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Morgan Ubeda. Local Amenities, Commuting Costs and Income Disparities Within Cities. 2020. halshs-03082448v1

HAL Id: halshs-03082448

<https://shs.hal.science/halshs-03082448v1>

Preprint submitted on 18 Dec 2020 (v1), last revised 1 Apr 2021 (v2)

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WP 2038 – December 2020

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commuting, amenities, income sorting, stratification

JEL codes:

R13, R14

Local Amenities, Commuting Costs and Income Disparities Within Cities*

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*I want to thank Pierre-Philippe Combes, Sonia Paty, Gilles Duranton, Jessie Handbury, Hans Koster and participants at the 14th UEA meeting in Philadelphia and 2019 Public Policy and Cities workshop in Lyon for their precious comments. I also thank Sylvie Charlot for helping me with accessing the restricted data, and the people at CASD who made the data available. I gratefully acknowledge financial support from GATE, Université Lyon 2, the Fulbright Program and the Agence Nationale de la Recherche (ANR) research program ANR-18-CE41-0003-02.

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1 Introduction

In this paper, I ask the following question: What are the effects of transportation policies on spatial inequalities and redistribution within metropolitan areas?

In Europe, almost a quarter of greenhouse gas emissions comes from the transportation sector, of which 72% comes from road transport.¹ In the us, these figures are respectively 28% and 59%.² To fight global warming and local pollution, cities around the world are trying to promote greener ways of commuting. In Paris for instance, the city plans to ban all thermal vehicles before 2030.³ On the other hand, segregation and spatial inequalities are another major challenge faced by cities all over the world. With the French Riots and the more recent Yellow Vests movement, anti-gentrification protests in London, Leipzig, Brooklyn or Seattle, the negative consequences of spatial inequalities can be seen in all major cities in the world.

Most of the literature on sorting has emphasized the role of amenities (Lee and Lin, 2018, Koster and Rouwendal, 2017, Glaeser et al., 2018, Garcia-López et al., 2018, Couture et al., 2019, Couture and Handbury, 2020), school spending (Epple et al., 2001, Calabrese et al., 2006, Rothstein, 2006, e.g.) and place-based policies (e.g. Pampillón et al., 2017) on income stratification.⁴ Yet, comparisons between cities show that polycentric cities that concentrate economic activity in peripheral sub-centers are less segregated than their monocentric counterparts (Garcia-López and Moreno-Monroy, 2018). This seems to indicate that job location and commuting are to be taken into account to explain spatial income distributions, so that one can wonder if it is possible to fill two needs with one deed and use transport improvements to reduce segregation.

To assess the stratifying and redistributive effect of transportation policies, I rely on the calibration and simulation of a quantitative spatial equilibrium model of a city. More precisely, I extend the model of Ahlfeldt et al. (2015) to introduce

¹*Greenhouse gas emissions from transport in Europe.* European Environment Agency, <https://www.eea.europa.eu/data-and-maps/indicators/transport-emissions-of-greenhouse-gases/transport-emissions-of-greenhouse-gases-12>, accessed on August 21, 2020.

²*Inventory of U.S. Greenhouse Gas Emissions and Sinks 1990–2018.* EPA 430-R-20-02.

³*Plan Climat*, available in French and English at <https://www.paris.fr/pages/nouveau-plan-climat-500-mesures-pour-la-ville-de-paris-5252>, accessed on August 21, 2020.

⁴Two exceptions are the concurrent studies of Tsivanidis (2019) and Gaigne et al. (2019). Tsivanidis (2019) uses a similar model to estimate the welfare effects of the TransMilenio rapid bus network in Bogotá. However, he does not focus on income stratification, nor does he consider the effects of legislation on car use. Gaigne et al. (2019) on the other hand do not model transport mode choice, and thus do not explore the effects of precise policies.

workers heterogeneity, both in terms of observable skill classes and unobserved talent/productivity. Within skill group, the income sorting of workers is governed by non-homotheticities in the preferences for housing, stemming from Stone-Geary preferences. These preferences imply that the willingness to pay rents in return for higher amenities and shorter commutes increases with income. I then calibrate the model to the Paris region and use model simulations to evaluate two transport policies: a) the Regional Express Rail (RER) and b) banning cars in the city.

The case of Paris is interesting for two reasons. First, it is a major European city, comparable in size, segregation and inequalities to other major metropolitan areas. Second, the impact of the RER has been studied previously using convincing IV strategies ([Mayer and Trevien, 2017](#), [Garcia-López et al., 2017](#)). It is thus possible to benchmark the model against some known results in the literature.

I find that the Regional Express Rail has very little impact on spatial income inequalities. Overall, the RER train system decreases the between-municipality coefficient of variation of mean incomes by only 1%, while the income gradient in the region is unaffected. It has, however, sizable welfare effects. Indeed, it accounts for 2.62% of the welfare of low-skilled workers and 1.64% of the welfare of high-skilled workers, reducing welfare inequalities by 1%.

Turning to the car ban counterfactual, the model predicts that it would foster suburbanization, leading to a decrease of the income premium of the city relative to the rest of region. Comparing with the close suburbs (10 kilometers away from the geographical center of the city), the income premium of the city would drop by 10% (1000€). This would however come at the cost of a substantial welfare loss, of 1.7% for low-skilled and 2% for high-skilled workers. However, these effects depend on the amenity gains from the policy. It would require a 10% increase in amenities in Paris from pollution reduction and regained floor space for the policy to break even and start having a positive welfare effect. At that point, the sorting effects of the policy would be reversed: the income premium of the city would increase by 14%. As richer workers bid for floor space in this high-amenity center, the effect on welfare inequalities also flips, and the policy starts benefiting more the affluent.

The paper also provides new within-city estimates of agglomeration effects on total factor productivity, skill bias of agglomeration effects and residential amenities spillovers. Agglomeration effects and residential amenity spillovers are estimated using model-based instruments, as introduced by [Allen et al. \(2020\)](#). I find agglomeration effects comparable in size to previous results using between-cities designs

(Combes and Gobillon, 2015), but substantially lower than other within-city estimates as Ahlfeldt et al. (2015) and Tsivanidis (2019). Keeping city structure constant, the elasticity of TFP to total city population is 0.022.

The first contribution of this paper is to quantify the effects of transport policies on spatial income disparities. Several studies have shown the decentralizing effects of public transit and road infrastructures on employment and population gradients (e.g. Mayer and Trevien, 2017, Garcia-López et al., 2017, Garcia-López, 2012, Gonzalez-Navarro and Turner, 2018, Baum-Snow, 2007), but none has quantified the effects of public transports or road accessibility on income segregation.

Second, the paper extends the existing results on the effects of the Regional Express Rail on suburbanization. Mayer and Trevien (2017) use an IV strategy to estimate the causal impact of being connected to the Parisian Regional Express Rail network on a subset of municipalities. They conclude to a sizeable suburbanization effect on both employment and residential populations, with a stronger effect for high skilled workers. I add to their results by estimating the impact of the RER network on every municipality in the area, allowing me to compute its total effect on employment, population and income gradients.

Finally, the present paper also contributes to the literature on within-city quantitative spatial equilibrium models. Several recent studies in urban economics use a similar structural approach (Couture et al., 2019, Almagro and Domínguez-Iino, 2019, Gaigne et al., 2019, Tsivanidis, 2019). I provide several robustness checks for the model fit, and make the case that these models can be used as stand-alone tools for policy evaluation. Indeed I estimate the model without targeting any particular policy and show that the model-based estimates are in line with reduced-form results on the RER network from Mayer and Trevien (2017). This lends credibility to using the model in cases where no natural experiment is available. Moreover, I estimate the housing consumption parameters that govern workers sorting on expenditure micro-data, and show that the model is able to fit the income sorting patterns in the data with those theoretically consistent parameters. Further, while I estimate amenities as structural residuals of the model as in Albouy (2016) and Ahlfeldt et al. (2015), I show that model-based amenities strongly correlate with observed amenities.

The remainder of the paper is organized as follows. Section 2 presents the model and discuss the mechanisms that lead to income sorting. Section 3 describes the estimation and calibration of the models parameters and local amenities. Section 4 discusses results. Finally, section 5 concludes.

2 Model

This section outlines the model and discusses workers sorting. The general structure of the model is similar to [Ahlfeldt et al. \(2015\)](#), with the addition of workers heterogeneity and Stone and Geary preferences.

2.1 Workers behaviour

A city or urban area is composed of S municipalities, denoted by i or j , each endowed with some land L_j . There are H workers in the city. Each worker has to choose in which municipality to live and in which municipality to work. Workers are perfectly mobile and receive their income from supplying labour to firms in their workplace. Firms use labour and floor space to produce a final good costlessly traded with the rest of the world.

There are two sources of heterogeneity in the model. First, workers are endowed with an observed type e , corresponding to their education level. Second, within skill classes, workers differ in their individual skills and abilities, denoted $l \in \mathbb{R}_+$. Following the canonical literature on the estimation of agglomeration economies (e.g. [Combes et al., 2008](#)) workers heterogeneity within observed skill classes is modeled in terms of efficient labour supply differences. More precisely, a worker with ability l is assumed to supply l units of efficient labour. Therefore, given wages per efficient labour unit w_{je} for education e in municipality j , a worker with ability l simply receives an income of lw_{je} . The distribution of skills in the city for each type e is fix and denoted \mathcal{F}_e .

In what follows, education level indices are omitted when they are not necessary.

Conditional on her place of residence $i = 1, \dots, S$ and her workplace $j = 1, \dots, S$, agent n with ability l receives a wage $lw_j - cd_{ij}$, where cd_{ij} are monetary transport costs, that she spends on a quantity x_{ijn} of the numéraire good and a quantity f_{ijn} of floor space. The numéraire is not subject to transport costs, and is therefore distributed at a constant price (normalized to unity) everywhere in the city. The budget constraint of n is thus

$$lw_j - cd_{ij} = Q_i f_{ijn} + x_{ijn}, \quad (1)$$

where Q_i is the residential floor space rent in municipality i .

Regarding workers preferences, I focus on the sorting of workers on the basis of local amenities, which precludes the use of homothetic preferences. Following [Gaigne](#)

et al. (2019) and Tsivanidis (2019) and departing from the Cobb-Douglas specification in Ahlfeldt et al. (2015), I assume that workers have Stone and Geary preferences

$$U_{ijn} \equiv z_{ijn} B_{ij} \left(\frac{x_{ijn}}{1 - \beta} \right)^{1 - \beta} \left(\frac{f_{ijn} - \underline{f}}{\beta} \right)^{\beta} \quad (2)$$

where $B_{ij} = B_i T_j \exp(-\tau d_{ij})$ are the local amenities perceived when living in i and working in j . They include B_i the proper residential amenities in i , the niceness of the workplace j besides its offered wage, T_j , and the utility cost of commuting between i and j , of the iceberg form $\exp(-\tau d_{ij})$ with d_{ij} the distance and τ a parameter. The random variable z_{ijn} captures idiosyncratic preferences of n for the commute ij , and $\beta \in (0, 1)$ and $\underline{f} \geq 0$ are parameters that govern workers preferences for housing.

Stone and Geary preferences have many interesting properties. First, whenever $\underline{f} > 0$, the (indirect) marginal rate of substitution between floor space costs Q_i and local amenities B_{ij} is increasing with income. This induces a relatively higher willingness to pay for high amenity levels for rich households than for poor households. It provides a parsimonious and theoretically sound foundation for income sorting on the basis of amenities. When $\underline{f} = 0$ preferences are simple Cobb-Douglas.

Second, Stone and Gary preferences imply linear expenditures for housing, which causes the share of total income spent on housing to decrease with income. This decrease is consistent with data on the housing consumption of french households. Indeed, our analysis of Expenditure Survey data in section 3.1 reports downward Engel curves ranging from 50% to 18% and shows that Stone and Geary preferences fit these curves well (cf Figure 2, section 3.1). This is in line with previous evidence using french data from Combes et al. (2018, p. 32, Table 6) who estimate that the share of housing in French households expenses is significantly decreasing in income. Finally, the parameter \underline{f} has a natural interpretation as an incompressible floor space consumption.

By maximizing (2) subject to the budget constraint (1), the individual demand for the private good (3), the individual demand for floor space (4), and the indirect utility of n when she chooses the commute ij (5) are respectively:

$$x_{ijn}^*(l) = (1 - \beta)(lw_j - cd_{ij} - Q_i \underline{f}), \quad (3)$$

$$f_{ijn}^*(l) = \beta \frac{lw_j - cd_{ij}}{Q_i} + (1 - \beta) \underline{f}, \quad (4)$$

$$V_{ijn}(l) = z_{ijn} B_{ij} (lw_j - cd_{ij} - Q_i \underline{f}) Q_i^{-\beta}. \quad (5)$$

As in [Ahlfeldt et al. \(2015\)](#), I assume that households are characterized by their idiosyncratic preference shocks, which are independent draws from a Fréchet distribution, with scale parameters E_{ij} , shape parameter $\epsilon > 1$ and cumulative distribution function

$$F_{ij}(z_{ijn}) \equiv \exp(-E_{ij}z_{ijn}^{-\epsilon}). \quad (6)$$

These preference shocks are observed by the workers, but not by the econometrician. Integrating over these idiosyncratic shocks gives the probability to choose a commute. From F the distribution of the preference shocks, we get G_{ij} the distribution of utilities for residents of i who work in j :

$$G_{ij}(v) = \Pr[V_{ijn} \leq v] = F \left[\frac{vQ_i^\beta}{B_{ij}(lw_j - Q_i f)} \right]. \quad (7)$$

Then, the probability that a worker will choose commute ij is the probability to realize a higher utility in ij than in any other commute km . Formally, this can be written

$$\pi_{ij}(l) \equiv \Pr[V_{ijn}(l) \geq V_{kmn}(l) \quad \forall km]. \quad (8)$$

Using G_{ij} and after integration⁵, one gets that

$$\begin{aligned} \pi_{ij}(l) &= \frac{\left[\tilde{B}_{ij}(lw_j - cd_{ij} - Q_i f)Q_i^{-\beta} \right]^\epsilon}{\sum_{i=1}^S \sum_{j=1}^S \left[\tilde{B}_{ij}(lw_j - cd_{ij} - Q_i f)Q_i^{-\beta} \right]^\epsilon} \\ &\equiv \frac{\phi_{ij}(l)}{\phi(l)}. \end{aligned} \quad (9)$$

with $\tilde{B}_{ij} = E_{ij}^{1/\epsilon} B_{ij}$ measuring adjusted amenities that take into account systematic deviations in preference shocks. When $lw_j - cd_{ij} < Q_i f$ however, utility is null and so is the numerator of the choice probability ϕ_{ij} . Since $\epsilon > 1$, these choice probabilities are still smooth and differentiable for any $w_j \in \mathbb{R}_+$ and any $Q_i \in \mathbb{R}_{++}$, as long as there is at least one commute in the city in which households can realize a positive utility.⁶

The total probability to reside in i for a worker with skills l , $\pi_{Ri}(l)$ (respectively working in j , $\pi_{Mj}(l)$) is the sum over workplaces j (respectively dwelling places i) of

⁵See [Ahlfeldt et al. \(2015\)](#) for details.

⁶Thereafter, I will implicitly assume $lw_j > Q_i f$ when writing down choice probabilities. If a worker gets too poor relative to floor space prices in the city, so that they cannot reach their incompressible floor space demand in any municipality, then it is simply assumed that they opt out from the city and leave.

the bilateral probabilities:

$$\pi_{R_i}(l) = \frac{\sum_{j=1}^S \phi_{ij}(l)}{\phi(l)}, \quad (10)$$

$$\pi_{M_j}(l) = \frac{\sum_{i=1}^S \phi_{ij}(l)}{\phi(l)}. \quad (11)$$

Thus, residential choice probabilities conditional on employment location are

$$\begin{aligned} \pi_{ij|j}(l) &= \frac{\phi_{ij}(l)}{\sum_{i=1}^S \phi_{ij}(l)} \\ &= \frac{\left[\tilde{B}_{ij}(lw_j - cd_{ij} - Q_i \underline{f}) Q_i^{-\beta} \right]^\epsilon}{\sum_{i=1}^S \left[\tilde{B}_{ij}(lw_j - cd_{ij} - Q_i \underline{f}) Q_i^{-\beta} \right]^\epsilon} \end{aligned} \quad (12)$$

Similarly, workplace probabilities conditional on residential location are

$$\begin{aligned} \pi_{ij|i}(l) &= \frac{\phi_{ij}(l)}{\sum_j \phi_{ij}(l)} \\ &= \frac{\tilde{B}_{ij}^\epsilon (lw_j - cd_{ij} - Q_i \underline{f})^\epsilon}{\sum_j \tilde{B}_{ij}^\epsilon (lw_j - cd_{ij} - Q_i \underline{f})^\epsilon}. \end{aligned} \quad (13)$$

Armed with these choice probabilities, that describe the spatial distribution of workers conditional on wages, rents and amenities, we can now discuss sorting.

2.2 The sorting of workers

When $\underline{f} > 0$, workers exhibit direct sorting, in the sense that high ability workkrs are willing to pay more in rents that poorer workers for an increase in residential amenities, and are willing to forego more wage per unit of labor for an increase in workplace niceness.

2.2.1 Residential location

Recall the probability for a worker to choose to reside in i conditional on her working in j defined at equation (12):

$$\pi_{ij|j}(l) = \frac{\left[B_i(lw_j - Q_i \underline{f} - cd_{ij}) Q_i^{-\beta} e^{-\tau d_{ij}} \right]^\epsilon}{\sum_{i=1}^S \left[B_i(lw_j - Q_i \underline{f} - cd_{ij}) Q_i^{-\beta} e^{-\tau d_{ij}} \right]^\epsilon}. \quad (14)$$

From this residential location choice probability, we can define a rate of substitution between rents and amenities as the variation in rents in i necessary to keep the share of j workers living in i stable when the amenities in municipality i increase/decrease. Formally, setting $\pi_{ij|j}$ constant gives

$$\left. \frac{dQ_i}{dB_i} \right|_{d\pi_{ij|j}(l)=0} (l) = -\frac{\partial_{B_i} \pi_{ij|j}(l)}{\partial_{Q_i} \pi_{ij|j}(l)}, \quad (15)$$

where $\partial_{Q_i} \pi_{ij|j}(l)$ is the partial derivative of residential choice probabilities with respect to rents,

$$\partial_{Q_i} \pi_{ij|j}(l) = -\epsilon \left[\frac{\beta}{Q_i} + \frac{f}{w_j l - Q_i \underline{f} - c d_{ij}} \right] \pi_{ij|i}(l) (1 - \pi_{ij|j}(l)), \quad (16)$$

while $\partial_{B_i} \pi_{ij|j}(l)$ is the partial derivative of residential choice probabilities with respect to local amenities,

$$\partial_{B_i} \pi_{ij|j}(l) = \frac{\epsilon}{B_i} \pi_{ij|i}(l) (1 - \pi_{ij|j}(l)). \quad (17)$$

Therefore, the (indirect) rate of substitution between rents and amenities is

$$\frac{B_i}{Q_i} \left. \frac{dQ_i}{dB_i} \right|_{d\pi_{ij|j}(l)=0} (l) = \frac{w_j l - c d_{ij} - Q_i \underline{f}}{\beta (w_j l - c d_{ij}) + (1 - \beta) Q_i \underline{f}}. \quad (18)$$

When $\underline{f} = 0$, i.e. when preferences are Cobb-Douglas, this elasticity boils down to $1/\beta$: every worker, rich or poor, skilled or unskilled, will keep her probability to choose a municipality constant when her rent increases by $1/\beta\%$ in exchange for a 1% increase in amenities. In fact in this case choice residential choice probabilities are independent of talent and wages: all else equal, skilled and unskilled households make the same residential choices.

Whenever $\underline{f} > 0$ however, this elasticity is strictly increasing in l . This means that when amenities in i increase, more productive and thus richer workers can accept a stronger increase in rents while keeping their probability to live in i constant. This is the basic direct sorting effect that is induced by non-homotheticities in housing demand, and that drives differences in residential location choices between rich and poor workers in the model. Note that thanks to this specification, the model does not a priori constrain the direction of sorting on distance. This is important when trying to assess the relative effects of commuting costs and amenities on workers repartition.

Similarly, we can define the willingness to pay at the residential location for an increase in travel time d_{ij} as

$$\frac{d_{ij}}{Q_i} \left. \frac{dQ_i}{dd_{ij}} \right|_{d\pi_{ij|j}(l)=0} (l) = -\frac{d_{ij} \partial_{d_{ij}} \pi_{ij|j}(l)}{Q_i \partial_{Q_i} \pi_{ij|j}(l)} = -\frac{c d_{ij} + \tau d_{ij} (w_j l - Q_i \underline{f} - c d_{ij})}{\underline{f} Q_i + \beta (w_j l - Q_i \underline{f} - c d_{ij})}. \quad (19)$$

This expression is always negative, showing that all workers must be compensated by a decrease in rents following an increase in commuting time for their choice probability to stay constant. Moreover, differentiating this expression with respect to income shows that it is decreasing in income if and only if $\underline{f}Q_i/\beta > c/\tau$. If the incompressible consumption of housing is high enough relative to the monetary cost of commuting, then all else equal rich workers sort closer to their workplace. If, on the other hand, the monetary cost of commuting superseeds the subsistence levels of housing consumption, then poorer households are willing to sacrifice more housing consumption to avoid the monetary costs of commuting and sort closer to their workplace.

2.2.2 Workplace

Looking at workplace location choice, conditional on residential location, choice probabilities in (13) become

$$\pi_{ij|i}(l) = \frac{\left[T_j(lw_j - Q_i \underline{f} - cd_{ij}) \right]^\epsilon}{\sum_{i=1}^S \left[T_j(lw_j - Q_i \underline{f} - cd_{ij}) \right]^\epsilon}, \quad (20)$$

so that one can define, in a similar fashion, the rate of substitution that captures the willingness to forego wages to benefit from higher amenities at the workplace:

$$\left. \frac{dw_j}{dT_j} \right|_{d\pi_{ij|i}(l)=0} (l) = - \frac{\partial_{T_j} \pi_{ij|i}(l)}{\partial_{w_j} \pi_{ij|i}(l)}, \quad (21)$$

where $\partial_{w_j} \pi_{ij|i}(l)$ is the partial derivative of workplace choice probability with respect to wages,

$$\partial_{w_j} \pi_{ij|i}(l) = \frac{\epsilon l}{w_j l - Q_i \underline{f} - cd_{ij}} \pi_{ij|i}(l) (1 - \pi_{ij|i}(l)), \quad (22)$$

while $\partial_{T_j} \pi_{ij|i}(l)$ is the partial derivative of workplace choice probabilities with respect to amenities at the workplace,

$$\partial_{T_j} \pi_{ij|i}(l) = \frac{\epsilon}{T_j} \pi_{ij|i}(l) (1 - \pi_{ij|i}(l)). \quad (23)$$

This gives a willingness to pay for workplace amenities equal to

$$\left. \frac{T_j}{w_j} \frac{dw_j}{dT_j} \right|_{d\pi_{ij|i}(l)=0} (l) = \frac{Q_i \underline{f} + cd_{ij}}{lw_j} - 1. \quad (24)$$

Whenever the commute has a positive probability to be selected, this quantity is strictly between zero and negative one, and monotonically decreasing with skills. All workers are willing to forego some income for an increase in their workplace quality, but for poorer workers the percentage increase needed to compensate a reduction in wages tends to infinity. This elasticity is also increasing in incompressible costs, so that all else equal workers living in more expensive municipalities or supporting higher monetary costs of commuting are less willing to forego wages for workplace niceness.

Finally, define in a similar fashion the willingness to pay at the workplace for an increase in distance as

$$\left. \frac{d_{ij}}{w_j} \frac{dw_j}{dd_{ij}} \right|_{d\pi_{ij}(l)=0} (l) = d_{ij} \frac{c + \tau(lw_j - Q_i \underline{f} - cd_{ij})}{lw_j}. \quad (25)$$

This expression is positive, so that every worker needs to be positively compensated in wages for an increase in distance. Differentiating this expression with respect to skill l , we get that it is increasing in skill if and only if $\tau(Q_i \underline{f} + cd_{ij}) > c$. If the costs induced by incompressible consumption are sufficiently high with respect to the monetary costs of commuting, then richer workers sort in workplaces closer to their dwelling place.

2.3 Aggregation

From individual choice probabilities, aggregate quantities at the municipal level can be computed as follows:

- Total residential population in i is given by summing residential probabilities over skill levels

$$H_{Ri} = H \int_0^\infty \pi_{Ri}(l) d\mathcal{F}(l), \quad (26)$$

- Total income of residents in i is given by summing wages over workplaces and skill levels

$$W_i = H \sum_j w_j \int_0^\infty l \pi_{ij}(l) d\mathcal{F}(l). \quad (27)$$

- Total supply of effective labour in j is given by summing the supply from all skills l

$$H_{Mj} = H \int_0^\infty l \pi_{Mj}(l) d\mathcal{F}(l), \quad (28)$$

with H the total population of the city.

Moreover, from with a Fréchet preference shock the expected utility is given by (cf. Ahlfeldt et al., 2015, for a proof)

$$\mathbb{E}(U|l) = \left[\sum_{i=1}^S \sum_{j=1}^S \left[\tilde{B}_{ij}(lw_j - cd_{ij} - Q_i f) Q_i^{-\beta} \right]^\epsilon \right]^{\frac{1}{\epsilon}}, \quad (29)$$

so that the total welfare of workers is

$$\mathbb{E}(U) = \int \mathbb{E}(U|l) d\mathcal{F}(l). \quad (30)$$

2.4 Production

Production in each municipality is assumed to be Cobb-Douglas over workforce \bar{H}_{Mj} and floor space F_{Mj} , with a share of floor space α :

$$y_j = A_j (\bar{H}_{Mj})^{1-\alpha} (F_{Mj})^\alpha, \quad (31)$$

where measured by A_j is a total factor productivity (TFP) term that varies between municipalities. Firms pay a rent Q_j per unit of floor space and a wage \bar{w}_j per unit of effective labour. Under these assumptions, the profit of firms in j is thus

$$A_j (H_{Mj})^{1-\alpha} (F_{Mj})^\alpha - Q_j F_{Mj} - \bar{w}_j \bar{H}_{Mj}. \quad (32)$$

The first order conditions of profit maximization yield the following conditional demands:

$$\begin{aligned} \bar{H}_{Mj} &= (1 - \alpha) \frac{y_j}{\bar{w}_j} \\ F_{Mj} &= \alpha \frac{y_j}{Q_j}. \end{aligned} \quad (33)$$

Rearranging gives the demand for commercial floor space, given workforce:

$$F_{Mj} = \frac{\alpha}{1 - \alpha} \frac{\bar{w}_j \bar{H}_{Mj}}{Q_j}. \quad (34)$$

Moreover, plugging these two equations into the firms production function gives the zero profits condition that has to hold if profit maximizing firms operate in municipality j :

$$A_j = \left(\frac{Q_j}{\alpha} \right)^\alpha \left(\frac{\bar{w}_j}{1 - \alpha} \right)^{1-\alpha}. \quad (35)$$

Finally, workforce \bar{H}_{Mj} is a CES aggregate over workers of high skill S and low skill L with an elasticity of substitution σ and high skill bias A_j^S :

$$\bar{H}_{Mj} = \left[A_j^S (H_j^S)^{\frac{\sigma-1}{\sigma}} + (1 - H_j^S) (H_j^L)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \quad (36)$$

2.5 The market for floor space

We assume that floor space is produced by a competitive development sector under CRS technology, using elastically supplied capital and land that is completely inelastically supplied. This implies an elastic supply of floor space, with a price elasticity inversely proportional to the share of land in the construction technology of the construction sector.

Formally, F_i the total floor space in i , available for both commercial and residential use, is supplied by a competitive development sector. Following [Combes et al. \(2017\)](#) and [Epple et al. \(2010\)](#), developers use land L_i with rental price R_i and capital K_i with rental price P (common to all locations) as inputs to a CRS Cobb-Douglas technology:

$$F_i = C_i K_i^{1-\mu} L_i^\mu. \quad (37)$$

Developers to treat land available for construction as given and fixed, $L_i = \bar{L}_i$,⁷ and maximize their profit by choosing how much capital to invest for land development in i . The first order conditions of this program give

$$K_i = \left[\frac{(1-\mu)C_i}{P} Q_i \right]^{\frac{1}{\mu}} \bar{L}_i, \quad (38)$$

which yields the following supply function:

$$F_i = \tilde{L}_i Q_i^{\tilde{\mu}}, \quad (39)$$

where $\tilde{L}_i \equiv \bar{L}_i C_i^{1/\mu} (\frac{1-\mu}{P})^{(1-\mu)/\mu}$ is a measure of land in i corrected by the constructibility in i and $\tilde{\mu} \equiv \frac{1-\mu}{\mu}$ is the rent elasticity of floor space supply.

On the demand side, the demand of floor space from firms is given, as a function of workforce, by equation (34). For residents, total demand can be computed by aggregating the individual demand in (4) over skills and commute probabilities:

$$F_{Ri} = \beta \frac{W_i}{Q_i} + (1-\beta) H_{Ri}, \quad (40)$$

where W_i and H_{Ri} are total income and residential populations respectively, as per equations (27), and (26). Therefore, the market clearing condition is given by equating floor space supply (39) to both these demands:

$$\tilde{L}_i Q_i^{\tilde{\mu}} = \frac{1-\alpha}{\alpha} \frac{\bar{w}_i \bar{H}_{Mi}}{Q_i} + (1-\beta) f_{-} H_{Ri} + \beta \frac{W_i}{Q_i}. \quad (41)$$

⁷Assuming that the supply of land is fixed does not seem to be a strong assumption in an urban context, where alternative uses of land such as agriculture are not a concern.

2.6 Agglomeration effects and spillovers

Local TFPs are allowed to depend on local workforce density:

$$A_i = \tilde{A}_i \left[\sum_j \exp(-\rho^A d_{ij}) \frac{\bar{H}_{Mj}}{L_j} \right]^{\lambda^A}, \quad (42)$$

where λ^A is the elasticity of TFP to total workforce in the city, while ρ^A is a spatial decay parameter measuring the reach of productivity spillovers.

High-skilled bias is allowed to depend on density in a similar way:

$$\frac{A_i^S}{1 - A_i^S} = \tilde{A}_i^S \left[\sum_j \exp(-\rho^S d_{ij}) \frac{\bar{H}_{Mj}}{L_j} \right]^{\lambda^S}. \quad (43)$$

Finally, residential amenities depend on a local market potential that aggregates total residential income around every location:

$$B_i = \tilde{B}_i \left[\sum_j \exp(-\rho^B d_{ij}) \frac{\bar{W}_j}{L_j} \right]^{\lambda^B}. \quad (44)$$

Table 1: List of parameters, estimation methods and sources.

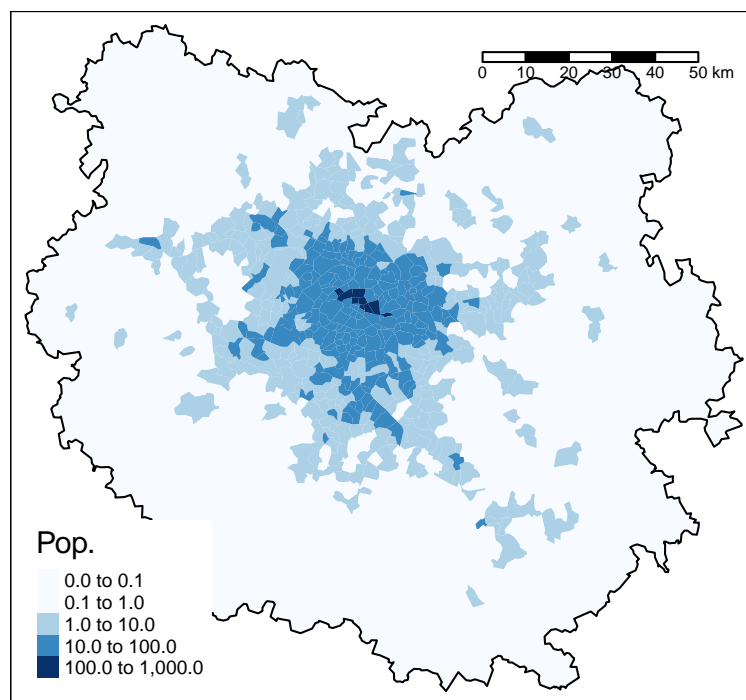
Quantity	Description	Method	Source*	Sect.
ϵ	Taste shock dispersion	Calibrated	Ahlfeldt et al. (2015)	3.1
τ	Utility cost of commuting	Estimated on commuting flows	DADS, TT, DVF	3.1
\underline{f}	Subsistence floor space quantity	Match housing Engel Curve	Expenditure survey	3.1
β	Floor space preference parameter	Match housing Engel Curve	Expenditure survey	3.1
w_1, \dots, w_J	Local wages	Mincer wage decomposition	DADS	3.2
\mathcal{F}^e	Talent distribution	Mincer wage decomposition	DADS	3.2
α	Floor space share in prod.	Calibrated	National Accounts	3.3
σ	Skill complementarity	Calibrated	Litterature	3.3
A_1, \dots, A_J	TFP	Zero profits condition	DADS, DVF	3.3
$\tilde{\mu}$	Building supply elasticity	Calibrated	Combes et al. (2017)	3.4
B_1, \dots, B_J	Residential amenities	Match residential population	DADS, TT, DVF	3.5
T_1, \dots, T_J	Workplace niceness	Match total labor supply	DADS, TT, DVF	3.5
ρ, λ	Spillovers	Model-Based instruments	DADS, TT, DVF	3.6

*: See text in section 3 for a description of the data.

3 Data and calibration

For the rest of the paper, I calibrate the model on the Urban Areas of Paris, in 2015 (represented in Figure 1). It is by far the biggest Urban Area in the country, and the one that exhibits the highest levels of spatial inequalities both in terms of rents and wages. It has been a major commercial and cultural hub for most of the country's history, and thus offers important historical and cultural amenities.

Figure 1: Residents per km^2



For the delineation of the city, I use the National Statistical Institute *Aires Urbaines*, that are constructed by sequential aggregation of municipalities around employment centers based on commuting flows. There has recently been a renewed interest in the literature about methods for delineating Urban Areas (see e.g. [Arribas-Bel et al., 2019](#), [de Bellefon et al., 2020](#)). For the purpose of the present paper, because the adjustment of the rent gradient is a key mechanism driving workers sorting as a response to changes in commuting costs, it is important that the limitations to urban sprawl imposed by the urban area boundaries do not influence the results. As illustrated in Figure 1, the

definition of urban areas used here allows for a wide buffer of low density areas (less than $1 h/km^2$) around the city center, which means that even when relaxing commuting costs area boundaries should not introduce artificial land scarcity.

Table 1 lists the parameters and fundamentals of the model, and the source and methods used to estimate or calibrate them, where the data sources are as follows.

Workers Microdata (DADS): The *Déclarations Automatiques de Sécurité Sociale* are an administrative, restricted-access dataset on the universe of French workers. Sent by employers to the social security administration on a yearly basis to be used for the computation of social security contributions. They contain the salaries, hours worked, occupation, workplace and dwelling place of every French employee. They are exhaustive on the universe of French private payroll employees and available from 1993 to 2015. However, it is not a proper panel as individual IDs are scrambled every two years. Absent data on education, I use occupation categories, and treat grey matter, managers and professionals as high skill workers and the rest of the workforce as low skill workers.

Household Expenditure survey: The *Enquête Budget des Familles* is a representative survey of French households expenditures conducted by the National Statistical Institute. It contains household composition, housing expenditures, household income and housing surface area. For the estimations, I pool the 2006 and 2011 waves of the survey.

Building transactions (DVF): The *Demande de Valeurs Foncières* is an open dataset, exhaustive on the universe of building transactions in France starting in 2014.

Land registry files (FF): The *Fichiers Fonciers* from the French tax administrations are an exhaustive dataset on the universe of French properties. They report, for each property in France, its floor space area and its fiscal status, either as a dwelling or as a place of business.

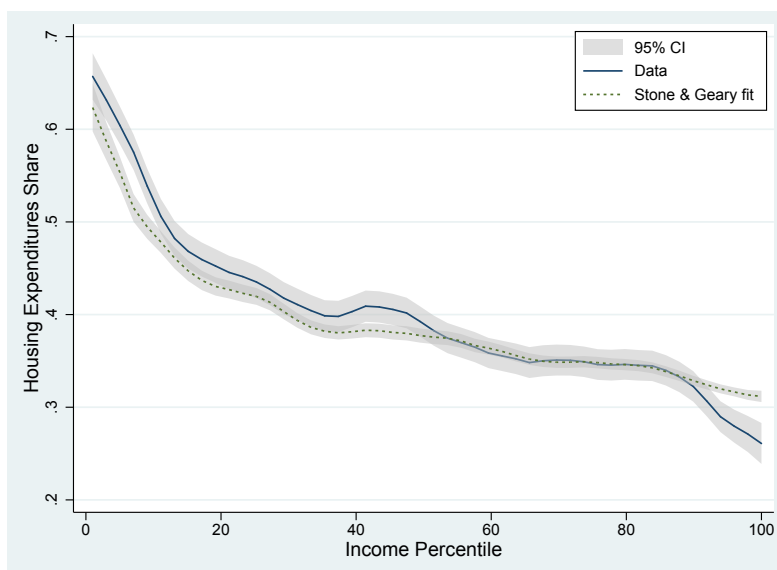
Travel Times (TT): Average road travel times between municipalities are computed using extractions of the road network from the OpenStreetMap project and the *dodgr* R package (?). For the public transport network, I use publicly available GTFS

transit timetables and compute travel times between municipality centroids at 8 in the morning on a tuesday.

3.1 Workers preferences

The taste shock dispersion parameter ϵ is calibrated to 6, following e.g. [Ahlfeldt et al. \(2015\)](#), [Ahlfeldt and Wendland \(2016\)](#).

Figure 2: Engel curve: data and Stone-Geart fit



Expenditure Survey data vs. Stone-Geary prediction, with parameters $\beta = 0.24$ and $\underline{f} = 22.62$

Housing consumption For the Stone and Geary demand parameters, β and \underline{f} , I set them to match the observed engel curve for housing in the Expenditure Survey data. This data gives monthly expenditures on housing, total floor space of the dwelling unit and monthly income and the number of workers for French households in 2006 and 2011. From the Stone-Geary specification of utility, the share of income dedicated to housing is given by (4) :

$$\frac{Q_i f_{ijn}^*}{lw_j} = \beta + (1 - \beta) \underline{f} \frac{Q_j}{lw_j}.$$

In the expenditure data, I compute lw_j and $Q_i f_{ijn}^*$ by dividing household income and expenditure by the number of workers in the household. Keeping only

households with above minimal wage workers and expenditure shares below one, the resulting Engel curve is plotted in Figure 2. It is downward slopping, and the Stone-Geary specification, with $\hat{\beta} = 0.24$ and $\hat{f} = 22.62$ is able to fit this relationship quite well, with significant discrepancies for the bottom and top deciles only.

Transport costs Assuming that workers choose their mode of transport solely based on travel times, and that this choice is subject to an iid Fréchet shock on transport mode with dispersion parameter θ , the probability to choose to take the car versus public transport is

$$\Pr(c|ij) = \frac{a_c d_{cij}^{\tau\theta}}{a_c d_{cij}^{\tau\theta} + d_{pij}^{\tau\theta}}$$

where a_c is a parameter and d_{cij} and d_{pij} are travel times between i and j respectively by car and by public transport.⁸ I estimate a_c and $\tau\theta$ by OLS, regressing log odd-ratios for each location-destination-type pair on the log-difference of travel times. The estimated $\tau\theta$ is -1.77 and -1.62 respectively for low skilled and high skilled workers, in line with estimated travel time disutility parameters in the literature. The expected utility of commuting is then (up to a multiplicative constant) $\hat{d}_{ij}^{1/\theta} = [a_c d_{cij}^{\tau\theta} + d_{pij}^{\tau\theta}]^{1/\theta}$. For the monetary cost of commuting, spending surveys from INSEE gives an average variable cost of car use of 2000€ a year. Dividing by the average distance by car of 32 kilometers, this yields a monetary cost of commuting of 66€ per kilometer per year. The expected cost of driving when living in i and working in j is then $\hat{cd}_{ij} = 66 \times \Pr(c|ij) \times d_{cij}$. I then plug in those costs to estimate τ in the bilateral choice probabilities in 9, that I repeat here for convenience:

$$\pi_{ij}(l) = \frac{[\tilde{B}_{ij}(lw_j - cd_{ij} - Q_i f) Q_i^{-\beta}]^\epsilon}{\sum_{i=1}^S \sum_{j=1}^S [\tilde{B}_{ij}(lw_j - cd_{ij} - Q_i f) Q_i^{-\beta}]^\epsilon}. \quad (45)$$

Given values for ϵ , β and $\tau\theta$ and monetary costs of commuting \hat{cd} , I solve for the unique $\tilde{B}_{ij}^\epsilon = B_{ij} \hat{d}_{ij}^{\epsilon/\theta}$ that rationalize the market share of each commutes using a classical BLP (Berry et al., 1995) contraction mapping. I estimate the dispersion parameters $\frac{\epsilon}{\theta}$ by regressing this pairwise attractiveness on the expected disutility of

⁸To be fully consistent with the model specification, one would need to compute the full expected utility of a commute over transport modes, that involves individual incomes and residential rents. Lacking individual data on incomes and transport mode, I rely on this approximation.

Table 2: Transport mode choice.

	(1)	(2)
	Low skill	High skill
ρ	-1.766*** [-1.794,-1.739]	-1.624*** [-1.660,-1.588]
Constant	-1.458*** [-1.479,-1.437]	-1.500*** [-1.525,-1.475]
r2	0.320	0.291
N	34326	18870

95% confidence intervals in brackets
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

travel and origin and destination fixed-effects:

$$\ln(\tilde{B}_{ij}^{\epsilon}) = \delta_i + \delta_j - \frac{\epsilon}{\theta} \ln(\hat{d}_{ij}) + e_{ij}. \quad (46)$$

As is common in the estimation of bilateral trade frictions, the transport infrastructure between a given pair of points may endogenously evolve based on the population commuting between those points. I thus instrument expected travel times using euclidian distance.

Table 3: Estimates of the dispersion parameter of mode choice

	(1)	(2)	(3)	(4)
	OLS Low skill	IV Low skill	OLS High skill	IV High skill
lexput	1.084*** (0.00396)	0.834*** (0.00528)	0.887*** (0.00486)	0.638*** (0.00712)
lprojleucli		-0.481*** (0.00695)		-0.375*** (0.00793)
_cons	-0.352*** (0.0278)	-2.185*** (0.0379)	-1.863*** (0.0311)	-3.349*** (0.0439)
ll	-110180.5	-107809.2	-67653.2	-66532.1
N	93385	93385	60854	60854
df.a	1391	1391	1387	1387
N_hdfe	2	2	2	2

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. “lexput” = ϵ/τ is the dispersion parameter. “lprojleucli” is the residual of a regression of expected commuting times on euclidian distance.

Table 3 reports the estimated elasticity of location choice to expected travel times disutility, controlling for the monetary costs of commuting. The estimated parameter is higher for high skilled workers, and IV parameters are lower than OLS parameters.

3.2 Municipal wages

In order to simulate the model, one needs to recover the distribution of skills within each worker type separately from the wages paid by firms per unit of labor. To do so, I regress the log of individual wages $\ln(w_n^e)$ for worker n with skill e on a set of individual variables X_n and workplace-type fixed effects $\ln(w_j^e)$:

$$\ln(w_n^e) = \ln(w_j^e) + \theta X_n + \epsilon_n \quad (47)$$

Once municipal wages $\ln(w_j^e)$ are estimated, I attribute everything else to individual productivities: $\ln(l_n) = \hat{\theta}X_n + e_n$. Since individual productivities and local wages are only identified up to scale, I normalize l_n by its geometric mean within each type e .

Table 4: Contribution of individual and local effects to mean wage.

	Standard Deviation	Correlation with (log) Mean wage	$\ln(w_j^e)$
(log) Mean wage	0.115	1.00	0.89
$\ln(w_j^e)$ (Local)	0.091	0.89	1.00
Mean individual effects	0.053	0.64	0.22

Standard deviation and correlation coefficients within city \times skill.

3.3 Local productivities and technology parameters

The CES aggregator for unskilled and skilled labor (36) implies (log) labor demand ratios

$$\ln \left(\frac{H_j^S}{H_j^L} \right) = -\sigma \ln \left(\frac{w_j^S}{w_j^U} \right) + \ln \left(\frac{A_j^S}{1 - A_j^S} \right). \quad (48)$$

I set σ the elasticity of substitution between high and low skilled workers equal to 1.5, which is the consensus value in the literature (see e.g. [Wingender, 2015](#), and references therein.). I then compute the skill-bias of labor demand in each municipality

by inverting (48)

$$\frac{A_j^S}{1 - A_j^S} = \frac{H_j^S / H_j^U}{(w_j^U / w_j^S)^\sigma}.$$

The consensus value for σ is at 1.5 for developed countries. From the Cobb-Douglas technology on the upper nest of the production function $y_j = A_j \bar{H}_{Mj}^{1-\alpha} F_{Mj}^\alpha$, the production parameter α is equal to the share of floor space in firms costs.

National accounts from *insee* report that the share of capital (GFCF) represents 30% of value added, while building and land make up 55% of capital expenditures of French firms. Normalizing so that floor space and labor shares sum to one, we get a share of land of $\alpha = 0.55 \times 0.3 / (0.7 + 0.55 \times 0.3) = 19\%$.

Because of changing definitions of taxable commercial and professional floor space, land registers are not very reliable in their reporting of non-residential surfaces. Still, using non-residential floor space from those files and average rents per squared meter from the building transactions data, I obtain a share of floor space in firms costs of 26%, while regressing floor space costs on total wage bill at the municipal level gives a coefficient of 0.28, implying a share $\alpha = 22\%$. Overall, the calibrated parameter from national accounts data is in line with raw correlations in the micro data, and I calibrate $\alpha = 20\%$.

Given this parameter, wage index \bar{w}_j and rents Q_j for each municipality j , I compute TFPs from the zero profits condition

$$A_j = \left(\frac{\bar{w}_j}{1 - \alpha} \right)^{1-\alpha} \left(\frac{Q_j}{\alpha} \right)^\alpha.$$

3.4 Construction sector

For the construction sector technology, I calibrate $1 - \mu$ the share of land using estimates in [Combes et al. \(2017\)](#). This gives a supply elasticity of $\tilde{\mu} = 1.17$ for Paris. Estimated long-term elasticities of housing supply in the literature for constrained cities range between 1 and 4 depending on the nature of the housing market. [Saiz \(2010\)](#) reports unweighted mean elasticities across US Metropolitan Areas (MSAs) of 2.5, while [Harter-Dreiman \(2004\)](#) reports ranges of elasticities of [1 – 2.1] for constrained housing markets and [2.6 – 4.3] for unconstrained cities, still in the US.

Given $\tilde{\mu}$ and households preference parameters, adjusted land areas \tilde{L}_i are

computed for all i to solve the floor space market clearing equation in (41):

$$\tilde{L}_i = Q_i^{-\bar{\mu}} \left(\frac{1 - \alpha}{\alpha} \frac{\bar{w}_i \bar{H}_{Mi}}{Q_i} + (1 - \beta) \underline{f} H_{Ri} + \beta \frac{W_i}{Q_i} \right).$$

3.5 Amenities

Given individual preference parameters $\epsilon, \beta, \tau, \underline{f}$, local wages w_j^e for every municipality and type and floor space rents Q_i^e for every municipality, we can compute total income at the workplace and at the residential place for each type

$$W_i^e = H \sum_j w_j \int_0^\infty l \pi_{ij}(l) d\mathcal{F}^e(l), \quad e = \{S, U\}$$

$$W_{Mi}^e = H w_j \sum_j \int_0^\infty l \pi_{ji}(l) d\mathcal{F}^e(l), \quad e = \{S, U\}.$$

I calibrate amenities B_i^e and labour supply shifters T_j^e to the unique values that match predicted total income to total income in the data for all i, j and e , conditional on preference parameters, wages and rents.

3.6 Spillovers and agglomeration effects

Having recovered TFPS A_j , skill bias A_j^S and residential amenities B_i^e , for $e = \{S, U\}$, I estimate the spillover parameters using a model-based instrument approach à la [Allen et al. \(2020\)](#). The main concern with naive non-linear least square estimation of the spillover parameters ρ and λ in (42), (43) and (44), is that of the simultaneity of populations and exogenous amenities. Taking (42) as an example, the equation that we would like to estimate is

$$A_i = \left[\sum_j \exp(-\rho^A d_{ij}) \frac{\bar{H}_{Mj}}{L_j} \right]^{\lambda^A} \tilde{A}_i,$$

where \tilde{A}_i , the error term, is composed of exogenous variables that influence local productivity, besides agglomeration effects that are captured by the term in brackets. Because workers tend to move to high-TFP places to enjoy higher wages, \tilde{A}_i is likely positively correlated with \bar{H}_{Mj} , so that we can expect naive estimates of λ to be biased upward.

This problem is not new, and there is a large body of literature concerned with designing ways to mitigate this endogeneity issue. The canonical approach (cf.

Combes and Gobillon, 2015) is to instrument populations by long lagged values of itself, while controlling for geographical features that are likely to be part of \tilde{A}_j . The reasoning behind those instruments is that technological change has been such over the years that determinants of productivity that attracted populations centuries ago are not relevant anymore (at least conditional on controls), and only affect productivity in so far as they anchored populations. The identifying assumption that underlies this approach is thus that once we control for persistent geographical features that may be relevant for today's firms (such as climate or access to water) the factors that drove the localization of XVIII century manufacturing are not directly relevant to the localization of modern-day industries.

However, while the identifying assumptions are plausible in the case of productivity, their application to estimating residential amenity spillovers is more problematic. Indeed, in the case of residential amenities, one can argue that most of the natural features, views, monuments and historical prestige that drove the localization of residents a few centuries ago are still relevant to the location choice of modern workers. Especially within cities, where fine geographical features can make all the difference between a cold swamp and a nice riverside, it would be hard to argue that we have access to detailed enough control variables to make historical populations a valid instrument.

To recover these spillover parameters, I thus follow Allen et al. (2020) and use *model-based instruments*, constructed using exogenous variables that would have been used as controls in a traditional IV approach. The advantage of this approach is that we do not need an exhaustive list of control variables, as long as they have some relevance to location choice.

In short, the method goes as follows:

1. Regress model fundamentals (A_i, B_i, A_i^S) on a set of exogenous local characteristics Z_i , and predict $(\hat{A}_i, \hat{B}_i, \hat{A}_i^S)$ using Z_i .
2. Simulate the model using $(\hat{A}_i, \hat{B}_i, \hat{A}_i^S)$ and a first guess λ, ρ for the agglomeration and spillover parameters as inputs. Denote (\hat{H}_{Mj}) the simulated workforce and (\hat{W}_i) the predicted incomes.
3. Estimate $\hat{\lambda}$ and $\hat{\rho}$ from the structural equations (42), (43) and (44), using the simulated variables (\hat{H}_{Mj}) and (\hat{W}_i) as instruments, *whilst controlling for Z_i* .

The validity of the instruments comes from the fact that, by construction, the

predicted values are not correlated to components of (A_i, B_i, A_i^S) that are not controlled for by Z_i in the last step of the procedure, so that we can safely assume the following moment conditions:

$$\begin{aligned}
\mathbb{E}[(\ln(\tilde{A}_i) - \beta_A Z_i) \times \delta_i^k(\hat{H}_M)] &= 0 & i = 1, \dots, J, & \quad k = 1, \dots, K \\
\mathbb{E}[(\ln(\tilde{A}_i^S) - \beta_A^S Z_i) \times \delta_i^k(\hat{H}_M)] &= 0 & i = 1, \dots, J, & \quad k = 1, \dots, K \\
\mathbb{E}[(\ln(\tilde{B}_i^e) - \beta_B Z_i) \times \delta_i^k(\hat{W})] &= 0 & i = 1, \dots, J, & \quad k = 1, \dots, K, \quad e = S, U,
\end{aligned} \tag{49}$$

where $\delta_i^k(X)$ denotes the average of X in the k th concentric annulus around i .

Note that identification does not only come from non-linearities of the model. Indeed when running the actual IV regression in step 3 of the procedure we only control for i 's own Z_i , whereas each equilibrium value \hat{H}_{Mj} is a combination of the whole Z and distances. Identification is thus achieved by using the model to weight distant values of Z and use them as instruments. When we suspect that one of the variables might have direct spillover effects on the productivity of neighboring municipality, such as access to a river, it is thus important to control for the direct effect of distance to this amenity by directly including it in Z .

As a first guess, I use the values estimated by [Ahlfeldt et al. \(2015\)](#) and set the TFP parameters to $\lambda^A = 0.07$ and $\rho^A = -0.35$ and the amenities parameters to $\lambda^B = .35$ and $\tau^B = -0.8$ for both the high skilled and low skilled amenity indices. For the skill bias, I simply set both parameters to zero. I then subtract the implied agglomeration effects from the estimated fundamentals and set out to explain the (log of the) remainder using exogenous variables. Table 22 in appendix reports the results of these first stage regressions. The included explanatory variables are mean altitude, maximum slope, the share of the area covered by water, distance to main train lines and distance to coasts, as well as dummies indicating that these distances are less than 5 kilometers. I also include a dummy variable for listed buildings and the number of listed buildings in the municipality. All regressions are within Urban Area. R-squared are 9% for skill bias, 15% for TFP, 52% and 68% for high and low skill amenities, and around 25% for labor supply shifters. All the F-stats are above 13.

Table 5 shows the results of the naive non-linear least squares and GMM estimates of the agglomeration effects for TFP and skill bias. Regarding TFP, the GMM estimates are lower than the OLS estimates, at a value of $\lambda^A = 0.028$ and a spatial decay equal to $\tau^A = 0.19$, although unprecisely estimated. These values are in line with existing estimates in the literature. Given the functional form of agglomeration effects, λ^A is the elasticity of TFP to a city-wide increase in population. As such, its value of 0.028

Table 5: Estimates of spillover parameters for productivity.

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP	TFP	TFP IV	AR	AR	AR 25 1
main						
lambda_YW_l	0.0401*** (0.00200)	0.0461*** (0.00246)	0.0224*** (0.00626)	0.0815*** (0.00613)	0.0951*** (0.00752)	0.0261 (0.0203)
tau_YW_l	-0.503*** (0.0812)	-0.516*** (0.0717)	-0.192 (0.135)	-0.539*** (0.129)	-0.546*** (0.111)	-0.265 (0.413)
lland			-0.0335** (0.0113)			-0.0762* (0.0363)
N	696	696	696	696	696	696
Controls	No	Yes	Yes	No	Yes	Yes
Ffirst			560.2			560.2
J			19.33			18.74
J-p			0.682			0.716
n_moments			32			32

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Lambda measures agglomeration and tau measures its spatial decay. Agglomeration effects are measured in terms of total workforce, defined as the CES aggregate for labor. “Controls” include the variable in Table 22 in Appendix. Columns with no first-stage F-stat and overidentification tests are NLS regressions, columns with those statistics are model-based IV regressions.

is quite close to between-cities estimates using the same data (cf. e.g. [Combes and Gobillon, 2015](#)). Regarding skill bias, the results are similar: the GMM elasticity is markedly lower than the NLS one, and so is the spatial decay parameter.

Similarly, Table 6 reports the estimated spillover effects for residential amenities, where the variable generating spillovers is total residential income per land unit. Instrumenting for total income shows that the least-square estimator strongly overestimates spillover effects for low skilled workers, but not so much for high skilled workers. The strength of the spillovers effects is more than twice as high for high skilled workers than for low skill workers.

3.7 Correlation between model-based and observed amenities

In this section, I look at the correlation between the amenities computed above and a set of observed variables, as a way to check the validity of the model specification. I

Table 6: Estimates of spillover parameters for amenities.

	(1)	(2)	(3)	(4)	(5)	(6)
	B0	B0	B0 IV	B1	B1	B1 IV
main						
lambda.WR.I	0.131*** (0.0177)	0.346*** (0.0222)	0.120* (0.0500)	0.264*** (0.0182)	0.516*** (0.0228)	0.258*** (0.0440)
tau.WR.I	-0.408* (0.185)	-0.779*** (0.100)	-0.649 (0.783)	-0.342*** (0.0785)	0.582*** (0.0577)	0.398* (0.198)
Controls	No	Yes	Yes	No	Yes	Yes
Ffirst			100.8			100.8
J			53.75			38.51
J-p			0.000290			0.0224
n.moments			34			34
N	696	696	696	696	696	696

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Lambda measures agglomeration and tau measures its spatial decay. Spillovers are measured in terms of total income per unit of land. "Controls" include the variable in Table 22 in Appendix. Columns with no first-stage F-stat and overidentification tests are NLS regressions, columns with those statistics are model-based IV regressions.

use the *Base Permanente des Équipements* dataset, a public dataset with the location of a wide range of endogenous amenities, from restaurants to swimming pools and general practitioners. A complete list of the variable used and associated descriptive statistics are reported in Table 23 in appendix.

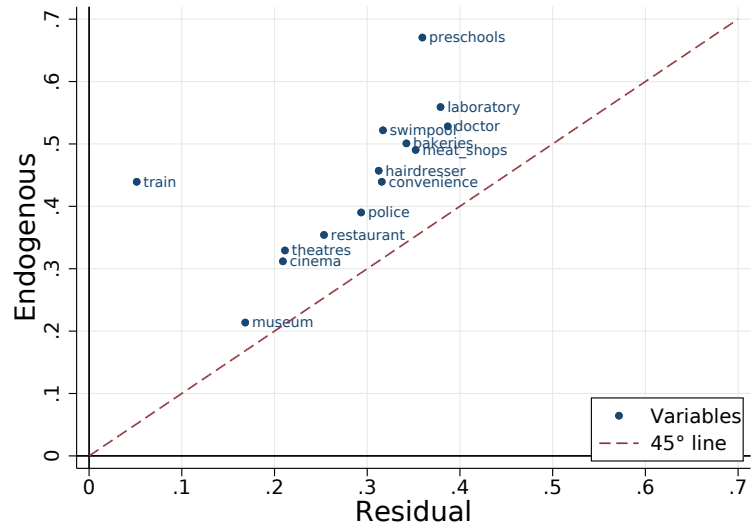
Table 7: R2 of observed amenities on model-implied amenities.

(a) Low skilled			(b) High skilled				
(1)	(2)	(3)	(1)	(2)	(3)		
All	Endogenous	Residuals	All	Endogenous	Residuals		
r2	.3593923	.5290109	.1820634	r2	.4672768	.5249098	.2053921

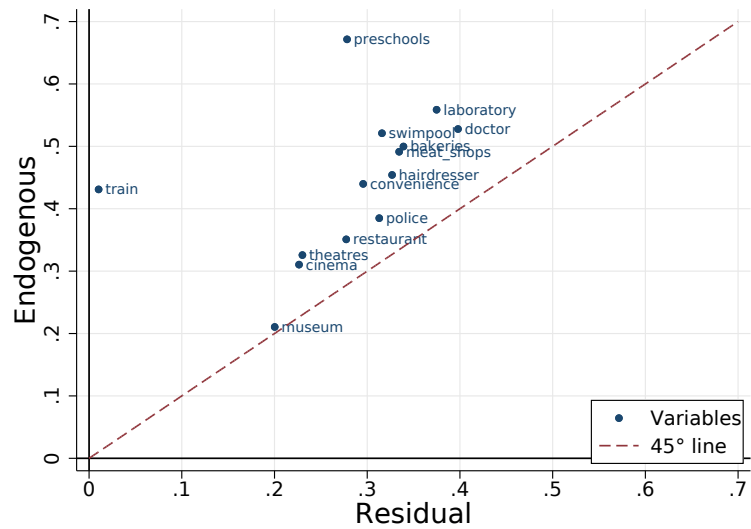
Table 7 reports the R^2 of regressions of model-based amenities on observed amenities. In total, observed amenities explain around 30% of the variations of estimated low-skill amenities, and 45% of the estimated high-skill amenities. The correlation is higher when focusing on the estimated endogenous amenities (50%) than when focusing on the residual (around 20%).

Figure 3: Correlations between observed and estimated amenities

(a) Low skilled



(b) High skilled



Note: each dot is an observed amenity. The y axis reads the correlation between this amenity and the model-based endogenous amenities, while the x axis reads its correlation with the residual (i.e. exogenous) amenities.

To further investigate the relationship between observed and model-implied amenities, Figure 3 reports correlation coefficients between observed and theoretical amenities both for high and low-skilled workers. The number of preschools, medical laboratories and doctors are the variables that correlate the most with endogenous amenities, whilst museums have the lowest correlation. Traditional endogenous amenities such as the number of restaurants, bakeries, hairdressers and convenience stores also correlate strongly with endogenous amenities.

All these observed amenities also correlate positively to residual, unobserved amenities. However all the dots lie above the 45° line, indicating that this correlation is systematically weaker than with endogenous amenities. This shows that the model-based endogenous amenities index captures most of the effect of observed amenities. Moreover, it is not surprising to see a positive correlation between the amenities residual and observed amenities, as we expect that high exogenous amenities anchor neighborhoods into high population, high endogenous amenities status.

4 Simulations

4.1 Model fit and overidentification tests

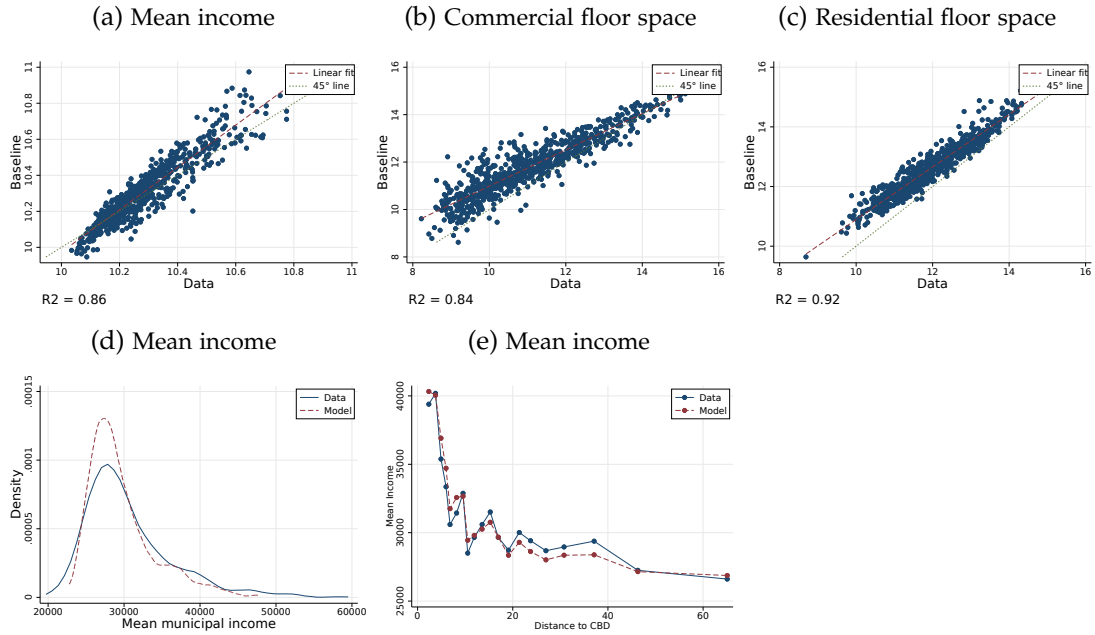
In this section, I report the results of a baseline simulation of the model with the estimated and calibrated parameter values from the previous section.

Simulations are computed using a fixed-point algorithm that reproduces a dynamic setup with myopic workers. At each iteration t , incomes w_{je}^t , rents Q_i^t and endogenous amenities and TFPs are computed that clear the floor space and labor markets, conditional on previous period repartition of workers over commutes. A new mass of workers is then computed for each commute using the bilateral choice probabilities. I then update incomes, rents and spillovers again, and the operation is repeated until the repartition of workers stabilizes.

In calibrating the model, I do not directly target mean incomes and I do not use the data on floor space. They are therefore good candidates to test the specification of the model.

Although the model perfectly fits total populations, wages and rents conditional on the other observed variables in the model, it is not possible to calibrate the model to perfectly match total incomes and total populations at the same time, i.e. to perfectly predict mean incomes. Instead, the relationship between populations and

Figure 4: Overidentification checks: data vs. non-targeted variables



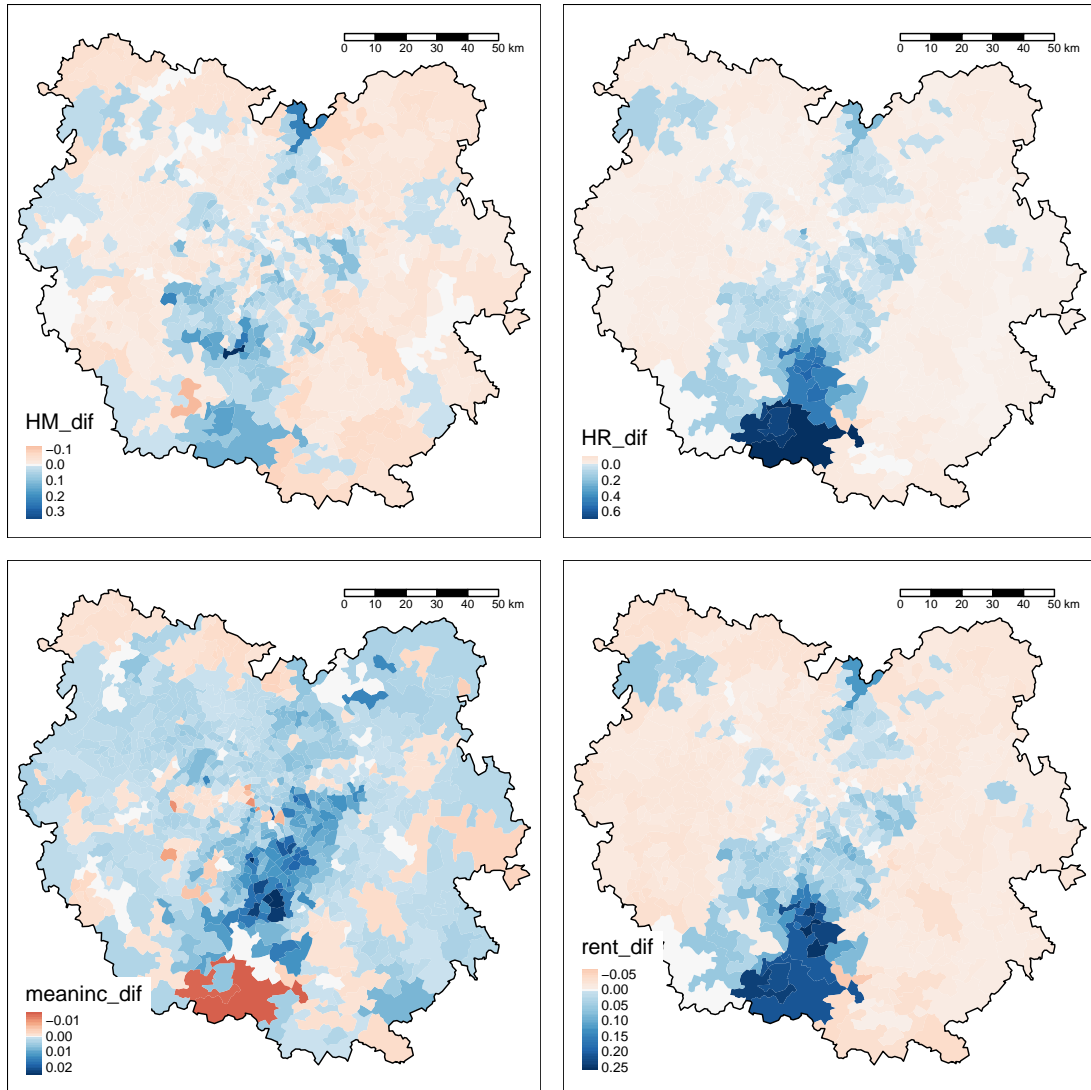
Note: Each observation is a municipality. (x axis) vs. model baseline simulations (y axis) for mean income (a), the total floor space of commercial building (b), and the total floor space of residential building (c). Panel (d) reports actual (solid) and predicted (dashed) density of mean incomes across municipalities. Panel (e) reports bin-scatters of actual (solid) and predicted (dashed) mean income as a function of distance to the city center.

income is determined by the non-homotheticities in workers preferences, their choice of workplace and the share of high-skilled workers in a given municipality. The model is able to capture mean incomes variations quite well (Figure 4 Panel (a), $R^2=0.86$), and although the model predicts less spatial disparities than observed, the shape of the distribution of mean incomes between municipalities (Figure 4 Panel (d)) is well captured. Finally, the specification of distance disutility allows to closely replicate the gradient of mean incomes in the city (Figure 4 Panel (e)).

Turning to commercial and residential floor space, they are well fitted with squared correlations of respectively 0.84 and 0.92, indicating that the demand functions are well calibrated. In Appendix A.6, I report maps of actual and predicted mean incomes and residential floor space. The model is able to closely replicate the spatial patterns of these variables.

4.2 Suburban train network (RER)

Figure 5: Contributions of the suburban train (RER) to municipal outcomes.



Note: Maps of the contribution of the RER network to the number of workers (HM), the number of residents (HR), average income of residents (meaninc) and rents (rent) in the Paris metropolitan area. Descriptive statistics in table 16.

In this section, I look at the effect of the public transport network on the structure of the city by simulating a counterfactual Paris in which suburban trains from the Regional Express Rail (RER) network are removed.

The RER is a suburban rail network made of radial lines connecting Paris to its suburbs. In 1965, a plan to turn the mono-centric area of Paris into a poly-centric region was devised by the French government, that revolved around developing new sub-centers — the *New Towns* — that would house secondary business districts and residential areas. The RER rail system was devised as a set of radial lines that would cross the region to connect those sub-centers to Paris, complemented by a set of new metropolitan highways.

Inaugurated in 1977, the RER network was initially composed of two lines, one crossing the region from north to south and the other one from east to west, and was later extended to four lines, with a fifth one constructed in 2015.

With more than 500 Km of lines, the Regional Express Rail is the backbone of the Parisian transport network. Indeed, Table 15 in appendix reports summary statistics of travel times between pairs of municipalities in the Region, with and without this allowing the use of the RER. On average, the RER lowers travel times between all pairs of municipalities in the region by 22%, and travel times to the city center by 20%. Moreover, its effect on travel times is higher for municipalities located between 10 and 60 kilometers from the city center, as municipalities located further away are not connected to the network while those located closer to the center can use the faster metro lines.

General effects of the RER Maps in Figure 5 shows the current contribution of the RER network to municipal outcomes. Contribution for variable y is measured as $1 - y_{\text{NoRER}}/y_{\text{Baseline}}$, where y_{NoRER} is the result of a simulation of the model with travel times computed by omitting the Regional Express Rail. It appears from these maps that the RER not only has a decentralizing effect on employment, populations, incomes and rents, but that this effect is heterogeneous conditional on distance. The biggest impact on populations and rents is measured for the most southern municipalities of the area, which are connected to the last stops of the D line of the RER, and otherwise poorly served by the classical regional train.

Quantitatively, Table 9 gives the effect of the RER network on the connected and non-connected municipalities in the region. On average, unconnected municipalities get a reduction in transport times by public transit of 12%, and connected municipalities by an additional 22%. Connected municipalities get a 5% increase in low-skilled population and a 6% increase in high-skilled population.

In turn, incomes increased by an average of 0.6% in connected municipalities, and

Table 9: Effect of the RER network on connected municipalities.

	(1)	(2)	(3)	(4)
	dlduration	Unskil. pop	Skilled pop	Mean Income
RER=1	-0.218*** (0.0208)	0.0549*** (0.00665)	0.0662*** (0.00955)	0.00296*** (0.000441)
Constant	-0.123*** (0.0104)	-0.00858** (0.00326)	0.00716 (0.00468)	0.00299*** (0.000216)
Observations	666	696	696	696
R ²	0.142	0.089	0.065	0.061

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Regressions of the difference in (log) outcome between baseline and no-RER simulations on a dummy equal to one if the municipality was eventually connected to the RER network.

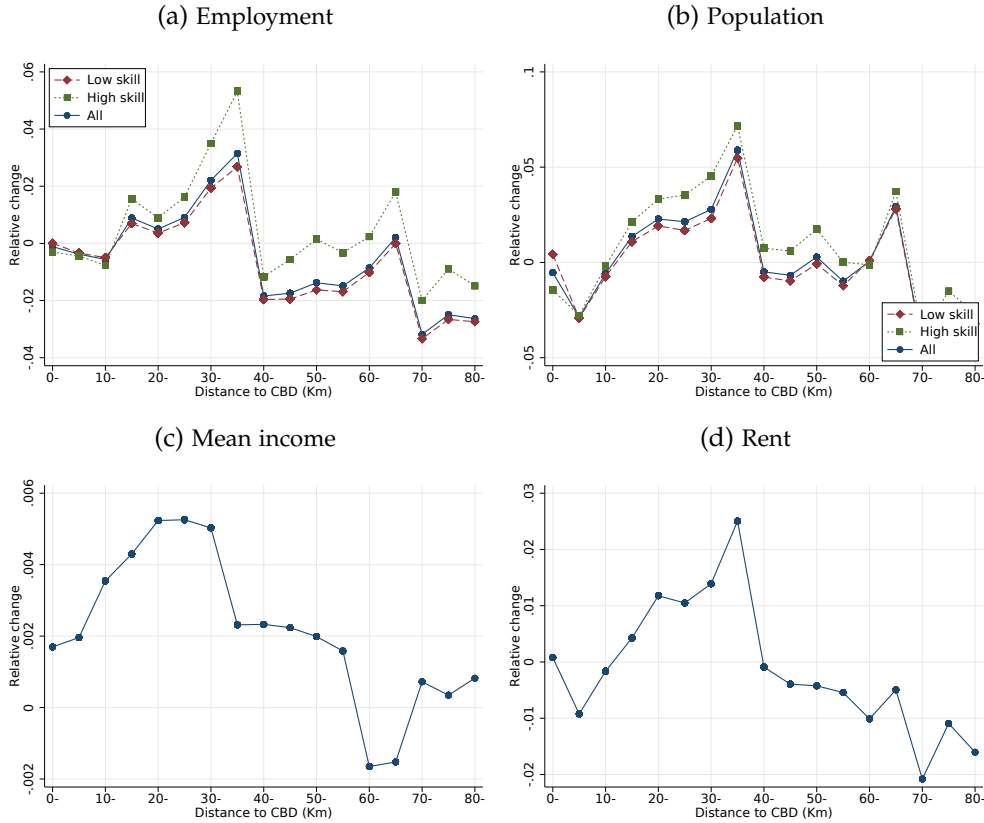
by 0.3% disconnected municipalities, showing a very modest effect of the RER on municipal incomes.

To better document how these treatment effects translate into total decentralizing effects, Figure 6 shows the contributions of the network to total outcomes in 5km bins from the city center, defined as the first district of Paris. On average, the network contributes to flattening the employment, population and rent gradients up to 45km away from the CBD. It does not, however, contribute negatively to populations nor employment in the CBD. Instead, suburbanization of residents comes from movements from the close suburbs towards the periphery while employment is mainly fueled by the localization of jobs within reach of the network, to the detriment of the more remote areas. Finally, the decentralizing effect on populations and employment is more important for high-skilled than low-skilled workers.

Sorting Whilst having a sizable impact on employment and populations, the RER network has little effect on income disparities between the center and the periphery. Looking at Panel (c) of Figure 6, the RER network causes an increase in incomes of only half a percent in the suburbs.

To measure more precisely the effect of the policy on spatial inequalities between Paris and its suburbs, compute the difference between mean incomes in the center and in the suburbs, 10 to 15 kilometers away. As showed in Column 5 of table 10, the contribution of the RER network is negative but very low: the city premium

Figure 6: Effect of the suburban train (RER) on employment, population, incomes and rents.



Note: Average contributions of the transport network to employment, population incomes and rents in bins of 5km from the city center (first district of Paris). Panels (a) and (b) are percent change of totals within bins, (c) and (d) are percent change of averages weighted respectively by population and residential floor space.

falls by only 0.4%. To give a broader picture, I measure total income segregation in the region as between-municipality standard deviation divided by total standard deviation. Similarly, the RER network has a negative but small effect : segregation only falls by 0.6%.

Redistribution Finally, I compute the contribution of the Regional Express Rail to workers welfare and welfare inequality. Although the effect of the RER on location choices is stronger for high-skilled than low-skilled workers, its total welfare effect is higher for the later group. As a result, it leads to a decrease in welfare inequalities.

Table 10: Aggregate effects of the RER network on incomes in the region.

	Mean	Total SD	Between SD	(%)	C-P
Baseline	31128.25	20705.11	3758.18	18.15	9936.27
Counterfactual	31071.03	20677.15	3774.15	18.25	9974.88
Effect (%)	0.18	0.14	-0.42	-0.56	-0.39

Column 1 is the average income over all workers. Column 2 is the total standard deviation of income over individual workers. Column 3 is the between-municipality standard deviation. Column 4 is the ratio between the two times 100. Column 5 is mean income in the center minus mean income 10 to 15 kilometers away from the center.

Table 11: Welfare of high and low-skill workers, with and without the Regional Express Rail.

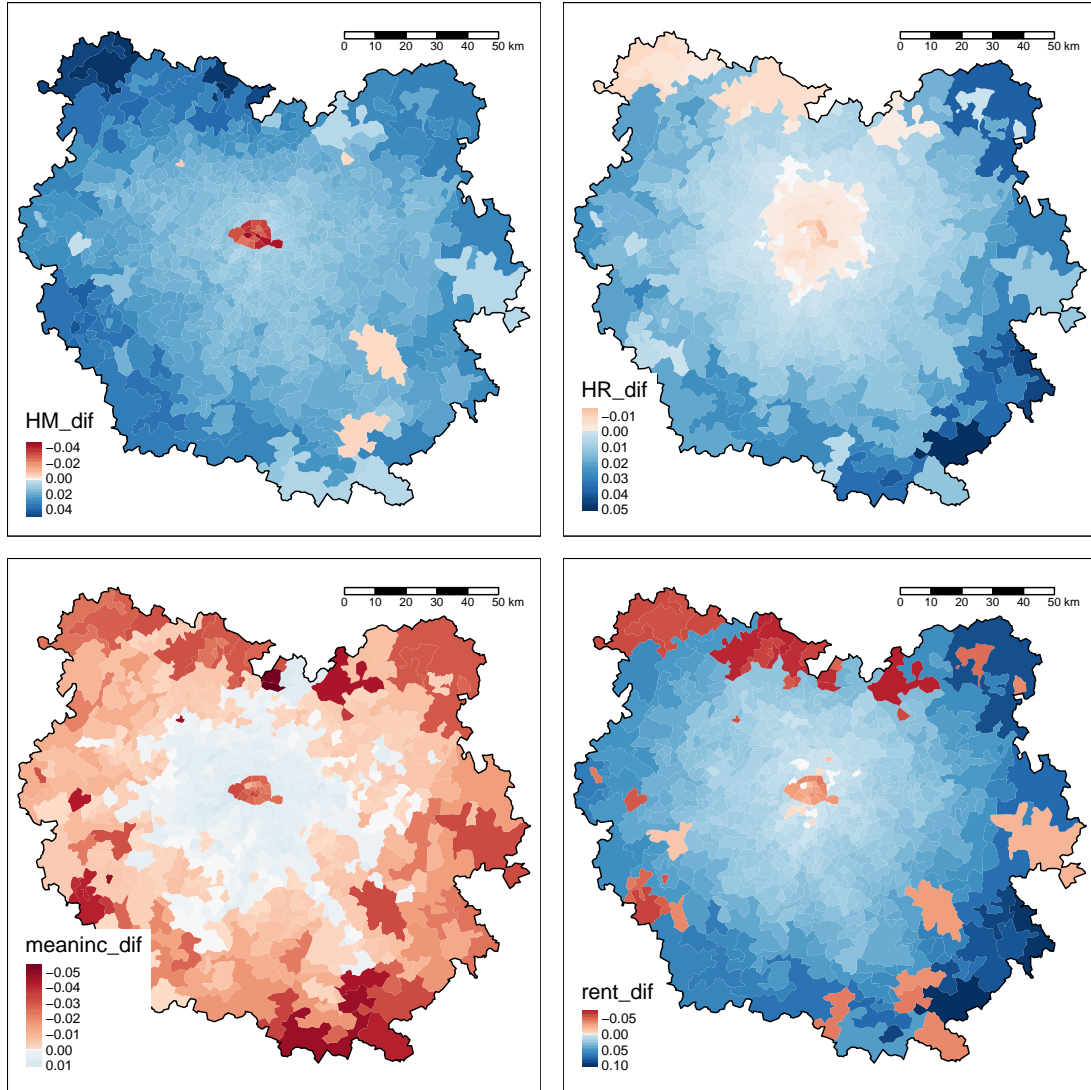
	Low skill	High skill	Ratio
Baseline	24163.71	176502.97	7.30
Counterfactual	23555.92	173920.36	7.38
Effect (%)	2.52	1.46	-1.08

Indeed, it accounts for 2.62% of the total welfare of low-skilled workers and 1.64% of that of high-skilled workers, thus reducing welfare inequalities by 1%.

Comparison with reduced-form results Mayer and Trevien (2017) evaluate the effect of the introduction of the regional rail system (RER) between 1970 and 1990 in the Paris area. The present simulation does not exactly replicate their setting, as my counterfactual simulation uses the current network without the RER, not the network as it was in 1970. Further, I study re-organization effects in a closed city when their measure takes into account both growth and relocation. Their sample includes the best part of municipalities located between 10 and 30 kilometers from the center of Paris (cf. Figure 2 and Table 3 therein). They measure an effect of 8.8% on employment, and a positive but unstable effect on populations, stronger for high-skilled workers. Table 17 in appendix reports treatment effects of the within distance bins from the center. Effects are increasing with distance to the center. Effects 20km away from the CBD are 5% on low-skilled populations and 7% on high-skilled population, and 4% on employment. Given the caveats above, these results are consistent with the findings of Mayer and Trevien (2017).

4.3 Banning cars from Paris

Figure 7: Effects of banning cars in Paris.



Note: Maps of the effects of banning commuting by cars to and from Paris on the number of workers (HM), the number of residents (HR), average income of residents (meaninc) and rents (rent) in the Paris metropolitan area. Inelastic floor space supply. Descriptive statistics in table 16.

In this section, I turn to counterfactual simulations where commuting by car is banned when commuting from or to the city of Paris, so that all commuters within Paris, between Paris and the suburbs or vice-versa have to take public transports for

commuting.

In 2017, following engagements taken as part of the 2015 COP21 agreements, the Council of Paris signed a document planning to ban thermal vehicles from its streets, with a plan of zero diesel cars by 2024 and zero thermal vehicles by 2030.⁹ This announcement has been a source of debate in the region, with some opponents pointing out that the measure, given the current costs of electric vehicles, might penalize suburban workers. To assess this statement, I consider the somewhat more excessive situation of a complete ban on cars, thermal or not, within the city of Paris. This is implemented by setting the probability to travel by car to zero for every trip from or to the city of Paris.

I focus on short-term effects where residential and commercial floor space are fixed to their baseline levels. Section A.5 in appendix shows tables and maps of an alternative simulation where floor space is elastic and landlords are allowed to convert between commercial and residential floor space.

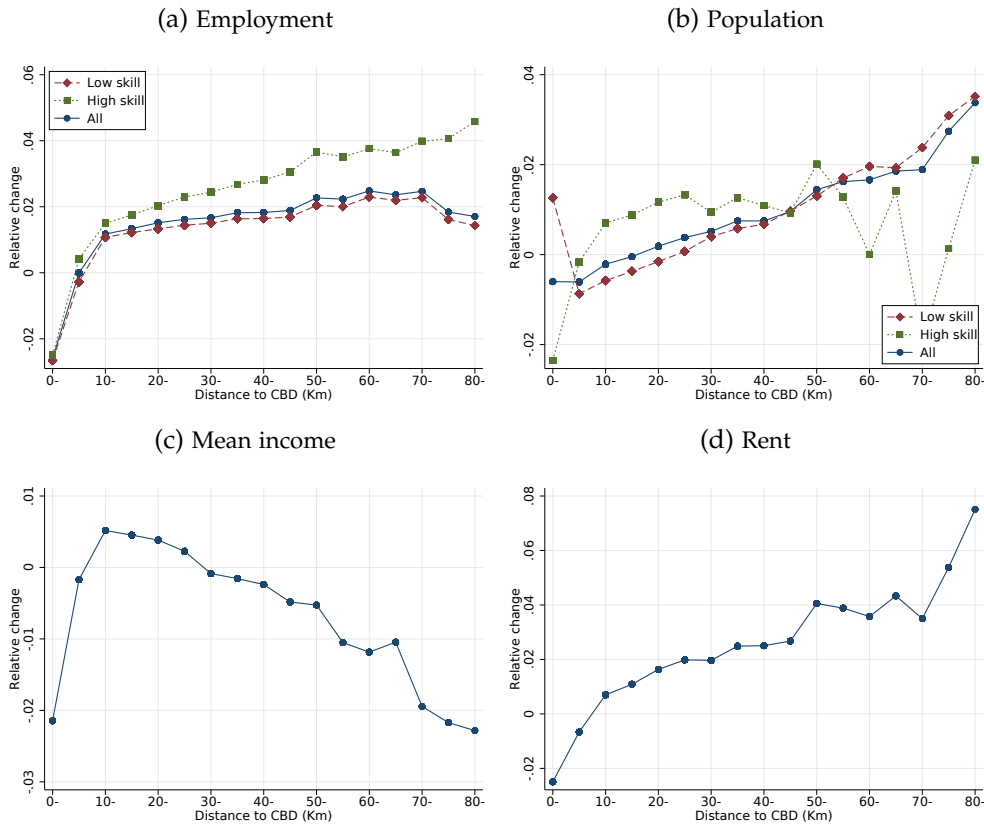
Figure 7 shows maps of the effect of a car ban on the Grand Paris region. Contrary to the predictions of a monocentric model, the model predicts that increasing the cost of accessing the city center would penalize the center itself, as firms and workers relocate outside of the city walls. This leads to a decrease in rents in the center, allowing for lower income residents to relocate within the city.

General effects Figure 8 Panel (a) shows the effect of the car ban on employment, population, income and rent gradients. The center of Paris experiences a loss in employment of 2%, that relocate 10km away from the center. Regarding populations, the center experiences a loss in high-skilled residents of 2.1%. For low-skilled workers, the pattern is u-shaped: their number increases by 1.4% in the center, decreases in the close suburbs and increases again in the more remote locations of the area.

Sorting Turning to income sorting, the outflow of high skilled workers and the lower rents in the center translate into a decrease of the income premium of the city, as incomes within 5 kilometers fall by 2%, and incomes in the suburbs rise by 0.5%. This effect corresponds to a drop of the mean income premium of the center relative to the close suburbs (from 10 to 15 kilometers) of €1012. This amounts to a 10% reduction from the baseline income gap of €9982. In terms of total spatial income heterogeneity,

⁹*Plan Climat*, available in French and English at <https://www.paris.fr/pages/nouveau-plan-climat-500-mesures-pour-la-ville-de-paris-5252>, accessed on August 21, 2020.

Figure 8: Effect of banning cars in Paris.



Note: Average effect of banning cars in Paris on employment, population, mean income and the between-municipality coefficient of variation of mean incomes in bins of 5km from the city center (first district of Paris). Inelastic floor space supply.

Table 12: Aggregate effects of banning in Paris on incomes in the region.

	Mean	Total SD	Between SD	(%)	C-P
Baseline	31128.25	20705.11	3758.18	18.15	9936.27
Counterfactual	31029.05	20594.19	3720.36	18.07	8924.20
Effect (%)	-0.32	-0.54	-1.01	-0.47	-10.19

Column 1 is the average income over all workers. Column 2 is the total standard deviation of income over individual workers. Column 3 is the between-municipality standard deviation. Column 4 is the ratio between the two times 100. Column 5 is mean income in the center minus mean income 10 to 15 kilometers away from the center.

the effect is nonetheless limited as the between-municipality standard deviation of mean incomes only falls by 1%. Because the total standard deviation of mean incomes also falls, relative segregation (measured as the ratio between the two) only decreases by 0.5%.

Table 13: Welfare of high and low-skill workers, effects of banning cars in the city center.

	Low skill	High skill	Ratio
Baseline	24163.71	176502.97	7.30
Counterfactual	23751.39	172996.91	7.28
Effect (%)	-1.71	-1.99	-0.28

Welfare Finally, the policy creates a welfare loss of 1.7% for low-skilled workers and 1.99% of high-skilled workers, slightly reducing welfare inequalities. These effects are quite substantial, as they are roughly of the same order of magnitude as the positive effects of the Regional Express Rail.

Increasing amenities in the center It should be noted, however, that these estimates do not take into account the direct effects of banning cars on local amenities in the center in terms of air quality improvement, noise reduction and alternative uses of streets — e.g. terraces. Predicting the magnitude of these effects is challenging, as we lack data on similar measures that would allow to estimate the elasticity of local residential amenities to banning cars from the city.

Therefore, I assess the potential importance of these effects by running alternative simulations where I artificially increase exogenous amenities in the city by 5%, 10% and 15%. In these simulations, I assume that the effects of the policy is proportional to the baseline valuation of residential amenities in the center, so that the relative increase in amenity valuation is identical for high and low-skilled workers.

In Table 14, I report the welfare effects of banning cars in Paris under those three alternative assumptions on the effects of the policy on residential amenities in the city. The break-even point for the policy is attained for an increase in amenities of 10%. At that point, the effect on low-skilled workers is -0.28% and the effect on high-skilled workers is of 0.03%. For a 15% increase in amenities, the welfare of unskilled workers increases by 0.42%, and the one of skilled workers by 1.07%. As high-skilled

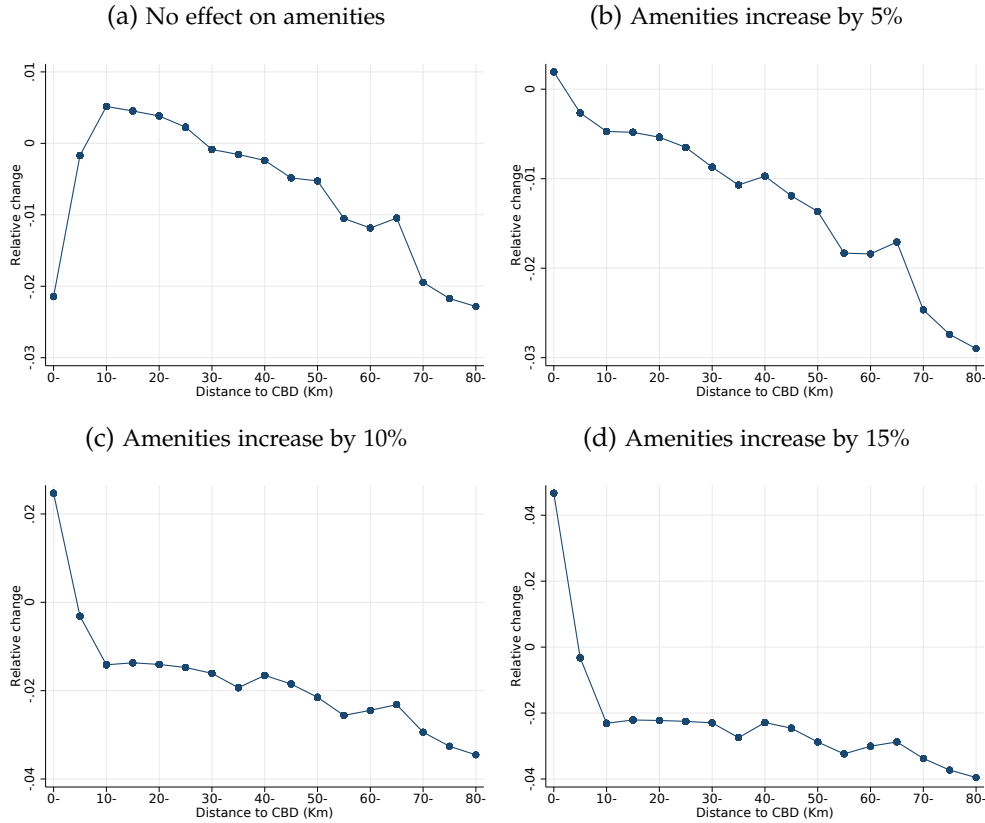
Table 14: Welfare of high and low-skill workers, effects of banning cars in Paris.
Alternative assumptions on the effects of the policy on amenities in the city.

	Low skill	High skill	Ratio
No effect on amenities			
Baseline	24163.71	176502.97	7.30
Counterfactual	23751.39	172996.91	7.28
Effect (%)	-1.71	-1.99	-0.28
Amenities increase by 5%			
Baseline	24163.71	176502.97	7.30
Counterfactual	23925.01	174755.48	7.30
Effect (%)	-0.99	-0.99	-0.00
Amenities increase by 10%			
Baseline	24163.71	176502.97	7.30
Counterfactual	24096.34	176553.78	7.33
Effect (%)	-0.28	0.03	0.31
Amenities increase by 15%			
Baseline	24163.71	176502.97	7.30
Counterfactual	24265.25	178386.81	7.35
Effect (%)	0.42	1.07	0.64

workers place a higher value on central amenities, the effect of the policy on welfare inequalities is reversed, and welfare inequality increases by 0.64%

Turning to spatial inequalities, a 5% increase in amenities is enough to reverse the effects of the policy. As documented in Panel (b) of Figure 9, at that point the policy increases the slope of the rent gradient in the whole region. Further, for a higher increase in amenities the mean income premium of the center over the suburbs increases substantially. For a 10% increase in amenities, mean income increases by 4.1% in the center and decreases by 2% in the periphery (10 kilometers away). As reported in Table 20 in appendix, this corresponds to a 14% increase in the income gap between the center and the periphery. Although inequalities between the center and the periphery increase, segregation as a whole drops by 5%.

Figure 9: Effect of banning cars in Paris on the income gradient in the region.
Alternative assumptions on the effects of the policy on amenities in the city.



Note: Average effect of banning cars in Paris on mean income in bins of 5km from the city center (first district of Paris), under alternative assumptions on the magnitude of the increase in amenities in the city due to the policy. Inelastic floor space supply.

5 Conclusion

In this paper, I use an equilibrium model of a metropolitan area to evaluate the impact of transportation infrastructures on spatial disparities within cities. Calibrating the model on Paris, it is able to closely replicate the spatial repartition of economic activities and the income gradient in the city. Further, simulated effects of public transports on local employment and population are in line with existing reduced-form results.

Simulating away the Regional Express Rail, the model shows that although public transportation increases suburbanization, its effect on income sorting between the city

and its suburbs is weak. It does, however, bring a higher welfare gain to low-skilled workers than high-skilled workers, reducing welfare inequalities. On the other hand, looking at an increase in travel time costs through banning cars in the city I find a sizable reduction in spatial inequalities between the city and its suburbs, at the cost of a total welfare loss for both skilled and unskilled workers.

The total welfare loss of banning cars is of a similar magnitude to the welfare gains from the Regional Express Rail, a very important transportation infrastructure. These effects depend however on the amenity gains from the policy. It would require a 10% increase in amenities in Paris from pollution reduction and regained floor space for the policy to break even and start having a positive welfare effect.

As these amenity effects are determinant in the total effect of the policy, further work should quantify them.

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A Additional results

A.1 Regional Express Rail

Table 15: Travel times in minutes, with and without the RER network.

Dist. to center (km)	To the whole region			To the city center		
	RER	No RER	Dif (%)	RER	No RER	Dif (%)
0-	94.67	111.29	18.83	39.67	41.39	5.16
5-	108.71	131.16	21.33	57.46	66.12	16.50
10-	117.28	144.60	23.54	67.09	80.07	20.98
15-	123.99	153.98	25.04	73.28	94.95	32.09
20-	132.44	160.57	22.02	82.69	103.12	25.66
25-	144.52	178.59	23.55	93.74	117.73	26.78
30-	152.99	190.51	25.38	100.49	124.28	24.69
35-	154.29	185.83	20.48	102.67	119.15	16.28
40-	165.80	202.63	22.26	112.26	130.47	15.55
45-	173.98	215.38	22.69	118.83	142.74	16.58
50-	188.50	220.03	16.44	131.79	140.92	6.17
55-	184.25	222.37	20.44	130.00	142.52	9.35
60-	179.69	235.56	28.57	121.19	150.67	19.57
65-	206.64	226.41	9.63	145.95	145.47	-0.22
70-	226.19	249.21	10.28	164.07	165.85	0.89
75-	231.49	254.32	9.13	171.35	171.45	0.06
Total	138.52	168.61	22.11	86.18	102.34	19.63

Average travel times in minutes. Each row is a distance bin (in km) to the city center. First three columns report the travel time toward the whole area, originating from a given bin. Three last columns report the travel time to the city center, originating from a given bin.

Table 16: Effects of the Regional Express Rail on municipalities

	Mean	S.D.	Min.	Q1	Q2	Max.
Mean income	0.0037	0.0051	-0.0153	0.0008	0.0055	0.0246
Unskilled population	0.0017	0.0697	-0.1502	-0.0381	0.0211	0.4206
Skilled population	0.0174	0.0920	-0.1980	-0.0348	0.0490	0.5431
Unskilled employment	-0.0025	0.0419	-0.1442	-0.0273	0.0113	0.2780
Rent	0.0038	0.0368	-0.0741	-0.0173	0.0138	0.2042

Descriptive statistics of the contribution of the RER network to municipal outcomes.
Each observation is a municipality in the Paris region. $N = 696$.

Table 17: Effects of the RER on connected municipalities.

	(1)	(2)	(3)	(4)	(5)	(6)
	Unskil. pop	Skilled pop	Unskil. Employ.	Skilled Employ.	Mean Income	dlduration
RER=1 × 10-	0.0357** (0.0114)	0.0405* (0.0162)	0.0272*** (0.00639)	0.0261*** (0.00697)	0.00317*** (0.000799)	-0.167*** (0.0364)
RER=1 × 20-	0.0522*** (0.0126)	0.0709*** (0.0178)	0.0404*** (0.00704)	0.0434*** (0.00768)	0.00380*** (0.000880)	-0.258*** (0.0401)
RER=1 × 30-	0.113*** (0.0161)	0.138*** (0.0228)	0.0829*** (0.00904)	0.0869*** (0.00986)	0.00290* (0.00113)	-0.320*** (0.0517)
RER=1 × 40-	0.113*** (0.0240)	0.154*** (0.0339)	0.0441** (0.0134)	0.0573*** (0.0146)	0.00183 (0.00168)	-0.278*** (0.0770)
RER=1 × 50-	0.389*** (0.0491)	0.610*** (0.0694)	0.0628* (0.0275)	0.133*** (0.0300)	0.00337 (0.00343)	-0.856*** (0.157)
RER=1 × 60-	0.547*** (0.0687)	0.769*** (0.0973)	0.130*** (0.0385)	0.226*** (0.0420)	-0.0158** (0.00481)	-0.758*** (0.220)
RER=1 × 70-	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
10-	0.00414 (0.0133)	0.0170 (0.0188)	0.00271 (0.00744)	0.00636 (0.00811)	0.00199* (0.000929)	-0.104* (0.0423)
20-	0.0234 (0.0126)	0.0451* (0.0178)	0.0137 (0.00704)	0.0201** (0.00768)	0.00372*** (0.000880)	-0.171*** (0.0401)
30-	0.0246 (0.0126)	0.0501** (0.0179)	0.0141* (0.00707)	0.0247** (0.00771)	0.00310*** (0.000883)	-0.139*** (0.0405)
40-	0.00957 (0.0135)	0.0290 (0.0191)	-0.00458 (0.00754)	0.00590 (0.00822)	0.00156 (0.000942)	-0.0471 (0.0439)
50-	0.0112 (0.0148)	0.0332 (0.0210)	-0.00820 (0.00831)	0.00457 (0.00907)	0.00120 (0.00104)	-0.0259 (0.0484)
60-	0.0216 (0.0154)	0.0399 (0.0218)	0.00371 (0.00861)	0.0171 (0.00939)	-0.000276 (0.00108)	-0.0118 (0.0516)
70-	-0.0139 (0.0184)	-0.00423 (0.0260)	-0.0144 (0.0103)	-0.00414 (0.0112)	0.000375 (0.00129)	0.0320 (0.0629)
Constant	-0.0226* (0.0109)	-0.0254 (0.0154)	-0.0158** (0.00608)	-0.0131* (0.00664)	0.000896 (0.000760)	-0.0302 (0.0346)
Observations	690	690	690	690	690	660
R ²	0.271	0.273	0.258	0.266	0.165	0.275

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Regressions of the difference in (log) outcome between baseline and no-RER simulations on a dummy equal to one if the municipality was eventually connected to the RER network. Heterogeneous effects as a function of distance to the city center.

A.2 Effects of the whole public transport network

Table 18: Welfare of high and low-skill workers, with and without public transports.

	Low skill	High skill	Ratio
Baseline	24163.71	176502.97	7.30
Counterfactual	20371.71	152456.75	7.48
Effect (%)	-15.69	-13.62	-2.45

Table 19: Aggregate effects the transport network on incomes in the Paris region.

	Mean	Total SD	Between SD	(%)	C-P
Baseline	31128.25	20705.11	3758.18	18.15	9936.27
Counterfactual	30999.66	20447.75	3863.23	18.89	9047.54
Effect (%)	0.41	1.24	-2.80	-4.09	8.94

Column 1 is the average income over all workers. Column 2 is the total standard deviation of income over individual workers. Column 3 is the between-municipality standard deviation. Column 4 is the ratio between the two times 100. Column 5 is mean income in the center minus mean income 10 to 15 kilometers away from the center.

A.3 Banning cars

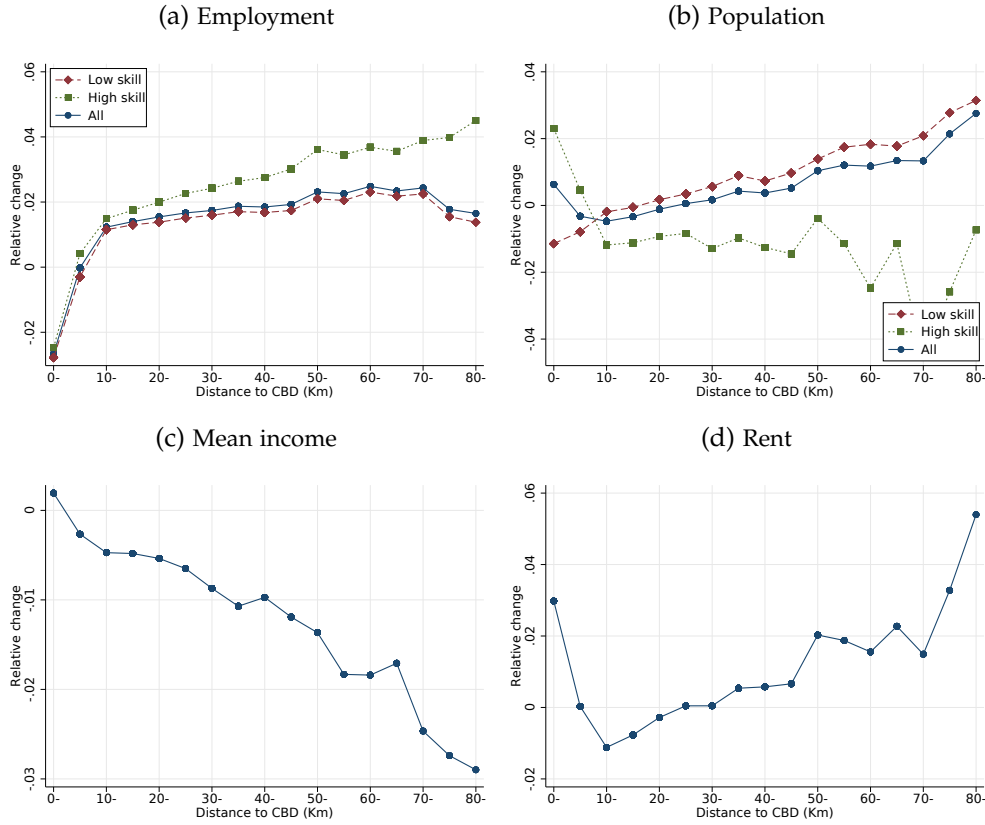
Table 20: Aggregate effects of banning cars from Paris.

	Mean	Total SD	Between SD	(%)	C-P
No effect on amenities					
Baseline	31128.25	20705.11	3758.18	18.15	9936.27
Counterfactual	31029.05	20594.19	3720.36	18.07	8924.20
Effect (%)	-0.32	-0.54	-1.01	-0.47	-10.19
Amenities increase by 5%					
Baseline	31128.25	20705.11	3758.18	18.15	9936.27
Counterfactual	30981.54	20551.58	3641.07	17.72	10155.12
Effect (%)	-0.47	-0.74	-3.12	-2.39	2.20
Amenities increase by 10%					
Baseline	31128.25	20705.11	3758.18	18.15	9936.27
Counterfactual	30946.56	20520.71	3570.15	17.40	11347.29
Effect (%)	-0.58	-0.89	-5.00	-4.15	14.20
Amenities increase by 15%					
Baseline	31128.25	20705.11	3758.18	18.15	9936.27
Counterfactual	30922.17	20499.26	3508.06	17.11	12493.45
Effect (%)	-0.66	-0.99	-6.66	-5.72	25.74

Column 1 is the average income over all workers. Column 2 is the total standard deviation of income over individual workers. Column 3 is the between-municipality standard deviation. Column 4 is the ratio between the two times 100. Column 5 is mean income in the center minus mean income 10 to 15 kilometers away from the center.

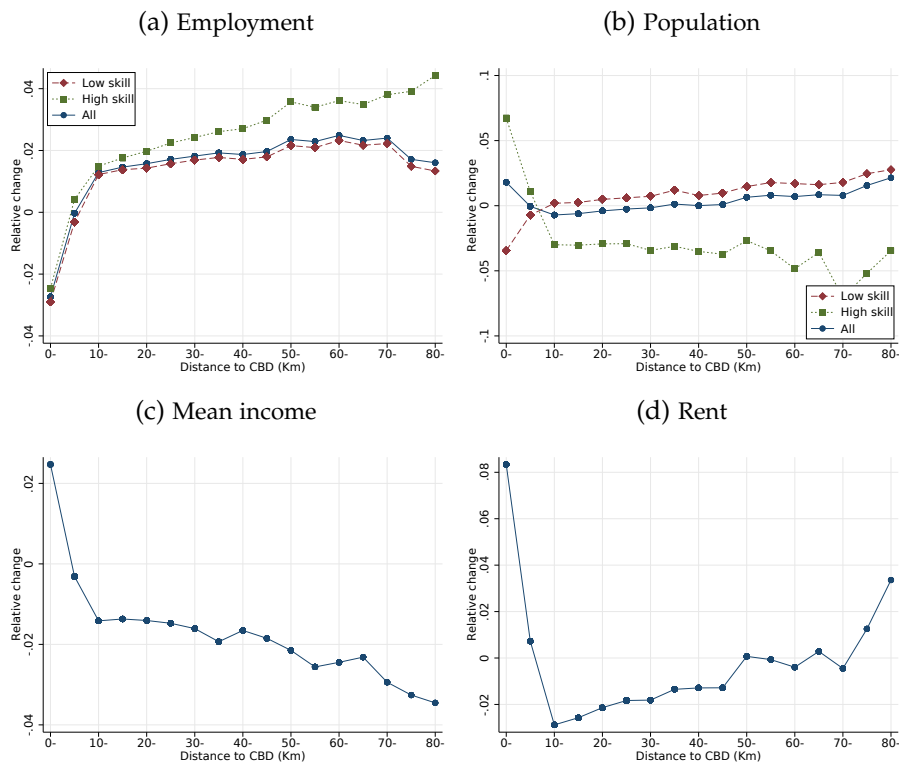
A.4 Banning cars: gradients with amenity gains

Figure 10: Effect of banning cars in Paris, 5% amenity increase in the city.



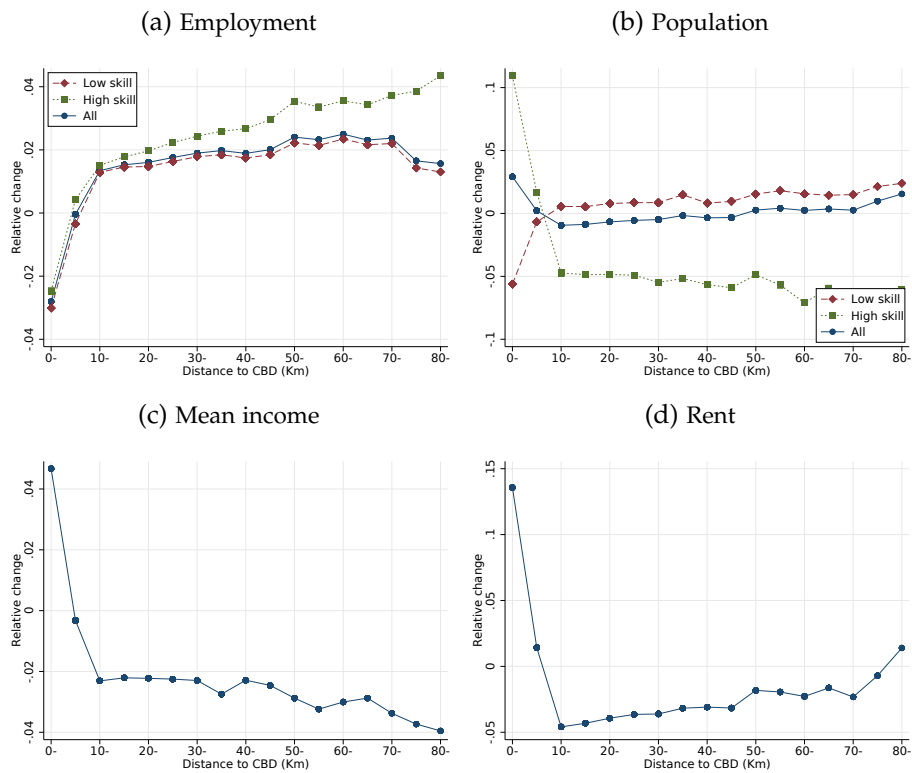
Note: Average effect of banning cars in Paris on employment, population, mean incomes and the between-city coefficient of variation of mean incomes, in bins of 5km from the city center (first district of Paris). Inelastic floor space supply.

Figure 11: Effect of banning cars in Paris, 10% amenity increase in the city.



Note: Average effect of banning cars in Paris on employment, population, mean incomes and the between-city coefficient of variation of mean incomes, in bins of 5km from the city center (first district of Paris). Inelastic floor space supply.

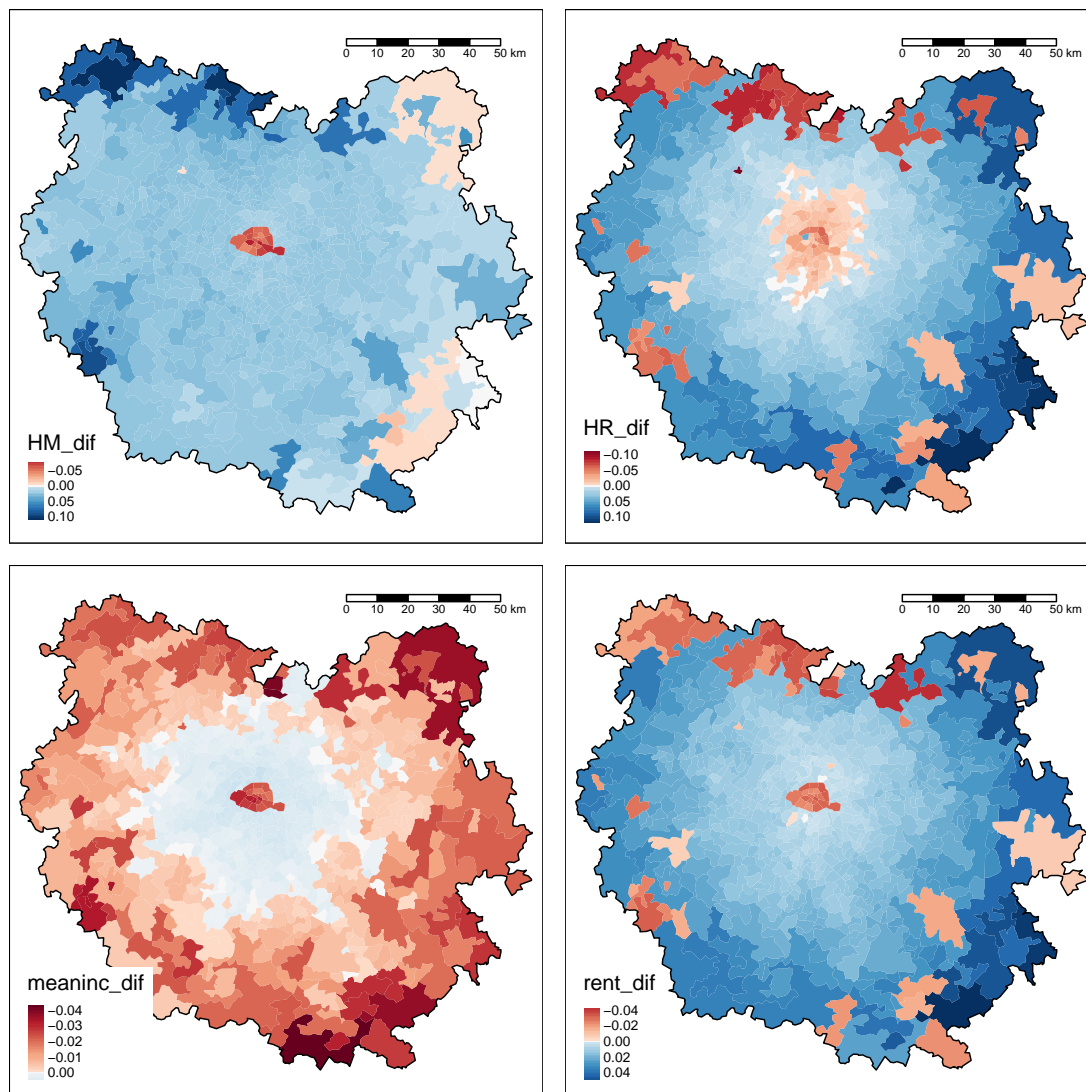
Figure 12: Effect of banning cars in Paris, 15% amenity increase in the city.



Note: Average effect of banning cars in Paris on employment, population, mean incomes and the between-city coefficient of variation of mean incomes, in bins of 5km from the city center (first district of Paris). Inelastic floor space supply.

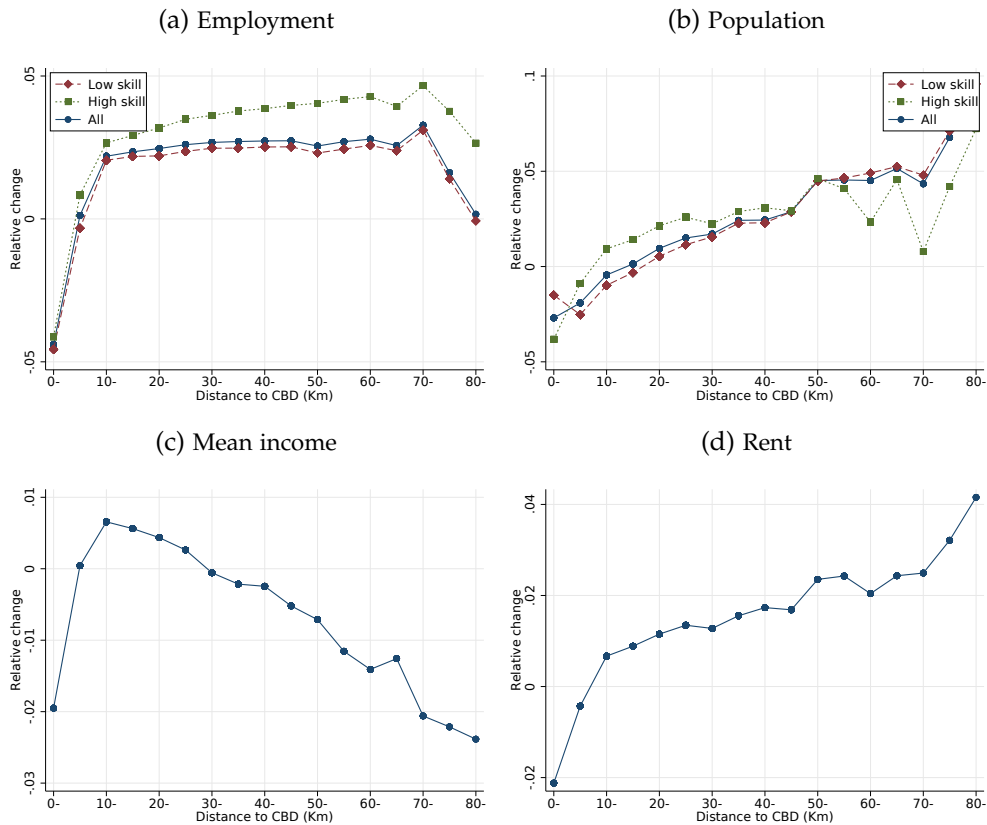
A.5 Banning cars: elastic floor space supply

Figure 13: Effects of banning cars in Paris.



Note: Maps of the effects of banning commuting by cars to and from Paris on the number of workers (HM), the number of residents (HR), average income of residents (meaninc) and rents (rent) in the Paris metropolitan area. Elastic floor space supply.

Figure 14: Effect of banning cars in Paris.



Note: Average effect of banning cars in Paris on employment, population, mean incomes and the between-city coefficient of variation of mean incomes, in bins of 5km from the city center (first district of Paris). Elastic floor space supply.

A.6 Baseline maps

Figure 15: Mean income. Actual (left) vs predicted (right)

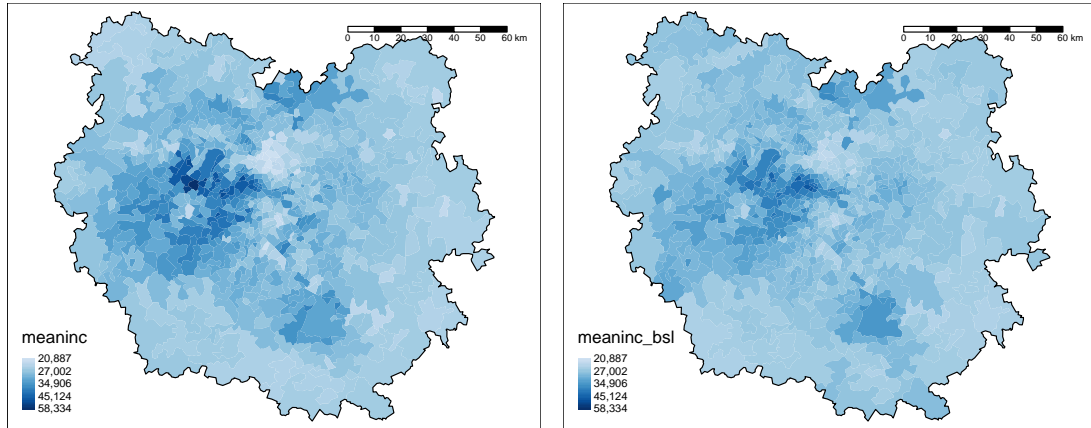
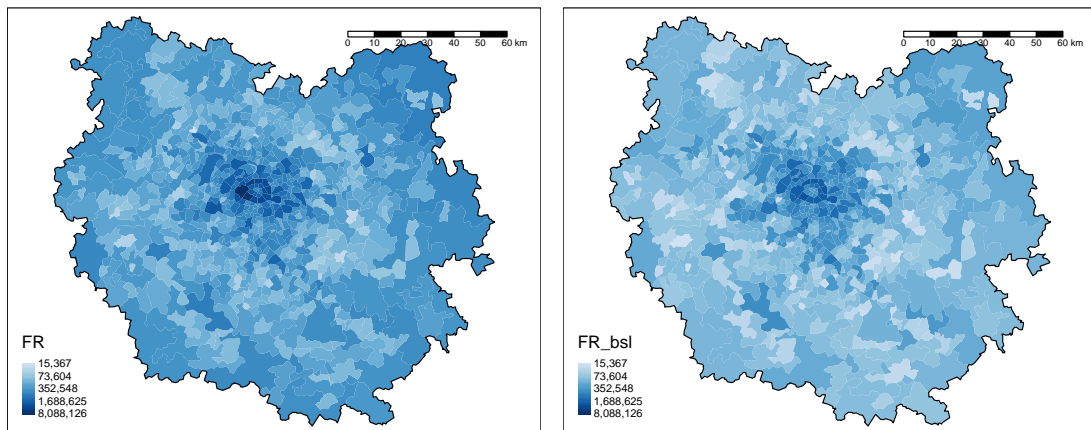


Figure 16: Residential floor space. Actual (left) vs predicted (right)



A.7 Estimates of the skill substitution parameter

The CES aggregator for unskilled and skilled labor (36) implies (log) labor demand ratios

$$\ln \left(\frac{H_j^S}{H_j^L} \right) = -\sigma \ln \left(\frac{w_j^S}{w_j^U} \right) + \ln \left(\frac{A_j^S}{1 - A_j^S} \right). \quad (50)$$

from which one would like to estimate the productivity parameter σ . Due to the simultaneity of supply and demand however, the price coefficient from a naive OLS regression is likely to be biased upward as a positive demand shock increases both prices and quantities. To overcome this challenge, I use minimum wage variations to instrument the log wage ratio. More precisely, for type e workers in year t I construct $\Delta \widehat{\ln(w_{j,t}^e)} = \ln(s_{j,t-1}^e \mathbf{w}_{j,t}^e + (1 - s_{j,t-1}^e) w_{j,t-1}^e) - \ln(s_{j,t-1}^e \mathbf{w}_{j,t-1}^e + (1 - s_{j,t-1}^e) w_{j,t-1}^e)$ as an instrument for the variation of the wage ratio between high-skilled and low-skilled workers. The identifying assumption is then that cross-sectional variations in the exposure to minimum wage shocks is uncorrelated to the evolution of skill bias.

Table 21: Estimates of $-\sigma$.

	Levels	FD	IV
$\ln \left(w_{jt}^S / w_{jt}^U \right)$	0.820*** (16.55)		
$\Delta \ln \left(w_{ij}^S / w_{jt}^U \right)$		-0.711*** (-24.79)	-1.529*** (-15.31)
_cons	2.410*** (80.38)	-0.0362*** (-14.33)	-0.0230*** (-7.03)
F excluded instru.			511.2
N	12270	10225	10225

Estimates of $-\sigma$ from regressing skill shares ratio on wage ratio. First column is the naive OLS estimate, pooling years 1995, 2000, 2005, 2008, 2010 and 2015. Second column is the first difference estimate, while the last column instruments first differences in wage ratio using first predicted differences from minimum wage shocks. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results of this estimation are reported in Table 21. The first column is the naive OLS

estimate, pooling years 1995, 2000, 2005, 2008, 2010 and 2015. The second column is the first difference estimate, while the last column instruments first differences in wage ratio using first predicted differences from minimum wage shocks. Unsurprisingly, the OLS estimate is highly biased. The estimated relationship between employment ratio and wage ratio is positive, as relative labor demand shocks drive both wage premium and quantities up. Taking first differences, the estimate becomes negative, but less than one in magnitude ($\sigma = 0.71$), implying skills complementarity. Finally, instrumenting for the wage ratio shows that high and low skill workforce are actually substitutes. The estimated parameter is $\sigma = 1.53$, very close to the usual consensus value of 1.5 found in the literature (see e.g. [Wingender, 2015](#), and references therein.)

A.8 Model based IV

Table 22: Decomposition of fundamentals.

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP	AS	B1	B0	T1	T0
Mean altitude (log)	0.0946*** (5.17)	-0.167** (-3.00)	-0.0972 (-0.89)	-0.370*** (-3.63)	-0.853*** (-5.48)	-0.765*** (-6.06)
Maximum slope (log)	0.00934*** (3.95)	-0.0410*** (-5.72)	-0.0222 (-1.55)	-0.0194 (-1.45)	-0.0924*** (-4.54)	-0.0800*** (-4.85)
Share covered by water	0.664*** (3.51)	-0.206 (-0.36)	0.0124 (0.01)	-1.548 (-1.53)	-4.719** (-3.04)	-4.338*** (-3.45)
Distance to river (log)	0.0145 (1.85)	0.0284 (1.20)	0.0246 (0.54)	0.00200 (0.05)	0.00809 (0.13)	0.0282 (0.54)
Distance to river ; 5km	-0.00475 (-0.27)	0.0773 (1.43)	0.164 (1.59)	0.170 (1.77)	0.350* (2.39)	0.355** (3.00)
Land area			0.513*** (14.50)	0.813*** (24.70)	0.0589 (1.17)	0.236*** (5.79)
Listed building dummy			-0.122 (-1.24)	-0.137 (-1.50)	-0.308* (-2.20)	-0.263* (-2.32)
Number of listed buildings			0.576*** (8.48)	0.434*** (6.87)	0.641*** (6.63)	0.537*** (6.86)
Constant	9.374*** (115.24)	0.379 (1.54)	-11.37*** (-23.85)	-11.14*** (-25.13)	3.424*** (5.05)	1.742** (3.17)
r2_within	0.147	0.0891	0.472	0.627	0.227	0.253
F	23.84	13.49	76.91	144.2	25.26	29.10
N	696	696	696	696	696	696

Regression of model fundamentals on exogenous variables. Predicted values from these regressions are used as inputs for the model simulation that generates instruments for incomes and workforce.

Table 23: Observed amenities

	count	mean	sd	min	max
meat_shops	696	.8831948	2.166097	0	24.65278
bakeries	696	1.915192	4.725206	0	40.40404
convenience	696	1.766946	5.252166	0	57.29167
restaurant	696	14.79053	59.61473	0	766.6667
preschools	696	.6877911	1.008322	0	7.142857
hairdresser	696	3.530352	9.460522	0	111.4583
swimpool	696	.1071565	.2320357	0	2.020202
museum	696	.043806	.2858894	0	5.128205
theatres	696	.1270503	.5421777	0	7.070707
cinema	696	.0956781	.3891422	0	6.976744
doctor	696	2.630785	5.836409	0	49.15966
laboratory	696	.2067682	.4275947	0	3.669725
police	696	.067342	.183323	0	1.834862
Distance to main line ; 5km	696	.5890805	.4923545	0	1

Description of observed amenities, in number per squared kilometer. Observation is a municipality. N=696.

B Geographical units

Because the estimation procedures used cannot handle geographical units with zero employment or zero residents, to ensure some precision in the estimation of local wages, rents, TFPs and amenities and to comply with legal regulations on exporting aggregates from restricted access microdata in France, I pull municipalities together into groups so that each group has at least 10 workers and 10 residents of each type. To minimize the heterogeneity between municipalities in a same group, I use a procedure that tries to minimize the rent differential between merged municipalities. More precisely, I use the following iterative procedure:

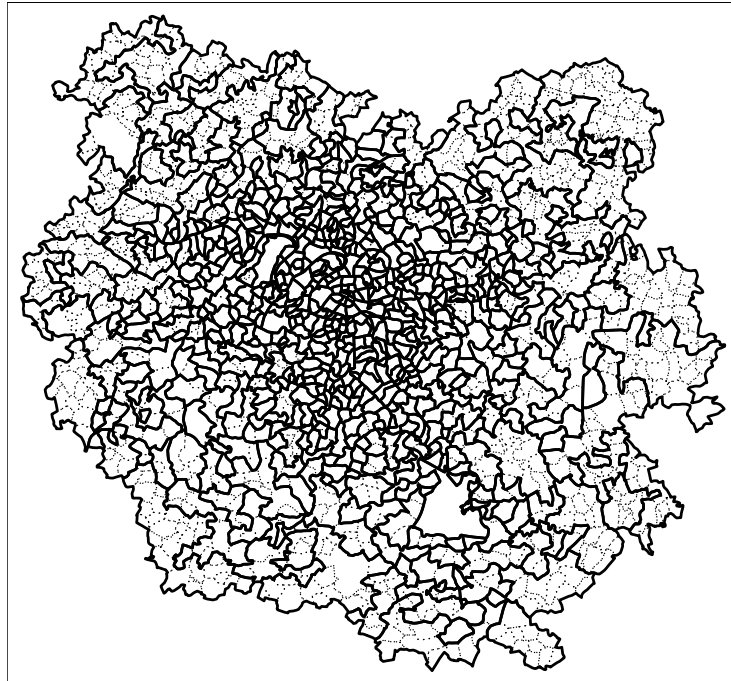
0. Create groups consisting of only one municipality. Make a list of the groups that do not meet the criterion.
1. If the list is empty, exit. Else, choose the first group of the list.
2. Amongst adjacent groups, find the one that has the closest average rent per squared meter and merge the two groups.
3. Place that group at the bottom of the list. Go to 1.

Rents are used to measure the distance between municipalities because it is the variable with the best coverage in the raw data, with no missing value at the municipal level. Second, rent is a good indicator of the general attractiveness of a location as it is strongly correlated with income and population. I therefore expect that pooling neighboring municipalities with similar rents will also minimize the within unit variation in populations, income and amenities. Overall, the procedure leaves central, highly densely populated areas unchanged and only pools peripheral, almost empty locations. These locations are highly homogenous in their emptiness and inexpensiveness, and they mainly serve as an outside option to allow workers to move out of the city center in counterfactual simulations as they have little weight in the estimation.

C Travel times

Travel times d_{ij} by car are computed for all pairs ij using the road network extracted from OpenStreetMap. They are computed in minutes between each pair of municipalities, and are theoretical travel times based on the road network and speed

Figure 17: Municipalities (dashed) and pooled units (solid) for the Urban Area of Paris.

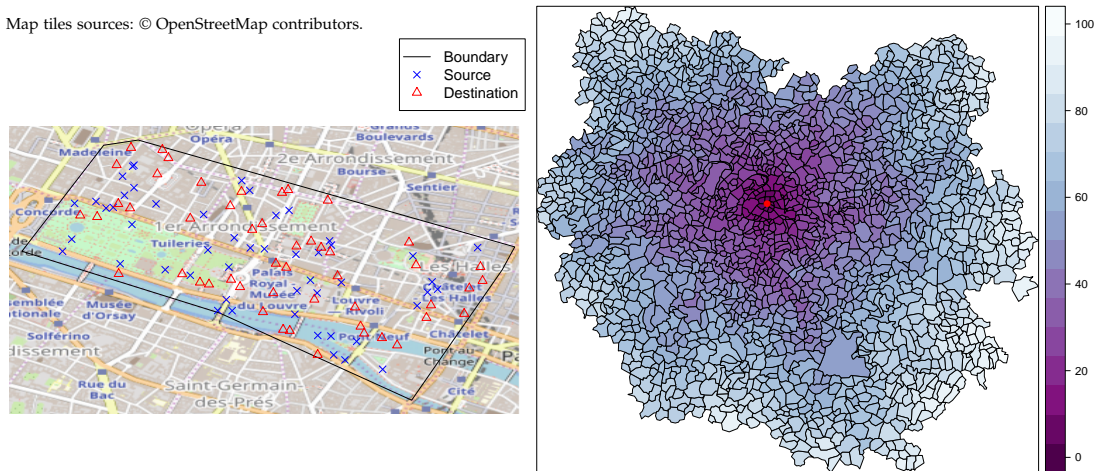


limits. Congestion is not taken into account. Figure 18b plots one line of the travel time matrix for the Urban Area of Paris. Travel times in the Paris area range from 7 minutes to two and a half hours.

To approximate the average travel time between municipalities, I average travel times between randomly drawn pairs of points within each municipalities. For each municipality pair, 50 origins and 50 destinations are randomly drawn. Figure 18a shows such a sample of origins and destinations within the first district of Paris. Given the 50 sources and 50 destinations, the 2500 pairwise travel times between them are computed and their average is taken as the average travel time within the municipality.

Figure 18: Examples.

Map tiles sources: © OpenStreetMap contributors.



(a) Example of sample points

(b) Travel times in minutes from the 1st district of Paris (red dot)