Frictional Labor Mobility*

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Abstract

We build a dynamic model of migration where, in addition to classical mobility costs, workers face informational frictions that decrease their ability to compete for distant job opportunities. We structurally estimate the model on a matched employer-employee panel dataset describing labor market transitions within and between the 100 largest French cities. Our identification strategy is based on the premise that frictions affect the frequency of job transitions, while mobility costs impact the distribution of accepted wages. We find that after controlling for frictions, mobility costs are one order of magnitude lower than previously reported in the literature and their effect on labor mobility and unemployment is significantly lower than the effect of informational frictions.

Keywords: mobility costs, informational frictions, local labor markets

JEL Classification: J61, J64, R12, R23

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Perhaps the simplest model would be a picture of the economy as a group of islands between which information flows are costly (Phelps, 1969).

**Introduction**

Local labor markets in developed countries are often characterized by striking economic disparities, which may persist despite substantial levels of labor mobility. As shown by Figure 1, even though France witnessed a steady 5% annual migration rate during the 1990s, the dispersion in local unemployment risk at the metropolitan area level remained almost unaffected.

![Figure 1: Labor mobility and local unemployment in France in the 1990s](image)

Notes: (i) Mobility rates: probability to have changed location in the past year, conditional on previous employment status; (ii) communes and départements are akin to US municipalities and counties, respectively; régions are similar to German Länder, with less autonomy; until 2016, there were 22 régions, 94 départements and over 36,000 communes in continental France; those three administrative levels form nested partitions of the French territory, unlike metropolitan areas, which are aggregates of communes and may cross département or region boundaries; (iii) Unemployment rates are computed on the 25-54 age bracket and for the 100 largest metropolitan areas in continental France, keeping a constant municipal composition based on the 2010 "Aires Urbaines" definition; (iv) Sources: Labor Force Surveys 1990-1999 and Census 1990 and 1999.
This paper aims to understand why despite similar cultural and labor market institutions, and the rapid progress of transportation and communication technologies, individuals do not take better advantage of the opportunity to move into more affluent cities. The traditional solution to this puzzle is a combination of individual preferences with mobility costs. On the static side, individuals do not change regions because of a strong “home state” bias unrelated to actual economic conditions. As for mobility costs, they provide a dynamic rationale by taking on extremely high values which equalize lifetime income differences across cities. We argue that even forward-looking, profit-maximizing, location-indifferent workers may remain stuck in inauspicious locations because they face search frictions on the labor market and because objective barriers to migration (information loss and relocation costs) rule out off-the-job migration as an optimal behavior in spatial equilibrium. In contrast to most of the existing literature, our theory does not rest upon any kind of spatial idiosyncrasy affecting workers’ utility or productivity and irrational beliefs that local economic downturns will eventually reverse. Regional mismatch will simply result from negative shocks following past location choices.

We build on the search framework of McCall (1970) to model a dynamic job search model that incorporates spatial segmentation between a large number of interconnected local labor markets, or “cities”. Local labor market conditions are characterized by city-specific job arrival rates and wage offer distributions, and potential local labor shocks are introduced through city-specific layoff rates. We consider the strategy of ex-ante identical workers, who engage in both off-the-job and on-the-job search, both within and between cities. A spatial equilibrium is achieved through the mobility of unemployed workers, who generate congestion externalities upon the non-pecuniary component of utility in each location, such that the mobility decision will be based on a cost and return analysis.

While most previous quantitative studies of migration rest upon a unidimensional conception of spatial constraints based on a black box called “mobility costs”, which encompass both impediments to the mobility of workers when it takes place (actual mobility costs) and impediments to the spatial integration of the labor market (workers’ ability to learn about remote vacancies), we believe that separating these mechanisms is important, as they do not take place at the same time nor affect the same economic outcomes. In cases where migration is inefficiently low, they will also imply different public policies: migration subsidies to lower mobility costs and a centralized placement agency to increase job search efficiency across space.

In our setting, there are three barriers to migration. First, physical distance between cities reduces
the efficiency of job search between cities as information loss decreases the likelihood of hearing about vacancies posted in other cities. This dimension of informational frictions, or “spatial frictions”, determines the centrality of each city in the system. Second, spatial segmentation introduces heterogeneity in city-level non-labor market dimension, referred to as “amenity”. This amenity impacts agents’ willingness to refuse a job somewhere else, even in instances where this decision appears as a sound decision from a pure labor-market standpoint. The ranking of each city according to amenities in addition to local labor market conditions generates its attractiveness in the system. Finally, workers face classical mobility costs, which are a lump sum that needs to be paid upon moving. As in Schwartz (1973), these costs encompass a fixed cost of losing local ties and connections, and a cost of moving from one place to another, which mostly depends on distance. Since the model is dynamic, the relative position of the city in the distribution of all possible mobility costs, which determines the level of accessibility of the city in the system, will also impact whether the offer was deemed acceptable in the first place.

The key innovation of our model is its ability to define “mobility-compatible indifference wages”, based on a dynamic utility trade-off between locations. These functions of wage, which are specific to each pair of cities, are defined by the worker’s indifference condition between her current state (a given wage in a given city) and a potential offer in a different city. They define a complex, but intelligible relationship between wages and the model primitives. As a consequence, the model is able to cope with various wage profiles over the life cycle, including voluntary wage cuts as in Postel-Vinay & Robin (2002). Indifference wages are strictly increasing in wages and can be used, in combination with the observed earning distributions, to recover the underlying wage offer distributions through a system of non-homogenous functional differential equations.

The model is solved using steady state conditions on market size, unemployment level and wage distributions. Our estimation uses the panel version of the French matched employer-employee database Declaration Annuelles de Donnees Sociales (DADS) from 2002 to 2007, with local labor markets defined at the metropolitan area level. The identification strategy is a major novelty of the paper: the identification of local labor market parameters and spatial friction parameters is based on the frequency of labor and geographical mobility whereas data on wages are only used to identify mobility costs. Therefore, we can disentangle the impact of mobility costs from that of spatial frictions on migration rate. The other breakthrough is computational. The model is based on a partition between submarkets that can, in theory, be as detailed as possible: we address the challenges raised by the
high dimensionality and we allow the final level of precision to only depend on the research question. In our case, we consider that local labor markets defined at the city level provide a more accurate description of the allocation between workers and firms. Yet, the model is fractal and may apply to the analysis of spatial segmentation at the neighborhood level within a single metropolitan labor market, or even to international migration. It is also transferable to occupational mismatch.

We believe that this paper provides a very complete representation of the complex dynamic trade-offs faced by workers when incorporating migration as a career decision. To do so, it relies on the existence of search frictions. Yet, we do not claim to provide here a fully specified search and matching characterization of the labor market. The search framework in general, and the wage-posting setting with homogeneous workers in particular, are not well equipped to deal jointly with individual and firm location decisions. The underlying reason is related to local matching parameters generating a finite distribution of city-specific reservation wages. In equilibrium, firms have a strategic interest to offer only wages that are marginally higher than reservation wages, yielding discontinuous wage offer distributions. As a consequence, we assume away the location decision of firms, and the related matching problem. Yet, we view our parameters as a measure of city-level hazard rates reflecting the efficiency in the allocation process of workers across firms within and between local labor markets.

Our results consist of a set of vectors of city-specific structural parameters and a set of matrices of parameters measuring spatial constraints between each pair of cities. We show that higher job arrival rates for employed workers are associated with higher local wage dispersion and that matching economies do exist in larger cities, which are characterized by higher job arrival rates overall and do not seem to suffer from lower cost-of-living-adjusted amenities. We also show that employed workers tend to leave (resp., move into) cities with lower (resp., higher) amenities, while the opposite is true for unemployed workers, and that cities with higher local job-finding rates are also better able to send their workers to other cities.

The average value of mobility costs roughly corresponds to eighteen months of work paid at minimum wage, and geographical distance accounts for up to 75% of variation in mobility cost. We show that both geographical distance and sectoral dissimilarity are stronger deterrents of the efficiency of spatial search for employed jobseekers, than for unemployed jobseekers. Moreover, the effect of sectoral differences on spatial frictions is two orders of magnitude higher than the effect of distance, which hints towards the existence of network-based coordination frictions, rather than a pure effect of physical deconnection. Finally, we provide a decomposition comparing the effects of spatial frictions
and mobility costs on unemployment and mobility. Overall, spatial frictions have a larger impact than mobility costs on both outcomes, especially if we seek to increase the level of spatial integration in the economy by increasing the quantity of information travelling across space or by lowering mobility costs. In particular, lowering mobility costs has almost no positive impact on unemployment.

**Relationship to the literature**

Our paper appeals to two strands of the literature: on the empirical side, it quantifies the determinants of migration; on the theoretical side, it uses recent advances in the search and matching literature to capture interactions between competing submarkets.

**Migration**  
Economists have long investigated the career choice of workers. Keane & Wolpin (1997) have shown that individuals make sophisticated calculations regarding work-related decisions, both in terms of pure labor market characteristics (industry, occupation, skills requirement) and location. In order to disentangle between the various underlying mechanisms, a structural approach seems natural. It was pioneered by Dahl (2002), who constructs a model of mobility and earnings over the US states and shows that higher educated individuals self-select into states with higher returns to education. However, as migration is an investment, it requires not only a static tradeoff between economic conditions, but also a comparison between expected future economic conditions (Gallin, 2004). In addition, and despite its interest and obvious links to the present paper, the classic perfect-competition approach cannot fully reconcile the equilibrium coexistence of both labor mobility and local labor market differences.¹

In this paper, we argue that friction-based search and matching models can tackle this puzzle. In recent years, structural estimations of equilibrium job search models have proven very useful to study various features of the labor market.² However, job search models rest upon a rather unified conception of the labor market, where segmentation, if any, is based on sectors or qualifications. In particular, they do not account for spatial heterogeneity, even though several well-documented

¹Following Harris & Todaro (1970), competitive models have first sought to explain rural/urban migration patterns in developing economies (Lucas, 1993). While both average wages and unemployment risk are taken into account in the Harris-Todaro framework, it is assumed that unemployment is confined to one area (cities) and the equilibrium is reached when the expected urban wage, adjusted for unemployment risk, is equal to the marginal product of an agricultural worker.
²The original job search literature emerges as an attempt to capture the existence of frictional unemployment. Interestingly, Phelps’ (1969) island parable is, at least metaphorically, related to this paper. The major breakthrough, due to Burdett & Mortensen (1998), allows to generate ex-post wages differential from ex-ante identical workers, and provides an intuitive way to evaluate the individual unemployment probability as well as the wage offer distribution without solving the value functions.
empirical facts suggest that the labor market may be described as an equilibrium only at a local level.\footnote{As shown by Manning & Petrongolo (2011) on the UK, matching functions exhibit a high level of spatial instability. By restricting their estimation sample to the Paris region, Postel-Vinay & Robin (2002) implicitly recognize this problem.}

From a practical viewpoint, the absence of space in search models can be explained by computational difficulties. Indeed, solving for search models with local labor markets requires handling multiple high-dimensional objects such as wage distributions. A standard solution is to consider a very stylized definition of space. This is the path taken by Baum-Snow \& Pavan (2012), who propose a model that includes several appealing features such as individual ability and location-specific human capital accumulation, but have to resort to a ternary partition of space between small, mid-sized and large cities.\footnote{The same is true with Head, Lloyd-Ellis \& Sun (2014), who construct a rich equilibrium job search model with heterogeneous locations, endogenous construction, and search frictions in the markets for both labor and housing, but calibrate the model on a binary partition of space, between high-wage and low-wage US cities, which would not fit our purpose as well. However, the fact remains that mobility costs and local amenities are difficult to interpret in the absence of a separate housing market. Modeling the housing market would constitute an interesting extension, but the data requirement would be very high: one would need to have access to census-type information on each worker. Current subsets of the Panel DADS data that have been matched with the Census are far from having enough observations to allow us to distinguish between a sufficient number of local labor markets.}

Our paper follows on from the work of Kennan \& Walker (2011), who develop and estimate a partial equilibrium model of mobility over the US states and provide many interesting insights with respect to the mobility decision of workers, including mobility costs. However, computing the model requires additional assumptions on individual information sets.\footnote{For example, it is assumed that individuals have knowledge over a limited number of local wage distributions, which correspond to where they used to live. In order to learn about another location, workers need to pay a visiting cost. These assumptions may not reflect the recent increase in workers’ ability to learn about other locations before a mobility (Kaplan \& Schulhofer-Wohl, 2016).}

Moreover, the low mobility rate is rationalized by the existence of extremely high mobility costs.\footnote{The combination of local idiosyncratic shocks with mobility costs is the traditional way of explaining the lack of convergence in local labor market conditions: for example, Lkhagvasuren (2012) shows that a model with stochasitic worker-location match productivity, combined by local trading frictions, can be used to explain persistence unemplyment disparities across U.S. states; even more recently, Nemov (2015) uses the slow worker reallocation mechanism induced by idiosyncratic preference shocks, mobility costs and imperfectly directed migration to explain the comovement of unemployment, housing prices and migration rates observed in a panel of U.S. cities.} Finally, a focus on the state level is not fully consistent with the theory of local labor markets, which are better proxied by metropolitan areas (Moretti, 2011).

**Job search and frictions between competing submarkets** There is a notable effort in the recent empirical job search literature to study search patterns in competing submarkets. These papers seek to provide new dynamic micro-foundations to the old concept of dualism in the labor market. The underlying idea is that jobs are not only defined by wages, but also by a set of benefits that are only available within some submarkets. This creates potential tradeoffs, for example between a more regulated...
sector which offers more employment protection (in terms of unemployment risk and insurance) and a less regulated sector, which allows for more flexibility and possibly better wage paths.\footnote{Postel-Vinay & Turon (2007) study the public/private pay gap in Britain and detect a positive wage premium in favor of the public sector both in instantaneous and in dynamic terms. Shephard (2014) distinguishes between part-time and full-time work to assess the impact of UK tax credit reform on individual participation choices.} In doing so, these models also provide more accurate estimates of the matching parameters, which are no longer averaged over sectors.

Our main reference is Meghir, Narita & Robin (2015), who study the impact of the existence of informality in Brazil on labor market outcomes. The authors consider a very general model where workers can switch between sectors and where job arrival rates (and the number of firms in each sector) are endogenously determined by firms’ optimal contracts. One noteworthy feature of this paper is that they do not need to define indifference conditions between sectors, because they directly focus on labor “contracts”, which summarize the entire discounted income flow, and may be recovered numerically.

While our framework is less general as it leaves firms’ behavior aside, we believe that it can also provide a useful complement to the previous paper for some aspects: first, we show that optimal contracts (or, in our case, indifference wages) may sometimes be recovered analytically; second, from a search-theoretic perspective, we allow for a more general definition of segmentation, where the option value of unemployment is location-specific and therefore, inherited from past decisions, whereas papers on dualism assume that the job finding rate for the unemployed is not impacted by the sector where workers were working before losing their job. Finally, we explicitly allow for mobility costs, which are analogous to switching costs in the dynamic discrete choice literature. To the best of our knowledge, this is the first paper to consider the problem of deterministic, move-specific switching costs within a dynamic search model. Our theoretical framework shows that this extension is not trivial. It also allows us to put the existing frictionless migration literature into perspective.

The rest of the paper is organized as follows. In section 1, we describe the French labor market as a spatial system; section 2 is the presentation of the model; section 3 explains our estimation strategy and the results are discussed in section 4.

1 Motivating facts

In this section, we provide descriptive evidence in favor of the modelling of the French labor market as a system of local labor markets based on metropolitan areas. These local labor markets present three
salient characteristics: (i) heterogeneity in terms of economic opportunities; (ii) interconnection through workers’ mobility; and (iii) stability in key economic variables. We first document the heterogeneity and the stability of the three features that will characterize a local labor market throughout the paper: its population, its unemployment rate and its wage distribution. Then, we describe workers’ mobility, both on the labor market and across space.

1.1 France as a steady state system of local urban labor markets

The functional definition of a metropolitan area brings together the notions of city and local labor market. A more precise partition of space, for instance based on municipal boundaries, would lead to a confusion between job-related motives for migration and other motives. French metropolitan areas (or “aires urbaines”) are continuous clusters of municipalities with a main employment center of at least 5,000 jobs and a commuter belt composed of the surrounding municipalities with at least 40% of residents working in the employment center. We will focus on the 100 largest metropolitan areas in continental France, as defined by the 2010 census. Below a certain population threshold, the assumption that each of these metropolitan areas is an accurate proxy of a local labor market becomes difficult to support. As shown in Figure 7 in Appendix D, metropolitan areas cover a very large fraction of the country. Paris and its 12 millions inhabitants stand out, before six other millionaire cities and eleven other metropolitan areas with more than 0.5 million inhabitants.

Population Since we do not model the participation choice of workers, labor force is analogous to population. Data from 1999 and 2006 Census shows that the Paris region accounts for more than 25% of total labor force in the first 100 cities. As shown in Figure 2, local labor force is Pareto-distributed and absolute variation in local labor force between 1999 and 2006 is negligible.\(^8\)

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\(^8\)According to the 2006 French Housing Survey, 16% of the households in the labor force who had been mobile in the past four years declared that the main reason for their move was job-related. However, this small proportion hides a large heterogeneity which is correlated with the scale of the migration, from 5% for the households who had stayed in the same municipality, to 12% for those who had changed municipalities while staying in the same county, to 27% for those who had changed counties while staying in the same region and to 49% for those who had changed regions.

\(^9\)US MSAs are defined along the same lines, except the unit is generally the county and the statistical criterion is that the sum of the percentage of employed residents of the outlying county who work in the center and the percentage of the employment in the outlying county that is accounted for by workers who reside in the center must be equal to 25% or more.

\(^10\)The smallest metropolitan area which will be isolated in our analysis is Narbonne, with 90,000 inhabitants in 2010. According to the 2010 US census, meeting the same level of precision on the US would require to distinguish between more than 360 cities.

\(^11\)This stability is at odds with the fact that metropolitan areas face diverse net migration patterns, which are driven by the migration of nonparticipants (retired, young individuals). According to Gobillon & Wolff (2011), 31.5% of French grandparents aged 68-92 in 1992 declared that they moved out when they retired. Among them, 44.1% moved to another region. Most of these migration decisions are motivated by differences in location-specific amenities or by the desire to live closer to other family members.
Notes: (i) Labor force is composed of unemployed and employed individuals aged between 15 and 64; (ii) the labor force in the 100 largest metropolitan areas in continental France amounts to 17.4 millions in 1999 and to 18.4 millions in 2006; (iii) The sum of the absolute values of location-by-location changes amounts to 1.1 million, i.e., 6% of total labor force in 1999. Source: Census 1999 and 2006.

**Unemployment** Figure 3 establishes that city-specific unemployment is quite stable over time, especially over a short period of stable aggregate unemployment. Such is the case from 2002 to 2007, both in terms of range and in terms of variation of the annual moving average. During those years, which correspond to Jacques Chirac’s second term, the French economy is in an intermediate state, between a short boom in the last years of the twentieth century and the Great Recession. For this reason, we focus on this period throughout the paper.

**Wage distributions** To compute city-specific earning distributions, we use data from the *Déclarations Annuelles des Données Sociales* (DADS). The DADS are a large collection of mandatory employer reports of the earnings of each employee of the private sector subject to French payroll taxes. The DADS are the main source of data used in this paper.\(^{12}\) Table 14 in Appendix C.2 reports the main mo-
Figure 3: Aggregate and local unemployment

Notes: (i) Top graph displays the quarterly unemployment rate in France: the darker background is the period under study; bottom graph displays the log unemployed population in the 100 largest metropolitan areas in continental France on December 31, 2001 and 2007; (ii) The unemployed population in 2002 corresponds to the unemployed population of the last day of 2001; it is adjusted to take into account the change in definition that occurred in unemployment statistics in 2005 (the adjustment factor is set equal to 0.81 to match the ratio of unemployed in France in the last quarter of 2007 as measured by the National Unemployment Agency to its counterpart in the last quarter of 2001); (iii) The sum of the absolute values of location-by-location changes amounts to 6.6% of total adjusted unemployed population in 2001; (iv) We use yearly administrative data from the National Unemployment Agency, which allows us to look at the absolute changes in the unemployed population. Source: Série Longue Trimestrielle INSEE (top) and National Unemployment Agency (bottom).

Wage distributions in the largest cities stochastically dominate wage distributions in smaller cities. The average wage (33.888 €) in Paris is 51.3% higher than the city-level average wage. Other large cities have similar wage premia. Although the wage premium in Paris may be partly offset by the cost of living, there exist persistent wage differentials among cities with comparable size and cost of living. For instance, Oloron is richer than all the other cities of Panel 2, including cities that are far larger. In addition, there is a strong positive correlation of 0.44 between wage dispersion and city size.  

13Our data selection procedure that excludes part-time workers and civil servants increases the wage gap between Paris and smaller locations. Using all the available payroll data in 2007, the mean wage in Paris is around 22,501€, which is 35% higher than the national average.
These trends are supported by the log-difference between the top and bottom decile (or between the 3rd and the 1st quartiles). They both indicate higher wage dispersion in Paris, mainly driven by the influence of high wages. On a smaller set of moments, Table 15 in Appendix C.2 shows that wage distributions do not vary a lot between 2002 and 2007. The ratios of the three quartiles and the mean of the log-wage distributions in 2007 and 2002 are closely distributed around 1 for the whole set of metropolitan areas.

**Workers' heterogeneity** Apart from the size of the labor force and the unemployment rate, other dimensions, such as the skill and the sectoral composition, are also important drivers of local labor market heterogeneity and dynamics. However, we believe that, as a first-order approximation, the assumption of workers' homogeneity is not too costly when focusing on a short period, because the distribution of observable characteristics across cities remains stable (see discussion in Appendix D.2).

### 1.2 Labor and geographical mobility

**Data** We now turn to the mobility patterns of jobseekers across France. To make a precise assessment regarding geographical transitions between each pair of cities, we use a specific subsample of the DADS data. Since 1976, a yearly longitudinal version of the DADS has been following all employed individuals born in October of even-numbered years. Since 2002, the panel includes all individuals born in October. Due to the methodological change introduced in 2002, and amid concerns about the stability of the business cycle, we focus on a six-year span between 2002 and 2007. The main restrictions over our sample are the following: first, to mitigate the risk of confusion between non-participation and unemployment, we restrict our sample to males who have stayed in continental France over the period; second, we exclude individuals who are observed only once. We end up with a dataset of 375,000 individuals and 1.5 millions observations (see appendix C.1, for more details).

Since the DADS panel is based on firms’ payroll reports, it does not contain any information on unemployment. However, it reports for each employee the duration of the job, along with the wage. We use this information to construct a potential calendar of unemployment events and, in turn, identify transitions on the labor market. As in Postel-Vinay & Robin (2002), we define a *job-to-job transition* as a change of employer associated with an unemployment spell of less than 15 days and we attribute the unemployment duration to the initial job in this case. Conversely, we assume that an unemployment spell of less than 3 months between two employment spells in the same firm only re-
reflects some unobserved specificity of the employment contract and we do not consider this sequence as unemployment. Finally, we need to make an important assumption regarding the geographical transitions of unemployed individuals: we attribute all the duration of unemployment to the initial location, assuming therefore that any transition from unemployment to employment with migration is a single draw. Hence, we rule out the possibility of a sequential job search whereby individuals would first change locations before accepting a new job offer. From a theoretical viewpoint, this means that mobility has to be job-related. From a practical viewpoint, in the DADS data, the sequential job search process is observationally equivalent to the joint mobility process.

**Labor market transitions** Table 1 describes the 719,601 transitions of the 375,276 individuals in our sample. Over our period of study, a third of the sample has recorded no mobility. This figure is similar to the non-mobility rate of 45% reported by Postel-Vinay & Robin (2002) from 1996 to 1998. Approximately 23% of the sample records at least one job-to-job transition, and the numbers of transitions into unemployment and out of unemployment are almost identical. Average wages are almost constant over time, as shown in the last line of the table. Job-to-job transitions are accompanied by a substantial wage increase (around 7%). Transitions out of unemployment lead to a wage that is 7% lower than the wage of employed workers who do not make any transition, 25% lower than the final wage of employed workers who have experienced a job-to-job transition, and roughly equal to

<table>
<thead>
<tr>
<th>Type of history</th>
<th>Characteristics of the spells</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of events</td>
</tr>
<tr>
<td>No transitions while employed</td>
<td>126,227</td>
</tr>
<tr>
<td>Out of unemployment</td>
<td>302,024</td>
</tr>
<tr>
<td>with mobility</td>
<td>59,605</td>
</tr>
<tr>
<td>without mobility</td>
<td>242,418</td>
</tr>
<tr>
<td>Job to job mobility</td>
<td>114,659</td>
</tr>
<tr>
<td>with mobility</td>
<td>26,199</td>
</tr>
<tr>
<td>without mobility</td>
<td>88,459</td>
</tr>
<tr>
<td>Into unemployment</td>
<td>302,918</td>
</tr>
<tr>
<td>Full sample</td>
<td>719,601</td>
</tr>
<tr>
<td>Individuals</td>
<td>375,276</td>
</tr>
</tbody>
</table>

Notes: (i) Wages are in 2002 Euros and spell durations in months; (ii) Time begins on January 1\(^{st}\) 2002. *Source: Panel DADS 2002-2007*

\[15\] For a recent example of a similar assumption, see Bagger, Fontaine, Postel-Vinay & Robin (2014).
the initial wage of individuals who will fall into unemployment. For this latter group, note that their initial employment spell is notably shorter than for the rest of the population, which suggests more instability.\footnote{In this table, as well as in our estimation, we assume that time starts on the first day of 2002. This left censoring is due to the fact that we do not have information about the length of unemployment for the individuals who should have entered the panel after 2002 but have started with a period of unemployment. Whereas, for employment spells, we could in theory use information about the year when individuals entered their current firm, we choose not to, to keep the symmetry between both kinds of initial employment status.}

**Geographical transitions** Geographical mobility accounts for 19.8\% of transitions out of unemployment and 22.9\% of job-to-job transitions. As shown by Table 2, Paris is both the most prominent destination and the city with the highest rate of transition (90.4\%) with no associated mobility.\footnote{Postel-Vinay & Robin (2002) report that 4.7\% of workers from the Paris region make a geographical mobility. They conclude that this low rate allows them to discard the question of interregional mobility.}

### Table 2: Mobility between the largest cities

<table>
<thead>
<tr>
<th>Origin</th>
<th>Paris</th>
<th>Lyon</th>
<th>Marseille</th>
<th>Toulouse</th>
<th>Lille</th>
<th>Rest of France</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paris</td>
<td>UE</td>
<td>90.704</td>
<td>0.693</td>
<td>0.519</td>
<td>0.478</td>
<td>0.349</td>
</tr>
<tr>
<td></td>
<td>EE</td>
<td>92.096</td>
<td>0.880</td>
<td>0.554</td>
<td>0.416</td>
<td>0.411</td>
</tr>
<tr>
<td>Lyon</td>
<td>UE</td>
<td>4.384</td>
<td>81.804</td>
<td>0.792</td>
<td>0.285</td>
<td>0.238</td>
</tr>
<tr>
<td></td>
<td>EE</td>
<td>6.930</td>
<td>30.890</td>
<td>1.148</td>
<td>0.349</td>
<td>0.492</td>
</tr>
<tr>
<td>Marseille</td>
<td>UE</td>
<td>4.299</td>
<td>1.283</td>
<td>82.112</td>
<td>0.589</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td>EE</td>
<td>7.548</td>
<td>2.157</td>
<td>75.200</td>
<td>0.522</td>
<td>0.417</td>
</tr>
<tr>
<td>Toulouse</td>
<td>UE</td>
<td>4.555</td>
<td>0.581</td>
<td>0.533</td>
<td>82.765</td>
<td>0.242</td>
</tr>
<tr>
<td></td>
<td>EE</td>
<td>5.162</td>
<td>0.667</td>
<td>0.632</td>
<td>83.778</td>
<td>0.140</td>
</tr>
<tr>
<td>Lille</td>
<td>UE</td>
<td>4.708</td>
<td>0.506</td>
<td>0.287</td>
<td>0.246</td>
<td>78.278</td>
</tr>
<tr>
<td></td>
<td>EE</td>
<td>5.543</td>
<td>0.720</td>
<td>0.251</td>
<td>0.376</td>
<td>77.231</td>
</tr>
<tr>
<td>Rest of</td>
<td>UE</td>
<td>0.041</td>
<td>0.012</td>
<td>0.005</td>
<td>0.007</td>
<td>0.008</td>
</tr>
<tr>
<td>France</td>
<td>EE</td>
<td>0.033</td>
<td>0.016</td>
<td>0.008</td>
<td>0.010</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Notes: (i) UE stands for transition out of unemployment and EE stands for job-to-job transition; (ii) Reading: among the transitions out of unemployment originating from the city of Lyon, 81.8\% led to a job in Lyon, 4.4\% led to a job in Paris and 0.8\% led to a job in Marseille. Source: Panel DADS 2002-2007

Table 3 completes this overview by comparing the mobility patterns within the Lyon region (also known as “Rhône-Alpes”) and between the Lyon region and Paris. Although Paris is the destination of a sizable share of mobile workers, geographical proximity can overcome this attractiveness, as shown for the cities of Grenoble, Saint-Etienne and Bourg-en-Bresse that are located less than 60 miles away from Lyon. As a consequence, we will incorporate distance between locations as a determinant of spatial frictions (see section 3 for details).

**Wage dynamics within and between cities** As shown in Table 4, wage dynamics following a job-to-job transition are characterized by two noteworthy features. First, they are not symmetrical: average
wages following a job-to-job transition with mobility into a given city are almost always higher than average wages following a job-to-job transition within the same city.\footnote{It should be noted that this pattern does not preclude the existence of mobility strategy with wage cut. There are numerous cases in the full data where workers do accept lower wages in between-cities on-the-job search than in within-cities on-the-job search. Between-cities on-the-job search with wage cut strategy involves mainly young workers.} This suggests that mobility costs are high compared to local differences in economic opportunities. Second, if mobility costs are mostly determined by the physical distance between two locations, wage dynamics cannot be fully rationalized by them. For example, as will be shown in section \ref{sec:4}, Paris does offer many more opportunities than Toulouse, yet workers who are leaving Lille require a higher wage in Paris (average earnings of \(\text{€}41,139\)) than in Toulouse (average earnings of \(\text{€}29,346\)). Since Paris is about four times closer to

\begin{table}[h]
\centering
\caption{Distance versus size: mobility within the Lyon region and between the Lyon region and Paris}
\begin{tabular}{lcccccc}
\hline
\textbf{Origin} & \textbf{Lyon} & \textbf{Grenoble} & \textbf{St-Etienne} & \textbf{Valence} & \textbf{Bourg} & \textbf{Paris} \\
\hline
\textbf{Lyon} & 81,804 & 1,523 & 1,146 & 0.277 & 0.584 & 4.384 \\
& 80,890 & 1,517 & 0.964 & 0.349 & 0.328 & 6.930 \\
\textbf{Grenoble} & 4,685 & 81,164 & 0.269 & 0.458 & 0.000 & 3.312 \\
& 11,905 & 72,247 & 0.074 & 1.637 & 0.000 & 4.092 \\
\textbf{St-Etienne} & 6,434 & 0.402 & 81,144 & 0.089 & 0.000 & 2.904 \\
& 8,313 & 0.372 & 82,382 & 0.372 & 0.000 & 1.365 \\
\textbf{Valence} & 2,860 & 1.049 & 0.286 & 73,117 & 0.000 & 3.337 \\
& 4,290 & 0.372 & 82,382 & 0.372 & 0.000 & 1.365 \\
\textbf{Bourg} & 9,091 & 0.455 & 0.227 & 0.455 & 73,182 & 0.682 \\
& 13,333 & 0.000 & 0.000 & 0.833 & 62,500 & 1.667 \\
\hline
\end{tabular}
\end{table}

\begin{table}[h]
\centering
\caption{Average wages following a job-to-job transition}
\begin{tabular}{lcccc}
\hline
\textbf{Paris} & Lyon & Marseille & Toulouse & Lille \\
\hline
Paris & 38,576 & 47,824 & 43,800 & 36,470 & 36,406 \\
& (36,739) & (351) & (221) & (166) & (164) \\
Lyon & 44,602 & 30,234 & 33,358 & 31,607 & 45,155 \\
& (338) & (3,945) & (56) & (17) & (24) \\
Marseille & 45,981 & 37,778 & 27,983 & 43,255 & 46,776 \\
& (217) & (62) & (2,162) & (15) & (12) \\
Toulouse & 36,926 & 37,196 & 34,720 & 28,454 & 41,579 \\
& (147) & (19) & (18) & (2,386) & (4) \\
Lille & 41,139 & 42,253 & 40,504 & 29,346 & 27,753 \\
& (177) & (23) & (8) & (12) & (2,466) \\
\hline
\end{tabular}
\end{table}
Lille than Toulouse, the addition of mobility costs alone cannot cope with this simple observation, unless we allow for heterogeneous local amenities (or, equivalently, local costs of living).

2 Job search between many local labor markets: theory

We develop a dynamic migration model where individuals can move between a set of interconnected local labor markets. We consider steady-state implications in terms of job search and migration behavior following our descriptive evidence. Our objective is to include the structural determinants of migration into a setting that allows us to quantify the respective roles of spatial frictions and mobility costs in worker’s geographical mobility.

2.1 Framework

We consider a continuous time model, where infinitely lived, risk neutral agents maximize their expected steady-state discounted (at rate $r$) future income. The economy is organized as a system $\mathcal{J}$ of $J$ interconnected local labor markets, or “cities”, where a fixed number of $M$ workers live and work. While the spatial position of each city $j$ within the system is exogenous, total population $m_j$ and unemployed population $u_j$, are determined by the job search process. Wage offers are drawn from a distribution $F(\cdot) \equiv \{F_j(\cdot)\}_{j \in \mathcal{J}}$ of support $[w, \bar{w}] \subset (b, \infty)$, resulting from firms’ exogenous wage posting strategy.\(^{19}\) Let $F_j(\cdot) \equiv 1 - F_j(\cdot)$. Workers do not bargain over wages. They only decide whether to accept or refuse the job offer they have received. We note $G(\cdot) \equiv \{G_j(\cdot)\}_{j \in \mathcal{J}}$ the resulting distribution of earnings observed in the economy.

Spatial segmentation and migration Cities are heterogeneous, both in terms of labor market and living conditions. Employed workers in city $j$ face a location-specific unemployment risk characterized by the layoff probability $\delta_j$. This probability reflects the idiosyncratic volatility of local economic conditions. When they become unemployed, workers receive uniform unemployment benefits $b$.

All workers in city $j$ face an indirect utility $\gamma_j$, which summarizes the difference between amenities and (housing) costs in city $j$. This parameter may be interpreted as the average valuation of city $j$ among the population of workers. It is an equilibrium object resulting from congestion externalities generated by perfectly mobile unemployed workers. The value of $\gamma_j$ is separable from the level of earnings, such that the instant value of a type-$i$ worker in city $j$ equals $y_i^e + \gamma_j$, with $y_i^u = b$ and $y_i^e = w$.

\(^{19}\)Although firms are present in the background of the model, we do not model their behavior because we believe it would require an explicit theory of location choice, agglomeration economies and wages, which is beyond the scope of this paper.
This specification accounts for differences in local costs of living, so that wages can still be expressed in nominal terms.

Workers are ex ante identical and fully characterized by their employment status $i = e, u$, their wage level $w$ when employed and their location $j \in J$. They engage in both off-the-job and on-the-job search. Their probability of receiving a new job offer depends on their current employment status, their location, as well as on the location associated with the job offer itself. Since we do not model these rates as originating from a matching function, they do not have a fully structural interpretation, even though they may arise from the spatial distribution of jobs and the heterogeneity in local matching technologies.

Frictions reduce the efficiency of job search between cities: type-$i$ workers living in location $j$ receive job offers from location $l \in J_j \equiv J - \{j\}$ at rate $s_{ji}^\lambda_j \leq \lambda_j^e$. In addition, when they finally decide to move from city $j$ to city $l$, workers have to pay a lump-sum mobility cost $c_{jl}$. They are perfectly mobile, in the sense that anybody can always decide to pay $c_{jl}$, move to city $l$ and be unemployed there. However, because of congestion externalities affecting the job finding rate for the unemployed $\lambda_j^u$ and the amenity value $\gamma_j$, this type of behavior will be ruled out in equilibrium and migration will only occur in case workers have found and accepted a job.

**Workers’ value functions** Let $(x)^+ \equiv \max\{x, 0\}$. Workers do not bargain over wages. They only decide whether to accept or refuse the job offer which they have received. The respective value functions of unemployed workers living in city $j$ and of workers employed in city $j$ for a wage $w$ are recursively defined by equations 1 and 2:

\[
\begin{align*}
    rV^u_j & = b + \gamma_j + \lambda_j^u \int_w^\infty (V^u_j(x) - V^u_j(w))^+ dF_j(x) + \sum_{k \in J_j} s_{jk}^u \lambda_k^u \int_w^\infty (V^u_k(x) - c_{jk} - V^u_j(w))^+ dF_k(x) \\
    rV^e_j(w) & = w + \gamma_j + \lambda_j^e \int_w^\infty (V^e_j(x) - V^e_j(w))^+ dF_j(x) + \sum_{k \in J_j} s_{jk}^e \lambda_k^e \int_w^\infty (V^e_k(x) - c_{jk} - V^e_j(w))^+ dF_k(x) + \delta_j [V^u_j - V^e_j(w)]
\end{align*}
\]

**2.2 Workers’ strategies**

Accepting an offer in a city conveys city-specific parameters. Jobs are defined by a non-trivial combination of wage and all the structural parameters of the economy, which determines the offer’s option value. By refusing an offer, workers would, in a sense, bet on their current unemployment against their future unemployment probability. A similar mechanism applies to job-to-job transitions. If
workers are willing to accept a wage cut in another location, this decision is somewhat analogous to buying an unemployment insurance contract, or a path to better wage prospects. This multivariate, and dynamic trade-off allows us to define spatial strategies, where workers' decision to accept a job in a given city is not only driven by the offered wage and the primitives of the local labor market, but also by the employment prospects in all the other locations, which depend upon the city's specific position within the system. The sequence of cities where individuals are observed can then be rationalized as part of lifetime mobility-based careers.

Definitions In order to formalize the previous statements, we now describe the workers' strategies. These strategies are determined by the worker's location, employment status, and wage. They are defined by threshold values for wage offers. These values are deterministic and similar across individuals since we assume that workers are ex-ante identical. They consist of a set of reservation wages and a set of sequences of mobility-compatible indifference wages.

A reservation wage corresponds to the lowest wage an unemployed worker would accept in her location. Reservation wages, which are therefore location-specific, are denoted \( \phi_j \) and verify \( V_u^j(\phi_j) = V_e^j(\phi_j) \). The reservation-wage strategy is denoted \( \phi \equiv \{ \phi_j \}_{j \in J} \). Mobility-compatible indifference wages are functions of wage which are specific to any ordered pair of locations \( (j, l) \in J \times J \). These functions associate the current wage \( w \) earned in location \( j \) to a wage which would yield the same ex-post utility in location \( l \), once the mobility cost \( c_{jl} \) is taken into account. They are denoted \( q_{jl}(-) \) and verify \( V_e^j(q_{jl}(w)) - c_{jl} \). The migration strategy is denoted \( q(-) \equiv \{ q_{jl}(-) \}_{(j, l) \in J \times J} \). The definition of \( q_{jl}(-) \) extends to unemployed workers in city \( j \) who receive a job offer in city \( l \): we have \( V_u^j = V_e^l(q_{jl}(\phi_j)) - c_{jl} \). Finally, let \( \chi_{jl}(w) \) denote another indifference wage, verifying \( V_e^j(w) = V_e^l(\chi_{jl}(w)) \). This indifference wage equalizes the utility levels between two individuals located in cities \( j \) and \( l \).

We shall therefore refer to it as the “ex-ante” indifference wage, unlike the “ex-post” indifference wage \( q_{jl}(w) \), which equalizes the utility level between one worker located in city \( j \) and the same worker after a move into city \( l \). By definition, ex-ante indifference wages have a stationary property, whereby \( \chi_{ik}(\chi_{jl}(w)) = \chi_{jk}(w) \). As will be made clear later, the introduction of \( \chi_{jl}(w) \) is important to understand the role of mobility costs in the dynamics of the model.

Proposition 1 OPTIMAL STRATEGIES

- Let \( \zeta_{jl} = \frac{r + \delta_l}{r + \delta_j} \). The reservation wage for unemployed workers in city \( j \) and the mobility-compatible indifference wage in city \( l \) for a worker employed in city \( j \) at wage \( w \) are defined as follows:
The interpretation of Equation 3 is straightforward: the difference in the instantaneous values of unemployment and employment (\(\phi_j - b\)) reflects an opportunity cost, which must be perfectly compensated for by the difference in the option values of unemployment and employment. Those are composed of two elements: the expected wages through local job search and the expected perfectly compensated for by the difference in the option values of unemployment and employment.

\[
\phi_j = b + (\lambda_j^u - \lambda_j^f) \int_{\phi_j}^{w} \Xi_j(x) dx + \sum_{k \in J_j} s_{jk}^u \lambda_k^u - s_{jk}^f \lambda_k^f \left( \int_{q_{jk}(\phi_j)}^{w} \Xi_k(x) dx - \bar{F}_k(q_{jk}(\phi_j)) c_{jk} \right)
\]

(3)

\[
q_{jl}(w) = \xi_{jl} w + (\xi_{jl} \gamma_j - \gamma_l) + (r + \delta) c_{jl} + (\xi_{jl} \delta_j \nu^u_j - \delta_j \nu^u_l) + \xi_{jl} \lambda_j^e \int_{q_{jl}(\phi_j)}^{w} \Xi_j(x) dx - \lambda_j^e \int_{q_{jl}(w)}^{w} \Xi_j(x) dx + \xi_{jl} \sum_{k \in J_j} s_{jk}^e \lambda_k^e \left( \int_{q_{jk}(\phi_j)}^{w} \Xi_k(x) dx - \bar{F}_k(q_{jk}(\phi_j)) c_{jk} \right) - \sum_{k \in J_j} s_{jk}^e \lambda_k^e \left( \int_{q_{jk}(\phi_j)}^{w} \Xi_k(x) dx - \bar{F}_k(q_{jk}(\phi_j)) c_{jk} \right)
\]

(4)

with:

\[
V^u_j = \frac{1}{\gamma_j} \left[ b + \gamma_j + \lambda_j^u \int_{\phi_j}^{w} \Xi_j(x) dx + \sum_{k \in J_j} s_{jk}^u \lambda_k^u \left( \int_{q_{jk}(\phi_j)}^{w} \Xi_k(x) dx - \bar{F}_k(q_{jk}(\phi_j)) c_{jk} \right) \right]
\]

(5)

\[
\Xi_j(w) = \frac{F_j(w)}{r + \delta_j + \lambda_j^e \Gamma_j^2(w) + \sum_{k \in J_j} s_{jk}^e \lambda_k^e \bar{F}_k(q_{jk}(\phi_j))}
\]

(6)

- Equations 3 and 4 define a system of \(l^2\) contractions and admit a unique fixed point.

- The optimal strategy when unemployed in city \(j\) is:
  1. accept any offer \(\varphi\) in city \(j\) strictly greater than the reservation wage \(\phi_j\)
  2. accept any offer \(\varphi\) in city \(l \neq j\) strictly greater than \(q_{jl}(\phi_j)\).

The optimal strategy when employed in city \(j\) at wage \(w\) is:

1. accept any offer \(\varphi\) in city \(j\) strictly greater than the present wage \(w\)
2. accept any offer \(\varphi\) in city \(l \neq j\) strictly greater than \(q_{jl}(w)\).

**Proof** In appendix A.1, we derive equations 3 and 4 using the definitions of \(\phi_j\) and \(q_{jl}(\cdot)\) and integration by parts. Then, in appendix A.2, we demonstrate the existence and uniqueness of the solution through an application of the Banach fixed-point theorem.

**Interpretation** The interpretation of Equation 3 is straightforward: the difference in the instantaneous values of unemployment and employment (\(\phi_j - b\)) reflects an opportunity cost, which must be perfectly compensated for by the difference in the option values of unemployment and employment. Those are composed of two elements: the expected wages through local job search and the expected wages through mobile job search, net of mobility costs.\(^{20}\)

The interpretation of Equation 4 is similar. The difference in the instant values of employed workers in location \(l\) and location \(j\) is \([q_{jl}(w) + \gamma_l] - [q_{jl}(w) + \gamma_j]\). The term \([\xi_{jl} \gamma_j - \gamma_l]\) is a measure of

\(^{20}\text{Note that the classical result whereby reservation wages are not binding stands true here, because agents are homogeneous and workers are allowed to transition into unemployment within the same city at no cost. Therefore, no firm will ever find it optimal to post a wage that is never accepted by a worker.}\)
the relative attractiveness of city $j$ and city $l$ in terms of amenities. The third term states that for job offers to attract jobseekers from distant locations, they have to overcome mobility costs. As for the difference in the option values of employment in city $j$ and employment in city $l$, it is threefold. The first part is independent of the wage level and given by the difference in the value of unemployment, weighted by unemployment risk $\delta_j$ or $\delta_l$. The second part is the difference in the expected wage following a local job-to-job transition and the third part is the difference in the expected wages that will be found through mobile job search, net of mobility costs.

This last term introduces the relative centrality and accessibility of city $j$ and city $l$. Centrality stems from the comparison of the strength of spatial frictions between the two locations $j$ and $l$ and the rest of the world: a worker living in city $j$ who receives an offer from city $l$ must take into account the respective spatial frictions from city $j$ and from city $l$ to any tier location $k$ that she may face in the future, in order to maximize her future job-offer rate. As for accessibility, it stems from the difference in the expected costs associated with mobile on-the-job search from city $j$ and from city $l$: an individual living in city $j$ who receives an offer from city $l$ must take into account the respective mobility cost from city $j$ and from city $l$ to any tier location $k$ that she may face in the future, in order to minimize the cost associated with the next move. Note that both the relative centrality and the relative accessibility measures depend on the current wage level $w$: cities may be more or less central and accessible depending on where workers stand in the earning distribution.

Finally, note that mobility costs impact the wage that will be accepted in the new city, which in turn impacts future wage growth prospects in this new city. In all generality, this dynamic feedback effect of mobility costs dramatically increases the state space, by making migration decisions depend on each worker’s entire migration history. Therefore, in order to keep the framework Markovian, one needs to assume that this mechanism is neglected by workers when they put together their migration strategies (see Appendix A.3 for details).

2.3 Steady-state

We use steady-state conditions on labor market flows along with spatial equilibrium conditions to solve our model.

**Spatial equilibrium** Workers in city $j$ are free to move into city $l$ upon paying a mobility cost $c_{jl}$ and becoming unemployed. Given the reservation wage strategy, this type of migration out of the labor market will mostly be an option for unemployed workers. However, the inflow of unemployed
workers into an attractive location will generate congestion externalities which will negatively impact local amenities and will also push housing prices upwards. In equilibrium, local amenities $\gamma_j$ adjust such that no individual agent has an incentive to move without a job offer, and leads to the following proposition:

**Proposition 2** CONGESTION — the vector of city amenities $\Gamma = \{\gamma_j\}_{j \in J}$ satisfies the set of constraints 7:

$$V_j^u \geq \max_{k \in J} \{V_k^u - c_{jk}\}$$

Steady state distribution of unemployment rates As already explained in section 1, a cross-sectional description of the labor market as a system of cities is fully characterized by a set of city-specific populations, unemployment rates and earning distributions. If these multi-dimensional outcome variables are constant, the economy can be said to have reached a steady-state. We now describe the theoretical counterparts to these three components.

At each point in time, the number of unemployed workers in a city $j$ is constant. A measure $u_j \lambda_j^u F_j(\phi_j)$ of workers leave unemployment in city $j$ by taking a job in city $j$, whereas others, of measure $u_j \sum_{k \in J \setminus j} s_{jk}^u \lambda_k^u F_k(q_{jk}(\phi_j))$, take a job in another city $k \neq j$. These two outflows are perfectly compensated for by a measure $(m_j - u_j) \delta_j$ of workers who were previously employed in city $j$ but have just lost their job. This equilibrium condition leads to the following proposition:

**Proposition 3** STEADY STATE UNEMPLOYMENT — the distribution of unemployment rates is given by $U = \{u_j\}_{j \in J}$, where:

$$u_j = \frac{\delta_j}{\delta_j + \lambda_j^u F_j(\phi_j) + \sum_{k \in J \setminus j} s_{jk}^u \lambda_k^u F_k(q_{jk}(\phi_j))}$$

Steady state distribution of city populations Similarly, at each point in time, population flows out of a city equal population inflows. For each city $j$, outflows are composed of employed and unemployed workers in city $j$ who find and accept another job in any city $k \neq j$; conversely, inflows are composed by employed and unemployed workers in any city $k \neq j$ who find and accept a job in city $j$. The equality between population inflow and outflow defines the following equation:

$$(m_j - u_j) \sum_{k \in J \setminus j} s_{jk}^e \lambda_k^e \int_{w}^{w} F_k(q_{jk}(x)) dG_j(x) + u_j \sum_{k \in J \setminus j} s_{jk}^u \lambda_k^u F_k(q_{jk}(\phi_j)) \equiv \lambda_j^e \sum_{k \in J \setminus j} s_{kj}^e (m_k - u_k) \int_{w}^{w} F_j(q_{kj}(x)) dG_k(x) + \lambda_j^u \sum_{k \in J} s_{kj}^u u_k F_j(q_{kj}(\phi_k))$$
Plugging Equation 8 into Equation 9, we recover a closed form solution for the system, written as:

$$M \mathcal{A} = 0$$

(10)

where $\mathcal{A}$ is the vector of city sizes $\{m_j\}_{j \in J}$ and $\mathcal{A}$ is the matrix of typical element $[\mathcal{A}]_{(j,l) \in J^2}$ defined by:

$$\mathcal{A}_{jj} = \frac{\lambda x F_j(\phi_j) + \frac{\sum_{k \in J} s_{jk} x_k F_k(q_{jk}(\phi_j))}{\sum_{k \in J, k \neq j} s_{jk} x_k F_k(q_{jk}(\phi_j))}}{\delta_j + \lambda x F_j(\phi_j) + \frac{\sum_{k \in J} s_{jk} x_k F_k(q_{jk}(\phi_j))}{\sum_{k \in J, k \neq j} s_{jk} x_k F_k(q_{jk}(\phi_j))}}$$

$$\mathcal{A}_{jl} = -\frac{\lambda x F_j(\phi_l) + \frac{\sum_{k \in J} s_{jk} x_k F_k(q_{jk}(\phi_l))}{\sum_{k \in J, k \neq j} s_{jk} x_k F_k(q_{jk}(\phi_l))}}{\delta_l + \lambda x F_l(\phi_l) + \frac{\sum_{k \in J} s_{lk} x_k F_k(q_{lk}(\phi_l))}{\sum_{k \in J, k \neq l} s_{lk} x_k F_k(q_{lk}(\phi_l))}} \quad \text{if } j \neq l$$

where off-diagonal elements equal the fraction of the population in the city in column who migrates into the city in row at any point in time, and diagonal elements equal the fraction of the population in the city in question who moves out at any point in time. This yields the following proposition:

**Proposition 4** **STEADY STATE POPULATION** — The distribution of city sizes is the positive vector $\mathcal{M} = \{m_j\}_{j \in J}$ s.t. $\sum_{j \in J} m_j = M$.

Note that Equation 9 defines a relationship between $m_j$ and all the other city sizes in $\mathcal{M}$, whereas it is not the case for $u_j$, which is determined by a single linear relationship to $m_j$. The flow of workers into unemployment in city $j$ is only composed of workers previously located in city $j$, whereas in Equation 9, the population in city $j$ is also determined by the flow of workers who come from everywhere else and have found a job in city $j$.

**Steady state distribution of observed wages** Finally, the distribution of observed wages is considered. Outflows from city $j$ are given by all the jobs in city $j$ with a wage lower than $w$ that are either destroyed or left by workers who found a better match. If it is located in city $j$, such match will correspond to a wage higher than $w$. However, if it is located in any city $k \neq j$, this match will only need to correspond to a wage higher than $q_{jk}(x)$, where $x < w$ is the wage previously earned in city $j$. The measure of this flow, which stems from the fact that we consider several separate markets, requires an integration over the distribution of observed wages in city $j$. Inflows to city $j$ are first composed of previously unemployed workers who find and accept a job in city $j$ with a wage lower than $w$. These workers may come from city $j$ or from any city $k \neq j$. However, they will only accept such a job if $w$ is higher than their reservation wage $\phi_j$ or than the mobility-compatible indifference wage of their reservation wage $q_{kj}(\phi_k)$. The second element of inflows is made of workers who were previously
employed in any city \( k \neq j \) at a wage \( x \) lower than the maximum wage such that moving to city \( j \) would yield a utility of \( V_j^x(w) \) (we denote this wage \( q_{kj}^{-1}(w) \)) and find a job at a wage between \( q_{kj}(x) \) and \( w \). Because of the existence of mobility costs, \( q_{kj}^{-1}(w) \neq q_{kj}(w) \) (see Section A.3 for details).

This is all summarized in Equation 11:

\[
(m_j - u_j) \left[ G_j(w) \left( \delta_j + \lambda_j^F \bar{F}_j(w) \right) + \sum_{k \in \mathcal{J}^j} \rho^e_{jk} \sum_{k \in \mathcal{J}^j} \int_{x}^{w} \bar{F}_k(q_{jk}(x)) dG_j(x) \right] \equiv (11)
\]

\[
\lambda_j^F \left[ \psi_{jj}(w) u_j (F_j(w) - F_j(\phi_j)) + \sum_{k \in \mathcal{J}^j} s^e_{jk} \psi_{jk}(w) u_k (F_j(w) - F_j(q_{kj}(\phi_k))) \right] + \lambda_j^e \sum_{k \in \mathcal{J}^j} s^e_{jk} (m_k - u_k) \int_{w}^{q_{kj}(w)} [F_j(w) - F_j(q_{kj}(x))] dG_k(x)
\]

where \( \psi_{kj}(w) = 1_{w > q_{kj}(\phi_k)} \) is a dummy variable indicating whether unemployed jobseekers in city \( k \) are willing to accept the job paid at wage \( w \) in city \( j \). Similarly, the integral in the last term gives the measure of job offers in city \( j \) that are associated with a wage lower than \( w \) yet high enough to attract employed workers from any city \( k \neq j \) and it is nil if \( q_{kj}^{-1}(w) < w \). These restrictions mean that very low values of \( w \) will not attract many jobseekers. We can differentiate Equation 11 with respect to \( w \).

This yields the following linear system of functional differential equations:

\[
f_j(w) = \frac{g_j(w) (m_j - u_j) \left[ \delta_j + \lambda_j^F \bar{F}_j(w) + \sum_{k \in \mathcal{J}^j} \rho^e_{jk} \sum_{k \in \mathcal{J}^j} \int_{x}^{w} \bar{F}_k(q_{jk}(x)) dG_j(x) \right]}{\lambda_j^F \left[ \psi_{jj}(w) u_j (F_j(w) - F_j(\phi_j)) + \sum_{k \in \mathcal{J}^j} s^e_{jk} \psi_{jk}(w) u_k (F_j(w) - F_j(q_{kj}(\phi_k))) \right] + \lambda_j^e \sum_{k \in \mathcal{J}^j} s^e_{jk} (m_k - u_k) \int_{w}^{q_{kj}(w)} [F_j(w) - F_j(q_{kj}(x))] dG_k(x)}
\]

(12)

In equilibrium, the instantaneous measure of match creations associated with a job paid at wage \( w \) and located in city \( j \) equals its counterpart of match destructions. Unlike the system 10, the uniqueness of the solution is not guaranteed. We defer the question of identification to section 3.2. We can then write the following proposition:

**Proposition 5** STEADY STATE WAGE OFFER DISTRIBUTIONS — The distribution of wage offers by location \( F(\cdot) \) is solution to the system 12.

**Summary** At steady state, this economy is characterized by a set of structural parameters and a wage offer distribution such that:

1. The reservation wage strategy \( \phi \) in Equation 3 describes the job acceptation behavior of immobile unemployed workers.

2. The mobility strategy between two locations \( q(\cdot) \) is defined by the indifference wage described in Equation 4.
3. The set of local amenities $\Gamma$ satisfies the market clearing constraints described by equation 7.

4. The set of unemployment rates $\mathcal{U}$ is given by Equation 8.

5. The set of city populations $\mathcal{M}$ is solution to the linear system 10.

6. The behaviour of firms, summarized by the set of wage offer distributions $F(\cdot)$ is solution to the system of functional differential equations 12.

### 3 Estimation

The model is estimated by simulated method of moments. The estimator minimizes the distance between a set of empirical moments and their theoretical counterparts, which are constructed by solving the steady-state conditions of the model. By definition, moments do not use of all the information in the data. However, given the size of the sample and the complexity of the model, a maximum likelihood approach is not currently feasible.

In Appendix B, we present a full set of solutions to solve the indifference wages and the functional equations. We take advantage of the structure of the model and use an embedded algorithm that allows us to recover a piecewise approximation of all indifference wages, and wage offer distributions. We detail here our choice of parameterization of spatial constraints and our identification strategy.

#### 3.1 Parameterization

In addition to 100 city-specific wage offer distributions, the model is based on a set of parameters $\theta = \{\lambda^e_j, \lambda^u_j, \delta_j, \gamma_j, s^e_{jk}, s^u_{jk}, c_{jk} \}_{(j,k) \in \mathcal{J} \times \mathcal{J}}$ such that $|\theta| = 30,100$ with $J = 100$. In practice, estimating parameters $s^l_{jl}$ and $c_{jl}$ for each pair of cities would be too computationally demanding and would require to drastically restrict $\mathcal{J}$. We take an alternative path and we posit and estimate two parsimonious parametric models:

$$s^l_{jl} = \frac{\exp(s^l_{j0} + s^l_{0l} + s^l_1 d_{jl} + s^l_2 d_{jl}^2 + s^l_3 h_{jl} + s^l_4 h_{jl}^2)}{1 + \exp(s^l_{j0} + s^l_{0l} + s^l_1 d_{jl} + s^l_2 d_{jl}^2 + s^l_3 h_{jl} + s^l_4 h_{jl}^2)}$$  \hspace{1cm} (13)

$$c_{jl} = c_0 + c_1 d_{jl} + c_2 d_{jl}^2$$  \hspace{1cm} (14)

where $s^l_{j0}$ and $s^l_{0l}$ are city-position (either on the sending or the receiving end of the job offer) fixed effects, $d_{jl}$ is the measure of physical distance between city $j$ and city $l$ and $h_{jl}$ is a dissimilarity index.
based on the sectoral composition of the workforce between 35 sectors.\textsuperscript{21}

The model rests upon the premise that spatial friction parameters take on values in $[0, 1]$, whereas the range of values for mobility costs is unrestricted. Given the lack of existing literature on the explicit structure of spatial frictions, we use a logistic function in Equation 13 because of its analytical properties.\textsuperscript{22} Equation 13 is akin to a standard gravity equation: the fixed effects measure the relative openness of the local labor markets: either the ability of each city to dispatch its jobseekers to jobs located elsewhere ($s_{j0}$) or to fill its vacancies with workers coming from other locations ($s_{0l}$), and the other parameters account for the effect of distance between two locations.\textsuperscript{23}

Physical distance is arguably the most important characteristic and both equations 13 and 14 rely on it. In addition, we allow spatial frictions to be also impacted by another measure of distance: sectoral dissimilarity, which proxies potential coordination frictions between the two locations. This feature is particularly important to rationalize job-to-job mobility rates between highly specialized but distant cities (for example, biotechnologies in Lyon and Strasbourg). We let returns to these two measures of distance vary by considering a second-order polynomial. Note that, in order to ensure continuity at the reservation wage, we assume that moving costs do not vary with labor market status, unlike spatial frictions.\textsuperscript{24} Also, our estimates of mobility costs will depend on the pair of cities involved, but not on the direction of the move.\textsuperscript{25}

Finally, in order to reduce the computational burden and ensure the smoothness of the density functions, we assume that $F(\cdot)$ follows a parametric distribution:

\[
F_j(x) = \text{betacdf}\left(\frac{x - b_j}{\mu_j - b_j}, \alpha_j, \beta_j\right)
\]

where $\text{betacdf}\{\cdot, \alpha_j, \beta_j\}$ is the cdf of a beta distribution with shape parameter $\alpha_j$ and scale parameter $\beta_j$. As argued by Meghir et al. (2015), this distribution is very flexible, without sacrificing parsimony. Under the specifications detailed in equations 13, 14 and 15, the number of parameters to be estimated amounts to 1,011.

\textsuperscript{21}We use the traditional Duncan index: if $v$ is a categorical variable defined by categories $k$ in proportions $v_j(k)$ and $v_l(k)$ in cities $j$ and $l$, $h_{jl} = \sum_k|v_j(k) - v_l(k)|$. In order to construct this variable, we use the 2007 version of a firm-level census called SIRENE.
\textsuperscript{22}See Zenou (2009) for a theoretical approach in terms of endogenous search intensity.
\textsuperscript{23}See Head & Mayer (2014) for the current state of the art about gravity equations.
\textsuperscript{24}This assumption may not be fully innocuous if unemployed jobseekers have access to some specific segments of the housing market, such as public housing.
\textsuperscript{25}This symmetry assumption could easily be relaxed, for instance by including an indicator variable on whether the destination city is larger or smaller than the departure city, as in Kennan & Walker (2011). However, as shown by Levy (2010) on US data, this may not be empirically relevant.
### 3.2 Identification

In this section, we discuss the identification of our model. A necessary condition of identification is the existence and uniqueness of the wage offer distribution, which is summarized in Proposition 6:

**Proposition 6**  
**EXISTENCE AND UNIQUENESS OF THE WAGE OFFER DISTRIBUTION** The system of differential equations \( f : \mathbb{R}^J \to (0, 1)^J \) has a unique fixed point.

**Proof** Existence stems from a direct application of *Schauder fixed-point theorem*. Regarding uniqueness, first note that since each \( f_j(\cdot) \) is a probability density function, it is absolutely continuous and its nonparametric kernel estimate is Lipschitz continuous; then, by contradiction, it is easy to show that two candidate solutions \( h^0(\cdot) \) and \( h^1(\cdot) \) cannot at the same time solve the differential equation, define a contraction, and be Lipschitzian. For more details, see Theorem 2.3 in Hale (1993).

**Identification in practice**  
Table 5 summarizes our choice of theoretical and empirical moments. As shown by Flinn & Heckman (1982) and Magnac & Thesmar (2002), structural parameters are identified from transition rates. Transitions out of unemployment to employment identify \( \lambda^u \) and \( s^u \). The same reasoning applies to the on-the-job search rates \( \lambda^e \) and \( s^e \). Finally, job destruction rates \( \delta \) are identified from transitions into unemployment. However, instead of using the raw transitions between employment and unemployment, we choose to identify \( \lambda^u \) and \( \delta \) using the city-specific populations and unemployment rates. The reason is threefold: first, since unemployment and population are the two most relevant dimensions of our model, we want to make sure that our estimation reproduces them as accurately as possible; second, given the structure of the DADS data, we think that the measurement of transitions into unemployment may sometimes lack precision; third, and most importantly, not using the transitions out of unemployment as a target moment provides us with a natural falsification test of our estimation results.

Given the parameterization of \( s^l_{jl} \), the model is over-identified: in particular, the \( 2J(J - 1) \) transition rates at the city-pair level that would be required to identify each parameter \( s^l_{jl} \) are no longer needed. In order to identify the fixed-effect components, we use the \( 2J \) total transitions rates into and out of any given city. On the other hand, the identification of the parameters related to the distance and the dissimilarity between two cities does still require transition rates at the city-pair level. Given that Equation 13 only specifies four parameters for each labor market status, we drastically restrict the set of city pairs, down to a subset \( \mathcal{T}_1 \subset \mathcal{J} \times \mathcal{J} \), with \( |\mathcal{T}_1| = 48 \), which we use in the estimation.\(^{26}\)

\(^{26}\) In practice, we use the off-the-job and job-to-job transitions rates from the urban areas ranked fourth to eleventh.
Table 5: Moments and Identification

<table>
<thead>
<tr>
<th>Empirical moments</th>
<th>Theoretical moments</th>
<th>Identifying Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate in city $j \in \mathcal{J}$</td>
<td>$u_j/m_j$</td>
<td>$\delta_j, \lambda^u_j$</td>
</tr>
<tr>
<td>Labor force in city $j \in \mathcal{J}$</td>
<td>$m_j$</td>
<td>$\delta_j, \lambda^u_j$</td>
</tr>
<tr>
<td>Transition rate $ee$ within city $j \in \mathcal{J}$</td>
<td>$\lambda^e_j \int \bar{F}_j(x) dG_j(x)$</td>
<td>$\lambda^e_j$, $\alpha_j$</td>
</tr>
<tr>
<td>Earning distribution in city $j \in \mathcal{J}$</td>
<td>$G_j$</td>
<td>$\alpha_j, \beta_j$</td>
</tr>
<tr>
<td>Transition rate $ee$ out of city $j \in \mathcal{J}$</td>
<td>$\sum_{k \in \mathcal{J}} s_{jk}^e \lambda^u_k \bar{F}<em>k(q</em>{jk}(w))$</td>
<td>$s_{j0}^u$</td>
</tr>
<tr>
<td>Transition rate $ee$ into city $l \in \mathcal{J}$</td>
<td>$\lambda^e_l \sum_{k \in \mathcal{J}} s_{kl}^e \lambda^u_k \bar{F}<em>k(q</em>{kl}(w))$</td>
<td>$s_{0l}^u$</td>
</tr>
<tr>
<td>Transition rate $ee$ out of city $j \in \mathcal{J}$</td>
<td>$\sum_{k \in \mathcal{J}} s_{jk}^e \lambda^e_k \int \bar{F}<em>k(q</em>{jk}(x)) dG_j(x)$</td>
<td>$s_{j0}^e$</td>
</tr>
<tr>
<td>Transition rate $ee$ into city $l \in \mathcal{J}$</td>
<td>$\lambda^e_l \sum_{k \in \mathcal{J}} s_{kl}^e \lambda^e_k \int \bar{F}<em>k(q</em>{kl}(x)) dG_k(x)$</td>
<td>$s_{0l}^e$</td>
</tr>
<tr>
<td>Transition rate $ee$ from city $j$ to city $l$, $(j, l) \in \mathcal{T}_1$</td>
<td>$s_{jl}^{eh} \lambda^h_l \bar{F}<em>l(q</em>{jl}(w))$</td>
<td>$s_{j1}^h, s_{j2}^h, s_{j3}^h, s_{j4}^h$</td>
</tr>
<tr>
<td>Transition rate $ee$ from city $j$ to city $l$, $(j, l) \in \mathcal{T}_2$</td>
<td>$s_{jl}^{eh} \lambda^h_l \int \bar{F}<em>l(q</em>{jl}(x)) dG_l(x)$</td>
<td>$s_{j1}^h, s_{j2}^h, s_{j3}^h, s_{j4}^h$</td>
</tr>
</tbody>
</table>

Accepted wage $ee$ between city $j$ and city $l$, $(j, l) \in \mathcal{T}_2$ | $q_{jl}(w^{init}_{eij})$ | $c_0, c_1, c_2$ |

Notes: (i) For details on the construction of the empirical moments, see Appendix C.3. (ii) In the third column, identifying parameters must be understood as the main parameters involved in the comparison of the two moments, even though all parameters are related to each other, in particular through the indifference wages.

While spatial friction parameters are identified from transition rates between pairs of cities, mobility costs are identified from data on wages. This strategy is made possible because we do not use wage data to approximate indifference wages. If the average wage accepted in city $l$ by jobseekers initially located in city $j$ differs from what is predicted by the labor market parameters, the level of centrality and the level of attractiveness of city $j$ and city $l$, this difference will be attributed to the specific distance between the two cities. To be more specific, let $w^{init}_{eij}$ denote the average initial wage of agents employed in city $j$ and who will experience a job-to-job transition within city $j$. Using the fact that $q_{jl}(\cdot)$ is a function, we consider as a theoretical moment, the difference between $q_{jl}(w^{init}_{eij})$ and $w^{init}_{eij}$ (which, by definition, is equal to $q_{jj}(w^{init}_{eij})$). The corresponding empirical moment is the difference between $w^{fin}_{eij}$ (the average wage after a job-to-job transition from city $j$ to city $l$), and $w^{fin}_{eij}$ (the average wage after a job-to-job transition within city $j$). Under the assumption that, con-
ditional on the local parameter values, jobseekers are as likely to draw a wage above their indifference wage when they do a job-to-job transition without mobility and when they do a job-to-job transition with mobility, these differences identify the mobility cost \( c_{jl} \). Given there only are three parameters to estimate, we select a subset of city pairs \( \mathcal{T}_2 \subset \mathcal{J} \times \mathcal{J} \) such that \(|\mathcal{T}_2| = 12\).

Finally, when all the parameters described in Table 5 have been estimated, we can recover the amenity parameters \( \gamma_j \) through an embedded algorithm that aims to satisfy the set of constraints described in Equation 7 (see Appendix B.4 for details).

### 3.3 Fit

We parameterize unemployment benefit \( b = €6,000 \) (an approximation of the minimum guaranteed income, which amounts to about half of the minimum wage) and \( r = 13.4\% \) (cumulated inflation from 2002 to 2007). The model is optimized using sequentially derivative free (Nelder-Mead, BoByQa, and Subplex) and Quasi-Newton optimization techniques (BFGS). Integrals are evaluated numerically using an Adaptive Gauss-Hermite Quadrature. Standard deviations are obtained using Laplace-Based Monte-Carlo Markov Chains starting from the optimum.

Figures 10 to 12 in Appendix D show that the model allows us to reproduce well many features of the data. The model predicts almost perfectly city-level job arrival rate for unemployed workers, even though transitions out of unemployment are not targeted in the estimation. In addition, the Pareto-shaped distribution of city sizes is almost perfectly replicated by the solution of a linear system of equations (figure 10). The mobility rates, which are not directly targeted by our estimation either, are also very well predicted, especially the in-migration rate for the unemployed and the out-migration rate for the employed (figure 11). There is more variation in the quality of the fit of city-specific wage distributions, but the fit is good, for all wage levels (figure 12).

### 4 Results

In this section, we first present our structural estimation results and in particular, the distribution of the city specific parameters and their relationship to city size. Then, we study the impact of distance

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29 If we did not use this differential approach, we would have to use the minimum observed values of accepted wages, which is not as well-behaved and would allow for more sampling error.

30 In practice, we use the average accepted wages following a job-to-job transition between the cities ranked second to fifth (Lyon, Marseille, Toulouse and Lille). This subset has to be more restrictive than \( \mathcal{T}_1 \) because, while very low transitions rates convey reliable information since they are drawn from large initial populations, they do not allow to compute accurate measures of average accepted wages. Note that for homogeneity concerns, we do not include Paris, because its size is too large compared to the other cities.
on spatial frictions and mobility costs. Finally, we provide a decomposition exercise to quantify the respective impact of spatial frictions and mobility costs on migration and unemployment.

4.1 A dataset of city-specific parameters

Table 6 provides summary statistics of the city-specific matching and amenity parameters and the four migration rates. The estimated values of $\lambda^u$, which range from 1.9 to 9.1, show substantial heterogeneity across cities, suggesting city average unemployment durations from 8 months to 3 years. The median value of 5 confirms the low transition rate of the French economy as documented by Jolivet, Postel-Vinay & Robin (2006). Local job finding rates for employed workers are low in comparison, but encompasses very diverse situations in terms of search intensity, likely more than for $\lambda^u$. In addition, this difference is partly compensated for by the relative weight of mobile job-to-job transitions, which is far more important. There still is considerable heterogeneity across cities, with an inter-decile ratio that is higher than for $\lambda^u$, whereas involuntary job separation rates are much less dispersed. Note that the distributions of in- and out-migration rates are very close to each other, in line with the steady state assumption on city populations.

<table>
<thead>
<tr>
<th></th>
<th>$\lambda^u_j$</th>
<th>$\lambda^e_j$</th>
<th>$\delta_j$</th>
<th>$\gamma_j$</th>
<th>$u_j e_l$</th>
<th>$e_j e_l$</th>
<th>$u_j e_l$</th>
<th>$e_j e_l$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>1.9</td>
<td>0.078</td>
<td>0.43</td>
<td>-5.8</td>
<td>0</td>
<td>0.042</td>
<td>0.0026</td>
<td>0.036</td>
</tr>
<tr>
<td>1st De.</td>
<td>3.2</td>
<td>0.092</td>
<td>0.53</td>
<td>-2</td>
<td>0.12</td>
<td>0.052</td>
<td>0.16</td>
<td>0.049</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>3.9</td>
<td>0.11</td>
<td>0.6</td>
<td>-0.72</td>
<td>0.21</td>
<td>0.065</td>
<td>0.26</td>
<td>0.061</td>
</tr>
<tr>
<td>40th Cent.</td>
<td>4.6</td>
<td>0.13</td>
<td>0.63</td>
<td>-0.17</td>
<td>0.32</td>
<td>0.073</td>
<td>0.36</td>
<td>0.071</td>
</tr>
<tr>
<td>Median</td>
<td>5</td>
<td>0.14</td>
<td>0.66</td>
<td>0</td>
<td>0.38</td>
<td>0.078</td>
<td>0.43</td>
<td>0.079</td>
</tr>
<tr>
<td>Mean</td>
<td>4.9</td>
<td>0.15</td>
<td>0.68</td>
<td>-0.44</td>
<td>0.49</td>
<td>0.082</td>
<td>0.49</td>
<td>0.082</td>
</tr>
<tr>
<td>5th</td>
<td>1.3</td>
<td>0.057</td>
<td>0.13</td>
<td>1.2</td>
<td>0.41</td>
<td>0.027</td>
<td>0.3</td>
<td>0.033</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>5.2</td>
<td>0.15</td>
<td>0.7</td>
<td>0.18</td>
<td>0.45</td>
<td>0.082</td>
<td>0.5</td>
<td>0.084</td>
</tr>
<tr>
<td>9th</td>
<td>6.4</td>
<td>0.2</td>
<td>0.82</td>
<td>0.47</td>
<td>1</td>
<td>0.12</td>
<td>0.91</td>
<td>0.12</td>
</tr>
<tr>
<td>Max</td>
<td>9.1</td>
<td>0.48</td>
<td>1.4</td>
<td>0.53</td>
<td>1.9</td>
<td>0.22</td>
<td>1.6</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Notes: (i) $u_j e_l$ is the out-migration rate for unemployed workers; (ii) $e_j e_l$ is the out-migration rate for employed workers; (iii) $u_j e_l$ is the in-migration rate for unemployed workers; (iv) $e_j e_l$ is the in-migration rate for employed workers. (v) Each distribution is evaluated on 99 cities; (vi) The numeraire of $\gamma$ is the maximum wage, roughly equal to 96,000 in 2002 €.

31 Those are respectively given by $\sum s_{jk} \lambda^u_j f_k(q_{jk}(w))$ and $\sum s_{jk} \lambda^e_j f^w_j f_k(q_{jk}(x))dG_j(x)$ for out-migration and by $\sum s_{jk} \lambda^u_j f_j(q_{jk}(w))$ and $\sum s_{jk} \lambda^e_j f^w_j f_j(q_{jk}(x))dG_k(x)$ for in-migration.
**Indifference functions**  Heterogeneous local parameters determine the relative strength (attractiveness, centrality) of each local labor market. Since the main mechanism of our model is based on $J(J - 1)$ indifference functions, we focus on a limited number of cities to illustrate its properties. We select Toulouse and Strasbourg, two growing cities of comparable size, respectively located in the South West and in the North East, and study the indifference wage associated with mobility toward cities located in the Center, North west, and South east. Figure 4 displays the nonlinear shape of the indifference wage functions for ten city pairs, and illustrates the numerical challenge raised by these objects: since the model does not include any support restriction on indifference wage, it is possible to observe negative indifference wages, implying that workers are willing to accept any wage offer as long as it covers moving costs.

**Figure 4: Leaving Toulouse and Strasbourg: ten examples of indifference wage functions**

The top graph shows that Toulouse, the fourth largest French city, is more attractive than Amiens, a middle-sized city in the north of Paris with a fragile economy. As confirmed in Table 7, Toulouse
Table 7: City-specific parameters: examples

<table>
<thead>
<tr>
<th>City</th>
<th>$\lambda_j^u$</th>
<th>$\lambda_j^e$</th>
<th>$\delta_j$</th>
<th>$\gamma_j$</th>
<th>$u_j e_l$</th>
<th>$e_j e_l$</th>
<th>$u_1 e_j$</th>
<th>$e_1 e_j$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Toulouse</td>
<td>5.20</td>
<td>0.31</td>
<td>0.43</td>
<td>0.31</td>
<td>0.32</td>
<td>0.13</td>
<td>0.43</td>
<td>0.16</td>
</tr>
<tr>
<td>Lille</td>
<td>4.43</td>
<td>0.30</td>
<td>0.55</td>
<td>0.33</td>
<td>0.25</td>
<td>0.15</td>
<td>0.26</td>
<td>0.16</td>
</tr>
<tr>
<td>Nantes</td>
<td>4.62</td>
<td>0.16</td>
<td>0.56</td>
<td>0.36</td>
<td>0.25</td>
<td>0.08</td>
<td>0.27</td>
<td>0.10</td>
</tr>
<tr>
<td>Tours</td>
<td>4.93</td>
<td>0.15</td>
<td>0.63</td>
<td>0.28</td>
<td>0.47</td>
<td>0.07</td>
<td>0.25</td>
<td>0.10</td>
</tr>
<tr>
<td>Orleans</td>
<td>6.61</td>
<td>0.14</td>
<td>0.57</td>
<td>0.21</td>
<td>1.34</td>
<td>0.08</td>
<td>0.31</td>
<td>0.09</td>
</tr>
<tr>
<td>Amiens</td>
<td>3.93</td>
<td>0.17</td>
<td>0.64</td>
<td>0.24</td>
<td>0.24</td>
<td>0.10</td>
<td>0.25</td>
<td>0.10</td>
</tr>
<tr>
<td>Strasbourg</td>
<td>6.00</td>
<td>0.16</td>
<td>0.66</td>
<td>0.41</td>
<td>0.75</td>
<td>0.08</td>
<td>0.23</td>
<td>0.10</td>
</tr>
<tr>
<td>Nice</td>
<td>5.37</td>
<td>0.16</td>
<td>0.83</td>
<td>0.48</td>
<td>0.45</td>
<td>0.07</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Grenoble</td>
<td>5.38</td>
<td>0.15</td>
<td>0.78</td>
<td>0.50</td>
<td>0.31</td>
<td>0.06</td>
<td>0.08</td>
<td>0.13</td>
</tr>
<tr>
<td>Annecy</td>
<td>6.14</td>
<td>0.16</td>
<td>0.82</td>
<td>0.49</td>
<td>0.79</td>
<td>0.08</td>
<td>0.15</td>
<td>0.12</td>
</tr>
<tr>
<td>Chambéry</td>
<td>6.13</td>
<td>0.14</td>
<td>0.65</td>
<td>0.50</td>
<td>0.60</td>
<td>0.06</td>
<td>0.12</td>
<td>0.13</td>
</tr>
<tr>
<td>Macon</td>
<td>6.60</td>
<td>0.13</td>
<td>0.72</td>
<td>0.47</td>
<td>1.35</td>
<td>0.07</td>
<td>0.17</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Notes: (i) see Table 6. (ii) The respective ranks of these twelve cities in the city size distribution are 4 (Toulouse), 5 (Lille), 7 (Nice), 8 (Nantes), 9 (Strasbourg), 10 (Grenoble), 21 (Orleans), 33 (Amiens), 44 (Annecy), 45 (Chambéry) and 88 (Macon).

dominates Amiens on all dimensions: its local labor market is more dynamic (higher $\lambda_j^u$ and $\lambda_j^e$, lower $\delta$), workers in Toulouse have a better access to the rest of the country (higher out-migration rates) and even amenities are higher in the “Pink city” than in the French “Venice of the North”. Workers migrating from Toulouse to Amiens may only do so with relatively low initial wage, and they will need a large compensation. On the other hand, amenities in Nantes, the eighth largest city located close to the Atlantic coast, are high enough to counterbalance a less dynamic labor market for any wage level. Lille, Tours and Orleans are intermediate cases, for various reasons. Lille benefits from slightly higher amenities, which confers an initial advantage, but its labor market is otherwise not as promising as Toulouse's: this shows indirectly through its much lower in-migration rates. As for Orleans and Tours, their main advantage is to work as a springboard for unemployed workers, who benefit from very high out-migration rates.

The second group is made of cities which, despite their very different sizes (from rank 7 to rank 88) exhibit strikingly similar profiles: high-amenity cities (mountains for Grenoble, Annecy and Chambéry, Riviera for Nice, famous wine-making region for Macon) with a high frequency of transitions into and out of unemployment (high $\lambda_j^u$ and high $\delta$) but relatively low opportunities for employed workers. Strasbourg, the city with the lowest amenities, suffers from an initial disadvantage: only Nice, a large but isolated city with a speculative housing market driven by a steady inflow of retirees, seems to require a compensation for low-wage workers. Note that, while all the indifference wages
involving Toulouse exhibit a wage gradient steeper than one, which shows that the dynamism of on-the-job search in Toulouse (and the opportunities that come along for high-wage workers) tends to increase its attractiveness through wage ladder, this is not the case for workers initially located in Strasbourg: the wage gradient is fairly flat. Another interesting feature is the crossing of the indifference wages involving Grenoble and Chambery, two neighbor cities with very high amenities, but where the latter, which is also the smaller of the two, seems to be offering more opportunities, at least for its unemployed workers.

**Large, medium and small cities** We use our estimation results to characterize the relationship between matching parameters and city size. To ease exposition we group cities into three categories that correspond to families of statistical relationship between matching rates and size. To that end, Figures 5 and 6 display the distribution of the eight objects described in Table 6 according to city size. Local job finding rates, both for unemployed and employed workers are, indeed, larger in larger cities. In addition, there is a positive correlation between them and city size among the group of large cities, whereas this is not the case elsewhere (Figure 5). A very similar pattern is observed for the migration rates, both into and out of large cities, but only for employed workers (Figure 6): large cities play a disproportionately large role in the spatial reallocation of employed workers within the urban system. This may be related to career mobility, whereby workers tend to be dispatched to large cities before, in some occasions, a subsequent mobility into a smaller location.

Since large cities are not characterized by higher job destruction rates or lower amenity levels, these figures suggest that workers in these cities benefit from high job finding rate possibly originating from matching economies which are not fully offset by congestion externalities or capitalized into local price levels. Although these findings suggest a duality in the typology of cities, it appears that on-the-job search opportunities increase with city population over the complete set of cities except an intermediate range of medium cities, over which the gradient is flat, and possibly slightly negative. These findings are possible only because of the heterogeneity within each class of city.

**Correlations** We now turn to the correlation between our parameters and the local distributions of earnings, captured by average and coefficient of variation of wages. The correlation matrix is displayed in Table 8 and shows a positive correlation ($\rho = 0.21$) between on-the-job search rate and wage dispersion at the city level, which is in line with the insights of the wage posting theory, as outlined by Burdett & Mortensen (1998). Second, a strong positive correlation between the average level of
Figure 5: Job-finding and layoff rates, local amenities and city size

Notes: (i) Estimated values of the structural parameters ($\lambda^u, \lambda^e, \delta, \gamma$) for the 20 largest cities, the 49 smallest cities and the 30 cities in between; The city 100 is made of all remaining metropolitan areas. It is included in the estimation but its parameters are not meaningful and therefore are not represented here.
Figure 6: Migration rates and city size

Notes: (i) Estimated values of the migration rates for the 20 largest cities, the 49 smallest cities and the 30 cities in between: The city 100 is made of all remaining metropolitan areas. It is included in the estimation but its parameters are not meaningful and therefore are not represented here.
earnings and the likelihood of receiving job offers is observed, unsurprisingly, for the job arrival rate of employed workers ($\rho = 0.52$), but also for the job arrival rate of unemployed workers ($\rho = 0.37$) as well. Third, cities with high local job finding opportunities are also well integrated in the urban system, both for unemployed workers ($\rho = 0.77$) or for employed workers ($\rho = 0.89$). Finally, employed workers tend to move into cities with higher amenities ($\rho = 0.30$) and move out of cities with lower amenities ($\rho = -0.29$), while the opposite logically stands true for unemployed workers.

### Table 8: Correlations between estimates and labor market primitives

<table>
<thead>
<tr>
<th></th>
<th>$\lambda^u_j$</th>
<th>$\lambda^e_j$</th>
<th>$\delta_j$</th>
<th>$\gamma_j$</th>
<th>$u_j e_l$</th>
<th>$e_j e_l$</th>
<th>$u_l e_j$</th>
<th>$e_l e_j$</th>
<th>$E(w)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda^e$</td>
<td>0.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta$</td>
<td>-0.03</td>
<td>0.11</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.46**</td>
<td>0.02</td>
<td>-0.20*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$u_j e_l$</td>
<td>0.77**</td>
<td>-0.16</td>
<td>0.04</td>
<td>0.47**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_j e_l$</td>
<td>-0.10</td>
<td>0.89*</td>
<td>0.04</td>
<td>-0.29**</td>
<td>-0.34**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$u_l e_j$</td>
<td>-0.18</td>
<td>-0.18</td>
<td>-0.16</td>
<td>-0.60**</td>
<td>-0.19</td>
<td>0.19</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$e_l e_j$</td>
<td>0.36**</td>
<td>0.89**</td>
<td>0.13</td>
<td>0.30**</td>
<td>0.09</td>
<td>0.66**</td>
<td>-0.41**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$E(w)$</td>
<td>0.37**</td>
<td>0.52**</td>
<td>-0.07</td>
<td>0.32**</td>
<td>0.14</td>
<td>0.40**</td>
<td>-0.17</td>
<td>0.60**</td>
<td></td>
</tr>
<tr>
<td>$cv$</td>
<td>0.14</td>
<td>0.21*</td>
<td>-0.08</td>
<td>-0.06</td>
<td>0.06</td>
<td>0.24*</td>
<td>0.24</td>
<td>0.13</td>
<td>-0.04</td>
</tr>
</tbody>
</table>

Notes: (i) Wage distributions are evaluated over the six-year span 2002-2007 (ii) ** $p < 0.01$, * $p < 0.05$; (ii) $E(w)$ is the average wage in each city and $cv$ is the coefficient of variation of wages in each city; (iii) Each correlation is evaluated on 99 cities.

### 4.2 Quantifying spatial constraints

We now turn to the quantification of spatial constraints implied by our parameter estimates. We first describe the distribution of mobility costs and show that they are one order of magnitude lower than previously reported in the frictionless literature. Then, we discuss the impact of physical and sectoral distance between cities on their ability to share information. Finally, we provide a simple decomposition exercise to evaluate the respective impact of mobility costs and informational frictions on aggregate labor mobility and unemployment.

**Reassessing the magnitude of mobility costs**  According to our results, average mobility costs are twenty times lower than the mobility cost found by Kennan & Walker (2011), who estimate a value of $312,000 for the average mover. There is a number of reasons that might explain these differences, but we believe the introduction of spatial frictions to be the main driver. Our estimates for Equation 14 indicate that the mobility cost function is given by $\hat{c}_{jl} = 12,003 + 725.56d_{jl} + 1.2292d_{jl}^2$, with 100 km as the unit for distance. This function is positive and increasing for all possible values of distance,
which means that we do not find any evidence of negative mobility costs (or relocation subsidies) in
the French labor market, at least at the city-pair level. It amounts to an (unweighted) average value of
€15,461, which is approximately equal to 1.5 times the annual minimum wage, or, more significantly,
to the first quartile of the annual wage distribution: such values remain economically meaningful,
and they surely prevent many workers at the bottom of the wage distribution from taking advantage
of distant job opportunities.

The fixed component of the mobility cost, equal to €12,003, may strike as high. However, one has
to bear in mind that it may include both relocation costs, transaction costs on the housing market
and psychic costs related to the loss of local network connections. On average, the distance penalty
amounts to about 22% of the total cost. However, as shown in Table 9, distance may account for up
to 75% of variation. Moving to Paris or Lyon, the two largest French cities, which also are the most
central among the eight first cities, is on average about 7% cheaper than moves toward Marseilles and
10% cheaper than mobility to Nice, and 90% of the moves involving either Lyon or Paris are cheaper
than half of the moves involving Nice.

Table 9: Distribution of the mobility costs involving all cities or one of the eight first cities

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Paris</th>
<th>Lyon</th>
<th>Marseilles</th>
<th>Toulouse</th>
<th>Lille</th>
<th>Bordeaux</th>
<th>Nice</th>
<th>Nantes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>12,160</td>
<td>12,324</td>
<td>12,200</td>
<td>12,380</td>
<td>12,384</td>
<td>12,190</td>
<td>12,859</td>
<td>12,327</td>
<td>12,427</td>
</tr>
<tr>
<td>1st De.</td>
<td>13,243</td>
<td>13,121</td>
<td>12,862</td>
<td>13,582</td>
<td>13,315</td>
<td>12,892</td>
<td>13,536</td>
<td>13,970</td>
<td>13,320</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>14,190</td>
<td>13,565</td>
<td>14,002</td>
<td>14,455</td>
<td>14,635</td>
<td>14,449</td>
<td>14,497</td>
<td>14,847</td>
<td>14,329</td>
</tr>
<tr>
<td>40th Cent.</td>
<td>14,947</td>
<td>14,516</td>
<td>14,567</td>
<td>15,542</td>
<td>15,293</td>
<td>15,331</td>
<td>15,350</td>
<td>15,924</td>
<td>15,402</td>
</tr>
<tr>
<td>Median</td>
<td>15,417</td>
<td>14,758</td>
<td>14,967</td>
<td>15,964</td>
<td>15,604</td>
<td>15,423</td>
<td>15,716</td>
<td>16,474</td>
<td>15,750</td>
</tr>
<tr>
<td>Mean</td>
<td>15,461</td>
<td>14,758</td>
<td>14,967</td>
<td>15,964</td>
<td>15,604</td>
<td>15,423</td>
<td>15,716</td>
<td>16,474</td>
<td>15,750</td>
</tr>
<tr>
<td>Sd</td>
<td>1,677</td>
<td>1,234</td>
<td>1,499</td>
<td>1,782</td>
<td>1,434</td>
<td>1,616</td>
<td>1,517</td>
<td>1,932</td>
<td>1,756</td>
</tr>
<tr>
<td>60th Cent.</td>
<td>15,874</td>
<td>15,196</td>
<td>15,329</td>
<td>16,580</td>
<td>16,126</td>
<td>15,954</td>
<td>16,254</td>
<td>17,219</td>
<td>16,342</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>16,630</td>
<td>15,674</td>
<td>15,935</td>
<td>17,294</td>
<td>16,860</td>
<td>16,577</td>
<td>16,836</td>
<td>17,816</td>
<td>16,985</td>
</tr>
<tr>
<td>9th De.</td>
<td>17,670</td>
<td>16,304</td>
<td>16,751</td>
<td>18,023</td>
<td>17,316</td>
<td>17,482</td>
<td>17,753</td>
<td>18,639</td>
<td>18,034</td>
</tr>
<tr>
<td>Max</td>
<td>21,208</td>
<td>17,116</td>
<td>19,204</td>
<td>20,246</td>
<td>17,861</td>
<td>18,263</td>
<td>18,659</td>
<td>21,208</td>
<td>18,838</td>
</tr>
</tbody>
</table>

Notes: (i) There are 9,702 possible moves between 99 cities; however, given the symmetry assumption $c_{ij} = c_{ji}$, only half of
these moves are needed to compute these distributions; (ii) Costs are given in 2002 €.

The content of spatial frictions  Cities differ along many dimensions that may explain the existence
of informational frictions. As detailed in Section 3.1, we focus on two characteristics: spatial distance
and sectoral dissimilarity between each pair of cities. Even though the correlation between these
two measures is strongly positive, there may be compensating differences: for instance, the distance
between Nice and Nantes (respectively, the seventh and the eighth city) is at the 97th percentile of
the distance matrix and their level of sectoral dissimilarity corresponds to the 37th percentile of the
dissimilarity matrix.

Our specification allows us to quantify the effect of geographical and sectoral differences on informational frictions between each pair of cities using the derivative of Equation 13 with respect to $d_{jl}$ and $h_{jl}$. Because of the city fixed effect in spatial frictions, the effect of distance is not uniform. Table 10 reports the distribution of the estimated elasticities of spatial search efficiency parameters for all city pairs $(j, l) \in J \times J$ and for all moves involving Paris, as well as distance elasticities involving Nice and dissimilarity elasticities involving Bordeaux. The elasticities $\epsilon$ are denoted $\epsilon^d_j$ for the elasticity of $s^d_{ijl}$ with respect to distance and $\epsilon^h_j$ for the elasticity of $s^d_{ijl}$ with respect to dissimilarity. For expositional purposes, the estimated values for $\epsilon^d_j$ are multiplied by 100.

Table 10: The effect of distance and dissimilarity on spatial frictions

<table>
<thead>
<tr>
<th></th>
<th>All city pairs</th>
<th>Paris</th>
<th>Nice</th>
<th>Bordeaux</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>-0.52</td>
<td>-0.29</td>
<td>-0.52</td>
<td>-0.29</td>
</tr>
<tr>
<td>1st De.</td>
<td>-0.32</td>
<td>-0.18</td>
<td>-0.37</td>
<td>-0.24</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>-0.26</td>
<td>-0.15</td>
<td>-0.21</td>
<td>-0.24</td>
</tr>
<tr>
<td>40th Cent.</td>
<td>-0.22</td>
<td>-0.13</td>
<td>-0.18</td>
<td>-0.18</td>
</tr>
<tr>
<td>Median</td>
<td>-0.19</td>
<td>-0.12</td>
<td>-0.16</td>
<td>-0.12</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.19</td>
<td>-0.15</td>
<td>-0.15</td>
<td>-0.12</td>
</tr>
<tr>
<td>Sd</td>
<td>0.09</td>
<td>0.12</td>
<td>0.11</td>
<td>0.14</td>
</tr>
<tr>
<td>60th Cent.</td>
<td>-0.16</td>
<td>-0.14</td>
<td>-0.22</td>
<td>-0.17</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>-0.12</td>
<td>-0.09</td>
<td>-0.16</td>
<td>-0.15</td>
</tr>
<tr>
<td>9th De.</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.11</td>
<td>-0.13</td>
</tr>
<tr>
<td>Max</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.02</td>
<td>-0.10</td>
</tr>
</tbody>
</table>

Notes: the elasticities are given by $\epsilon^d_j = \frac{s^d_{ijl} + 2s^d_{1j}d_{jl}}{1 + \exp(x^d_{ijl})}$ and $\epsilon^h_j = \frac{s^h_{ijl} + 2s^h_{1j}h_{jl}}{1 + \exp(x^h_{ijl})}$, with $x^d_{ijl} = \logit(s^d_{ijl})$.

Both physical distance and sectoral dissimilarity increase the level of spatial frictions as expected. However, the effect is larger for dissimilarity than for geographical distance: by two orders of magnitude, with a median distance elasticity of -0.19% and -0.14% for unemployed and employed workers, respectively, against a median of -19% and -59% for dissimilarity. Whereas, as shown previously, physical distance does substantially impact mobility costs, it has almost no effect on spatial frictions. The other striking result is that dissimilarity plays a much more important role for employed workers, which is easy to understand, since a large share of job-to-job transitions take place within the same sector. If anything, the reverse is true for the impact of distance, which seems to be somewhat more important for unemployed workers: unemployed jobseekers benefit less from large firm networks with formal matchmaking processes, they have to rely more on unofficial channels which are more

$^{32}$ The estimates of $s^d_{ik}$, $(i, k) = (e, u) \times \{(1, 4)\}$, that enter in the specification of the spatial frictions are significantly different from zero. Standard errors are available upon request.
sensitive to distance.

Location matters: Paris, a very central city, has a lower than average median distance elasticity, unlike Nice, for which it is higher. The same stands true for dissimilarity: more specialized cities are more sensitive to dissimilarity than others. Spatial frictions involving Bordeaux, the sixth city with a median dissimilarity index of 0.139, are less dissimilarity elastic than average, whereas the opposite is true for Paris (median dissimilarity index of 0.202), which is fairly specialized given its unique role in the French economy.

**Decompositions: the impact of spatial constraints on mobility and unemployment** Finally, we use our estimation results to compare the respective impacts of mobility costs and spatial frictions on labor mobility and unemployment in the economy. Local unemployment \( U_j = u_j/m_j \) is the unemployment rate in city \( j \), as defined in equation 8. Local mobility is measured by the migration rate out of city \( j \), \( \mu_j \), which is an employment status weighted sum of mobile job finding rate for unemployed workers and for employed workers. It is defined by equation 16:

\[
\mu_j = \sum_{k \notin j} \left( \frac{u_j}{m_j} s_{jk}^u \lambda_k \tilde{F}_k(q_jk(w)) + \left( 1 - \frac{u_j}{m_j} \right) s_{jk}^e \lambda_k \tilde{F}_k(q_jk(x)) \int_{\omega}^{w} F_k(q_jk(x)) dG_j(x) \right) \tag{16}
\]

We proceed as follows: for a given scalar \( \omega \), and for a matrix \( x \), we compute the vectors of counterfactual unemployment rates \( U_j(x) \equiv U_j(\omega x) \) if \( x = s_{jk}^u \) or \( x = s_{jk}^e \) and \( U_j(x) \equiv U_j(\frac{1}{\omega} x) \) if \( x = c_{jk} \). We then define \( \Delta U_j(x) \equiv U_j(x) - U_j \). Counterfactual mobility rates are computed the same way. We consider that the level of spatial integration in the economy is increased by \( 100(\omega - 1)\% \) if \( \omega > 1 \) and decreased by \( 100(1 - \omega)\% \) if \( \omega < 1 \). Results are described in Table 11 for five values of \( \omega \), from \( \omega = 0.1 \) to \( \omega = 2 \).

Local labor markets are not all equally integrated into the system of cities, which is reflected in the high level of heterogeneity displayed by the effects of spatial constraints. A striking example is that for only one of the 30 effects described in the table, the maximum and the minimum effects are of the same sign. This shows how differently the cities, depending on their location, their level of specialization and the dynamism of their internal labor market, would react to a change in spatial constraints. Increasing the efficiency of spatial job search for the unemployed by 50% (\( \omega = 1.5 \)) translates into a 31.3% decrease in the unemployment rate in Maubeuge (rank 61), into a 21.1% decrease in Lyon and only a 11.8% decrease in Nice. Avignon (rank 45, +1.5%), among a few others, even witnesses an increase in unemployment: for them, indirect effects of the increase in \( s_{jk}^u \), which lead to an increase in indifference wages departing from Avignon, overcome the direct impact of enlarging the information
## Table 11: The effect of spatial frictions and mobility cost on local unemployment and mobility

<table>
<thead>
<tr>
<th></th>
<th>( \Delta U_j(s_{j1}^\omega) )</th>
<th>( \Delta U_j(s_{j1}^\omega) )</th>
<th>( \Delta U_j(c_{j1}) )</th>
<th>( \Delta \mu_j(s_{j1}^\omega) )</th>
<th>( \Delta \mu_j(s_{j1}^\omega) )</th>
<th>( \Delta \mu_j(c_{j1}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \omega = 0.1 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>-1.054</td>
<td>-0.221</td>
<td>-39.259</td>
<td>-90.719</td>
<td>-90.000</td>
<td>-1,823.833</td>
</tr>
<tr>
<td>1st Dec.</td>
<td>7.924</td>
<td>-0.037</td>
<td>-19.720</td>
<td>-89.887</td>
<td>-33.451</td>
<td>-323.102</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>12.079</td>
<td>-0.012</td>
<td>-0.318</td>
<td>-88.371</td>
<td>-19.846</td>
<td>-84.800</td>
</tr>
<tr>
<td>Median</td>
<td>26.119</td>
<td>0.000</td>
<td>6.889</td>
<td>-82.283</td>
<td>-4.729</td>
<td>-1.521</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>38.131</td>
<td>0.006</td>
<td>11.702</td>
<td>-68.790</td>
<td>-0.859</td>
<td>28.688</td>
</tr>
<tr>
<td>9th Dec.</td>
<td>47.109</td>
<td>0.080</td>
<td>13.423</td>
<td>-47.951</td>
<td>-0.105</td>
<td>63.993</td>
</tr>
<tr>
<td>Max</td>
<td>69.966</td>
<td>0.185</td>
<td>17.255</td>
<td>3.819</td>
<td>3.164</td>
<td>87.504</td>
</tr>
<tr>
<td>( \omega = 0.2 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>-2.616</td>
<td>-0.196</td>
<td>-23.647</td>
<td>-82.627</td>
<td>-80.000</td>
<td>-1,367.687</td>
</tr>
<tr>
<td>1st Dec.</td>
<td>7.308</td>
<td>-0.032</td>
<td>-7.965</td>
<td>-80.144</td>
<td>-29.588</td>
<td>-313.282</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>10.866</td>
<td>-0.011</td>
<td>-1.638</td>
<td>-79.811</td>
<td>-17.582</td>
<td>-74.031</td>
</tr>
<tr>
<td>Median</td>
<td>22.763</td>
<td>0.000</td>
<td>0.655</td>
<td>-74.310</td>
<td>-4.207</td>
<td>-0.882</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>31.551</td>
<td>0.005</td>
<td>2.730</td>
<td>-58.065</td>
<td>-0.755</td>
<td>26.302</td>
</tr>
<tr>
<td>9th Dec.</td>
<td>39.792</td>
<td>0.072</td>
<td>3.501</td>
<td>-36.554</td>
<td>-0.093</td>
<td>60.168</td>
</tr>
<tr>
<td>Max</td>
<td>57.720</td>
<td>0.166</td>
<td>6.562</td>
<td>17.906</td>
<td>3.550</td>
<td>86.937</td>
</tr>
<tr>
<td>( \omega = 0.5 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>-4.269</td>
<td>-0.110</td>
<td>-6.454</td>
<td>-62.359</td>
<td>-50.000</td>
<td>-422.193</td>
</tr>
<tr>
<td>1st Dec.</td>
<td>2.147</td>
<td>-0.018</td>
<td>-1.523</td>
<td>-55.997</td>
<td>-18.310</td>
<td>-153.352</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>6.546</td>
<td>-0.006</td>
<td>-0.269</td>
<td>-53.343</td>
<td>-10.367</td>
<td>-41.396</td>
</tr>
<tr>
<td>Median</td>
<td>13.113</td>
<td>0.000</td>
<td>0.152</td>
<td>-49.835</td>
<td>-2.569</td>
<td>-0.714</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>17.063</td>
<td>0.004</td>
<td>0.484</td>
<td>-39.808</td>
<td>-0.455</td>
<td>25.750</td>
</tr>
<tr>
<td>9th Dec.</td>
<td>21.768</td>
<td>0.043</td>
<td>0.779</td>
<td>-20.129</td>
<td>-0.058</td>
<td>48.814</td>
</tr>
<tr>
<td>Max</td>
<td>29.656</td>
<td>0.105</td>
<td>1.329</td>
<td>42.638</td>
<td>3.569</td>
<td>85.301</td>
</tr>
<tr>
<td>( \omega = 1.5 )</td>
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<tr>
<td>Min</td>
<td>-31.387</td>
<td>-0.168</td>
<td>-0.777</td>
<td>-79.112</td>
<td>-9.470</td>
<td>-491.100</td>
</tr>
<tr>
<td>1st Dec.</td>
<td>-25.208</td>
<td>-0.084</td>
<td>-0.382</td>
<td>-21.732</td>
<td>0.085</td>
<td>-115.230</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>-22.241</td>
<td>-0.010</td>
<td>-0.216</td>
<td>-25.519</td>
<td>0.245</td>
<td>0.349</td>
</tr>
<tr>
<td>Median</td>
<td>-18.503</td>
<td>0.000</td>
<td>-0.010</td>
<td>55.525</td>
<td>4.969</td>
<td>32.386</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>-11.339</td>
<td>0.009</td>
<td>0.071</td>
<td>91.766</td>
<td>16.514</td>
<td>44.141</td>
</tr>
<tr>
<td>9th Dec.</td>
<td>-2.398</td>
<td>0.030</td>
<td>0.848</td>
<td>103.235</td>
<td>36.264</td>
<td>52.647</td>
</tr>
<tr>
<td>Max</td>
<td>22.570</td>
<td>0.164</td>
<td>6.755</td>
<td>309.482</td>
<td>100.000</td>
<td>62.657</td>
</tr>
<tr>
<td>( \omega = 2 )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>-63.190</td>
<td>-0.680</td>
<td>-1.147</td>
<td>-81.030</td>
<td>0.000</td>
<td>-1207.644</td>
</tr>
<tr>
<td>1st Dec.</td>
<td>-56.200</td>
<td>-0.279</td>
<td>-0.611</td>
<td>-4.567</td>
<td>0.498</td>
<td>-170.735</td>
</tr>
<tr>
<td>1st Qu.</td>
<td>-53.104</td>
<td>-0.053</td>
<td>-0.301</td>
<td>57.138</td>
<td>2.381</td>
<td>-5.647</td>
</tr>
<tr>
<td>Median</td>
<td>-44.021</td>
<td>0.000</td>
<td>-0.052</td>
<td>204.334</td>
<td>21.982</td>
<td>35.933</td>
</tr>
<tr>
<td>3rd Qu.</td>
<td>-34.738</td>
<td>0.039</td>
<td>0.215</td>
<td>373.167</td>
<td>63.661</td>
<td>49.889</td>
</tr>
<tr>
<td>9th Dec.</td>
<td>-13.487</td>
<td>0.109</td>
<td>1.050</td>
<td>528.088</td>
<td>137.977</td>
<td>59.818</td>
</tr>
<tr>
<td>Max</td>
<td>11.160</td>
<td>0.676</td>
<td>7.970</td>
<td>1050.569</td>
<td>400.000</td>
<td>70.217</td>
</tr>
</tbody>
</table>

Notes: (i) Distribution of the relative impact, in percentage points, of decreasing \( \omega < 1 \) or increasing \( \omega > 1 \) the level of spatial integration on the distribution of local unemployment rates and local out-migration rates; (ii) For consistency between the respective impacts of spatial frictions and mobility costs, the former are multiplied by \( \omega \), whereas the latter are divided by \( \omega \); (iii) The residual city 100 is not included.
set available to workers who are unemployed there. As for Paris, it is almost unaffected (-2.5%), because its size and the dynamism of its internal labor market make it much less dependent on access to the other cities.

In spite of this heterogeneity, several features stand out. First, the median impact of $s_{jk}$ on both outcomes is much higher than the median impact of $s_{jk}^u$ or $c_{jk}$. Second, the only way of significantly reducing unemployment is to increase $s_{jk}^u$: if those parameters are doubled, this leads to more than a 35% decrease in local unemployment for 75 cities. By comparison, the maximum impact of dividing mobility costs by two is a 1% decrease in local unemployment, and both the effect of lower mobility costs and the effect of more efficient spatial job search for employed workers, albeit small, display considerable heterogeneity. Reducing mobility costs does not have any sizeable beneficial impact on unemployment in most cities because mobility costs only make up for a small fraction of the indifference wages. Yet, very high mobility costs may still act as a deterrent, by shutting down some of the migration strategies still available to unemployed workers: for example, a tenfold increase in mobility costs ($\omega = 0.1$) has a median effect of 6.9%, which remains lower than the 26.1% effect of a tenfold decrease in $s_{jk}^u$, but is not so by two or three orders of magnitude, as is the case when $\omega > 1$.

If one focuses on median impact, this asymmetry seems to be reversed for labor mobility. For example, a 50% reduction in spatial frictions for the unemployed increases mobility by +55.5%, against only +5% for the same decrease in frictions for employed workers, but a substantial +32.4% for mobility cost. On the other hand, the median impact of mobility costs when $\omega < 1$ is very low. This suggests two remarks. First, the impact of $s_{jk}^u$ strikes as low: this is due to the fact that employed workers are far less mobile than their unemployed counterparts, and the impact of spatial constraints on labor mobility is difficult to interpret because of the composition effect shown in equation 16, which introduces a spuriously positive correlation between unemployment and labor mobility. Second, even if the median impact of mobility costs on migration is very close to zero for lower levels of spatial integration, unlike for unemployment, some of the local migration rates are tremendously impacted by increased mobility costs: when $\omega < 1$, the impact of mobility costs on mobility is higher that the maximum impact of reducing $s_{jk}^u$ in about 20% of the cities.

Therefore, in order to study the impact of these outliers and get a better sense of the overall impact of spatial constraints, we also propose a way to aggregate the effects on these local outcomes. Aggregate labor mobility $\mu \equiv \sum_j \frac{m_j}{M} \mu_j$ and aggregate unemployment rate $U \equiv \sum_j \frac{m_j}{M} U_j$ are the population-weighted averages of all the local mobility and unemployment rates. We compute the effect on these
two outcomes while keeping the distribution of city population constant, so that $\Delta U \equiv \sum_j \frac{m_j}{M_j} \Delta U_j$ and $\Delta \mu \equiv \sum_j \frac{m_j}{M_j} \Delta \mu_j$. By doing so, we focus the analysis on the direct role of spatial constraints, without taking into account the global reallocation of workers over the whole set of labor markets with different economic and matching conditions. Results are presented in Table 12 and confirm the asymmetric impact of mobility costs on unemployment. Even if the impact of spatial frictions is still higher, the 3.7% impact of a tenfold increase in mobility costs is economically significant. In order to achieve the same increase in unemployment, unemployed workers must be made 23% less efficient in finding a job in another city ($\omega = 0.77$). On the other hand, the 12.1% decrease in unemployment obtained from a 50% more efficient spatial job search for the unemployed is definitely out of reach if the only available instrument is to lower mobility costs.

Table 12: The effect of spatial frictions and mobility cost on aggregate unemployment and mobility

<table>
<thead>
<tr>
<th>$\omega$</th>
<th>$\Delta U(s^U_{jl})$</th>
<th>$\Delta U(s^e_{jl})$</th>
<th>$\Delta U(c_{jl})$</th>
<th>$\Delta \mu(s^U_{jl})$</th>
<th>$\Delta \mu(s^e_{jl})$</th>
<th>$\Delta \mu(c_{jl})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>18.313</td>
<td>-0.006</td>
<td>3.716</td>
<td>-85.736</td>
<td>-3.258</td>
<td>-14.382</td>
</tr>
<tr>
<td>0.2</td>
<td>15.580</td>
<td>-0.006</td>
<td>-0.102</td>
<td>-76.054</td>
<td>-2.867</td>
<td>-12.693</td>
</tr>
<tr>
<td>0.5</td>
<td>8.618</td>
<td>-0.003</td>
<td>-0.004</td>
<td>-48.570</td>
<td>-1.729</td>
<td>-3.043</td>
</tr>
<tr>
<td>1.5</td>
<td>-12.143</td>
<td>0.006</td>
<td>-0.082</td>
<td>68.646</td>
<td>3.186</td>
<td>15.688</td>
</tr>
<tr>
<td>2</td>
<td>-34.389</td>
<td>-0.000</td>
<td>-0.086</td>
<td>285.641</td>
<td>12.880</td>
<td>13.036</td>
</tr>
</tbody>
</table>

Notes: (i) Relative impact, in percentage points, of decreasing ($\omega < 1$) or increasing ($\omega > 1$) the level of spatial integration on aggregate unemployment rate and labor mobility; (ii) The aggregate is an average of all the local effects weighted by exogenous population share; (iii) For consistency between the respective impacts of spatial frictions and mobility costs, the former are multiplied by $\omega$, whereas the latter are divided by $\omega$. (iv) The residual city is included.

Finally, according to these aggregate effects, the asymmetry between the impact of increasing mobility costs and the impact of decreasing them is less pronounced for labor mobility: because of the compensation between the direct effect of mobility costs on employment status specific mobility rates and the indirect composition effect of mobility costs on the unemployment rate, both increased and decreased mobility costs may have a significant -albeit modest- impact on labor mobility.

Another interesting result is the fact that, beyond heterogeneous effect, increasing the efficiency of spatial search for employed workers may have an adverse impact on aggregate unemployment: this feature does not stem from a competition effect (the matching parameters are kept unchanged in this simple decomposition exercise), but from the fact that the value of future jobs slightly decreases as a result of higher values of $s^e_{jk}$ (see Equation 6). However, this mechanism is not economically significant.
Conclusion

In this paper, we propose a job search model to quantify the impact of mobility costs and informational frictions on workers’ migration. In contrast to Shimer’s (2007) mismatch theory, whereby migration decisions are driven by the irrational belief that local economic downturns will eventually reverse, we argue that forward-looking profit-maximizers may remain stuck in unfavorable locations. From a computational standpoint, in contrast to the reference work by Kennan & Walker (2011), we show that the random search technology makes it possible to consider the full state space of a discrete choice model at the city level. Our estimation results show that mobility costs are lower by at least one order of magnitude when we take into account the frictional dimension of job-related migration, and in particular the ability of information to travel across space. This result potentially has numerous public policy implications.

Our results also shed new light on the determinants of the city size wage premium. The frictionless economic geography literature has focused on the determinants of the wage growth across cities. Although individual wages are disconnected from productivity in our setup, the existence of search frictions allows us to reproduce both the upwards shift and the greater variability of the earning distributions, without resorting, neither to human capital accumulation, nor to production externalities. We can rationalize wage dynamics through the optimal strategy of a worker that consists in accepting any wage higher than her reservation wage, and working her way up to the top of the wage distribution by on-the-job search. These simple Markovian dynamics between labor markets of unequal size are strong enough to generate such spatial pattern.

Notwithstanding, our model has several important limitations. First, it cannot be used to analyze the sorting of workers across cities, which has been shown to be a major driver of spatial wage differences (Combes, Duranton & Gobillon, 2008). Second, in the spirit of Cahuc, Postel-Vinay & Robin (2006), one might want to incorporate the fact that cities vary in the number and size of firms and so that some locations provide workers with more opportunities for wage bargaining than others: in order to truly understand the contribution of location in the variation of lifetime inequalities, this dimension cannot be overlooked. More generally, we leave largely unexplored the firms’ side of the dynamic location model. Whereas a mere extension à-la Meghir et al. (2015) would not convey much interest without an explicit theory of location choice, agglomeration economies and wages, we believe such explicit theory to be a promising venue for future research.
References


A Theory: proofs and discussions

A.1 Expressions

Reservation wages $\phi_j$ and indifference wages $q_{jl}(w)$ verify:

$$V^u_j \equiv V^u_j(\phi_j)$$
$$V^e_j(w) \equiv V^e_j(\chi_{jl}(w))$$
$$V^e_j(w) \equiv V^e_j(q_{jl}(w)) - c_{jl}$$

Equations 1 and 2 can be rewritten as:

$$r V^u_j = b + \gamma_j + \lambda^u_j \int_{\phi_j}^{w} \left[ V^e_j(x) - V^u_j(x) \right] dF_j(x) + \sum_{k \in J_j} s^u_{jk} \lambda^u_k \int_{\phi_k}^{w} \left[ V^e_k(x) - c_{jk} - V^u_k \right] dF_k(x)$$
$$r V^e_j(w) = w + \gamma_j + \lambda^e_j \int_{w}^{w} \left[ V^e_j(x) - V^e_j(w) \right] dF_j(x) + \sum_{k \in J_j} s^e_{jk} \lambda^e_k \int_{\phi_k}^{w} \left[ V^e_k(x) - c_{jk} - V^e_j(w) \right] dF_k(x) + \delta_j [V^u_j - V^e_j(w)]$$

After integration by parts of equations 20 and 21, we get:

$$V^u_j = \frac{1}{r} \left[ b + \gamma_j + \lambda^u_j \int_{\phi_j}^{w} \Xi_j(x) dx + \sum_{k \in J_j} s^u_{jk} \lambda^u_k \int_{\phi_k}^{w} \Xi_k(x) dx - \bar{F}_k(q_{jk}(\phi_j)c_{jk}) \right]$$
$$V^e_j(w) = \frac{1}{r + \delta_j} \left[ w + \gamma_j + \lambda^e_j \int_{w}^{w} \Xi_j(x) dx + \sum_{k \in J_j} s^e_{jk} \lambda^e_k \int_{\phi_k}^{w} \Xi_k(x) dx - \bar{F}_k(q_{jk}(w)c_{jk}) \right]$$

where:

$$\Xi_j(x) = F_j(x) dV^e_j(x) = \frac{\bar{F}_j(x)}{r + \gamma_j + \lambda^e_j \bar{F}_j(w) + \sum_{k \in J_j} s^e_{jk} \lambda^e_k \bar{F}_k(q_{jk}(w))}$$

Finally, using Equations 17 and 19, we find that $\phi_j$ and $q_{jl}(w)$ are given by Equations 3 and 4.

A.2 Existence and uniqueness

From Equation 4, we derive the following proposition:

**Proposition 7** Let’s denote by $W = [\underline{w}, \overline{w}]$ the support of the wage distribution. $W$ is a closed subset of a Banach space. The set of functions $q_{jl}(\cdot)$ defines a contraction. In addition, they have a unique fixed point.

**Proof** Consider a grid with minimal value $w_0$. Given that $q_{jl}$ is differentiable, equation 28 can be
restated in the differential form as:

$$q_{jl}(w) = q_{jl}(w_0) + \int_{w}^{w_0} h_{jl}(x, q_j(x)) \, dx,$$  \hspace{1cm} (25)

where \( q_j(x) \equiv \{q_{jk}(x)\}_{k \in J_j} \). Starting from initial value \( w \), we can use Picard’s iterative process \( (q^{(1)}_{jl}, \ldots q^{(k)}_{jl}) \) to show that:

$$q^{(m)}_{jl}(w) = K^{(m)}(w_0)(w)$$  \hspace{1cm} (26)

with \( K(q_{jl})(w) = q_{jl}(w_0) + \int_{w}^{w_0} h(x, q_j(x)) \, dx \) and \( h_{jl}(x, q_j(x)) = d q_{jl}(x, q_j(x)) \). Since \( dV^e(\cdot) > 0 \) and \( dV^f(\cdot) > 0 \), we have \( d q_{jl}(\cdot) > 0 \); moreover, given that all the structural matching parameters \( (s^i, \lambda^i, \delta) \) are positive and the interest rate \( r \) is strictly positive, \( d q_{jl}(\cdot) \) can be bounded. Therefore, it is easy to see that \( d h_{jl}(\cdot) = d^2 q_{jl}(\cdot) \) is also bounded. As a consequence, \( d q_{jl}(x, q_j(x)) \) is Lipschitz continuous.

The [Banach fixed-point theorem](https://en.wikipedia.org/wiki/Banach_fixed-point_theorem) states that equation 25 has a unique solution.

### A.3 Discussion: the impact of mobility costs

We discuss here the impact of introducing mobility costs, both from a theoretical viewpoint and in relationship to the frictionless migration literature. We first show that, in order to fully derive a model where workers are only described by their current situation, we need to make an additional assumption regarding the impact of mobility costs on their mobility decisions. Then, we show how we can recover a more classical expression that summarizes the determinants of the migration decision in a frictionless framework.

**Past dependence in indifference wages** Mobility costs yield a non-trivial past dependence in the definition of indifference wages: they impact the wage that will be accepted in the new city, which in turn impacts future wage growth prospects in this new city; this difference in terms of option value will have an additional impact on indifference wages, and so forth. As shown in Equation 27, this dynamic feedback effect will mechanically exacerbate the difference between ex-ante and ex-post indifference wages:

$$q_{jl}(w) = \chi_{jl}(w) + (r + \delta_l)c_{jl} + \lambda^e_l \int_{\chi_{jl}(w)} \Xi_l(x) \, dx + \sum_{k \in J_l} s^e_{lk} \lambda^e_k \int_{q_{lk}(\chi_{jl}(w))}^{q_{ll}(\chi_{jl}(w))} \left[ \Xi_k(x) - f_k(x)c_{lk} \right] \, dx \hspace{1cm} (27)$$
Because of this feature, indifference wages do not have a tractable closed-form solution, unless workers are characterized by their entire migration history. Our solution is to assume that jobseekers facing a mobility decision evaluate the value of mobile on-the-job-search without taking into account the wage supplement associated with past mobility costs. Under this assumption, ex-post indifference wages can be recovered thanks to the stationary property of ex-ante indifference wages. Equation 27 becomes:

\[ q_{jl}(w) = \chi_{jl}(w) + (r + \delta) c_{jl} \]  

(28)

with:

\[ \chi_{jl}(w) = \zeta_{jl} w + \zeta_{jl} \gamma_j - \gamma_j + \zeta_{jl} \delta_j V_j^u - \delta_j V_j^u + \zeta_{jl} \lambda_j^e \int_{w}^{\infty} \Phi_j(x) dx - \lambda_j^f \int_{\chi_{jl}(w)}^{\infty} \Phi_l(x) dx \]  

(29)

\[ V_j^u = \frac{1}{r} \left[ b + \gamma_j + \lambda_j^u \int_{b}^{\infty} \Phi_j(x) dx + \sum_{k \in J} s_{jk} \lambda_k^u \left( \int_{\chi_{jk}(\phi_j)}^{\infty} \Phi_k(x) dx - \bar{F}_k(\chi_{jk}(w)) c_{jk} \right) \right] \]  

(30)

\[ \Phi_j(x) = \frac{F_j(x)}{r + \delta_j + \lambda_j^f \bar{F}_j(x) + \sum_{k \in J} s_{jk} \lambda_k^f \bar{F}_k(\chi_{jk}(x))} \]  

(31)

When thinking about subsequent moves from the job in city \( l \) that is currently under consideration, a worker in city \( j \) takes as a fallback value her initial discounted utility \( V_j^u(w) \) and therefore, a wage in city \( l \) equal to \( \chi_{jl}(w) \).\(^{34}\) As shown in Equation 29, this assumption preserves the main dynamic effect of mobility costs, based on the relative accessibility of city \( j \) and city \( l \) and measured by the difference between \( c_{jk} \) and \( c_{lk} \) for every third city \( k \). A behavioral interpretation is that workers paid \( w \) in city \( j \) may be able to gather information about the prospects of their counterparts in another city \( l \) (other workers paid \( \chi_{jl}(w) \)) but they cannot gather information about workers just like them who would have experienced the exact mobility from a wage \( w \) in city \( j \) to a wage \( q_{jl}(w) \) in city \( l \).

Note that equation 28 also gives the inverse function \( q_{jl}^{-1}(w) = \chi_{jl}(w - (r + \delta) c_{jl}) \).

### Interpretation

The traditional frictionless migration literature appeals to the existence of high mobility costs to account for low migration patterns. Matching frictions alone cannot be a substitute for mobility costs because they cannot reconcile within-city job-finding patterns with between-city mobility rates, even in the presence of differences in local amenities. However, our model makes it possible to assume that the only spatial constraints are mobility costs: in terms of the model, this

\(^{34}\)See the Pandora stopping problem described in Weitzman (1979) for a similar assumption. This is akin to partial myopia. As discussed in Eckstein & van den Berg (2007), full myopia would be for workers to always consider \( w \) as the fallback wage.
means that $s_{jk} = 1$. This assumption dramatically affects the computation of transition rates, populations and unemployment rates: under constant matching rates, the predicted mobilities skyrocket, unless indifference wages become prohibitively high. The equation of indifference wages simplifies to:

\[
q_{jl}(w) = \xi_{jl}w + (r + \delta_j)c_{jl} + \xi_{jl}w_j - \gamma_l + \xi_{jl}\delta_jV_l^j - \delta_lV_l^j + \sum_{k \in J} (\zeta_{jl} - 1) \lambda_k^e \int_{\chi_{jk}(w)} \Phi_k(x)dx - \sum_{k \notin J} \lambda_k^e F_k(\chi_{jk}(w)) (\zeta_{jl}c_{jk} - c_{lk}) \tag{32}
\]

Equation 32 shows that the crucial role of mobility costs in frictionless models is comprised by our model as a special case where unemployment risk can be neglected. Indeed, this is easy to see that:

\[
\lim_{(\delta_j, \delta_l) \to (0,0)} q_{jl}(w) = w + r c_{jl} + w_j - \gamma_l - \sum_{k \notin J} \lambda_k^e F_k(\chi_{jk}(w)) (c_{jk} - c_{lk}) \tag{33}
\]

The first four terms on the right-hand side feature a classical expression where mobility decisions are driven by wage levels, capitalized mobility costs and differences in local amenities. Since differences in local amenities cannot explain the coexistence of low mobility rates both out of and into the same city, the only factor left is mobility costs. Because of on-the-job search, the relative accessibility of cities $j$ and $l$, which determines the cost of subsequent moves, still comes into play: if city $l$, in addition to being far from city $j$, is also not easily accessible to the other cities, this will reduce the migration rate to city $l$ even more.
B  Algorithm and numerical solutions

B.1  Algorithm

Let $g(\cdot) \equiv \{g_j(\cdot)\}_{j \in J}$. The set of theoretical moments $m(\theta)$ is simulated thanks to an iterative algorithm, which can be summarized as follows:

1. Given data on wage, evaluate $G(\cdot)$ and $g(\cdot)$

2. Set an initial guess for $\theta$ and $F(\cdot)$

3. Given $\theta$ and $F(\cdot)$, solve Equation 4 to recover indifference wages $q(\cdot)$

4. Solve Equation 10 to recover equilibrium population $\mathcal{M}$

5. Solve Equation 12 to update the distribution of job offers $F(\cdot)$

6. Solve Equation 7 to update the distribution of local amenities $\Gamma$

7. Update $\theta$ using the maximum of $\mathcal{L}(\theta)$.

8. Repeat steps 3 to 7 until convergence.

B.2  Indifference wages

The model raises several numerical challenges, in particular in steps 3 and 5. In step 3, $q(\cdot)$ defines a system of $J^2 - J$ equations, to be solved $\dim(\mathcal{W})$ times. Moreover, since $\Phi_j(\cdot)$ is a function of all $\{\chi_{jk}(\cdot)\}_{k \in J_j}$, the numerical integration of $\Phi_j(\cdot)$ requires a prior knowledge of the functional form of all $\{\chi_{jk}(\cdot)\}_{k \in J_j}$. A potential solution to this problem would be to parameterize $q(\cdot)$ as a polynomial function of wages and structural parameters. However, this would obliterate any prospect to identify separately mobility costs, amenities and labor market matching parameters. Instead, we take advantage of the structure of the model and we use an embedded algorithm that allows us to recover a piecewise approximation of all indifference wages.

Remember that for any $w^* > w$ and a relatively small $h$, Newton's formula yields:

$$\chi_{jil}(w^*) = \chi_{jil}(w) + h d \chi_{jil}(w)$$

---

See section 3.2 for details.
and that $\chi(w)$ is given by equation 35:

$$
\chi_j(w) = \zeta_j \left( w + y_j + \frac{1}{r} \left[ b + \gamma_j \right] \right) - \left( y_j + \frac{1}{r} \left[ b + \gamma_j \right] \right) + \frac{\Delta \delta_j}{r} \int_{w}^{\infty} \Phi_j(x) dx - \frac{\Delta \delta_j}{r} \int_{w}^{\infty} \Phi_j(x) dx + \lambda_j^* \int_{\chi_j(w)}^{\infty} \Phi_j(x) dx
$$

Equation 35.

Indifference wages can then be recovered using a sequential process, on a grid of wages $w_i$:

3.1 Declare an initial guess $\chi^0(w)$ for $\chi(w)$

3.2 Update the initial guess until convergence of $\chi(w)$

3.3 Use the values of $\chi(w)$ to iteratively recover $\chi(w_1)$, then $\chi(w_2)$, up to $\chi(\overline{w})$.

In step 3.1, $\chi^0(w)$ is constructed using numerical guesses for $\int_{w}^{\infty} \Phi_j(x) dx$, $\int_{\chi_j(w)}^{\infty} \Phi_j(x) dx$ and $F_k(\chi_jk(w))$ for all $(j, k) \in J \times J$. In step 3.2, we take advantage of the recursive structure of equation 35 and construct $\chi^{n+1}(w) = \text{function}\left(\chi^n(w)\right)$. In step 3.3, we use Equation 34 to move up the wage ladder. By definition, $V^e_j(w) = V^e_j(\chi_j(w))$, so that $dV^e_j(w) = d\chi_j(w)dV^e_j(\chi_j(w))$. Combining equation 24 with equation 29, we then get:

$$
d\chi_j(w) = \frac{r + \delta_j + \lambda_j^* F_1(\chi_j(w)) + \sum_{k \in J \setminus j} s_{jk}^{e} \lambda_k^* F_k(\chi_jk(w))}{r + \delta_j + \lambda_j^* F_j(w) + \sum_{k \in J \setminus j} s_{jk}^{e} \lambda_k^* F_k(\chi_jk(w))}
$$

B.3 Wage distributions

Once the indifference wages are recovered, we can turn to the evaluation of the wage distributions (step 5 in the general algorithm). There are two difficulties when solving for the system defined by Equation 12. First, for any system of three cities or more, the system can only be solved numerically. Second, the system is composed of functional equations, which standard differential solvers are not designed to handle. Our solution is twofold. First, as explained in Section 3.1, we assume that $F(\cdot)$ follows a can be proxied by a beta distribution. Then, since our empirical counterparts are based on real wages, we treat the empirical cdf $G(\cdot)$ as unknown and we estimate the set of parameters

---

36Two-sector models, such as the one presented in Meghir et al. (2015), yield systems of two ordinary differential equations. These systems can be rewritten in a way such that they still admit a closed-form solution.
\( \alpha = \{\alpha_j\}_{j \in \mathcal{J}} \) and \( \beta = \{\beta_j\}_{j \in \mathcal{J}} \) which minimize the distance between the empirical cdf \( G(\cdot) \) and its theoretical counterpart. This theoretical counterpart is given as the solution to the following functional equation, derived from Equation 12:

\[
g_j(w) = f_j(w) \times \frac{\lambda^j_1 \left( \psi_j(w) u_j + \sum_{k \in \mathcal{J}, j} s^j_0 \psi_j(w) u_k \right) + \lambda^j_2 \left( (m_j - u_j) G_j(w) + \sum_{k \in \mathcal{J}, j} s^j_1 (m_k - u_k) G_k(q^j_k(w)) \right)}{(m_j - u_j) \left( \delta_j + \lambda^j_1 T_j(w) + \sum_{k \in \mathcal{J}, j} s^j_0 \lambda^j_2 T_k(q^j_k(w)) \right)}
\]  

(37)

The original algorithm is modified to take into account the estimation of \( \alpha \) and \( \beta \). At step 2, we set an initial guess \( (\alpha^0, \beta^0) \). At step 5, we need a solution \( G(\cdot) \) to Equation 37 in order to update \( (\alpha, \beta) \). We develop a simple iterative process based on Euler’s approach. That is, given an initial \( G_j(w) \),

5.1 Assume that \( g_j(\cdot) = f_j(\cdot) \) and \( \forall k \in \mathcal{J}, G_k(\cdot) = F_k(\cdot) \). From equation 37, this yields \( G^0_j(w) \) as a solution to:

\[
g^0_j(w) = f_j(w) \times \frac{\lambda^j_1 \left( \psi_j(w) u_j + \sum_{k \in \mathcal{J}, j} s^j_0 \psi_j(w) u_k \right) + \lambda^j_2 \left( (m_j - u_j) F_j(w) + \sum_{k \in \mathcal{J}, j} s^j_1 (m_k - u_k) F_k(q^j_k(w)) \right)}{(m_j - u_j) \left( \delta_j + \lambda^j_1 T_j(w) + \sum_{k \in \mathcal{J}, j} s^j_0 \lambda^j_2 T_k(q^j_k(w)) \right)}
\]  

(38)

and equation 12 becomes a standard ODE.

5.2 Set the step size \( h \) and use Euler’s method to approximate the sequence of \( G_j(\cdot) \).

5.3 Derive estimate for \( G_l(q_{jl}(w)) \) for all \( j \in \mathcal{J} \).

5.4 Use estimates of \( G_l(q_{jl}(w)) \) to solve the functional differential equation 37.

5.5 Repeat steps 5.3 to 5.4 until convergence.

Once a solution for \( G_l(\cdot) \) is recovered, we update \( \alpha \) and \( \beta \) by minimizing the distance between \( G(\cdot) \) and \( \hat{G}(\cdot) \) over the space of beta distributions.

### B.4 Local amenities

Step 6 is completed using an embedded ranking algorithm which proceeds as follows:

1. Set the initial guess \( \forall j \in \mathcal{J} : \gamma^0_j = 0 \)

2. Order the corresponding values \( V^0_j \) and let \( j^0 = \arg \min_{j \in \mathcal{J}} V^0_j \)

3. Set \( \forall k \in \mathcal{J} : \gamma_1^k = V^0_k - (V^0_j + c^0_k) \) and update \( V^1_k = V^0_k + \gamma_1^k \)

4. Repeat steps 2 and 3 until convergence.
C Data

C.1 Data selection

The initial sample is composed of 43,010,827 observations over the period 1976-2008. Our sample selection is as follows:

- We restrict the sample to observations recorded between 2002 to 2007, related to the main job of individuals in urban continental France

- We dispose of female workers as well as individuals who at some point were older than 58 years, and younger than 15 years.

- We drop individuals who at some point were working: in the public sector, as apprentice, as home workers, and part time workers.

- We drop individuals who at some point had a reported wage that is inferior to the 900 euros per month (the net minimum wage is around 900 euros): or a monthly wage higher than 8,000 euros: The first case is considered as measurement error; whereas the second case reflects a real situation, it extends the support of wage distributions too dramatically for very few individuals (about 1% of the population).

- Finally, for computational reasons, we get rid of individuals observed only once

Finally, we end up with the dataset described in Table 13.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Individuals</th>
<th>Number of Observations</th>
<th>Min</th>
<th>Mean</th>
<th>Median</th>
<th>Max</th>
<th>Min</th>
<th>Mean</th>
<th>Median</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>310,153</td>
<td>332,446</td>
<td>95</td>
<td>1,581</td>
<td>433</td>
<td>84,302</td>
<td>97</td>
<td>1,662</td>
<td>445</td>
<td>90,452</td>
</tr>
<tr>
<td>2003</td>
<td>297,697</td>
<td>311,309</td>
<td>99</td>
<td>1,505</td>
<td>406</td>
<td>80,981</td>
<td>101</td>
<td>1,556</td>
<td>412</td>
<td>84,950</td>
</tr>
<tr>
<td>2004</td>
<td>308,179</td>
<td>321,557</td>
<td>107</td>
<td>1,558</td>
<td>424</td>
<td>84,104</td>
<td>108</td>
<td>1,607</td>
<td>433</td>
<td>88,027</td>
</tr>
<tr>
<td>2005</td>
<td>310,949</td>
<td>325,580</td>
<td>71</td>
<td>1,573</td>
<td>441</td>
<td>84,911</td>
<td>72</td>
<td>1,627</td>
<td>449</td>
<td>89,600</td>
</tr>
<tr>
<td>2006</td>
<td>316,613</td>
<td>332,848</td>
<td>105</td>
<td>1,604</td>
<td>436</td>
<td>86,712</td>
<td>106</td>
<td>1,664</td>
<td>449</td>
<td>91,525</td>
</tr>
<tr>
<td>2007</td>
<td>313,693</td>
<td>335,460</td>
<td>111</td>
<td>1,597</td>
<td>432</td>
<td>86,029</td>
<td>112</td>
<td>1,677</td>
<td>455</td>
<td>92,169</td>
</tr>
<tr>
<td>Total</td>
<td>477,068</td>
<td>2,548,719</td>
<td>260</td>
<td>8,467</td>
<td>1,877</td>
<td>650,010</td>
<td>65</td>
<td>1,917</td>
<td>454</td>
<td>135,460</td>
</tr>
</tbody>
</table>

Notes: (i) Metros are here the clusters of municipalities forming the 199+1 metropolitan areas in 2010; (ii) Source: Panel DADS 2002-2007
C.2 Descriptive statistics on city-specific wage distributions

Table 14: Local wage distributions
Panel 1: the nine largest cities

<table>
<thead>
<tr>
<th>Moments</th>
<th>City 1</th>
<th>City 2</th>
<th>City 3</th>
<th>City 4</th>
<th>City 5</th>
<th>City 6</th>
<th>City 7</th>
<th>City 8</th>
<th>City 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{10}$</td>
<td>14,478</td>
<td>14,264</td>
<td>13,624</td>
<td>13,758</td>
<td>13,407</td>
<td>13,796</td>
<td>13,540</td>
<td>14,166</td>
<td>14,264</td>
</tr>
<tr>
<td>$Q_1$</td>
<td>18,327</td>
<td>17,060</td>
<td>16,141</td>
<td>15,576</td>
<td>16,117</td>
<td>16,151</td>
<td>15,648</td>
<td>17,074</td>
<td>17,074</td>
</tr>
<tr>
<td>$Q_2$</td>
<td>25,815</td>
<td>21,774</td>
<td>20,854</td>
<td>20,093</td>
<td>19,701</td>
<td>20,236</td>
<td>20,768</td>
<td>20,396</td>
<td>21,640</td>
</tr>
<tr>
<td>$E$</td>
<td>33,888</td>
<td>27,221</td>
<td>25,486</td>
<td>24,751</td>
<td>24,628</td>
<td>26,296</td>
<td>25,143</td>
<td>25,565</td>
<td>25,565</td>
</tr>
<tr>
<td>$Q_3$</td>
<td>39,351</td>
<td>30,686</td>
<td>29,868</td>
<td>27,711</td>
<td>27,820</td>
<td>27,848</td>
<td>28,792</td>
<td>27,001</td>
<td>27,001</td>
</tr>
<tr>
<td>$P_{90}$</td>
<td>59,755</td>
<td>45,591</td>
<td>41,450</td>
<td>43,890</td>
<td>40,890</td>
<td>39,759</td>
<td>40,871</td>
<td>40,113</td>
<td>40,113</td>
</tr>
<tr>
<td>$\sqrt{\frac{Q_2}{Q_1}}$</td>
<td>1.68</td>
<td>1.07</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
</tr>
<tr>
<td>$P_{99}/P_{10}$</td>
<td>4.12</td>
<td>3.19</td>
<td>3.04</td>
<td>3.13</td>
<td>3.04</td>
<td>2.88</td>
<td>3.36</td>
<td>2.88</td>
<td>2.81</td>
</tr>
</tbody>
</table>

Panel 2: nine other cities

<table>
<thead>
<tr>
<th>Moments</th>
<th>City 20</th>
<th>City 30</th>
<th>City 40</th>
<th>City 120</th>
<th>City 130</th>
<th>City 140</th>
<th>City 220</th>
<th>City 230</th>
<th>City 240</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{10}$</td>
<td>13,826</td>
<td>13,490</td>
<td>12,823</td>
<td>12,350</td>
<td>13,287</td>
<td>13,192</td>
<td>13,663</td>
<td>13,760</td>
<td>13,154</td>
</tr>
<tr>
<td>$Q_1$</td>
<td>16,311</td>
<td>15,628</td>
<td>14,615</td>
<td>14,599</td>
<td>15,130</td>
<td>14,857</td>
<td>15,547</td>
<td>17,200</td>
<td>17,312</td>
</tr>
<tr>
<td>$Q_2$</td>
<td>20,329</td>
<td>19,123</td>
<td>17,817</td>
<td>16,946</td>
<td>18,125</td>
<td>17,635</td>
<td>18,249</td>
<td>22,763</td>
<td>17,648</td>
</tr>
<tr>
<td>$E$</td>
<td>24,554</td>
<td>23,240</td>
<td>21,207</td>
<td>21,442</td>
<td>21,467</td>
<td>20,451</td>
<td>22,224</td>
<td>24,630</td>
<td>19,704</td>
</tr>
<tr>
<td>$Q_3$</td>
<td>27,384</td>
<td>25,584</td>
<td>23,332</td>
<td>22,564</td>
<td>23,568</td>
<td>23,385</td>
<td>22,408</td>
<td>29,868</td>
<td>21,175</td>
</tr>
<tr>
<td>$P_{90}$</td>
<td>39,290</td>
<td>38,530</td>
<td>32,973</td>
<td>32,151</td>
<td>32,379</td>
<td>31,982</td>
<td>31,360</td>
<td>33,586</td>
<td>30,842</td>
</tr>
<tr>
<td>$\sqrt{\frac{Q_2}{Q_1}}$</td>
<td>1.68</td>
<td>1.07</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
</tr>
<tr>
<td>$P_{99}/P_{10}$</td>
<td>2.84</td>
<td>2.85</td>
<td>2.57</td>
<td>2.41</td>
<td>2.43</td>
<td>2.42</td>
<td>2.29</td>
<td>2.44</td>
<td>2.28</td>
</tr>
</tbody>
</table>

Notes: (Wages are in 2002 Euros and wage distributions are evaluated over the six-year span 2002-2007. Source: Panel DADS 2002-2007; for details on the sample, see Section 1.2.

Table 15: Stability of the wage distributions

<table>
<thead>
<tr>
<th>Moments</th>
<th>$P_{10}$</th>
<th>$P_{20}$</th>
<th>$P_{30}$</th>
<th>$P_{40}$</th>
<th>$P_{50}$</th>
<th>$P_{60}$</th>
<th>$P_{70}$</th>
<th>$P_{80}$</th>
<th>$P_{90}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q_{2007}/Q_{2002}$</td>
<td>1.005</td>
<td>1.006</td>
<td>1.007</td>
<td>1.008</td>
<td>1.008</td>
<td>1.009</td>
<td>1.009</td>
<td>1.010</td>
<td>1.011</td>
</tr>
<tr>
<td>$Q_{2}/Q_{1}$</td>
<td>1.005</td>
<td>1.006</td>
<td>1.007</td>
<td>1.007</td>
<td>1.007</td>
<td>1.008</td>
<td>1.009</td>
<td>1.009</td>
<td>1.011</td>
</tr>
<tr>
<td>$E_{2007}/E_{2002}$</td>
<td>1.005</td>
<td>1.006</td>
<td>1.007</td>
<td>1.007</td>
<td>1.007</td>
<td>1.008</td>
<td>1.009</td>
<td>1.009</td>
<td>1.011</td>
</tr>
<tr>
<td>$Q_{3}/Q_{2}$</td>
<td>1.003</td>
<td>1.006</td>
<td>1.006</td>
<td>1.007</td>
<td>1.007</td>
<td>1.008</td>
<td>1.009</td>
<td>1.009</td>
<td>1.011</td>
</tr>
</tbody>
</table>

Notes: (i) Deciles of the distributions of ratios of the moments of the city-specific log-wage distributions in 2007 and in 2002 Source: Panel DADS 2002-2007; for details on the sample, see Section 1.2.
C.3 Empirical moments used in the first column in Table 5

**Unemployment rate in city** \( j \): ratio of the number of individuals who should be in the panel in city \( j \) on January 1\(^{st}\) 2002 but are unobserved (henceforth, assumed unemployed) to the sum of this number and the number of individuals observed in city \( j \) on January 1\(^{st}\) 2002

**Population in city** \( j \): number of individuals observed in the panel between 2002 and 2007 in city \( j \)

**Transition rate ee within city** \( j \): ratio of the number of job-to-job transitions within city \( j \) observed over the period, to the potentially-employed population in city \( j \) (population as defined above multiplied by one minus the unemployment rate as defined above)

**Earning distribution in city** \( j \): quantiles in city \( j \) on a grid of 17 wages over the period

**Transition rate ue (resp., ee) out of city** \( j \): ratio of the number of transitions out of unemployment (resp., the number of job-to-job transitions) out of city \( j \) observed over the period, to the potentially-unemployed (resp., potentially-employed) population in city \( j \) (population as defined above multiplied by the unemployment rate as defined above)

**Transition rate ue (resp., ee) into city** \( l \): ratio of the number of transitions out of unemployment (resp., the number of job-to-job transitions) into city \( l \) observed over the period, to the potentially-unemployed (resp., potentially-employed) population in all cities \( k \neq l \)

**Transition rate ue (resp., ee) from city** \( j \) **to city** \( l \): ratio of the number of transitions out of unemployment (resp., the number of job-to-job transitions) from city \( j \) to city \( l \) observed over the period, to the potentially-unemployed (resp., potentially-employed) population in city \( j \)

**Accepted wages ee from city** \( j \) **to city** \( l \): average wage following a job-to-job transition from city \( j \) to city \( l \) observed over the period.
D Figures

D.1 Maps

Figure 7: The French urban archipelago

Notes: the spatial unit is the municipality. There are more than 700 metropolitan areas according to the 2010 definition. In dark, the border of the municipalities that constitute the largest 200 metropolitan areas. In light, the border of all the other municipalities within a metropolitan area.

Source: INSEE, Census 2007

Figure 8: The metropolitan areas in subset $\mathcal{F}_1$ (left) and subset $\mathcal{F}_2$ (right)

Notes: (i) see Figure 7; (ii) Subset $\mathcal{F}_1$ is used to identify the effect of physical distance and dissimilarity on spatial frictions based on pair-specific out-of-unemployment and job-to-job transition rates; subset $\mathcal{F}_2$ is used to identify the effect of physical distance on moving costs based on pair-specific average accepted wages after a job-to-job transition with mobility.
D.2 Worker heterogeneity

As documented elsewhere, developed countries such as France have witnessed an increase in overall skill level and in the share of the service sector during the past decades. Over a long period, these wide recomposition patterns make it unlikely that an equilibrium model could effectively be used. We do not address this issue in this paper. However, we believe that, as a first-order approximation, the assumption of workers’ homogeneity is not very costly when focusing on a short time-span. As shown in Figure 9, these reallocations, roughly described as a linear process, affect all cities in a very similar fashion between 1999 and 2006 and the position of each city in the hierarchy of skill and sectoral composition is very stable across the period.

Figure 9: Heterogeneity and stability in skill and sectoral composition

Notes: (i) Shares are computed on the 25-54 age bracket for the population of men (left) and the population of men workers (right) and for the 200 largest metropolitan areas in continental France, keeping a constant municipal composition based on the 2010 "Aires Urbaines" definition; (ii) The respective equations of the least squares line are $\hat{C}_{06} = 1.18 \times C_{99} + 0.02$ (left) and $\hat{S}_{06} = 0.67 \times S_{99} + 0.26$ (right). Source: INSEE, Census 1999 and 2006
D.3 Fit of the model

Figure 10: Fit: local transition rates, unemployment rate and city size

- Unemployment
- Log population
- Job arrival rate: unemployed
- Job arrival rate: employed

Data vs. Model comparison for the fit of the model.
Figure 11: Fit: migration rates

Out–migration: unemployed

Out–migration: employed

In–migration: unemployed

In–migration: employed
Figure 12: Fit: wage distributions

Wage dist: min wage

Wage dist: 4 min wage

Wage dist: 6 min wage

Wage dist: 8 min wage