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CENTRO STUDI LUCA D'AGLIANO
DEVELOPMENT STUDIES WORKING PAPERS

N. 198

March 2005

Job Search in Thick Markets: Evidence from Italy

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8th May 2005

Abstract

I analyze empirically the effects of both urban and industrial agglomeration on men's and women's search behavior and on the efficiency of matching. The analysis is based on the Italian Labor Force Survey micro-data, which covers 520 randomly drawn Local Labor Market Areas (66 per cent of the total) over the four quarters of 2002. I compute transition probabilities from non-employment to employment by jointly estimating the probability of searching and the probability of finding a job conditional on having searched, and I test whether these are affected by urbanization, industry localization, labor pooling and family network quality. In general, the main results indicate that urbanization and labor pooling raise job seekers' chances of finding employment (conditional on having searched), while industry localization and family network quality increase only men's. Moreover, neither urban nor industrial agglomeration affect non-employed individuals' search behavior; although men with thicker family networks search more intensively.

*Bank of Italy and University of Oxford. E-mail address: sabrina.diaddario@bancaditalia.it. This work owes much to extensive discussions with Eliana Viviano. I am particularly grateful for her invaluable help with the attrition analysis and with some aspects of programming. I also thank Erich Battistin, Massimo Caruso, William Greene, Vernon Henderson, Barbara Petrongolo, Alfonso Rosolia, Margaret Stevens, and William Strange for their helpful comments and suggestions. Finally, I thank both the participants to the CEPR conference "Integration and Technological Change: Challenges for European Regions" (11-13 June 2004, Paris) and those of the Labor Economics seminar held at the University of Oxford on 2nd December, 2004. The views expressed in this paper are those of the author and do not involve the responsibility of the Bank.

1 Introduction

Matching models are widely used to analyze the process of job formation in the presence of labor market frictions. These models are typically taken to operate, and empirically estimated, at the national level (see Petrongolo and Pissarides (2001) for a survey). In a context of slow mobility of labor, however, the matching of workers and jobs may occur instead at a much more localized level (e.g., at the local labor market level), and in particular, it may be affected by the degree of urban or industrial agglomeration. Local markets, for instance, may differ in the presence of skill heterogeneities: according to Marshall's "labor pooling hypothesis", agglomeration lowers the degree of mismatch between the skills required by firms and those offered by workers, improving the quality of the match. Also, denser markets may be characterized by a lower degree of information imperfection. Finally, congestion depends on population and firm density, which may vary to a great extent across local markets.

The majority of the literature analyzes labor market dynamics by focusing on the unconditional hazard rate into employment. However, since the latter is the product of the probability of searching and the probability of finding a job conditional on having searched, it is interesting to explore the extent to which transitions to employment are due to the effort individuals devote to job seeking or to the employment chances per unit of search.[1] Moreover, these two stages of the search process can be differently affected by agglomeration externalities: local hazard rates through changes in the overall labor demand and supply, and in the technology of matching; job seekers' propensity to search through individual resources, search costs and returns, and hazard rates.

In this paper I empirically analyze the impact of agglomeration on both the individual's search intensity and the hazard rate into employment. The sign of the final outcome of agglomeration effects is not *a priori* obvious. Indeed, on the cost side, on the one hand more agglomerated areas may be characterized by lower search intensity because of higher search costs due to congestion (e.g., traffic jams). On the other hand, a shorter distance to job interviews, more frequent "face-to-face contacts", and the presence of thicker informal networks lowering information asymmetries may reduce both commuting and information-gathering costs, which increase the individual intensity of search. Another factor on the cost side that may increase search intensity in the more agglomerated areas, is the higher cost of living (e.g., housing costs), as it raises the opportunity cost of staying unemployed. On the return side, agglomeration may increase job seekers' search intensity by raising local wages or improving hazard rates. The latter, in turn, depend on the intensity of job

[1] Peracchi and Viviano (2004) are one of the few exceptions in the literature exploiting this relationship.

advertising, the thickness of the labor market, and the technology of matching. While there is some empirical evidence of higher wages in agglomerated areas, the net effect of agglomeration on labor market tightness and on the technology of matching is less clear-cut. Indeed, agglomeration may raise both the demand and the supply of labor, so that it is not obvious whether it would make markets more or less tight. With regards to the technology of matching, whether the size of the market improves or depresses the contact rate (per unit of search), depends on whether congestion effects dominate over "thick" markets externalities (see Petrongolo and Pissarides, 2001). Finally, also the effect on match quality is uncertain: on the one hand, the pooling of specialized labor improves the efficiency of matches; on the other hand, knowing that in agglomerated areas the probability of a meeting is higher, job seekers may become choosier, which lowers the probability of job offer acceptance. Which of these effects will prevail is thus a matter of empirical investigation.

In this paper I use the Italian Labor Force Survey micro-data to estimate the effects of agglomeration on employment probabilities and job search intensity. First, to measure the effects of *urban agglomeration* I use a dummy for "large city", equal to one if the individual resides in a local labor market system (LLM) with a population above $404,526$ inhabitants. In contrast to the majority of the studies that use arbitrary cut-off points, I adopt the same threshold value devised by Di Addario and Patacchini (2005) on the basis of spatial autocorrelation analysis applied to Italian LLMs. However, since the spatial unit of analysis is crucial to determine the existence and extent of agglomeration externalities (Arzaghi and Henderson, 2004), I also use a continuous variable: the LLM population size.[2] Second, to measure the effects of *industrial agglomeration* I use both a "super-district" dummy (denoting the LLMs with a high presence of small and medium sized manufacturing firms) and a traditional-sector-specialization index, proxying the effect of labor pooling. Third, I use the number of employed individuals in the household as a proxy for *network quality* (see Wahba and Zenou, 2003), under the assumption that family networks are important to find employment and that employed individuals have access to larger networks than unemployed ones (as they presumably have more information on job offers). In particular, I divide the Italian territory into three sets of LLMs: large cities, small towns containing super-districts, and non-industrial small towns. I am thus able to compare the labor market dynamics of non-employed people living in urban and industrially agglomerated areas to those living in the rest of the country. This method enables me to compare the urbanization and industry localization effects on search behavior and

[2] According to Rosenthal and Strange (2004) the size of the area may matter, as externalities decay quickly over space (within 10 miles). However, the logarithm of LLM area is rarely significant in my regressions. While in theory both population size and density may generate agglomeration externalities on search behavior, in practise this does not seem to be the case in Italy and in the UK (for the latter, see Petrongolo and Pissarides, 2004).

employment probabilities, which, to my knowledge, has not been analyzed before.

Overall, my results indicate that urbanization increases mens' chances of finding employment below the $2,400,000$-inhabitant threshold, while the positive externalities generated by localization appear only beyond a certain threshold (e.g., in the industrial clusters with a higher share of small manufacturing firms). In contrast, women's employment chances always increase with labor market size but are not affected by industrial agglomeration. Living in a more skill-homogenous labor market, however, increases the probability of finding a job for both men and women. As to search intensity, job seekers' behavior is not affected by either urban nor industrial agglomeration. Finally, having a larger family network increases men's chances of employment but also their search effort.

These findings suggest that the externalities generated by agglomeration on search behavior and employment probabilities vary according to individuals' gender, and to both the type and the degree of agglomeration considered. This has important policy implications.

First, one of the reasons why agglomeration externalities have gender-specific effects on labor markets dynamics may depend on the absence of policies aimed at supporting mothers' employment during child care. This, on the one hand, may contribute to the persistence of the traditional division of labor in the household, making men and women face different opportunity search costs; on the other hand it could favor job discrimination against women.[3]

Second, if the spatial concentration of small and medium sized industrial firms improves the efficiency of matching, it might be advisable to favor the emergence or the development of industrial clusters.[4] However, my results indicate that not all industrial districts reduce frictions, as the probability of finding a job per unit of search is significantly higher in super-districts but not in industrial districts. While the super-districts subset has been identified out of industrial districts on the basis of statistical criteria (namely, firm size and sector concentration), it would be important to study more in detail whether they also differ along other lines (e.g., product quality, organization of the production process, etc.). Furthermore, it might be useful to investigate more in detail why super-districts improve only the matching of men.

Third, the absence of urbanization effects on men's hazard rates beyond the $2,400,000$-inhabitant

[3] Some evidence of wage discrimination in Italy is reported in de Blasio and Di Addario (2005), who also show that, after controlling for observable individual characteristics, women have a lower probability of becoming entrepreneurs than men.

[4] Although this is a controversial issue. Since the 1990s, Italy provides subsidies to promote and sustain industrial districts, but according to some authors (e.g., Putnam, 1993) the genesis of Italian industrial districts has been a slow process, with roots in historical events that took place centuries ago, and thus cannot be fostered by any policy.

threshold might imply that the cities above it (i.e., Rome, Milan and Naples) are "too big", possibly because of decreasing returns in the local matching function. According to Au and Henderson (2004), however, being "too small" is worst than being "too big": the loss of real output per worker generated by under-sized cities is much larger than that originating from oversize (-16 percent against -6 percent). Knowing which is the optimal size of Italian cities would be important, as increasing the dimension of under-sized cities (for a given industrial composition) generates more productivity gains than reducing that of over-sized ones.

The paper is structured as follows. The next section presents the theoretical framework; Section 3 reports the empirical model, Section 4 the data set and the variables; Section 5 discusses the estimation results; and Section 6 concludes.

2 The theoretical framework

In the standard search and matching literature (for instance, Pissarides, 2000), the number of matches M is expressed as an increasing and concave function of the amount of workers searching for employment and the number of vacant positions. To study the effects of agglomeration on search, I assume that the national labor market is geographically segmented. Thus, every geographical unit or local labor market j has a matching function specific to the area, both in terms of arguments (as in Patacchini and Zenou, 2003) and in terms of technology:

$$M_j = M_j(s_j J_j, a_j V_j) \tag{1}$$

where J_j is the number of searchers in local labor market j, s_j the area's average search intensity, V_j the amount of vacancies, and a_j the area's intensity of job advertising.

The rate of job-finding for an individual i searching with intensity s_{ij} is:

$$m(s_{ij}, a_j\theta_j) = s_{ij}\frac{M_j(s_j J_j, a_j V_j)}{s_j J_j} = s_{ij} h_j(a_j\theta_j) \tag{2}$$

where h_j is the rate of matching per unit of search,[5] and $\theta_j = V_j/s_j J_j$ is a measure of the area's labor market tightness.

[5] That is, the rate at which a worker searching with unit intensity will find a job, if s_{ij} is normalized to be between 0 and 1. Under this normalization, in the empirical part of the paper (Section 4) I take s_{ij} to be the probability of searching and h_j to be the hazard rate (i.e., the probability of finding a job conditional on having searched). Note that the individual's job-finding-rate can be expressed as a function of labor market tightness only under the assumption of constant returns to scale of the matching function.

Let a job seeker's budget constraint be:

$$b = C_j(s_{ij}) + c_j z_{ij} \tag{3}$$

with:

$$C_j(s_{ij}) = d_j s_{ij}^{\gamma}, \gamma > 1 \tag{4}$$

where b denotes the income of a non-employed person, $C_j(s_{ij})$ the cost of search, z_{ij} a real consumption good bundle, and c_j the area cost of living (e.g. housing costs). I assume that agents' utility from consumption $u(z_{ij})$ is an increasing and concave function of z_{ij}. The expected intertemporal utility (in steady state) achieved by an unemployed agent is therefore:

$$rW_{ij}^{U} = u\left(\frac{b - C_j(s_{ij})}{c_j}\right) + s_{ij} h_j(a_j \theta_j)(W_{ij}^{E} - W_{ij}^{U}) \tag{5}$$

where W_{ij}^{E} is her expected lifetime utility when currently employed and r the discount rate.

The optimal level of search intensity s_{ij}^{*} a job seeker will exercise is that which maximizes (5): $\partial W_{ij}^{U} / \partial s_{ij} = 0$, or (at an interior solution):

$$u'(z_{ij}) \frac{C_j'(s_{ij})}{c_j} = h_j(a_j \theta_j)(W_{ij}^{E} - W_{ij}^{U}) \tag{6}$$

Job seekers are thus faced with a trade-off between the marginal cost of increased search effort in terms of current consumption and the marginal increase in their chances of finding a job that it induces. Thus, whether search is more or less intense in agglomerated areas depends on whether labor market size lowers the costs of search and/or increases its returns. I take this simple model as the starting point to discuss the mechanisms through which agglomeration may affect individuals' search behavior.

2.1 The effects of agglomeration

On the cost side, there are two channels through which agglomeration may affect search: search costs and the cost of living.

With respect to the former, a shorter distance to job interviews or more frequent face-to-face contacts due to physical proximity may reduce both transportation costs and the costs of acquisition of information on vacancies.[6] In denser areas, search costs may be lower also because of the presence

[6] From the firm's perspective, in Wheeler (2001) per-worker firm recruitment costs decrease with population density, as the frequency of interactions enhances the arrival rate of potential workers for a job opening, which has a fixed cost.

of thicker informal networks facilitating the diffusion of information on job opportunities (Wahba and Zenou, 2003). In contrast, congestion (e.g., more intense traffic jams, crowded buses, etc.) may, on the contrary, increase search costs and thus reduce individuals' search intensity.

With regards to the cost of living, more congested areas are likely to suffer from higher house prices and rents, which, by increasing the cost of staying unemployed with respect to lower-density areas, should induce job seekers to search more intensively. This effect occurs whenever the unemployment benefit b is either fixed or less responsive to the local cost of living c_j than local nominal wages; in fact, there is evidence that wages are actually higher in denser areas, and b will include some nationally determined benefits that are not indexed for local cost-of-living.

On the return side (the hazard rate), there are four main channels through which agglomeration may affect search: wages, vacancy advertisement, labor market tightness, and the technology of matching.

First, job seekers may search more intensively in agglomerated areas because they have a higher utility from employment than elsewhere. Indeed, according to the literature on agglomeration, in larger labor markets wages may be higher than average because of the productivity gains generated by the Marshallian externalities.[7] However, a higher expectation of future earnings has also the indirect effect of increasing reservation wages, which lowers the job seeker's acceptance probability and thus the hazard rate and the intensity of search.

Second, if agglomeration increased labor market tightness it would also raise hazard rates and thus individuals' search intensity. However, whether markets are more or less tight in agglomerated areas is itself a question of empirical investigation, as there are reasons to expect the number of both applications and vacancies to be higher than in non-agglomerated zones.[8] Again, the positive direct impact of tighter labor markets on hazard rates could be partly offset by an increase in reservation wages, lowering unemployed workers' job acceptance probabilities (though the other side of the coin is that firms become less choosey about whom they hire as their difficulties in filling vacancies raise).

[7] For empirical results on higher urban wages see, for instance, Glaeser and Mare' (2001) for the US and Di Addario and Patacchini (2005) for Italy, though de Blasio and Di Addario (2005) do not find evidence of different average earnings in Italian industrially agglomerated areas (Industrial Districts).

[8] According to Helsley's and Strange's (1990) model, the competition externality that firms generate when locate in a city (due to the fact that other firms' profits are reduced) prevails on the productivity externality (due to the fact that the productivity of all workers is enhanced). Under free entry, this leads to "too many" firms in cities, which implies, other things being equal, a higher vacancy-to-unemployment ratio. Since there are no reliable data on vacancies in Italy, I cannot empirically test the existence of differentials in local labor market tightness due to agglomeration. These can only be inferred from the impact of urbanization and localization on individual hazard rates, which are increasing in market tightness and can be measured directly (see Section 5).

Third, agglomeration may increase job seekers' propensity to search by intensifying firms' job advertising. Also this channel operates through an improvement of the hazard rate. The impact of agglomeration on the intensity of job advertising is twofold. On the one hand, if more agglomerated areas were characterized by tighter labor markets they would also exhibit less intense job advertising, since in this case a lower chance of filling their vacancies would discourage firms from advertising their positions (a sort of "discouraged-job" effect). On the other hand, denser areas may be characterized by more intense job advertising for mainly three reasons. Firstly, because the existence of thicker networks[9] may reduce the cost incurred by firms in advertising their vacant positions. Secondly, because the higher number of job seekers may allow employers to more easily cover any fixed costs of advertisement. Thirdly, because of a greater average labor productivity.[10] In all these cases, job seekers exercise more effort simply because they have better chances to find a job and are hence more encouraged to search than elsewhere.[11]

Finally, search intensity depends on the technology of matching. Agglomeration may have an impact both on the chances and on the quality of matching.[12] With respect to the former, on the one hand the greater concentration and / or specialization of matching agents in agglomerated areas may increase the effective job contact rate, and thus the hazard rate. On the other hand, a higher density may actually lower the meeting rate if congestion effects dominate over "thick" markets externalities.[13] Furthermore, even when the contact rate (per unit of search) is improved job seekers may react by becoming choosier and accepting job offers less frequently, thereby depressing the hazard rate. Which type of external (dis)economy will prevail is, ultimately, a matter of empirical investigation.

With respect to the quality of matches, according to Marshall's "labor pooling hypothesis" agglomeration improves the matching efficiency between jobs and workers, as the areas where many specialized firms concentrate tend to attract the job seekers with the specific skills required

[9] These can either be informal (e.g., Marshall's "industrial atmosphere") or real network agencies (Arzaghi and Henderson, 2004).

[10] See Pissarides (2000) for a partial equilibrium analysis of job advertising and Ciccone and Hall (1996) – among others – for the evidence on higher labor productivity in denser areas.

[11] As Pissarides (2000) notices, this is the reverse of the discouraged-worker effect.

[12] See Duranton and Puga (2004) for a survey. Note that agglomeration may also affect the elasticities of the matching function with respect to job seekers and vacancies, so as to generate increasing returns to scale. As a matter of fact, the majority of the empirical studies (see Petrongolo and Pissarides (2001) for a review) finds constant returns to scale in the aggregate matching function, possibly because reservation wages adjust to offset the scale effects generated in the contact technology or in the productivity of job matches (Petrongolo and Pissarides, 2004).

[13] See Petrongolo and Pissarides (2001). Besides the negative externality generated by a job seeker on the other, other sources of congestion may derive from local "dis-amenities" such as more traffic jams, crowded subways, pollution etc. For a survey on agglomeration externalities see Rosenthal and Strange (2004) and Duranton and Puga (2004).

(for a survey, see Duranton and Puga (2004) and Rosenthal and Strange, 2004). Thus, on the one hand the better expected quality of matches may raise the job seekers' probability of acceptance as firms make more attractive offers, but on the other hand agents' choosiness (i.e., reservation wages) may again increase, which would go in the opposite direction.[14]

In conclusion, it is certainly very difficult to predict the sign of the net agglomeration effect on hazard rates and search intensity, as the equilibrium generating them is very complex. The aim of this section was really the highlighting of some of the possible mechanisms at work and the introduction of a note of cautiousness in the interpretation of the results.

3 The empirical model

As I showed in the previous section (equation (6)), the transition probabilities from non-employment into employment depend on two elements, one determined by agents' search behavior and the other one by the matching process. In order to empirically examine the impact of agglomeration on the transition probabilities between labor market states, thus, one needs to find measures of both the individual's propensity to search and of the effectiveness of matching.

I shall define s_{it} as the probability that a non-employed person looks for a job at time t,[15] and h_{it} as the probability that she finds employment at time $t+1$, conditional on having searched. Each person who was not employed at time t can be in one of the possible three states at time $t+1$:

1. they sought employment between t and $t+1$ and found a job (E_{t+1});
2. they sought employment between t and $t+1$ but did not find a job (U_{t+1});
3. they did not seek employment between t and $t+1$ (O_{t+1}).

Let $\tilde{s}_{it}$ be the latent variable determining whether a non-employed person looks for a job at time t (i.e., the difference in her expected utility from searching and not searching) and $\tilde{h}_{it}$ the variable determining whether a job seeker finds employment at time $t+1$ (incorporating both the likelihood of her meeting a prospective employer and the sign of the surplus generated by that match). Even

[14] Petrongolo and Pissarides (2004) suggest that when agglomeration improves the quality of matches and the mean of the wage offer distribution increases, job seekers raise their reservation wages so as to offset any positive effect on hazard rates. Conversely, when agglomeration raises the arrival rate of job offers (for instance, through a higher vacancy-to-unemployment ratio), hazard rates tend to increase while individual wages do not.

[15] Note that in the theoretical model presented in Section 2, s_{it} was a continuous variable greater of equal to zero denoting the number of search units supplied by the individual i. Here, without loss of generality, I am normalizing search intensity to be between zero and one.

though $\tilde{h}_{it}$ and $\tilde{s}_{it}$ are not observable, I can express them as a function of two non-coincident sets of individual and location-specific variables, X_{it} and Z_{it} (detailed in Section 5), using the Labor Force Survey micro-data on labor market transitions:[16]

$$\tilde{h}_{it} = \beta' X_{it} + \epsilon_{1t} \tag{7}$$

and

$$\tilde{s}_{it} = \gamma' Z_{it} + \epsilon_{2t} \tag{8}$$

The probability of observing a person who has searched at time t is thus $Pr(\gamma' Z_{it} + \epsilon_{2t} > 0 | \; Z_{it})$, which I assume to be a probit $\Phi(\gamma' Z_{it})$. Similarly, the probability of observing a job seeker finding a job at $t+1$ is $Pr(\beta' X_{it} + \epsilon_{1t} > 0 | \; X_{it}) = \Phi(\beta' X_{it})$.

My econometric methodology will consist in the joint estimation of s_{it} and h_{it} by maximum likelihood. To ensure robustness, two alternative econometric specifications will be estimated.

I first consider a simple search model where (after controlling for observable characteristics) individuals can be treated as identical, in the sense of being randomly matched to vacancies. In this framework, the transition probability from non-employment into employment is the product of the probability of searching s_{it} and the probability h_{it} that a job seeker finds a job. Thus, I will estimate s_{it} and h_{it} by maximizing the following likelihood function (as in Peracchi and Viviano, 2005):[17]

$$L = \prod_{i \in \{E_{t+1}\}} [\Phi(\beta' X_i)][\Phi(\gamma' Z_i)] \prod_{i \in \{Ut+1\}} [1 - \Phi(\beta' X_i)][\Phi(\gamma' Z_i)] \prod_{i \in \{Ot+1\}} [1 - \Phi(\gamma' Z_i)] \tag{9}$$

If there was unobservable heterogeneity among workers, however, the probabilities of searching and finding a job (conditional on the X_i and Z_i's) would not be independent. I therefore correct the above maximum-likelihood estimation to take into account the fact that the hazard-rate equation can be estimated only on the censored sample of the agents who search ($Z_{it}\gamma + \varepsilon_{i2} > 0$). To do so I adopt the method proposed by van de Ven and van Praag (1981) for bivariate probit models with sample selection. In this case, the likelihood function is:

[16] Even though in the estimations I allow for location-specific effects, in this exposition I take the geographic area indexes j as implicit in the individual characteristics of agent i.

[17] A large part of the empirical literature on hazard functions (see Devine and Kiefer (1991) for a review) assumes that the error terms are distributed according to a logistic function. I adopt here a normal distribution to be consistent with the second econometric model (see below). In any case, I also tested all the specifications reported in Section 5 assuming a logistic distribution and obtained very similar results (available upon request).

$$L = \prod_{i \in \{Et+1\}} \Phi_2(\beta' X_i, \gamma' Z_i, \rho) \prod_{i \in \{Ut+1\}} \Phi_2(-\beta' X_i, \gamma' Z_i, -\rho) \prod_{i \in \{Ot+1\}} [1 - \Phi(\gamma' Z_i)] \tag{10}$$

where Φ_2 is the bivariate standard normal cumulative distribution of the joint probability of s_{it} and h_{it}, and ρ is the correlation between the error terms. This method corrects the bias that arises from using (9) when the error terms in equations (7) and (8) contain some common omitted variable.

The results of the two estimation methods are reported in Section 5.

4 The data

4.1 The data set

For the empirical estimation I use the Labor Force Survey (LFS), conducted in the year 2002 by the Italian National Statistical Office (Istat). This survey is the main source of information on individuals' working condition, unemployment and job search behavior, in addition to their personal characteristics.

The survey is conducted quarterly in two stages: about $1,300$ municipalities are sampled at the first stage, and about $70,000$ households at the second one. The LFS follows a rotating scheme according to which each family is interviewed for two successive rounds, and then again for two other consecutive waves after two quarters of interruption, for a total of four times. So, theoretically 50 per cent of the sample is kept constant between two consecutive rounds. The LFS has a natural longitudinal dimension with people followed up to fifteen months, but the linkage of individual records across surveys can be problematic, because of the lack of a personal identifier and because of reporting errors in the household code.

Istat currently provides yearly longitudinal files linked with a stochastic matching algorithm, but these files do not contain information about individuals' place of residence and cannot be used to study the effects of agglomeration on labor market dynamics. In this paper, I reconstructed the longitudinal quarterly transitions with a deterministic method linking individuals' records on the basis of the family identifier and some time-invariant information (i.e., the date of birth and sex; see the Appendix for further details), which enables me to recover 75 percent of the potential longitudinal sample. The loss of the remaining observations could be a potential source of bias for my estimates in case it was not randomly distributed. Even though it cannot be known whether theses losses are due to random reporting errors in the key variables or to the non-random exit of some individuals from the LFS ("attrition"), I can test the hypothesis of random loss of information.

In the Appendix I describe the methodology adopted and report the test results, which confirm the validity of my deterministic matching procedure for constructing an appropriate panel dataset for the analysis of labor market dynamics.

4.2 The agglomeration variables

In this paper most agglomeration variables are defined at the "local labor market" (LLM) level. LLMs are clusters of municipalities aggregated on the basis of the residents' daily commuting flows to their place of work.[18] LLMs are relatively self-contained, in that, by definition, they offer employment to at least 75 per cent of their residing workers, both with respect to the total number of workers in the area and with respect to the total number of residents. Exhaustive partitions of the territory based on worker commuting have been devised in many OECD countries,[19] since they reflect local labor market conditions better than administrative areas do. The literature on matching is increasingly basing the empirical analysis on LLMs, in order to avoid a geographical aggregation bias in contexts of imperfect labor mobility. The geographical reach of agglomeration externalities is itself at the center of the literature debate, and may depend on the specific phenomenon analyzed.[20] In this respect, the characteristic of self-containment makes LLMs particularly suited to be my spatial unit of analysis, since it enhances, by construction, the likelihood that a job seeker searches within the boundaries of the labor market where he resides.

Various measures of agglomeration, both urban and industrial, are examined.

Urbanization is measured with the LLM population size.[21] Since the absolute level of population increases very gradually across LLMs, with the largest variations occurring only at the upper end of the distribution, I also use a "large city" dummy to test whether agglomeration economies manifest themselves only beyond a certain threshold value. Nevertheless, the choice of a threshold defining a large city is not a straight-forward issue; it should not be arbitrary and should plausibly be country-specific.[22] Thus, this paper adopts the threshold level of $404,526$ inhabitants devised by Di Addario

[18] The flows are obtained from the 1991 Population Census data. I assigned each LFS observation to a LLM with an Istat's algorithm matching LLMs to municipalities.

[19] The UK, for instance, has been divided into 308 "Travel-To-Work Areas" (OECD, 2002).

[20] See Arzaghi and Henderson (2004) for a discussion on this issue and Petrongolo and Pissarides (2001) for a review of matching studies based on LLMs.

[21] I also tested the joint effect of logarithm of LLM population size and logarithm of LLM area, but the latter was never significant. Also Petrongolo and Pissarides (2004) make a case for using the UK's Travel-To-Work Areas size rather than their density, in contrast with the earlier literature (e.g., Ciccone and Hall (1996) or Coles and Smith, 1996), stating that density was more important than population or employment size in generating externalities.

[22] The Italian population, for instance, is much more dispersed over the territory than the US one, suggesting the use of different threshold values in the two countries.

and Patacchini (2005) on the basis of spatial autocorrelation analysis applied on Italian LLMs.[23] The intuition behind this methodology is that in order for a LLM to be classified as a large city, its population: 1) must be above the national average, and 2) must not be randomly distributed (i.e., it must show a significantly positive or negative correlation with that of the neighboring LLMs). In order to further check the sensitivity of the results to the specific threshold adopted, I also run the same regressions on the sub-sample excluding the three largest LLMs (those with a population above $2,400,000$ inhabitants).[24]

Industry localization is measured by two variables: the Cannari's and Signorini's (2000) "super-district" dummy and the traditional-sector-specialization Pavitt index. Super-districts are the "industrial district" subset with a higher incidence of LLM small-firm manufacturing employment. Industrial districts, in turn, are identified by an Istat algorithm associating each LLM a dummy variable equal to one if the area shows both a dominant sectoral specialization and a higher-than-average share of small and medium enterprises and manufacturing employment.[25] The LLM traditional-sector-specialization Pavitt index is taken as a proxy of labor pooling / industrial-district agglomeration, since the latter are characterized by a high specialization in traditional sectors. This variable should enable me to assess the effect of localization through an improvement of the *quality* of matches rather than through an increase of their *quantity*, since labor pooling reduces the degree of mismatch between the skills required by the firms and those offered by the workers, raising the efficiency of the match.

Last, the only measure of agglomeration that is not based on LLMs is the number of employed household members, that I take as a proxy of *network quality*.[26] The idea is that family networks are important to find employment and that employed individuals have access to better quality networks than unemployed ones (as they presumably have more information on job offers). The validity of this variable relies on the absence of unobserved characteristics (such as ability) shared among family members.

[23] More specifically, the authors use the Moran Scatterplot in conjunction to the Local Spatial Autocorrelation Statistics.

[24] That is, the LLMs containing Rome, Milan and Naples, the three largest municipalities in the Center, North, and South of the country. The population of the remaining LLMs is below $1,500,000$ inhabitants.

[25] See de Blasio and Di Addario (2005) for a more detailed explanation of how industrial districts are identified by Istat and Cannari and Signorini (2000) for a description of the methodology used to single out super-districts. Note that I also tested the effect of the industrial district dummy, but do not report the results here as this variable was never significant.

[26] Similarly to Wahba and Zenou (2003), who use the number of family members who are in the labor force.

4.3 A "natural" experiment

The LLM characteristic of self-containment together with a very limited mobility of labor, make Italy a sort of "natural" experiment for analyzing agglomeration effects, as under these conditions LLMs can conceivably be considered as separated markets and the urbanization and localization variables as exogenous. If, on the contrary, the latter were endogenous (e.g., because correlated to some omitted unobservable variable), the agglomeration effects on hazard rates and search intensity would not be correctly detected. For instance, if it were the case that the most able job seekers moved to the largest cities,[27] the urbanization effect on hazard rates would be biased upwards (provided that the probability of finding a job increased with city size and that ability could be observed by the employer before forming the match). In contrast, if the more generous government support or the presence of a stronger informal labor market in the largest cities attracted particularly the less able or lazier people, the urbanization coefficients on hazards would be biased downwards.

Nevertheless, the risk that either the most or the least able people move to the most agglomerated areas is little in Italy, since labor mobility is, in general, particularly low. Indeed, even the unemployed job seekers, who are generally the most likely to migrate (Dohmne, 2005), are unwilling to move out of their town of residence to find a job. As Table 1 shows, up to 80 percent of the unemployed Italians are ready to accept a job only in their LLM of residence, and more than 41 percent just in their own municipality.[28] The table also indicates that only 1.7 percent of the non-employed individuals in working age interviewed in the four 2002 waves were absent from their household of residence at the time of the interview, and just one-fifth of those who had been away for more than a year (a merely 1.2 percent of the total) was looking for a job. Mobility is low also amongst the employed individuals: the share of those who work in a province different from the one of their residence is less than 7 percent (Table 1).

Labor mobility has been decreasing over time, especially with respect to long-distance movements (Cannari, Nucci and Sestito, 2000): between 1960s and 1990s the share of inter-town changes of residence in total population fell from 0.3 to 0.2 percent. The authors show that a large part of this reduction is explained by a house price increase over the period in the areas with better

[27] In a context where people have a preference for urban consumption amenities this phenomenon could occur because the most able individuals, who can command higher wages, might be better capable to afford the big cities' higher cost of living. Although in Italy urban wage differentials may not be large enough to attract workers to large cities: wage premia are $2-3$ percent large in nominal terms (Di Addario and Patacchini, 2005), much less than in the US (33 percent; Glaeser and Mare', 2001).

[28] In each LLM there are, on average, 10.3 municipalities.

employment perspectives relatively to the rest of the country (namely, the North versus the South).

The rigidities in the housing market can certainly discourage geographic mobility.

First of all, the presence of rent controls down-sizes the private rented sector, rationing rents and increasing workers' moving costs. The degree of imperfection of the Italian rental market is apparent from the figures on the distribution of rent contract types. In 2000, the share of non-liberalized rents was still surprisingly low: only 16 percent of rent contracts were in derogation from the rent-control law,[29] 35 percent of households were still under controlled rents ('equo canone' law), up to a quarter of contracts were informal, more than 16 per cent regarded council housing, and almost 5 per cent were subsidized (Di Addario, 2002).

Secondly, the large transaction costs for buying and selling a house further increase migration costs and discourage owner-occupiers from becoming renters when relative price change,[30] thus increasing the bias towards owner-occupation. The share of owner-occupying households is indeed rather high in Italy (about 70 percent of total), which further hampers mobility (see Henley, 1998).[31] As a matter of fact, homeowners have a lower propensity to move than renters (after controlling for individual characteristics; Di Addario, 2002).[32] The propensity to change house is generally low even within the same city: figures from the 2000 Bank of Italy's Survey of Household Income and Wealth indicate that only 7 percent of households are planning to change house in the next two years.[33]

Finally, the sub-optimal size of the market rented sector together with the high transaction costs for buying and selling a house may also bias people's choices towards commuting rather than changing residence. However, this would not raise endogeneity issues in my agglomeration variables, since they are defined on the basis of LLMs, which are self-contained precisely in terms of workers' daily commuting flows.

[29] Before 1992 the 'equo canone' law put ceilings on rents. Afterwards rents were liberalized for new contracts, in derogation from the rent-control law (L.359/1992).

[30] In Italy tenure choices may be less responsive to prices than in the US, where the housing market is characterized by a high residential mobility across States.

[31] Note that according to Dohmen (2005): 1) high homeownership rates lead to greater unemployment, and 2) migration is more sensitive to wage than to unemployment differentials. Indeed, after controlling for individual characteristics, the probability of owner-occupying is higher in the South of Italy (Di Addario, 2002), where migration rates are low in spite of the presence of higher unemployment rates than in the North (see Table 3). Also in line with Dohmen's (2005) theory, in Italy wage differentials over the territory are rather small in size.

[32] The author also shows that immigrants are less likely to buy the house of residence, confirming a bigger difficulty or reluctance to settle in a province different from one's own.

[33] The data does not enable me to tell whether people intend to change house within or across LLMs, but since the most frequently reported motivation for moving is the purchase of a house, I presume that the majority of the expected moves would be within the same municipality.

4.4 The sample

In 2002 LFS surveyed 777,248 individuals. In order to analyze transition probabilities I restricted the sample to the people who were surveyed for at least two consecutive waves. Since my analysis concerns the labor market dynamics of non-employed persons, I also excluded those already employed at time t, and those either below the age of 15 or above that of 64. After excluding those for whom there were missing observations on the relevant variables, the data set comprises 71,286 non-employed individuals.

In Italy there are 784 LLMs. LLM population size, density and area vary greatly. The mean population size is 73,424 inhabitants, ranging from 2,901 in Limone sul Garda to 3,311,431 in Rome. Density ranges from a minimum of 10 inhabitants per square Kms. (Crodo) to a maximum of 3,250 (Naples), with a mean of 184.6. Finally, the mean of the LLM area distribution is 384 square Kms. ranging from 10.4 (Capri) to 3,539 (Rome). Nineteen of the 784 LLMs have a population above the 404,526 inhabitant threshold and 99 are classified as super-districts (199 as industrial districts).

My sample includes 520 LLMs (66 percent of the total), and comprises an average of 137 individuals per LLM. Since the LFS survey is stratified to represent Italian regions and municipalities, all the 19 large cities are always sampled (for a total of 20,335 observations).[34] Furthermore, even though the LFS was not designed to represent the super-district population, the sample distribution reflects that found at the national level: the percentage of LLMs classified as super-districts is 12.6 in Italy and 13.5 in my sample (for a total of 5,285 individuals in 70 super-districts).

5 Empirical analysis

I now turn to the empirical estimation of the determinants of individual search intensities and hazard rates, examining in particular whether these probabilities differ between agglomerated and non-agglomerated areas. The estimations were conducted separately for men and women and, unsurprisingly, labor market dynamics turned out to be substantially different for the two groups.

5.1 Descriptive statistics

Table 2 reports the quarterly transition probabilities and flows both at the aggregate level and for men and women separately. The transition matrix shows that in Italy there is a high unemployment

[34] These are (in descending order of population levels): Rome, Milan, Naples, Turin, Bari, Florence, Genoa, Palermo, Bologna, Catania, Venice, Padua, Desio, Taranto, Verona, Bergamo, Cagliari, Como and Lecce.

persistence, as 63 percent of the people unemployed in the quarter preceding the interview are still unemployed in the successive quarter. While these numbers are very similar for men and women, significant gender differences can be found in other respects. First, in the average probability of finding a job, conditional on being non-employed at time t: the transition probability from unemployment into employment is almost 18 percent for men and only 10 percent for women, and the respective probabilities of finding a job for those recorded as inactive at time t are 5 and 3 percent respectively.[35] Second, the transition probability from unemployment into inaction, greater than that into employment for both sexes, is much larger for women than for men (in line with other empirical results, e.g., Broersma and Van Ours, 1999). Finally, Table 2 shows that the flows from inactivity to employment as a percentage of the working age population are generally more substantial than those from unemployment into employment (1.4 versus 0.8 percent; in line with previous results, e.g., Petrongolo and Pissarides, 2001). In light of this fact, and consistently with the most recent literature (Broersma and Van Ours (1999); Brandolini *et al.*, 2004), I shall estimate hazards from non-employment to employment rather than from unemployment.

The Italian labor market is known to be segmented with respect to territory (see, for instance, Peracchi and Viviano, 2005). While, traditionally, labor market conditions are analyzed at the macro-area level (North, Center, and South),[36] I examine whether they also differ along the degree of urban and / or industrial agglomeration. Table 3 reports descriptive statistics for the year 2002 on the employment, unemployment and activity rates for all the agglomeration units considered in this paper (large cities, super-districts, and industry-thin small-sized towns). It also shows the share of job seekers in total non-employed population and the hazard rate into employment. The former, computed as the ratio between the sum of the employed and unemployed persons at the time of the interview and the non-employed people who actively searched in the preceding quarter, can be interpreted as a measure of average search intensity.[37] The hazard to employment is the probability that a job seeker finds a job between successive quarters, and is computed as the ratio

[35] However, when expressed in percentage of the working age population, the flows from inactivity to employment are larger for women than for men.

[36] In 2002, for instance, unemployment rates ranged from 3 percent in the North-East to 14 percent in the South, while employment rates ranged, respectively, from 64 percent to 50 percent (see Table 3).

[37] Note that in this paper the pool of job seekers is larger than the set of the people recorded as unemployed according to the ILO definition. In line with a large part of the empirical literature on matching (see Petrongolo and Pissarides (2001) for a survey), I assume that each search period (the time interval between t and $t+1$) lasts three months. Thus, to ensure temporal consistency between stock and flow data (transitions to employment) the job seekers' pool must comprise all non-employed people, willing to start working immediately, whose last search action took place in the previous quarter – rather than in the previous month, as it is in the ILO definition (see Brandolini *et al.* (2004), and Peracchi and Viviano (2005) for a discussion).

between those moving into employment between time t and $t+1$ and total job seekers.

In 2002 the unemployment rate ranged from a minimum of 3 percent in super-districts to a maximum of 10 percent in large cities. Conversely, employment rates were lowest in large cities and highest in super-districts (55 percent against 65 percent). These patterns are largely confirmed at the macro-area level, so that they cannot be explained by the fact that most industrial districts are located in the regions of the Center-North-East of the country.[38] With regards to labor market dynamics, the industrially denser areas show the lowest share of job seekers and the highest hazards to employment from non-employment (respectively, 11 and 57 percent). In contrast, large cities show the lowest hazards to employment, probably in large part due to the greater stock of job seekers concurring for available jobs. These offsetting effects are mostly confirmed in all the Italian macro-areas.

The descriptive statistics of Table 3 would thus indicate that agglomeration is associated with specific labor market dynamics. In particular, these results suggest that search intensity is highest in large cities and hazard rates are highest in super-districts. The impact of agglomeration, however, can be better analyzed in a more comprehensive model where the features of the local labor markets and the characteristics of individuals are taken into account.

5.2 Empirical specification

The empirical models proposed in Section 3 can be used for this purpose. In the remainder of this section, I will first examine a baseline model estimating the parameters of the log-likelihood functions (9) and (10) on the basis of individual and local labor demand characteristics, then test the existence of agglomeration effects on both hazard rates to employment and search intensity.

The hazard rate to employment depends first of all on variables affecting local labor demand conditions and the individual's productivity. The former are proxied with three set of indicators. First, two indexes meant to capture contemporaneous labor demand shocks: the share of employees working overtime in total workers and the average number of extra-hours worked.[39] The coefficients on these variables should be either significantly positive or zero, depending on whether demand expansion is or is not fully compensated by overtime work increases. In the latter case, a rise of overtime work would be accompanied by an increase in the number of vacancies, which, other

[38] Also, note that within the South the super-district unemployment and employment rates are of a comparable size (respectively, 3 and 63 percent) to those in the North.

[39] I am aware that these indexes are imperfect proxy for demand, as they could also reflect supply-side conditions. Ideally, I should control for vacancies (even though the majority of hazard studies does not; Petrongolo and Pissarides, 2001), but there are no data for Italy.

things being equal, would improve the hazard rate. In contrast, if all the demand increase was entirely compensated by overtime work, my indicators should not affect the hazard rate. The second local labor market variable I consider is the geographical density of job seekers (similarly to Petrongolo, 2001).[40] Since, as shown in Section 2, hazard rates are increasing in local labor market tightness, I expect job seeker density to have a negative sign. The third set of variables includes the LLM Pavitt specialization indices.[41] In particular, I expect hazard rates to be higher in the LLMs with a more intense concentration of labor-intensive industries, under the hypothesis that the areas characterized by a large presence of traditional sectors can be taken as proxies for industry concentration (see Section 4.2). The personal characteristics that I use to control for the individual's productivity are age, age squared, and educational attainment (first degree, high school, compulsory education). I also control for search duration (0–1 month, 1–5 months, 6–11 months), expecting it to be inversely related to the chances of finding a job. Finally, I control for a dummy denoting whether the individual had previous work experience, as well as for seasonal and geographical dummies.

As seen in the theoretical model (equation (6)), an agent's optimal search intensity s_{it} depends on the hazard rate h_{it} into employment that he anticipates facing if he searches. In estimating the equation for search intensity, I therefore include all the individual and labor-market explanatory variables used in the hazard-rate equation. In order to proxy for the value (monetary and other) of non-search activities, which I expect to lower the probability of participation in any given application round (i.e., search intensity), I also include the individual's position within the household (single living alone, household head, and spouse), the self-perceived work status (housewife, student, or retired),[42] and the number of non-working people in the household.[43]

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[40] I also used the logarithm of the total labor force and that of the population above the age of 15, with no different results.

[41] I computed the Pavitt specialization indexes at the LLM level from the 1996 Industry Census, using data on more than 700,000 firms. The index is defined as follows:

$$I_{j,LLM} = \frac{(\frac{E_j}{E_m})_{LLM}}{(\frac{E_j}{E_m})_{Italy}} \tag{11}$$

where E is employment, j represents the Pavitt sector (i.e., high technology, specialization, scale intensive, and traditional), and m manufacturing.

[42] Since the household decisions are linked by a budget constraint, the position in the household may matter. Note that the sum of the three self-perceived work status dummies equals to being inactive at time t.

[43] Using data at the provincial level from the *Consulente Immobiliare*, I also controlled for house prices and rents, but these were never significant. I used data for 2002, the oldest year available (1965 for house prices, and 1993 for rents) and the average of the entire period.

5.3 The results

5.3.1 Baseline model

Tables 4 and 5 present the results of the baseline model for men and for women, respectively. To show the robustness of my results, in each table I report the outcomes of both the econometric models discussed in Section 3 ((9) and (10)). In spite of the fact that the Wald-test always rejects the null hypothesis of zero correlation between the error terms, confirming the presence of a selection bias, the two estimation methods provide the same signs and statistical significance levels for almost all the regressors considered in the hazard rate equation (which is the one subject to the selection problem).

a) Hazard rates

In the baseline model for men (Table 4), hazard rates are higher in the North-East, for those with previous work experience, the less educated, and the older population.[44] As expected, the probability of moving from non-employment into employment decreases with search duration (see, among others, Lancaster, 1979). In particular, individuals who have been searching for less than one month have a chance of finding a job twice as large as those who have been searching for more than one year.[45] As expected, higher LLMs' job seeker density reduces the probability of finding a job, probably because of the congestion that unemployed workers create on each other (see Burgess, 1993 or Petrongolo and Pissarides, 2001), whereas a LLM's specialization in labor-intensive sectors increases it. Surprisingly, a higher LLM share of overtime workers in total workers lowers hazard rates,[46] while average extra-hours worked do not have any significant impact. In contrast to the male population, women have a higher chance to find a job when they are younger and when they have a University degree, and a lower chance if they live in the South (Table 4).[47]

b) Search propensities

For both men and women, search intensity increases with education, age, past work experience, and with residing in the North-East. In contrast, students, retired workers and housewives search

[44] Even though these last two results are in contrast with some empirical studies on the UK (e.g., Lancaster, 1979), they are in line with previous findings on Italy (see, for instance, Peracchi and Viviano, 2005).

[45] In general, marginal effects have been computed at the mean for the continuous variables and for a discrete change from 0 to 1 for the dummy variables.

[46] This may be a sign that overtime work is mostly supply-driven: the extent to which people are willing to work extra hours, firms reduce the hiring rate. A possible explanation of why individuals should differ in their willingness to work extra hours is provided by Rosenthal and Strange (2002), according to whom in large markets people work more in order to signal their ability in a rivalrous context (the "urban rat race").

[47] These results are less surprising than those for men, which could possibly derive from the composition of the non-working population (e.g., a higher incidence of men difficult to employ, such as long-term unemployed, or people with health problems).

less intensively, probably because these categories of job seekers assign a higher value to non-search activities than those who perceive themselves as unemployed. Interestingly, the position in the household matters differently for the two sexes, as being a household head or a spouse increases the probability of searching for men but decreases it for women (with respect to being an offspring or having other positions within the household). This different behavior probably reflects the tendency for wives and mothers to stay at home,[48] and a greater need for non-employed husbands and fathers, who are most often the primary earners in the household, to increase their search effort. Finally, the LLM job seeker density is positive and significant only for men, implying that women do not exercise more effort when competition for vacant jobs raises, while men do.

5.3.2 Effects of agglomeration

To examine the effects of agglomeration on s_i and h_i, I add the variables discussed in Section 4 to the baseline specification. Table 6 summarizes the results on hazard rates and search intensity for the econometric model correcting for sample selection ((10)).[49] Thus, I first consider the joint effect of the large city dummy, the industry localization variables and the proxy for family networks (first specification).[50] I then substitute the large city dummy with LLM population size (second column). In the third and fourth columns I replicate the first two specifications on the sub-sample excluding the three largest LLMs.[51]

a) Hazard rates

Thus, after controlling for LLM job seekers' density, which captures the negative congestion externality exercised by unemployed workers on each other (see Petrongolo, 2001), I find that urban agglomeration has an overall positive effect on the probability of finding a job, both when

[48] Note that this may be due to child care, as Italy lacks of policies aimed at supporting mothers' employment. In order to test this hypothesis, I also ran the same regressions (not reported here) on the parent sub-sample, controlling for the number of children below the age of six. I find that a marginal increase in this variable lowers women's probability of searching by 1 percent (at 1 percent statistical significance), but does not affect men's behavior. This result supports the view that men and women have different behavior because the traditional household division implies that they face different (opportunity) costs of search.

[49] From now on I will not report the results for (9) – available upon request – because the Wald-test always rejects the null hypothesis of no selection bias. In any case, the two models provide very similar outcomes on the sign and statistical significance of the agglomeration variables.

[50] I also considered the effect of each of these variables separately, with no different results. Note that whether the signs and the statistical significance of the urbanization and localization dummies can correctly identify agglomeration differentials in employment probabilities and search behavior clearly relies on LLMs to be separated markets (see, for instance, Coles and Smith (1996) or Duranton and Monastiriotis, 2002), as discussed in Section 4.3.

[51] The number of observations drops from $25,116$ to $22,332$ in the men's sub-sample and from $46,131$ to $40,885$ in the women's case. The non-employed individuals residing in the excluded LLMs amount to $2,848$ for Rome, $1,835$ for Milan, and $3,530$ for Naples.

I measure it with the large city dummy and when I estimate it with LLM population size.[52] Indeed, both variables are positive and significant, in the women's sub-sample at the 1 percent level (specifications (6.5)–(6.6)). In the men's sub-sample, the large city dummy is significant at the 5 percent level, while population size has a p-value of 0.17 (specifications (6.1) and (6.2)); however, once I exclude the three largest LLMs from the sample the significance level of population raises to 7 percent (column (6.4)).[53]

For localization to create significantly positive net externalities a minimum degree of firm thickness is necessary. Indeed, searching in more industrially agglomerated areas raises men's probability of finding employment only above a certain threshold of manufacturing small-sized firm concentration. Thus, other things being equal, living in a super-district increases a man's chance of finding a job (columns (6.1) and (6.2)), while residing in an industrial district does not have any effect.[54] However, in contrast with the men's case, the super-district variable is never significant for women (columns (6.5)–(6.6)).[55] Further evidence on the existence of positive industry localization effects is given by the traditional-sector-specialization Pavitt index, proxying labor pooling. Contact rates being equal, a better expected quality of matches should imply a higher hazard rate (since on the one hand, job seekers might be choosier, but on the other hand firms make more attractive offers, which increases the worker's acceptance probability). As Table 6 shows, the labor pooling proxy is always positive and significant for both men and women,[56] supporting the hypothesis that industry localization improves the quality of matches.[57]

Finally, in line with the priors, the proxy for quality of family networks has a positive effect on the chances of employment in all the specifications tested for men; though it does not affect

[52] This finding could be due to various factors: tighter markets (more intense job advertising or more vacancies), urban wage premia, higher meeting rates, better quality of matches (see Section 2).

[53] This result implies that in Rome, Milan and Naples men do not benefit from agglomeration externalities, perhaps because these cities are over-sized with respect to men's employment possibilities.

[54] Since the ID dummy is non-significant in any specification and sample I tested, I do not report the results for this variable (though they can be requested).

[55] Possibly, this is because in Italy industry is more male-oriented than the tertiary sector.

[56] However, this variable loses significance in the restricted female sub-sample (specifications (6.7)-(6.8)), implying that women's match quality improves especially after the $2,400,000$–inhabitant threshold.

[57] Note that Petrongolo and Pissarides (2004) find that in the UK agglomeration increases the quality of the match (proxied by average wages) with no effect on hazard rates, as reservation wages raise to fully compensate the higher earnings (i.e., people become choosier and accept job offers less frequently). However, in Italy agglomeration-driven wage differentials are rather small in size: wage premia are just $2-3$ percent large in big cities (Di Addario and Patacchini (2005); against 33 percent in the US, according to Glaeser and Mare', 2001) and non-existent in Industrial Districts (de Blasio and Di Addario, 2005). It is thus conceivable that in agglomerated areas also reservation wage differentials (on which, unfortunately, there are not reliable data) are not large enough to offset any other positive impacts on hazard rates.

women's likelihood of finding a job (columns (6.5)–(6.6)).[58]

b) Search intensity

I now turn to the effects of agglomeration on men's and women's search behavior. The bottom part of Table 6 shows the results.

In spite of the fact that urbanization improves the employment chances per unit of search, in general job seekers do not search more intensively in big cities (columns (6.9), (6.10) and (6.13)).[59] This may seem somewhat surprising, as job-seekers should increase their propensity to search when their chances of finding a job rise. However, in terms of the model presented in Section 2 this could be explained by the fact that in the most populated areas search cost increases offset the higher chances of employment. Indeed, the large commuting costs due to congestion (travelling on crowded public transportation, spending time in traffic, etc.) may discourage people from searching even though they have a higher probability of finding a job.[60]

Similarly, industry localization does not affect men's search behavior, in spite of the fact that it raises their employment probabilities. Indeed, neither men nor women search any differently in the more industrially agglomerated areas (columns (6.9)-(6.10) and (6.13)–(6.14)). Also the traditional sector index is always non-significant.

Finally, in accord with the results on hazard rates, the thicker family networks are the higher the search effort men exercise to look for a job, while women's search is never affected by the number of employed individuals in the household.

6 Conclusions

In this paper I analyze agglomeration effects on individual search intensity and hazard rates for both Italian men and women. More specifically, I empirically examine whether population size, small-sized manufacturing firm concentration, traditional sector specialization, and quality of family networks generate overall net positive or negative externalities. In particular, while agglomeration

[58] This could occur either because networking is a more male-oriented search channel, or because female networks are of a lower quality. It is also possible that women living in families where more members work are choosier, as they can benefit from a higher income and thus presumably have a higher reservation wage (in contrast, men might not "afford" to be choosey because of the different role they have in the household). Furthermore, note that the fact that the number of employed household members has an opposite effect for men and women contrasts with the hypothesis that this variables captures, rather than network quality, unobservable ability shared by the members of the same family.

[59] The only exception to this finding regards specification (6.14).

[60] Although in the model presented in Section 2 the causality runs only from search intensity to hazard rates (and not viceversa), an alternative explanation of this finding could be that people do not need to exert a higher level of search effort to find a job precisely because they have greater chances of employment.

effects are usually studied either at the urban or at the industry level, I am able, by using an Istat algorithm that identifies the more densely industrialized LLMs, to compare urbanization and localization effects.

Thus, I find that both matching and search are sensitive to the type of agglomeration of the local labor market. In general, urbanization increases the job seekers' probability of finding a job (per unit of search) independently of their gender, while industry localization raises only men's chances. Residing in a LLM highly specialized in traditional sectors, on the other hand, increases hazard rates for both men and women, suggesting that labor pooling improves the efficiency of the matching between jobs and workers. Finally, the size of family networks, proxied by the number of employed members in the household, increases the probability of finding a job only for men.

As to search intensity, on average it is not affected by either urbanization nor industrial agglomeration. A possible explanation of why the intensity of search does not increase despite higher hazard rates is that job seekers are discouraged from bearing the higher commuting costs produced by the presence of a large population mass (i.e., travelling on congested public transportation, spending time in traffic, etc.). Last, consistently with having higher chances of finding employment, the men who have larger family networks search more intensively, while women's behavior is not affected by the thickness of networks.

While these findings hold on average, it is interesting to analyze whether they occur at any level of agglomeration or only above certain threshold values. In this paper I show that results are sensitive to the degree of agglomeration of the local labor market. In particular, industry localization creates positive net economies only in super-districts (as opposed to industrial districts), that is, in the subset of industrial clusters with the highest concentration of small and medium firms in the manufacturing sector; for "regular" districts, there is no significant effect. Moreover, I find that mens' employment chances raise with the degree of urbanization only up to the $1,500,000$-inhabitant threshold, possibly because Rome, Milan and Naples are too congested, while in these cities the quality of women's matches is higher than elsewhere.

Last, while it is well known that labor markets dynamics are gender-specific, it is less obvious this is also the case for agglomeration externalities (even though this result is not new in the literature: see, for instance, Rosenthal and Strange, 2002). A possible explanation can be found in the behavioral differences between men and women due to the different role they traditionally have in the household, which makes them face different opportunity costs of search. These differences might be exacerbated by the lack of policies aimed at supporting mothers' employment during child care.

Table 1: **Mobility attitudes**

Acceptable job location by those unemployed				
Own municipality	Daily commuting distance	Anywhere in Italy	Anywhere	
41.3	38.8	14.9	5.0	

Job location of those employed				
Own municipality	Other municipality in same province	No fixed place	Other province or abroad	
55.2	30.7	6.9	7.1	

Presence in the household at the time of interview				
Present	Absent for less 1 year	Absent for more 1 year and searching	Absent for more 1 year not searching	
98.3	0.6	0.2	0.9	

Source: authors' elaboration on LFS data.

Table 2: **Average Transition Probabilities**

	Quarterly transition probabilities			
	Employed$_{t+1}$	Unemployed$_{t+1}$	Inactive$_{t+1}$	Total
			Men and Women	
Employed$_t$	96.9	0.9	2.2	100.0
Unemployed$_t$	13.9	62.6	23.6	100.0
Inactive$_t$	3.5	3.9	92.6	100.0
Population composition$_{t+1}$	54.6	5.7	39.7	100.0
			Men	
Employed$_t$	97.5	0.9	1.6	100.0
Unemployed$_t$	17.8	63.7	18.5	100.0
Inactive$_t$	4.9	4.7	90.4	100.0
Population composition$_{t+1}$	68.2	5.3	26.5	100.0
			Women	
Employed$_t$	95.9	1.0	3.2	100.0
Unemployed$_t$	10.4	61.7	27.9	100.0
Inactive$_t$	2.8	3.5	93.7	100.0
Population composition$_{t+1}$	41.5	6.1	52.9	100.0
	Quarterly transition flows			
	Employed$_{t+1}$	Unemployed$_{t+1}$	Inactive$_{t+1}$	Population composition$_t$
			Men and Women	
Employed$_t$	52.4	0.5	1.2	54.1
Unemployed$_t$	0.8	3.7	1.4	5.8
Inactive$_t$	1.4	1.6	37.1	40.0
Population composition$_{t+1}$	54.7	5.7	39.6	100.0
			Men	
Employed$_t$	66.0	0.6	1.1	67.7
Unemployed$_t$	1.1	3.4	1.0	5.4
Inactive$_t$	1.3	1.3	24.3	26.9
Population composition$_{t+1}$	68.3	5.3	26.4	100.0
			Women	
Employed$_t$	38.9	0.4	1.3	40.6
Unemployed$_t$	0.7	3.9	1.8	6.3
Inactive$_t$	1.5	1.8	49.8	53.1
Population composition$_{t+1}$	41.1	6.1	52.8	100.0

Source: elaboration on LFS (January-April 2002). Note: flows are expressed in percentage of the working age population.

Table 3: **Descriptive statistics.**

	Employment rate	Unemployment rate	Job seekers	Activity rate	Hazard into employment
			Italy		
Large city	54.7	10.2	17.0	60.9	24.7
Large city and super-district	63.3	3.7	8.0	65.7	29.5
Small town and super-district	64.6	3.0	11.0	66.6	56.9
Small town - other	54.6	9.8	17.1	60.6	32.5
Industrial district	63.3	3.5	10.5	65.7	51.2
			North-West		
Large city	61.9	5.3	11.5	65.4	36.6
Large city and super-district	63.3	3.7	8.0	65.7	29.5
Small town and super-district	63.9	2.1	6.4	65.2	60.8
Small town - other	62.7	4.3	10.7	65.5	47.5
Industrial district	63.1	3.5	8.9	65.4	48.2
			North-East		
Large city	62.2	3.3	8.7	64.3	55.5
Large city and super-district	–	–	–	–	–
Small town and super-district	65.4	2.4	11.3	70.0	62.7
Small town - other	65.3	4.0	14.2	68.1	55.3
Industrial district	65.1	2.8	10.6	66.0	59.5
			Center		
Large city	59.1	7.3	15.8	63.8	19.3
Large city and super-district	–	–	–	–	–
Small town and super-district	64.2	4.4	13.8	67.2	49.4
Small town - other	55.9	7.3	14.0	60.3	35.6
Industrial district	62.9	4.7	13.8	66.3	47.6
			South		
Large city	42.1	21.4	23.4	53.5	19.8
Large city and super-district	–	–	–	–	–
Small town and super-district	62.5	2.5	13.4	64.1	70.3
Small town - other	45.1	17.5	21.1	54.7	24.8
Industrial district	53.4	5.6	10.5	56.6	38.8

Source: elaboration on the LFS, year 2002. Note that the only LLM that is both a large city and a super-district is that of Desio.

Table 4: **Baseline models for men**

	Hazard to employment				Search intensity			
	Probit		Heckprobit		Probit		Heckprobit	
	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.
LLM's job seekers (log)	-0.10	0.000	-0.09	0.000	0.02	0.374	0.01	0.383
LLM's area (log)	0.05	0.154	0.03	0.378	-0.05	0.093	-0.04	0.096
LLM's average extra hours worked	0.05	0.947	-0.14	0.841	-0.54	0.350	-0.54	0.339
LLM's share of overtime workers in total workers	-0.01	0.195	-0.01	0.131	-0.01	0.199	-0.01	0.189
LLM's sector of specialization: high technology	0.15	0.078	0.14	0.078	-0.02	0.722	-0.02	0.749
LLM's sector of specialization: specialization	0.21	0.200	0.19	0.246	-0.12	0.279	-0.12	0.267
LLM's sector of specialization: scale intensive	0.33	0.044	0.29	0.081	-0.12	0.319	-0.12	0.321
LLM's sector of specialization: traditional	0.73	0.023	0.68	0.031	-0.23	0.319	-0.22	0.344
Quarter I (seasonal dummy)	0.06	0.205	0.06	0.183	0.01	0.749	0.01	0.737
Quarter II (seasonal dummy)	0.07	0.165	0.07	0.166	0.07	0.013	0.07	0.014
North-East	0.17	0.088	0.16	0.106	0.12	0.052	0.12	0.053
Center	0.00	0.997	-0.01	0.921	-0.04	0.503	-0.04	0.449
South	-0.18	0.059	-0.14	0.117	0.03	0.612	0.03	0.610
Age	0.01	0.304	0.05	0.000	0.09	0.000	0.09	0.000
Age squared	0.00	0.684	0.00	0.000	0.00	0.000	0.00	0.000
University degree or higher	-0.16	0.102	-0.11	0.196	0.23	0.001	0.24	0.001
High school	-0.15	0.016	-0.16	0.006	0.04	0.296	0.04	0.292
Compulsory education	-0.12	0.047	-0.14	0.016	-0.01	0.697	-0.01	0.770
Past work experiences	0.20	0.001	0.26	0.000	0.10	0.058	0.10	0.039
Search duration: less than 1 month	1.38	0.000	0.80	0.000	-1.02	0.000	-1.01	0.000
Search duration: 1-5 months	0.54	0.000	0.55	0.000	0.13	0.036	0.14	0.033
Search duration: 6-11 months	0.31	0.000	0.29	0.000	-0.05	0.500	-0.05	0.513
Single living alone					0.07	0.246	0.05	0.450
Household head					0.12	0.045	0.08	0.150
Spouse					0.39	0.001	0.35	0.003
Student					-0.15	0.140	-0.25	0.009
Housewife					-1.13	0.000	-1.12	0.000
Other inactive condition					-1.34	0.000	-1.36	0.000
Number of non-working household members					0.01	0.411	0.01	0.271
Constant	-1.63	0.001	-2.20	0.000	0.03	0.946	-0.02	0.956
Number of observations:	25,116		25,116					
of which uncensored:			5,545					

Source: author's elaboration on LFS data. Note: White-robust standard errors adjusted for clustering.

Table 5: **Baseline models for women**

	Hazard to employment				Search intensity			
	Probit		Heckprobit		Probit		Heckprobit	
	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.
LLM's job seekers (log)	-0.06	0.010	-0.05	0.014	0.00	0.918	0.00	0.912
LLM's area (log)	0.07	0.095	0.06	0.102	0.01	0.714	0.01	0.730
LLM's average extra hours worked	-0.45	0.496	-0.45	0.481	0.05	0.920	0.05	0.913
LLM's share of overtime workers in total workers	0.01	0.346	0.00	0.435	-0.01	0.138	-0.01	0.133
LLM's sector of specialization: high technology	0.14	0.113	0.12	0.147	-0.06	0.337	-0.06	0.334
LLM's sector of specialization: specialization	0.22	0.157	0.20	0.169	-0.05	0.573	-0.06	0.566
LLM's sector of specialization: scale intensive	0.24	0.246	0.22	0.277	-0.09	0.418	-0.09	0.414
LLM's sector of specialization: traditional	0.99	0.015	0.96	0.015	0.02	0.934	0.02	0.934
Quarter I (seasonal dummy)	0.03	0.536	0.03	0.486	0.04	0.194	0.04	0.180
Quarter II (seasonal dummy)	0.06	0.235	0.05	0.302	0.00	0.978	0.00	0.974
North-East	0.18	0.043	0.18	0.045	0.08	0.128	0.08	0.127
Center	-0.08	0.287	-0.08	0.282	-0.06	0.206	-0.06	0.202
South	-0.34	0.000	-0.33	0.000	-0.04	0.405	-0.04	0.405
Age	-0.04	0.000	-0.03	0.015	0.06	0.000	0.06	0.000
Age squared	0.00	0.000	0.00	0.010	0.00	0.000	0.00	0.000
University degree or higher	0.13	0.166	0.20	0.036	0.19	0.000	0.20	0.000
High school	-0.03	0.719	-0.01	0.903	0.08	0.011	0.08	0.010
Compulsory education	-0.09	0.239	-0.09	0.221	0.01	0.693	0.01	0.714
Past work experiences	0.23	0.000	0.29	0.000	0.13	0.000	0.13	0.000
Search duration: less than 1 month	1.36	0.000	0.95	0.000	-1.05	0.000	-1.06	0.000
Search duration: 1-5 months	0.60	0.000	0.60	0.000	0.15	0.013	0.15	0.014
Search duration: 6-11 months	0.51	0.000	0.51	0.000	0.07	0.208	0.07	0.213
Single living alone					-0.09	0.211	-0.09	0.204
Household head					-0.15	0.003	-0.14	0.005
Spouse					-0.30	0.000	-0.30	0.000
Student					-1.05	0.000	-1.04	0.000
Housewife					-1.27	0.000	-1.27	0.000
Other inactive condition					-0.97	0.000	-0.99	0.000
Number of non-working household members					0.02	0.071	0.02	0.064
Constant	-1.88	0.000	-2.09	0.000	-0.06	0.848	-0.04	0.895
Number of observations:	46,131		46,131					
of which uncensored:			5,731					

Source: author's elaboration on LFS data. Note: White-robust standard errors adjusted for clustering.

Table 6: **Hazard to employment and search intensity (bivariate probit with sample selection)**

	Hazard to employment: men							
	(6.1)		(6.2)		(6.3)(*)		(6.4)(*)	
	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.
LLM's job seekers (log)	-0.122	0.000	-0.116	0.000	-0.123	0.000	-0.127	0.000
LLM's area (log)	0.026	0.435	0.036	0.278	0.020	0.551	0.023	0.481
LLM's population			0.036	0.179			0.219	0.069
Large city dummy	0.165	0.063			0.192	0.041		
Super-district dummy	0.192	0.061	0.202	0.056	0.192	0.062	0.198	0.061
Employed family members	0.051	0.026	0.051	0.026	0.045	0.069	0.046	0.062
Labor pooling	0.714	0.033	0.782	0.009	1.467	0.003	1.327	0.003
	Hazard to employment: women							
	(6.5)		(6.6)		(6.7)(*)		(6.8)(*)	
	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.
LLM's job seekers (log)	-0.100	0.000	-0.102	0.001	-0.111	0.000	-0.130	0.000
LLM's area (log)	0.054	0.165	0.075	0.053	0.063	0.119	0.066	0.096
LLM's population			0.144	0.004			0.352	0.000
Large city dummy	0.248	0.004			0.232	0.007		
Super-district dummy	0.099	0.281	0.094	0.312	0.095	0.299	0.091	0.324
Employed family members	0.030	0.303	0.031	0.279	0.033	0.280	0.033	0.273
Labor pooling	0.951	0.021	1.283	0.004	1.092	0.192	1.064	0.192
	Search intensity: men							
	(6.9)		(6.10)		(6.11)(*)		(6.12)(*)	
	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.
LLM's job seekers (log)	0.020	0.328	0.003	0.884	0.008	0.709	0.018	0.454
LLM's area (log)	-0.043	0.118	-0.043	0.107	-0.033	0.211	-0.032	0.233
LLM's population			0.035	0.386			-0.112	0.207
Large city dummy	-0.026	0.689			-0.050	0.425		
Super-district dummy	0.030	0.560	0.030	0.566	0.028	0.583	0.029	0.569
Employed family members	0.039	0.017	0.038	0.019	0.034	0.060	0.033	0.061
Labor pooling	-0.248	0.286	-0.156	0.533	-0.418	0.308	-0.419	0.315
	Search intensity: women							
	(6.13)		(6.14)		(6.15)(*)		(6.16)(*)	
	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.	Coeff.	P-val.
LLM's job seekers (log)	0.000	0.986	-0.023	0.166	-0.012	0.466	-0.017	0.414
LLM's area (log)	0.008	0.731	0.010	0.655	0.017	0.472	0.015	0.531
LLM's population			0.063	0.030			0.004	0.972
Large city dummy	-0.007	0.896			-0.024	0.668		
Super-district dummy	-0.009	0.880	-0.010	0.863	-0.010	0.857	-0.010	0.857
Employed family members	-0.006	0.678	-0.007	0.632	-0.004	0.786	-0.004	0.775
Labor pooling	0.024	0.921	0.182	0.415	-0.017	0.967	-0.002	0.996

Source: author's elaboration on LFS data. Note: White-robust standard errors adjusted for clustering.

(*) Computed on the sub-sample excluding the three largest LLMs (i.e., Rome, Milan, and Naples).

Appendix 1

I reconstructed the LFS longitudinal data with the deterministic method. The loss of observations implied by this method can be due to reporting errors in the household identifier or in the other individual variables (typically, the date of birth), but it can be also due to genuine "attrition": this is the loss of information deriving from the non-availability of some of the people to be re-interviewed at time $t+1$. In what follows I use the term "attrition" for both types of losses.

If the information loss was correlated to working condition changes, attrition would be a potential source of bias for the estimation of labor market dynamics. This typically occurs when people change residence because they find employment in a different location, in which case the exit from the LFS sample is determined by a movement towards employment.

In order to test for the effects of attrition in the estimation of labor market dynamics, I follow the approach proposed by Jiménez-Martín and Peracchi (2003), looking at individuals' survey participation at time t, $t+1$ and $t+4$ (i.e., respectively, one quarter and one year after the first LFS interview). As Jiménez-Martín and Peracchi (2003), I identify two sets of individuals: (1) those participating at all the three surveys (full-time respondents); and (2) those participating at time t and $t+1$ but not at time $t+4$ (non full-time respondents). More formally, let D be an indicator equal to 1 if the person is a full-time respondent and to 0 elsewhere. Non-working individuals at time t can be either unemployed (U) or out of the labor force (O). At time $t+1$ they can be either employed (E), or unemployed (U) or out of the labor force (O). Let π_{ij}^{D} be the probability of moving from state $i = U, O$ at time t to state $j = E, U, O$ at time $t+1$, for an individual whose sample participation is denoted by $D = 0, 1$. Attrition may bias transition probabilities if

$$\pi_{ij}^{0} \neq \pi_{ij}^{1} \tag{12}$$

for $i = U, O$, $j = E, U, O$.

Consider the statistic $l_{ij} = \pi_{ij}^{0} - \pi_{ij}^{1}$. If attrition was not a source of bias for transition probabilities, under the null hypothesis l_{ij} would be equal to zero. In other words, if full time respondents and people who are subject to attrition have the same probability to move towards all the other labor market states then I can assume that attrition does not affect transition probabilities.

Critical values for l_{ij} can be easily derived. Because of the central limit theorem, l_{ij} divided by its standard error has a t-Student's distribution. Rejection at 95 percent significance level, for instance, occurs for values of l_{ij} greater than 2 in absolute value. Table 6 reports the test statistics by gender, age group (15-34 and 35+) and area of residence (North–West, North–East, Center, South). As the table shows, the test results confirm the adequacy of the adopted matching procedure in my study of labor market movements, for all the socio-demographic groups considered.

Table A1. Testing for the effect of attrition

	Men		Women	
	Age 15–34	Age 35–64	Age 15–34	Age 35–64
	North West			
l_{UE}	0.33	-0.10	0.35	0.13
l_{UU}	-0.44	-0.25	0.31	-0.27
l_{UO}	0.07	-0.05	-0.20	-0.28
l_{OE}	0.09	0.02	-0.04	0.00
l_{OU}	-0.06	0.00	-0.03	0.01
l_{OO}	0.03	0.02	-0.06	0.35
	North East			
l_{UE}	-0.39	0.21	-0.91	-0.04
l_{UU}	-0.46	-1.05	0.02	-0.43
l_{UO}	0.57	0.23	0.03	-0.21
l_{OE}	0.15	0.05	-0.07	-0.02
l_{OU}	-0.02	-0.01	-0.10	-0.04
l_{OO}	-1.31	0.12	-0.95	-0.19
	Centre			
l_{UE}	0.07	0.01	0.13	0.00
l_{UU}	-0.10	-0.54	-0.11	0.03
l_{UO}	-0.10	0.65	0.12	-0.44
l_{OE}	-0.01	-0.05	0.02	0.04
l_{OU}	0.03	0.01	0.01	0.02
l_{OO}	-0.73	0.34	-1.00	-0.66
	South			
l_{UE}	-0.06	0.22	-0.09	-0.06
l_{UU}	-0.91	-2.03	-1.14	-0.34
l_{UO}	-0.18	0.00	-0.11	-0.24
l_{OE}	-0.10	-0.01	-0.01	0.02
l_{OU}	-0.29	0.01	-0.20	0.00
l_{OO}	-0.80	0.08	-1.55	-1.38

Source: authors' elaboration on LFS data.

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