

Document de Travail Working Paper 2012-22

Local Job Accessibility Measurement:
When the Model Makes the Results
Methodological Contribution and Empirical Benchmarking
on the Paris Region

Matthieu Bunel
Elisabeth Tovar



UMR 7235

Université de Paris Ouest Nanterre La Défense
(bâtiment G)
200, Avenue de la République
92001 NANTERRE CEDEX

Tél et Fax : 33.(0)1.40.97.59.07
Email : nasam.zaroualete@u-paris10.fr

université
Paris | **Ouest**

Nanterre La Défense

Local Job Accessibility Measurement: When the Model Makes the Results Methodological Contribution and Empirical Benchmarking on the Paris Region

Matthieu Bunel (Université de Caen and CREM)

and

Elisabeth Tovar (Université de Paris Ouest Nanterre La Défense and EconomiX)

Abstract

This paper focuses on local job accessibility measurement. We propose an original model that uses national exhaustive micro data and allows for i) a full estimation of job availability according to an extensive set of individual characteristics, ii) a full appraisal of job competition on the labour market and iii) a full control of frontier effects. By matching several exhaustive micro data sources on the Paris region municipalities, we compare the results produced by this benchmark model to a representative set of alternative models, we show that the model may indeed make the results as far as local job accessibility is concerned. Significant empirical differences do stem from the use of different Local Job Accessibility measures. Moreover, these differences are spatially differentiated across the Paris region municipalities. In particular, we show that failing to use a model where job availability is fully estimated according to individual characteristics may lead to the over-estimation of the job accessibility levels of notably under-privileged municipalities.

Keywords: job accessibility measurement, Paris Region, benchmarking, geo-referenced microdata

JEL classification: R11, J61

1. Introduction

Since John Kain's formulation of the Spatial Mismatch¹ hypothesis (Kain, 1968), it is widely acknowledged that that space is a key factor when understanding individual differences in unemployment and job search success rates. Kain postulated that the African American low employment rate was due to the increasing distance between their inner-city residential location and the jobs that were being progressively relocated in the suburbs, poor accessibility to jobs leading to high unemployment.

From the start, many empirical papers have tested the empirical relevance of Kain's hypothesis and the relative importance of its theoretical determinants: (i) accessibility factors, (ii) individual characteristics and (iii) neighbourhood characteristics. On the US context, early empirical studies dealing with the impact of job accessibility on employment presented mixed conclusions. Kain (1992) and Ilhanfledt and Sjoquist (1998) pointed that these discrepancies probably stemmed from methodological difficulties when assessing local job accessibility (LJA). Subsequent papers, building on improved LJA measures, did indeed validate the Spatial Mismatch Hypothesis, showing i) that poor LJA does have an adverse effect on employment outcomes (Ong and Miller, 2005; Johnson, 2006) and that ii) living in a deprived neighbourhood does have a negative effect on job achievement (Massey *et al.*, 1991, Ronsenbaum and Harris, 2001).

On the European context, empirical studies of the Spatial Mismatch are fewest and recent. Korsu and Wenglenski (2010) explain that until recently European cities were believed to be relatively impervious to spatial mismatch because of their compact structure that allows for a good accessibility to jobs for all workers and because of their low levels of spatial segregation. However, growing evidence supports the idea that European cities in general and the Paris region in particular may be increasingly vulnerable to spatial mismatch: a vigorous and socially differentiated urban sprawl (Cheshire, 1995), the identification of lastingly well-being-deprived clusters of neighbourhoods (Bourdeau-Lepage and Tovar, 2011), the location-driven discrimination on the job market (Duguet *et al.*, 2012)... From these evolutions emerges a relatively new but burgeoning European Spatial Mismatch empirical literature. For British cities, Houston (2005) and Patacchini and Zenou (2005); for Dutch cities, see Musterd *et al.*(2003) and van der Klaauw and van Ours (2003); on Brussels, see Dujardin *et al.* (2008); on Madrid and Barcelona, see Matas *et al.* (2010).

On the Paris context, many recent papers have presented quite contradictory conclusions on both the reality of the Spatial Mismatch and on the relative role of its determinants. Whereas

¹ Kain's hypothesis lead to the production of a great number of theoretical models presenting alternative mechanisms leading to Spatial Mismatch; presenting this abundant literature is well beyond the scope of this paper.

Marpsat and Laurent (1997) find no effect of local negative socio-economic externalities on unemployment, Choffel and Delattre (2003), Gobillon and Selod (2007) and Duguet *et al.* (2009) find negative neighbourhood effects. On the accessibility factor, Gaschet and Gaussier (2004), Gobillon and Selod (2007) and Duguet *et al.* (2009) find a very weak or inexistent negative effect of poor LJA on employment. By stark contrast, Korsu and Wenglenski (2010) that low job accessibility significantly affects long-term unemployment for under-skilled workers. However, they also find that neighbourhood effects have a stronger impact on unemployment than accessibility factors.

It is interesting to note that many of these papers rely on different LJA measures. For example, while most papers rely on spatially aggregated macro data, Korsu and Wenglenski (2010) use exhaustive census micro data that allows for the differentiation of accessibility measures according to socio-economic status. One can wonder whether the discrepancies found in the recent empirical Spatial Mismatch literature reflect actual empirical differences or do simply stem from the model used to assess LJA. This paper aims to provide empirical evidence on this matter: if the differences are methodologically-induced, the collective effort in the construction of new and improved LJA measures – to which we contribute in this paper by proposing an original model – is relevant and should be carried on. This may prove to be particularly important from a public-policy oriented point of view, especially if the empirical differences that come from using different LJA models are spatially differentiated across the city's territory. In this case, using a LJA model or another may significantly affect the recommendations issued for the local targeting of anti-Spatial Mismatch public policies, overshadowing the empirical reality of the Spatial Mismatch itself.

In Section 2, we first enumerate the key methodological issues of LJA measurement (proximity, frontier effects, job availability and job competition modelling) and present the different strategies followed in the recent literature to assess each of these elements. Then, we propose an original alternative model that, in particular, relies on national exhaustive micro data and allows for i) a full estimation of job availability according to an extensive set of individual characteristics, ii) a full appraisal of job competition on the labour market and iii) a full control of frontier effects. In Section 3, we present the data and the study area, the Paris Region. Section 4 develops the benchmarking strategy used to test the hypothesis that using different LJA models may lead to significantly different assessments of the LJA level of the Paris Region 1300 municipalities. In Section 5, we show that this hypothesis is empirically validated, identify the key methodological issues that induce significant empirical discrepancies and show that the model-induced differences are spatially differentiated across the Paris region municipalities. In Section 6 we conclude the paper and discuss further desirable research on LJA measures.

2. Measuring LJA: Literature Review and Original Extension

Accessibility can be assessed in different ways (Morris *et al*, 1979, Harris, 2001). For instance, Handy and Niemeier (1997) define accessibility as a characteristic of metropolitan areas. Here, we use a disaggregated definition of local accessibility, in the spirit of Hansen's *gravity-based* formalization (Hansen 1959), where local accessibility is linked with the number of potentially available opportunities.

In this paper, we focus on *job* opportunities, and discuss the ways in which LJA measures take into account travel costs such as travel distance and time (Kawabata and Shen, 2007), but also local competition on the labour market (Weibull, 1976, Shen, 1998, Harris, 2001 and van Wee *et al*, 2001). More specifically, in this section, we examine three major methodological issues of measuring LJA. We do not claim to address the full scope of the methodological issues that matter in LJA measurement. Even if exhaustivity was possible, tackling too many methodological dimensions would necessarily create a great number of possible combinations, which would complicate the empirical benchmarking presented in Section 4. From a practical point of view, addressing issues such as the different ways of defining job opportunities² themselves (vacancies, local job growth, actual occupied jobs...) or of modelling the public transportation system (Détang-Dessandre and Gagné, 2009, Matas *et al*, 2010) would mean using and the matching a great number of geo-referenced databases which may not be available at a micro level.

We focus on the three aspects of LJA measurement that are very diversely treated in the recent empirical Spatial Mismatch literature, *i.e.* (1) job *reachability*, (2) job *availability* and (3) local job *competition*. Building on this discussion, we propose an original model that, in particular, relies on a full estimation of both job availability and local job competition.

2.1. Modelling how distance affects the jobs' actual reachability

Assessing job *reachability* means tackling two different issues. First, modelling job *proximity*, *i.e.* devising a procedure to delimit the area within which jobs can be reached by any given worker so that jobs that distant from the worker's residential location are less reachable than

² We do not discuss in this methodological section (and, do not, in the empirical part of the paper, benchmark) the alternative definitions of job opportunities. In their seminal methodological paper, Ihlanfeldt and Sjøkist (1998) claim that vacancies are the optimal proxy for job opportunities, but, because of data availability constraints, other variables are often used in the literature. Raphael (1998) pleads local job growth as an alternative variable. However, there is no guarantee that job growth is correlated with the actual number of available jobs in any census tract, or that such a correlation, were it to be proven, would be identical across all municipalities. Jayet (2000) and Korsu and Wenglenski (2010) prefer the use of actual occupied jobs as a valid second-best strategy, which we also follow in this paper.

closer ones. Second, frontier effects must be tackled.

Job Proximity

Let $Pool_t^{p_k}$ be number of jobs with that are potentially *reachable* form the census track t .

In the literature different models p_k are used to measure the *proximity* of any job Job_t located in municipality t' any worker living in municipality t .

At an extreme, distance can be thought as being insuperable, and the municipalities of an agglomeration are modelled as isolated local labour markets. In this case, the jobs considered to be within a worker's reach are limited to the ones that are located in his residential municipality, and $Pool_t^{p_k}$ is simply Job_t , the number of jobs that are available on the worker's residential municipality. However, in 2006, 71.70% of the employed males did not work on their residential municipality in the Paris Region. At the other extreme, if we consider that spatial frictions are null, there is only one regional-sized global labour market and all jobs are reachable to any worker, irrelevantly of his residential location.

Between these two polar and trivial cases, three models p_k coexist in the literature. In the discrete approach (model p_1), all jobs within a particular distance are reachable, while those that are located further are excluded from the worker's local labour market. For example, Korsu and Wenglenski (2010) consider that jobs that are located less than 60 minutes away from one's residential municipality are reachable, such as in Equation (1), where

$I(Time_{tt'} \leq 60min)$ is an indicator function which is equal to 1 if the time travel by personal car between municipalities t and t' is under 60 minutes and equal to 0 otherwise.

$$Pool_{tk}^{p_1} = \sum_{t'} I(Time_{tt'} \leq 60 min) Job_{t'k} \quad (1)$$

In continuous models with decay function, such as in Bania *et al.* (2008), Allard and Danziger (2002), Cervero *et al.*, (1999) or Sanchez *et al.* (2004), jobs given weights that are inversely correlated with distance. Proximity between municipalities t and t' can be either measured using straight-line distance $Dist_{tt'}$ (Equation 2, model p_2) or time travel $Time_{tt'}$ (Equation 3, model p_3).

$$Pool_{tk}^{p_2} = \sum_{t'} Job_{t'} e^{(\lambda Dist_{tt'})} \quad (2)$$

$$Pool_{ik}^{p_3} = \sum_{t'} Job_t \cdot e^{(\lambda Time_{it'})} \quad (3)$$

As in Rogers (1997), the mixed model (p_4) uses concentric time-travel rings within which all jobs receive the same weight, as in Equation (4), where the time-travel rings rank from commutes that last under 15 minutes to commutes that last between 60 and 90 minutes. This model is interesting because it allows a better fitting with actual transportation patterns than using a decay function. Moreover, using an exponential decay function as in Equation (2) may over-weight distant jobs and under-weight closer ones³. In the original model that we propose in this paper, we assess proximity using this mixed method.

$$Pool_{ik}^{p_4} = \sum_{t'} I(Time_{it'} \leq 15 \text{ min}) Job_t + 0.8 \sum_{t'} I(15 \text{ min} < Time_{it'} \leq 20 \text{ min}) Job_t + 0.6 \sum_{t'} I(20 \text{ min} < Time_{it'} \leq 30 \text{ min}) Job_t + 0.5 \sum_{t'} I(30 \text{ min} < Time_{it'} \leq 40 \text{ min}) Job_t + 0.25 \sum_{t'} I(40 \text{ min} < Time_{it'} \leq 50 \text{ min}) Job_t + 0.15 \sum_{t'} I(50 \text{ min} < Time_{it'} \leq 60 \text{ min}) Job_t + 0.05 \sum_{t'} I(60 \text{ min} < Time_{it'} \leq 90 \text{ min}) Job_t \quad (4)$$

Frontier Effects⁴

Frontier effects stem from the artificial truncation of the pool of reachable jobs because of administrative constraints to data availability (model f_1).

This is problematic for two reasons. First, workers can and do apply to jobs outside of their residential region, and frontier effects may lead to underestimate the number of accessible jobs, especially for the workers who live close to the region's administrative boundaries. Second, workers face the competition not only of the other workers who live in their own residential region, but also of those that live outside its boundaries.

In the Paris region, Gilli (2005) shows that the Paris metropolitan area far over-compasses the Paris region administrative boundaries. We also show in Figure 1 that if very few of the workers who live in the Paris region work outside of it, the proportion of outside workers that live close to its administrative boundary and that work in the Paris region is very high. Frontier effects management seems very necessary when studying LJA issues in the Parisian context.

In this paper, because we use nation-wide datasets, we can assess the empirical

³ For instance, a job located 15 minutes away from a worker's residential location will be given a weight ranging between 0.85 and 0.75 while a job located 1 hour away from a worker's residential location will be given a weight ranging between 0.55 and 0.33.

⁴ In this paper, we call "frontier effects" the empirical consequences of using geographically truncated data. We do not refer to the literature on the effects of the frontiers themselves on individual or firm behaviour.

consequences of this theoretical risk, and show whether nullifying frontier effects (model f_2) or not (model f_1) leads to significant empirical discrepancies when measuring LJA.

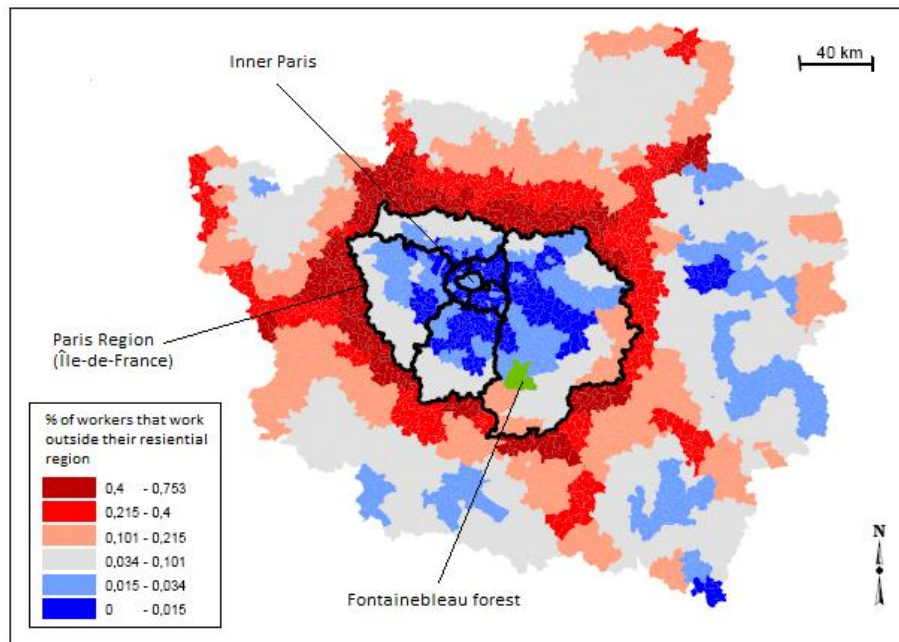


Figure 1. Frontier effects in the Paris Region

2.2. Job Availability

Second, even if a job is *reachable*, it will not necessarily be *available* to any worker: individual characteristics determine the actual matching of jobs and workers. The literature has progressed by providing increasingly differentiated ways (a_i) of measuring job *availability*

$$Avail_t^{a_1}$$

A first model (a_1) consists in using aggregated data both on the supply and the demand side of the market, i.e. comparing the stock of workers living in any given municipality with the stock of jobs that are reachable by them. On the French context, see for example Choffel and Delattre (2003), Gobillon and Selod (2007), Bania *et al.* (2008) and Duguet *et al.*, (2009). On the American context, see Massey *et al.* (1991), Rosenbaum and Harris (2001), Ong and Miller (2005) and Johnson (2006). In this case, the job availability of municipality t $Avail_t^{a_1}$

is equal to the pool $Pool_t^{p_k}$ of jobs that are reachable from track t (according to the proximity measure p_k).

Recent papers use census micro data that allow for an unidimensional subsetting of the local labour market (model a_2), which improves the modelling of the matching between jobs and workers. In model (a_2), the job availability $Avail_t^{a_1}$ for municipality t is equal to the pool $Pool_{t,q}^{p_k}$ of jobs within the subset q that are reachable from track t according to the proximity measure p_k .

Using model (a_2) is problematic because it means making implicit assumption that any job of a given socio-economic status (Korsu and Wenglenski, 2010) or education level (Matas *et al.*, 2008) is potentially identically available to any worker of the same socio-economic status (or education level). This is questionable. The relevance of the socio-economic statuses' definition in French statistics is an ongoing debate (see Héran, 1984, Duriez *et al.*, 1991 for early discussions). Also, even if socio-economic affiliation may be important for one's perception of one's social status, its influence on the decision to apply for any given job and its role on a firm's hiring decisions is less straightforward. It is true that probability that a worker with no degree is hired as an executive is likely to be very low: however, diploma downgrading (*déclassement scolaire*) is a long-established stylized fact of the French labour market (Fourgeot and Gautié, 1997; Nauze-Fichet and Tomanisi, 2002) – and may have worsened in recent years (Chauvel, 2006, Duru-Bellat, 2006, Maurin, 2009, Peugny, 2009).

All in all, the matching between jobs and workers depend on a greater number of factors and that isolated determinants such as socio-economic status and diploma. In this paper, we propose to use an original and fully estimated job availability measure (a_3) based on a 3-step econometric strategy.

Step 1. Estimating employment probabilities conditional to individual characteristics.

First, using the Labour Force Survey for the 2004-2006 period, we estimate, at the region level and for the active males, the global employment probability of holding a job conditional to the vector of individual characteristics X_{ik} .

We use the following control variables: age (in four categories: under 25, between 25 and 39, between 25 and 55), family status (man living alone, man living in a couple without children under 6, man living in a couple with at least a child under 6), level of education (in six categories: no qualification, vocational qualifications (BEP, CAP), technical or professional baccalaureate, general baccalaureate, under-graduate and graduate).

We add three additional variables. First, because Oswald (1996) pointed out the positive correlation between homeownership and unemployment, we introduce a covariate

representing the homeownership situation (in 4 categories: house owner, flat owner; renter of a subsidized home; renter of an unsubsidized home). Second, to take into account local labour market specificities, we introduce the unemployment rate of Employment Area (*Zone d'Emploi*)⁵. Lastly, since an individual's employment situation depends strongly of his past employment status, we introduce the worker's employment status the year before.

Let E^* and Job^* be two latent variables related to the observed employment status (E) and type of Job respectively (Job),

$$E_i^* = X_i \beta + \eta_{i1} \quad (5)$$

$$Job_i^* = X_i \gamma + \eta_{i2} \quad (6)$$

We observe $E=1$ if the individual i is employed and $E=0$ otherwise. X are the exogenous explanatory variables presented below and β is the vector of coefficients to estimate.

Therefore:

$$E_i = \begin{cases} 1 & \text{if } E_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

By assuming that η_i are i.i.d. of a type-I distribution, a simple logit model follows:

$$P(E=1|X) = \frac{\exp(\beta X)}{1 + \exp(\beta X)} \quad (7)$$

The marginal effect of this model is obtained by equation (8):

$$\frac{\partial P(E=1|X)}{\partial X} = \frac{\exp(\beta X)}{[1 + \exp(\beta X)]^2} \beta \quad (8)$$

Step 2. Estimating the workers' predicted labour market situation.

Then, for each active male worker i that lives in any municipality $t = 1, \dots, T=1300$ of the Paris region, we use the Dwellings census database to collect the information on his vector of individual characteristics X_i . Using the global coefficients $\hat{\beta}$ for the individual characteristics estimated in Step 1, we can therefore estimate the global employment

⁵ The French National Statistics Institute defined 348 Employment Areas (Zones d'Emploi) determined by the fact that most of the people who live in such area also work in it.

probability \hat{P}_{itk} of each active male i living in district t of the Dwellings census database.

To determine the predicted probability of labour market situation for the workers of the French Census we use the accept-reject simulator. The estimates \hat{P}_{itk} allows us to calculate the deterministic part of probability. To determine the predicted choices we assess the stochastic part of the probability of each choice. For that purpose we draw in a type I extreme value (Weibull) distribution some series of pseudo residuals \hat{P}_{itk} for $i = 1, \dots, N$ and $t = 1, \dots, T$.

The *c.d.f.* of a Weibull distribution is $F(\eta) = \exp(-\exp(\eta))$. Then a drawn x in a random distribution (Halton serie) gives a pseudo-residual $\hat{\eta}_{itk} = -\ln(-\ln(x))$. For each draw we determine which professional situation is obtained. The simulated probability is the proportion of draws that are accepts.

Let's define an indicating variable I_{itk}^r such as:

$$I_{itk}^r = \begin{cases} 1 & \text{if } \hat{U}_{it}^r > \hat{U}_{itk}^r \\ 0 & \text{otherwise} \end{cases}$$

So, we first compute $U_{itk}^r = \hat{\beta} X + \hat{\eta}_{itk}^r$

$$\hat{P}_t(t) = \frac{1}{R} \sum_{r=1}^R I_{it}^r$$

Then, the simulated probability is calculated as follows:

We fix $R=300$ for the calculation of each simulated probability.

Step 3. Estimated available district job pool

Using the ASDS database, we compute, for each district t , the number of existing jobs Job_t . With the reachability measures defined above, we then determine the pool

$Pool_{it}$ of jobs that are *accessible* to any individual living in the district t . Finally, by

multiplying the accessible jobs stock of Step 2 $Pool_{it}$ with the individual employment

probabilities of Step 1 \hat{P}_{it} , we estimate the pool of jobs $Avail_{itk}$ that are available

to any worker i living in municipality t .

Appendix 1 provides the results at the district (*département*) level using this methodology. When comparing our results with the aggregated observed employment situation described in administrative files (ADSD and unemployed database of Pôle Emploi), we observe some small differences, but the magnitude and the rank of the departments are roughly respected.

2.3. Local Job Competition

The last issue needed to address to measure LJA is the modelling of job competition (model c_m). Even if a job is *reachable* by and *available* to a worker, its actual *accessibility* also depends on the number of competitors that could also claim to form a match with it (Weibull, 1976, Ilhanfeldt, 1993, Harris, 2001, Van Wee *et al*, 2001, Kawabata and Shen, 2007).

In most papers on LJA, the competitors of the tract t workers are usually defined as the workers that are reachable from tract t (see Bania *et al.*, 2008; Duguet *et al.*, 2009) (Partial Job Competition, model c_1): in Figure 2 the competitors of Worker 1 for Job A are the workers who live within Worker 1's prospection ring (blue ring): Worker 3 and Worker 4 are both computed as Worker 1's competitors for Job A, while Worker 2 is not. However, in Figure 2 Job A is clearly within Worker 2's and outside Worker 3's prospection rings: Worker 4 and Worker 2 should be included among the competitors of Worker 1 for Job A, while Worker 3 shouldn't (see Détang-Dessandre and Gaigné, 2009, for a similar discussion).

Here, we propose to use a full definition of job competition (model c_2). First, we identify the reachable and available jobs j for any worker i living in municipality t . Second, we measure, for each of these jobs, the number of actual labour market competitors, i.e. the number of workers whom the job is also reachable and available. The number of competitors for worker i is then measured as the sum of his actual competitors for all jobs j *without double counting*. Then, for any municipality t , LJA is defined as the ratio of weighted reachable jobs to the number of labour market competitors for these jobs.

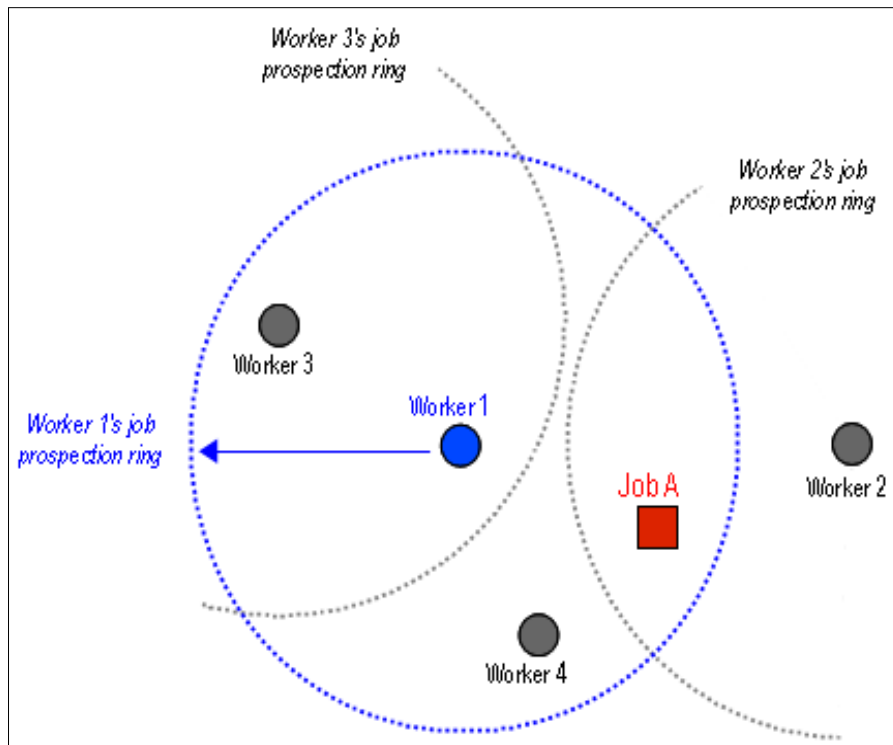


Figure 2. Partial vs. Full Job Competition

3. Data and area study

3.1. The data

We compute the job access of each male worker between 20 and 55 years old that lived in the Paris region in 2006 by measuring his estimated probability of finding a job conditionally to his individual characteristics. To do so, we use survey, census and administrative microdata as well as exhaustive municipality-to-municipality commute times. Descriptive statistics are presented in Appendix 2.

- The 2006 **French Census Dwellings** database provides information on individual nationality, age, gender, diploma, socio-economic group, job quality, mobility and dwellings characteristics.
- **The Annual Declarations of Social Data (ADSD) database** are collected by the French Institute for Statistics (INSEE). It is mandatory for most employers and self-employed in France for pension, benefits and tax purposes. That there is a unique record for each employee/establishment/year combination. The ADSD database includes data on wages, qualifications, industry and geographical localization. Employees included in the ADSD database represented (90%) of the private labour

force in the Paris region in 2006.

- **The Labour Force Survey (LFS)** is used to measure unemployment in the sense of the International Labour Organization. It provides data on the professions, on working hours and on casual employment.
- **Commute times.** For all time-based proximity measures, we use a comprehensive matrix of municipality-to-municipality commute times by automobile provided by the GIS software Chronomap.

3.2. The area study

The Paris Region consists in 1300 municipalities (1280 municipalities or *communes* and 20 downtown *arrondissements*) and 8 districts (*départements*). It is the most populated, rich and economically developed region in France with 21.6% of the French population in 2006 for 28.1% of its GDP. Its GDP per capita was 43,818 euros in 2006 (vs. 28,475 for whole country) and its GDP per job amounted to 92,736 euros (vs. 71,415 euros) (data: INSEE). There were 2.315 million male workers in the Paris region labour market, for 3.977 million available jobs in the private sector. In 2006, 72.60% of the male workers lived in a district (*département*) where the ratio between jobs and labour force was above 1. This ratio was very high in Inner Paris (district 75) and in a 'primary ring' composed by districts 92 (Hauts-de-Seine), 93 (Seine Saint Denis) and 94 (Val-de-Marne). It decreased steadily in the outer districts of the region. There were also many intra-regional home-to-work commutes: in 2006, only 28.30% of the male workers worked and lived in the same municipality.

4. Benchmarking strategy

To assess whether the model specification of local accessibility measurement has a significant empirical effects, we compute the Pearson correlation coefficients between i) the LJA levels of the 1300 Île-de-France municipalities obtained with a representative selection of the models reviewed in Section 2 and ii) the LJA levels measured with an original, fully estimated, benchmark model⁶.

For all models, LJA of municipality t $Access_t^{c_m, a_l, P_k, f_j}$ is defined as the ratio of the number of available jobs $AvailJobs_t^{a_l, P_k, f_j}$ to the number of labour market

⁶ The whole set of Pearson correlation coefficients computed between all methods is available upon request.

competitors $AvailComp_t^{c_m, a_l, P_k, f_j}$ that are reachable from municipality t (equation 9).

$$Access_t^{c_m, a_l, P_k, f_j} = \frac{AvailJobs_t^{a_l, P_k, f_j}}{AvailComp_t^{c_m, a_l, P_k, f_j}} \quad (9)$$

In the original benchmark model (Model B), we fully estimate the job availability probability (model a_2) and fully take into account the job competition on the labour market (model m_2). We also measure job proximity using the mixed concentric-rings model because it allows a better fitting with actual transportation patterns (model p_4). Finally, because we rely on nation-wide data, we nullify frontier effects (model f_1).

The “naïve” model (Model N) does not take into account jobs that are located outside a worker’s own municipality, is sensitive to frontier effects, does not estimates the job availability probability and partially takes job competition into account.

Models T• and G• are similar to the benchmark model with the exception of their proximity specification, and use a decay-based function. Models T use time-based distances, while models G• use orthodromic distances. To examine the results sensitivity to the decay parameter λ , we alternatively set low (Models T1 and G1), medium (Models T2 and G2) and high (Models T3 and G3) values for λ . By doing so, we keep consistency with the literature. Also, with parameter λ set to 0,05 in G• models (0,01 in T• models), jobs located at 14 kms (30 minutes) of a worker's location are modelled to be "half-reachable", which is consistent with the fact that 34 min and 10 km are the average commuting time in the Capital Region (DREIF, 2011).

Model F is similar to the benchmark model except that in this model we do not use nation-wide data to measure job proximity, and limit ourselves to jobs that are situated within the Paris Region, therefore ridding the results with frontier effects. In Model C, job competition is not fully measured, by contrast with the benchmark model B. Last but not least, in Model A we do not fully estimate the job availability probability.

5. Results

The results presented in Table 1 show that *i)* using different models for assessing LJA does lead to significantly different empirical results and that, moreover, *ii)* the empirical discrepancies are not consistent across the area study, particularly affecting unprivileged areas.

Table 1. Pearson correlation coefficients of Local Job Accessibility levels						
Model	Municipalities(nb)					
	All (1300)	Large* (299)	Frontier# (497)	Deprived\$ (145)	Unemployed§ (322)	Residential% (221)
N	0,855	0,642	0,589	0,626	0,432	0,576
T1	0,900	0,830	0,514	0,971	0,851	0,799
T2	0,934	0,957	0,628	0,992	0,963	0,960
T3	0,953	0,988	0,708	0,997	0,989	0,988
G1	0,457	0,606	0,038	0,591	0,522	0,444
G2	0,464	0,628	0,026	0,617	0,544	0,470
G3	0,473	0,634	0,078	0,625	0,553	0,481
F	0,893	0,848	0,621	0,900	0,828	0,854
C	0,886	0,756	0,651	0,711	0,749	0,685
A	0,998	0,970	0,993	0,997	0,978	0,984

All Pearson correlation coefficients are significant at 1%.

* Municipalities with over 4,500 inhabitants. This subsample includes more than 85% of the Paris region population.

Frontier municipalities and their neighbors (assessed using a level 2 Queen binary contiguity matrix).

\$ Particularly disadvantaged municipalities that are the target of specific local public policies and house one or more Priority zone for Education (*Zone d'éducation prioritaire*, ZEP) or Difficult Urban Zone (*Zone urbaine sensible*, ZUS).

§ Municipalities where men-unemployment was over 6.5% in 2006.

% Urban municipalities that belong to the Paris urban zone (as defined by the National Institute for Statistics, INSEE) but where there are more inhabitants than jobs. These residential municipalities (*banlieues dortoir*) are located at the outskirts of the Paris urban zone.

First, not surprisingly, as far as *proximity* is concerned, relying on distance-based models instead of time-based ones is likely to lead to very different results: distance-based Models

G• are clearly very poorly correlated with the time-based benchmark model B (Pearson coefficient equal to 0,457 for the strongest decay parameter). This is especially true for the municipalities that are located the further away from Inner Paris: time-based models should be used whenever possible in order to accurately take into account the effects of transportation system structure on the assessment of LJA.

Also, among time-based models, if using a continuous, decay-based specification (Models T•) versus a concentric-rings one (benchmark Model B) does not lead to significant different results when focusing on all municipalities, once again differences for the farthest municipalities. However, for frontier municipalities ,where jobs are more distant from the workers', the difference is bigger, even if decay-based specifications (Models T•) tend to over-weight distant jobs.

Interestingly, among time- and distance-based models, the decay parameter λ does not have a significant empirical impact on LJA measurement: whatever the sub-group of municipalities, models T1, T2 and T3's correlation with the benchmark model B are very similar, and the same is true for models G1, G2 and G3. This means that, at least for a roughly monocentric region such as Île-de-France, disagreement on the decay parameter specification is not likely to matter much, since the job gradient with the distance to the central business district is pretty steep anyway. This, however, could be vastly different for more polycentric regions.

Second, poor *frontier effects* management (in Model F) doesn't affect much the LJA ranking of the Paris region municipalities (correlation coefficient equal to 0,893 with the benchmark model). For any given proximity model, the further away a job, the lowest its weight, and other major French job clusters (Lyon, Marseille, Bordeaux, Strasbourg...) are very far from the Paris Region, which is surrounded by an extended area where there are very few jobs. All in all, failing to register the jobs located outside the Paris region frontier is not likely to modify the LJA level of any given municipality. However, this is less true for the "frontier municipalities", i.e. those that are located close to the region's border, where poor frontier effects management leads to a drop of the correlation coefficient to 0,621. For these remote municipalities, where jobs are scarce, ignoring the jobs and, more so, the competitors that are located just outside the border is empirically likely to have more consequences.

Third, fully or partially taking into account the extent of *job competition* (Model C) does not lead to very different LJA rankings (correlation coefficient equal to 0,886). However, again, this is less true for some specific municipalities: namely, for the "residential municipalities", the LJA levels correlation coefficient drops to a mere 0,685. These municipalities are predominantly located at the outskirts of the Paris urban area; due to the ongoing

suburbanization of the Paris region, they house many suburbanites that massively commute towards Inner Paris, which still concentrates the majority of available jobs. For these workers, using a partial measurement of job competition means ignoring the competition of the many other distant suburbanites that also seek jobs in Inner Paris – but that come from suburbs that are far away from their own prospection ring. Not taking fully into account the job competitors as explained in Section 2 could therefore lead to artificially overestimate the LJA of residential suburbs, preventing the identification (anremedial) of their specific employment difficulties.

Finally, we find interesting results as far as *job availability* is concerned. Strikingly, we find no evidence of any significant differences between the LJA ranking of the Paris region municipalities with (Model B) or without (Model A) fully estimating the job availability probability (correlation coefficient equal to 0,998). Moreover, this result holds for all municipality sub-groups, and particularly for deprived and high-unemployment municipalities. For these municipalities, we expected that estimating more accurately the job availability probability would lead to significantly different (and lower) LJA levels; this is not, apparently, the case.

However, the picture shifts when we depart from an aggregate point of view and examine the spatial dispersion of the differences in LJA levels between models A and B.

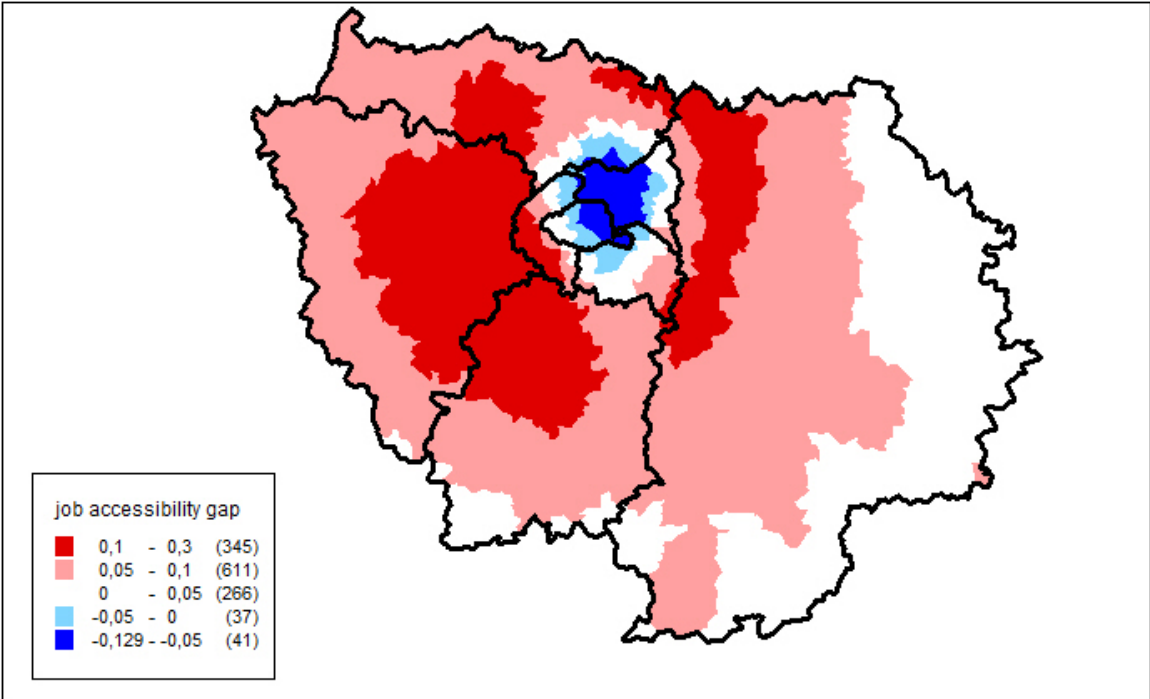


Figure 3. Job accessibility difference between models with and without a full estimation of the job availability probability

As visible in Figure 3, the expected difference is true for a cluster of municipalities, where failing to use a full estimation of the job availability probability leads to over-estimate the local job accessibility level (in blue in Figure 3). This cluster spreads, from the Northern municipalities of Inner Paris to Roissy, across most of the Seine-Saint-Denis (93) district. It regroups municipalities that are particularly deprived, whatever the measure of deprivation (Tovar, 2010, Bourdeau-Lepage and Tovar, 2011). As a result, fully estimating LJA does clearly highly matter, from a spatialized point of view, in order to avoid under-estimating the low job accessibility levels of the most underprivileged of the Paris Region municipalities.

6. Conclusion

In this paper, we tested the empirical consequences of using different models for measuring Local Job Accessibility. If “the rule makes the result”, it is important to keep progressing in the development of more accurate models for assessing Local Job Accessibility. After identifying four key elements of LJA measurement (Job Proximity, Frontier Effects, Job Availability and Local Job Competition), we contribute to this collective effort by proposing a model where, in particular, job availability is fully estimated using microdata on individual characteristics.

By benchmarking our models with a representative sample of alternative models, we show that using different methods does indeed lead to potentially globally biased results. We also show that some model elements have stronger empirical effects than others: for example, using time- or distance-based proximity measures matter more than the specification of the decay function. More importantly, we show that the methodologically-induced empirical differences can vary across the region’s municipalities, according to their distance to the region’s administrative frontier, their unemployment level or the presence of distant municipalities with overlapping job prospection areas. More specifically, failing to fully estimate the job availability element of LJA assessment may lead to over-estimate the local job accessibility of particularly under-privileged areas, which may have significant consequences on local unemployment alleviating public policies.

Further research on these issues may progress in different directions: first, our benchmarking results were found on a specific context (the Paris Region). It remains to be seen if the relative importance of the four methodological issues tackled in this paper as far as empirical discrepancies is concerned is robust to testing in another context. Also, our benchmarking strategy relies on the use of Spearman correlation coefficients and the mapping of the different LJA levels produced by alternative modeling strategies. Other criteria could be used

(such as in, for example, Harris, 2001).

7. References

- Allard S.W., Danziger S.H (2002) Proximity and Opportunity: How Residence and Race Affect the Employment of Welfare, *Housing Policy Debate*, 13 (4), pp.675-700.
- Bania N., Leete L., Coulton C. (2008) Job Access, Employment and Earnings: Outcomes for Welfare Leavers in a US Urban Labour Market, *Urban Studies*, 45 (11) pp.2179–2202.
- Bourdeau-Lepage L. and Tovar E, (2011), "Well-being in the Paris region: widening regional disparities despite overall improvement", *Metropolitics*, 12 October 2011.
- Cervero R., Rood T., Appleyard B., 1999, Tracking accessibility: employment and housing opportunities in the San Francisco Bay area, *Environment and Planning A*, 31 (7), pp.1259–1278.
- Chauvel L., 2006, *Les Classes moyennes à la dérive*, Paris, Seuil.
- Cheshire P., 1995, A new phase of urban development in western Europe? The evidence for the 1980s, *Urban Studies*, 32, pp. 1045–1063.
- Delattre E. Choffel P., (2003). Effets locaux et urbains sur les parcours de chômage Une analyse microéconométrique sur le panel de chômeurs TDE-MLT, *Premières Synthèses*, DARES, 43.1,
- Détang-Dessendre C., Gagné C. (2009), Unemployment duration, city size, and the tightness of the labor market, *Regional Science and Urban Economics*, 39, pp. 266–276.
- Duguet E., L'Horty Y., du Parquet L., Petit P. and Sari F. (2012) "Les effets du lieu de résidence sur l'accès à l'emploi : une expérience contrôlée sur des jeunes qualifiés en Ile-de-France" *Économie et Statistique*, forthcoming
- Duguet E., L'Horty Y., Sari F., 2009, Sortir du chômage en Île-de-France. Disparités territoriales, spatial mismatch et ségrégation résidentielle, *Revue Economique*, vol 60, pp. 979-1010.
- Dujardin C., Selod H., Thomas I. (2008) Residential Segregation and Unemployment: The Case of Brussels, *Urban Studies*, 45(1) 89–113.
- Duriez B., Ion, J., Pinçon, M., Pinçon-Charlot, M., 1991, Institutions statistiques et nomenclatures socioprofessionnelles, *Revue française de sociologie*, 32-1, p. 29-59.
- Duru-Bellat M. (2006) *L'inflation scolaire*, Paris, Seuil.
- Gaschet F., Gaussier N. (2004) Urban segregation and labour markets within the Bordeaux Metropolitan Area: an investigation of the spatial friction, *Cahiers du GRES* n°2004-19, 28 p.
- Gilli F (2005) Le Bassin parisien : une région métropolitaine, *Revue Européenne de Géographie*, 324
- Gobillon L., Selod H. (2007) Les déterminants locaux du chômage en région parisienne, *Économie et Prévision*, vol 4-5, n°180-181, pp. 19-38.
- Handy S., Niemeier D., 1997, Measuring accessibility: an exploration of issues and alternatives, *Environment and Planning A*, 29, pp. 1175–1194.
- Hansen, W. 1959. How Accessibility Shapes Land Use. *Journal of the American Institute of Planners* 25:73–6.
- Harris B., 2001, Accessibility: concepts and application, *Journal of Transportation and Statistics*, 4 (2-3), pp.15-30.

- Héran, F., 1984, L'assise statistique de la sociologie, *Économie et Statistique*, n° 168, pp.23-35.
- Houston, D., 2005, Employability, Skills Mismatch and Spatial Mismatch in Metropolitan Labour Markets, in *Urban Studies*, Vol 42, No.2, pp. 221-243.
- Ihlanfeldt K., Sjoquist D., 1998, The spatial mismatch hypothesis: a review of recent studies and their implications for welfare reform, *Housing Policy Debate*, 9 , pp. 849–892.
- Ihlanfeldt K., 1993, The spatial mismatch between jobs and residential locations within urban areas. *Cityscape*, 1, pp.219-244.
- Jayet H., 2000, «Villes et marchés du travail », in *Ville et emploi. Le territoire au cœur des nouvelles formes du travail*, E. Perrin and N. Rousier (Eds.), Paris, L'Aube, pp.53-64.
- Johnson R., 2006, Landing a job in urban space: the extent and effects of spatial mismatch, *Regional Science and Urban Economics*, 36, pp. 331–372.
- Kain J, 1968, Housing Segregation, Negro Employment, and Metropolitan Decentralization, *Quarterly Journal of Economics*, 82, p. 175-197.
- Kain J, 1992, The Spatial Mismatch Hypothesis: Three Decades Later, *Housing Policy Debate*, 3, pp. 371-460.
- Kawabata M., Shen Qing (2007) Commuting Inequality between Cars and Public Transit: The Case of the San Francisco Bay Area, 1990-2000, *Urban Studies*, 44 (9), pp.1759-1780.
- Korsu E., Wenglenski S. (2010) Job Accessibility, Residential Segregation, and Risk of Long-term Unemployment in the Paris Region, *Urban Studies*, 47(11) 2279–2324.
- Marpsat, M. and Laurent, R. (1997) Le chômage des jeunes est-il aggravé par l'appartenance à un quartier en difficulté, in: *En marge de la ville, au cœur de la société: ces quartiers dont on parle*, pp. 231–251, Paris: Éditions de l'Aube.
- Massey D., Gross A., Eggers M., 1991, Segregation, the concentration of poverty, and the life chances of individuals, *Social Science Research*, 20 (4), pp. 397–420.
- Maurin E (2009) *La peur du déclassement. Une sociologie des récessions*, Paris, Seuil.
- Morris J.M., Dumble P.L., and Wigan. M.R (1979) Accessibility indicators for transport planning. *Transport Research*, Vol. 13 A, pp. 91-109.
- Musterd, S., Ostendorf, W. and Vos, S. de (2003) Environmental effects and social mobility, *Housing Studies*, 18(6), pp. 877–892.
- Nauze-Fichet, E., Tomanisi, M. (2002) Diplôme et insertion sur le marché du travail : approches socioprofessionnelle et salariale du déclassement, *Economie et Statistique*, n°354, pp.21-48.
- Ong P. M., Miller D., 2005, Spatial and transportation mismatch in Los Angeles, *Journal of Planning Education and Research*, 25 (1), pp. 43–56.
- Oswald, A.J. (1996) A conjecture on the explanation for high unemployment in the industrialized nations: Part I, *mimeo*, Warwick University.
- Patacchini E., Zenou Y., 2005, Spatial mismatch, transport mode and search decisions in England, *Journal of Urban Economics*, 58, pp. 62–90.
- Peugny C., 2009, *Le Déclassement*, Paris, Grasset.
- Raphael, S. (1998) The spatial mismatch hypothesis and black youth joblessness: evidence from the San Francisco Bay area, *Journal of Urban Economics*, 43, pp. 79–111.
- Rogers C., 1997, Job search and unemployment duration: implications for the spatial mismatch hypothesis, *Journal of Urban Economics*, 42, pp. 109–132.

Rosenbaum E., Harris L., 2001, Residential mobility and opportunities: early impacts of the moving to opportunity demonstration in Chicago, *Housing Policy Debate*, 12 (2), pp. 321–346.

Sanchez, T. W., Shen, Q. and Peng, Z. R. (2004) Transit mobility, jobs access, and low-income labour participation in US metropolitan areas, *Urban Studies*, 41, pp. 1313–1331.

Shen, Q. (1998) Location characteristics of inner city neighborhoods and employment accessibility of low-wage workers, *Environment and Planning B*, 25(3), pp.345-365.

Silverman, B. (1986) *Density Estimation for Statistics and Data Analysis*, London, Chapman and Hall

Tovar E., 2010, Ségrégation et formes d'emploi à Paris, *Revue d'Economie Régionale et urbaine*, pp. 111-134.

Klaauw, B. van der and Ours, J. van (2003) From welfare to work: does the neighbourhood matter?, *Journal of Public Economics*, 87, pp. 957–985.

Van Wee B., Hagoort M., Annema J.A., 2001, Accessibility measures with competition, *Journal of Transport Geography*, 9, pp.199-208.

Weibull J.W., 1976 An axiomatic approach to the measurement of accessibility, *Regional Science and Urban Economics*, 6, pp. 357-379.

Appendix 1. Gap between estimated and observed unemployment by district

	Actual	Estimated
<i>Estimated(1)</i>		
Total	8.5%	7.4%
Paris	9.3%	10.8%
Seine et Marne	7.0%	5.3%
Yvelines	6.5%	5.4%
Essonne	6.4%	5.5%
Hauts-de-Seine	7.8%	8.1%
Seine-St-Denis	11.7%	10.7%
Val-de-Marne	8.1%	8.0%
Val-d'Oise	8.7%	6.6%

(1) Estimation obtained by using our estimation applied to Census Dwellings sample.

(2) Pôle-Emploi for the unemployment rate and Dads for the qualification in the private sector (males between 20 and 55 years old).

Appendix 2. Descriptive Statistics

	French LFS	French Census
<i>Individual variables</i>		
15-19 years	0,3%	0,4%
20-24 years	4,9%	5,6%
25-39 years	46,4%	46,4%
40-54 years	48,4%	47,6%
Age	38,711	
Married	45,4%	54,0%
Children less than 6 years old	14,8%	29,2%
Children between 6 and 18 years old	23,9%	35,9%
<i>Diploma variables</i>		
Upper education	12,2%	15,9%
Graduate	11,8%	13,1%
BAC pro	9,6%	9,5%
BAC	5,8%	7,1%
BEP	31,3%	32,6%
No degree	29,3%	21,8%
<i>Oswald's Hypothesis</i>		
House	47,2%	55,5%
Size of the House	27,4%	17,5%
Owner-occupied	45,5%	51,4%
Living in publicly owned units	18,8%	15,6%
Renter-occupied in a no publicly owned units	35,7%	33,0%
<i>Neighbourhood variable</i>		
Unemployment rate	7,8%	7,7%
<i>Localisation</i>		
Ile-de-France	21,7%	20,4%
Acquaine	3,8%	4,7%
Bretagne	3,9%	5,0%
Centre	2,9%	4,2%
Lorraine	4,0%	4,0%
Nord-pas-Calais	9,2%	6,7%
Paca	5,6%	6,9%

Rhône-Alpes	10,0%	10,0%
Other	38,9%	38,2%
<hr/>		
<i>Labor status in t</i>		
Unemployed	13,0%	8,6%
Employed	87,0%	91,4%
<hr/>		
<i>Labor status in t+1</i>		
Out of the labor market	3,8%	n.a
Unemployed	10,4%	n.a
<hr/>		

Source: French LFS and Census (Dwellings database).