-	-	-	0.5861	0.7488
Observations	264	264	264	264	264	264
Instruments						
Pop. density 1871	Y	Y	N	N	Y	Y
Pop. density 1910	N	N	Y	Y	Y	Y

Notes: All estimations are performed with 2SLS IV regressions. The first step regression is the same as in table 1. Y ('Yes') and N ('No') indicate the instruments used in the columns. All regressions include a constant term. Coefficients are reported with robust standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. The first-stage statistic is the Kleibergen-Paap rk Wald F-statistic, which is reported for a weak identification test. The critical value for 10% maximal IV size of Stock and Yogo (2005) weak identification test is 16.38 for columns (1) to (4) and 19.94 for columns (5) and (6). The overidentification p-value is derived from the Sargan-Hansen Test of overidentifying restrictions, which tests the joint null hypothesis that the instruments are valid.

D Quantification and algorithms for the counterfactuals

D.1 Quantification

The empirical city sizes in 2017 are taken as the equilibrium under local governments in the model, i.e., factual city sizes in 2017 correspond to N_{it}^{*}. We follow DP (2023) in assuming that the city populations in the first year from which our analysis starts, i.e., the year 1995, are the cities' incumbents and we take the additional city population that enters cities from 1995 to 2017 to be the newcomers (if positive). We employ the following approximations for the estimated parameters: $\sigma = 0.018, \eta = 0.031, \gamma = 0.071$ and $\theta = 0.068$, and we use $\lambda = 0.18$.

Cities. The local productivities are filtered from the wage equation, where w_{it} is approximated with the average annual wage in the city for the year 2017

$$A_{it}^{p} B(\psi)^{1+\sigma} = w_{it} / {N_{it}^{*}}^{\sigma+\eta}. \tag{D1}$$

The fiscal transfer rate is calculated from the optimality condition for the urban costs by normalizing $\tau_t \equiv 10{,}000$ as

$$\varphi_i = \frac{net-transfers_{it-HSS}}{nuc_{it} \cdot N_{it}} = \frac{(1+\gamma){\Lambda_i}^{\gamma} \cdot net-transfers_{it-HSS}}{\tau_t \, {N_{it}^{*}}^{\gamma+\theta+1}}. \tag{D2}$$

This calculation uses the net-transfers across German cities, $net - transfers_{it-HSS}$, which were established by Henkel et al. (2021) for their own project and which they generously provided to us (see footnote 26 in the main text).

Consumption amenities can be filtered from the equation for the optimal city sizes as follows,

$$A_i^{c} = \frac{\gamma+\theta}{(\sigma+\eta)(1+\gamma)} \frac{(1-\varphi_i)\,\tau_t}{A_{it}^{p} B(\psi)^{1+\sigma} \Lambda_i^{\gamma}} \, {N_{it}^{*}}^{(\gamma+\theta)-(\sigma+\eta)}. \tag{D3}$$

Rural area. To calculate the fiscal transfer per capita in the rural area κ_r, we sum up the transfers across all city locations. The (negative) balance divided by the rural population then captures the transfers per person from cities to the rural area.

The productivity in the rural area is calculated from the condition that the real income in the smallest city has to be equal to the real income in the rural area, $\underline{v}_{it}^{*} = v_{rt}^{*}$ as

$$A_{rt} = \left(\underline{v}_{it}^{*} - \kappa_r\right) {N_{rt}^{*}}^{\lambda}. \tag{D4}$$

The spatial distribution of productivities, consumption amenities, and fiscal transfer rates is illustrated by figure D1. Table D1 shows the ranking of cities by their real income under local governments.

Panel A: Productivities Panel B: Cons. amenities Panel C: Fiscal transfer rates

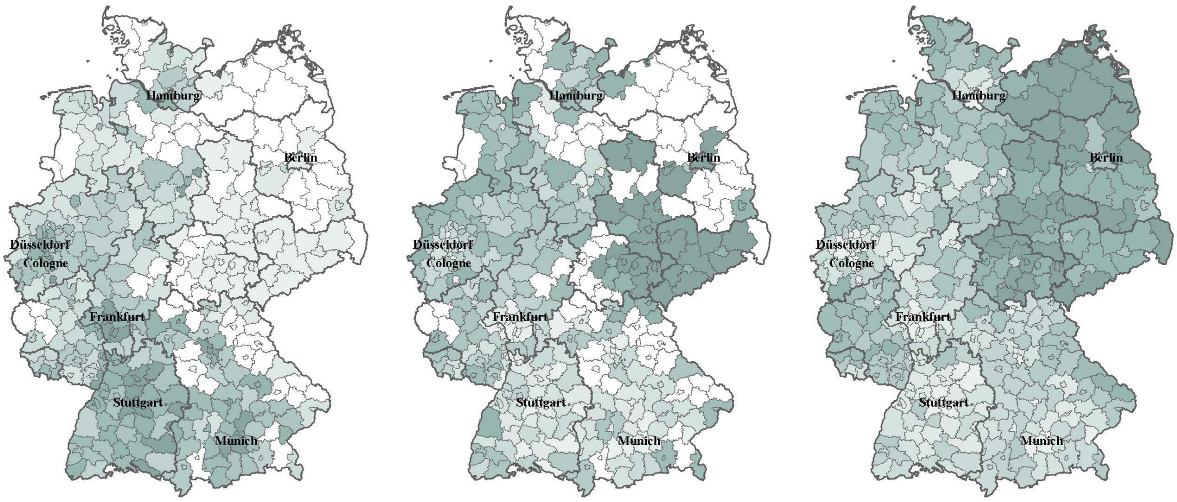

Figure D1: Productivities, consumption amenities, and fiscal transfer rates

Notes: The maps visualize the spatial distribution of productivities, consumption amenities, and fiscal transfer rates. In panels A and B, darker shading indicates higher values. White areas belong to district regions classified as rural. In panel C, darker areas indicate recipient regions and bright areas donor regions.

D.2 Consumption amenities

To relate the theoretically predicted consumption amenities to an empirical measure of consumption amenities, we collect fifteen different data sources on location attractiveness. These measures can be grouped into seven categories: nature, overnight stays, cultural institutions, crime, pollution, education quality, and quality of the health system.

The category **nature** comprises the area in sqm covered by forest in 2017, the area in sqm covered by bodies of water in 2017 (both provided by the BBSR), and the sunshine duration measured with yearly averages of sun hours between 1991 and 2020 (provided by German Weather Service '*Deutscher Wetterdienst*'). The variable **overnight stays** is defined as the number of overnight stays in tourist facilities in 2017 (provided by BBSR). **Cultural institutions** encompass the number of libraries and cinemas in 2017 (provided by the BBSR).

Crime is measured by the number of violent crimes – murder, homicide, rape, sexual coercion, sexual assault, robbery, serious bodily harm, extortionate kidnapping, hostage-taking, and attacks on air and sea transport – and the number of street crimes – theft, pickpocketing, sexual harassment, robbery, serious bodily harm, property damage – per 100,000 inhabitants in 2017 (provided by the crime statistics of the Federal Criminal Police Office). **Pollution** is assessed using average fine dust and nitrogen dioxide pollution in $\mu g/m^3$ between 2013 and 2022 (provided by Germany's central environmental authority '*Umweltbundesamt*' and German Weather Service '*Deutscher Wetterdienst*').

Education quality is represented by two variables: accessibility of educational institution, measured by car travel time in minutes in 2016 (provided by Thünen-Landatlas) and the share of children under the age of 3 in day care facilities compared to children of the corresponding age group in 2017 (provided by the BBSR). **Health system quality** includes the number of hospital beds per 1,000 inhabitants in 2017, family doctors per 10,000 inhabitants in 2017, and nursing homes places per 10,000 inhabitants in 2017 (provided by the BBSR).

Table D1: Descriptive regression analysis for consumption amenities

	Coefficient	R-squared
Nature index		
Log area in sqm covered by forest, 2017	0.1101*** (0.0208)	0.0969
Log area in sqm covered by bodies of water, 2017	0.2263*** (0.0252)	0.2357
Yearly averages of sun hours 1991-2020	-0.0012*** (0.0004)	0.0409
Overnight stays		
Log number of overnight stays, 2017	0.1206*** (0.0305)	0.0565
Cultural institutions index		
Log number of libraries in 2017	0.1687*** (0.0431)	0.0553
Log number of cinemas in 2017	0.1120*** (0.0410)	0.0281
Crime index		
Violent crimes per 100,000 inhabitants, 2017	0.0001 (0.0003)	0.0001
Street crimes per 100,000 inhabitants, 2017	0.0001 (0.0001)	0.0083
Pollution index		
Average fine dust pollution, 2013-2022	0.0086 (0.0228)	0.0005
Average nitrogen dioxide pollution, 2013-2022	-0.0399*** (0.0071)	0.1069
Education index		
Accessibility of educational institutions, 2016	0.1010*** (0.0188)	0.0991
Share of children in day care facilities, 2017	0.0241*** (0.0024)	0.2801
Health system index		
Hospital beds per 1,000 inhabitants, 2017	-0.0014 (0.0103)	0.0001
Family doctors per 10,000 inhabitants, 2017	0.0897 (0.0551)	0.0100
Places in nursing homes per 10,000 inhabitants, 2017	0.0072*** (0.0010)	0.1599

Notes: Column 1 shows the coefficients in a bivariate regression of each empirical measure of consumption amenities on the theoretical consumption amenities from our model. Standard errors are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels. Column 2 shows the corresponding R^2.

To combine the various measures of location attractiveness into a single index of consumption amenities, we use principal component analysis (PCA). This method extracts a uni-dimensional measure for each district region which can best predict the many amenities in each district region. Since some amenity categories have more data sources than others, principal component analysis may disproportionately weight categories with more variables. To address this, we first construct an amenity subindex for each category using the first principal component of the variables within that category. We then create an overall amenity index from the first principal components of the category-specific subindices.

Table D2: Principal component analysis for the empirical amenity index

	Loading	Unexplained variance
Nature index	0.5471	0.1985
Overnight stays	0.1385	0.9486
Cultural institutions index	0.0566	0.9914
Crime index	-0.4306	0.5036
Pollution index	-0.5186	0.2799
Education index	0.4715	0.4049
Health system index	0.0388	0.9960

Notes: The table reports the loadings and the unexplained variance on each subindex to create the overall amenity index using principal component analysis (PCA).

Table D2 reports the results of bivariate regressions, examining the relationship between each empirical measure of consumption amenities and the model implied consumption amenities. In addition, figure D2 shows the correlation between the seven subindices and the theoretical consumption amenities. The nature index, overnight stays, cultural institutions index, education index, and health system index are all positively correlated with theoretical consumption amenities. While the crime index also shows a positive correlation, the relationship is not statistically significant. In contrast, the pollution index has a negative correlation. Table D3 presents the loadings on each amenity subindex from the PCA. The index accurately places positive loadings on the nature index, overnight stays, cultural institutions index, education index, and health system index. The crime and pollution index accurately receive negative loadings. The correlation between the overall amenity index and the theoretical consumption amenities is plotted in panel H of figure D2. The pure correlation is 0.3718. The slope coefficient from a bivariate regression is 0.1067 and statistically significant.

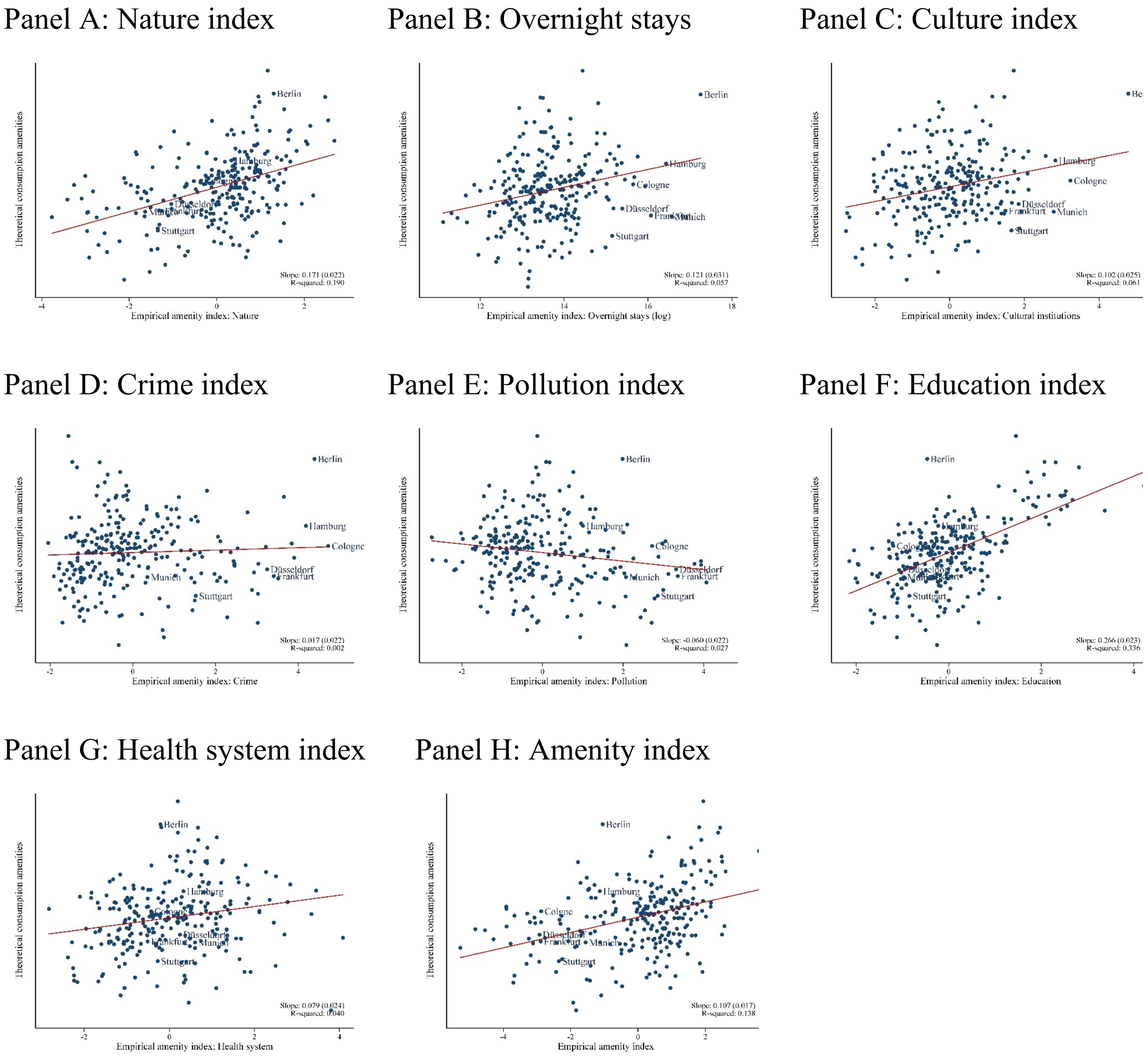

Figure D2: Theoretical consumption amenities against empirical amenities

Notes: This figure plots the theoretical consumption amenities from our model against the nature index, the number of overnight stays, the cultural institutions index, the crime index, the pollution index, the education index, the health system index, and our overall amenity index.

D.3 Counterfactual: Expansion of the Top Seven

The city population is increased by 10% in the following seven cities: Berlin, Hamburg, Munich, Cologne, Frankfurt, Stuttgart, and Düsseldorf ($\widehat{N}_{it} = 1.1N_{it}$). The scenario is implemented by a reduction in land-use regulations in these cities.

Algorithm. Incumbents in other cities than the top seven have no incentive for increasing their cities' housing supply and their city sizes remain unchanged by adjusting their land-use regulations. Hence, the residents migrating to the top seven cities first come from the rural area. Due to the fall in rural population, income in the rural area increases. When the income in the rural area rises, it exceeds the real income of incumbents in the cities with the lowest real incomes. Consequently, the cities with the lowest real incomes are vacated, and the former residents of these cities also migrate to the top seven cities.

Residents from the rural area and the least productive cities migrate to the top seven cities until the size of these cities increases by 10 percent, respectively, and the spatial equilibrium condition is restored. This means that the real income of residents in the new least developed city is equal to the income in the rural area.

New distribution of population. First, the number of residents that move to the top seven cities are calculated such that the city sizes of these seven cities increase by 10 percent, respectively. Then, the following algorithm is executed iteratively.

1. The least developed city is vacated, and the residents move to the top seven cities. The remaining residents, that are still needed to let the city sizes of these seven cities increase by 10 percent, are assumed to migrate from the rural area to those cities.
2. In response to the fall in rural population, the income in the rural area increases. The new income in the rural area is calculated according to
$$\hat{v}_{rt} = A_{rt}\widehat{N}_{rt}^{\ -\lambda} + \kappa_r \tag{D5}$$
and compared to the real income of the new least developed city without land-use regulations.
3. If the real income in the new least developed city is equal to the income in the rural area, the algorithm stops as the spatial equilibrium condition is retained again. If the income in the rural area exceeds the real income in the new marginal city, the algorithm continues by also vacating the second least productive city.

Real income changes. The real income changes for the rural population and newcomers (independently of whether they remain at their location or move to a new city) is given by

$$v_{rt} = A_{rt}N_{rt}^{-\lambda} + \kappa_r \qquad \Rightarrow \qquad \frac{\hat{v}_{it}^{newc}}{v_{it}^{*\,newc}} = \frac{\hat{v}_{rt}}{v_{rt}^{*}} = \frac{A_{rt}\hat{N}_{rt}^{-\lambda}+\kappa_r}{A_{rt}N_{rt}^{*\,-\lambda}+\kappa_r} - 1, \tag{D6}$$

where $\hat{N}_{rt}$ is the counterfactual population in the rural area. The real income loss for incumbents in the top seven cities is given by

$$v_{it} = A_{it}^{p}B(\psi)^{1+\sigma}N_{it}^{\sigma+\eta} - \frac{1-\varphi_i}{A_i^c\Lambda_i^{\gamma}}\frac{\tau_t}{1+\gamma}N_{it}^{\gamma+\theta} \qquad \Rightarrow \qquad \frac{\hat{v}_{it}}{v_{it}^{*}} - 1, \tag{D7}$$

where $N_{it} = \hat{N}_{it}$ is used for the calculation of $\hat{v}_{it}$ and $N_{it} = N_{it}^{*}$ for the calculation of v_{it}^{*}. All residents migrating to the top seven cities are assumed to become newcomers in these cities, regardless of whether they were incumbents or newcomers in their city of origin. +Further, the counterfactual real income for newcomers in cities is equal to the counterfactual income in the rural area. Hence, the real income gain for incumbents displaced from city j to one of the top seven cities i is given by

$$\frac{\hat{v}_{rt}}{v_{jt}^{*}} - 1 = \frac{A_{rt}\hat{N}_{rt}^{-\lambda}+\kappa_r}{v_{jt}^{*}} - 1, \qquad \text{with } v_{jt}^{*} = \frac{(\gamma+\theta)-(\sigma+\eta)}{(\sigma+\eta)(1+\gamma)}\frac{\tau_t(1+\varphi_i)}{A_i^c\Lambda_i^{\gamma}}N_{it}^{*\,\gamma+\theta}. \tag{D8}$$

D.4 Counterfactual: Social optimum

A counterfactual shift from the local government allocation to the social optimum, as described in section 2.3 and analytically detailed in appendix A.3, is considered.

Algorithm. The optimal city size distribution is determined by the following set of equations:

$$\mu = \underline{v}_{it}^{opt} = \underline{A}_{it}^{p}B(\psi)^{1+\sigma}\underline{N}_{it}^{opt\,\sigma+\eta} - \frac{1-\varphi_i}{(1+\gamma_i)A_i^c\Lambda_i^{\gamma_i}}\underline{N}_{it}^{opt\,\gamma+\theta} \tag{D9}$$

$$\mu = (1+\sigma+\eta)B(\psi)^{1+\sigma}A_{it}^{p}N_{it}^{opt\,\sigma+\eta} - \frac{(1+\gamma+\theta)(1-\varphi_i)}{(1+\gamma)A_i^c\Lambda_i^{\gamma}}N_{it}^{opt\,\gamma+\theta} \tag{D10}$$

$$N_{rt}^{opt} = \left(\frac{A_{rt}}{\mu-\kappa_r}\right)^{1/\lambda} \tag{D11}$$

and the population constraint $N_{rt}^{opt} + \int_{\underline{A}_{it}^{p}}^{\infty} N_{it}(A_{it}^{p})dG(A_{it}^{p}) = N_t$. As the marginal city in the social optimum is at its locally efficient scale, it holds that $\underline{N}_{it}^{opt} = N_{it}^{*}$.

The optimal city size distribution is calculated iteratively. First, it is assumed that only the two cities with the highest real income are developed in the social optimum. The Lagrange parameter is then pinned down by the real income of the city with the lowest real income (here: the second city) that is developed at its locally efficient size. Given a value for μ, the remaining optimal city sizes (here: the first city) are calculated numerically from the condition:

$$\mu = (1+\sigma+\eta)B(\psi)^{1+\sigma}A_{it}^{p}N_{it}^{opt\,\sigma+\eta} - \frac{(1+\gamma+\theta)(1-\varphi_i)}{(1+\gamma)A_i^c\Lambda_i^{\gamma}}N_{it}^{opt\,\gamma+\theta}. \tag{D12}$$

The population in the rural area is calculated for a given value of μ by

$$N_{rt}^{opt} = \left(\frac{A_{rt}}{\mu - \kappa_r}\right)^{1/\lambda}. \tag{D13}$$

Last, it is checked whether the distribution of the population among cities and the rural area add up to the total population in the economy (Germany). If this is the case, the optimal city size distribution is found. If not, the city with the next highest real income is developed.

Real income changes. For the change in real income, it is assumed that all residents that migrate to a new city become newcomers in these cities in the counterfactual scenario. The real income change for the rural population and newcomers (independently of whether they remain at their location or move to a new city) is given by $v_{rt}^{opt}/v_{rt}^{*} - 1 = \frac{A_{rt}{N_{rt}^{opt}}^{-\lambda} + \kappa_r}{A_{rt}{N_{rt}^{*}}^{-\lambda} + \kappa_r} - 1$. The real income change for remaining incumbents in cities is given by $v_{it}^{opt}/v_{it}^{*} - 1$. The real income change for incumbents displaced from city j is given by $v_{rt}^{opt}/v_{jt}^{*} - 1$.

D.5 Ranking of cities

Table D3: Ranking of cities by their real income

Real income Rank	City name	Population Rank	Population Level
1	Erlangen, Stadt	256	110,998
2	München, Landeshauptstadt	3	1,456,039
3	Böblingen	39	389,548
4	Frankfurt am Main, Stadt	7	746,878
5	München	49	346,433
6	Ingolstadt, Stadt	218	135,244
7	Stuttgart	8	632,743
8	Ludwigshafen am Rhein, Stadt	187	168,497
9	Wolfsburg, Stadt	242	123,914
10	Main-Taunus-Kreis	119	236,969
11	Hochtaunuskreis	120	235,995
12	Leverkusen, Stadt	193	163,577
13	Düsseldorf, Stadt	9	617,280
14	Bodenseekreis	142	214,655
15	Gross-Gerau	90	271,403
16	Bonn, Stadt	55	325,490
17	Darmstadt/Darmstadt-Dieburg	29	454,302
18	Erlangen-Höchstadt	217	135,334
19	Ludwigsburg	19	542,630
20	Heidenheim	226	132,006
21	Esslingen	20	532,447
22	Mannheim, Universitätsstadt	66	307,997
23	Heilbronn, Stadt/Heilbronn	27	465,885
24	Freising	176	177,997
25	Rhein-Neckar-Kreis	18	546,745
26	Köln, Stadt	5	1,080,394
27	Ulm, Universitätsstadt	240	125,596
28	Hamburg, Freie und Hansestadt	2	1,830,584
29	Wiesbaden, Landeshauptstadt	83	278,654
30	Starnberg	215	135,545
31	Biberach	156	198,265
32	Offenbach am Main, Stadt	237	126,658
33	Germersheim	234	128,477
34	Mülheim an der Ruhr, Stadt	181	171,265
35	Karlsruhe, Stadt/Karlsruhe	6	754,592
36	Heidelberg, Stadt	194	160,601
37	Salzgitter, Stadt	262	104,548
38	Hohenlohekreis	255	111,392
39	Offenbach	47	351,692
40	Mettmann	25	485,409
41	Mainz-Bingen	149	209,785
42	Nürnberg, Stadt	22	515,201
43	Rhein-Kreis Neuss	30	449,408
44	Essen, Stadt	13	583,393
45	Rems-Murr-Kreis	34	424,878
46	Rastatt/Baden-Baden	78	284,934
47	Ostalbkreis	62	312,422
48	Regensburg, Stadt/Regensburg	50	343,094
49	Mainz, kreisfreie Stadt	141	215,110
50	Augsburg, Stadt	74	292,851
51	Münster, Stadt	60	313,559
52	Braunschweig, Stadt	106	248,023
53	Reutlingen	76	285,754
54	Bremen, Stadt	15	568,006
55	Tuttlingen	209	139,397
56	Altötting	258	110,338

Table D3: Ranking of cities by their real income (continued)

Real income Rank	City name	Population Rank	Population Level
57	Fürth, Stadt	238	126,526
58	Duisburg, Stadt	23	498,110
59	Main-Spessart	239	126,523
60	Lörrach	124	228,314
61	Tübingen	128	225,755
62	Region Hannover	4	1,152,675
63	Göppingen	98	256,345
64	Krefeld, Stadt	126	226,699
65	Neu-Ulm	179	172,546
66	Rottweil	210	138,858
67	Rhein-Erft-Kreis	26	467,209
68	Schweinfurt/Schweinfurt, Stadt	186	168,542
69	Städteregion Aachen	16	554,068
70	Dortmund, Stadt	12	586,600
71	Pfaffenhofen a.d. Ilm/Neuburg-Schrobenhausen	130	222,408
72	Freiburg im Breisgau/Breisgau-Hochschwarzwald	24	492,041
73	Remscheid, Stadt	257	110,584
74	Kassel, Stadt/Kassel	32	437,410
75	Rheingau-Taunus-Kreis	168	186,602
76	Regionalverband Saarbrücken	53	330,150
77	Konstanz	80	284,015
78	Rhein-Pfalz-Kreis/Frankenthal (Pfalz)/Speyer	101	252,977
79	Kiel, Landeshauptstadt	107	247,943
80	Dachau	201	152,703
81	Weilheim-Schongau/Garmisch-Partenkirchen	131	222,407
82	Wuppertal, Stadt	45	353,590
83	Donau-Ries/Dillingen a.d. Donau	125	228,202
84	Stade	153	201,887
85	Rottal-Inn/Dingolfing-Landau	139	216,202
86	Ebersberg	207	140,800
87	Emmendingen	191	164,712
88	Freudenstadt	248	117,456
89	Bielefeld, Stadt	52	332,552
90	Herne, Stadt	200	156,490
91	Oldenburg (Oldenburg), Stadt	189	167,081
92	Saarpfalz-Kreis	204	143,402
93	Schwarzwald-Baar-Kreis	148	211,207
94	Forchheim	251	115,681
95	Gelsenkirchen, Stadt	95	260,305
96	Koblenz, kreisfreie Stadt	252	113,844
97	Unterallgäu/Memmingen, Stadt	170	186,014
98	Landsberg am Lech	247	119,141
99	Pforzheim/Enzkreis	57	322,658
100	Landshut/Landshut, Stadt	123	228,432
101	Düren	92	262,889
102	Ennepe-Ruhr-Kreis	56	324,670
103	Zollernalbkreis	166	188,170
104	Siegen-Wittgenstein	84	277,977
105	Bad Tölz-Wolfratshausen/Miesbach	127	225,761
106	Main-Kinzig-Kreis	36	418,208
107	Sigmaringen	228	130,192
108	Aschaffenburg/Aschaffenburg, Stadt	111	243,897
109	Schwäbisch Hall	162	194,203
110	Fürstenfeldbruck	134	217,831
111	Eichstätt	227	131,646
112	Calw	197	157,424
113	Soest	71	301,693
114	Gütersloh	44	363,049

Table D3: Ranking of cities by their real income (continued)

Real income Rank	City name	Population Rank	Population Level
115	Würzburg, Stadt/Würzburg/Kitzingen	40	378,404
116	Märkischer Kreis	37	413,383
117	Oberbergischer Kreis	89	272,968
118	Bremerhaven, Stadt	254	113,026
119	Oberhausen, Stadt	147	211,422
120	Oberallgäu/Kempten (Allgäu),/Lindau (Bodensee)	69	304,046
121	Wetteraukreis	68	305,312
122	Bochum, Stadt	42	365,529
123	Berlin, Stadt	1	3,613,495
124	Bergstrasse/Odenwaldkreis	43	365,377
125	Lahn-Dill-Kreis	99	254,164
126	Minden-Lübbecke	64	311,207
127	Segeberg	88	274,025
128	Mönchengladbach, Stadt	93	262,188
129	Alb-Donau-Kreis	161	194,629
130	Olpe	219	134,808
131	Marburg-Biedenkopf	109	246,165
132	Neuwied	172	181,655
133	Rheinisch-Bergischer Kreis	81	283,344
134	Rhein-Sieg-Kreis	11	599,056
135	Ravensburg	82	283,264
136	Warendorf	85	277,458
137	Nürnberger Land	184	169,752
138	Lippe	48	349,069
139	Günzburg	241	124,519
140	Ortenaukreis	33	425,932
141	Recklinghausen	10	616,824
142	Giessen	91	267,056
143	Hagen, Stadt	167	187,730
144	Peine	221	133,368
145	Kaiserslautern/Kaiserslautern, kr.f. Stadt	151	205,333
146	Paderborn	67	305,362
147	Erding	213	136,884
148	Fürth	250	116,193
149	Rosenheim/Rosenheim, Stadt	58	322,529
150	Solingen, Klingenstadt	195	158,803
151	Donnersbergkreis/Kusel	203	145,866
152	Main-Tauber-Kreis	225	132,189
153	Wesel	28	460,666
154	Saarlouis	160	195,815
155	Bottrop, Stadt	249	117,364
156	Neumarkt i.d. OPf	223	132,644
157	Pinneberg	61	312,662
158	Unna	38	393,934
159	Göttingen	54	328,036
160	Hameln-Pyrmont	202	148,296
161	Waldshut	183	170,198
162	Gifhorn	178	175,079
163	Miltenberg	233	128,484
164	Bamberg/Bamberg, Stadt	129	223,763
165	Neunkirchen	222	133,297
166	Neckar-Odenwald-Kreis	205	143,376
167	Alzey-Worms/Worms, kreisfreie Stadt	146	211,600
168	Hochsauerlandkreis	94	261,591
169	Kelheim	246	121,119
170	Lübeck, Hansestadt	137	216,318
171	Stormarn	114	242,472
172	Osnabrück/Osnabrück, Stadt	21	520,514

Table D3: Ranking of cities by their real income (continued)

Real income Rank	City name	Population Rank	Population Level
173	Viersen	72	298,733
174	Herzogtum Lauenburg	159	196,074
175	Coburg/Coburg, Stadt	235	128,121
176	Roth/Schwabach, Stadt	190	166,882
177	Herford	103	251,539
178	Limburg-Weilburg	180	171,971
179	Hildesheim	86	276,640
180	Friesland/Wilhelmshaven, Stadt/Wittmund	121	231,556
181	Mayen-Koblenz	143	213,554
182	Steinfurt	31	446,565
183	Augsburg	105	249,838
184	Hamm, Stadt	175	179,185
185	Verden	214	136,590
186	Trier, kreisfreie Stadt/Trier-Saarburg	96	258,545
187	Bad Kreuznach/Birkenfeld	118	238,277
188	Cuxhaven/Wesermarsch	75	287,122
189	Dresden, Stadt	17	551,072
190	Merzig-Wadern/St. Wendel	165	191,523
191	Südliche Weinstraße/Landau in der Pfalz, kr.f. Stadt	199	156,914
192	Borken	41	369,718
193	Rendsburg-Eckernförde/Neumünster, Stadt	46	352,357
194	Heinsberg	100	253,106
195	Kleve	63	311,270
196	Potsdam, Stadt	177	175,710
197	Waldeck-Frankenberg	198	157,256
198	Bad Dürkheim/Neustadt an der Weinstraße, St.	169	186,092
199	Passau/Passau, Stadt	115	242,285
200	Northeim/Holzminden	152	204,190
201	Südwestpfalz/Pirmasens, Stadt/Zweibrücken, Stadt	182	170,376
202	Euskirchen	164	192,127
203	Aurich/Emden, Stadt	116	240,556
204	Coesfeld	133	219,360
205	Fulda	132	221,783
206	Westerwaldkreis	154	201,039
207	Schaumburg	196	157,883
208	Rhein-Lahn-Kreis	244	122,381
209	Altenkirchen (Westerwald)	232	128,791
210	Leipzig, Stadt	14	581,980
211	Rhein-Hunsrück-Kreis/Cochem-Zell	192	164,600
212	Berchtesgadener Land	261	105,052
213	Goslar	212	137,563
214	Vechtachen	208	140,540
215	Harburg	104	251,511
216	Schwalm-Eder-Kreis	174	180,754
217	Wolfenbüttel/ Helmstedt	145	212,157
218	Werra-Meissner-Kreis	263	101,101
219	Plön	231	128,842
220	Ahrweiler	230	128,914
221	Aichach-Friedberg	224	132,596
222	Diepholz/Delmenhorst, Stadt	73	293,533
223	Höxter	206	141,565
224	Chemnitz, Stadt	108	246,855
225	Erfurt, Stadt	144	212,988
226	Leer	185	168,946
227	Nienburg (Weser)	245	121,470
228	Cham	236	127,339
229	Osterholz	253	113,105
230	Ammerland	243	123,377

Table D3: Ranking of cities by their real income (continued)

Real income Rank	City name	Population Rank	Population Level
231	Oldenburg	229	129,924
232	Hof/Hof, Stadt/Wunsiedel i. Fichtelgebirge	140	215,208
233	Rostock, Stadt	150	208,409
234	Cloppenburg	188	167,925
235	Ostholstein	155	200,584
236	Magdeburg, Stadt	117	238,478
237	Potsdam-Mittelmark/Brandenburg an der Havel	77	285,100
238	Halle (Saale), Stadt/Saalekreis	35	424,667
239	Cottbus, Stadt/Spree-Neisse	136	216,492
240	Jena, Stadt/Saale-Holzland-Kreis/Saale-Orla-Kreis	87	275,590
241	Nordwestmecklenburg/Schwerin, Landeshauptstadt	102	252,790
242	Kronach/Lichtenfels	220	134,251
243	Zwickau	59	319,988
244	Meissen	113	242,862
245	Ilm-Kreis	259	108,830
246	Anhalt-Bitterfeld/Dessau-Rosslau, Stadt	112	243,375
247	Weimarer Land/Weimar, Stadt/Sömmerda	135	216,584
248	Harz	138	216,299
249	Nordsachsen	157	197,794
250	Barnim	173	180,864
251	Saalfeld-Rudolstadt	260	107,368
252	Salzlandkreis	163	192,739
253	Vogtlandkreis	122	229,584
254	Leipzig	97	258,008
255	Mansfeld-Südharz	211	138,013
256	Bautzen	70	302,634
257	Burgenlandkreis	171	181,968
258	Eichsfeld	264	100,645
259	Gotha	216	135,521
260	Greiz/Gera/Altenburger Land	79	284,784
261	Mittelsachsen	65	308,153
262	Sächsische Schweiz-Osterzgebirge	110	245,418
263	Stendal/Altmarkkreis Salzwedel	158	197,643
264	Erzgebirgskreis	51	340,373

Notes: The table shows the ranking of cities by their real income under local governments together with their rank in the population distribution.