Measuring quality of life under spatial frictions *

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Abstract

Using a quantitative spatial model as a data-generating process, we explore how spatial frictions affect the measurement of quality of life. We find that under a canonical parameterization, mobility frictions—generated by idiosyncratic tastes and local ties—dominate trade frictions—generated by trade costs and non-tradable services—as a source of measurement error in the Rosen-Roback framework. This non-classical measurement error leads to a downward bias in estimates of the urban quality-of-life premium. Our application to Germany reveals that accounting for spatial frictions results in larger quality-of-life differences, different quality-of-life rankings, and an urban quality-of-life premium that exceeds the urban wage premium.

Key words: Housing, spatial frictions, rents, prices, productivity, quality of life, spatial equilibrium, wages

JEL: J2, J3, R2, R3, R5

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1 Introduction

More than 50% of the world's population lives in cities. In developed countries, the share is significantly higher. In developing countries, it is rapidly rising. Productivity advantages and correspondingly higher wages have been identified as potential drivers of urbanization since at least Marshall (1890). Indeed, there is abundant evidence confirming that productivity in cities is higher, making them attractive places to work (Combes and Gobillon, 2015).[1] Intuitively, cities may also be attractive places to live as they host urban amenities such as ethnic restaurants, music venues, or art galleries. While there is a sizable economics literature concerned with the measurement of quality of life (QoL) in the tradition of Rosen (1979) and Roback (1982),[2] there is, however, little evidence for a positive urban quality-of-life premium (Albouy, 2011; Ahlfeldt and Pietrostefani, 2019).

Our methodological contribution is to revisit the literature on the measurement of QoL, incorporating recent advances in quantitative spatial economics (Allen and Arkolakis, 2014; Ahlfeldt et al., 2015; Zabek, 2024).[3] Our central argument is that by accounting for spatial frictions, quantitative spatial models provide a framework for the measurement of QoL that reduces non-classical measurement error. Employing a quantitative spatial model with canonical building blocks as the data-generating process (DGP), we show in a Monte Carlo study that the Rosen-Roback framework tends to understate QoL differences across cities. Measurement error is correlated with city size, resulting in a downward bias in estimates of the urban QoL premium. This may explain why the extant literature has failed to establish a positive urban QoL premium. An application to Germany illustrates how our approach to measuring QoL leads to greater variation in QoL across cities, affects the order of QoL rankings, and gives rise to an urban QoL premium that exceeds the urban wage premium. As a tangible contribution to the applied literature, we provide an accessible GitHub toolkit with parsimonious data requirements that solves for a new QoL measure that accounts for trade-cost-induced variation in tradable goods prices, input-price-induced variation in non-tradable services prices (trade frictions) as well as imperfectly elastic local labour supply due to idiosyncratic tastes and local ties (mobility frictions).[4]

Conceptually, the economics literature treats QoL as a location-specific shifter in a utility function, akin to total factor productivity in a production function. Empirically, it is challenging to measure this utility shifter since it is impossible to observe all amenities that contribute to the QoL a city offers. And even if they were observable, their contributions to the latent variable would not be obvious. Therefore, the literature relies on spatial equilibrium models to invert unobserved QoL from observed wages and living costs. In the canonical Roback (1982)

[1] See for example, Ciccone and Hall (1996); Combes et al. (2008); Glaeser and Maré (2001).

[2] Notable applications include Albouy et al. (2013); Albouy and Lue (2015); Albouy (2016); Albouy et al. (2016); Blomquist et al. (1988); Gabriel and Rosenthal (2004); Rappaport (2009). Desmet and Rossi-Hansberg (2013) develop a complementary approach that does not require rents.

[3] Notable contributions include Heblich et al. (2020); Monte et al. (2018); Redding (2016). See Redding and Rossi-Hansberg (2017) for a review of recent advances.

[4] The toolkit is available at https://github.com/Ahlfeldt/ABRSQOL-toolkit and includes functions with user-friendly syntax for MATLAB, Stata, R, and Python.

version, the latter are approximated by housing costs as all other goods are assumed to be freely tradable. Further assuming that workers are homogeneous and perfectly mobile, any difference in QoL between two cities must be compensated for by differences in wages and rents in the spatial equilibrium. Therefore, the inverse real wage represents a theory-consistent measure of QoL. This frictionless spatial equilibrium framework has remained a workhorse tool in urban economics for decades (Glaeser and Gottlieb, 2009).

More recently, the literature has moved on to incorporate mobility and trade frictions into the spatial equilibrium framework. As discussed by Moretti (2011), idiosyncratic tastes for locations imply a mobility friction since small changes in wages, rents, or amenity values will no longer trigger oceans of workers to change their location. Extreme-value distributed taste shocks have, since then, become an integral part of quantitative spatial models to generate imperfectly elastic labour supply and housing demand at any location (Ahlfeldt et al., 2015; Redding, 2016).[5] The important implication for the measurement of QoL is that, unlike in the Rosen-Roback framework, wages and rents can no longer be assumed to reflect labour supply and housing demand conditions exclusively. A city—in the quantitative spatial model and in reality—may offer high wages due to a productive tradable sector and low rents due to a productive housing construction sector. Through the lens of the Rosen-Roback framework, where labour supply and housing demand are perfectly elastic, the city's productivity-induced high real wage would be wrongly attributed to a low QoL. Since more productive cities grow larger, this measurement error is negatively correlated with city size. Therefore, we expect the absence of idiosyncratic tastes in the Rosen-Roback framework to lead to a downward bias in estimates of the urban QoL premium.

Another reason the local labour supply is imperfectly elastic is that workers often have strong local ties. Intuitively, they may choose to stay in their hometowns near family and friends, even if it means forgoing opportunities to move to cities with higher wages or a better QoL. The idea that spatial relocation is costly has a long tradition in the literature on the economics of migration, going back at least to Sjaastad (1962).[6] It is well-established that workers require large wage or amenity premiums at potential migration destinations to leave their hometowns (Bryan and Morten, 2019). Consequentially, local ties affect the spatial equilibrium distribution of real wages within a suitably extended quantitative spatial model (Zabek, 2024). By implication, the real wage no longer fully reflects a city's QoL. A city—in the quantitative spatial model and in reality—may offer low wages and high rents due to a large number of workers who grew up in the city and are reluctant to give up their local ties. Through the lens of the Rosen-Roback framework, the low real wage would be misinterpreted as a high QoL that is universally appreciated, including by those who do not consider the city their hometown. Since a larger city naturally has more workers considering it their hometown, we expect the absence of local ties in the Rosen-Roback framework to lead to an upward bias in estimates of the urban QoL premium.

[5] Other applications include Fajgelbaum et al. (2019); Heblich et al. (2020); Monte et al. (2018).

[6] Important recent contributions in this literature include Artuç et al. (2010); Desmet et al. (2018); Caliendo et al. (2019); Kennan and Walker (2011).

In a parallel movement, the quantitative spatial economics literature has adopted tools from the international trade literature to generate a gravity structure of trade between regions in a country (Allen et al., 2020; Head and Mayer, 2014). Love for variety in conjunction with distance-dependent trade costs result in tradable goods prices that vary across cities (Allen and Arkolakis, 2014; Redding and Rossi-Hansberg, 2017). Spatially variant tradable goods prices—which are absent in the Rosen-Roback framework—matter for the measurement of QoL since tradable goods are an important component of real living costs. A city—in the quantitative spatial model and in reality—may offer low tradable goods prices due to great market access. Through the lens of the Rosen-Roback framework, living costs and, consequentially, QoL would appear greater than they are. Since the home-market effect leads to concentrations of large cities in agglomerated regions, such as the coastal areas in the US or the Rhine-Ruhr area in Germany, this measurement error is likely positively correlated with city size. Therefore, we expect the absence of frictions in the exchange of tradable goods in the Rosen-Roback framework to lead to an upward bias in the urban QoL premium.

Certain goods, such as restaurant visits or haircuts, are subject to prohibitive trade costs. Diamond and Moretti (2021) show that such local services account for a significant fraction of consumption expenditure and exhibit substantial variation in prices across space. Recent quantitative spatial models feature a sector that produces such services using labour and floor space as inputs (Caliendo and Parro, 2015; Caliendo et al., 2018a). Similar to the prices of tradable goods, the prices of local services lead to a measurement error in inverse real wages and hence in QoL in the Rosen-Roback framework. Since QoL is negatively capitalised in wages and positively capitalised in land prices, the direction of the measurement error due to the omission of local services in the Rosen-Roback framework is theoretically ambiguous.

While the intuition for the QoL measurement error in the Rosen-Roback framework is strong, a quantification of the magnitude of the problem is still outstanding. In fact, given that the expected biases arising from the omission of idiosyncratic tastes, local ties, trade costs, and local services point in different directions, it is not even a priori clear whether estimates of the urban QoL premium within the Rosen-Roback framework are biased upwards or downwards. To fill this gap in the literature, we must inevitably take a stance on the true values of QoL against which we wish to benchmark some estimates derived from the Rosen-Roback framework. This is a non-trivial problem, given that QoL is a latent variable that cannot be observed directly. To tackle this problem, we assume that the true DGP conforms to a quantitative economic geography model with frictional trade as in Allen and Arkolakis (2014) and Redding and Rossi-Hansberg (2017), augmented by a local services sector (Caliendo and Parro, 2015), idiosyncratic worker tastes (Ahlfeldt et al., 2015), and local ties (Zabek, 2024). We deliberately choose not to innovate in developing certain parts of the model but to combine established building blocks routinely employed to account for spatial frictions. In other words, we quantify the measurement error in older literature that abstracted from spatial frictions, assuming that collective progress in the fields of economic geography and urban economics has brought us closer to a realistic understanding of a world with spatial frictions. Of course, for our analysis to be insightful, the reader must be willing to share this view.

To stay reasonably close to the Rosen-Roback based QoL literature, our model is static. The distribution of workers across hometowns, and hence the hometown population of each city, is exogenous. However, conditional on accepting a utility cost associated with leaving their hometown due to the loss of social ties, workers are free to choose where to live, as in Bryan and Morten (2019). Spatial equilibrium requires that expected utility is equalized across all cities and all goods (housing, tradable goods, local services) and factor (labour, land) markets clear. Given the absence of closed-form solutions for the spatial general equilibrium, we quantify the measurement error of the popular Rosen-Roback measure of QoL in a Monte Carlo setting. The application of a quantitative general equilibrium spatial model as a DGP to benchmark an established measurement procedure is novel. The closest analogue is the Monte Carlo study in Adão et al. (2023), who employ the quantitative trade model by Fajgelbaum et al. (2020) as the true DGP into which they inject measurement error to evaluate the performance of their proposed specification tests.

For our purposes, the Monte Carlo setting provides the ideal testing ground to maximise external validity. We generate 1,000 synthetic countries on a square featureless plain of about the area of Germany, each of which contains 144 cities of equal area. For each city and country, we randomise city-specific housing productivity, labour productivity, QoL, and hometown population shares (under the constraint that they sum to one). We also randomly choose the country-specific parameters that govern the heterogeneity of idiosyncratic tastes and the strength of local ties since these are arguably the parameters that are least consensual in the literature. We solve the model separately for each synthetic country and use the model solutions for city-specific wages and rents to compute the canonical Rosen-Roback measure of QoL, which we then compare with the 'true' value specified in the DGP to quantify the measurement error.

Under our arguably canonical parameterization, the measurement error is large. For a city that has a 'true' relative advantage of 50% in terms of QoL over a reference city, the Rosen-Roback measure understates this relative advantage by about 25%, on average. A decomposition reveals that this measurement error is driven more by mobility frictions than by trade frictions. The implication for the applied literature is that, in improving the measurement of QoL, the priority should be to account for both types of mobility frictions. In fact, our Monte Carlo experiments reveal that controlling for trade frictions without addressing mobility frictions may actually increase measurement error. Moreover, since the directions of the measurement error originating from the omission of idiosyncratic tastes and local ties point in the opposite direction, measurement error may increase if only one of the two mobility frictions is accounted for.

Another important lesson from our Monte Carlo experiments is the significant heterogeneity in measurement error, both between and within artificial countries. In artificial countries with less heterogeneity in idiosyncratic tastes and weaker local ties, the measurement error is generally smaller because local labour supply is more elastic. This mitigates a key source of measurement error in the Rosen-Roback framework, which stems from the assumption of perfectly elastic labour supply and housing demand: labour demand and housing supply shocks that are capitalized into real wages are misattributed to the labour supply and housing demand side. Since the measurement error remains substantial for all empirically plausible parameter values, we consider it unlikely that there are many countries in the real world where the measurement error is negligible.

We also find sizable heterogeneity in measurement error across artificial cities within artificial countries. Positive differences in fundamentals such as QoL, floor space productivity and labour productivity, which lead to positive differences in the resident population, increase the measurement error. In contrast, positive differences in hometown population reduce the measurement error. The net effect over the plausible parameter space is a downward bias in the urban QoL premium estimated from the Rosen-Roback framework. This suggests that one reason why the existing literature hasn't found a positive urban QoL premium may be related to measurement error.

To illustrate the impact of accounting for spatial frictions in the measurement of QoL in a real-world setting, we quantify our model for 141 German commuting zones. The spread in the QoL measure inverted from our quantitative spatial model is somewhat larger than that of the Rosen-Roback measure, but more importantly, there are significant changes in the order of the ranking. Hamburg swaps places with Munich to become the city with the highest QoL. Frankfurt climbs one place (to 4^{th}), Düsseldorf seven places (to 5^{th}). At the extreme, Chemnitz climbs 62 places (to 39^{th}), while Lörrach falls 49 places (to 86^{th}). Only two cities do not change their rank: Berlin (3^{rd}) and Höxter (131^{st}). The average absolute change in rank is 17. Our fully theory-consistent measure of QoL is somewhat data-intensive in that it requires measures of hometown population, prices of tradable goods and local services, in addition to the more readily available resident population and the conventional Rosen-Roback inputs (wages and house prices). However, a crude data version of the measure, which approximates hometown population with a 30-year residence population lag and abstracts from variations in non-housing costs, still significantly reduces measurement error relative to the Rosen-Roback measure.[7] Thus, controlling for mobility frictions represents a relevant and easy-to-implement improvement in the measurement of QoL, complementing recently proposed corrections for commuting costs and taxes.(Albouy and Lue, 2015; Albouy, 2016).

Consistent with our Monte Carlo simulations, we find a much larger urban QoL premium when spatial frictions are taken into account. A German city that is on average twice as large offers a 22% higher QoL to the average resident (the marginal resident is indifferent). This premium is almost twice as large as estimated in the Rosen-Roback framework (14%) and about five times as large as the urban wage premium (4%). These estimates do not imply that city size causes higher QoL, as the urban QoL premium is a descriptive concept. It is quite possible that certain cities offer high QoL and therefore grow large because they are located in places with natural amenities such as mountains, rivers or oceans. Whether city size has a causal effect on QoL is a separate question, which arguably becomes more relevant in the light of our findings. In any case, our results show that QoL is a more important determinant

[7] A refined version using model-derived tradable goods and local services prices (generated by our toolkit) performs marginally better.

of the high urbanization rate in Germany—and possibly elsewhere—than has previously been recognized.

The remainder of the paper is structured as follows. Section 2 presents stylized evidence that motivates our analyses. Section 3 outlines the model. Section 4 studies the error in the Rosen-Roback-based measurement of QoL within a Monte Carlo setting. Section 5 provides an application and Section 6 concludes by summarizing the implications for related literature and future research.

2 Stylized facts

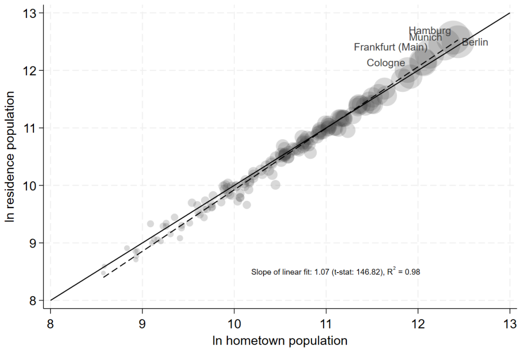
Taking Germany as a case in point, Figure 1 presents some stylized facts of the spatial economy that highlight the role of QoL as an important determinant of local labour supply and motivate our choice of building blocks for our model. In all panels, we compare local labour markets, which are delineated on the basis of commuting patterns by Kosfeld and Werner (2012). For simplicity, we refer to them as cities.

Panel (a) documents that a city's hometown population—the number of workers who grew up in the city, regardless of where they currently live—is a striking predictor of the city's current population. This is consistent with a large fraction of workers living in their hometowns and suggests an important role for local ties in shaping location decisions as pointed out by Zabek (2024) for the US.[8] Nevertheless, some workers do leave their hometowns. The estimated slope parameter in Panel a) is greater than one (at the 1% significance level), implying that workers are more likely to move from small cities to large cities than vice versa. The most popular explanation for this trend towards higher urbanization, developed in literature going back to Marshall (1890), is that higher productivity leads to higher wages in larger cities, resulting in the so-called urban wage premium. Panel (b) supports this view, as the largest cities, indeed, tend to pay high wages. In relative terms, however, the cost of living in large cities is even higher than wages, due to higher prices for housing and non-housing goods, as shown in panel (c). Indeed, panel (d) shows that large cities are the most successful in attracting workers from other hometowns while offering the lowest real wages. This striking feature of the data suggests that the desire to satisfy the consumption of housing and non-housing goods is not the primary driving force behind the increasing agglomeration of workers in large cities. The obvious alternative explanation is QoL. If workers are willing to give up local ties to move to large cities, only to receive lower real wages, large cities must offer high QoL in return. We call this phenomenon the urban QoL premium.

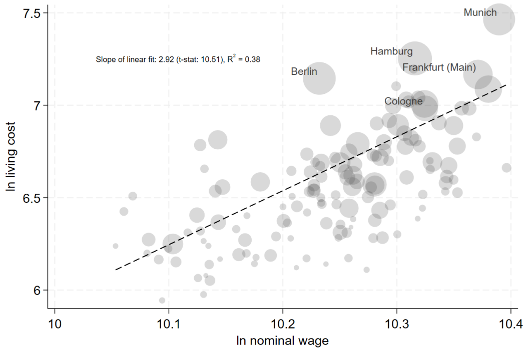
While the intuition is straightforward, the correct measurement of QoL is challenging. The typical approach in the literature rooted within the Rosen-Roback framework is to use the vertical deviation from the linear fitted line in panel (b) as a relative measure of a city's QoL. Mostly, the simplifying assumption is made that non-housing goods are perfectly tradable and that prices do not vary across space—perhaps because housing prices are easier to observe

[8] In our sample of workers who had started an apprenticeship since the early 1990s, this proportion was about 72% in 2015.

Figure 1: Stylized facts of the spatial economy

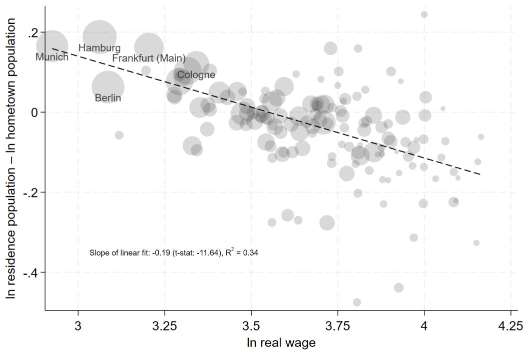


(a) Hometown vs. residence population



(b) Nominal wage vs. living cost

(c) Housing vs. non-housing cost



(d) Real wage vs. residence population surplus

Notes: Unit of observation are the 141 local labour markets (LLM) as defined by Kosfeld and Werner (2012). Employment and nominal wages are from the Employment History (BeH) data set. Hometown refers to the LLM in which a person started apprenticeship training. Regional wages are adjusted for skill composition using regressions of individual wages against LLM and worker fixed effects (Abowd et al., 1999). We compute living costs as the geometric mean of goods and services price levels from Weinand and Auer (2020) as well as housing prices from Ahlfeldt et al. (2023) using an expenditure share on housing of 0.33 and equal shares for non-housing goods and services (Statistisches Bundesamt, 2020). All values are observed in 2015. Subsection 5.1 provides a more detailed description of the underlying data. Marker size is proportionate to total employment.

than non-housing prices. Given that housing and non-housing prices are correlated (see panel c), relying on house prices as the sole source of variation in the cost of living will lead to systematic measurement error. At a deeper conceptual level, another problem is that the Rosen-Roback framework abstracts from idiosyncratic tastes for locations. As a city grows, it becomes increasingly difficult to attract workers because the idiosyncratic utility of moving to a city decreases for the marginal individual. Larger cities must offer higher QoL to compensate for this lower idiosyncratic utility – a phenomenon that is not accounted for in the canonical Rosen-Roback framework. At the same time, it would be premature to conclude that QoL in large cities is necessarily higher than implied by the Rosen-Roback framework because, as shown in panel (a), large cities can draw from larger pools of workers with local ties. Local ties, which are also missing in the Rosen-Roback framework, potentially offset the low idiosyncratic utility draws for workers living in large cities, so that the direction of the bias of the urban QoL premium estimated within the Rosen-Roback framework is theoretically ambiguous. These observations lead us to develop a quantitative framework for measuring QoL that extends the canonical Rosen-Roback framework by allowing for trade cost-induced variation in the prices of tradable goods, input price-induced variation in the prices of non-tradable services (trade frictions), and imperfectly elastic local labour supply due to heterogeneous tastes and local ties (mobility frictions).

3 Model

We develop a spatial general equilibrium model with frictions in the trade of goods and the mobility of workers. The economy consists of a set of cities $i, j \in J$ and is populated by $\bar{L} = \sum_m \bar{L}_m^b$ mobile workers who grew up in different hometowns $m \in J$. We refer to the measure of workers born in a location m as the hometown population, $\bar{L}_m^b$. Each city hosts immobile owners of land, $\bar{T}_i$, and capital, K_i. There is no commuting between cities, so workers live in the city where they work and vice versa.

3.1 Preferences

Worker ω from hometown m living in city i derives utility from the consumption of goods ($C_{i\omega}$) and floor space ($h_{i\omega}$) according to

$$U_{im\omega} = \left(\frac{C_{i\omega}}{\alpha}\right)^{\alpha} \left(\frac{h_{i\omega}}{1-\alpha}\right)^{1-\alpha} \exp[a_{im\omega}], \tag{1}$$

where $C_{i\omega} = (Q_{i\omega}^t/\beta)^{\beta}(q_{i\omega}^n/(1-\beta))^{1-\beta}$ summarizes the consumption of a CES-aggregate of tradable differentiated varieties (superscript t), shipped from origin j to destination i, $q_{ji\omega}^t$,

$$Q_{i\omega}^t = \left[\sum_{j \in J} \left(q_{ji\omega}^t\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

and a local non-traded homogeneous good (superscript n), $q_{i\omega}^n$. The idiosyncratic amenity component $\exp[a_{im\omega}] = \exp[a_{i\omega} + \mathbb{1}\{m = i\} \cdot (\xi/\gamma)]$ is modeled as a stochastic preference shock for each location i, that is shifted upwards if the residence corresponds to the hometown. In particular, $a_{i\omega}$ is drawn from a type-I-extreme value (Gumbel) distribution:

$$F_i(a) = \exp\left(-\tilde{A}_i \exp\left\{-\left[\gamma a + \Gamma\right]\right\}\right) \quad \text{with} \quad \gamma > 0, \tag{3}$$

where $\tilde{A}_i \equiv (A_i)^{\gamma}$ represents the mean of the amenity shock and Γ is the Euler-Mascheroni constant.[9] In the following, we take the component A_i as a measure of local QoL and consider

[9]This implies that shocks are i.i.d across individuals and locations. This approach is established in the literature and has been applied to describe productivity distributions, e.g., in Eaton and Kortum (2002), or individual preferences, e.g., in Ahlfeldt et al. (2015).

it as an exogenous utility shifter that captures the effects of (dis)amenities, as is common in the literature on the estimation of local non-marketed goods (Roback, 1982; Blomquist et al., 1988; Albouy, 2011). The composite parameter $\exp[(\xi/\gamma)] > 1$ captures workers' valuation of local ties in their hometowns. The parameter γ controls the dispersion of individual amenity shocks. Such amenity shocks to individual utility induce idiosyncrasy in tastes in tastes and generate imperfectly elastic local labour supply, leading to imperfect spatial arbitrage (Moretti, 2011).[10] Since all workers in a location make the same consumption choices, we will suppress the subscript ω in the following whenever clarity permits.

3.2 Technology

Developers supply floor space under perfect competition according to a Cobb-Douglas production function that combines capital with location-specific land, $\bar{T}_i$, as in Ahlfeldt et al. (2015):

$$H_i^S = \eta_i \left(\frac{\bar{T}_i}{\delta}\right)^{\delta} \left(\frac{K_i}{1-\delta}\right)^{1-\delta}. \tag{4}$$

η_i denotes total factor productivity, capturing the role of regulatory (e.g. height restrictions) and physical (e.g. a rugged surface) constraints (Saiz, 2010), and δ controls the relative importance of both input factors. Floor space is used by workers for residential purposes and by firms in the non-tradable goods sector as a production input.

Capital is mined by local capital owners at zero cost and supplied at an exogenous rate, r_i^K, set by local municipalities.[11] Both capital owners and landowners spend constant shares β and $1-\beta$ of their incomes, $r_i^K K_i$ and $r_i \bar{T}_i$, on tradables and non-tradables locally. We denote as r_i the endogenous price for one unit of land.[12] Under the assumptions made, we obtain imperfectly elastic floor space supply while ensuring that local expenditures are proportional to the wage bill which helps with tractability. Our formulation nests the setup with one tradable non-housing good and inelastic floor space supply in Monte et al. (2018) as a special case with $\beta = 1$ and $\delta = 1$.

Each location produces a unique tradable and differentiated variety (Armington, 1969) using labour L_i^t as the only production input according to:[13]

$$q_i^t = \varphi_i L_i^t. \tag{5}$$

We also allow for endogenous labour productivity, $\varphi_i = \bar{\varphi}_i L_i^{\zeta}$, which increases in local employment according to the agglomeration elasticity ζ.

[10] Such a setup yields similar predictions to a framework based on region-specific migration frictions (Desmet et al., 2018).

[11] Intuitively, we can think of local capital as bricks and stones retrieved from local mines at a constant marginal cost.

[12] Profit maximisation of developers pins down the value of the local capital input as $r_i^K K_i = \frac{1-\delta}{\delta} r_i \bar{T}_i$.

[13] The setup with labour as the only factor of production follows Monte et al. (2018). Intuitively, tradable goods are produced by manufacturing firms located close to the city margin. Since the agricultural land rent varies little within a country, abstracting from floor space in the production of tradable goods comes with little loss of generality.

Production of the non-tradable good requires both labour and floor space based on the following Cobb-Douglas structure:

$$q_i^n = \nu_i^n \left(\frac{\varphi_i L_i^n}{\mu} \right)^{\mu} \left(\frac{H_i^n}{1-\mu} \right)^{1-\mu}, \tag{6}$$

where L_i^n is the labour demand for the production of non-tradables and ν_i^n is a region-sector-specific productivity shifter. H_i^n denotes floor space input and the Cobb-Douglas parameter μ governs the input shares of each factor.

3.3 Trade

Utility maximization provides optimal aggregate demand at location i for tradable and differentiated goods from origin j, $q_{ji}^t = (p_{ji}^t)^{-\sigma}(P_i^t)^{\sigma-1}\beta E_i$, where p_{ji}^t is the consumer price of a variety produced in j and consumed in location i and $E_i = \alpha w_i L_i + r_i \bar{T}_i + r_i^K K_i$ captures total non-housing expenditures in city i. For local non-traded services we get $q_i^n = (1-\beta)E_i/p_i^n$, where p_i^n denotes the price of services in i. Workers receive region-specific wages w_i as compensation, while $P_i^t = [\sum_j (p_{ji}^t)^{1-\sigma}]^{1/(1-\sigma)}$ describes the price index of the final good dual to Eq. (2). The optimal demand for housing by workers is $H_i^r = (1-\alpha)w_i L_i/p_i^H$ with the price for housing being p_i^H.

Trade in differentiated varieties is subject to bilateral iceberg trade costs such that $\tau_{ji} > 1$ units must be shipped from j for one unit to arrive at destination i. Perfect competition in tradable and non-tradable sectors equates prices to marginal costs, so we get $p_{ji}^t = \tau_{ji} w_j/\varphi_j$ and $p_i^n = \nu_i^n (w_i/\varphi_i^n)^{\mu}(p_i^H)^{1-\mu}$. Furthermore, the trade structure implies an expenditure share of customers in i on differentiated varieties shipped from j as follows:

$$\chi_{ji} = \frac{p_{ji}^t q_{ji}^t}{\sum_k p_{ki}^t q_{ki}^t} = \frac{(\tau_{ji} w_j/\varphi_j)^{1-\sigma}}{\sum_k (\tau_{ki} w_k/\varphi_k)^{1-\sigma}}. \tag{7}$$

3.4 Location choice

Under the distributional assumptions on the idiosyncratic utility component, we obtain the probability that a worker from hometown m lives in location i:

$$\lambda_{im} = \frac{(A_i w_i/\mathcal{P}_i)^{\gamma} \cdot \exp[\mathbb{1}\{m=i\} \cdot \xi]}{\sum_{j \in J} (A_j w_j/\mathcal{P}_j)^{\gamma} \cdot \exp[\mathbb{1}\{m=j\} \cdot \xi]}, \tag{8}$$

where we have defined the aggregate consumer price index $\mathcal{P}_i \equiv \left(P_i^t\right)^{\alpha\beta} (p_i^n)^{\alpha(1-\beta)}(p_i^H)^{1-\alpha}$. Summing over all hometown probabilities, we obtain the residential choice probability:

$$\lambda_i = \sum_m \lambda_{im} = \frac{(A_i w_i/\mathcal{P}_i)^{\gamma}}{\sum_{j \in J} (A_j w_j/\mathcal{P}_j)^{\gamma}} \left(\sum_{m \neq i} \Psi_m^b \bar{L}_m^b + \Psi_i^b \cdot \exp[\xi] \bar{L}_i^b \right) / \bar{L}, \tag{9}$$

with $\Psi^b_m = \left(1 + \frac{(\exp[\xi]-1)(A_m w_m/\mathcal{P}_m)^\gamma}{\sum_{j\in J}(A_j w_j/\mathcal{P}_j)^\gamma}\right)^{-1} < 1$ the utility discount associated with having left the hometown. The probability of residing in i increases in QoL and nominal wages and declines in the aggregate consumer price index. Due to local ties, the residential choice probability also depends on the distribution of the hometown population. For given hometown population, the probability of living in i increases in ξ, owing to an increasing value of local ties, $\Psi^b_i \cdot \exp[\xi] > 1$. The number of workers residing in i is $L_i = \lambda_i \bar{L}$.[14]

The mobility of workers equalizes the expected utility in equilibrium, which is given by

$$\bar{W} = \ln\left[\sum_{j\in J}(A_j w_j/\mathcal{P}_j)^\gamma \cdot \exp[\mathbb{1}\{m=j\}\cdot\xi]\right]^{\frac{1}{\gamma}}. \tag{10}$$

3.5 General equilibrium

Land market and floor-space market clearing. On the land market, the constant expenditure rule implies $r_i = \delta p^H_i H^S_i/\bar{T}_i$. Combining this equation with the profit-maximising supply of floor-space, $H^S_i = \tilde{\eta}_i \bar{T}_i r_i^{1-\delta}/\delta$, and adjusted floor space productivity, $\tilde{\eta}_i \equiv \eta_i/(r^K_i)^{1-\delta}$, delivers the equilibrium relationship between land rents and floor-space prices:

$$r_i = \left(\tilde{\eta}_i p^H_i\right)^{\frac{1}{\delta}}. \tag{11}$$

To derive the floor space market equilibrium, $H^S_i = H^D_i$, we start with the demand side. Floor space is needed for residential purposes, H^r_i, and as an input for the production of non-tradables, H^n_i, so $H^D_i = H^r_i + H^n_i$. Using the fact that the return to floor-space input in the production of non-tradables is a constant share $1-\mu$ of expenditure, we obtain $H^n_i = (1-\beta)(1-\mu)[\alpha w_i L_i + p^H_i H^D_i]/p^H_i$, where the second term in brackets is total income of capital owners and landowners. Demand for residential housing is given as $H^r_i = (1-\alpha)w_i L_i/p^H_i$ as introduced in Section 3.1. Replacing land rents in optimal housing supply according to Eq. (11) delivers $H^S_i = \tilde{\eta}^{\frac{1}{\delta}}\bar{T}_i(p^H_i)^{\frac{1-\delta}{\delta}}/\delta$. The market clearing price for floor space solves $H^S_i = H^D_i$ and is thus given by

$$p^H_i = \left(\frac{\tilde{\alpha}\delta w_i L_i}{\tilde{\eta}_i^{\frac{1}{\delta}}\bar{T}_i}\right)^\delta, \tag{12}$$

where $\tilde{\alpha} \equiv (1/[1-(1-\mu)(1-\beta)] - \alpha)$ is a constant.

Tradable goods market clearing. Since tradable goods firms spend revenues from all regions, weighted by expenditure shares, on labour input, we obtain:

$$w_i L^t_i = \sum_{j\in J}\frac{(\tau_{ij}w_i/\varphi_i)^{1-\sigma}}{\sum_k(\tau_{kj}w_k/\varphi_k)^{1-\sigma}}\beta\left(\alpha+\tilde{\alpha}\right)w_j L_j, \tag{13}$$

[14]Note that if the utility gain from living in one's hometown is negligible (e.g. $\exp(\xi) \to 1$), there is no discount associated with living elsewhere, such that $\left(\sum_{m\neq i}\Psi^b_k L^b_m + \left(\Psi^b_i \cdot \exp[\xi]\right)\bar{L}^b_i\right) \to \bar{L}$.

where we used the equilibrium conditions on the markets for floor space, land and capital.

Local services market clearing. Since local services firms spend the share μ of local revenues on labour input, we obtain:

$$w_i L_i^n = \mu(1-\beta)(\alpha+\tilde{\alpha})\, w_i L_i \tag{14}$$

Local labour resource constraint. All workers in city i must work either in the tradable goods or the local services sector:

$$L_i = L_i^t + L_i^n \tag{15}$$

National labour market clearing. Total employment in i must equate to labour supply.

$$L_i = \lambda_i \bar{L} \tag{16}$$

Given the model primitives, a general equilibrium of the economy is referenced by a vector of the endogenous objects $\mathbf{V} = \{L_i^n, L_i^t, p_i^H, p_i^n, P_i^t, r_i, w_i\}$ and a scalar $\bar{W}$ which are jointly determined by Eqs. (11)–(16) and the definition of the aggregate consumer price index. We solve for $\mathbf{V}$ using a conventional numerical fixed-point algorithm described in Appendix A.2. For given primitives and structural parameters as well as values of $\mathbf{V}$, there is a recursive structure that solves for all other endogenous objects. While the gravity trade structure in our model could theoretically lead to multiple equilibria, it is well understood that the equilibrium is unique under plausible parameterizations (Allen and Arkolakis, 2014; Allen et al., 2024). Indeed, the solutions returned by our solution algorithm are insensitive to the chosen starting values under the parameterizations chosen in Sections 4 and 5.

4 Monte Carlo study

To understand the measurement error arising from the absence of spatial frictions in the Rosen-Roback framework, we assume that the true DGP corresponds to the quantitative spatial model outlined in Section 3. As there is no closed-form solution to the model, we proceed with a Monte Carlo study. We solve the model for randomised values of its primitives, including QoL, as well as selected parameters, and generate the Rosen-Roback measure based on the resulting equilibrium wages and rents. The measurement error is defined as the relative difference between the Rosen-Roback measure and the 'true' QoL in the DGP. We calculate the bias in the estimated urban QoL premium by comparing how the Rosen-Roback and 'true' measures of QoL increase in the equilibrium city population.

4.1 Setting

For our Monte Carlo study, we generate 1,000 artificial countries within a stylized geography of a square with a side length of 500 km. We overlay this square with 12×12 equally sized grid cells corresponding to $J = 144$ artificial cities.[15] We compute all bilateral distances between

[15] The side length and number of grid cells are chosen to approximate the actual geographic area and number of cities (local labour markets) of Germany, as described in more detail in Section 5.

the geographic centroids of the grid cells and parameterize trade costs as $\tau_{ij} = (\exp[-\iota * \ln dist_{ij}])^{\frac{1}{1-\sigma}}$, using $\iota = -1$ and $\sigma = 5$ as conventional in the trade literature (Head and Mayer, 2014).[16] Using bilateral distances, we compute a measure of market potential $\mathcal{M}_i = \sum_{j \in J}(1/dist_{ij})$ as an (inverse) measure of remoteness.

For all $1,000 \times J = 144,000$ artificial cities, we first randomly draw the hometown population $\bar{L}^b_m$, which we take as exogenous. The consensus in the literature is that city sizes follow Zipf's Law and can be modelled by log-normal distributions (Eeckhout, 2004). Therefore, we draw a city's log hometown population from a normal distribution with a mean of 0 and a standard deviation of 0.85, which delivers a rank-size coefficient close to one. We normalize the hometown population so that $\sum_m \bar{L}^b_m = \bar{L}$. Similarly, we draw fundamentals $\{\ln A_i, \ln \bar{\varphi}_i, \ln \tilde{\eta}_i\}$ in logs from normal distributions with mean zero and a standard deviation of 0.25 which ensures that equilibrium residence population, L_i, also approximates Zipf's Law.[17] We normalize these fundamentals as well as hometown population and market potential by the values of a numéraire location.

For each of the 1,000 artificial countries, we draw values of the parameters governing the heterogeneity of idiosyncratic tastes, γ, and the valuation of local ties, ξ, from uniform distributions in the limits $[1.1; 10]$ and $[0, 10]$ respectively. Empirical estimates of the taste heterogeneity parameter range from 2-3 for larger spatial units such as counties and states (Monte et al., 2018; Fajgelbaum et al., 2019) to higher values of up to $\gamma = 7$ for smaller units such as housing blocks (Ahlfeldt et al., 2015; Heblich et al., 2020). Less is known about the workers' valuation of local ties. Our reference point is a value of $\xi = 5$, which ensures that, on average, about 50% of workers live in their hometown, as documented by Zabek (2024) for the US.

We set the expenditure share on non-housing goods to $\alpha = 0.7$ (Combes et al., 2019), the share of expenditure on tradable goods at total non-housing expenditure to $\beta = 0.5$ (Caliendo et al., 2018b), the housing supply elasticity to $\delta = 0.3$ (Baum-Snow and Han, 2024), and the share of labour in the production of local services to $\mu = 0.8$ (Greenwood et al., 1997). For the agglomeration elasticity, we use $\zeta = 0.02$ as a typical value found by studies controlling for unobserved worker heterogeneity (Combes and Gobillon, 2015).

Under this parameterization, we solve the model 1,000 times to obtain values of the equilibrium vector $\mathbf{V}$ for each artificial country (see Appendix A.2 for details). We end up with an artificial world of 144,000 cities in 1,000 countries, for which we observe prices and quantities of all goods and factors, so that we can easily compute the canonical Rosen-Roback measure of QoL, as well as more refined measures that account for selected spatial frictions.

[16] As they are not our main parameters of interest, we normalize the sector-specific production shifter in the non-tradable sector, ν^n_i, to unity for all locations in our Monte Carlo study. Table A2 provides an overview of selected parameters and definitions.

[17] We truncate the normal distributions by 0.65 from below and above to avoid generating cities with implausibly large or small populations. All the main results are insensitive to the truncation.

4.2 Measurement error in quality of life

To understand the measurement error in the canonical Rosen-Roback measure, it is instructive to reformulate Eq. (9) and express all model elements x in ratios relative to a numéraire location j, such that $\hat{x} \equiv x_i/x_j \; \forall \; i \in J$. This delivers the relative QoL in the most general version of our model as

$$\hat{A} = \frac{(\hat{P}^t)^{\alpha\beta}(\hat{p}^n)^{\alpha(1-\beta)}(\hat{p}^H)^{1-\alpha}}{\hat{w}} \left(\hat{L}/\hat{\mathcal{L}}\right)^{\frac{1}{\gamma}}, \tag{17}$$

where we define $\mathcal{L}_i \equiv (\exp[\xi] - 1)\, \Psi_i^b \bar{L}_i^b + \sum_{m\in J} \Psi_m^b \bar{L}_m^b$.

Notice that Eq. (17) nests QoL as in the canonical Rosen-Roback case that abstracts from trade costs ($\tau_{ij} \to 1$ and, hence, $\hat{P}^t \to 1$), local services ($\beta \to 1$), idiosyncratic tastes ($\gamma \to \infty$) and local ties ($\gamma \to \infty$ and/or $\xi \to 0$):[18]

$$\hat{A}_{RR} = \frac{\left(\hat{p}^H\right)^{1-\alpha}}{\hat{w}}. \tag{18}$$

Relating Eq. (18) to Eq. (17) and taking logs delivers the QoL measurement error within the Rosen-Roback framework as well as the contributions of each of the four spatial frictions:

$$\mathcal{E} \equiv \ln \frac{\hat{A}_{RR}}{\hat{A}} = \underbrace{-\,\alpha\beta \ln \hat{P}^t}_{\text{trade costs}} \; \underbrace{-\,\alpha(1-\beta)\ln \hat{p}^n}_{\text{local services}} \; \underbrace{-\,(1/\gamma)\ln \hat{L}}_{\text{idiosyncratic tastes}} \; \underbrace{+\,(1/\gamma)\ln \hat{\mathcal{L}}}_{\text{local ties}} \tag{19}$$

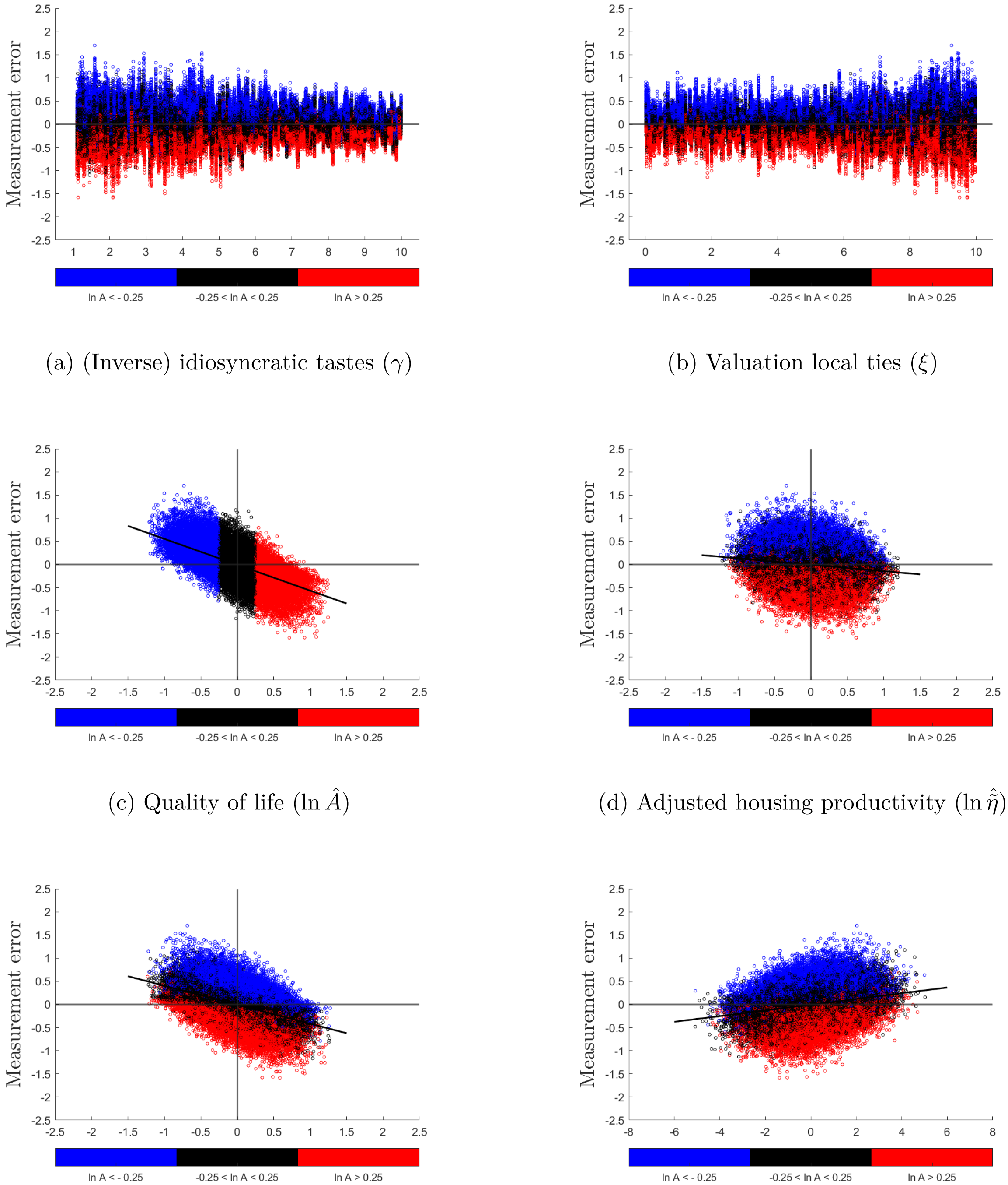
4.2.1 Determinants of the measurement error

In Figure 2 we scatter the measurement error defined in Eq. (19) against various forcing variables in our Monte Carlo experiments. In each panel, each point represents an artificial city in one of the artificial countries. A common feature to all panels is that QoL differences (relative to the numéraire location) are generally underestimated within the Rosen-Roback framework. For positive QoL differences in the DGP marked by red dots ($\ln \hat{A} > 0.25$), the error is negative for the most part. The error is mostly positive for negative differences (blue dots for $\ln \hat{A} < -0.25$), which also implies that the magnitude of the relative QoL difference is underestimated. One explanation is that for imperfectly mobile workers, differences in QoL must be larger than the inverse real wage differentials alone would suggest, since a high-QoL city, in attracting more workers, must compensate the marginal worker for lower idiosyncratic utility and foregone local ties to other places.

The role of mobility frictions is substantiated by panels (a) and (b), which plot the measurement error against the values of the country-specific structural parameters $\{\gamma, \xi\}$. Panel (a) reveals that the measurement error converges asymptotically to zero as workers' tastes become more homogeneous and local labour supply becomes more elastic, i.e. at higher values

[18] We refer to the baseline case in Roback (1982) without non-tradable goods and also allow for $\delta < 1$, which implies an elastic supply of land. As can easily be seen below, this assumption does not affect our results.

Figure 2: Measurement error in the full model



(a) (Inverse) idiosyncratic tastes (γ)

(b) Valuation local ties (ξ)

(c) Quality of life ($\ln \hat{A}$)

(d) Adjusted housing productivity ($\ln \hat{\tilde{\eta}}$)

(e) Fundamental labour productivity ($\ln \hat{\tilde{\varphi}}$)

(f) Hometown population ($\ln \hat{\tilde{L}}^b$)

Notes: Measurement error is defined as $\mathcal{E} = (1/\gamma)(\ln \mathcal{L}^b - \ln \hat{L}) - \alpha\beta \ln \hat{P}^t - \alpha(1-\beta) \ln \hat{p}^n$. We run $N = 1{,}000$ Monte Carlo simulations for a synthetic economy with $J = 144$ local labour markets.

of γ. Formally, the third and fourth terms in Eq. (19) approach zero as $\gamma \to \infty$. Intuitively, compensating differentials in real wages to offset idiosyncratic taste shocks become less important when workers care less about the particularities of individual cities. Local ties also become less important because their utility value, $\exp(\xi/\gamma)$, is a decreasing function of γ. For a related reason, we observe in panel (b) that the magnitude of the measurement error is smaller when local ties are weaker at given values of γ, i.e. at lower values of ξ. Formally, the fourth term in Eq. (19) approaches zero as $\xi \to 0$. Intuitively, compensating differentials in real wages to offset local ties become less important when workers are less attached to their hometowns.

Turning to the city-specific fundamentals, panel (c) shows that the (magnitude of the) measurement error increases in the (magnitude of the) relative QoL differences. Intuitively and all else equal, a city with a high QoL is more attractive and grows larger. In a world with mobility frictions, growing cities attract marginal workers with lower idiosyncratic utility and an increasing share of workers with local ties in other hometowns. An increasingly larger city-specific QoL must compensate for these declining worker-specific utility components to keep the marginal worker indifferent. Therefore the measurement error in the Rosen-Roback QoL measure—which abstracts from idiosyncratic tastes and local ties—is larger for high QoL cities that grow larger.

Panels (d) and (e) illustrate how variation in the other fundamentals adds to the problem. Panel (d) reveals that the (magnitude of the) measurement error increases in the (magnitude of the) relative adjusted differences in housing productivity. Intuitively, higher floor space productivity and lower interest rates on capital are floor space supply shifters that, given a downward sloping housing demand, reduce floor space prices for reasons unrelated to housing demand. However, in the Rosen-Roback framework, lower rents due to higher floor space supply are misattributed to floor space demand (and labour supply), as housing demand (and labour supply) is assumed to be perfectly elastic. Likewise, panel (e) reveals that the (magnitude of the) measurement error increases in the (magnitude of the) relative fundamental labour productivity differences. Intuitively, fundamental labour productivity is a labour demand shifter which, given an upward-sloping labour supply, raises wages for reasons unrelated to labour supply. However, in the Rosen-Roback framework, higher wages due to higher labour productivity are misattributed to labour supply, which is assumed to be perfectly elastic.

Naturally, cities with relative advantages in QoL, housing productivity, and fundamental labour productivity grow larger, ceteris paribus. The common implication of panels (c) to (e) is that measurement error increases in the resident population. As shown in panel (f), the effect of a relatively larger hometown population is the opposite. To develop intuition, it is useful to recall that, holding the hometown population constant, a large residence population implies a marginal worker deriving a lower idiosyncratic utility. This decrease in worker-specific utility must be compensated for by a higher city-specific QoL in order to keep the marginal worker indifferent. This is the intuition behind the third term in Eq. (19). Of course, a larger residence population can also arise when a city has a larger hometown population, as more workers are likely to stay to maintain local ties. These worker-specific local ties compensate for a low idiosyncratic utility, and hence there is less need for the city to offer a high QoL to keep the marginal worker indifferent. Therefore, the effect of the hometown population, which enters via $\hat{\mathcal{L}}$, points in the opposite direction to the residence population, $\hat{L}$, in Eq. (19). The

Table 1: Heterogeneity in measurement error

Frictions controlled:	(1)	(2)	(3)	(4)	(5)
Trade Costs		✓			
Local services			✓		
Local ties				✓	
Idiosyncratic tastes					✓
Measurement error: Intercept	-0.288	-0.305	-0.300	-0.169	-0.090
Parameters and regional fundamentals:					
(Inverse) taste heterogeneity: γ-3	0.026	0.023	0.023	0.015	0.018
Strength of local ties: ξ-5	-0.017	-0.015	-0.015	0.015	-0.037
Market access: $\ln \hat{\mathcal{M}}$	-0.087	-0.156	-0.048	-0.053	-0.004
Quality of life: $\ln(\hat{A}/1.5)$	-0.711	-0.754	-0.741	-0.427	-0.212
Relative floor-space productivity : $\ln \hat{\eta}$	-0.189	-0.205	-0.270	-0.105	0.014
Relative worker productivity: $\ln \hat{\varphi}$	-0.547	-0.611	-0.591	-0.309	-0.130
Relative hometown population: $\ln \hat{L}^b$	0.073	0.062	0.065	-0.132	0.223
Interaction effects:					
$\ln \hat{\mathcal{M}} * (\gamma - 3)$	0.010	0.007	0.009	0.008	0.005
$\ln(\hat{A}/1.5) * (\gamma - 3)$	0.065	0.056	0.058	0.039	0.042
$\ln \hat{\eta} * (\gamma - 3)$	0.022	0.019	0.020	0.019	0.009
$\ln \hat{\varphi} * (\gamma - 3)$	0.054	0.047	0.048	0.033	0.033
$\ln \hat{L}^b * (\gamma - 3)$	-0.005	-0.004	-0.004	0.025	-0.031
$\ln \hat{\mathcal{M}} * (\xi - 5)$	-0.006	-0.004	-0.006	0.006	-0.013
$\ln(\hat{A}/1.5) * (\xi - 5)$	-0.042	-0.036	-0.038	0.039	-0.091
$\ln \hat{\eta} * (\xi - 5)$	-0.015	-0.013	-0.014	0.011	-0.031
$\ln \hat{\varphi} * (\xi - 5)$	-0.036	-0.031	-0.032	0.034	-0.078
$\ln \hat{L}^b * (\xi - 5)$	0.018	0.016	0.017	-0.022	0.045
Observations	144,000	144,000	144,000	144,000	144,000
Adjusted R^2	0.977	0.985	0.984	0.783	0.807

Notes: Each column represents a different measurement error for a location with 50% higher quality of life than the numéraire location, so $\hat{A} = 1.5$. In column (1), we ignore all spatial frictions; in column (2), we control for trade costs; in column (3), we control for differences in non-tradable service prices; in column (4) we control for local ties and in column (5) we control for migration frictions. All explanatory variables are expressed relative to a numéraire location. The mobility friction parameter γ and local ties valuation ξ are re-scaled to have a zero value at $\gamma = 3$ and $\xi = 5$, respectively, so we can interpret the intercept as the measurement error for otherwise identical locations. Given the high number of Monte Carlo iterations, all coefficients are highly significant at all common levels so we do not report standard errors for the sake of brevity.

important implication for the correct measurement of QoL is that accounting for idiosyncratic tastes without accounting for local ties, and vice versa, may increase rather than decrease measurement error.

In Figure 2, we have focused on the intuition behind the third and fourth terms in Eq. (19), as there is an intuitive connection between residence and hometown population and the randomized primitives of the model (the forcing variables in the Monte Carlo simulations). The link between the prices of tradable goods and local services that enter Eq. (19) and the primitives of the model is less direct since goods and services prices depend on input prices, which are endogenous objects in our general equilibrium model. In any case, the correlation between the measurement error, $\mathcal{E}$, and tradable goods prices, $\hat{P}^t$, and local services prices, $\hat{p}^n$ is weaker than those reported in Figure 2, suggesting that trade frictions are less consequential for the correct measurement of QoL than mobility frictions (see Appendix B.2).

4.2.2 Multivariate analysis of measurement error

One overarching takeaway of Figure 2 is that the measurement error in the Rosen-Roback QoL measure cannot be summarized by a single number. It depends on the fundamentals of an artificial city as well as the heterogeneity of idiosyncratic tastes and the strength of local ties in an artificial country. In fact, it must depend on the interactions. At higher values of γ and lower values of ξ, idiosyncratic utility and local ties—from which the Rosen-Roback framework abstract—become less relevant. Since labour supply and housing demand become more elastic, labour demand and housing supply shocks that confound the interpretation of real wage differences as compensating differentials become less consequential.

To quantify the measurement error, $\mathcal{E}$, in light of this heterogeneity, we regress $\mathcal{E}$ against the artificial country-specific values of the parameters governing the dispersion of idiosyncratic tastes, γ, and the strength of local ties, ξ, the artificial city-country-specific fundamentals $\{\hat{A}, \hat{\tilde{\eta}}, \hat{\tilde{\varphi}}\}$, hometown population, $\hat{\tilde{L}}^b$, and the artificial city-specific market access measure, $\hat{\mathcal{M}}$, which summarizes relative advantages due to trade gravity, as well as the interaction of γ and ξ with $\{\hat{A}, \hat{\tilde{\eta}}, \hat{\tilde{\varphi}}, \mathcal{M}, \hat{\tilde{L}}^b\}$. For a more intuitive interpretation of the constant, we transform the regressors as follows: For the relative QoL measure, we use $\ln(\hat{A}/1.5)$; for idiosyncratic taste heterogeneity, we use $\gamma - 3$; for the strength of local ties, we use $\xi - 5$; for all other regressors, we simply take the log. The constant then summarizes the average measurement error for an artificial city that has a 50% higher QoL than the numéraire city, is identical to the numéraire city in all other respects, and is located in an artificial country where $\gamma = 3$—arguably the consensus value in the literature (Redding, 2016)—and $\xi = 5$, which ensures a typical share of about 50% of workers living in their hometowns (Zabek, 2024).

We report the results of the regression analysis in Column (1) of Table 1. Given the high R^2, a large number of observations, and the strong economic rationale for the relevance of the covariates, it is no surprise that all estimated regression coefficients are statistically significant at the 1% level. Hence, we omit standard errors for a more compact presentation. For the reference artificial city (with a relative QoL advantage of 50%) in the reference artificial country ($\gamma = 3, \xi = 5$), we find that the Rosen-Roback framework underestimates the true QoL $\hat{A}$ by 25% ($= \exp[-0.288] - 1$). In keeping with expectations, the magnitude of the measurement error is smaller when there is less idiosyncratic taste heterogeneity. For the measurement error to become zero for our reference city, we would require an increase in γ by 11 units. This implies a dispersion parameter in the range of $\gamma = 14$, which is well outside the typical range of estimates in the literature. Likewise, the magnitude of the measurement error is smaller when local ties are weaker. However, even at the theoretical lower bound of $\xi = 0$ (a reduction by five units), the measurement error remains sizable at -18.4%. Hence, it seems unlikely that there are many countries in the real world where measurement error is negligible.

The measurement error increases in positive relative differences in market access, QoL, floor space productivity, and exogenous labour productivity. In keeping with Figure 2, relative differences in QoL and fundamental labour productivity are particularly consequential. For example, the measurement error increases to -43.5% when a city has a relative QoL advantage of 100% instead of 50% over the numéraire city. Maintaining a relative QoL advantage of 50% and adding a 50% advantage in terms of relative labour or housing productivity, increases the bias to -40% or -30.5%, respectively.[19] We require an increase in γ by approximately 10 to bring the marginal effects of these covariates close to zero, which is well outside the range of estimates in the literature. Reducing ξ to zero reduces these marginal effects by about one-third.

In further keeping with Figure 2, the effect of positive differences in the hometown population points in the opposite direction. For a city with a relative QoL advantage of 50% over the numéraire city, the measurement error will be approximately zero only if the hometown population is about 50 times the one of the numéraire location. In this case, the Rosen-Roback measure would be accidentally correct, as the measurement error from the fourth term in Eq. (19) would offset the error originating from the other terms. More generally, this counterweight implies that it is crucial to take local ties into account when considering the effects of idiosyncratic tastes in measuring QoL, otherwise there is an inherent risk of turning an underestimation of QoL differences into an overestimation.

4.2.3 Relative importance of trade and mobility frictions

Having established that the measurement error in the Rosen-Roback QoL measure is sizable and highly heterogeneous, we now turn to quantifying the relative importance of spatial frictions. To this end, we compute three adjusted measurement errors of the form $\mathcal{E} - \mathcal{X}$, where $\mathcal{X}$ corresponds to one of the terms highlighted in Eq. (19). We use these adjusted errors as dependent variables in regressions that are otherwise identical to Table 1, Column (1) throughout Columns (2)-(5). The constants can be interpreted as the measurement error for the reference city (with a relative QoL advantage over the numéraire location of 50% in a country with $\gamma = 3$ and $\xi = 5$) that prevails when we control for the respective friction.

As mentioned in the context of Figure 2, simple scatter plots suggest that the correlations between $\mathcal{E}$ and the trade-friction-related variables $\{\hat{P}^t, \hat{p}^n\}$ are weaker than those with the mobility-friction-related variables $\{\hat{L}, \hat{\hat{L}}^b\}$. Table 1 substantiates this impression. In Column (4), the magnitude of the measurement error for the reference location is reduced by 37.8% relative to Column (1) (to 15.6 pp) once local ties are accounted for. In Column (5), the reduction even amounts to 65.6% (to 8.6 pp) when idiosyncratic tastes are accounted for instead. In contrast, the magnitude of the measurement error for the reference location hardly changes when we account for variation in tradable goods (Column 1) and local services (Column 2) prices. In fact, measurement error even slightly increases. By implication, leaving frictional trade unaccounted for causes upward measurement error in the Rosen-Roback QoL measure. The reason is that judging from the Rosen-Roback measure, a high QoL city appears less affordable than it is since tradable and non-tradable goods prices are relatively lower in high-QoL cities. Intuitively, a city with a greater QoL, ceteris paribus, has a lower wage due

[19]We calculate the change in measurement error when assuming regions' primitives differ by a further 50% according to $(1.5^{\text{coef}} - 1) * \exp(-0.288)$.

to enhanced labour supply. A lower wage maps into a lower price of local services for which labour is the most important input. The logic extends to tradable goods prices since households also consume differentiated varieties from local producers. The implication is that accounting for trade frictions improves the measurement of QoL only if mobility frictions are already accounted for. Perhaps counterintuitively, using a refined cost-of-living index that accounts for variations in prices of tradable goods and local services within the Rosen-Roback framework might actually increase measurement error.

As a final piece of evidence to inform the priorities when improving the measurement of QoL, we present the results of a Shapley decomposition of the variance of the measurement error across all artificial cities and countries. We obtain the following relative contributions of the four terms on the right-hand side of Eq. (19): tradable goods, 10.14%; local services, 4.45%; idiosyncratic tastes, 18.80%; and local ties, 66.61%. As expected given the evidence reviewed so far, mobility frictions are more important than trade frictions. However, the impact of the latter, especially that of tradable goods, is not negligible. Reconciling the results of the Shapley decomposition with those reported in Table 1, we conclude that trade frictions may have a sizable impact on the measurement error for individual cities but less so on the systematic error for cities with similar QoL. This is because QoL is less correlated with market access than city size, which endogenously responds to QoL.

For the interested reader, we provide a sensitivity analysis in which we separately increase or decrease the values of parameters $\{\alpha, \beta, \mu, \sigma, \delta, \iota\}$ by 25% in Appendix Section B.3 to better reflect the range of parameter estimates from the literature. All conclusions presented above are qualitatively and quantitatively insensitive to these changes. Quantitatively, changes in the value of σ and α (for floor-space productivity) are most consequential. Yet, even for the alternate values of σ and α, the measurement error for the reference city remains within a close range of 23.4-26% (vs. 25% in the baseline).

4.3 Urban quality of life premium

The results in Table 1 imply that the measurement error, $\mathcal{E}$, is correlated with city size since it is correlated with various fundamentals that determine city size. Consequentially, we expect biased estimates of the urban QoL premium within the Rosen-Roback framework, though the direction of the bias is theoretically ambiguous.

To quantify this bias, we follow the literature and define the urban QoL premium as the elasticity of QoL with respect to city size (Ahlfeldt and Pietrostefani, 2019; Albouy, 2011). We know from Eq. (9) that in the DGP, we can parameterise city size as $\hat{L}(\hat{A}, \hat{\tilde{\eta}}, \hat{\tilde{\varphi}}, \hat{\mathcal{M}}, \hat{\tilde{L}}^b) = c\hat{A}^{\gamma} \exp\left(\epsilon(\hat{\tilde{\eta}}, \hat{\tilde{\varphi}}, \hat{\mathcal{M}}, \hat{\tilde{L}}^b)\right)$, where c is a constant and $\epsilon(\hat{\tilde{\eta}}, \hat{\tilde{\varphi}}, \hat{\mathcal{M}}, \hat{\tilde{L}}^b)$ is a residual term that captures that city size also depends on the other structural fundamentals $\{\hat{\tilde{\eta}}, \hat{\tilde{\varphi}}, \hat{\mathcal{M}}, \hat{\tilde{L}}^b\}$. Following the literature, we can estimate the urban QoL premium using the following OLS specification:

$$\ln \hat{A} = \tilde{c} + \rho \ln \hat{L} + \left[-\frac{1}{\gamma}\epsilon\right], \tag{20}$$

where $\tilde{c} \equiv -\frac{1}{\gamma} \ln c$ and the term in brackets constitutes the regression residual. Notice that we do not expect the estimated urban QoL premium, $\hat{\rho}$, to correspond to $\frac{1}{\gamma}$ as implied by Eq. (9) since $\hat{L}$ and ϵ are necessarily correlated given their dependence on similar fundamentals. Therefore, the estimated urban QoL premium is purely descriptive and simply summarises how QoL differs between cities of different sizes; it does not measure the causal effect of city size on QoL. The Rosen-Roback framework, however, does not even recover this descriptive statistic correctly. Using Eq. (19) in Eq. (20), we obtain:

$$\ln \hat{A}_{RR} = \tilde{c} + \rho_{RR} \ln \hat{L} + \left[\mathcal{E} - \frac{1}{\gamma} \epsilon \right]. \tag{21}$$

Theoretically, OLS estimation of Eq. (21)—which corresponds to the standard approach in the literature—will deliver an estimate $\hat{\rho}_{RR} \neq \hat{\rho}$ if $\mathbb{E}(\hat{L}'\mathcal{E}) \neq 0$. Since we control the DGP, it is straightforward to compute the estimation bias $\mathcal{B} = \hat{\rho}_{RR} - \hat{\rho}$ from the estimates of two separate OLS regressions of $\ln \hat{A}$ and $\ln \hat{A}_{RR}$ against $\ln \hat{L}$ within our artificial data set.

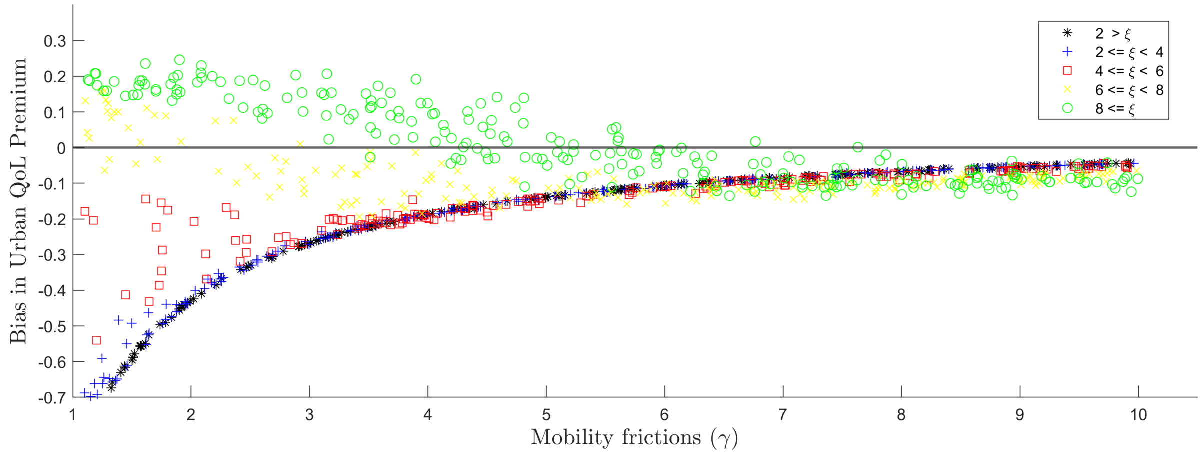
We expect $\mathcal{B} \neq 0$ since, according to Eq. (19), several components of $\mathcal{E}$ are correlated with $\hat{L}$. First, there is a mechanical correlation with $\hat{L}$ (third term). Second, as discussed earlier, we expect the prices of tradable goods and local services prices to be correlated with city size (first two terms). Third, $\hat{\mathcal{L}}$, which captures local ties, is normally correlated with the resident population, $\hat{L}$, since the hometown population, $\hat{\tilde{L}}^b$, is correlated with both $\hat{L}$ (see Eq. (9)) and $\hat{\mathcal{L}}$ (see Eq. (17)).

Since the contribution of $\{\hat{P}^t, \hat{p}^n\}$ to $\mathcal{E}$ is modest, as shown in Section 4.2, the bias, $\mathcal{B}$, will depend strongly on the strength of the correlation between $\hat{\mathcal{L}}$ and $\hat{L}$. This correlation is governed by ξ, which determines the strength of local ties. If $\xi = 0$, there is no correlation between $\hat{\mathcal{L}}$ and $\hat{L}$, since $\hat{\mathcal{L}}$ collapses to unity. The mechanical correlation between $\mathcal{E}$ and $\hat{L}$ then implies an underestimation of the urban QoL premium within the Rosen-Roback framework. However, given the opposite signs of the third and fourth terms in Eq. (17), the negative bias can turn into a positive bias if ξ is sufficiently large (since the correlation between $\hat{\mathcal{L}}$ and $\hat{L}$ will be positive).

Intuitively, a city with a larger residence population, given hometown population and real wage, must compensate the marginal worker for a lower idiosyncratic utility through a QoL that is larger than measured by the Rosen-Roback framework (where idiosyncratic tastes are missing). This leads to a downward bias of the urban QoL premium in the Rosen-Roback framework. However, if the hometown population is sufficiently large, local ties will ensure that, for a given real wage, the city will retain a large residence population even if QoL is lower than measured by the Rosen-Roback framework (where local ties are also missing). This can lead to an upward bias of the urban QoL premium in the Rosen-Roback framework. Therefore, we expect the strength of local ties (governed by ξ) to quantitatively and qualitatively determine the bias in the estimated urban QoL premium.

From separate estimations of Eqs. (20) and (21) for each artificial country, we obtain an artificial country-specific measure of the bias in the Rosen-Roback estimate of the urban QoL premium, $\mathcal{B}$. Each estimate is represented by a point in Figure 3. We plot $\mathcal{B}$ as a function of

Figure 3: Bias in urban quality of life premium



Notes: The bias in the urban QoL premium is defined as $\mathcal{B} = \rho_{RR} - \rho$ where $\hat{\rho}_{RR}$ and $\hat{\rho}$ as estimated from artificial-country-specific regressions of the Rosen-Roback QoL measure and the true (within our DGP) QoL measure against residence population (in logs).

the artificial country-specific idiosyncratic taste heterogeneity parameter, γ, differentiating by the strength of local ties governed by ξ. As expected, the bias approaches zero as the value of γ increases, and the largest contributors to $\mathcal{E}$ in Eq. (19) are reduced (terms three and four). At the consensus value of $\gamma = 3$, we observe large heterogeneity in the bias across artificial countries ranging from about -0.3 to +0.25. This is a large range, given that costs and benefits associated with urbanization generally scale in city size at elasticities close to zero (Ahlfeldt and Pietrostefani, 2019).

For $\xi < 6$, the Rosen-Roback framework consistently underestimates the urban QoL premium, such that $\mathcal{B} < 0$. Yet, for very strong local ties, e.g. $\xi > 8$, we may obtain an overestimation bias. Such values, however, are much larger than our estimate of $\xi = 5.6$ from the real-world data set used in Sections 2 and 5 (see Appendix C.2). Moreover, we consider our estimate to be an upper bound in international comparison since the share of the hometown population in the resident population, at 0.7, is much higher than the typical value of 0.5 (Zabek, 2024). We therefore consider it likely that Rosen-Roback-based estimates of the urban QoL premium suffer from an underestimation bias in most countries, which may explain why the literature has struggled to find positive urban QoL premiums (Ahlfeldt and Pietrostefani, 2019; Albouy, 2011, 2016).

In defining priorities for improving the estimation of the QoL premium, it is worth recalling that mobility frictions dominate trade frictions as a source of measurement error in QoL (see Section 4.2.2). Indeed, controlling for selected contributors to the bias in the estimated urban QoL premium, as defined in Eq. (19) confirms that this insight carries through to the bias in the urban QoL premium. Thus, accounting for mobility frictions is more important than accounting for trade frictions to reduce estimation bias. When addressing mobility frictions, however, it is important to account for idiosyncratic tastes and local ties simultaneously, otherwise, there is a risk that the bias may actually increase in absolute terms (see Appendix B.4 for details).

5 Application

We now quantify the model in a real-world setting to illustrate the impact of spatial frictions on the measurement of QoL. Using Germany as a case in point, we compute three QoL measures: a measure that corresponds to the conventions in the Rosen-Roback literature, $\hat{A}_{RR}$; a measure that is fully consistent with our model, $\hat{A}$, and a crude-data version of our preferred measure, $\hat{A}_{CD}$, which may be more widely applicable due to parsimonious data requirements. We discuss our data and the quantification of the model in Section 5.1 before comparing the resulting QoL and implied urban QoL premiums in Sections 5.2 and 5.3.

5.1 Data and quantification

As an empirical counterpart to the cities indexed by i in the model, we choose 141 German labour market regions defined by Kosfeld and Werner (2012) based on commuting data. For simplicity, we refer to these regions as cities when presenting our results. The centre of a labour market region is the municipality with the largest number of workers. We provide a brief discussion of the dataset we collect for these units below and refer to Appendix C.1 for further details.

We use the Integrated Employment Biographies (IEB) from Germany's Institute for Employment Research to obtain employment at the workplace and wages in 2015. The data cover the universe of 16-65 year old regular employees with social security insurance in Germany. We restrict the sample to workers who have completed vocational training (about 65% of all workers), as this allows us to code their hometown as the city where they received their vocational qualification. This choice is motivated by the observation that most workers in Germany receive vocational training in the cities where they completed their schooling.[20] We further restrict the sample to workers who have completed their vocational training after 1990 to avoid selection due to missing information on vocational training completed in East Germany. To address top-coding, we apply a procedure to impute censored wages based on Card et al. (2013). We aggregate daily imputed wages into annual wages and regress these, after taking logs, against individual fixed effects and region-year fixed effects, recovering the latter as a sorting-adjusted region-year wage index (Glaeser and Maré, 2001; Combes et al., 2008).

To construct the aggregate consumer price index, we rely on information about floor-space prices and local prices for tradable and non-tradable goods. We take 2015 floor-space prices from Ahlfeldt et al. (2023) who provide a property price index for the 141 Geman local labour market regions based on asking prices from immobilienscout24.de – Germany's largest online platform. This index controls for property characteristics and commuting, in line with Combes et al. (2019). Regional tradable goods and local services prices for 2015 are based on county-

[20]Empirical evidence for this observation is provided by Hoffmann and Wicht (2023), who use microdata from the National Educational Panel Survey (NEPS) to examine the extent of spatial mobility among school leavers who continue on to apprenticeships. According to their results, about 78% of the 2011-2017 school leaver cohorts start apprenticeship training in a company located in the same labour market region where they completed their schooling, while 22% start training in a different region.

level price indices from Weinand and Auer (2020). We aggregate their values to local labour market regions using employment weights.

To complete the quantification of the model-consistent QoL measure according to Eq. (17), we set the expenditure share of housing to $1-\alpha = 0.33$ (Statistisches Bundesamt, 2020), the expenditure share for tradable goods to $\beta = 0.34$ (based on own estimation) and the preference heterogeneity parameter to $\gamma = 3$ (Krebs and Pflüger, 2023). Since we are not aware of an extant estimate of the value of local ties in Germany, we estimate ξ using a log-linearised version of Eq. (8). To this end, we regress the log of the bilateral residence-birthplace population, $L_{im} = \lambda_{im}\bar{L}$, against the dummy denoting hometown-residence bilaterals, $\mathbb{1}\{m = i\}$, residence fixed effects that absorb all other objects in the numerator, and hometown fixed effects, which absorb multilateral resistance in the denominator. The coefficient on the dummy delivers $\xi = 5.6$ (see Appendix C.2 for details). This estimate is somewhat larger than the value of $\xi = 5$ calibrated in Section 4, which is consistent with the workers in our sample, at 70%, having an unusually high probability of residing in their hometown (Zabek, 2024, documents a probability of 50% for the US).[21]

Our theory-consistent QoL measure, $\hat{A}$, is admittedly somewhat data-demanding. For one thing, our microdata enables the computation of a hometown population measure, at least for a subset of the total population. In other contexts, however, researchers may not be able to observe the distribution of hometown population for workers currently observed in the labour market. For another, we observe prices of tradable goods and local services, but regional non-housing prices are not available for many countries and periods. Therefore, we also construct a variant of our QoL measure that requires only crude data, $\hat{A}_{CD}$. For one thing, we set the prices of tradable goods and local services to uniform values, which, according to the results of our Monte Carlo simulations in Section 4, should introduce limited error. For another, we use a standard population measure from the census as a proxy for the residence population and the 30-year lag of the resident population as a proxy for the hometown population since most workers currently active in the labour market grew up where their parents lived when they were young.[22] In another variant, largely relegated to the appendix, we exploit the fact that the structure of our model allows the construction of theory-consistent price indices using more accessible variables such as regional wages, sectoral employment and bilateral trade costs (see Appendix A.3).

5.2 Quality of life measures

We use the data described in Section 5.1 to compute our measure of QoL, $\hat{A}$, for German cities according to Eq. (17). Since there is no analytical solution for $\hat{A}$, we use a numerical solution

[21] For postcodes, Büchel et al. (2020) find a lower effect of return migration on migration probabilities in their conditional logit model, which suggests that local ties are weaker when measured on the neighbourhood scale.

[22] We use regional population data from the years 2015 and 1985, respectively. The data are provided by the Federal Office for Building and Regional Planning at the county level, which we aggregate to the level of the 141 labour market regions that are used in the empirical analysis.

algorithm described in Appendix A.1.2.[23] We refer interested readers to our GitHub toolkit, which provides a convenient way to replicate our measure in other contexts.[24]

We map this novel QoL index in the left panel of Figure 4. In the right panel, we show how this measure deviates from the canonical Rosen-Roback measure, $\hat{A}_{RR}$, defined in Eq. (18). A striking feature of Figure 4, which reinforces the descriptive evidence from Section 2, is that the largest cities (Berlin, Hamburg, Munich) offer the highest QoL. Second tier cities such as Frankfurt, Cologne or Düsseldorf also offer high QoL. It is worth noting that these large cities also appear as high QoL cities in the canonical Rosen-Roback measure (see Appendix C.3 for a map). However, as shown in the right-hand panel of Figure 4, the Rosen-Roback measure understates QoL in large cities compared to our preferred QoL measure. The differences between the two measures extend beyond the largest cities, suggesting that there is considerable scope for our new measure to influence QoL rankings.

We illustrate how our new measure changes the QoL ranking in Table 2, focusing on the five cities with the highest and the five cities with the lowest values in our preferred QoL measure. Columns (1) and (2) summarize the QoL ranking based on the quantitative spatial model (defined in Eq. (17), referred to as QSM, best data). Columns (3) and (4) show the corresponding QoL ranking for the Rosen-Roback case, which does not control for differences in residence population, hometown population, and prices of non-housing goods (defined in Eq. (18)). To ease the comparison, Column (5) computes the relative difference between the Rosen-Roback and the QSM measures. The next three Columns (7)-(9) replicate Columns (3)-(5) for the crude-data version of our measure, which uses the deep lag of residence population as a proxy for hometown population and abstracts from differences in non-housing prices.

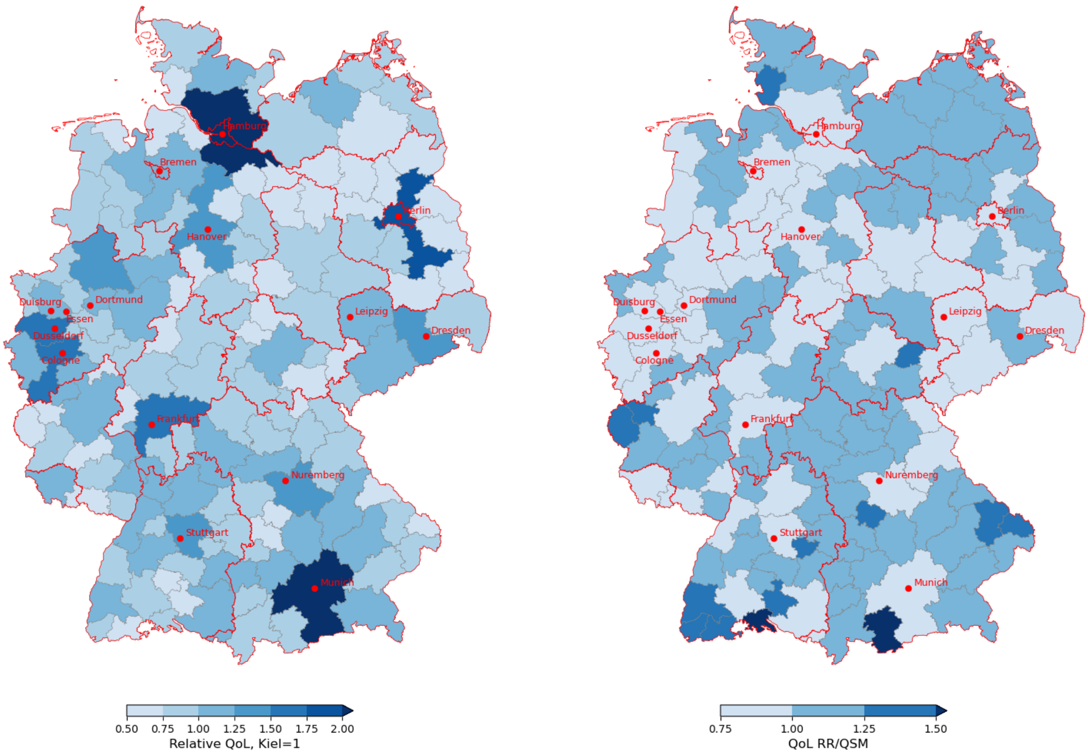
Confirming the visual impression from Figure 4, the range of the QoL measure based on the QSM is about 13% larger than that of the Rosen-Roback measure. For all five top ranking QoL cities, we obtain higher QoL values (relative to the numéraire city of Kiel) using the quantitative spatial model. Similarly, the measure derived from the quantitative spatial model is smaller for all five bottom ranking cities. Thus, the real-world example summarized in Table 2 confirms one of the main findings of our Monte Carlo experiments in Section 4, which is that the Rosen-Roback framework tends to understate relative QoL differences.

Since there is sizable heterogeneity in the relative differences between the two QoL measures (see Column (5)), the ranking changes. When the QoL is inferred from the quantitative spatial model instead of the Rosen-Roback framework, Hamburg overtakes Munich to become the city with the highest QoL. Frankfurt climbs one rank (from 5$^{\text{th}}$ to 4$^{\text{th}}$), and Düsseldorf even climbs seven ranks (from 12$^{\text{th}}$ to 5$^{\text{th}}$). Similar ordinal effects are observed at the bottom of the ranking: Freyung-Grafenau drops by 11 ranks, Vulkaneifel even by 33 ranks, and Stendal climbs by two.

[23]Our solutions are insensitive to starting values under the chosen parameterization. This is consistent with the existence of a unique mapping from observed outcomes to fundamental amenity value (conceptually equivalent to QoL) in the absence of spatial spillovers, as shown by Allen and Arkolakis (2014), as long as the congestion force is large enough.

[24]The toolkit is available at `https://github.com/Ahlfeldt/ABRSQOL-toolkit` and includes functions with user-friendly syntax for MATLAB, Stata, R, and Python.

Figure 4: Quality of life in Germany



(a) Quantitative spatial model (QSM)

(b) Rosen-Roback vs. QSM

Notes: Both maps illustrate $\ln(\hat{A})$. Panel (a) is based on the quantitative spatial model (QSM); panel (b) shows the ratio of RR over QSM.

The left panel of Figure 5 illustrates that there is substantial ordinal error in Rosen-Roback-based QoL rankings across the entire distribution. In fact, besides Berlin (ranked 3$^{\text{rd}}$), only Würzburg (ranked 25$^{\text{th}}$) and Celle (ranked 122$^{\text{nd}}$) maintain the same rank in both rankings. There are extreme cases of measurement error; for example, Chemnitz climbs 64 ranks (to 40$^{\text{th}}$), whereas Lörrach and Waldshut fall by 50 ranks (to 88$^{\text{th}}$ and 107$^{\text{th}}$, respectively). On average, the absolute difference between the QoL ranks derived from the Rosen-Roback framework and our quantitative spatial model is 17. The right panel of Figure 5 illustrates how the measurement error in our crude-data version of our preferred measure is substantially lower than in the Rosen-Roback measure. On average, the absolute difference between the QoL ranks derived from the Rosen-Roback framework and our quantitative spatial model is about 10 (about two-thirds of the Rosen-Roback measure). Hence, our crude-data variant of our QoL measure represents a potentially useful alternative to the Rosen-Roback measure in sparse-data environments.

The data set used in this exemplary application is usually rich in that we observe wages, employment (at residence and hometown), and house prices in a panel setting. However, we only observe one cross-section of tradable goods prices and local services prices. The

Table 2: Quality of life rankings

	QSM, best data		Rosen-Roback			QSM, crude data		
	Rank	$\hat{A}$	Rank	$\hat{A}_{RR}$	(4)/(2)	Rank	$\hat{A}_{CD}$	(7)/(2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hamburg	1	2.081	2	1.737	0.834	2	1.648	0.792
München	2	2.033	1	1.963	0.965	3	1.644	0.809
Berlin	3	1.851	3	1.678	0.907	1	1.758	0.950
Frankfurt am Main	4	1.696	5	1.520	0.896	4	1.441	0.850
Düsseldorf	5	1.566	12	1.335	0.853	5	1.392	0.889
...	...	...	...	...	...	...	...	...
Freyung-Grafenau	137	0.538	126	0.688	1.278	139	0.547	1.017
Kronach	138	0.526	132	0.651	1.237	140	0.538	1.021
Stendal	139	0.522	141	0.575	1.101	130	0.617	1.183
Vulkaneifel	140	0.519	107	0.773	1.488	141	0.525	1.010
Uelzen	141	0.510	137	0.637	1.248	138	0.548	1.073
Standard deviation		0.276		0.253			0.223	

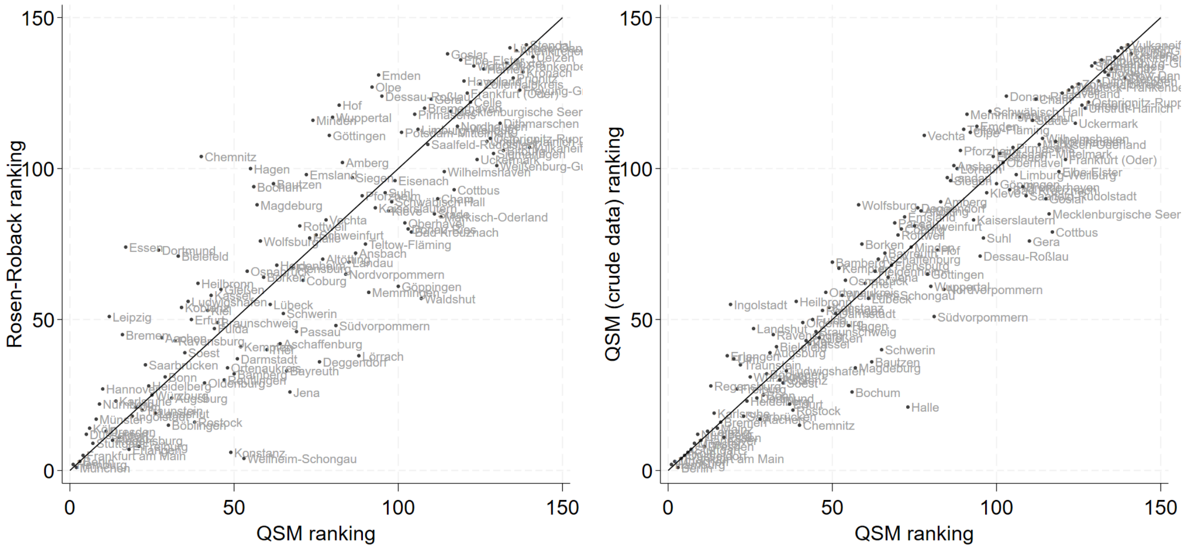
Notes: The table shows measures of relative QoL for the labour market regions with the 5 highest and the 5 lowest values according to the full specification in Eq. (17) (*QSM*). The numéraire location is *Kiel*. Columns (1) and (2) report QoL estimates and the corresponding ranks based on Eq. (17). Columns (3) and (4) report QoL estimates and the corresponding ranks based on Eq. (18). Columns (6) and (7) report QoL estimates and the corresponding ranks based on Eq. (17) using census population as a proxy for residence population, the 30-year lag of residence population as a proxy for hometown population and uniform prices for non-housing goods.

structure of our model, however, allows us to predict prices of tradable goods and local services as discussed in Appendix A.3. Reassuringly, we find that a QoL measure that uses model-generated prices of tradable goods and local services instead of observed prices closely resembles our preferred QoL measure in 2015. Computing this measure for 2007 and 2019 reveals a great degree of persistence within the top-10 cities in the QoL ranking, but significant changes outside. In particular, cities that were historically dependent on heavy industry or coal mining have seen their relative quality of life decline in recent decades. As non-housing prices are often unavailable for small spatial units, the model's ability to predict non-housing price indices may prove useful beyond our specific application.

5.3 Urban quality of life premium

Figure 4 and Table 2 reveal that, for the largest cities in Germany, the Rosen-Roback framework generates lower QoL-values than the quantitative spatial model. This suggests a downward bias in the estimated urban QoL premium derived from the Rosen-Roback framework, consistent with theoretical expectations discussed in Section 4.3. To quantify the downward bias for Germany, we estimate Eqs. (20) and (21) and report the results in Figure 6a. As already suggested by Figure 4, we find a well-defined positive correlation between QoL and city size for both measures. However, the urban QoL premium is much larger when estimated from the quantitative spatial model. The city size elasticity of the QoL measure from the quantitative spatial model is 0.29. This implies that ceteris paribus, a German city with twice the residence

Figure 5: Comparison of QoL rankings



(a) Rosen-Roback (A_{RR})

(b) QSM, crude data (A_{CD})

Notes: QSM ranking is the ranking based on QoL measure derived from the quantitative spatial model, $\hat{A}$. Rosen-Roback ranking is the same derived from the Rosen-Roback QoL measure, $\hat{A}_{RR}$. QSM, crude data is the ranking based on the QoL measure derived from the quantitative spatial model using the 30-year lag of residence population as a proxy for hometown population and uniform prices for non-housing goods.

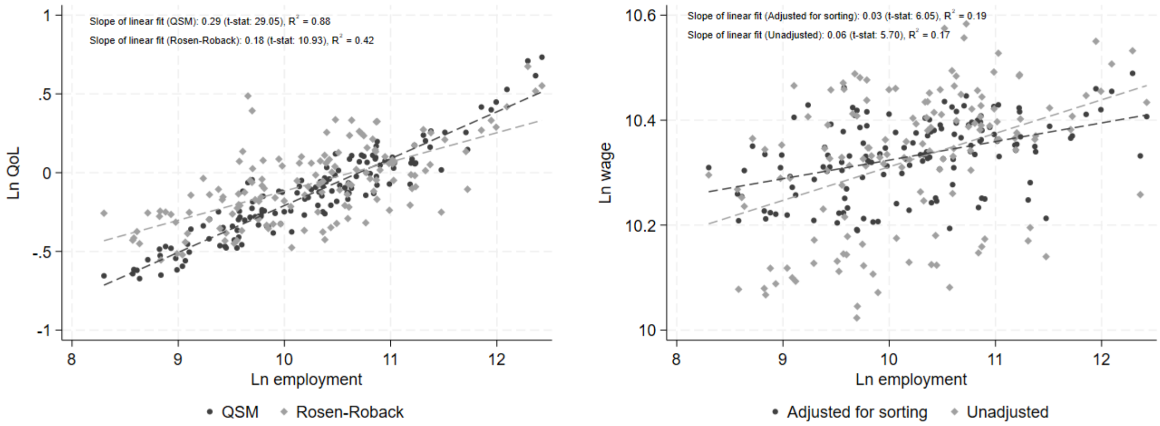
population offers a $2^{0.29} - 1 = 22\%$ higher QoL. At $2^{0.18} - 1 = 13\%$, this premium is almost halved when derived from the Rosen-Roback framework. If we are willing to believe that the quantitative spatial model is a plausible approximation of the true DGP in Germany, the downward bias in the Rosen-Roback framework is large at 40%. Of course, it is quite conceivable that the urban QoL premium is smaller in other countries, such as the US, where Rosen-Roback estimates do not suggest a positive urban QoL premium (Albouy, 2011). At the same time, the relatively large downward bias found for Germany may suggest that more countries may have a positive urban QoL premium than is generally assumed (as already suggested by the Monte Carlo simulations in section 4).

To put the estimated urban QoL premium into perspective, Figure 6b provides analogous estimates of the urban wage premium. A large literature has documented higher wages in cities, and Germany is no exception. The average wage increases in city size at an elasticity of about 0.06. When skill heterogeneity is controlled for through individual worker fixed effects, the estimate halves. [25] These estimates are within the typical range found in the literature (Combes and Gobillon, 2015). Strikingly, even the lower bound estimate of the urban QoL premium derived from the Rosen-Roback framework exceeds the upper bound estimate of the urban wage premium unadjusted for the skill composition of the workforce.

It is worth recalling that the urban QoL premium and the urban wage premium are de-

[25] Conditional on worker fixed effects, the urban wage premium is identified from the change in wages that workers experience when they move to cities of different sizes (Combes et al., 2008).

Figure 6: Urban quality-of-life premium vs. urban wage premium



(a) Urban quality of life premium

(b) Urban wage premium

Notes: QSM is the QoL measure derived from the quantitative spatial model, $\hat{A}$. Rosen-Roback is the same derived from the Rosen-Roback QoL measure, $\hat{A}_{RR}$. Adjusted worker wages are from regressions of log wages against worker and region-fixed effects, where the latter are recovered as a regional wage index adjusted for sorting.

scriptive concepts. They summarize the benefits workers derive from being located in large cities in Germany. Whether higher wages and QoL arise from favourable fundamentals that attract workers or genuinely city-size-related agglomeration economies is a separate question. Regardless of the underlying mechanisms, however, Figure 6 suggests that in Germany, high QoL is an even more important reason for workers to locate in large cities than high wages.[26] This is a striking result given that, since Marshall (1890), the literature has mostly focused on productivity as the main reason why workers concentrate in cities.

6 Conclusions

We show that by abstracting from spatial frictions, estimates of QoL derived from the Rosen-Roback framework suffer from a downward measurement error that increases in city size. This result reconciles a growing literature that has emphasized the consumption benefits that cities offer (Glaeser et al., 2001; Diamond, 2016) with a classical literature on the measurement of QoL that has found limited evidence for an urban QoL premium (Roback, 1982; Albouy, 2011). We document a positive QoL premium for Germany and argue that it may extend to many other countries once spatial frictions are accounted for. Indeed, QoL may be just as important an agglomeration force driving urbanization as productivity.

Our results have important implications that extend beyond the QoL literature. Since the pioneering work of Roback (1982), the neoclassical spatial equilibrium framework has been the workhorse tool for the valuation of amenities (Glaeser and Gottlieb, 2009; Greenstone, 2017).[27]

[26] Note that in our quantitative spatial model, a one per cent increase in QoL has the same effect on indirect utility as a one per cent increase in wages.

[27] Typical examples include clean air (Chay and Greenstone, 2005), safety (Linden and Rockoff, 2008), or public schools (Cellini et al., 2010).

To this end, the literature correlates differences in real living costs—often approximated by differences in house prices—with differences in amenities to recover their shadow prices. The role of the shadow price is to map a difference in amenity endowment between two cities into a difference in worker utility. The downward bias in the variance of QoL in the Rosen-Roback framework, therefore, suggests a downward bias in the estimated shadow price derived from the Rosen-Rosen framework, especially in the largest locations. Quantifying the magnitude of this bias is an important avenue for further research.

As shown by Fajgelbaum and Gaubert (2020), accounting for spatial differences in QoL is crucial for deriving optimal spatial policies.[28] In spatial equilibrium, high-QoL regions have lower real wages. Since the marginal value of real consumption is higher, fiscal transfers to regions with higher QoL should be welfare enhancing under realistic parameterizations and all else equal. A key finding of our analysis is that the canonical Rosen-Roback framework understates QoL in large cities. By implication, spatial policies derived within the Rosen-Roback framework may lead to the underprovision of public goods in large cities, leading to misallocation. Quantifying the welfare cost of sub-optimal spatial policies that may arise from the mismeasurement of QoL represents another avenue for future research.

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A Model

This appendix adds to Section 3 in the main paper, which introduces our quantitative spatial model. We discuss how to quantify the model to rationalize observed data in Section A.1. In Section A.2, we outline the numerical procedure used to solve for the equilibrium values within the model conditional on given primitives. This procedure is, in particular, employed in our Monte Carlo simulation study as described in section 4.

A.1 Quantifying the model

In this appendix, we outline how to quantify our model from Section 3 to rationalize observed data and solve for the primitives of the model $(A_i, \tilde{\eta}_i, \bar{\varphi}_i, \nu_i^n)$.

Quantifying the general equilibrium model requires data on employment by location and sector (L_i^n, L_i^t), regional wage data (w_i) and local price levels that vary by expenditure category (p_i^H, p_i^n, P_i^t). Furthermore, one requires data on the hometowns of all employed workers $(\bar{L}_m^b)$ and the area of all locations $(\bar{T}_i)$ as well as their bilateral distances $(dist_{ij})$. Apart from these data, we also require values for all structural parameters $\{\alpha, \beta, \gamma, \delta, \zeta, \iota, \mu, \sigma, \xi\}$.

In a nutshell, the quantification consists of three steps. First, we settle on parameter values for $\{\alpha, \gamma, \delta, \zeta, \iota, \mu, \sigma, \xi\}$. Second, we infer the value for β that is implicitly determined by observed data conditional on set parameter values. Third, we invert the structural fundamentals given the full set of parameter values $\{\alpha, \beta, \gamma, \delta, \zeta, \iota, \mu, \sigma, \xi\}$ and observed data.

Table A1: Parameter values for model quantification (Germany as a case in point)

Parameter	Description	Approach	Source
Preferences			
$1 - \alpha = 0.3$	Housing share in consumption	Set	Combes et al. (2019)
$\gamma = 3$	Labour supply elasticity	Set	Krebs and Pflüger (2023)
$\beta = 0.34$	Tradable goods share	Est.	Inferred from data
$\xi = 5.6$	Hometown valuation	Est.	Own estimation
Production			
$\delta = 0.3$	Share of land in production	Set	Baum-Snow and Han (2024)
$\iota = 1$	Distance elasticity	Set	Head and Mayer (2014)
$\sigma = 5$	Regional varieties substitution	Set	Head and Mayer (2014)
$\mu = 0.8$	Labour share in production	Set	Greenwood et al. (1997)
$\zeta = 0.02$	Productivity spillovers	Set	Combes and Gobillon (2015)

A.1.1 Structural parameters

Table A1 provides an overview of our parameter value choices. All parameter values are set to established values in the literature or estimated from data with one exception. The tradable goods share in consumption of non-housing goods, β, is implicitly determined by the observed values of endogenous variables $\{w_i, L_i^n\}$ and the set parameter value for μ. We solve for the consumption share of non-tradables, $1-\beta$, that rationalizes aggregate goods-market-clearing in the sector for non-tradable services, Eq. (14):

$$1 - \beta = \frac{\sum_{i \in J} w_i L_i^n}{(1-\mu)\sum_{i\in J} w_i L_i^n + \mu \sum_{i \in J} w_i L_i}.$$

We estimate the value for the hometown values parameter ξ using a moment condition that directly follows from our model (see Appendix C.2 for details). For all other parameters, we use canonical parameter values from the literature.

A.1.2 Inverting quality of life

In this Appendix, we discuss how our structural model can be used to invert quality of life in the presence of spatial frictions. As highlighted in Eq. (17), relative QoL $\hat{A}$ is perfectly identified up to a normalization (or numéraire location) and given by:

$$\hat{A} = \frac{(\hat{P}^t)^{\alpha\beta}(\hat{p}^n)^{\alpha(1-\beta)}(\hat{p}^H)^{1-\alpha}}{\hat{w}} \left(\hat{L}/\hat{\mathcal{L}}\right)^{\frac{1}{\gamma}},$$

In Algorithm 1, we use pseudo-code to outline how a dataset with observed endogenous variables, $\{L_i, \bar{L}_i^b, p_i^H, p_i^n, P_i^t, w_i\}$, the exogenous variable, $\bar{L}_i^b$, and the structural parameters $\{\alpha, \beta, \gamma, \xi\}$ can be used to identify QoL under mobility (local ties, idiosyncratic tastes) and trade frictions (variation in tradable goods and non-tradable service prices).

Allen and Arkolakis (2014) show that in the absence of spatial spillovers (in productivity and amenity), there is a unique mapping from the data to the primitives of the model for given values of structural parameters as long as the congestion force (here arising from inelastically supplied land) dominates the agglomeration force (here arising from love for variety and positive trade costs). The practical implication of this property is that our QoL solver is invariant to starting values. To substantiate this insight in the context of our model (which does not feature spatial spillovers in productivity of or amenity), we draw N=1000 different starting values for A_i from a uniform distribution in the bounds $(0.5; 1.5)$ and invert the relative quality of life for each of these starting guesses of the solver. Reassuringly, in each of these simulations, we invert exactly the same level of relative QoL, such that we conclude that the observed data uniquely maps into the model fundamentals.

For the interested user, we provide an accessible toolkit that implements the pseudo-code of Algorithm 1 as a MATLAB function, a Stata ado programme, as well as R and Python packages. The toolkit is available at `https://github.com/Ahlfeldt/ABRSQOL-toolkit`.

Algorithm 1: Numerical solution algorithm to invert QoL

Start with values for variables $\{L_i, \bar{L}_i^b, p_i^H, p_i^n, P_i^t, w_i\}$ and structural parameters $\{\alpha, \beta, \gamma, \xi\}$

Normalise employment and birth-place population data, such that $\bar{L} = \sum_{i \in J} L_i = \sum_{i \in J} \bar{L}_i^b$

Calculate relative values of all variables with respect to a numéraire location (e.g. in "hat-algebra"): $\hat{\mathcal{V}} = \{\hat{L}, \hat{\bar{L}}^b, \hat{p}^H, \hat{p}^n, \hat{P}^t, \hat{w}\}$

Solve for the aggregate consumer price index $\mathcal{P}_i \equiv \left(P_i^t\right)^{\alpha\beta} (p_i^n)^{\alpha(1-\beta)} (p_i^H)^{1-\alpha}$.

Set convergence parameter $\kappa \in (0, 1)$

Set precision rule to govern deviation between guesses and model solution.

Set $count = 1$

Guess values of A_i and normalise relative to numéraire location

while $count < maxiter$ **do**

  Solve for Ψ_i^b by using its definition below Eq. (9), such that $\Psi_i^b = \left(1 + \frac{(\exp[\xi]-1)(A_i w_i/\mathcal{P}_i)^\gamma}{\sum_{j \in J}(A_j w_j/\mathcal{P}_j)^\gamma}\right)^{-1}$

  Solve for $\mathcal{L}_i$ by using its definition below Eq. (17), such that $\mathcal{L}_i \equiv (\exp[\xi] - 1)\, \Psi_i^b \bar{L}_i^b + \sum_{m \in J} \Psi_m^b \bar{L}_m^b$

  Solve for $\hat{\mathcal{L}}$.

  Solve for relative QoL, $\hat{A}^{\text{new}}$, by using Eq. (17).

  Check deviation between guesses and model solution

$$target = round(abs(\hat{A}^{\text{new}} - \hat{A}), precision)$$

  if $target == 0$ **then**

    break;

  else

    Update initial guesses or updated values of $\hat{A}$:

$$\hat{A}^{\text{up}} = A^{\text{up}} = \kappa \cdot \hat{A}^{\text{new}} + (1 - \kappa) \cdot \hat{A}$$

    Use updated values and re-iterate

$$A_i = \hat{A} = \hat{A}^{\text{up}}$$

Result: Equilibrium values of $\hat{A}$

A.1.3 Solving for worker and floor-space productivities

We solve for adjusted floor space productivities using the market clearing condition on the market for floor space, Eq. (12):

$$\tilde{\eta}_i = \frac{1}{p_i^H} \left(\frac{\tilde{\alpha} \delta w_i L_i}{\bar{T}_i}\right)^\delta,$$

Relative worker productivities are identified—up to a normalization—from goods market clearing in the market for tradable goods, Eq. (13). In doing so, we first calibrate the bilateral trade cost matrix to follow the trade literature (Head and Mayer, 2014): we compute all bilateral distances between the geographic centroids of the regions while parameterising trade costs as $\tau_{ij} = (\exp[-\iota * \ln dist_{ij}])^{\frac{1}{1-\sigma}} d_j$, where we set $\{\iota = -1, \sigma = 5\}$ and introduce d_j as a destination-specific component of trade costs. This component captures regional attributes that affect trade costs to all other regions, such as direct access to the highway network, a natural harbour, or an airport, and allows the model to exactly match observed tradable goods prices.

In Algorithm 2, we use pseudo-code to outline how a dataset with the endogenous variables $\{L_i, L_i^t, P_i^t, w_i\}$, the structural parameters $\{\alpha, \beta, \zeta, \iota, \mu, \sigma\}$ and bilateral distances can be used to identify worker productivities—up to a normalization—as well as the trade-cost shifter.

Lastly, we use data on wages (w_i), floor space prices (p_i^H), price levels in the non-tradable sector (p_i^n) and previously inverted productivities ($\hat{\varphi}$) to identify the relative productivity shifters that are specific to the service sector:

$$\hat{\nu}^n = \frac{\hat{p}^n}{(\hat{w}/\hat{\varphi})^{\mu}(\hat{p}^H)^{1-\mu}}.$$

Algorithm 2: Numerical solution algorithm to invert worker productivities

Start with values for variables $\{L_i, L_i^t, P_i^t, w_i\}$ and structural parameters $\{\alpha, \beta, \zeta, \iota, \mu, \sigma\}$

Calculate relative tradables prices and wages $\{\hat{P}^t, \hat{w}\}$

Set convergence parameter $\kappa \in (0, 1)$

Set precision rule to govern deviation between guesses and model solution.

Set $count = 1$

Set $iter = 1$

Guess values of d_j

while $count < maxiter$ **do**

  Calculate $\tau_{ij} = (\exp[-\iota * \ln dist_{ij}])^{\frac{1}{1-\sigma}} * d_j$

  while $iter < maxiter$ **do**

    Guess values of φ_i

    Calculate right-hand side of Eq. (13), rhs_i

    Check deviation between rhs_i and $w_i L_i^t$

$$target = round(abs(rhs_i - w_i L_i^t, precision)$$

    if $target == 0$ **then**

      break;

    else

      Update initial guesses or updated values of φ_i:

$$\varphi_i^{\text{up}} = \varphi_i / [rhs_i / (w_i L_i^t)]$$

      Use updated values and re-iterate

$$\varphi_i = \kappa \varphi_i^{\text{up}} + (1 - \kappa) \varphi_i$$

  Calculate model-consistent price levels for tradable goods:

$$\hat{P}^{t,\text{model}} = [\sum_i \tau_{ij} (\hat{w}/\hat{\varphi})^{1-\sigma}]^{1/(1-\sigma)}$$

  Check deviation between $\hat{P}^t$ and $P_j^{t,\text{model}}$

$$target = round(abs(\hat{P}^t - \hat{P}^{t,\text{model}}, precision)$$

  if $target == 0$ **then**

    break;

  else

    Update initial guesses or updated values of d_j:

$$d_j = \hat{P}^t / \hat{P}^{t,\text{model}}$$

Calculate $\hat{\bar{\varphi}} = \hat{\varphi} \hat{L}^{-\zeta}$

Result: Equilibrium values of $\{d_j, \hat{\bar{\varphi}}\}$

A.2 Solving the model

Within quantitative spatial models, there are typically no analytical solutions for the spatial equilibrium, and our model is no exception. Still, there is a unique mapping from the model's primitives to the equilibrium vector $\mathbf{V} = \{L_i^n, L_i^t, w_i, r_i, p_i^H, \mathcal{P}_i\}$ which we exploit in a standard fixed-point numerical solver that converges rapidly. As discussed in the main paper, we calculate all bilateral distances between all grid points, $dist_{ij}$, and then parameterize trade costs as $\tau_{ij} = (\exp[-\iota * \ln dist_{ij}])^{\frac{1}{1-\sigma}}$. Further, we normalize the sector-specific production shifter for non-tradable services, ν_i^n, to unity in all locations.

Algorithm 3 then provides pseudo-code to outline how identified model fundamentals $\{A_i, \bar{L}_i^b, \bar{T}_i, \tilde{\eta}_i, \bar{\varphi}_i, \tau_{ij}\}$ and the structural parameters $\{\alpha, \beta, \gamma, \delta, \zeta, \mu, \xi, \sigma\}$ can be combined to solve for the equilibrium vector $\mathbf{V}$.

In the absence of spatial spillovers (in productivity and amenity), there is generally a unique solution in a quantitative spatial model if the congestion force (here arising from inelastically supplied land) dominates the agglomeration force (here arising from love for variety and positive trade costs) under the chosen parameterization (Allen and Arkolakis, 2014; Redding and Rossi-Hansberg, 2017) The practical implication of this property is that our equilibrium solver is insensitive to starting values. To substantiate this insight in the context of our model, we perform an additional Monte Carlo simulation where we show that randomization of the starting values to the solving Algorithm 3 still yields the same equilibrium vector $\mathbf{V}$. In particular, we draw $N = 1000$ random starting vectors for the vectors $\{L_i, w_i\}$ from a uniform distribution in the bounds $\{0.5; 1.5\}$, but normalize the guesses for employment by a common factor such that they sum to $\bar{L}$ in the aggregate. We then solve for the equilibrium vector $\mathbf{V}$ for each of the randomized sets of starting values. Reassuringly, in each of the N simulations, we solve for the same spatial equilibrium, which we take as an indication that the spatial equilibria for which we solve in the Monte Carlo study of Section 4 are unique (at the very least for empirically relevant parametrizations).

Algorithm 3: Numerical solution algorithm

Given values for primitives $\{A_i, \bar{L}_i^b, \bar{T}_i, \tilde{\eta}_i, \bar{\varphi}_i, \tau_{ij}\}$ and structural parameters $\{\alpha, \beta, \gamma, \delta, \zeta, \mu, \xi, \sigma\}$ define set of endogenous variables $\mathbf{V} = \{L_i^n, L_i^t, w_i, r_i, p_i^H, \mathcal{P}_i\}$

Set convergence parameter $\kappa \in (0, 1)$

Set precision rule to govern deviation between guesses and model solution.

Set maximum number of iterations to *maxiter*

Set $count = 1$

Guess values of w_i and L_i

while $count < maxiter$ **do**

- Solve for L_i^n by using Eq. (14).
- Solve for L_i^t by using the labour resource constraint, Eq. (15).
- Solve for p_i^H by using Eq. (12).
- Solve for r_i by using Eq. (11).
- Solve for the aggregate consumer price index $\mathcal{P}_i \equiv \left([\sum_j (\tau_{ji} w_j/\varphi_j)^{1-\sigma}]^{1/(1-\sigma)}\right)^{\alpha\beta} (w_i/\varphi_i)^{\mu}(p_i^H)^{1-\mu})^{\alpha(1-\beta)}(p_i^H)^{1-\alpha}$, where we have used the expressions for prices of tradable goods, $p_{ji}^t = \tau_{ji} w_j/\varphi_j$, the CES-price index $P_i^t = [\sum_j (p_{ji}^t)^{1-\sigma}]^{1/(1-\sigma)}$, and non-tradable goods, $p_i^n = (w_i/\varphi_i)^{\mu}(p_i^H)^{1-\mu}$ in the aggregate consumer price index $\mathcal{P}_i \equiv \left(P_i^t\right)^{\alpha\beta} (p_i^n)^{\alpha(1-\beta)}(p_i^H)^{1-\alpha}$.
- Then compute new values of initial (or updated) guesses:
- Compute w_i^{new} by using Eq. (13). Normalise mean wages to unity, e.g. by $w_i^{new} = w_i^{new}/mean(w_i^{new})$
- Compute λ_i and derive value for L_i^{new} using Eq. (16).
- Check deviation between guesses and model solution

$$target1 = round(abs(w_i - w_i^{new}), precision)$$
$$target2 = round(abs(L_i - L_i^{new}), precision)$$

- **if** $target1 == 0 \;\; \& \;\; target2 == 0$ **then**
  - break;
- **else**
  - Update initial guesses or updated values of w_i and L_i:

$$w_i^{up} = \kappa w_i + (1-\kappa) w_i^{new}$$
$$L_i^{up} = \kappa L_i + (1-\kappa) L_i^{new}$$

  - Use updated values and re-iterate

$$w_i = w_i^{up}$$
$$L_i = L_i^{up}$$

- Compute other endogenous variables (e.g. quantities) as needed.

Result: Equilibrium values of $\mathbf{V}$

A.3 Using the model to predict non-housing price indices

From Eq. (17) it is evident that measuring QoL while accounting for trade frictions requires measures of tradable goods and local services prices. If no such price index is at hand, we can use the structure of the model to solve for a non-housing price index from employment and wage data. Intuitively, we set the structural fundamentals, $\{\nu_i^n, d_j\}$, which rationalize observed tradable goods and local services prices in the quantification described in Section A.1, to uniform one. Otherwise, we follow the same steps to invert worker productivity, which is then used to predict tradable goods and local services prices.

We invert worker productivities using the tradable goods market condition in Eq. (13) using the same values for parameters $\{\alpha, \beta, \zeta, \iota, \mu, \sigma\}$ as in Section A.1, and a simplified version of Algorithm 2. Since we do not require model-predicted tradable goods prices, $P^{t,model}$ to match values in data, P^t, the outer loop becomes redundant so that we iterate over guessed values of worker productivity φ in the inner loop, holding the destination-specific trade cost component constant at $d_j = 1$. Consequentially, the data requirements for this procedure, compared to Section A.1, drop to observed values of endogenous variables as well as a bilateral distance matrix.

With worker productivity at hand, the model-consistent tradable goods price index can be computed as

$$\hat{P}^t = \left[\frac{\sum_{i\in J}\left(\tau_{ij} w_i/\varphi_i\right)^{1-\sigma}}{\sum_{i\in J}\left(\tau_{ik} w_i/\varphi_i\right)^{1-\sigma}}\right]^{\frac{1}{1-\sigma}},$$

with $\tau_{ij} = (\exp[-\iota * \ln dist_{ij}])^{\frac{1}{1-\sigma}}$. Similarly, given the assumption of uniform productivity in local services, $p^n = 1$, it is straightforward to compute the local services price index as

$$\hat{p}^n = (\hat{w}/\hat{\varphi})^{\mu}(\hat{p}^H)^{1-\mu}.$$

B Monte Carlo study

This appendix complements the Monte Carlos analysis in Section 4.

B.1 Parameter choices

Table A2 provides an overview of the parameter value choices in the Monte Carlo study. Additionally, we recap how the model fundamentals are determined.

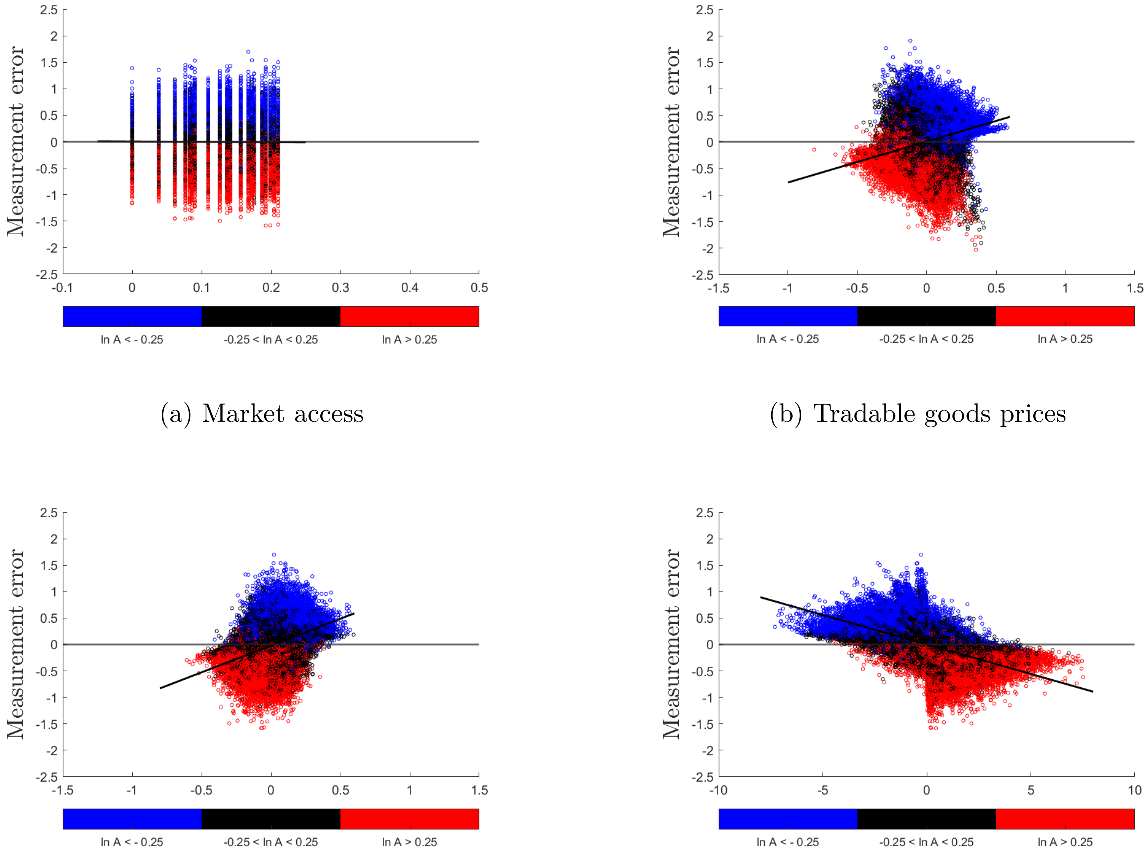
B.2 Measurement error

Figure A1 complements Figure 2 in the main paper by correlating the measurement error in the Rosen-Roback QoL measure, $\mathcal{E}$, against additional variables. As in Figure 2, each dot corresponds to one artificial city in the synthetic data set generated in Section 4. In panel (a), we consider market access, $\mathcal{M}$, as a covariate. Our market access measure solely depends on geography, which is exogenous and held constant across all Monte Carlo experiments. Therefore,

Table A2: Parameter values

Parameter	Description	Approach	Source
Preferences			
$1-\alpha=0.3$	Housing share in consumption	Set	Combes et al. (2019)
$\beta=0.5$	Tradable goods share	Set	Caliendo et al. (2018)
Production			
$\delta=0.3$	Share of land in production	Set	Baum-Snow and Han (2024)
$\iota=1$	Distance elasticity	Set	Head and Mayer (2014)
$\sigma=5$	Regional varieties substitution	Set	Head and Mayer (2014)
$\mu=0.8$	Labour share in production	Set.	Greenwood et al. (1997)
$\zeta=0.02$	Productivity spillovers	Set.	Combes and Gobillon (2015)
Regional fundamentals			
$\bar{L}=J$	Number of workers	Set	
$T_i=1$	Land Area	Set	
$dist_{ij}$	Geographical Distance	Set	
τ_{ij}	Trade cost	Set	$\tau_{ij}=(\exp[-\iota*\ln dist_{ij}])^{\frac{1}{1-\sigma}}$
$\mathcal{M}_i$	Market access measure	Set	$\sum_{j\in J}(Y_j/dist_{ij})$
$\ln L^b$	Log Birth Place Population	Sim.	$\sim\mathcal{N}(0,0.85)$
$\ln A_i$	Log Quality of life	Sim.	$\sim\mathcal{N}(0,0.25)$
$\ln\eta_i$	Floor space productivity	Sim.	$\sim\mathcal{N}(0,0.25)$
$\ln\bar{\varphi}_i$	Worker productivity	Sim.	$\sim\mathcal{N}(0,0.25)$
γ	Labour supply elasticity	Sim.	$\sim U(1.1;10)$
ξ	Value of Birth Place Location	Sim.	$\sim U(0;10)$

Figure A1: Measurement error: Other outcomes



(a) Market access

(b) Tradable goods prices

(c) Local services prices

(d) Residence/hometown population

Notes: Measurement error is defined as $\mathcal{E} = (1/\gamma)(\ln \mathcal{L}^b - \ln \hat{L}) - \alpha\beta \ln \hat{P}^t - \alpha(1-\beta)\ln \hat{p}^n$. All covariates are in logs. We run $N = 1,000$ Monte Carlo simulations for a synthetic economy with $J = 144$ local labour markets.

it varies between artificial cities, but not between countries. Ceteris paribus, we expect it to be negatively correlated with tradable goods prices. Yet, we find no correlation between market access and measurement error. We do find a weakly positive correlation between tradable goods prices and measurement error in panel (b). However, within groups of similar relative QoL values, the correlation is negative. We observe the same pattern for local service prices in panel (c). Descriptively, we do not find strong evidence that trade frictions significantly shape measurement error in the Rosen-Roback QoL measure.

In panel (d), we examine another endogenous outcome: the ratio of residence population to hometown population. We find a pronounced negative correlation between this ratio and the measurement error, which reinforces the patterns observed in the correlations with fundamentals in panels (a) to (c) of Figure 2. The underestimation of relative QoL differences within the Rosen-Roback framework is particularly pronounced in cities that, due to positive fundamentals, attract a large residence population relative to the hometown population.

B.3 Sensitivity analysis

In Table A3 we analyse how sensitive our regression results are to the parameter choices by decreasing (increasing) each by 25% and repeating our Monte Carlo study. For sake of brevity, we only display the marginal effects of the main variables for the full measurement error $\mathcal{E}$.

In Table A4 we replicate Table 1 from the main paper for $1,000$ countries whose stylized geography more closely resembles the one from the USA. In particular, we set $J = 400$ and consider rectangular countries with side length 2750 (km). We draw all fundamentals from the same distributions and use the same parametrisation as in the main paper.

B.4 Urban quality-of-life premium

This section complements Section 4.3 in the main paper. In Figure 3, we correlate the bias in the Rosen-Roback estimate of the urban QoL premium with the synthetic country-specific value of the taste dispersion parameter γ, distinguished by the strength of local ties (governed by ξ).

In Figure A2, we quantify the impact of controlling for selected frictions on the bias in the estimated urban QoL premium. To compute the bias, we now use adjusted QoL measures, $\ln \hat{A}_{RR} - \mathcal{X}$ when estimating Eq. (21), where $\mathcal{X}$ corresponds to one of the terms highlighted in Eq. (19). For ease of interpretation, we focus only on the empirically relevant cases where $\xi < 6$ and the total bias is consistently negative.

Conditional on controlling for local ties, the remaining measurement error causing the bias in the urban QoL premium is primarily driven by the omitted control for idiosyncratic tastes. Consequentially, the urban QoL premium is underestimated for the most part. Likewise, controlling for idiosyncratic tastes, the omission of the control for local ties typically results in a sizable overestimation of the urban QoL premium. Echoing Table 1, controlling for trade frictions without addressing mobility frictions has mostly quantitatively small effects. Moreover, it does not necessarily reduce the bias in the urban QoL premium unless mobility frictions are already accounted for. The important takeaway for the applied literature is that to avoid biased estimates of the urban QoL premium, accounting for mobility frictions is more important than accounting for trade frictions. When addressing mobility frictions, it is important to account for idiosyncratic tastes and local ties simultaneously, otherwise, there is a risk that the bias, in absolute terms, actually increases.

Table A3: Sensitivity analysis

	(1)	(2)	(3)	(4)
	$\alpha_1 = 0.75 * \alpha$	$\alpha_2 = 1.25 * \alpha$	$\beta_1 = 0.75 * \beta$	$\beta_2 = 1.25 * \beta$
Measurement bias: Intercept	-0.284	-0.286	-0.285	-0.296
(Inverse) taste heterogeneity: γ-3	0.026	0.025	0.027	0.030
Strength of local ties: ξ-5	-0.015	-0.016	-0.016	-0.016
Market access: $\mathcal{M}_i$	-0.081	-0.075	-0.090	-0.100
Quality of life: $\ln(\hat{A}/1.5)$	-0.705	-0.704	-0.712	-0.719
Relative floor-space productivity : $\ln \hat{\eta}$	-0.316	-0.220	-0.177	-0.197
Relative worker productivity: $\ln \hat{\varphi}$	-0.502	-0.541	-0.546	-0.540
Relative hometown population: $\ln \hat{L}^b$	0.092	0.072	0.081	0.075
	$\mu_1 = 0.75 * \mu$	$\mu_2 = 1.25 * \mu$	$\sigma_1 = 0.75 * \sigma$	$\sigma_2 = 1.25 * \sigma$
Measurement bias: Intercept	-0.287	-0.301	-0.266	-0.281
(Inverse) taste heterogeneity: γ-3	0.019	0.022	0.029	0.030
Strength of local ties: ξ-5	-0.014	-0.013	-0.021	-0.015
Market access: $\mathcal{M}_i$	-0.085	-0.080	-0.103	-0.098
Quality of life: $\ln(\hat{A}/1.5)$	-0.729	-0.736	-0.671	-0.696
Relative floor-space productivity : $\ln \hat{\eta}$	-0.165	-0.179	-0.167	-0.192
Relative worker productivity: $\ln \hat{\varphi}$	-0.583	-0.579	-0.469	-0.518
Relative hometown population: $\ln \hat{L}^b$	0.073	0.068	0.095	0.073
	$\delta_1 = 0.75 * \delta$	$\delta_2 = 1.25 * \delta$	$\iota_1 = 0.75 * \iota$	$\iota_2 = 1.25 * \iota$
Measurement bias: Intercept	-0.291	-0.293	-0.286	-0.294
(Inverse) taste heterogeneity: γ-3	0.026	0.026	0.026	0.027
Strength of local ties: ξ-5	-0.017	-0.017	-0.021	-0.016
Market access: $\mathcal{M}_i$	-0.099	-0.086	-0.135	-0.105
Quality of life: $\ln(\hat{A}/1.5)$	-0.725	-0.718	-0.695	-0.714
Relative floor-space productivity : $\ln \hat{\eta}$	-0.189	-0.170	-0.172	-0.206
Relative worker productivity: $\ln \hat{\varphi}$	-0.570	-0.550	-0.514	-0.541
Relative hometown population: $\ln \hat{L}^b$	0.069	0.072	0.089	0.070

Notes: Each column represents the measurement error of the full model for a location with 50% higher quality of life than the numéraire location (so $\hat{A} = 1.5$) and when a structural parameters is decreased (increased) by 25%. All explanatory variables are expressed relative to a numéraire location. The mobility friction parameter γ and local ties valuation ξ are re-scaled to have a zero value at $\gamma = 3$ and $\xi = 5$, respectively, so we can interpret the intercept as the measurement error for otherwise identical locations. Given the high number of Monte Carlo iterations, all coefficients are highly significant at all common levels so we do not report standard errors for the sake of brevity.We use the same explanatory variables as in Table 1 of the main paper.

C Application

This appendix complements the application of our approach to the measurement of QoL in Germany in Section 4.

Table A4: Determinants of the measurement bias - Large country

Frictions controlled:	(1)	(2)	(3)	(4)	(5)
Trade Costs		✓			
Local services			✓		
Local ties				✓	
Idiosyncratic tastes					✓
Measurement error: Intercept	-0.277	-0.300	-0.289	-0.196	-0.048
Parameters and regional fundamentals:					
(Inverse) taste heterogeneity: γ-3	0.026	0.022	0.024	0.018	0.015
Strength of local ties: ξ-5	-0.014	-0.012	-0.013	0.012	-0.030
Market access: $\ln \hat{\mathcal{M}}$	-0.077	-0.144	-0.041	-0.052	0.005
Quality of life: $\ln(\hat{A}/1.5)$	-0.688	-0.743	-0.717	-0.465	-0.140
Relative floor-space productivity : $\ln \hat{\eta}$	-0.177	-0.198	-0.258	-0.128	0.054
Relative worker productivity: $\ln \hat{\bar{\varphi}}$	-0.529	-0.609	-0.570	-0.361	-0.048
Relative hometown population: $\ln \hat{L}^b$	0.055	0.046	0.050	-0.118	0.188
Interaction effects:					
$\ln \hat{\mathcal{M}} * (\gamma - 3)$	0.008	0.005	0.008	0.006	0.005
$\ln(\hat{A}/1.5) * (\gamma - 3)$	0.065	0.054	0.059	0.041	0.041
$\ln \hat{\eta} * (\gamma - 3)$	0.022	0.019	0.020	0.023	0.005
$\ln \hat{\bar{\varphi}} * (\gamma - 3)$	0.054	0.045	0.049	0.041	0.028
$\ln \hat{L}^b * (\gamma - 3)$	-0.004	-0.003	-0.003	0.023	-0.027
$\ln \hat{\mathcal{M}} * (\xi - 5)$	-0.005	-0.004	-0.005	0.005	-0.011
$\ln(\hat{A}/1.5) * (\xi - 5)$	-0.036	-0.030	-0.033	0.034	-0.080
$\ln \hat{\eta} * (\xi - 5)$	-0.012	-0.010	-0.011	0.010	-0.026
$\ln \hat{\bar{\varphi}} * (\xi - 5)$	-0.028	-0.024	-0.026	0.029	-0.065
$\ln \hat{L}^b * (\xi - 5)$	0.016	0.013	0.015	-0.022	0.043
Observations	400,000	400,000	144,000	144,000	144,000
Adjusted R^2	0.973	0.984	0.980	0.770	0.774

Notes: Each column represents a different measurement error for a location with 50% higher quality of life than the numéraire location, so $\hat{A} = 1.5$. In column (1), we ignore all spatial frictions; in column (2), we control for trade costs; in column (3), we control for differences in non-tradable service prices and in column (4) we control for migration frictions. All explanatory variables are expressed relative to a numéraire location. The mobility friction parameter γ is re-scaled to have a zero value at $\gamma = 3$, so we can interpret the intercept as the measurement error for otherwise identical locations. Given the high number of Monte Carlo iterations, all coefficients are highly significant at all common levels so we do not report standard errors for the sake of brevity. We truncate the normal distributions by 0.65 from below and above to avoid generating cities with implausibly large or small populations. All the main results insensitive to the truncation.

C.1 Data sources

This appendix complements Section 5.1 in the main paper. For our application, we require four sets of data compiled for consistent spatial units: Employment, wages, floor space prices, and non-housing prices.

Spatial unit. According to Kosfeld and Werner (2012), the delineation of German labour market areas is based on combining one or more administrative regions at the county level to create self-contained labour markets. The boundaries of local labour markets are defined such that commuting within labour market regions is relatively large compared to commuting between regions (subject to an upper limit on commuting time of 45-60 minutes).

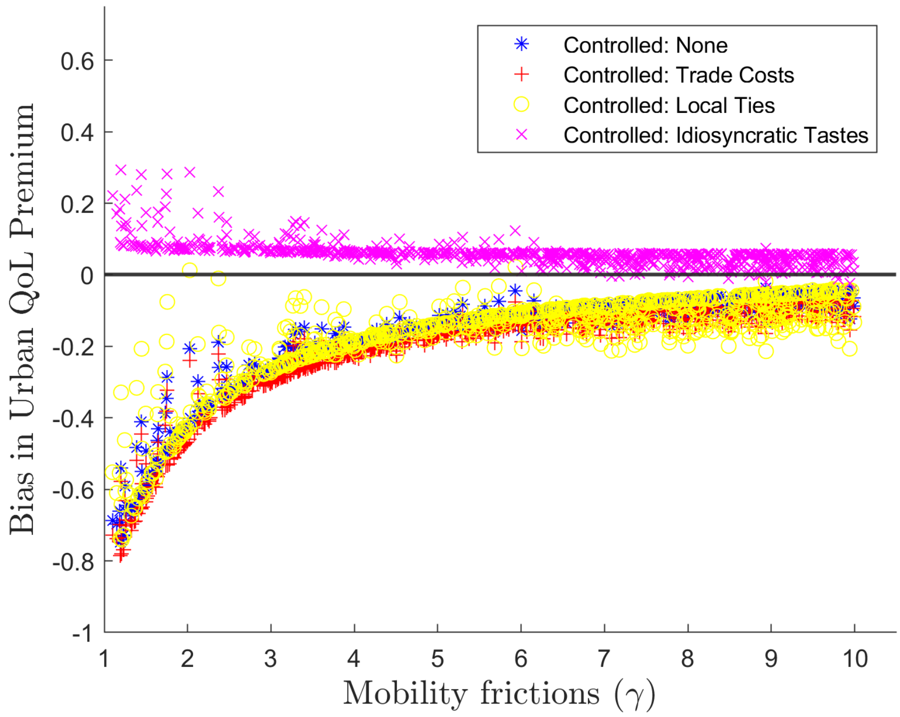


Figure A2: Bias in urban QoL premium: Controlling for selected migration frictions. For ease of interpretation we focus only the empirically relevant cases where $\xi < 6$, and drop all other Monte Carlo scenarios for this figure.

Population. Our measures of population – residence population and hometown population – are derived from individual-level social security data that are contained in the Integrated Employment Biographies (IEB). This data set covers daily information on the labour market biographies of the universe of employees in Germany (except for civil servants and the self-employed). To prepare the data set for our empirical analysis, we proceed in the following way. First, we retain information on all workers who are employed subject to social security contributions at any point between 1993 and 2019. Within a given year, we restrict the sample to individuals who are employed on 30 June of that year and select the employment spell that contains this reference date. If a person has multiple employment spells that contain the reference data, we sequentially apply the following criteria to determine which spell to keep: a) the longest employment spell, b) the employment spell with the highest wage and c) a random employment spell. Second, we address the fact that wages in the IEB data are censored and perform an imputation procedure that is based on Card et al. (2013) and described in further detail in Stüber et al. (2023). Third, we retain those workers whose highest skill level is a completed apprenticeship, who started their training in the year 1993 or later and who were between 15 and 25 years old at that time. The choice of this group is motivated by the possibility to use the region of a person's training firm, which is observed in the IEB data, as a proxy for a person's hometown, which is not observed. Since reliable data on East Germany is only available from 1993, using earlier apprenticeship cohorts is not feasible. This procedure yields a total of 5.8 million individuals, who are employed in 2015 and for whom the region of their training firm is observed. To assess robustness of our findings, we further restrict the sample by only including individuals with German nationality as the former are more likely to have grown up in Germany as opposed to foreigners who might have come to Germany shortly before starting apprenticeship training and for whom the region of the training firm would therefore not be a suitable measure of their hometown. This restriction is potentially relevant as the years 2015 and 2016 saw a large number of refugee migrants arrive in Germany (e.g., Hayo and Roth, 2024). Applying this restriction reduces sample size to 5.6 million workers in the year 2015. **Residence population** is defined as the (contemporaneous) number of employees in a local labour market, L_i. For most analyses, this quantity refers to the year 2015. For the specific sample that we use for the empirical analysis, the average residence population across the 141 labour market regions stands at 41,114. Values range from about 4,000 in the labour market region *Vulkaneifel* to approximately 250,000 in *Hamburg*. **Hometown population** is defined as the number of employees who started their apprenticeship training in the same region, L_m. Since every individual in the data set is assigned a residence region and a hometown region, the mean value of both measures across labour market regions is identical. Moreover, regions that are large in the present also tend to have had a relatively large number of apprenticeship trainees, leading to a positive correlation between residence population and hometown population. We argue that the region in which a person started her apprenticeship training represents a good proxy for her hometown because empirical evidence suggests that a large share of individuals start apprenticeship training in the region in which they also completed schooling (Hoffmann and Wicht, 2023).

Census population. To construct the crude-data QoL version, we replace measures of the residence and the hometown population, which are based on the IEB, with publicly available total population measures. Specifically, we use a labour market's population size in 2015 as a a measure of residence population and its population size in 1985 as a measure of hometown population. Both population variables are based on data from the *Federal Institute for Research on Building, Urban Affairs and Spatial Development* (BBSR) that were initially provided at the county level and which we aggregate to the level of the 141 labour market regions.

Tradable sector. We assign individuals to the (non-)tradable sector based on the 2-digit sector they are employed in. For this purpose, we employ the classification of 2-digit sectors as tradable or non-tradable from Gregory et al. (2021). About 43% of individuals are employed in the tradable sector.

Productivity. We use information from the universe of workers who are observed as employed subject to social security (including apprentices) on June 30 to estimate the region-specific productivity, which maps into the wage. In line with the standard approach in the agglomeration literature (Combes and Gobillon, 2015), we assume that worker productivity $\varphi_i(\omega)$ is a multiplicative function of a region-specific component φ_i and an individual component $\rho_i(\omega)$. Following the conventions in labour economics (Abowd et al., 1999), we define $\rho_i(\omega) = \exp(\bar{\rho}(\omega) S_i^L(\omega) z^L f_i^L(\omega))$ as a function of unobserved time-invariant individual productivity $\bar{\rho}(\omega)$, observable worker characteristics $S_i^L(\omega)$ (dummies for whether a worker is in an apprenticeship or works part-time, with z^L being the marginal effects) and a stochastic residual term $f_i^L(\omega)$. This yields the following estimation equation for individual wages:

$$\ln w_i(\omega) = \bar{\rho}(\omega) + S_i^L(\omega) z^L + \tilde{\varphi}_i + f_i^L(\omega). \tag{22}$$

In estimating Eq. (22), we remove all observations of individuals who never change their place of employment. We recover $\tilde{\varphi}_i$ as a log index of region-specific productivity, which we re-scale such that the averages match the group-specific log annual earnings in the raw wage data.

C.2 Estimation

This section compliments Section 5.1 in the main paper by showing additional detail on the estimation of the parameter governing the strength of local ties, ξ.

To estimate ξ, we start from Eq. (9), multiply by $\bar{L}$ and take logs. This delivers the regression specification:

$$\ln L_{im} = \xi \mathbb{1}\{m = j\} + \mathcal{R}_i + \mathcal{H}_m + \nu_{im}, \tag{23}$$

where $\mathbb{1}\{m = j\}$ is a dummy that indicates when the residence is equal to the hometown, $\mathcal{R}_i \equiv \gamma \ln(A_i w_i / \mathcal{P}_i)$ denotes residence fixed effects, $\mathcal{H}_m \equiv \ln\left(\sum_{j \in J} (A_j w_j / \mathcal{P}_j)^\gamma \cdot \exp[\mathbb{1}\{m = j\} \cdot \xi]\right)$ denotes hometown fixed effects, and ν_{im} is the regression residual that accounts for measurement error.

A standard problem arising when estimating log-linearized gravity equations is many bilaterals do not have positive values. In Table A5, we address this problem by applying the conventional $\ln(y + 1)$ transformation to the dependent variable in Columns (2) and (5) and using a PPML estimator in Columns (3) and (6). The PPML estimator yields an estimate of ξ of about 5.6 – regardless of whether the full sample is used or the sample of German nationals. By contrast, using the sample of non-zero bilateral population cells or applying the log-transformation yields an estimate of slightly above 7.

C.3 Rosen-Roback quality of life

Figure A3 compares our preferred QoL measure, A, to the canonical Rosen-Roback measure, A_{RR}.

One insight from Figure 4 is that, qualitatively, the two measures based on the quantitative spatial model and the Rosen-Roback framework exhibit a similar spatial pattern. The largest cities Berlin, Hamburg, and Munich are among the places with the greatest QoL, but the similarities extend beyond these cities. Quantitatively, however, the differences are striking. Interpreted through the lens of the quantitative spatial model, there is much more variation in QoL than when the inference is based on the Rosen-Roback framework. As argued in Section 4, this is the expected result when QoL and city size are positively correlated.

Table A5: Estimation of ξ

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample			German nationals		
	OLS	OLS	PPML	OLS	OLS	PPML
Same region ($\mathbb{1}\{m = j\}$)	7.2243***	7.1358***	5.5885***	7.2123***	7.1232***	5.5830***
	(0.0793)	(0.0749)	(0.0350)	(0.0796)	(0.0753)	(0.0346)
Residence fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hometown fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Non-zero	All	All	Non-zero	All	All
Observations	18742	19881	19881	18724	19881	19881
R^2	.59	.622		.589	.621	

Notes: Unit of observation is residence-hometown population. The dependent variable is the log of residence-hometown population $L_{im} = \lambda_{im}\bar{L}$. Robust standard errors. The non-zero sample are bilaterals with positive residence-hometown population. In Columns (2) and (5), the dependent variable is transformed to $\ln(y + 1)$. Columns (1)-(3) use the full sample, while Columns (4)-(6) are restricted to German nationals. Robust standard errors in parenthesis; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C.4 Predicted non-housing price index

We observe the prices of tradable goods and local services in 2015, but not before or after. However, to gain insight into how quality of life has changed over time, we can use the model to predict prices of tradable goods and services, as discussed in Appendix A.3. With predicted prices for 2007 (the earliest house prices from Ahlfeldt et al. (2022)) and 2019 (the most recent IAB data), we can calculate how relative QoL has changed over a period of more than 20 years.

The first insight from Table A6 is that, taking 2015 as a case in point, the QoL measure using our predicted prices (PP) is a good approximation of our preferred QoL measure (QSM). This is reassuring, as it suggests that the long-term change in relative QoL revealed by the measures using predicted prices is informative. At the top of the distribution, we observe a striking degree of persistence in the QoL ranking. Within the top-5, only Berlin moved up one place. The only other changes within the top-10 are Münster (up 2 places) and Hanover (up 5 places). Outside the top-10, the changes are more significant. Among the cities that have lost the most are many of Germany's former industrial heartlands, such as Chemnitz, Gera, Hagen and Bochum, which have struggled with economic transition, deindustrialisation and demographic decline. Many of these cities were historically dependent on heavy industry or coal mining, making them particularly vulnerable to structural change.

Table A6: Quality of life in 2015 and 2019

	QSM 2015		PP 2015		PP value		Rank
City	Rank	Value	Rank	Value	2007	2019	change
Hamburg	1	2.08	1	1.91	1.76	1.85	0
München	2	2.03	2	1.89	1.79	1.90	0
Berlin	3	1.85	3	1.70	1.49	1.72	1
Frankfurt am Main	4	1.70	4	1.58	1.66	1.60	-1

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Table A6 continued from previous page

City	QSM 2015		PP 2015		PP value		Rank
	Rank	Value	Rank	Value	2007	2019	change
Düsseldorf	5	1.57	5	1.44	1.48	1.46	0
Köln	6	1.52	6	1.39	1.41	1.40	0
Stuttgart	7	1.49	7	1.39	1.38	1.39	0
Münster	8	1.30	8	1.25	1.23	1.30	2
Nürnberg	9	1.29	11	1.23	1.23	1.21	0
Hannover	10	1.29	12	1.21	1.21	1.25	5
Dresden	11	1.27	10	1.24	1.28	1.15	-9
Leipzig	12	1.22	15	1.16	1.23	1.16	-6
Regensburg	13	1.22	9	1.24	1.22	1.22	2
Karlsruhe	14	1.19	17	1.16	1.20	1.15	-1
Mainz	15	1.18	13	1.19	1.22	1.13	-7
Bremen	16	1.18	21	1.12	1.06	1.15	19
Essen	17	1.16	37	1.02	1.17	1.00	-27
Erlangen	18	1.13	14	1.19	1.13	1.13	2
Ingolstadt	19	1.12	18	1.15	1.15	1.14	2
Ulm	20	1.12	20	1.12	1.08	1.09	5
Freiburg	21	1.11	16	1.16	1.15	1.17	7
Traunstein	22	1.11	19	1.13	1.11	1.19	13
Saarbrücken	23	1.10	32	1.06	1.02	0.86	-27
Heidelberg	24	1.10	24	1.09	1.17	1.10	-6
Würzburg	25	1.09	27	1.08	1.09	1.10	5
Landshut	26	1.09	22	1.12	1.12	1.13	1
Dortmund	27	1.09	41	1.00	1.10	0.98	-22
Aachen	28	1.08	35	1.04	1.05	0.96	-12
Bonn	29	1.08	29	1.07	1.11	1.07	-3
Böblingen	30	1.07	25	1.09	1.13	1.10	-5
Augsburg	31	1.07	30	1.07	1.10	1.16	14
Ravensburg	32	1.07	33	1.04	1.06	1.07	5
Bielefeld	33	1.06	39	1.01	1.06	1.02	0
Koblenz	34	1.06	38	1.02	1.06	1.05	6
Soest	35	1.06	34	1.04	1.02	1.00	6
Ludwigshafen	36	1.06	40	1.00	1.09	1.01	-9
Erfurt	37	1.05	36	1.03	1.16	1.01	-21
Rostock	38	1.03	23	1.09	1.09	1.07	0
Heilbronn	39	1.03	45	0.99	1.04	1.04	8
Chemnitz	40	1.02	58	0.94	1.17	0.86	-58
Oldenburg	41	1.01	31	1.06	0.98	1.06	27
Kiel	42	1.00	42	1.00	1.00	1.00	11
Kassel	43	0.99	49	0.98	0.98	0.99	15
Fulda	44	0.99	44	1.00	1.00	1.03	22
Braunschweig	45	0.98	50	0.98	1.02	1.01	9
Gießen	46	0.98	54	0.95	0.98	0.96	6
Reutlingen	47	0.97	47	0.98	1.01	1.02	12
Ortenaukreis	48	0.96	46	0.98	0.97	0.98	11
Konstanz	49	0.96	28	1.07	1.08	1.13	12

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Table A6 continued from previous page

City	QSM 2015		PP 2015		PP value		Rank
	Rank	Value	Rank	Value	2007	2019	change
Bamberg	50	0.95	43	1.00	1.04	0.99	0
Darmstadt	51	0.94	53	0.96	1.05	0.95	-17
Kempten	52	0.94	51	0.97	0.95	0.99	24
Weilheim-Schongau	53	0.94	26	1.08	1.08	1.10	6
Osnabrück	54	0.94	56	0.95	0.95	0.94	11
Hagen	55	0.93	76	0.87	1.02	0.82	-40
Bochum	56	0.93	77	0.86	1.01	0.83	-32
Magdeburg	57	0.92	67	0.90	1.06	0.89	-30
Wolfsburg	58	0.92	61	0.93	1.01	0.90	-17
Borken	59	0.92	63	0.92	0.91	0.92	21
Trier	60	0.92	52	0.96	1.00	0.95	-4
Lübeck	61	0.91	60	0.93	0.97	0.98	15
Bautzen	62	0.91	68	0.90	0.94	0.71	-41
Heidenheim	63	0.91	69	0.90	0.94	0.92	11
Aschaffenburg	64	0.90	59	0.94	1.00	0.95	0
Schwerin	65	0.89	66	0.91	1.01	0.89	-17
Bayreuth	66	0.89	55	0.95	0.95	0.97	15
Jena	67	0.89	48	0.98	1.04	0.96	-12
Flensburg	68	0.88	65	0.91	0.88	0.91	29
Passau	69	0.88	57	0.94	0.92	0.98	31
Rottweil	70	0.88	74	0.88	0.93	0.92	13
Coburg	71	0.88	64	0.92	0.97	0.86	-9
Emsland	72	0.88	75	0.87	0.88	0.85	16
Halle	73	0.88	79	0.85	1.00	0.83	-27
Minden	74	0.87	84	0.83	0.93	0.84	0
Schweinfurt	75	0.86	73	0.88	0.91	0.93	23
Deggendorf	76	0.86	62	0.93	0.91	0.99	39
Altötting	77	0.85	72	0.88	0.93	0.93	16
Vechta	78	0.85	71	0.88	0.85	0.91	39
Göttingen	79	0.85	83	0.83	0.92	0.79	-7
Wuppertal	80	0.83	102	0.77	0.93	0.76	-23
Südvorpommern	81	0.83	70	0.89	0.95	0.84	-11
Hof	82	0.81	92	0.80	0.94	0.81	-13
Amberg	83	0.81	87	0.82	0.89	0.82	7
Nordvorpommern	84	0.80	80	0.84	0.96	0.89	-4
Landau	85	0.79	81	0.84	0.87	0.87	25
Siegen	86	0.78	97	0.79	0.85	0.76	8
Ansbach	87	0.78	86	0.82	0.89	0.73	-19
Lörrach	88	0.78	78	0.86	0.87	0.85	21
Pforzheim	89	0.78	93	0.80	0.89	0.83	8
Teltow-Fläming	90	0.78	85	0.83	0.98	0.79	-35
Memmingen	91	0.78	82	0.84	0.88	0.87	22
Olpe	92	0.78	104	0.77	0.86	0.78	4
Kaiserslautern	93	0.77	88	0.81	0.87	0.78	2
Emden	94	0.77	106	0.77	0.86	0.80	13

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Table A6 continued from previous page

City	QSM 2015 Rank	QSM 2015 Value	PP 2015 Rank	PP 2015 Value	PP value 2007	PP value 2019	Rank change
Dessau-Roßlau	95	0.76	107	0.76	0.93	0.76	-24
Suhl	96	0.76	94	0.80	0.89	0.73	-16
Kleve	97	0.76	91	0.80	0.85	0.77	6
Schwäbisch Hall	98	0.76	101	0.78	0.84	0.81	25
Eisenach	99	0.75	90	0.80	0.97	0.72	-48
Göppingen	100	0.75	89	0.81	0.91	0.84	7
Potsdam-Mittelmark	101	0.75	99	0.78	0.86	0.78	9
Oberhavel	102	0.74	96	0.79	0.95	0.80	-17
Donau-Ries	103	0.74	95	0.80	0.83	0.77	15
Bad Kreuznach	104	0.74	98	0.79	0.84	0.79	17
Pirmasens	105	0.72	112	0.74	0.87	0.73	-10
Limburg-Weilburg	106	0.72	111	0.74	0.86	0.75	-4
Waldshut	107	0.71	103	0.77	0.75	0.73	13
Bremerhaven	108	0.71	114	0.73	0.75	0.75	18
Saalfeld-Rudolstadt	109	0.71	105	0.77	0.93	0.72	-31
Gera	110	0.71	113	0.73	0.92	0.65	-44
Stade	111	0.71	109	0.76	0.78	0.77	21
Cham	112	0.70	108	0.76	0.83	0.79	23
Märkisch-Oderland	113	0.70	100	0.78	0.85	0.76	4
Wilhelmshaven	114	0.69	110	0.75	0.78	0.72	8
Goslar	115	0.69	121	0.69	0.88	0.68	-27
Mecklenburgische Seenplatte	116	0.68	116	0.71	0.84	0.70	-3
Cottbus	117	0.66	117	0.71	0.85	0.68	-12
Nordhausen	118	0.66	115	0.71	0.79	0.70	-1
Elbe-Elster	119	0.65	123	0.68	0.84	0.66	-14
Havelland	120	0.64	122	0.69	0.73	0.63	-2
Frankfurt (Oder)	121	0.63	130	0.65	0.81	0.68	-6
Celle	122	0.63	124	0.67	0.70	0.68	8
Waldeck-Frankenberg	123	0.63	128	0.65	0.72	0.66	4
Uckermark	124	0.63	118	0.70	0.79	0.62	-13
Zollernalbkreis	125	0.62	129	0.65	0.73	0.70	11
Hameln	126	0.62	127	0.65	0.73	0.63	-4
Unstrut-Hainich	127	0.62	119	0.69	0.74	0.61	-10
Ostprignitz-Ruppin	128	0.62	120	0.69	0.75	0.64	-4
Sigmaringen	129	0.60	125	0.66	0.67	0.67	12
Weißenburg-Gunzenhausen	130	0.59	126	0.66	0.77	0.62	-12
Dithmarschen	131	0.58	132	0.65	0.67	0.70	21
Bitburg	132	0.58	131	0.65	0.70	0.60	-3
Höxter	133	0.57	133	0.62	0.69	0.58	-4
Lüchow-Dannenberg	134	0.55	137	0.61	0.72	0.59	-8
Prignitz	135	0.54	134	0.61	0.66	0.52	-4
Altenkirchen	136	0.54	139	0.58	0.65	0.62	5
Freyung-Grafenau	137	0.54	135	0.61	0.61	0.68	22
Kronach	138	0.53	138	0.59	0.68	0.56	-4
Stendal	139	0.52	141	0.57	0.70	0.53	-9

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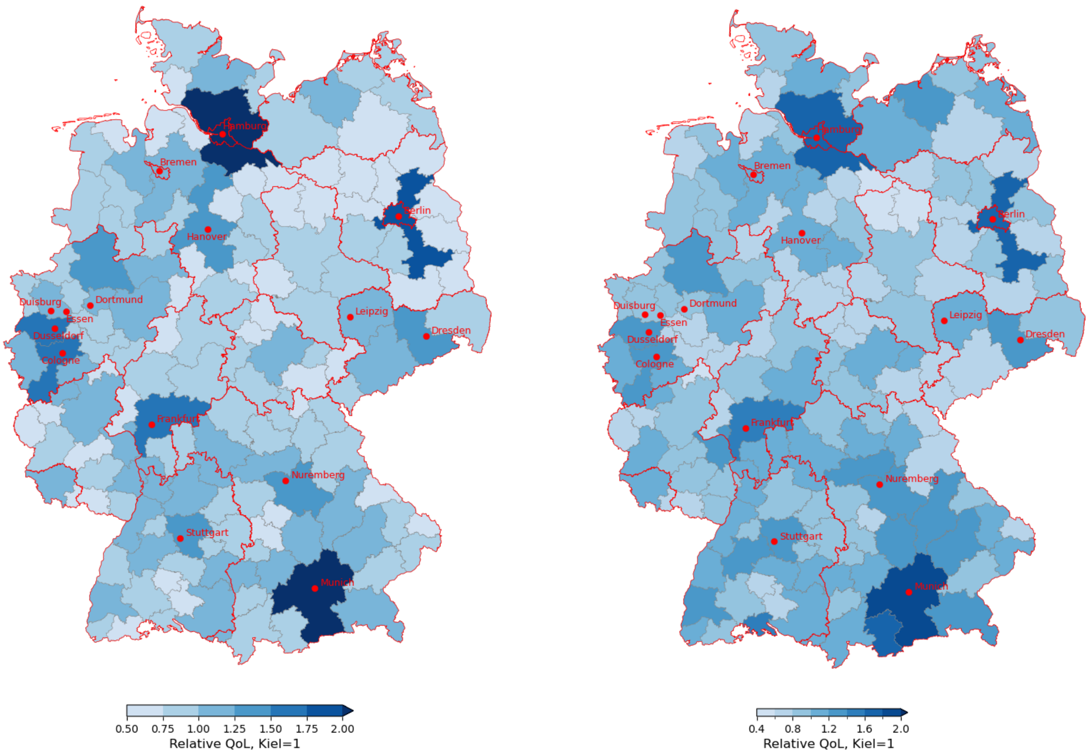
Table A6 continued from previous page

City	QSM 2015 Rank	QSM 2015 Value	PP 2015 Rank	PP 2015 Value	PP value 2007	PP value 2019	Rank change
Vulkaneifel	140	0.52	136	0.61	0.59	0.54	2
Uelzen	141	0.51	140	0.57	0.64	0.62	8

Notes: Change in rank is computed from 2007 to 2019. Positive numbers reflect an improvement in QoL.

Figure A3: Quality of life in Germany



(a) Quantitative spatial model

(b) Rosen-Roback

Notes: Both maps illustrate $\ln(\hat{A})$. Panel (a) is based on the quantitative spatial model (QSM); panel (b) shows QoL based on the canonical Rosen-Roback case (RR).

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