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Competing for opportunity: Transport infrastructures and localized unemployment

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Abstract

Unemployment rates vary significantly across neighborhoods and worker types, yet the role of transport infrastructures in explaining these disparities remains unexplored. We propose a quantitative urban model with frictional unemployment and heterogeneous workers where better connections between neighborhoods might exacerbate unemployment disparities due to competition among workers. We document this phenomenon using a difference-in-differences to estimate the impact of the creation of the Paris Regional Express Rail (RER). We find that the project increased the unemployment rate of low-skilled workers, but not of their high-skilled counterparts. In Paris, differences in job market access reduce unemployment inequalities between college graduates and the rest of the population.

JEL Codes – R31, R52, R21
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1 Introduction

Low-skill workers and minorities are unevenly distributed in large urban areas, leading to significant unemployment disparities between neighborhoods. Since the seminal contribution of Kain (1968), the spatial mismatch hypothesis suggests that these disparities might be exacerbated when low-employability workers live far from job opportunities. Can transportation infrastructure help reduce unemployment disparities within a city? We present a novel framework to address this question.

To guide our modeling assumptions, we start by documenting key stylized facts about commute times, distances, and unemployment in the Paris urban area from 1968 to 2016. First, we document a greater integration of the metropolitan labor market. Since the 1970s, significant improvements in transport infrastructures have been associated with a reduction in travel time between zip code, a decline in the proportion of households residing and working within the same zip code, and longer commutes. Today, regardless of where people live, most of them work in a different zip code than where they live. Second, contrary to expectations, this labor market integration (LMI) did not standardize localized unemployment rates within the Paris Metropolitan Area. In fact, our analysis reveals that there is still a strong dispersion of local unemployment rates, with high unemployment zip codes located close to the economic core of the area. Further, unemployment rates *decrease* with the average travel time to jobs, even within education groups. These two observations seem to challenge the idea that, absent composition effects, being closer to jobs improves labor market outcomes.

We then introduce a theoretical framework that incorporates endogenous frictional unemployment within a quantitative urban labor market featuring workers endowed with heterogeneous productivity, that translates to heterogeneous labor market outcomes. In our model, firms that use floor space and workers as inputs post vacancies targeted to specific types of workers that differ in their productivity, while workers choose where to look for a job taking into account commuting times. To focus on labor market mechanisms, we use a static framework that explicitly accounts for sorting while keeping residential location fixed.

We show theoretically that a greater labor market integration might exacerbate unemployment rate disparities, as a better integration means more opportunities in the rest of the city but also more competition in one's backyard. We show that the latter effect tends to dominate for low employability workers, except if they initially suffered from a strong spatial mismatch, i.e. if they had a sufficiently lower access to job opportunities. Our model therefore delivers a simple message about LMI: it reduces labor market disparities if and only if there is enough spatial mismatch to begin with.

We then use our model to provide a new measure of spatial mismatch. We do so by using our static model to decompose employment rate inequalities between groups of workers both in 1968 and 2016. We quantify to which extent the employment gap between any two groups is due to differences in access to workplaces with different market tightness, using data on commuting flows and local employment rates by type. When decomposing the gap between university graduates and lower educational attainments, our results point to the opposite of spatial mismatch, as differences in job market access *reduce* the employment gap between high and low education workers, both in 1968 and 2016.

As spatial mismatch was low in 1968, we then empirically test the predictions of our model through a natural experiment: the expansion of the Regional Express Rail (RER) network in the Paris Urban Area from 1975 to 1990. By employing municipalities not benefiting from the project and with a similar initial level of unemployment as a control group, we find that low education residents of the connected municipalities saw their unemployment rates increase, while the unemployment rate of high education residents was unaffected. At the same time, seen as workplaces these municipalities attracted more workers from the rest of the urban area, consistent with our competition mechanism. Our experiment also allows us to rule out the influence of alternate explanations, such as sorting, raising homeownership rates, or changing sectoral composition.

We make four key contributions. First, we develop a new micro-founded model of a frictional urban labor market with heterogeneous workers. Our framework enhances urban unemployment modeling by incorporating worker heterogeneity into a labor demand structure inspired by Stole and Zwiebel (1996) and Helpman and Itskhoki (2010), while adopting a labor supply approach in the spirit of Ahlfeldt et al. (2015) and Manning and Petrongolo (2017). This allows us to introduce frictional unemployment into quantitative urban models (Redding and Rossi-Hansberg 2017; Redding 2023), bridging the gap between these two research streams. While the previous contributions investigating spatial mismatch and urban unemployment focus on the role of residential sorting (Selod and Zenou 2006), we put forward a new mechanism: competition for workplace. We obtain original predictions about the impact of integrating labor markets on the unemployment of heterogeneous workers.

Second, we improve on past measurement of job accessibility (Andersson et al. 2018) using our model to develop theoretically consistent measures of employment accessibility and spatial mismatch accounting for competing searchers and worker heterogeneity. This allows us to decompose unemployment rates differentials between categories of workers separating the contributions of geography from individual factors. Our method only requires data on travel times, commuting flows, and local unemployment rates by type of workers, and thus could be applied to study labor market outcome differentials between any arbitrary groups.

Third, we provide some new results regarding space and unequal labor market outcomes, using our decomposition to test for the spatial mismatch of low-skilled workers in the Paris area. We document a ”reverse mismatch”, and show that the role of geography remains quantitatively modest compared to individual factors. While previous contributions already downplayed the role of spatial mismatch (Marinescu and Rathelot 2018; Gobillon and Selod 2021; Card, Rothstein, and Yi 2024), we go even further by arguing that spatial separation can even act as a safeguard, protecting low employability workers from high-skilled competition.

Finally, we provide new causal evidence on the impact of transport infrastructures on localized employment, using a natural experiment in a long difference-in-differences framework. While Place Based policies and desegregation programs have been carefully documented (Neumark and Simpson 2015; Chetty, Hendren, and Katz 2016), few evaluations document the capacity of transport infrastructures to reduce unemployment. Tyndall (2021) is an exception. He shows that transport infrastructures are associated with residential displacements in accessible locations which cancels out potential benefits for low-skilled workers. Taking advantage of the rigidity of the French housing market where a large share of dwellings are rent controlled, as in several large metropolitan areas worldwide, we investigate the impact of transport infrastructures on low skilled unemployment when limited sorting occurs. We show adverse effects for low-skilled workers, and substantiate our proposed mechanism, highlighting that an improvement in the connection of poor neighborhoods can lead to a relative increase in unemployment rates due to competition effects.

The rest of the paper is structured as follows. Section 2 reviews the four streams of literature to which we contribute and details our contributions. Section 3 presents a set of stylized facts documenting the persistence of localized unemployment rate disparities despite growing labor market integration. Section 4 introduces our theoretical framework showing how labor market integration affects localized unemployment. Section 5 calibrates our model to quantify spatial mismatch. Section 6 introduces our reduced form analysis investigating the impact of transport infrastructures on localized unemployment. Section 7 concludes.

2 Position in the literature

This article contributes to four streams of literature. The first one is related to urban labour economics (Zenou 2009b) and the literature investigating the sources and consequences of the spatial dispersion of localized unemployment rates (Murphy 1985a, 1985b) accounting for inter-city migrations (Schmutz and Sidibé 2019; Bilal 2023). We complement this literature by investigating localized unemployment rate dispersion within large cities, accounting for commuting and sorting patterns. Thus, we start from the literature studying spatial segregation based on income levels (Brueckner, Thisse, and Zenou 1999), ethnic group membership (Bayer, McMillan, and Rueben 2004; Bayer, Fang, and McMillan 2014), or employment status (Zenou 2000; Wasmer and Zenou 2002, 2006; Bayer, Ross, and Topa 2008). While taking sorting for granted, we investigate the "spatial mismatch hypothesis" (Kain 1968) – the relationship between distance and unemployment as reviewed by Gobillon, Selod, and Zenou (2007) where minorities suffer from a double penalty (low employability and a long distance to jobs) - in a setting where unemployment is frictional and firms location endogenous. We provide a micro-funded definition of Market Access complementing the work of Andersson et al. (2018). As Détang-Dessendre and Gaigné (2009) we also emphasize the importance of competition between workers in a spatial setting and the role of travel time. Building on the earlier urban search literature (Brueckner and Martin 1997; Arnott 1998; Coulson, Laing, and Wang 2001; Zenou 2009c), the closest papers to our are Manning and Petrongolo (2017) and Marinescu and Rathelot (2018). Our main differences arise from the fact that we explicitly model the city structure, firms' location decisions, workers' heterogeneity, and discuss the implication of the model in terms of transport policy. We are also related to Tyndall (2021) but while we allow for segregation we don't explicitly model residential choice and labor force participation and instead introduce endogenous search frictions. Tyndall (2021) shows that better transport infrastructures do not always benefit to poor households living in deprived neighborhoods because of gentrification. We argue that, even without residential sorting, the competition for jobs in a world with frictional labor markets and heterogeneous workers alone implies that policies that effectively connect workers to the labor market can still have adverse effects on employment. Moreover, our theoretical results highlight the necessary conditions under which better transport infrastructures might improve the labor outcomes of the less productive workers: that the initial conditions exhibit strong enough spatial mismatch. The remaining mechanisms explored in the literature, such as sorting and labor market participation, will only make the transport infrastructures less effective at reducing frictional unemployment. Quantitatively, the conclusions of our calibration align with those of Gobillon, Rupert, and Wasmer (2014), Marinescu and Rathelot (2018), Card, Rothstein, and Yi (2024), and Heuermann and Vom Berge (2024), asserting that labor market factors, not geography, remain the primary drivers of unemployment and the microgeography of joblessness in large cities.

The second strand of literature to which we contribute involves the evaluation of place-based policies aimed at reducing localized unemployment rates. These policies can be employed to stimulate employment either at the city level, as seen in works like Bartik (2020) and Bilal (2023), or within specific neighborhoods. Our focus lies predominantly on the latter, community development policies aimed at fostering economic activity and alleviating unemployment within small, disadvantaged neighborhoods. Ihlanfeldt and Sjoquist (1998) identify three primary categories of policies designed to curtail urban unemployment disparity: a) relocating individuals closer to job opportunities (desegregation), b) bringing job opportunities closer to people (local employment promotion), and c) enhancing the connections between job opportunities and potential workers improving information circulation and reducing transportation time and costs (what we label hereafter labor market integration). As stated by Gobillon and Selod (2021), previous evaluations indicate that desegregation policies (a) may offer certain advantages in particular for young children (Ludwig et al. 2013) but might require additional assistance to help voucher recipient to move to the new neighborhood (Bergman et al. 2024). Furthermore, fiscal incentives to encourage job relocation (b) have demonstrated minimal influence on job creation (Gobillon, Magnac, and Selod 2012), particularly in cases where these regions are poorly connected (Briant, Lafourcade, and Schmutz 2015). These incentives may even result in localized job displacement without net job creation at the level of zip codes or municipalities (Mayer, Mayneris, and Py 2017). Finally, Gobillon and Selod (2021) concludes that while improvements in transportation infrastructures (c) might hold promise, they present challenges in terms of assessment and implementation. Furthermore, from a theoretical perspective, such improvements are costly to execute and could potentially lead to neighborhood gentrification as documented in Tyndall (2021), disproportionately affecting impoverished households. Through an exploration of the effects of Railway Network development contributing to the labor market integration, we introduce novel findings to this body of literature. Our analysis takes advantage of the relative rigidity of the French housing market where a large share of dwellings are rent controlled and mobility is low (Chapelle, Wasmer, and Bono 2019) as in several large metropolitan areas worldwide (Arnott 1998; Glaeser and Luttmer 2003; Diamond, McQuade, and Qian 2019). Such a setting allows us to measure the impact of better transport infrastructures when limited sorting occurs. This exercise reveals transport infrastructures can potentially exacerbate unemployment within the most economically disadvantaged neighborhoods. This confirms that, as gentrification, our new mechanism —competition for jobs— might counteract their anticipated labor market benefits, at least for a subset of the population.

Third, our contribution enriches the literature by documenting the intricate relationship between transport infrastructures and the labor market. This question triggered both theoretical and empirical research. Theoretical works emerged from the seminal monocentric framework (Alonso 1964; Muth 1969; Mills 1972), they introduced the concept of unemployment by incorporating efficiency wages (Zenou 2000) or labor market frictions (Wasmer and Zenou 2002, 2006; Zenou 2009a). This framework has been used to explore the connections between the land market, transport policies, and the labor market (Zenou 2011a, 2011b) or the study of the spatial mismatch hypothesis (Brueckner and Zenou 2003; Zenou 2009c). Our theoretical framework shares similarities with this stream of research as we introduce a frictional labor market in an urban setting. As in this class of models, the interaction between labor and land markets is mostly mediated through the land costs incurred by firms and commuting costs. However, we differ from these works by relaxing the monocentric assumption, allowing firms and workers to be located in the same neighborhoods and workers to chose their workplace as in Manning and Petrongolo (2017). The empirical research explored the effects of highways on congestion (Duranton and Turner 2011), urban growth (Duranton and Turner 2012), and the dispersal of jobs and sprawl (Baum-Snow 2007). Subsequently, a body of work documented the influence of public transport networks on various aspects such as city growth (Gonzalez-Navarro and Turner 2018), air pollution (Gendron-Carrier et al. 2022), and Foreign Direct Investment (Bono et al. 2022). Our contribution documents the link between transport networks and the labor market. Within this realm, Mayer and Trevien (2017) documented the positive effects of transport infrastructures on local employment within interconnected municipalities. These findings found reinforcement in the works of Garcia-López, Hémet, and Viladecans-Marsal (2017a) and Garcia-López, Hémet, and Viladecans-Marsal (2017b), who demonstrated how the expansion of railway networks facilitated job decentralization. Nevertheless, until now, only Tyndall (2021) has investigated the impact of new transit infrastructures on localized unemployment. Hence, we extend this line of inquiry by investigating the repercussions on localized unemployment rates and by documenting the beneficiaries of the generated employment opportunities. The fact that new transport infrastructures might generate a rise in localized unemployment rate is new to the literature. Moreover, some recent work on the Parisian region documented the impact of a drop in monetary costs of transport on unemployment highlighting that lower fees might slightly reduce unemployment (Pascal 2021), echoing previous evidence on randomized vouchers (Franklin 2017) and the predictions of Zenou (2009c). The fact that these policies seem to be able to produce positive impacts can be explained in our framework by the fact that these shocks are essentially be seen as one-way roads, improving accessibility for the — small — targeted population, without generating the competition effects that we put forward in this paper.

Fourth, we contribute to the literature on quantitative spatial equilibrium models. Integrating elements from quantitative urban models à la Ahlfeldt et al. (2015), urban labor market models à la Marinescu and Rathelot (2018) and Manning and Petrongolo (2017), and labor demand à la Stole and Zwiebel 1996; Cahuc, Marque, and Wasmer 2008, we bridge the gap between these related strands of literature. Since the seminal contribution of Ahlfeldt et al. (2015), an expanding body of research is using quantitative equilibrium models based on discrete-choice models of location and floor space market clearing (Redding and Rossi-Hansberg 2017, Redding 2023). In this literature, researchers studied the welfare effects of transport policies Severen (2021) and Allen, Arkolakis, and Li (2020) as well as their redistributive effects (Akbar 2022a; Tsivanidis 2019) and their effects on sorting (Akbar 2022b; Tyndall 2021). This paper introduces endogenous frictional unemployment and productivity heterogeneity as Schmutz and Sidibé (2019) and Bilal

(2023) but in a urban equilibrium model, i.e within city. To do so, we borrow the labor demand model of Stole and Zwiebel 1996, integrating it in an urban model. We also build on Manning and Petrongolo (2017), but our works differ in several ways. First, we explicitly incorporate space in the model with local labor demand and supply functions subject to agglomeration effects. Second, our model allows us to derive analytical predictions in particular but interesting cases. Finally and more importantly, we take into account worker heterogeneity and the potential for firms to direct their openings.

3 Descriptive evidence

3.1 Data

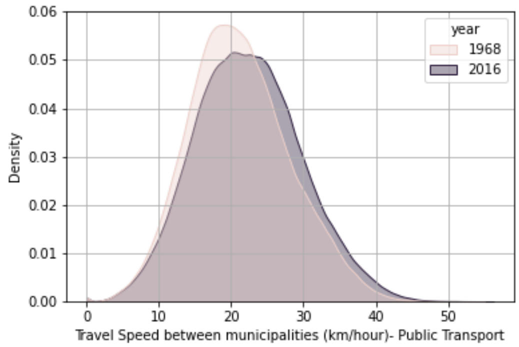
In this section, we begin by documenting two key observations about unemployment and commuting in the Paris urban area. We utilize data from municipalities within the Paris urban region. This level of aggregation corresponds to what is known as zip codes in the United States and encompasses relatively small areas, with an average surface of about 9 square kilometers. Our data is drawn from the long-run series provided by the French census, spanning from 1968 to 2016. The majority of the data is sourced from tabulations conducted by the French National Statistical Institute (INSEE) and is accessible online. For information on mobility, unemployment and the active population, we rely on tabulations derived from the exhaustive population until 1999 and then from a rolling sample starting in 2006 as INSEE adopted a continuous sampling approach, providing data comparable over five-year intervals. Additionally, prior 2006, data related to commute flows, workplace locations and unemployment by level of diploma are obtained from tabulations based on a 20% or 25% sample, as these information were not digitized for the exhaustive dataset.

3.2 Increasing Labour Market Integration

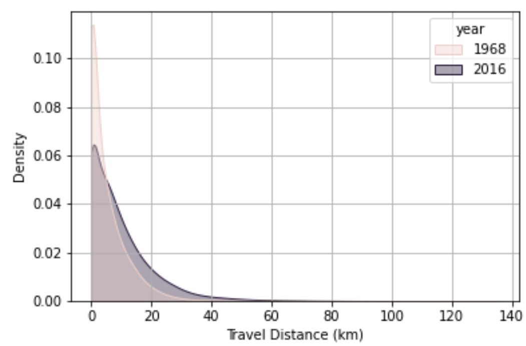
We first start documenting the rising integration of the Parisian market. We characterize this labor market integration by the fact that one can observe a stronger connections between municipalities as workers tend to live and work in increasingly distant places. This situation seems to be facilitated by the large improvements in the transport network that reduced the average travel time between every municipalities.

Faster and Further: Since the 1968 census, Paris Urban Area experienced massive public investments designed to reduce transport time within the region. The most notable improvements in the mass transit railway network is the development of the Regional Railway Express (RER) that facilitated the circulation of regional trains within Paris increasing dramatically the frequency of trains (Mayer and Trevien 2017) and dramatically improving the market access for all types of workers regardless of their qualification (Viguié et al. 2023). The first RER line, Line A, commenced operations in 1977, paving the way for a network that now comprises 10 lines and over 250 stations. In parallel with the RER's expansion, the Paris Metro network has also undergone significant growth, extending its reach to serve a wider area of the city and its inner suburbs. The most recent addition to the Métro network is Line 14, which opened in 2019, providing a vital east-west link across the city. Moreover, 4 new automatic metro lines creating a ring in the suburbs of Paris are currently being built which, once completed in 2035, should double the size of the railways network. Complementing the RER and Métro networks, the Île-de-France region has also invested in the development of tram and bus rapid transit lines. To illustrate the consequences of these investments, we take advantage of a novel dataset provided by Viguié et al. (2023) documenting the travel time between all municipalities in public transport in the morning for 1968 and 2016. We report the change in the distribution of speed of these travels in Figure 1. One can note a significant shift of the distribution between both periods where the average speed for all possible trips increases from 20 to 22km/H. Consistent with the literature, a faster transit allows workers to live further away from jobs. We illustrate this phenomenon in panel b) of Figure 1. By employing a complementary sample tracking the workplace location we compute the average commuting distance. For each worker, we calculated the geodesic distance between their municipalities of work and residence. This data reveals a marked increase in commute distances. In 1968, most people worked and lived within a 5 km radius. By 2016, this scenario had shifted dramatically as the average distance to go to work went from 4.8 km to 9.5km. While speed and distance increased travel time remained relatively constant.

Figure 1: Travel speed and commute distances, 1968-2016



(a) Changes in inter-municipal travel speed, 1968-2016

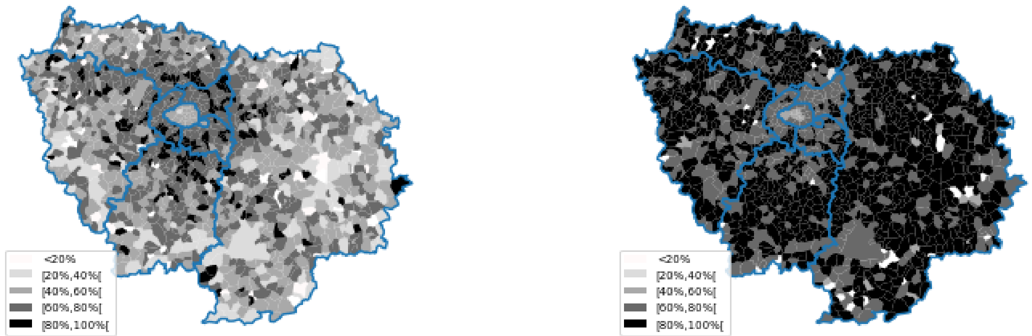


(b) Changes in commute distances, 1968-2016

Sources: Authors' computation based on Viguié et al. (2023) and the French Population Census 1968 and 2016

Growing connection between municipalities : To illustrate further the growing connection between the different areas of the Greater Paris labor market, we also exploit the full count data, looking at the evolution of the mobility rate– the proportion of workers residing and working in different municipalities that we report in panel a) and b) of Figure 2. The proportion of individuals working and living in different municipalities rose from 70% to 80% between 1968 and 2016. Moreover, the dispersion in municipal mobility rates witnessed a dramatic decline. Workers in suburban municipalities, previously mostly working and living in the same municipality, experienced convergence toward an 80% mobility rate, the urban area's average. Irrespective of their specific location within the urban area, most municipalities now exhibit mobility rates exceeding 60%. Moreover, this trend does not only concern suburbian cities, the integration of Parisian districts also increased and the share of workers living in Paris but working in its suburbs rose from 15% in 1968 to 30% in 2016. This growth appears also relevant in other large urban areas outside France as in the United State (Monte, Redding, and Rossi-Hansberg 2018).

Figure 2: Homogeneous mobility rates; 1968-2016



(a) Mobility rates : 1968

(b) Mobility rates: 2016

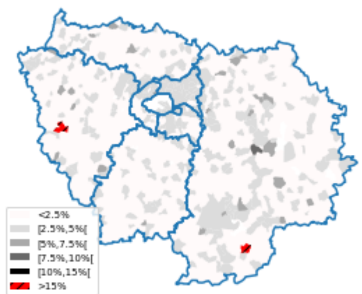
Sources: Authors' computation based on the French Census 1968 and 2016. Mobility rates for all municipalities are based on the full count census while they are based on the 1/4 census for the parisian districts (arrondissements) where the definition of the variable work and live in the same municipality changes across time in the full count data.

3.3 The location of unemployed

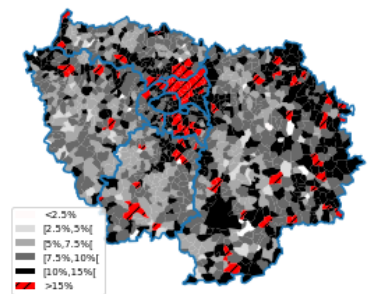
While population and jobs decentralization that accompany improvements in transport infrastructures have been carefully documented (Mayer and Trevien 2017; Baum-Snow 2007; Duranton and Turner 2012). The geographical patterns of unemployment remained relatively overlooked. We now turn to long-term series of municipal-level unemployment rates in order to investigate where do unemployed reside. While the labor market has been integrating with large improvements in the connectedness between municipalities, we observe persistently high level of unemployment in areas very close to jobs in particular for low skilled worker.

Persistent Dispersion of Unemployment Rates: The unemployment rate in the greater Paris Area, as measured by the census, began at 2% in 1968 and escalated to 8% in 1982 following the oil shock, eventually stabilizing around 12%. The maps further aid in identifying spatial patterns. In Panel a) and b) in Figure 3, we illustrate the evolution of the unemployment rates in the municipalities of the greater Paris region from 1968 to 2016. It is worth noting that municipalities with slightly higher unemployment rates in 1968 are these that exhibits the highest unemployment rates after the oil shock as supported in Appendix Table A.1.To explore the drivers of these spatial disparities we explore the correlation between the share of workers without a diploma and the unemployment rates in both year. Unsurprisingly, Municipalities incurring the highest unemployment rates both in 1968 and in 2016 appear to be municipalities concentrating workers without diploma.

Figure 3: Unemployment dispersion in Paris Urban Area; 1968-2016



(a) Unemployment : 1968



(b) Unemployment: 2016

(c) Unemployment and diploma, 1968

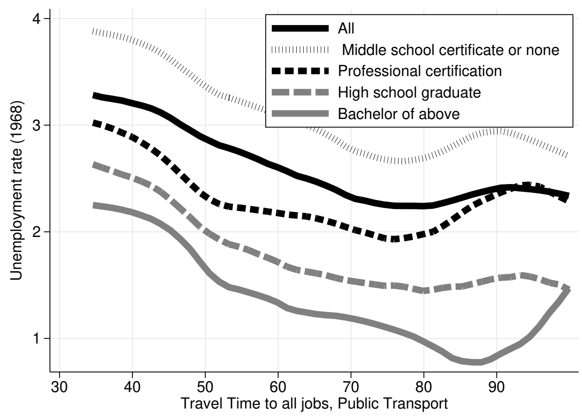
(d) Unemployment and diploma, 2016

Sources: Authors' computation based on the French Census 1968 and 2016. Observations are all municipalities in the Paris Region (Ile-de-France) and the 20 Parisian Administrative districts (arrondissements)

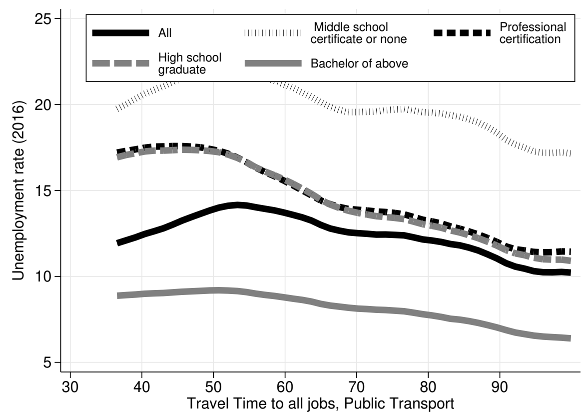
Unemployed live relatively close to jobs In Figure 5, we examine the statistical relationship between the localized unemployment rate and integration into the urban labor market, as measured by the average travel time to jobs via public transport, using data from Viguié et al. (2023) and from the DRIEAT (see Appendix A.2). Panels a) and b) show the correlation between average transport time using public transport and the localized unemployment rates for all active individuals in 1968 and 2016. Panel c) and d) use the transport time using a personal vehicle instead of public transport. Maybe surprisingly, we find mostly a *negative* relationship between travel time to all jobs in the area and unemployment rate, meaning that on average workers in better connected municipalities are more often unemployed or that unemployed live relatively close to jobs. Moreover, it is worth noting that this relationship tends to be stronger within each education group. Indeed, if one can observe a small rise in the unemployment rate for all workers from 40 to 50 minutes when using public transport in 2016, this effect tends to disappear within most of the education groups suggesting that it is mostly driven by sorting. Overall, our findings rejoin the recent observation by Card, Rothstein, and Yi (2024) in large US cities where minorities with higher unemployment rates also tend to live closer to jobs and show that localized unemployment rates are associated with sorting (i.e workers' characteristics) rather than travel time to jobs.

The rest of the paper is dedicated to investigate both theoretically and empirically the relative importance of individual productivity, sorting and access to jobs in determining localized unemployment rates. In a nutshell, we argue that most of the heterogeneity in localized unemployment rates comes from sorting. Moreover, we will show that well connected municipalities might have higher unemployment rates in part because more jobs also means more competition. We will demonstrate both theoretically and empirically that better connection can increase localized unemployment rates. In the following section, we will propose a framework to explore the mechanisms behind transport infrastructures and localized unemployment, and a decomposition formula to quantify the share of unemployment differences between skill groups driven by differences in access to jobs.

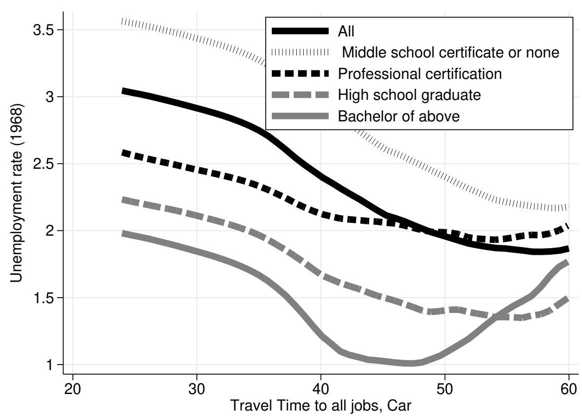
Figure 5: Unemployment and travel time to jobs by education, 1968 and 2016



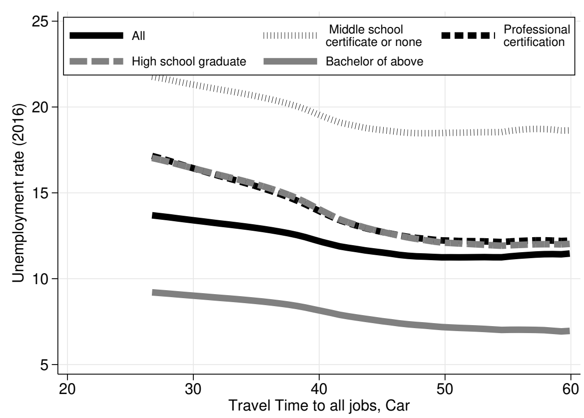
(a) Unemployment and Travel Time to all jobs by public transport, 1968



(b) Unemployment and Travel Time to all jobs by public transport, 2016



(c) Unemployment and Travel Time to all jobs by car, 1968



(d) Unemployment and Travel Time to all jobs by car, 2016

Author's computation using an Epaniechnikov Kernel of order 0 estimates based on municipal level data exctracted from the 1968 and 2016 French census produced by the INSEE and inter-municipal travel times from Viguié et al. (2023). Local unemployment rates are computed for 4 level of education for each municipality or administrative districts (arrondissements) of the census. Each observation is weighted with its corresponding number of active in the category.

4 Labour Market Integration in a frictional urban labor market

In this section, we analyze the effect of LMI on urban unemployment in a simple frictional urban labor market. The goal of the model is to understand the labor market effects of LMI when heterogeneous workers can compete for jobs across interconnected labor markets. To keep the model as tractable as possible, we focus on an urban labor market conditional on residential location: workers choose their place of work, and wages adjust accordingly. As in Ahlfeldt et al. (2015) location decisions are modeled using a Fréchet discrete choice framework, leading to tractable gravity equations. Our main contribution to this framework is the introduction of a frictional spatial labor market with heterogeneous workers.

4.1 Frictional Unemployment

The goal of this section is to develop a tractable model of frictional unemployment to better understand the impact of LMI on the employment of heterogeneous workers. In particular, we want to build a model that can illustrate the local labor market effects that arise when asymmetric municipalities are connected. Because this mechanism essentially pertains to labor demand and frictional job markets, we do not explicitly model worker sorting and labor market participation and choose to work conditional on residential location and labor market participation. As we will see, our model still yields a decomposition of unemployment rates that allows us to quantify the importance of sorting for local labor market disparities. On the demand side, we treat each workplace j as an independent market, subject to its own matching function — though markets are connected through workers' decisions to apply in any of them. Each municipality has a representative firm and a matching function that determines the number of jobs based on the number of open positions and the number of candidates in the municipality. For the matching function formulation and wage determination, we build on Stole and Zwiebel (1996), Carrère, Grujovic, and Robert-Nicoud (2020), and Helpman and Itskhoki (2010). For the labor supply, we build on the discrete-choice formulation of quantitative urban models (Ahlfeldt et al. 2015), and on the labor supply model of Manning and Petrongolo (2017).

4.1.1 Firms

We assume a representative firm per municipality j, producing output y_j sold to the rest of the world at a unit price. The firm's technology is Cobb-Douglas

$$y_j = A_j(H_j)^{\alpha}(F_j^M)^{1-\alpha}, \tag{1}$$

with A_j being total factor productivity, H_j the labor employed in j, and F_j^M the built-up area used by firms in j. The parameter α represents the labor share in firm costs. Workers are heterogeneous and belong to discrete categories $k \in 1, ..., K$. Workers of type k are characterized by a productivity σ_k, such that total labor quantity in j is $H_j = \sum_i H_{kj}\sigma_k$, where H_{kj} is the number of worker of category k employed in j.

Firms can discriminate based on worker type, explicitly targeting the number of vacant positions V_{kj} they open for each type k. Given a number of candidates S_{kj} of type k and open positions V_{kj}, a Cobb-Douglas matching function determines the number of type-k workers employed in j:

$$H_{kj} = (V_{kj})^{1-\lambda}(S_{kj})^{\lambda}, \tag{2}$$

where λ is a parameter that we assume constant in the region.

From the firm's perspective, hiring a worker requires opening

$$\frac{V_{kj}}{H_{kj}} = \left(\frac{V_{kj}}{S_{kj}}\right)^{\lambda} = \theta_{kj}^{\lambda} \tag{3}$$

positions. We let ν be the unit cost of opening a position, the cost of opening a position per worker c_{kj} is therefore

$$c_{kj} = \nu\theta_{kj}^{\lambda}. \tag{4}$$

As we will see later, the assumption that the vacancy costs are essentially costs *per worker*, and not costs per *effective units of labor* will yield increasing hiring probabilities along the skill ladder.

Denoting w_{kj} as the wage paid by a firm in j to a worker in group k, the expected profit of a firm in j becomes

$$A_j(H_j)^{\alpha}(F_j^M)^{(1-\alpha)} - \sum_k (w_{kj} + c_{kj})H_{kj} - Q_j^M F_j^M, \tag{5}$$

where Q_j^M is the commercial rent in j. Hence, the first K first order conditions for profit maximization equate the marginal productivity of labor r_{kj} to the total cost per worker, i.e.,

$$r_{kj} \equiv \sigma_k r_j \equiv \sigma_k \alpha A_j \left(\frac{F_j^M}{H_j}\right)^{1-\alpha} = c_{kj} + w_{kj}, \tag{6}$$

while the last condition equates rent to marginal productivity of built-up area

$$Q_j^M = (1-\alpha) A_j \left(\frac{H_j}{F_j^M}\right)^{\alpha}. \tag{7}$$

4.1.2 Wage Bargaining

For all matches kj, the firm's surplus is $r_{kj} - w_{kj}$, and the worker's surplus is w_{kj} their realized wage. Once a match is made, we assume the firm and worker share the total surplus according to a Nash solution[1]

$$w_{kj} = \arg\max_{w} \left[r_{kj} - w\right]^{1-\chi} [w]^{\chi}, \tag{8}$$

yielding $w_{kj} = \chi r_{kj}$. With the first order condition (6), this leads to $w_{kj} = \sigma_k w_j$, and $c_{kj} = \sigma_k c_j$, with $w_j = \chi r_j$ and $c_j = (1-\chi) r_j$. Therefore, the wage is the product of a term representing workers' marginal productivity at the place of employment w_j and a term for individual productivity σ_k.

4.1.3 Factor demand functions

Finally, combining the first order equations (6) and (7) with wage bargaining (8) yields the demand for floor space, which will be used to define the equilibrium of the model.

$$F_j^M = \frac{1-\alpha}{\alpha} \frac{w_j}{\chi Q_j} H_j, \tag{9}$$

while profit maximization yields

$$A_j = \left(\frac{Q_j^M}{1-\alpha}\right)^{1-\alpha} \left(\frac{w_j}{\chi \alpha}\right)^{\alpha}. \tag{10}$$

1. In Appendix E.1, we show that allowing for intra firm bargaining *à la* Stole and Zwiebel (1996), as in Helpman and Itskhoki (2010), yields rigorously identical results up to a multiplicative constant—which does not change our results.

4.1.4 Labor Market Tightness

Based on the definition of hiring cost, we have $c_{kj} = \nu\theta_{kj}^{\lambda} = \sigma_k c_j$, implying that

$$V_{kj} = \left(\sigma_k \frac{c_j}{\nu}\right)^{\frac{1}{\lambda}} S_{kj} \tag{11}$$

We denote $\tilde{\sigma}_i \equiv \sigma_i^{1/\lambda}$, total candidate applications $S_j \equiv \sum_i S_{kj}$, and total vacancies $V_j \equiv \sum_k V_{kj}$. The overall tightness in j is therefore $\theta_j \equiv V_j/S_j$. Additionally, we define $\bar{\tilde{\sigma}}_j \equiv \sum_k \frac{S_{kj}}{S_j}\tilde{\sigma}_k$ as the average productivity of candidates in j. Summing (11) over k, we then obtain

$$\theta_{kj} = \frac{\tilde{\sigma}_k}{\bar{\tilde{\sigma}}_j}\theta_j \equiv \tilde{\sigma}_k\tilde{\theta}_j. \tag{12}$$

This relatively simple model of labor demand thus captures behaviors of workers' selection based on productivity. A worker of type k has a probability of finding a job that is a product of the ratio of total applications and vacancies in j, θ_j, and a term depending on i's quality relative to other candidates in the workplace. Intuitively, this comes from the fact that the cost per vacancy ν is a cost per individual worker, but workers differ in the effective units of labor that they supply. This puts a wedge between marginal costs and benefits of workers with different productivity. In equilibrium, firms close that gap by targeting their vacancies so that differences in expected vacancy costs per workers reflect differences in marginal productivity. [2]

In what follows, we let $\tilde{\theta}_j \equiv \theta_j/\bar{\tilde{\sigma}}_j$ be the market tightness adjusted for the quality of labor supply in municipality j, so that the kj-specific job finding probability is $\ell_{kj} = \sigma_k^{\frac{1-\lambda}{\lambda}}\tilde{\theta}_j^{1-\lambda}$, and the kj wage is $w_{kj} = \nu\sigma_k\tilde{\theta}_j^{\lambda}\chi/(1-\chi)$.

4.2 Labor Supply

In what follows, we focus on the choice of a workplace conditional on a place of residence. Worker n living in i with productivity σ_k decides in which municipality $j = 1, ..., J$ to apply for a job. We assume that a worker can only apply to one place at a time. When a worker of type in k applies to j, they have a probability $\ell_{kj} = \theta_{kj}^{1-\lambda}$ of being hired. In that case, they receive a wage w_{kj}. Further,

2. Note that we don't need the vacancy cost to be completely independent of productivity, nor do we need marginal productivity to be linear in individual talent. If vacancy costs were a function of productivity $\nu(\sigma_k)$, hiring probabilities should still increase with talent as long as $\nu(\sigma)$ increases more slowly than marginal productivity.

utility when living in i and working in j is subject to a (possibly type-specific) iceberg commuting cost d_{ijk} and an idiosyncratic taste shock z_{ijkn}. Thus, worker n will choose to apply to j if

$$z_{ijkn} d_{ijk} \ell_{kj} w_{kj} \geq z_{ilkn} d_{ilk} \ell_{kl} w_{kl} \qquad \forall l. \tag{13}$$

Assuming that the idiosyncratic components z_{ijkn} are independently and identically Fréchet distributed with a dispersion parameter ϵ, the mass of workers of type k choosing to apply in j, conditional on living in i, is given by the following choice probabilities:

$$\pi_{j|ik} = \frac{d_{ijk}^{\epsilon} \ell_{kj}^{\epsilon} w_{kj}^{\epsilon}}{\sum_{j=1}^{J} d_{ijk}^{\epsilon} \ell_{kj}^{\epsilon} w_{kj}^{\epsilon}}. \tag{14}$$

More than one application We assumed that a worker can only choose to apply to one workplace. While this assumption might seem restrictive, the application shares that we derive in equation (14) are equal to the bilateral number of applications in the job search model of Manning and Petrongolo (2017) when workers are endowed with a fixed number of applications that they can send to different workplaces. Our labor supply equation could therefore be derived from their setup.

Bargaining, commuting costs and idiosyncratic shock In our framework, the specific value of the Fréchet shock and commuting times drop out from the bargaining game. This is because the bargaining stage happens after workers commit to apply to their workplace, the utility is multiplicative, and we assume a static framework where workers' outside options are normalized to zero. In a model with monetary (additive) commuting costs, workers would bargain over the wage net of commuting costs, making the final wage dependent on commuting costs. This would complicate the analysis of the impact of transport infrastructures by creating an additional mechanism. Indeed, firms still adjust their labor demand to equalize total expected costs and benefits for each worker type, but the expected cost is inflated by the share of the commuting costs bargained by workers. This leads firms to direct less vacancies towards workers living far away. A transport infrastructure improvement would then increase the number of vacancies directed towards the newly connected workers, improving their job finding rate. While investigating this mechanism could be of theoretical interest, it is unlikely to be empirically relevant in our setting. At the time of writing, annual subscription prices for the Île-de-France transit network vary depending on zoning between €74.8 per month and €86.4 per month, i.e. a less than €12 difference, of a negligible order of magnitude when compared to wages. More broadly, even if we considered other factors that might make employers discriminate based on distance such as punctuality and direct impact on productivity, existing empirical studies do not find meaningful discrimination on distance (Gobillon and Selod 2021). On the other hand, application probabilities decrease quickly with distance (Marinescu and Rathelot 2018): the first order effect of commuting costs is on labor supply.

4.3 Closing the model

To close the model, we specify the shape of agglomeration effects, and the equilibrium on the firm floor-space market.

4.3.1 Agglomeration effects

We allow for total factor productivity to be subject to external agglomeration effects. Specifically, we assume that total factor productivity in any municipality j is given by $A_j = a_j H_j^{\gamma}$, where γ is the magnitude of the agglomeration effects.

4.3.2 Commercial floor space

Conditional on residential locations, the equilibrium allocation of workers is determined on the commercial floor space market. Developers construct buildings in each municipality using land L_i and a mobile factor K_i. We assume a standard Cobb Douglas production function for construction, $F_i = C_i L_i^{\mu} K_i^{1-\mu}$, where μ represents the share of land in construction costs, and C_i is a local level of buildability. We assume that developers take the available land in each municipality as given and adjust only their level of investment in mobile factors. Additionally, land use regulations are modeled by setting the share of land reserved for commercial use as s_i^M. With Q_i^M the cost of commercial buildings, the building supply function is given by:

$$F_i^M = \tilde{L}_i s_i^M (Q_i^M)^{\tilde{\mu}}, \tag{15}$$

where $\tilde{\mu} = \frac{1-\mu}{\mu}$ is the price elasticity of building supply, and $\tilde{L}_i = \frac{1-\mu}{P_K}^{\frac{1-\mu}{\mu}} C_i^{\frac{1}{\mu}} L_i$ measures the available land in i, adjusted for buildability and mobile factor price.

4.3.3 Equilibrium

We now can define an equilibrium of the model as a situation in which the floor space market for firms clears, subject to the matching process, labor supply and labor demand derived above. Formally, we give Definition 1.

Definition 1. An equilibrium of the model conditional on residential populations (P_i) and productivities (σ_i), available floor space $(L_j s_j^M)$, and exogenous productivities (a_j), is thus defined as a vector of wages w_j that clear the commercial floor space market subject to agglomeration effects, the choice probabilities in (14) and the profit maximization equation (10):

$$\tilde{L}_j s_j^M (Q_j^M)^{1+\tilde{\mu}} = \frac{1-\alpha}{\alpha\chi} w_j H_j, \tag{16}$$

$$A_j = \left(\frac{Q_j^M}{1-\alpha}\right)^{1-\alpha} \left(\frac{w_j}{\alpha\chi}\right)^{\alpha}, \tag{17}$$

$$A_j = a_j H_j^{\gamma}, \tag{18}$$

$$H_j = \sum_i \sum_k \sigma_k P_{rk} \ell_{ijk} \pi_{j|ik}. \tag{19}$$

In appendix E.2, we show that as long as agglomeration effects are not too strong, this spatial labor market with matching admits a unique equilibrium:

Proposition 1. *Assume that $\gamma < \dfrac{1-\alpha}{1+\tilde{\mu}}$, then this model has a unique equilibrium.*

Specifically, $\gamma < (1-\alpha)/(1+\tilde{\mu})$ is a condition that ensures that labor demand in each municipality, including agglomeration effects, is downward slopping. For standard values of the labor share α = 0.7, we get that the agglomeration elasticity should be lower than 0.3 for an inelastic floor space supply, or 0.15 for a supply elasticity equal to one. In any case, we stand comfortably above 0.04, the upper bound of the estimated agglomeration elasticity of Combes et al. (2010) for France and the recommended value of Ahlfeldt and Pietrostefani (2019).

4.4 Employment rates and LMI

We now turn to the discussion of unemployment rates in the model, how they are affected by changes in transportation costs, and how improving labor market integration might play with pre-existing differences in endowments to shape the gains and losses of heterogeneous workers. Derivations are available in appendix E.

Unemployment and job market access The total employment rate of type k living in i is the sum over all potential job places of the share of applications to that job site and the probability to match conditional on applying, i.e. letting ρ_{ik} be the unemployment rate of k in i:

$$\begin{aligned} 1-\rho_{ik} &= \sum_j \ell_{ijk}\pi_{j|ik} \\ &= \sigma_k^{\frac{1-\lambda}{\lambda}} \frac{\sum_j d_{ijk}\tilde{\theta}_j^{1-\lambda+\epsilon}}{\sum_l d_{ilk}\tilde{\theta}_l^{\epsilon}} \\ &\equiv \sigma_k^{\frac{1-\lambda}{\lambda}} \times MA_{ik}. \end{aligned} \tag{20}$$

In our setting, the equilibrium employment rate in any given municipality is the product of a term increasing with productivity σ_k that is the direct effect of skill on employability, and a market access term MA_{ik} that only depends on commuting costs and labor market tightness in the city and summarizes the impacts of geography and equilibrium forces on employment.

Therefore, our model provides a fully micro-funded theoretical framework for multiplicatively separable employment rates, as assumed implicitly in the empirical spatial mismatch literature where employment rates are regressed on the log of some measure of market access (e.g. in Andersson et al. 2018).

4.4.1 Theoretical predictions

While the properties of equilibrium allocations are difficult to characterize analytically with arbitrary geographies, we solve our model in the polar cases of completely isolated and integrated economies. To simplify notations, in what follows we write i to denote both a type and a residential location. Note that this is without loss of generality, as we can always redefine types $i = (i,k)$ corresponding to the intersection of residential locations and types without changing the model and its equilibrium.

Equilibrium in autarky We start by analyzing the properties of the model when every municipality is in autarky, i.e. when commuting costs are infinite between any pair of municipalities. In this perfectly segmented city, we assume that there is perfect segregation: workers of each type can only work in their own backyard.

Result 1. *Assume that $\gamma < (1-\alpha)/(1+\tilde{\mu})$. Consider an isolated municipality i, i.e. $d_{ij} = 0$ for all $j \neq i$ and $d_{ii} = 1$. Then*

(a) The market access MA_i is i) increasing in productivity-adjusted available land $a_j^{\frac{1+\tilde{\mu}}{1-\alpha}} \tilde{L}_j$; ii) decreasing in local population P_i; and iii) decreasing in productivity σ_i.

(b) The employment rate is increasing in σ_i.

Our first theoretical result (Result 1) shows that for an isolated economy the employment rate is lower when population is large, and higher when there is more land available for firms, when firms are more productive, and when workers are more productive. However, while the net effect of residents' productivity on employment rate is positive, a higher productivity leads to a lower market access. When labor productivity in an isolated municipality increases, there is a positive direct effect on employment (through the first term in (20)), but a negative equilibrium effect due to the fact that workers are now also competing with more productive peers. This means that all else equal, in autarky the labor market equilibrium forces dampen labor market disparities: while high-σ workers still enjoy a higher employment rate than their low-σ counterparts, the difference would be larger if they faced the same competition.

Equilibrium in a fully integrated labor market We then characterize the equilibrium in a fully integrated labor market, where workers are not confined in their own backyard anymore but instead have access to jobs in every part of the city at no extra costs. This means that labor market conditions will be equalized across space.

Result 2. *Assume that $\gamma < (1-\alpha)/(1+\tilde{\mu})$. Define a fully integrated equilibrium as a situation where $d_{ij} = d > 0$ for all i, j. Then the effect of going from autarky to full integration is increasing in σ, increasing in population and decreasing in productivity-adjusted land.*

We summarize the effect of the transition from autarky to full integration in Result 2. Because full integration equalizes opportunities across the city, it will benefit more the workers with an initially lower market access. Coming from a full autarky situation, we show that the LMI should bring more benefits to more productive workers. This is because high-skilled workers face an easier competition when applying in formerly entirely low-skilled workplaces, while the newly opened labor market is more competitive for low-skilled workers while the extra inflow of high-skilled workers increases competition in their home market. However, we show that integration should also bring more benefits to workers with smaller backyards, i.e. who initially had access to less productive land and who were facing a more crowded labor market. Intuitively, this is because geographically disadvantaged workers can now sell their labor in less crowded markets, which offer higher expected wages, while workers that had access to the best productive locations do not gain much from the possibility to apply to less productive workplaces. Thus, although moving to full integration will all else equal benefit more productive workers, the total effect of the labor market integration will also depend on the initial situation of different worker types. In particular, if low skilled workers were initially penalized by a limited access to productive firms and land, then labor market integration could improve their employment outcomes.

Result 3. *Assume that $\gamma < (1-\alpha)/(1+\tilde{\mu})$, and let $\widehat{1-\rho_i}$ be the change in the probability to be employed going from autarky to full integration. Then*

$$\mathrm{Cov}\left[\log(\sigma_i), \log(\widehat{1-\rho_i})\right] < 0$$

if and only if, in autarky,

$$\frac{1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}}{\lambda}\mathrm{V}[\log(\sigma_i)] < \frac{1+\tilde{\mu}}{1-\alpha}\mathrm{Cov}\left[\log(\sigma_i), \log\left(a_i\right)\right] + \mathrm{Cov}\left[\log(\sigma_i), \log\left(\frac{\tilde{L}_i}{P_i^{1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}}}\right)\right].$$

Result 3 formalizes this intuition by looking at the conditions under which the (log of) productivity is negatively correlated with the (log of) the change in employment rates, i.e. situations in which labor market integration reduces employment disparities. We show that this is the case if and only if there was a sufficiently strong mismatch, where we measure mismatch as the correlation between workers' productivity and their access to productive land per capita and firms with a high productivity. We interpret this result as meaning that there needs to be a strong enough spatial mismatch (the more productive group being advantaged by its localisation) for

LMI to have a chance to reduce labor market outcome differentials.

An immediate corollary of this result is that if there is not a lot of variation in accessible land per capita or the exogenous component of TFP, then there is little possibility for spatial mismatch and the labor market integration is unlikely to benefit unskilled workers. In fact, in a featureless city where only worker productivity varies (but firm productivity and land endowments are equal everywhere) the employment rate increases for those above the average city-wide productivity and decreases for those below..

Result 4. *Assume that $\gamma < (1-\alpha)/(1+\tilde{\mu})$. Define a featureless city as a city where $\bar{L}_j = \bar{L}$, $a_j = a$ and $P_i = P$ for all j. Then in a featureless city, going from autarky to full integration the employment rate of i increases if and only if $\sigma_i^{\frac{1}{\lambda}} \geq J^{-1} \sum_i \sigma_i^{\frac{1}{\lambda}}$.*

This illustrates that without mismatch, labor market integration can actually hurt the labor market outcomes of lower skilled workers. This is because when the labor market is integrated, formerly fully low-skilled municipalities start opening high-skilled vacancies, and conversely. They do so until job filling probabilities adjust in such a way that the expected costs and benefits of vacancies are equalized between types. Because high-skilled workers have a higher marginal productivity, they get more vacancies than low-skilled workers.

Discussion To summarize our model predicts that in isolation, labor market frictions all else equal dampen employment inequalities between more or less productive workers, as it benefits workers with an initially bad labor market access. Thus in general, except if i) there are strong variations in factors that drive exogenous local TFP and in available land for firms, and ii) more vulnerable workers only have access to the most crowded and less productive places (i.e. there is spatial mismatch), labor market integration will favor productive workers.

5 Structural decomposition of local unemployment rates

We now move on to a quantitative exercise where we use our model to decompose unemployment rate differentials across skill groups, isolating the impact of labor market access from employability heterogeneity, separately for 1968 and 2016. Our decomposition only involves the labor supply component of the model and takes labor market tightness across the city as given. It is therefore robust to alternative specifications of labor demand.

In our empirical implementation, worker types correspond to education levels $k \in \{A, B, C, D\}$, where the letters correspond to increasing educational achievements: middle school certificate or none (A), professional certification (B), high-school graduate (C), and bachelor or higher (D). We allow productivity to differ between residential locations for a same educational attainment, allowing us to capture potential sorting effects beyond those four education levels. We note σ_{ik} the productivity of residents of i with education k. The goal of the remainder of that section is to estimate the contribution of market access differentials to unemployment differences between those four groups.

5.1 Unemployment gap decomposition

As we saw in equation (20), in our framework the employment rate of workers can be written as the product between a direct productivity effect and a market access term, that acts as a sufficient statistic for the accessibility to more or less tight sub-markets. We will now use this result to construct a decomposition of unemployment differences between categories of workers. Let the population of any group k living in i be N_{ik}. Let $\bar{u}_k$ be the total unemployment rate of type-e workers:

$$\bar{u}_k \equiv \sum_i \frac{N_{ik}}{N_k} u_{ik},$$

and define in a similar fashion $\overline{MA}_k$ the average market access faced by type-e workers and $\overline{\sigma_k}$ the average of $\sigma_{ik}^{\frac{1-\lambda}{\lambda}}$ for type-k workers. Finally, let $\text{Cov}_k(x, y)$ be the population-weighted covariance between two variables x and y within a group k. Then, we can write the difference in average unemployment rates between any two groups k and k' as

$$\begin{aligned}
\bar{u}_k - \bar{u}_{k'} = \quad & \bar{\sigma}_{k'}(\overline{MA}_k - \overline{MA}_{k'}) && \text{Average MA} \\
+ \; & \overline{MA}_{k'}(\bar{\sigma}_k - \bar{\sigma}_{k'}) && \text{Average productivity} \\
+ \; & \text{Cov}_k(\sigma, MA) - \text{Cov}_{k'}(\sigma, MA) && \text{Within-group covariance} \\
+ \; & (\overline{MA}_k - \overline{MA}_{k'})(\bar{\sigma}_k - \bar{\sigma}_{k'}) && \text{Differential returns}
\end{aligned} \tag{21}$$

Thus, we can express the employment gap as the sum of four terms. First, an average market access term, that is the difference that would be observed if k had the same productivity as k' but differences in market access remained. Second, an average productivity term, that is the difference that would be observed if k faced the same market access as k', but differences in productivity remained. Third, and a within-groups covariance term that captures differences in within group sorting between the two groups, i.e. how the more productive members of the group are located in areas with a higher or lower market access. Finally, a residual differential returns term that captures the fact that the returns to the proximity to jobs increase with productivity. These two last terms are small in our empirical application.

5.2 Quantification

We now calibrate and estimate the parameters and variables that we need to implement the decomposition above. To do so, we first calibrate some parameters from the literature. Second, we recover the distance parameters using a gravity equation on employed workers. Third, we recover θ_j for all j from the estimated taste for distance and the observed commuting flows, which allows us to recover the job market access for every residential location. Finally, we recover σ_{ik} using this market access and the observed unemployment rates by municipality of residence and education level.

Calibrated parameters We calibrate a number of parameters. First, the share of labor in the costs of firms is set to $\alpha = 0.8$ following the French National Accounts. Then, the agglomeration effects are set to $\delta = 0.04$, following the recommendations of Ahlfeldt and Pietrostefani (2019) and the estimations on French data of Combes et al. (2010). Following Carrère, Grujovic, and Robert-Nicoud (2020), we set the matching parameter to $\lambda = 0.6$. The floor space supply elasticity is set to $\tilde{\mu} = 0.25$, corresponding to the estimates of Chapelle, Eyméoud, and Wolf (2023) on French data. Finally, for the Fréchet dispersion parameter we set $\epsilon = 5$ as a central value from the literature. In appendix D, we report versions of the results in this section under different values of ϵ and λ. Our conclusions remain unchanged under these alternative parameter values.

Transport mode and distance disutility First, we need to parameterize the iceberg cost d_{ijk}. We incorporate the choice of transport mode into the model and assume that workers simultaneously choose where to apply and which transport mode to use for commuting if they get hired. Workers with different education levels are allowed to have different preferences. We parametrize the iceberg costs as

$$d_{ijkm} = t_{ijm}^{-\tau_{mk}} \bar{u}_{mk}, \tag{22}$$

where $\bar{u}_{mk}$ captures the average preference of workers of type e for mode m, the elasticity of commuting costs to travel time is τ_{km}, and t_{ijm} is the travel time between i and j using mode m. We also assume that idiosyncratic taste shocks are mode-specific z_{ijmn} and still Fréchet with parameter ϵ. Under these assumptions, we again obtain the choice probabilities equation (**??**), with $d_{ijm} = \sum_m \bar{u}_{mk} t_{ijmk}^{-\tau_{mk}\epsilon}$, while the mode-specific choice probabilities for type-k workers are given by

$$\pi_{jm|ik} = \frac{\bar{u}_{mk} t_{ijm}^{-\epsilon\tau_{mk}} \ell_{ijk}^{\epsilon} w_{ijk}^{\epsilon}}{\sum_{l=1}^{J} d_{ilk}^{\epsilon} \ell_{ilk}^{\epsilon} w_{ilk}^{\epsilon}}. \tag{23}$$

We then estimate the travel time disutility parameters τ_{mk} separately for each year, educational attainment and transport mode. These parameters can be estimated from gravity equations on bilateral employment flows. Indeed, the expected number of ik workers employed in j and using mode m is $P_{ik}\ell_{ijk}\pi_{jm|ik}$, which from equation (23) rewrites

$$P_{ik}\ell_{ikj}\pi_{jm|ik} = P_{ik} \frac{\bar{u}_{mk} t_{ijm}^{-\epsilon\tau_{mk}} \ell_{ijk}^{1+\epsilon} w_{ijk}^{\epsilon}}{\sum_l d_{ilk} \ell_{ilk}^{\epsilon} w_{ilk}^{\epsilon}}, \tag{24}$$

which has the form of a traditional gravity equation. We implement this estimation by estimating the following equation separately for each year, education group using Poisson Pseudo-Maximum Likelihood (PPML):

$$\mathbb{E}(N_{ijm}) = \exp\left\{\iota_{im} + \zeta_{jm} + \beta_m \log t_{ijm}\right\}, \tag{25}$$

where N_{ijm} is the number employed workers living in i, working in j and using mode m from our census data, $\beta_m = -\tau_m\epsilon$ is the commuting gravity elasticity, and ι and ζ are origin and destination fixed-effects. Because such a regression is potentially plagued by measurement errors and reverse causality, we instrument travel times using euclidian distance. This is implemented using a two-step control function approach (Wooldridge 2014): we first regress the log of travel times on euclidian distance and origin and destination fixed-effects, an then include the residuals of this equation when estimating (25).

This equation is estimated separately for 1968 and 2016, each education level, and each considering two modes of transportation: private cars and public transit. We report the results of these sixteen separate gravity equations in table 1. We also report non instrumented versions of this equation, as well as supporting charts, in Appenxix C. With the gravity parameters estimated, we then calibrate $\bar{u}_{mk}$ to match the aggregate mode shares for each education level. Finally, we construct for each type k of worker the commuting value of every origin destination pair as $d_{ijk} = \sum_m \bar{u}_{mk} t_{ijm}^{-\epsilon\tau_{mk}}$ separately for each year.

Table 1: Commuting gravity estimations

Mode	Private vehicle				Public transit			
Education	A	B	C	D	A	B	C	D
					Panel A: 1968			
log Travel time	-2.383***	-2.132***	-1.918***	-1.682***	-3.831***	-3.386***	-3.351***	-2.969***
	(0.0352)	(0.0368)	(0.0496)	(0.0640)	(0.1029)	(0.1041)	(0.1256)	(0.1137)
First stage resid.	1.673***	1.431***	1.232***	0.9322***	1.748***	1.388***	1.356***	0.9172***
	(0.1062)	(0.1081)	(0.1339)	(0.2042)	(0.1834)	(0.1726)	(0.2225)	(0.1889)
Squared Correlation	0.86807	0.80694	0.70659	0.78029	0.93066	0.89499	0.88365	0.91071
Observations	1,484,197	855,040	562,275	377,880	1,583,822	852,202	766,228	305,016
					Panel C: 2016			
log Travel time	-2.145***	-2.080***	-2.025***	-1.875***	-3.532***	-3.485***	-3.192***	-2.399***
	(0.0156)	(0.0130)	(0.0140)	(0.0186)	(0.0556)	(0.0571)	(0.0639)	(0.0700)
First stage resid.	0.8519***	0.6838***	0.6649***	0.6942***	1.581***	1.457***	1.211***	0.4641***
	(0.0660)	(0.0654)	(0.0655)	(0.0746)	(0.1115)	(0.1097)	(0.1141)	(0.1171)
Squared Correlation	0.84813	0.83625	0.81613	0.80822	0.92931	0.91946	0.91196	0.89162
Observations	1,358,086	1,447,800	1,372,870	1,422,549	829,652	914,196	837,810	967,246

Two-way clustered standard-errors in parenthesis. Gravity commuting equations estimated by PPML separately for each year, education level, and transport mode. All the specifications include origin and destination fixed-effects. Education levels: A: middle school certificate or none; B: professional certification; C: high-school diploma; D: bachelor or above. First stage resid.: residual of a linear regression of the log of travel time on Euclidian distance, including origin and destination fixed-effects.

Tightness Armed with our estimated transport disutility and calibrated parameters ϵ and λ, we calibrate the adjusted market tightness in each workplace $\tilde{\theta}_j$. To do so, we use the census commuting data to solve for the $\tilde{\theta}_j$ that match total employment in each workplace $N_{.j.} \equiv \sum_e \sum_i N_{ijk}$ given employment in each residential location $N_{i.k} \equiv \sum_j N_{ijk}$. Indeed, the predicted share of type-k workers being employed in j amongst those that live in i and hold a job is $\pi_{j|ikW} \equiv \ell_{ijk}\pi_{j|ik} / (\sum_j \ell_{ijk}\pi_{j|ik})$. Given $N_{i.k}$, the total number of employed workers in j is thus $\hat{N}_{.j.} = \sum_i \sum_k N_{ik.}\pi_{j|ikW}$. From equation (24), we get

$$\hat{N}_{.j.} = \sum_i \sum_e N_{ik.} \frac{d_{ikj}\tilde{\theta}_j^{1-\lambda+\epsilon}}{\sum_l d_{ikl}\tilde{\theta}_l^{1-\lambda+\epsilon}}.$$

Using a BLP-type (Berry, Levinsohn, and Pakes 1995) contraction mapping algorithm, we solve for the unique $\tilde{\theta}_j$ so that $\hat{N}_{.j.} = N_{.j.}$ for all j.

Worker productivity With $\tilde{\theta}_j$ calibrated for all j, we can compute MA_{ik} for all residential location and education level. Letting $\hat{u}_{ik}$ be the unemployment rate observed in the data, we can back-out $\hat{\sigma}_{ik}$ the residential productivity of type-k residents of location i:

$$\hat{\sigma}_{ik} = \left(\frac{1-\hat{u}_{ik}}{MA_{ik}}\right)^{\frac{\lambda}{1-\lambda}}.$$

5.3 Results

With our values for worker productivity and market access for each residential location and education level, we can compute all the terms of the our decomposition formula in equation 21. Note that contrary to commuting flows conditional on being employed, the market access term MA_i is not invariant to the scale of θ_j. Thus, we cannot say anything about the relative contribution of geography on the absolute level of unemployment in the area while relying only on our commuting flow data. However, $\sigma^{\frac{1-\lambda}{\lambda}}$ and MA are both estimated up to a multiplicative constant, and these constants are exactly inversely proportional to each other. Therefore, all the terms in our decomposition are scale-invariant, and can safely be interpreted as contribution of each term to the unemployment rates *differentials*. Differently put, while we would need an additional input to pin down the exact value of the market access terms and worker productivity, relative differences of those quantities between worker types are well identified from differences in commuting and

Table 2: Decomposition of unemployment rates differences

Education	U. Rate	Difference with highest education				
		Total	Prod	MA	Returns	Cov
Panel A: 1968						
A	3.24	1.53	4.26	-2.91	0.13	0.05
B	2.36	0.64	3.78	-3.36	0.13	0.09
C	1.98	0.27	2.09	-1.91	0.04	0.04
D	1.71	0.00	0.00	0.00	0.00	0.00
Panel B: 2016						
A	20.41	11.90	13.70	-2.14	0.32	0.02
B	14.58	6.07	8.58	-2.82	0.26	0.05
C	14.76	6.25	7.57	-1.45	0.12	0.01
D	8.51	0.00	0.00	0.00	0.00	0.00

Unemployment rates (in %) and decomposition of the unemployment rate differential (in percentage points) between each educational attainment group and group D. Education levels: A: middle school certificate or none; B: professional certification; C: high-school diploma; D: bachelor or above. Columns 3 to 7 correspond to terms in equation (21): Total is the total difference in unemployment rates, Prod is the "Average productivity" term, MA is the "Average MA" term, Returns is the "Differential returns" term, and Cov is the "Within-group covariance" term.

unemployment patterns.

We report the results of the decomposition in Table 2, separately for 1968 and 2016. In the first column, we report the unemployment rate for each type of worker. In the five remaining columns, we report the difference in rate with respect to the highest skill level (college degree or higher) according to equation (21). As showed in the stylized facts section, as unemployment rates exploded over the past fifty years the spread between the most educated and less educated workers increased widely, while the premium of high-school graduates over professional certifications disappeared.

Examining columns four and five, we observe that for both years and across all education levels, the primary factor contributing to the unemployment gap is differences in individual employability. Actually, the impact of average market access is negative: if only market access differences were considered, low-skilled workers would actually have a *lower* unemployment rate than high-skilled workers. Furthermore, the magnitude of these effects is economically significant, ranging from 1 to 2.7 percentage points. For example in 2016, the employment rate differential between the most uneducated and the most educated categories is 11.9 percentage points. According to our decomposition, it would be 13.7 points, or 1.6 points *higher*, if both categories faced the same market access and only differences in relative productivity subsisted.

Thus, the results of our decomposition do not support the presence of any spatial mismatch in the Paris area, but rather point to some *reverse mismatch*, whereby differences in job market access reduce the employment gap. Our quantification therefore confirms and formalizes the intuition developed in the descriptive section of the paper: in the case of Paris and regarding employment rate differentials between skills, there is not spatial mismatch. Rather, low-productivity workers enjoy a better job accessibility relative to skilled labor, and education-specific factors drive most of the employment gap.

Finally, comparing both years, we can see that the magnitude of these market access effects slightly decreased for all categories, meaning that the labor market integration and changes in residential structure in the city reduced the reverse mismatch that low skilled workers were benefiting from. Still, this variation is negligible when compared to the evolution of individual productivity: quantitatively, the evolution of the unemployment rate gap between education groups can mainly be attributed to employability.

6 Transport Networks and unemployment : evidence from a natural experiment

Our theoretical results suggest that low productivity workers may experience a higher unemployment rates in better connected areas when spatial mismatch remains limited. Moreover, our structural decomposition suggests that in 1968, spatial mismatch was not a contributing factor to low skilled unemployment. In this section, we leverage the natural experiment provided by the RER extension in the Paris area to evaluate the causal relationship between labor market integration and low skilled unemployment rates

6.1 Background

Paris urban area offers an interesting setting to isolate the causal impact of transport time on localized unemployment rates. Indeed, around 1965, the urban area initiated some major transformations driven by the creation of New Towns located between 20 and 35 kilometers from the city center of Paris (Loumeau 2024). These New Towns were supposed to house between 500,000 and 1,000,000 inhabitants and to contribute to a more even distribution of the population. Alongside, the government also planned massive improvement of the transport infrastructures with the creation of the Regional Express Rail (RER) network creating several kilometers of new lines. As exposed in Mayer and Trevien (2017), the main innovation consisted in improvements of existing lines with a creation of tunnels under Paris allowing to connect different lines while increasing the train frequency. According to Viguié et al. (2023), this improved network is the most significant structural changes that occured in Ile-de-France over the last 40 years. It resulted in the largest decline in travel time to potential jobs in the urban area that was estimated to be around 3% citywide and homogeneous across income groups.

6.2 Econometric Specification and sample

We propose to confront our predictions with the natural experiment constituted by the development of the Regional Express Rail (RER) using a difference-in-difference approach. To this end, we want to identify the causal impact of an improvement in the connectedness to the new network on unemployment. We thus want to identify the following two way fixed effect equation.

$$u_{i,t} = \alpha_i + \delta_t + \beta RER_i \times 1_{t>1975} + X_{i,t} + \epsilon_{i,t} \tag{26}$$

Where $u_{i,t}$ is the unemployment rate of municipality i at time t, α_i and δ_t are municipality and time fixed effects. RER is a dummy indicating whether the municipality was connected to the Regional Express Rail network from 1975 and the vector $X_{i,t}$ offers the possibility to control for potential time varying confounding factors and relax the parallel trend assumption if necessary. The opening of the RER extensions taking place between 1975 and 1982, we thus estimate our equation with a standard to way fixed effect as the composition of the treatment and control group is fixed across time (De Chaisemartin and d'Haultfoeuille 2020; Borusyak, Jaravel, and Spiess 2024).

While the procedure of selection of our treatment and control municipalities will be detailed in next section, Table 3 reports their main features. One can note that these are intermediate cities located on average at 15 km from Paris center, with a relatively high density of jobs and unemployment rate relatively close to the urban area's average. These municipalities have relatively close features although one can note some statistically significant differences in the municipality size, job density and the distance from Paris. Table B.1 in Appendix also reports the features of all municipalities in Paris Region.

Table 3: Balance Checks

	Control group			Treatment Group			Comparison		
variable	Mean	SD	N	Mean	SD	N	Diff	Tstat	pvalue
Population (1968)	16025	16824	64	29976	21186	32	-13951	-3.506	0.000698
Population (1975)	17775	17075	64	32855	22765	32	-15080	-3.639	0.000447
mobility	0.476	0.133	64	0.436	0.113	32	0.0408	1.488	0.140
Unemployed	321.0	355.3	64	606.2	474.2	32	-285.1	-3.305	0.00135
Active	8356	8211	64	15520	10623	32	-7164	-3.645	0.000438
unemployment rate (1968)	0.0352	0.00951	64	0.0370	0.00787	32	-0.00179	-0.919	0.360
Share foreigners (1968)	0.0717	0.0257	64	0.0699	0.0287	32	0.00176	0.304	0.762
Share social housing (1975)	0.136	0.114	64	0.215	0.113	32	-0.0789	-3.202	0.00186
Ownership rate (1968)	0.538	0.144	64	0.447	0.112	32	0.0909	3.121	0.00239
Distance from Paris	16.56	4.583	64	13.66	4.652	32	2.904	2.913	0.00448
Share with higher education	0.143	0.0906	64	0.120	0.0766	32	0.0229	1.228	0.223
Share with no diploma	0.220	0.0437	64	0.243	0.0574	32	-0.0233	-2.211	0.0294

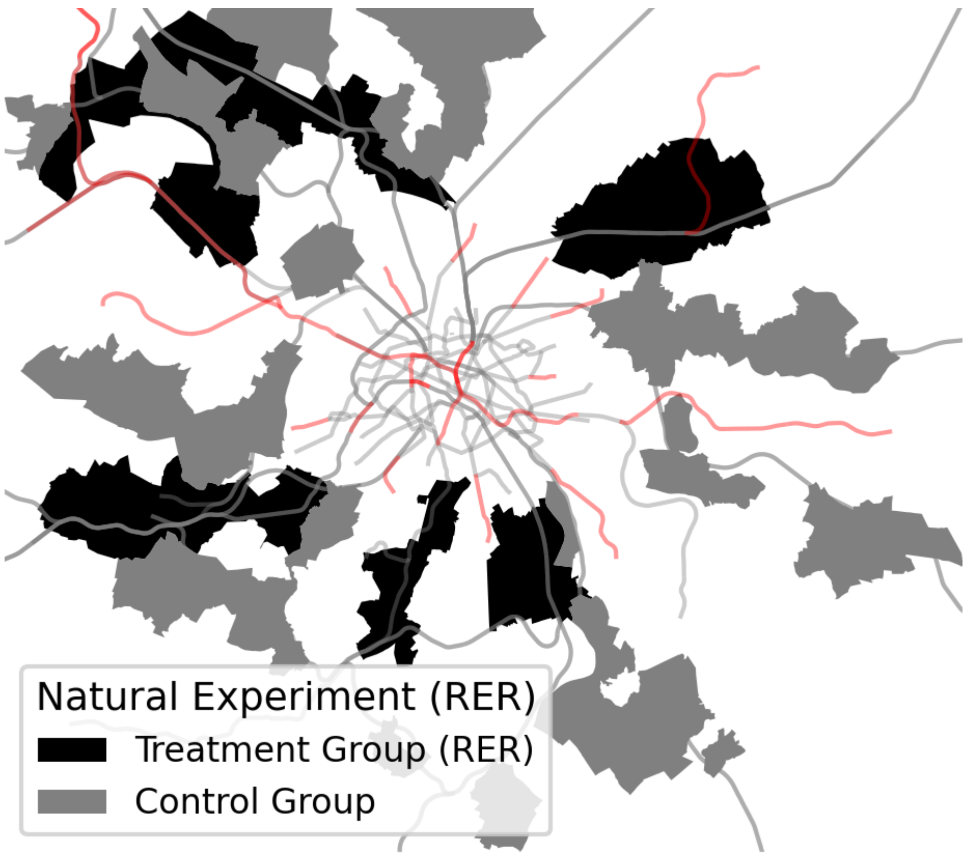
6.3 Identification

The identification of β which is the coefficient of interest is challenging and might be subject to two different biases generated by reverse causality and unobserved variables.

1. **Selection of the treatment and control groups:** First, there may be concerns that public authorities selectively favored certain municipalities with distinct characteristics and dynamics. Following the approach of Mayer and Trevien (2017), our analysis focuses on intermediate cities that were incorporated into the service area due to their existing train stations on pre-established lines connecting Paris center to a new town. Consequently, it could be argued that these municipalities were inadvertently connected to the RER network. These cities are situated along nineteenth-century railways, subsequently integrated into the RER system. This consideration mitigates worries that enhancements in transportation infrastructures were influenced by the municipalities' unobserved traits or by deliberate

adjustments to the network. For comparison, we select as a control group intermediate municipalities with train stations on lines that did not receive RER upgrades. We depict both the control and treatment groups, along with the network expansions prior to 1990, in Figure 7. According to the authors, the treatment group saw a reduction of 6 minutes in the average travel time to Paris, a reduction four times larger than for the control group. Additionally, we conduct a robustness analysis using an alternative identification strategy that leverages deviations from the initial plans to define an alternate control group.

Figure 7: Treatment and control groups



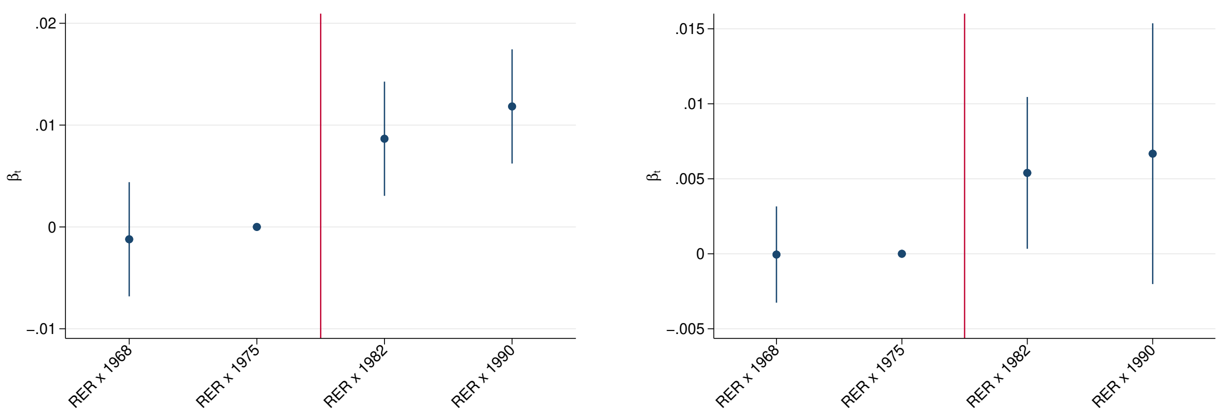
Source: Mayer and Trevien (2017).

2. **Investigating pre-trends:** To further relieve concerns on reverse causality we investigate the pre-trends. To check that both groups of municipalities had similar unemployment trends before the deployment of the network we report the dynamics of both groups in Appendix Figure B.1 and perform the following event study starting in 1968 exploiting the fact that extensions started from 1975:

$$u_{i,t} = \alpha_i + \gamma_t + \sum_{t=1975}^{1990} \beta_t \times RER_i + \epsilon_{i,t} \tag{27}$$

We report β_t in Figure 8. On can observe a comparable dynamics between the control and the treatment group before 1975. Panel a) report our results without any control, we do not find any evidence of significant pre-trend between 1968 and 1975 even if the point estimate for 1968 is slightly negative. In panel b), we introduce controls, our results remain qualitatively unchanged and the point estimate for 1968 is now a precise zero.

Figure 8: Impact of the RER connection on municipal unemployment: Event Study plots



(a) Without control

(b) With controls

Note: Reported coefficients from the equation $u_{i,t} = \alpha_i + \gamma_t + \sum_{t \neq 1975} \beta_t \times RER_i + \epsilon_{i,t}$. Where RER_i takes value one if the municipality benefited from the RER extension. Sample is the same as Mayer and Trevien (2017). Standard errors are clustered at the municipality level. Panel a) includes no controls. Panel b) includes controls interacted with time fixed effects as column (4) in Table 4

3. **Controlling for initial conditions:** Third, to account for the potential influence of initial differences of municipalities on the evolution of their unemployment rate we compare the treatment and control groups in 1968 and 1975 (see Table 3 above). We thus follow Mayer and Trevien (2017) and control for these differences in initial conditions interacting with time fixed effect to allow for municipalities with different initial conditions to behave differently. We thus include distance and employment density dummies. Moreover, as our research questions is related to unemployment and not the provision of local jobs, we account for

one other important threats related to the housing market. Since the seminal contribution of Oswald (1996), a literature has developed highlighting a persistent correlation between local homeownership rates and unemployment. Interestingly,the initial homeownership rates are also lower in municipalities connected to the RER. As for population we cannot directly control for the evolution of homeownership rates which might vary as a result of the better connection afterward. We thus also control for the differences in initial rates interacting the the 1968 homeownership rates with time fixed effects.

4. **Controlling for simultaneous policies:** The investigation of pre-trends and the control for initial conditions cannot rule out time varying shocks. There are few shocks likely to be systematically correlated with the deployment of transport infrastructures. The most important arises from the fact that transport infrastructures might be combined with voluntary housing policies. To account for this eventuality we thus control for the change in the share of social housing in the municipality which is only available from 1982 in the census table. We combine this information with the year of completion to estimate the number of social dwellings in 1975 as well. We control for the contemporaneous share of social housing in the municipality. This allows to control for the deployment of social housing programs while improving the transport infrastructures.

6.4 Baseline Results

We now turn to the estimation of the net effect of the railway network estimating equation 26 which is reported in panel a) of Table 4. The first column reports the simplest two way fixed effect with no control. Columns (2) interacts the population in 1968 with year fixed effects and also interact distance and employment density dummies as in Mayer and Trevien (2017). Point estimates are slightly reduced. To account for the strong persistence of unemployment, column (3) also interacts the 1968 unemployment rates with time fixed effects. Column (4) interacts the 1968 ownership rate with years fixed effect. Results remain the same. Finally we introduce the share of social housing in the last column. The number of observation drops as we lose the year 1968 where the share of social housing is missing but the coefficient of interest remains very close. Overall our results point toward a positive and significant effect of an improvement in the municipality's connectedness on unemployment. Municipalities connected to the RER see a rise of their unemployment rate of 0.6 percentage point when compared with similar unconnected municipalities.

Our model predicts an increase in unemployment rate for low skilled workers. In panel b) to d), we also use the 20% sample to compute an unemployment rate by level of diploma for each municipality. We estimate our model on the alternate unemployment rates. Results are in line with our expectation as we found an increase of 1 percentage points for workers with a professional certification or a middle school diploma, and no significant effect for the two groups that are high school graduates or above. Pre-trends for these subsamples are reported in Appendix Figure B.2.

Overall, these results indicate that a 10% reduction in travel time (Mayer and Trevien 2017) is associated with a 1 percentage point increase in the unemployment rate among low-skilled workers and a 0.6 percentage point increase for the overall workforce. While this effect appears economically significant, it is important to note that the RER represents a structural transformation in transport infrastructure. This not only improved theoretical travel times but also significantly enhanced the reliability of the system. These changes contributed to job decentralization (Garcia-López, Hémet, and Viladecans-Marsal 2017b, 2017a) and drove a 13% increase in the number of jobs between 1975 and 1990 in the treated municipalities (Mayer and Trevien 2017).

Table 4: Impact of the Regional Express Railway on unemployment: Main specification

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Unemployment rate (u)				
Panel a) All workers					
$RER \times Post$	0.0113***	0.00576*	0.00589**	0.00606**	0.00545*
	(0.00284)	(0.00295)	(0.00293)	(0.00290)	(0.00278)
N	384	384	384	384	288
R^2	0.905	0.934	0.934	0.934	0.931
Panel b) Middle school certificate or none					
$RER \times Post$	0.0152***	0.00882**	0.0101**	0.0101**	0.0101**
	(0.00396)	(0.00438)	(0.00421)	(0.00403)	(0.00393)
N	384	384	384	384	288
R^2	0.860	0.895	0.901	0.901	0.895
Panel c) Professional certification					
$RER \times Post$	0.00789**	0.00720**	0.00789**	0.00828***	0.0107***
	(0.00305)	(0.00291)	(0.00303)	(0.00307)	(0.00355)
N	384	384	384	384	288
R^2	0.685	0.722	0.724	0.733	0.682
Panel d) High school graduate					
$RER \times Post$	0.00904**	0.00522	0.00525	0.00493	0.00434
	(0.00372)	(0.00346)	(0.00355)	(0.00379)	(0.00455)
N	383	383	383	383	287
R^2	0.557	0.615	0.627	0.629	0.579
Panel e) Bachelor of above					
$RER \times Post$	0.00179	0.00123	0.000959	0.00214	0.00300
	(0.00350)	(0.00433)	(0.00414)	(0.00428)	(0.00509)
N	384	384	384	384	288
R^2	0.482	0.525	0.537	0.545	0.486
Municipality FE (α_i)	Y	Y	Y	Y	Y
Year FE (δ_t)	Y	Y	Y	Y	Y
$ln(pop_{1968}) \times \delta_t$	N	Y	Y	Y	Y
Distance and density $\times \delta_t$	N	Y	Y	Y	Y
$u_{1968} \times \delta_t$	N	N	Y	Y	Y
$Owners_{1968} \times \delta_t$	N	N	N	Y	Y
Social Housing	N	N	N	N	Y

Estimates of the difference-in-difference equation $u_{i,t} = \alpha_i + \delta_t + \beta RER_i \times 1_{t>1975} + X_{i,t} + \epsilon_{i,t}$
Distance controls are based on Mayer and Trevien (2017) and corresponds categorical variables for [5,10[, [10,15[, [15,20[and [20,25[of the geodesic distance from Paris in kilometers. Population density controls are based on Mayer and Trevien (2017) and corresponds to categorical variables for [0,1000[, [1000,2500[, [2500,5000[, [5000,10000[, and > 10000. $Owners_{1968}$, u_{1968} and $ln(pop_{1968})$ are respectively the homeownership rate, the unemployment rates and the log of the population in 1968. Social Housing is contemporaneous share of social housing, only available from 1975, hence reducing the number of observations.
Standard errors in parentheses are clustered at the municipality level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.5 Robustness checks

We now present a series of additional regression analyses detailed in the Appendix, aimed at reinforcing the robustness of our findings and exploring potential mechanisms underlying our model. First, we conduct a range of robustness checks to ensure that our results are not confounded by various trends in the labor market. These analyses are designed to confirm that our main finding is robust to different ways of measuring unemployment and to build our control group. Second, we estimate additional regressions, including placebo regressions, to investigate potential mechanisms and rule out alternate theories that may explain the observed relationship.

1. **Alternate unemployment variables and control groups:** We use some alternate measures of unemployment and an alternate control group in Appendix Table B.2.

    - **Accounting for the age structure:** Our unemployment variable results from the row counts of unemployed and active population. The National Statistical Agency provides alternate local unemployment rates based on the population aged between 25 and 54 years. We thus reproduce the analysis using these alternate rates. Results in Appendix Table B.2 remain unchanged.

    - **Unemployment rate by sex:** As our period of study coincides with a rise in female participation. Considering that female might be more sensitive to commuting time, we perform the analysis separately for male and female in Appendix Table B.2. Results are close between both groups.

    - **Using the Labour force survey definition:** We also use alternate unemployment rates adjusted to match the aggregate Labour force survey (LFS) unemployment rates exploiting the cross sectional relationship between unemployment rates from the census and the LFS, results in Appendix Table B.2 display a smaller rise which is not surprising as the overall rise in unemployment is less important over the period when using the LFS.

    - **Alternate control group** Mayer and Trevien (2017) alternatively use deviation from the initially planned network to define another control group. When using these municipalities in Appendix Table B.2, results remain unchanged.

2. **Mechanisms and placebo tests:** In Appendix Table B.3 and B.4 we investigate the chan-

nels suggested by the model and perform additional placebo tests to check for alternate mechanisms likely to drive the variations in unemployment rates

- **Impact of the RER on the number of jobs and municipal population:** We first (column 2) reproduce the results from Mayer and Trevien (2017) investigating the impact of the RER on the **estimated** number of jobs coming from the complementary exploitation of the census (a random sample of 20% from the full count census[3]) and the population. Our results are fully in line with theirs: better connection is indeed associated with a higher growth rate of jobs and no change in population.

- **Competition from workers living in the broader urban area:** We also investigate the impact of the RER connection on the number of workers living in another municipality in column 4. As expected, better connected municipalities are associated with a growth in the number of workers living in the broader urban area while working in the connected municipality.

- **RER and Participation rate:** In a framework with classical unemployment as Tyndall (2021), better infrastructures can reduce the opportunity cost of working and raise the number of people looking for a job. If the demand for workers does not adjust, the unemployment rate can also naturally rise. To rule out this alternate explanation, we look at the impact of the RER on the participation rate in columns 5 (defined as the total workforce, both employed and looking for a job, divided by the total population of the municipality). We do not find any significant association between the connection with the RER and the participation rate.

- **Potential changes in the sectoral composition:** A potential confounding factor could arise if municipalities connected with the RER are specialized in a sector that went though a specific decline over the period, as the industry following the oil shock. We thus look at the impact of the RER on the share of residents working in the industry sector in column 6. We do not find any significant effect supporting this hypothesis.

- **The influence of sorting and intercensus mobility:** New transport infrastructures might generate residential sorting. In particular, if the RER attracted more workers

3. Unfortunately the place of work was not digitized systematically for the full count census but only for this subsample

with low employability, this sorting effect could drive our results. While estimation within education group should relieve this concern, we also investigate the impact of the RER on the share of high-skilled residents (bachelor or above) and low-skilled residents (without a diploma). We do not find any evidence in favor of this sorting effect. While the RER is weakly associated with a rise in the intercensus mobility rate in column 9, we find a small positive but not significant effect on education in column 7 and 8.

7 Conclusion

Unemployment rates significantly differ across neighborhoods in large urban areas. Using Paris as a case study, we present new evidence of persistent disparities in unemployment rates, despite increased labor market integration. We propose a novel spatial equilibrium model with frictional unemployment that can help analyzing the relationship between market access and unemployment. In our framework, improved connectivity can raise unemployment rates of low skill workers if spatial mismatch is limited. We then use our model to measure the contribution of access to jobs to the joblessness of low-productivity workers in the Parisian region. We find that spatial mismatch is not a major component of the large observed heterogeneity in localized unemployment rates. We finally show that the creation of the Paris Regional Express Rail increased the unemployment gap between high and low skill worker confirming the prediction of our framework. While transport policies can generate welfare gains and reduce pollution, at least in Paris, their ability to reduce localized unemployment rates and improve employment opportunities for low-skilled workers is limited.

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A Data Appendix

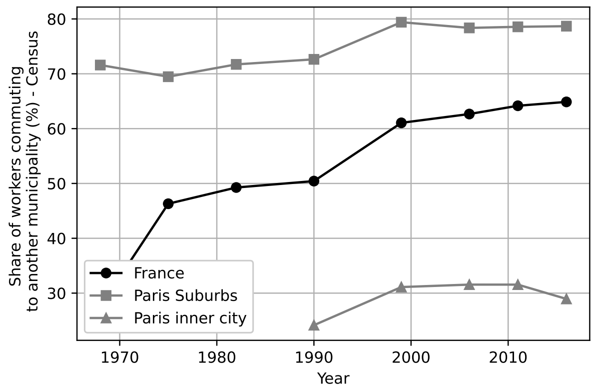
A.1 Construction of the localized mobility rates

We systematically extract data from the census tabulation obtaining the count of workers both residing and working within the same municipality, denoted as NC_m (Not Commuting). Leveraging the count of employed workers, R^e_m (Residing), within each municipality, we establish a mobility rate – the proportion of workers residing and working in different municipalities – defined as follows:

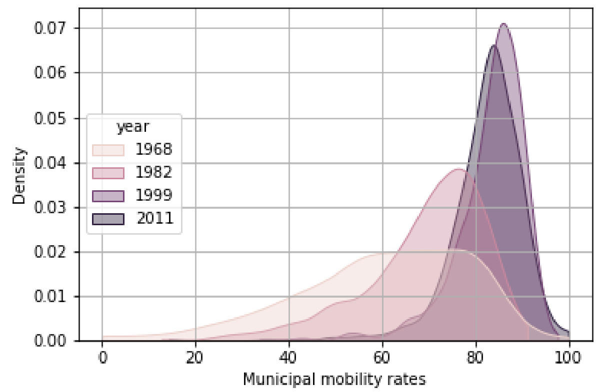
$$Mobility\ Rate_m = 1 - \frac{NC_m}{R^s_m} \tag{A.1}$$

The outcomes of our investigation are depicted in Figure A.1. In panel a), we present the mobility rate for France, the Paris suburbs, and Paris itself from 1990 onwards. The distinction between Paris and its suburbs arises due to a data series rupture resulting from the specific arrangement of Paris into 20 "arrondissements." Notably, the census question's context changed before 1990, inquiring about workers residing and working within the same arrondissement or even neighborhood, and subsequently focusing on workers residing and working within the city of Paris. Overall, Figure A.1 illustrates that mobility rates in the Paris area initially exceeded those in the rest of France. We use the 1/4 micro data in order to explore the evolution of these variables between 1968 and 2016 using two alternate approaches. First, as illustrated in Figure 2, we treat each district as a municipality and compute the mobility rate in both year. Alternatively we treat Paris as a single municipality, the share of workers living in Paris but working outside Paris was 15% in 1968 and rose to 30% in 2016. This aligns with the monocentric nature of the region, with a concentration of jobs in Paris' inner city.

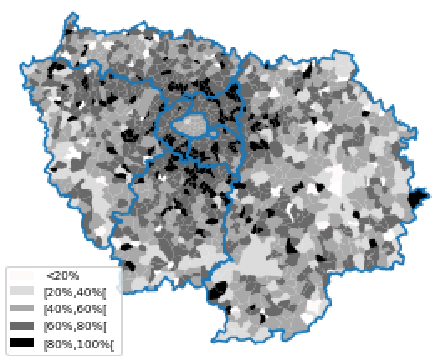
Figure A.1: Mobility rates; 1968-2016



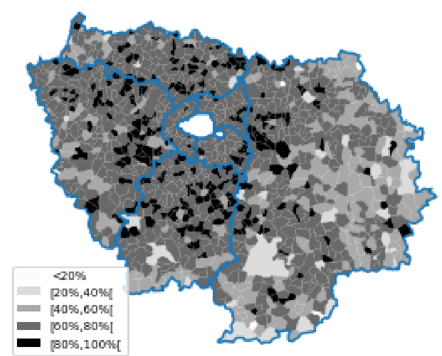
(a) Regional and National mobility rates



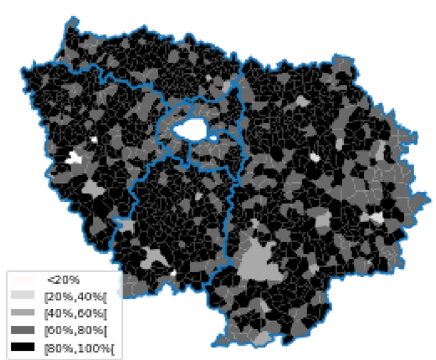
(b) Mobility rates Dispersion in Paris suburbs (1968-2016)



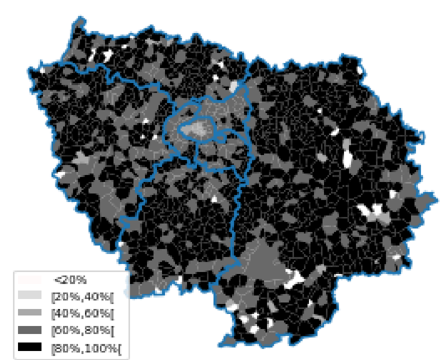
(c) Mobility rates : 1968



(d) Mobility Rates: 1982



(e) Mobility rates : 1999



(f) Mobility rates: 2016

A.2 Construction of the average travel time to all jobs

We take advantage of a novel dataset, provided by the DRIEAT and Viguié et al. (2023), on commuting time between municipalities at morning rush hour when using public transport and car to explore current integration of the Parisian labor market, the correlation of localized travel time with unemployment and compute localized commuting time by municipalities and mean of transport. In panel a) of Figure A.2, we display the average travel time *using public transport* to all jobs of the agglomeration. To create this indicator, we take the travel time using public transport between municipalities created by the DRIEAT. This travel time is composed of four main estimated component: 1) the average estimate time to reach the closest public transport infrastructures by car (if needed) or 2) walking, 3) waiting times at each node, 4) time spent in public transport and 5) time to reach the final destination once out. We thus get an average travel time in public transport, $t^p_{i,j}$ between municipality i and j. We then combine this dataset with the local estimates of municipal jobs at the place of work provided in the Census J_j. For each municipality i, we then computed an average travel time to all jobs in the municipality

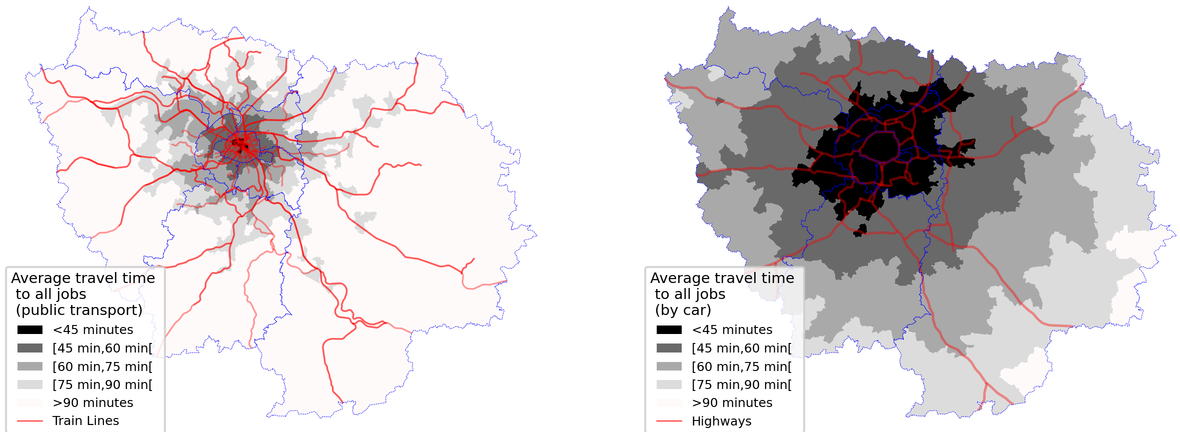
$$AT^p_i = \frac{\sum_{a \neq i} t^p_{i,a} \times J_a}{\sum_{a \neq i} J_a} \tag{A.2}$$

The average travel times are reported in background of panel a) in Figure A.2, one can note that the very center of Paris is extremely close to all jobs and has an average travel time of 45 minutes to any jobs in the region. This is not surprising given the strong monocentric nature of the area (Chapelle, Wasmer, and Bono 2021). However, given the relatively high density and the radial nature of the network, the urban core remains also has a relatively high connectedness to all jobs with the inner periphery having an average travel below 60 minutes to all jobs and the broader one at less than one hour and a quarter. This urban core concentrates most of the population of the area, thus regardless of where they live workers of the area can on average reach a job in less than one hour using public transport. We now perform the same exercise using the travel time matrix between municpalities by car giving us $t^c_j i$ accounting for congestion during rush hours. We can compute an average travel time by car to all jobs for each municipality:

$$AT^c_i = \frac{\sum_{a \neq i} t^c_{i,a} \times J_a}{\sum_{a \neq i} J_a} \tag{A.3}$$

that we report in panel b).

Figure A.2: Average travel time to all jobs and Transport infrastructures, 2016



(a) Transport Time to Jobs and Transport Network (Public transport)

(b) Transport Time to Jobs and Road Network (Personal Vehicle)

A.3 Construction of the average geodesic distance travelled

To estimate average municipal commuting time we take advantage of the commuting flows from the census. This dataset contains the municipality of work, the municipality of residence and the most common mean of transport used. We can thus get an estimate of the number of worker living in municipality i and commuting to municipality j using the transport mode m $W_{i,j}^m$ that we combine with our with the geodesic distance between two municipalities $d_{i,j}$ to compute the average geodesic distance travelled to go to work as reported in panel c) and d) of Figure 2:

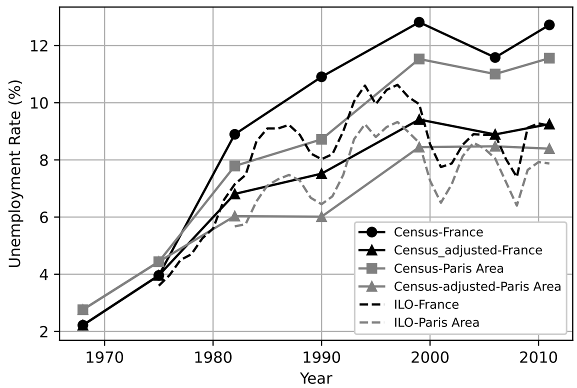
$$AD_i = \frac{\sum_a \sum_m d_{i,a} \times W_{i,a}^m}{\sum_a \sum_m W_{i,a}^m} \tag{A.4}$$

A.4 Robustness: Unemployment rates dispersion

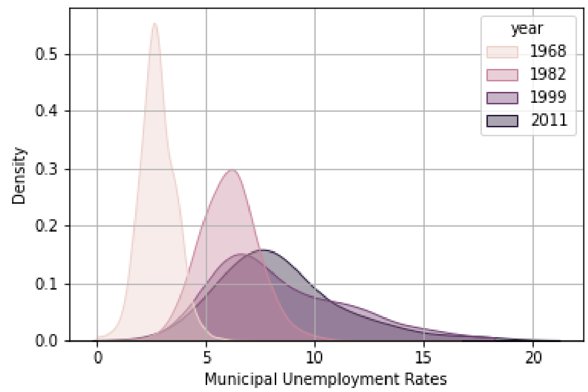
It's important to highlight that the level of unemployment in the census differs from the one provided by the Labour Force Survey (LFS), resulting in a tendency to overestimate the overall unemployment rate by approximately 4 percentage points. Standard unemployment measurements are unavailable at the municipal level due to slight discrepancies between the census questions and the LFS. Nonetheless, when comparing our series with the more recent official unemployment rates provided by INSEE for broader geographical units such as departments [4], the correlation with our aggregated figures exceeds 0.9. We can utilize the cross-sectional relationships for overlapping years to adjust the census unemployment rates to align with the LFS definition. Appendix Figure A.3 presents our stylized findings using these adjusted local unemployment rates, with the results remaining qualitatively consistent.

4. https://www.insee.fr/fr/statistiques/2012804

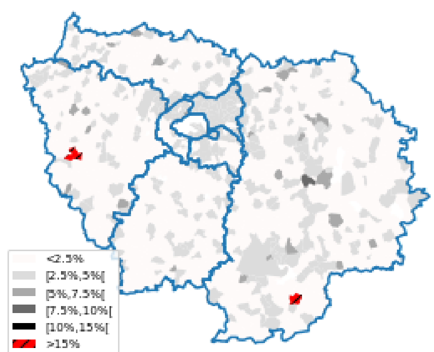
Figure A.3: Unemployment dispersion in Paris Urban Area; 1968-2011



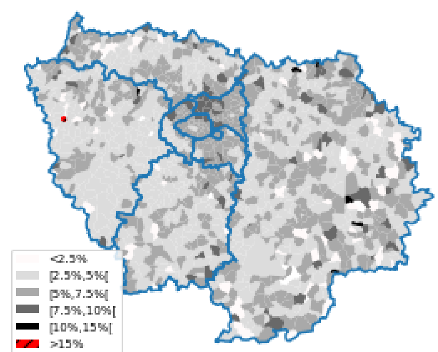
(a) Regional and National unemployment rates



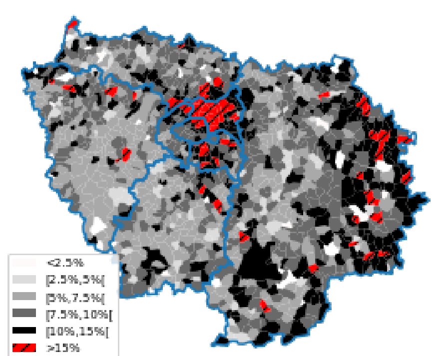
(b) Unemployment Dispersion in Paris Area (1968-2011)



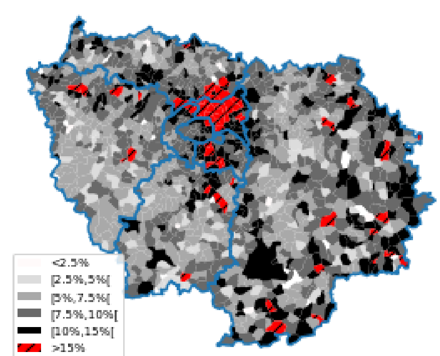
(c) Unemployment : 1968



(d) Unemployment: 1982



(e) Unemployment : 1999



(f) Unemployment: 2011

A.5 Additional statistics on unemployment rates

Spatial persistence of localized unemployment rates Localized unemployment rates exhibit a remarkable persistence. Municipalities with the highest unemployment rates in 1968 experienced the most significant increases in unemployment rates. This intuition is corroborated by Table A.1. Correlation coefficients between yearly unemployment rates are notably high, particularly between the most recent census waves where the correlation exceeds 0.9. Even when comparing the 1968 and the most recent census data, the correlation remains as strong as 0.5.

	1968	1975	1982	1990	1999	2006	2011
1968	1.00	0.65	0.61	0.60	0.56	0.54	0.51
1975	0.65	1.00	0.69	0.67	0.62	0.61	0.61
1982	0.61	0.69	1.00	0.90	0.88	0.85	0.84
1990	0.60	0.67	0.90	1.00	0.95	0.93	0.92
1999	0.56	0.62	0.88	0.95	1.00	0.97	0.96
2006	0.54	0.61	0.85	0.93	0.97	1.00	0.96
2011	0.51	0.61	0.84	0.92	0.96	0.96	1.00

Table A.1: Weighted Correlation

B Robustness checks: The impact of the RER on unemployment

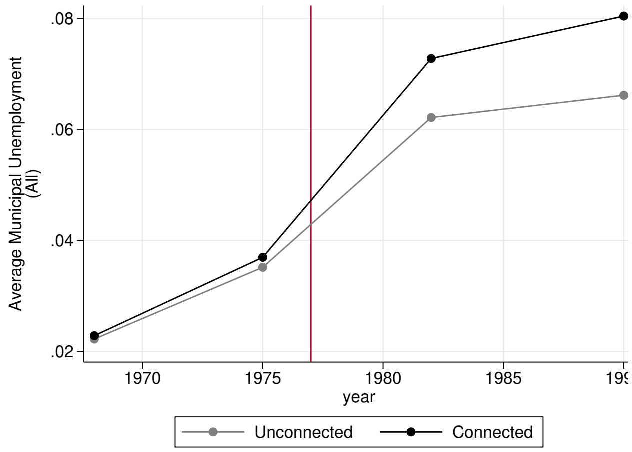
B.1 Characteristics of the treatment and control groups

Table B.1: Sample characteristics

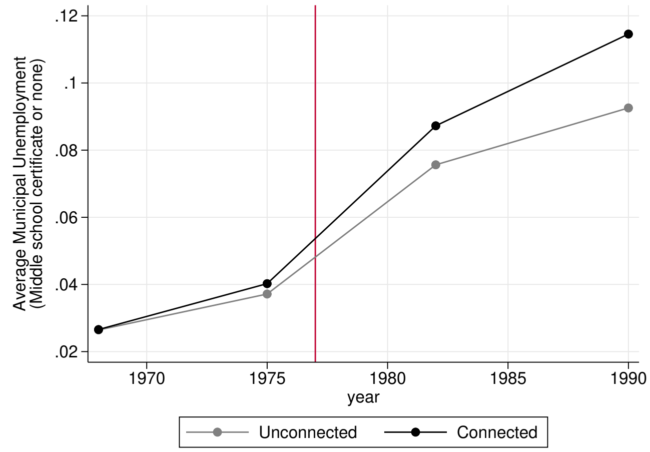
	Control group			Treatment Group			Paris Urban Area		
variable	Mean	SD	N	Mean	SD	N	Mean	SD	N
Population (1968)	16025	16824	64	29976	21186	32	7131	21573	1297
Population (1975)	17775	17075	64	32855	22765	32	7616	20553	1297
Area	6.014	3.373	64	6.601	4.884	32	9.288	7.808	1297
Job Density	1018	1409	64	1753	1503	32	887.8	5332	1297
unemployed	321.0	355.3	64	606.2	474.2	32	157.7	520.1	1297
active	8356	8211	64	15520	10623	32	3698	10538	1297
unemployment rate	0.0352	0.00951	64	0.0370	0.00787	32	0.0324	0.0180	1297
Share foreigners	0.0717	0.0257	64	0.0699	0.0287	32	0.0751	0.0561	1295
Share Social Housing	0.136	0.114	64	0.215	0.113	32	0.0609	0.123	1297
share homeowners	0.538	0.144	64	0.447	0.112	32	0.598	0.165	1297
Distance From Paris	16.56	4.583	64	13.66	4.652	32	40.83	20.51	1284
share high skilled	0.143	0.0906	64	0.120	0.0766	32	0.0852	0.0848	1297
share low skilled	0.220	0.0437	64	0.243	0.0574	32	0.325	0.133	1297

Sources: Author's computation using data from the French Census of 1968 and 1975 and data provided by Mayer and Trevien (2017).

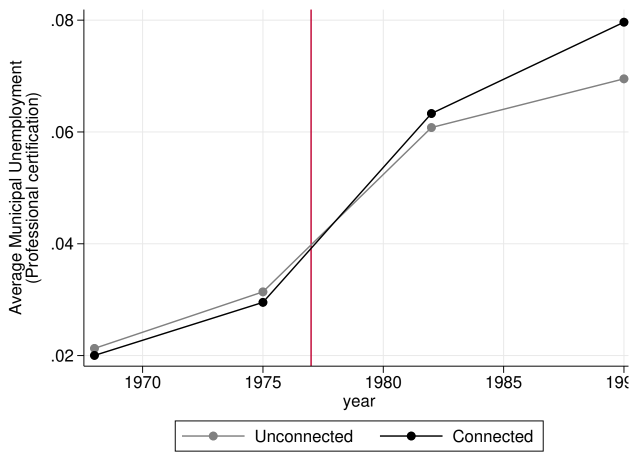
Figure B.1: Change in average Municipal Unemployment rates; 1968-1990



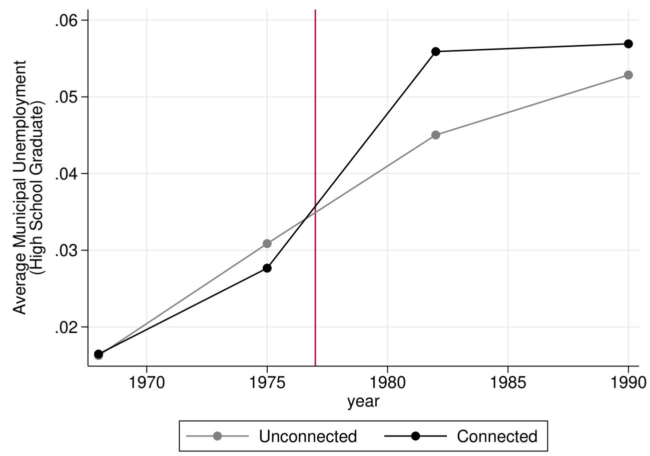
(a) All workers



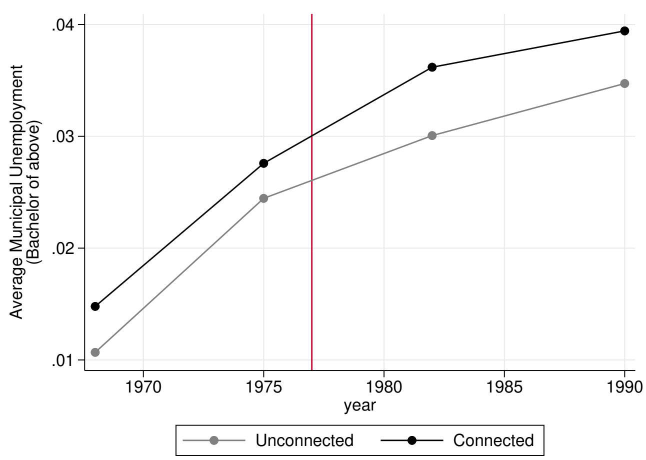
(b) Middle school certificate or none



(c) Professional Certificate



(d) High school degree



(e) Bachelor or above

B.2 Alternate dependant variables and control group

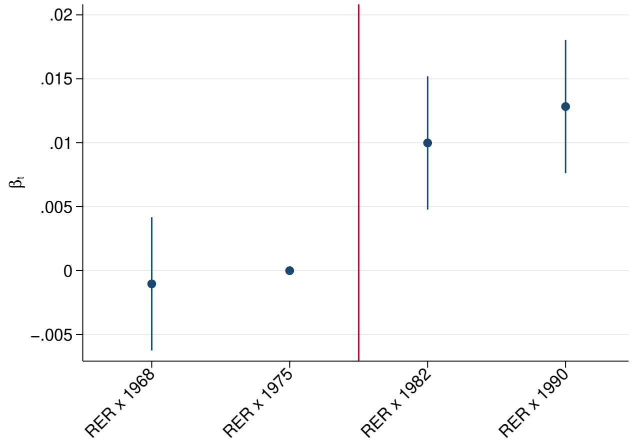
We investigate our effect on alternate definitions of unemployment.

Table B.2: Alternate Dependent variables and control group

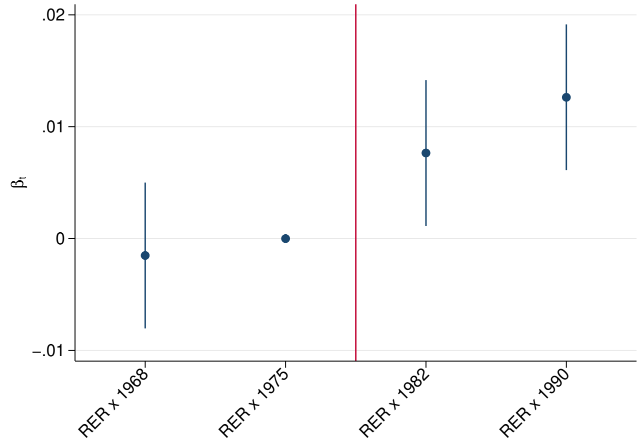
	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Unemployment rate (u)				
Panel a) Adjusted UNemployment rate to match ILO agregate rates					
$RER \times Post$	0.00711***	0.00444**	0.00401**	0.00421**	0.00355*
	(0.00189)	(0.00185)	(0.00190)	(0.00186)	(0.00184)
N	384	384	384	384	288
R^2	0.822	0.861	0.877	0.877	0.885
Panel b) Unemployment rate 25-54 years old					
$RER \times Post$	0.00982***	0.00617**	0.00700**	0.00730**	0.00768***
	(0.00264)	(0.00300)	(0.00297)	(0.00294)	(0.00287)
N	384	384	384	384	288
R^2	0.822	0.861	0.877	0.877	0.885
Panel c) Unemployment rate for men					
$RER \times Post$	0.0119***	0.00566**	0.00587**	0.00598**	0.00490*
	(0.00276)	(0.00249)	(0.00247)	(0.00245)	(0.00251)
N	384	384	384	384	288
R^2	0.883	0.927	0.928	0.928	0.924
Panel d) Unemployment rate for women					
$RER \times Post$	0.0109***	0.00636*	0.00625	0.00645*	0.00646*
	(0.00327)	(0.00379)	(0.00378)	(0.00376)	(0.00350)
N	384	384	384	384	288
R^2	0.887	0.909	0.910	0.910	0.907
Panel e) Alternate control group					
$RER \times Post$	0.0101***	0.00488*	0.00510*	0.00546*	0.00490*
	(0.00284)	(0.00286)	(0.00284)	(0.00281)	(0.00267)
N	444	444	444	444	333
R^2	0.897	0.927	0.928	0.929	0.929
Municipality FE (α_i)	Y	Y	Y	Y	Y
Year FE (δ_t)	Y	Y	Y	Y	Y
$ln(pop_{1968}) \times \delta_t$	N	Y	Y	Y	Y
Distance $\times \delta_t$	N	Y	Y	Y	Y
$u_{1968} \times \delta_t$	N	N	Y	Y	Y
$Owners_{1968} \times \delta_t$	N	N	N	Y	Y
Social Housing	N	N	N	N	Y

Estimates of the difference-in-difference equation $u_{i,t} = \alpha_i + \delta_t + \ betaRER_i \times 1_{t>1975} + X_{i,t} + \epsilon_{i,t}$
Distance controls are based on Mayer and Trevien (2017) and corresponds categorical variables for [5,10[, [10,15[, [15,20[and [20,25[of the geodesic distance from Paris in kilometers. Population density controls are based on Mayer and Trevien (2017) and corresponds to categorical variables for [0,1000[, [1000,2500[, [2500,5000[, [5000,10000[, and > 10000. $Owners_{1968}$, u_{1968} and $ln(pop_{1968})$ are respectively the homeownership rate, the unemployment rates and the log of the population in 1968. Social Housing is contemporaneous share of social housing, only available from 1975, hence reducing the number of observations.
Standard errors in parentheses are clustered at the municipality level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

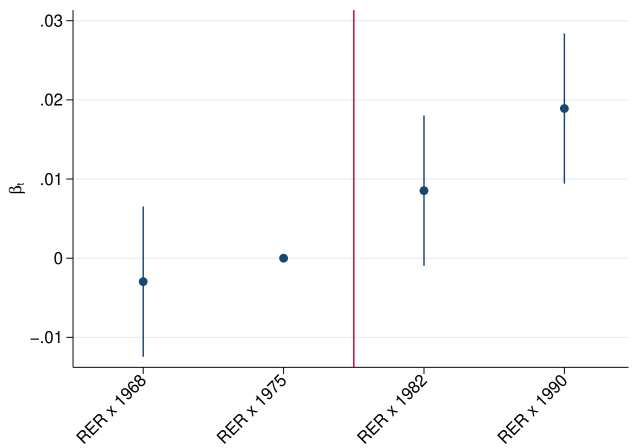
Figure B.2: Event study on alternate unemployment rates



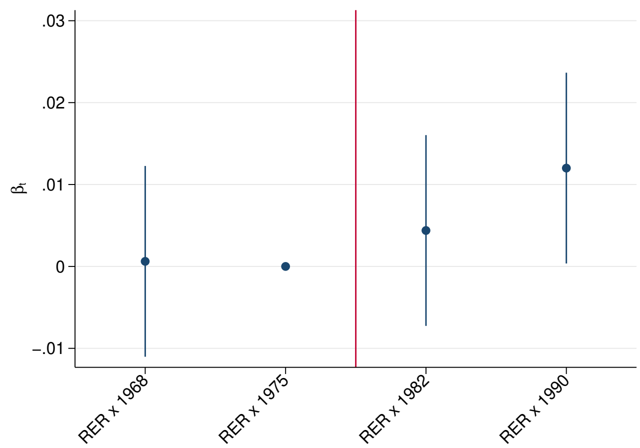
(a) Male unemployment



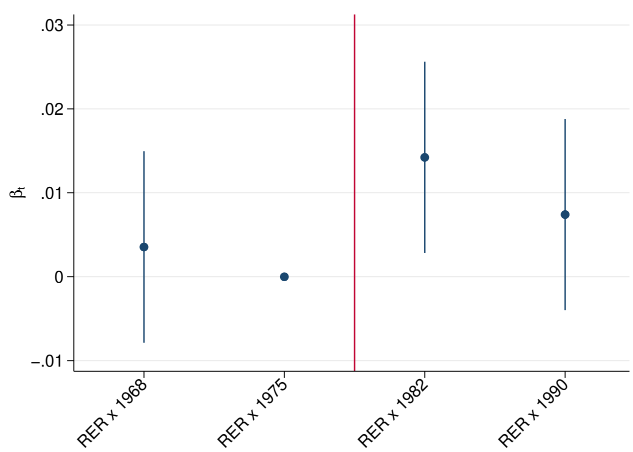
(b) Female unemployment



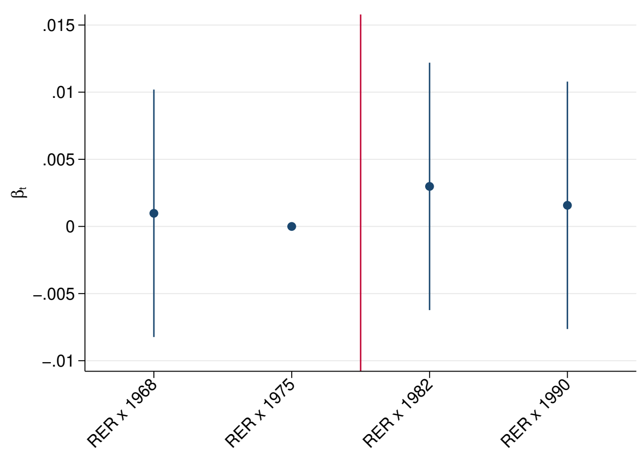
(c) Middle school certificate unemployment



(d) Professional certificate unemployment



(e) High school graduate unemployment



(f) Bachelor and above unemployment

B.3 Placebo tests and mechanisms

We reproduce the main specification in long difference from Mayer and Trevien (2017) to investigate the impact of the RER infrastructures on jobs and population growth and perform placebo tests for alternate potential explanations behind the documented rise in unemployment rates. We thus estimate

$$\Delta y_{i,1990-1975} = \beta RER_i + \gamma X_i + \epsilon_i \tag{B.1}$$

Results are reported in Table B.3.

Table B.3: Placebo and mechanisms, long difference

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ u	Δ ln(jobs)	Δ ln(outside)	Δ ln(pop)	Δ participation	Δ industry	Δ educ (high)	Δ educ (low)	Δ res. mobility
RER	0.00782*	0.139***	0.164**	0.0507	0.00356	-0.00564	0.00191	-0.00844	0.0235
	(0.00423)	(0.0503)	(0.0713)	(0.0414)	(0.00480)	(0.0182)	(0.00990)	(0.00728)	(0.0191)
N	96	96	96	96	96	96	96	96	96
R^2	0.313	0.332	0.360	0.320	0.230	0.319	0.171	0.081	0.294
Distance	Y	Y	Y	Y	Y	Y	Y	Y	Y
Population density	Y	Y	Y	Y	Y	Y	Y	Y	Y

Estimates of the long difference equation $\Delta y_{i,1990-1975} = \beta RER_i + \gamma X_i + \epsilon_i$
Distance controls are based on Mayer and Trevien (2017) and corresponds categorical variables for [5,10[, [10,15[, [15,20[and [20,25[of the geodesic distance from Paris in kilometers. Population density controls are based on Mayer and Trevien (2017) and corresponds to categorical variables for [0,1000[, [1000,2500[, [2500,5000[, [5000,10000[, and > 10000.
Robust standard errors
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We also perform the analysis with a standard difference-in-difference equation as in equation 26:

$$Y_{i,t} = \alpha_i + \delta_t + \beta RER_i \times 1_{t>1975} + \epsilon_{i,t} \tag{B.2}$$

Table B.4: Placebo and mechanisms, Two Ways Fixed Effects

	(1) u	(2) ln(jobs)	(3) ln(outside)	(4) ln(pop)	(5) participation	(6) industry	(7) educ (high)	(8) educ (low)	(9) res. mobility
RERx Post	0.00699**	0.0953***	0.164**	0.0454	-0.000821	-0.00860	0.00368	-0.00918	0.0268*
	(0.00319)	(0.0359)	(0.0699)	(0.0358)	(0.00365)	(0.0151)	(0.00685)	(0.00636)	(0.0160)
N	288	288	192	288	288	288	288	288	288
R^2	0.916	0.990	0.985	0.995	0.889	0.893	0.973	0.904	0.654
Municipality FE (α_i)	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE (δ_t)	Y	Y	Y	Y	Y	Y	Y	Y	Y
Distance	Y	Y	Y	Y	Y	Y	Y	Y	Y
Population density	Y	Y	Y	Y	Y	Y	Y	Y	Y

Estimates of the difference-in-difference equation $u_{i,t} = \alpha_i + \delta_t + \beta RER_i \times 1_{t>1975} + X_{i,t} + \epsilon_{i,t}$
Distance controls are based on Mayer and Trevien (2017) and corresponds categorical variables for [5,10[, [10,15[, [15,20[and [20,25[of the geodesic distance from Paris in kilometers. Population density controls are based on Mayer and Trevien (2017) and corresponds to categorical variables for [0,1000[, [1000,2500[, [2500,5000[, [5000,10000[, and > 10000. The number of workers coming from outside in not available for the year 1968 thus reducing the number of observations.
Standard errors in parentheses are clustered at the municipality level
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Gravity equation

C.1 Estimations, without instrumenting

Table C.1: Commuting gravity estimations, no IV

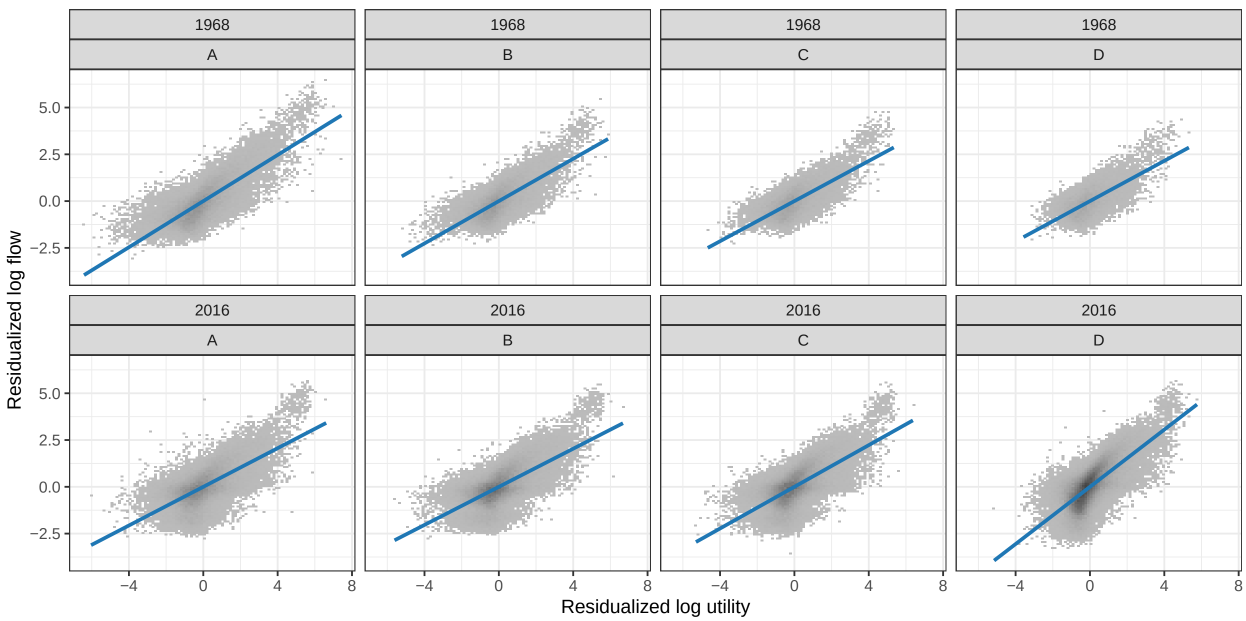
Mode	Private vehicle				Public transit			
Education	A	B	C	D	A	B	C	D
				Panel A: 1968				
log Travel time	-2.326***	-2.070***	-1.856***	-1.627***	-3.324***	-2.985***	-2.959***	-2.712***
	(0.0380)	(0.0395)	(0.0512)	(0.0639)	(0.0750)	(0.0786)	(0.0967)	(0.1061)
Squared Correlation	0.84077	0.76958	0.67476	0.78264	0.91762	0.87931	0.86528	0.89637
Observations	1,484,197	855,040	562,275	377,880	1,583,822	852,202	766,228	305,016
				Panel C: 2016				
log Travel time	-2.130***	-2.069***	-2.012***	-1.860***	-3.059***	-3.042***	-2.827***	-2.265***
	(0.0161)	(0.0137)	(0.0145)	(0.0201)	(0.0321)	(0.0349)	(0.0414)	(0.0560)
Squared Correlation	0.84479	0.83234	0.81424	0.80055	0.92927	0.92055	0.91168	0.89058
Observations	1,358,086	1,447,800	1,372,870	1,422,549	829,652	914,196	837,810	967,246

Two-way clustered standard-errors in parenthesis. Gravity commuting equations estimated by PPML separately for each year, education level, and transport mode. All the specifications include origin and destination fixed-effects. Education levels: A: middle school certificate or none; B: professional certification; C: high-school diploma; D: bachelor or above.

C.2 Supporting charts

First, we show that the form of the gravity fits the data well. For each year and education level, we compute the log travel time utility between each origin-destination pair $\log d_{ije} = \log \sum_m c_{em} t_{ijm}^{-\tau\epsilon_{em}}$, and the log of the total number of workers working in j and living in i. We then residualize each variable on a set of origin and destination fixed-effects, and plot residualized log flows against residualized log utility in Figure C.1.

Figure C.1: Commuting gravity: flows against estimated utility.



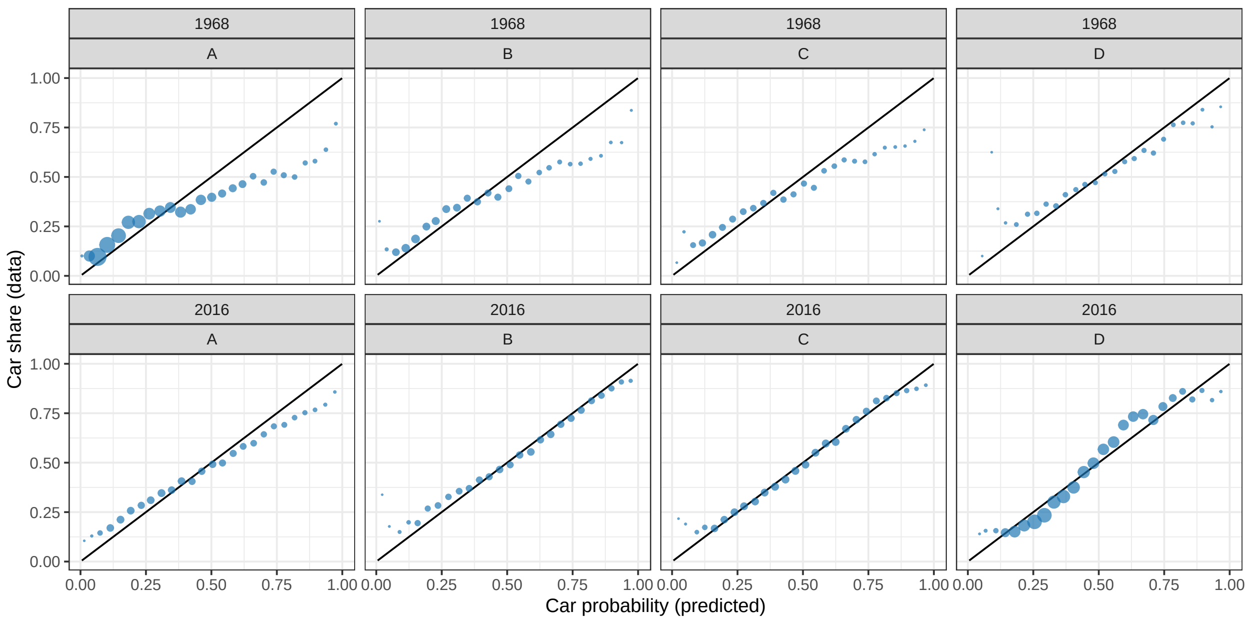
Log bilateral flows against log travel times, separately for each transport mode and year. Both variables are residualized on a set of origin and destination fixed-effects.

To further investigate the fit of the model, we look at the travel mode choice. From our parametrization of the iceberg costs in equation (22), the share of workers of type e using mode m, conditional on working in j and living in i is

$$\frac{t_{ijm}^{-\tau_{me}} \bar{u}_{me}}{\sum_m t_{ijm}^{-\tau_{me}} \bar{u}_{me}}.$$

We compute the predicted share of workers commuting by car accordingly, for each education level and year, and report a binscatter of the actual car share vs predicted probability in Figure C.2.

Figure C.2: Predicted car use against actual car share



Average actual car use for 25 intervals of predicted car probability. Point size proportional to the number of workers in each cell.

D Alternative calibrations

In this section, we report the results of our decomposition under alternative values of the calibrated parameters. In particular, we repeat the model inversion of Section 5.2 with alternative values for ϵ and λ, and we report the corresponding versions of table 2.

Table D.1: Decomposition of unemployment rates differences, $\epsilon = 2$.

Education	U. Rate	Difference with highest education				
		Total	Prod	MA	Returns	Cov
			Panel A: 1968			
A	3.24	1.53	6.57	-5.72	0.38	0.30
B	2.36	0.64	6.43	-6.70	0.44	0.48
C	1.98	0.27	3.50	-3.58	0.13	0.22
D	1.71	0.00	0.00	0.00	0.00	0.00
			Panel B: 2016			
A	20.41	11.90	15.92	-5.03	0.87	0.14
B	14.58	6.07	11.54	-6.61	0.83	0.31
C	14.76	6.25	9.07	-3.27	0.32	0.13
D	8.51	0.00	0.00	0.00	0.00	0.00

Unemployment rates (in %) and decomposition of the unemployment rate differential (in percentage points) between each educational attainment group and group D. Education levels: A: middle school certificate or none; B: professional certification; C: high-school diploma; D: bachelor or above. Columns 3 to 7 correspond to terms in equation (21): Total is the total difference in unemployment rates, Prod is the "Average productivity" term, MA is the "Average MA" term, Returns is the "Differential returns" term, and Cov is the "Within-group covariance" term.

Table D.2: Decomposition of unemployment rates differences, $\epsilon = 8$.

Education	U. Rate	Difference with highest education				
		Total	Prod	MA	Returns	Cov
Panel A: 1968						
A	3.24	1.53	3.37	-1.93	0.07	0.02
B	2.36	0.64	2.78	-2.24	0.06	0.04
C	1.98	0.27	1.51	-1.29	0.02	0.02
D	1.71	0.00	0.00	0.00	0.00	0.00
Panel B: 2016						
A	20.41	11.90	13.06	-1.36	0.19	0.01
B	14.58	6.07	7.70	-1.79	0.15	0.01
C	14.76	6.25	7.11	-0.93	0.07	0.00
D	8.51	0.00	0.00	0.00	0.00	0.00

Unemployment rates (in %) and decomposition of the unemployment rate differential (in percentage points) between each educational attainment group and group D. Education levels: A: middle school certificate or none; B: professional certification; C: high-school diploma; D: bachelor or above. Columns 3 to 7 correspond to terms in equation (21): Total is the total difference in unemployment rates, Prod is the "Average productivity" term, MA is the "Average MA" term, Returns is the "Differential returns" term, and Cov is the "Within-group covariance" term.

Table D.3: Decomposition of unemployment rates differences, $\lambda = 0.4$.

Education	U. Rate	Difference with highest education				
		Total	Prod	MA	Returns	Cov
		Panel A: 1968				
A	3.24	1.53	5.23	-4.03	0.21	0.12
B	2.36	0.64	4.88	-4.66	0.23	0.20
C	1.98	0.27	2.70	-2.60	0.07	0.09
D	1.71	0.00	0.00	0.00	0.00	0.00
		Panel B: 2016				
A	20.41	11.90	14.50	-3.14	0.50	0.05
B	14.58	6.07	9.66	-4.14	0.44	0.11
C	14.76	6.25	8.12	-2.10	0.19	0.04
D	8.51	0.00	0.00	0.00	0.00	0.00

Unemployment rates (in %) and decomposition of the unemployment rate differential (in percentage points) between each educational attainment group and group D. Education levels: A: middle school certificate or none; B: professional certification; C: high-school diploma; D: bachelor or above. Columns 3 to 7 correspond to terms in equation (21): Total is the total difference in unemployment rates, Prod is the "Average productivity" term, MA is the "Average MA" term, Returns is the "Differential returns" term, and Cov is the "Within-group covariance" term.

Table D.4: Decomposition of unemployment rates differences, $\lambda = 0.8$.

Education	U. Rate	Difference with highest education				
		Total	Prod	MA	Returns	Cov
		Panel A: 1968				
A	3.24	1.53	3.04	-1.57	0.05	0.01
B	2.36	0.64	2.40	-1.83	0.04	0.02
C	1.98	0.27	1.30	-1.06	0.01	0.01
D	1.71	0.00	0.00	0.00	0.00	0.00
		Panel B: 2016				
A	20.41	11.90	12.84	-1.09	0.15	0.00
B	14.58	6.07	7.39	-1.44	0.12	0.01
C	14.76	6.25	6.95	-0.75	0.06	0.00
D	8.51	0.00	0.00	0.00	0.00	0.00

Unemployment rates (in %) and decomposition of the unemployment rate differential (in percentage points) between each educational attainment group and group D. Education levels: A: middle school certificate or none; B: professional certification; C: high-school diploma; D: bachelor or above. Columns 3 to 7 correspond to terms in equation (21): Total is the total difference in unemployment rates, Prod is the "Average productivity" term, MA is the "Average MA" term, Returns is the "Differential returns" term, and Cov is the "Within-group covariance" term.

E Proofs and additional theoretical results

E.1 Intra-firm bargaining

As in Helpman and Itskhoki (2010), we allow for intra-firm bargaining as analyzed by Stole and Zwiebel (1996). We extend the results in Helpman and Itskhoki (2010) by allowing for arbitrary bargaining weights and heterogeneous workers. With intra-firm bargaining, workers can renegotiate their wage every time a worker leaves or joins the firm. Thus, agents internalize the indirect effect that a marginal worker has on the entire wage bill of the firm. Let χ be the bargaining weight of the firm. Then in the Stole and Zwiebel (1996) game, workers and firms share the marginal revenue of their match proportionally to the weight:

$$\tilde{\chi}\frac{\partial}{\partial H_{ij}}\left(A_j(H_j)^{\alpha}(F_j^M)^{1-\alpha}-\sum_k w_{kj}H_{kj}\right)=(1-\tilde{\chi})w_{ij},$$

yielding a system of K differential equations for the K wage functions w_k:

$$\tilde{\chi}\alpha\sigma_i A_j\left(\frac{F_j^M}{H_j}\right)^{1-\alpha}=w_{ij}+\tilde{\chi}\sum_k H_{kj}\frac{\partial w_{kj}}{\partial H_{ij}}.$$

Cahuc, Marque, and Wasmer (2008) propose a general discussion of intra-firm bargaining with heterogeneous workers, and in particular they derive formulas for the solutions to this system of differential equations with arbitrary production functions. In the Cobb-Douglas case, the solution must be of the form $w_{kj}=\sigma_k D_j H_j^{\alpha-1}$. Then $\partial w_{kj}/\partial H_{ij}=\sigma_k D_j\sigma_i(\alpha-1)H_j^{\phi-1}$. Substituting into the equation above, we get

$$\begin{aligned}\tilde{\chi}\alpha\sigma_i A_j\left(\frac{F_j^M}{H_j}\right)^{1-\alpha}&=\sigma_i D_j H_j^{\alpha-1}+\tilde{\chi}\sum_k H_{kj}\sigma_k D_j\sigma_i(\alpha-1)H_j^{\phi-1}\\&=\sigma_i D_j H_j^{\alpha-1}+\tilde{\chi}D_j\sigma_i(\alpha-1)H_j^{\alpha-1}\\&=(1+(\alpha-1)\tilde{\chi})w_{ij}.\end{aligned}$$

and thus the solution writes

$$w_{ij}=\frac{\tilde{\chi}\alpha}{(1-\tilde{\chi})+\tilde{\chi}\alpha}\sigma_i A_j\left(\frac{F_j^M}{H_j}\right)^{1-\alpha}\equiv\sigma_i w_j. \qquad \text{(E.1)}$$

Anticipating the bargaining solution, firms chose the number of workers of each type to maximize

$$\frac{(1-\tilde{\chi})}{(1-\tilde{\chi})+\tilde{\chi}\alpha} A_j (H_j)^{\alpha} (F_j^M)^{(1-\alpha)} - \sum_k c_{kj} H_{kj} - Q_j^M F_j^M.$$

Hence, the first K first order conditions for profit maximization equate the marginal productivity of labor to the total cost per worker, i.e.,

$$\frac{(1-\tilde{\chi})}{(1-\tilde{\chi})+\tilde{\chi}\alpha} \alpha \sigma_k A_j \left(\frac{F_j^M}{H_j}\right)^{1-\alpha} = c_{kj} = \frac{1-\tilde{\chi}}{\tilde{\chi}} \sigma_k w_j, \tag{E.2}$$

while the last condition equates rent to marginal productivity of built-up area:

$$Q_j^M = \frac{(1-\tilde{\chi})}{(1-\tilde{\chi})+\tilde{\chi}\alpha} (1-\alpha) A_j \left(\frac{H_j}{F_j^M}\right)^{\alpha}. \tag{E.3}$$

Combining (E.2) and (E.3) and the expression for revenues of the firm, we finally get

$$F_j^M = \frac{\alpha}{1-\alpha} \frac{1-\tilde{\chi}}{\tilde{\chi}} \frac{w_j}{Q_j^M} \tag{E.4}$$

and

$$\frac{(1-\tilde{\chi})}{(1-\tilde{\chi})+\tilde{\chi}\alpha} A_j = \left(\frac{1-\tilde{\chi}}{\tilde{\chi}} \frac{w_j}{\alpha}\right)^{\alpha} \left(\frac{Q_j^M}{1-\alpha}\right)^{1-\alpha}. \tag{E.5}$$

Equations (E.4) and (E.4) are equal to equations (9) and (10) up to a multiplicative constant, which has no impact on the rest of the article.

E.2 Proposition 1: existence and unicity

To ease notations and without loss of generality, we start by dropping one subscript. Define new types $i \equiv (i, k)$ so that productivity is $\sigma_i = \sigma_k$, residential populations are $P_i = P_{ik}$, job finding rates are $\ell_{ij} = \ell_{ijk}$, and application probabilities are $\pi_{j|ik}$. This defines an an equivalent representation of the initial economy where each type i is a residence/skill pair. Equation (19) then rewrites

$$H_j = \sum_i \sigma_i P_i \ell_{ij} \pi_{j|i}, \tag{E.6}$$

avoiding the need for an extra index and an extra summation.

We rewrite the system of $4\times J$ equations of Definition 1 as a system of J land market clearing equations to solve for J wages. Then, we rewrite this system as a fixed-point problem, and finally we show that when $\gamma < (1-\alpha)(1+\mu)$ the corresponding mapping is a contraction.

First, substituting (17) into (16), we get that

$$\tilde{L}_j \left[(1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}}\right]^{1+\tilde{\mu}} \frac{\alpha}{1-\alpha} = \left(\frac{w_j}{\chi}\right)^{1+\alpha\frac{1+\tilde{\mu}}{1-\alpha}} H_j A_j^{-\frac{1+\tilde{\mu}}{1-\alpha}},$$

Plugging in the definition of agglomeration effects (18), we further get that

$$\bar{L}_j = w_j^{1+\alpha\frac{1+\tilde{\mu}}{1-\alpha}} H_j^{1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}},$$

where $\bar{L}_j \equiv a_j^{\frac{1+\tilde{\mu}}{1-\alpha}} \tilde{L}_j \left[(1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}}\right]^{1+\tilde{\mu}} \frac{\alpha}{1-\alpha}(\chi)^{1+\alpha\frac{1+\tilde{\mu}}{1-\alpha}}$. Finally, plugging-in the labor supply equation (E.6), we obtain a system of J equations that we solve for the J unknown w_j:

$$\bar{L}_j \nu^{\left[1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}\right]\frac{1-\lambda}{\lambda}} = w_j^{1+\alpha\frac{1+\tilde{\mu}}{1-\alpha}+\left[1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}\right]\frac{1-\lambda+\epsilon}{\lambda}} \left[\sum_i d_{ij} \frac{\sigma_i^{\frac{1}{\lambda}} P_i}{\sum_k d_{ik} w_k^{\frac{\epsilon}{\lambda}}}\right]^{1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}}. \tag{E.7}$$

Then, let $\kappa \equiv 1 + \alpha\frac{1+\tilde{\mu}}{1-\alpha} + \left[1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}\right]\frac{1-\lambda+\epsilon}{\lambda}$ and let $\Lambda_j = \bar{L}_j \nu^{\left[1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}\right]\frac{1-\lambda}{\lambda}}$. Further, let $\tilde{w}_j \equiv -\kappa \log w_j$. Then equation (E.7) rewrites:

$$\begin{aligned}
\tilde{w}_j &= -\log \Lambda_j + \left(1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}\right) \log\left[\sum_i d_{ij} \frac{\sigma_i^{\frac{1}{\lambda}} P_i}{\sum_k d_{ik} \mathrm{e}^{-\frac{\epsilon}{\lambda\kappa}\tilde{w}_k}}\right] \\
&\equiv f_j(\tilde{w}).
\end{aligned}$$

For all k and j in $1, ..., J$, the partial derivative of f_j is

$$\frac{\partial f_j}{\partial \tilde{w}_k} = \left(1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}\right)\frac{\epsilon}{\lambda\kappa}\sum_i s_{ji} x_{ki},$$

where

$$s_{ji} \equiv \frac{d_{ij}\dfrac{\sigma_i^{\frac{1}{\lambda}} P_i}{\sum_k d_{ik}\mathrm{e}^{-\frac{\epsilon}{\lambda\kappa}\tilde{w}_k}}}{\sum_i d_{ij}\dfrac{\sigma_i^{\frac{1}{\lambda}} P_i}{\sum_k d_{ik}\mathrm{e}^{-\frac{\epsilon}{\lambda\kappa}\tilde{w}_k}}},$$

and

$$x_{ki} \equiv \frac{d_{ik} \mathrm{e}^{-\frac{\epsilon}{\lambda \kappa} \tilde{w}_k}}{\sum_k d_{ik} \mathrm{e}^{-\frac{\epsilon}{\lambda \kappa} \tilde{w}_k}}.$$

Assume that aggregate labor demand is downward slopping, i.e. that $\gamma < \frac{1-\alpha}{1+\tilde{\mu}}$ as stated in the proposition, then $\frac{\partial f_j}{\partial \tilde{w}_k} > 0$ and

$$\begin{aligned}
\sum_k \left| \frac{\partial f_j}{\partial \tilde{w}_k} \right| &= \left(1 - \gamma \frac{1+\tilde{\mu}}{1-\alpha} \right) \frac{\epsilon}{\lambda \kappa} \\
&= \frac{\left(1 - \gamma \frac{1+\tilde{\mu}}{1-\alpha} \right) \epsilon}{\lambda + \lambda \alpha \frac{1+\tilde{\mu}}{1-\alpha} + \left(1 - \gamma \frac{1+\tilde{\mu}}{1-\alpha} \right) (\epsilon + 1 - \lambda)} \\
&\in (0, 1).
\end{aligned}$$

Thus, the Jacobian of $f(\tilde{w}) \equiv (f_j(\tilde{w}))_{j=1}^J$ has a spectral radius less than one : f is a contraction. From the contraction mapping theorem, as an application from $\mathbb{R}^J$ to itself it admits a unique fixed-point.

E.3 Result 1: autarky

In autarky, there are no spatial interactions and the model can be solved analytically. First, we solve for equilibrium wages. From equation (E.7) setting $d_{ij} = 0$ for all $i \neq j$ and $d_{ii} = 1$ for all i, and with Λ_i as in E.2 the equilibrium condition becomes for all i

$$\Lambda_i = w_i^\kappa \left(\frac{\sigma_i^{\frac{1}{\lambda}} P_i}{w_i^{\frac{\epsilon}{\lambda}}} \right)^{1 - \gamma \frac{1+\tilde{\mu}}{1-\alpha}},$$

while the equilibrium employment rate becomes

$$1 - \rho_i = \sigma_i^{\frac{1-\lambda}{\lambda}} w_i^{\frac{1-\lambda}{\lambda}},$$

and therefore

$$1 - \rho_i = \sigma_i^{\frac{1-\lambda}{\lambda} \left[1 - \phi \frac{\omega}{\lambda} \right]} \left[\frac{\Lambda_i}{P_i^\omega} \right]^{\frac{1-\lambda}{\lambda} \phi},$$

where $\omega \equiv 1 - \gamma\frac{1+\tilde{\mu}}{1-\alpha}$ and $\phi \equiv \left(\kappa - \frac{\epsilon}{\lambda}\omega\right)^{-1}$ and $\kappa \equiv 1 + \alpha\frac{1+\tilde{\mu}}{1-\alpha} + \omega\frac{1-\lambda+\epsilon}{\lambda}$. If $\omega < 1$, then $\phi > 0$. Therefore, ρ_i is decreasing in Λ_i (which is itself increasing in $\tilde{L}_i$ and a_i) and increasing in P_i. Further, if $\omega < 1$ then $\frac{\omega}{\lambda}\phi = \omega / \left[\omega + \lambda\alpha\frac{1+\tilde{\mu}}{1-\alpha} + \lambda(1-\omega)\right] < 1$, which shows that $1-\rho_i$ is increasing in σ_i.

E.4 Result 2: full integration

In a full integration setting, the model can also be solved analytically. Let $d_{ij} = d$ for all i and j, then the employment rate in any municipality i collapses to

$$1 - \rho_i = \sigma_i^{\frac{1-\lambda}{\lambda}} \frac{\sum_j w_j^{\frac{1-\lambda+\epsilon}{\lambda}}}{\sum_j w_j^{\frac{\epsilon}{\lambda}}} \equiv \sigma_i^{\frac{1-\lambda}{\lambda}} \frac{V}{W},$$

where V and W are defined accordingly. Note that they do not depend on d or i, which immediately shows that the market access does not depend on the scale of transportation costs, and is the same for every municipality.

Further, writing the ratio of employment rates in the fully integrated and full autarky equilibria gives

$$\widehat{1-\rho_i} = \frac{V}{W}\left[\frac{P_i^{\omega}}{\Lambda_i}\right]^{\frac{1-\lambda}{\lambda}\phi} \sigma_i^{\frac{1-\lambda}{\lambda}\frac{\phi\omega}{\lambda}}, \tag{E.8}$$

which immediately shows that labor market integration favors more productive and more "crowded" municipalities.

Then we compute V and W and the market access V/W. Let Λ_i and κ be as in E.2, and ω as in E.3 and further define the total productivity-weighted population in the city as $\Pi \equiv \sum_j \sigma_j^{\frac{1}{\lambda}} P_j$. Then under the assumption that $d_{ij} = d$, equation (E.7) rewrites

$$w_i^{\kappa} = \Lambda_i \left(\frac{W}{\Pi}\right)^{\omega}, \tag{E.9}$$

Define $\Omega \equiv \sum_i \Lambda_i^{\frac{\epsilon}{\lambda\kappa}}$. Then, we can sum (E.9) and solve for W:

$$W = \Pi^{-\frac{\epsilon}{\lambda}\omega\phi} \times \Omega^{\kappa\phi}. \tag{E.10}$$

Similarly, we define $\Theta \equiv \sum_i \Lambda_i^{\frac{\epsilon+1-\lambda}{\lambda\kappa}}$ and sum (E.9) to obtain

$$V = \Pi^{-\frac{\epsilon+1-\lambda}{\lambda\kappa}\omega\left(1+\frac{\epsilon}{\lambda}\omega\phi\right)} \times \Omega^{\frac{\epsilon+1-\lambda}{\lambda}\omega\phi} \times \Theta. \tag{E.11}$$

Combining (E.10) and (E.11) we get an expression for the job market access in the integrated city:

$$\frac{V}{W} = \left(\sum_i \sigma_i^{\frac{1}{\lambda}} P_i\right)^{-\frac{1-\lambda}{\lambda}\omega\phi} \times \frac{\sum_i \Lambda_i^{\frac{\epsilon+1-\lambda}{\lambda\kappa}}}{\left(\sum_i \Lambda_i^{\frac{\epsilon}{\lambda\kappa}}\right)^{1-\frac{1-\lambda}{\lambda}\omega\phi}}. \tag{E.12}$$

E.5 Result 3: integration and initial mismatch

Taking the log of (E.8) gives

$$\log\left(\widehat{1-\rho_i}\right) = \log\left(\frac{V}{W}\right) + \frac{1-\lambda}{\lambda}\phi \log\left[\frac{P_i^{\omega}}{\Lambda_i}\right] + \frac{1-\lambda}{\lambda}\frac{\phi\omega}{\lambda}\log(\sigma_i)$$

so that

$$\text{Cov}\left[\log\left(\widehat{1-\rho_i}\right), \log(\sigma_i)\right] = \frac{1-\lambda}{\lambda}\phi\text{Cov}\left[\log\left(\frac{P_i^{\omega}}{\Lambda_i}\right), \log(\sigma_i)\right] + \frac{1-\lambda}{\lambda}\frac{\phi\omega}{\lambda}\text{V}\left[\log(\sigma_i)\right].$$

which is negative if and only if

$$\begin{aligned}
\frac{\omega}{\lambda}\text{V}\left[\log(\sigma_i)\right] &< -\text{Cov}\left[\log\left(\frac{P_i^{\omega}}{\Lambda_i}\right), \log(\sigma_i)\right] \\
&= \text{Cov}\left[\log\left(\frac{a_j^{\frac{1+\tilde{\mu}}{1-\alpha}}\tilde{L}_j\left[(1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}}\right]^{1+\tilde{\mu}}\frac{\alpha}{1-\alpha}(\chi)^{1+\alpha\frac{1+\tilde{\mu}}{1-\alpha}}\nu^{\left[1-\gamma\frac{1+\tilde{\mu}}{1-\alpha}\right]\frac{1-\lambda}{\lambda}}}{P_i^{\omega}}\right), \log(\sigma_i)\right] \\
&= \frac{1+\tilde{\mu}}{1-\alpha}\text{Cov}\left[\log(a_j), \log(\sigma_i)\right] + \text{Cov}\left[\log\left(\frac{\tilde{L}_i}{P_i^{\omega}}\right), \log(\sigma_i)\right],
\end{aligned}$$

where the second line uses the definition of Λ_i in section E.3 and the last one uses the properties of the logarithm and the fact that constants don't covarry. Substituting the definition of ω gives Result 3.

E.6 Result 4: integration in a featureless city

Assume a featureless city where only productivity can varry, i.e. that $P_i = P$ and $\Lambda_i = \Lambda$ for all i. Then the market access (E.12) becomes

$$\frac{V}{W} = \left[\frac{J^{\omega} \Lambda}{\left(\sum_i \sigma_i^{\frac{1}{\lambda}} \right)^{\omega} \times P^{\omega}} \right]^{\frac{1-\lambda}{\lambda}\phi}$$

and the change in employment rate (E.8) rewrites

$$\begin{aligned} \widehat{1-\rho_i} &= \left[\frac{J^{\omega} \Lambda}{\left(\sum_i \sigma_i^{\frac{1}{\lambda}} \right)^{\omega} P^{\omega}} \right]^{\frac{1-\lambda}{\lambda}\phi} \times \left[\frac{P^{\omega}}{\Lambda} \right]^{\frac{1-\lambda}{\lambda}\phi} \times \sigma_i^{\frac{1-\lambda}{\lambda}\frac{\phi\omega}{\lambda}} \\ &= \left[\frac{J}{\left(\sum_i \sigma_i^{\frac{1}{\lambda}} \right)} \right]^{\frac{1-\lambda}{\lambda}\phi\omega} \times \sigma_i^{\frac{1-\lambda}{\lambda}\frac{\phi\omega}{\lambda}}, \end{aligned}$$

which is greater than one if and only if $\sigma_i^{\frac{1}{\lambda}} > \frac{\sum_j \sigma_j^{\frac{1}{\lambda}}}{J}$, as stated.