An empirical micro matching model with an application to Italy and Spain*

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Abstract

A large literature investigates the role of frictions in explaining labor market dynamics. Their presence is often summarized by an aggregate matching function relating the number of job matches to total unemployment and total vacancies. Most empirical specifications, however, are only reduced forms with no microfoundation. Further, for many countries, empirical research on the matching function cannot be carried out because data on vacancies are simply not available. This paper looks at a job match as a transition from non-employment into employment. This transition is decomposed in two parts, one determined by the matching technology and one by individual search intensity. We show how the microfounded model of Pissarides (1979) can be identified using only microdata on labor market transitions. This enables us to obtain a measure of market tightness even without information on the demand side of the market. The method is then applied to estimating the Italian and Spanish matching functions using data from the quarterly labor force surveys.

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1 Introduction

Labor markets are characterized by flows of workers moving from one labor market condition to another. For example, individuals change their working status by moving from inactivity to participation, from unemployment to employment, and from employment to retirement. Given the large social losses implied by unemployment, it is hardly surprising that the most studied labor market movement is from unemployment into employment.

A transition from unemployment into employment occurs when a job seeker and a vacancy meet through a decentralized process which can be affected by a variety of frictions (heterogeneity in required and offered skills, different location of workers and firms, information imperfections, congestion, etc.). As a consequence of these frictions, not all vacancies may be filled, even in the presence of unemployed workers. Frictions are then the main source of equilibrium unemployment. It is now common to model the presence of frictions by an aggregate matching function (see for example Pissarides 2000 and Petrongolo & Pissarides 2001). By analogy with the aggregate production function, this is a relationship that takes the stock of job seekers and vacancies as inputs, and gives the total number of job matches as output.

The standard approach to estimating the matching function relies on aggregate time series data on flows into employment, under the assumption of long term stability of the matching process. Data availability and definitional problems crucially affect the quality of the inference. While reliable data on labor market flows and unemployment exist for many countries, data on vacancies are in general not available, except for a few countries where vacancy registration is required by law (Israel for example, see Yashiv 2000) or surveys on vacancies are conducted on a regular basis. Instead, different proxies for vacancies are often used, with effects on the interpretation of the corresponding results and the possibility to carry out international comparisons.

The standard approach to estimating the matching function is also affected by a number of problems related to the definition of the other input to the matching function, namely the stock of job seekers. In practice, it is not obvious how to define the set of individuals who are "at risk" to be matched with a vacancy. A natural choice consists of those unemployed at a given point in time. However, evidence from many countries shows that a sizeable component of movements into employment consists of people recorded as out of the labor force (see for example Clark & Summers 1979, and Jones & Riddell 1999). This observation has led to empirical specifications that include as inputs those out of the labor force (Broesma & van Ours 1999, and Mumford & Smith 1999). Unfortunately, because of the lack of microfoundation of the resulting matching functions, these models do not help clarify the nature of the matching process for the different types of non-employment.

In this paper, we look at a job match as a transition from non-employment (unemployement or out of the labor force) to employment. For simplicity, we do not consider how vacancies are created, nor job-to-job movements. We first show how the microfounded urn-ball matching model proposed by Pissarides (1979) can be estimated using only microdata on labor market transitions, like those generally collected by standard labor force surveys. This enables us to derive a measure of market tightness even with very limited information on the demand side of the market. Although our empirical results strongly depend upon the assumptions about the matching technology, the proposed method can be considered as a useful tool for empirical analyses of the matching function when no data on vacancies are available or their quality is poor. It can also be useful when good data on vacancies are available, because it allows one to compare the findings of a standard (reduced form) aggregate model with the micro evidence.

Second, in addition to estimating the transition probability into employment, we also estimate the probability that a non-employed person decides to search for a job. This probability, which can be interpreted as a measure of search intensity, allows us to distinguish between different types of non-employed people.

We then apply the proposed method to estimate the Italian and Spanish matching functions using micro-data from the national labor force surveys. Because of the very similar design of the two surveys, we can get comparable information on the matching process.

The remainder of this paper is organized as follows. Section 2 presents our estimation method. Section 3 describes the data. Section 4 presents some descriptive statistics and the results of our modeling exercise. Finally, Section 5 concludes.

2 Modeling labor market dynamics

Section 2.1 summarizes the main features of the empirical approach commonly used to study the matching function. Section 2.2 presents our method, which exploits the link between individual transitions and the aggregate matching function. This allows us to derive the main features of the matching function using data on individual labor market movements. Finally, Section 2.3 analyzes the link between individual search intensity and hazard rates.

2.1 Matching functions

An aggregate matching function is a relationship

$$M = M(V, S) \tag{1}$$

between, on the one hand, the total number of matches M and, on the other hand, the total number of vacancies V and of job seekers S. A matching function $M(\cdot)$ is typically assumed increasing in both arguments and concave.

Under the further assumption of constant returns to scale, we have that $M/S = M(\theta, 1) = m(\theta)$, where $\theta = V/S$ is a measure of market tightness. In order to estimate model (1), one needs to specify a functional form for the matching function and collect data on M, V and S.

The elasticities η_V and η_S of M with respect to V and S measure the positive externalities (thick-market effect) caused, respectively, by firms on job seekers and by job seekers on firms. On the other hand, $\eta_V - 1$ and $\eta_S - 1$ measure the negative externalities (congestion) caused, respectively, by firms on each other and by job seekers on each other. The interpretability of model parameters in terms of elasticities partly explains the success of the log-linear (Cobb-Douglas) specification $M = \alpha V^{\beta} S^{\gamma}$. This specification is convenient but, like other commonly adopted functional forms, lacks microfoundation. This implies that it is often unclear how to interpret the estimates obtained, and how to relate them to observed labor market dynamics (Coles & Smith 1996). It is also difficult to explain the effects of individual or aggregate variables on the matching process and, as a consequence, these variables enter the matching function simply as shift variables.

The interpretation and robustness of the estimated elasticities depend also on the way in which the variables M, V and S are defined and measured. Consider first the stock of vacancies V. In order to get good estimates of the matching technology, good data on vacancies are needed. When they are not available, as it often happens, proxies for vacancies are typically used, such as help-wanted indices derived from newspaper advertisements, or the number of vacancies registered at job centres, often adjusted in some way (see for example Storer 1993, Coles & Smith 1996, and Berman 1997). These data sources, however, need not correspond to total vacancies available at a given time, because firms could adopt other methods to advertise their vacant positions, like for example internet, private employment agencies or informal networks.

When data on vacancies are proxied by some downward biased index, the associated coefficient is also likely to be estimated with bias. The sign and magnitude of this bias is determined by two sources of distortion. The first is the standard attenuation bias due to measurement errors.

The second can be of any sign, and depends on the correlation between the adopted vacancy index and the measurement error (see Broesma & van Ours 1999 for an example). Because of these two potentially offsetting effects, the direction of the bias is undetermined and the estimated elasticity to vacancy should be interpreted with caution. This is especially true with international comparisons, where the proxies used may be different across countries.

Consider now the problem of identifying the pool of job seekers S. Early studies adopt very simple models where S corresponds to total unemployment and, consequently, M is equal to the outflow from unemployment into employment (see for example Pissarides 1986 and Layard *et al.* 1991). Most of these studies find that the matching process satisfies the hypothesis of constant returns to scale. They also find that a plausible range for the elasticity to unemployment is between .5 and .7. A range for the elasticity to vacancies is instead between .3 and .5, suggesting that the supply side of the market has a greater influence on the matching process (see Petrongolo & Pissarides 2001 for a review).

Several empirical studies show that a large part of the hires occurring during a given period consist of people recorded as inactive at the beginning of the period (see for example Clark & Summers 1979 and Jones & Riddell 1999). Therefore, recent literature on the matching function expresses total labor availability S as a function $S = g(U, O)$ of the stock U of unemployed and the stock O of people out of the labor force. The resulting matching function takes the form $M = M(V, g(U, O))$, where M is now the total flow from non-employment into employment. In the simplest case, $g(U, O)$ is just the sum of the unemployed and people out of the labor force. In other cases, g is modeled as a more complex function of U and O (for example, Broesma & van Ours 1999 propose a Cobb-Douglas specification). In these studies, the estimated elasticity to S is generally lower than .5, confirming how relevant is the definition of the inputs for the analysis of job match elasticities (see also Blanchard & Diamond 1989). The general problem of lack of microfoundation of standard empirical matching models gets even worse when the pool of job seekers S is represented by a (non-microfounded) function like $g(U, O)$. An aggregate function for S is neither useful to interpret the labor supply behavior of the different groups of non-employed people (men versus women, younger versus older people, etc.), nor to evaluate how they may influence the matching rate.

In the next two sections, the problem of measuring the two inputs to the matching function will be addressed using a micro model for transition probabilities.

2.2 A microfounded hazard model

At the micro level, a job match implies a transition from non-employment to employment. Let h be the (discrete-time) hazard that a non-employed person finds a job between time t and time $t+1$. It follows from (1) that $h = M/S$. In the special case of constant returns to scale, $h = m(\theta)$.

In order estimate this hazard rate, we need to specify a functional form for h. As for the matching function, we can choose any function whose values are comprised between 0 and 1. However, we can go a step forward in the study of the matching process and adopt a microfounded matching function. Consider the basic urn-ball micro matching model proposed by Pissarides (1979). In this model, time is partitioned into a number of intervals of fixed length ("application rounds") during which job seekers apply for a job and firms select among the applicants to cover their vacancies.[1] Assume that, in each application round, job seekers can send just one application for a vacant job. A job seeker knows where vacancies are located, but not if other seekers are applying for the same job. As a result, a vacancy may receive several applications, or no application at all. In this simple model, frictions are entirely due to workers' coordination failure. Also assume that, when a firm receives more than one application, it selects a worker at random. Applicants who are not selected return to the pool of job seekers. Under this set of assumptions, one obtains the following microfounded constant-returns-to-scale matching function (see Pissarides 1979, and Petrongolo & Pissarides 2001)

$$M = V(1 - e^{-1/\theta}) \tag{2}$$

where $\theta = V/S$ is market tightness. The resulting employment hazard is

$$h = \frac{M}{S} = \theta(1 - e^{-1/\theta}).$$

The market tightness parameter θ can easily be estimated by maximum likelihood using micro-data on individual transitions. Given a random sample of n people who are non-employed at time t, the individual contribution to the sample likelihood is

$$\ell_i = \begin{cases} \theta(1 - e^{-1/\theta}), & \text{if finds employment at } t+1, \\ 1 - \theta(1 - e^{-1/\theta}), & \text{otherwise.} \end{cases} \tag{3}$$

Notice that θ can be estimated even in the absence of data on vacancies. Thus, model (2) not only gives a microfounded hazard rate, but also allows us to estimate a measure of market tightness

[1] In this paper, we adopt the standard assumption that an application round lasts for one quarter. This assumption is implicitly made by all those studies where the matching function is estimated on quarterly data (see for example Storer 1994 and Castillo *et al.* 1998).

compatible with the observed transitions, even when the lack of data on vacancies prevents direct estimation of the matching function.

2.3 Introducing search intensity

The model presented in the previous section is a simple two-state model where non-employed people find employment with probability h. However, not all the non-employed search for employment at a given time. A simple way of describing the labor supply behavior of non-employed people is through search intensity. Search intensity is a measure of the effort applied in job search, under the assumption that a higher intensity implies a higher probability of finding a job. We shall assume that each non-employed person is characterized by a search intensity level s which depends on individual preferences, search costs and the expected return of searching. In what follows, without loss of generality, we normalize s to be between 0 (does not want to search) and 1 (active job seekers).

Petrongolo and Pissarides (2001) propose a simple way to introduce search intensity into the urn-ball model presented in the previous section. In their framework, job seekers simply choose the total number of application rounds they want to participate. Search intensity, defined as the individual probability of participating to a given application round, can then be measured by the fraction of application rounds a job seeker decides to participate. Within this framework, the transition probability from non-employment into employment can be decomposed in two parts: (i) the probability s of participating to an application round, and (ii) the probability $\theta(1-e^{-1/\theta})$ that, conditional on participating to an application round, a person finds employment, where now $\theta = V/[\sigma(U+O)]$ and σ is mean search intensity in the population.

The individual contribution to the sample likelihood is now

$$\ell_i = \begin{cases} 1-s, & \text{if does not participate,} \\ s\theta(1-e^{-1/\theta}), & \text{if search is succesfull,} \\ s[1-\theta(1-e^{-1/\theta})], & \text{if search is not succesfull.} \end{cases} \tag{4}$$

After suitably parameterizing s, and possibly θ, as functions of observables, ML estimates of the model parameters may again be obtained from micro-data on transitions.

3 Data

This section summarizes the main features of the data that we use. We first describe the Italian and Spanish quarterly labor force surveys (LFS) (Section 3.1), and then present some descriptive statistics (Section 3.2).

3.1 The Italian and Spanish labor force surveys

The Italian and Spanish LFSs share a lot of common features, both in their design and the nature of the information collected. Therefore, even if the two surveys are not fully harmonized, it is possible to compare individual labor market status and many relevant aspects of job search behavior.

Both surveys are rotating quarterly sample surveys. In Italy, the rotation scheme is 2–2–2, that is, people are interviewed for two consecutive quarters, remain out of the sample for two quarters, and are interviewed again for two more quarters. Thus, each quarter sample consists of four rotation groups, in any two-quarter period there are two overlapping rotation groups and, for any rotation group, the second pair of interviews occurs one year later in the same quarters as the first pair. In Spain, instead, each quarter sample consists of six rotation groups, each rotation group is interviewed for six consecutive waves and, in any two-quarter period, there are five overlapping rotation groups, one exits the sample and is replaced by a new one.

The Spanish LFS (*Encuesta de Poblacion Activa*) is conducted by the Spanish National Statistical Office (INE), that regularly produces two types of files, a cross-sectional and a longitudinal file. Cross-sectional files contain detailed information about individuals, households and the place of living (municipality and region). In the longitudinal files, information about households and their place of living is instead omitted. This information can be easily added by matching the longitudinal and the cross-sectional files using the individual identifiers and the other variables common to both files. This matching procedure leads to a 100 percent match rate.

Unlike Spain, longitudinal files of the Italian LFS (*Rilevazione Trimestrale delle Forze di Lavoro*) are not produced on a regular basis. This paper uses a preliminary version of the October 1999–October 2000 quarterly matched data, available thanks to a joint research project of the Italian National Statistical Institute (ISTAT) and the Bank of Italy. In the Italian LFS, linkage of individual records is problematic because of the lack of a unique personal identifier and reporting errors in the household identifier (Paggiaro & Torelli 1999). The procedure adopted by ISTAT matches individuals on the basis of time invariant information (gender, date of birth, etc.) and information which varies monotonically (e.g. educational attainments). Sample attrition and matching errors do not allow for a perfect match between consecutive surveys and, each quarter, on average about 6 percent of the original sample is lost. As for the Spanish case, where the loss of units is entirely due to sample attrition (Jiménez-Martín & Peracchi 2002), this loss of information does not seems to affect the estimates of transition probabilities (Viviano 2002).

Following most of the empirical literature on the matching function, we focus on quarter-to-quarter transitions. Our estimates are based on the surveys conducted between October 1999 and October 2000. For each country, we pool in a single data set the four quarterly waves conducted in 2000 (October 1999–January 2000, January 2000–April 2000, April 2000–July 2000, and July 2000–October 2000). The final samples, consisting only of working-age individuals (aged 16–64), amount to more than 200,000 observations in each country.[2]

3.2 Some descriptive statistics

Italy and Spain are characterized by a high and unevenly distributed unemployment, concentrated among women and younger people (see Table 1).[3] Differences by gender are stronger in Spain than in Italy, whereas the opposite is true for the differences by age group. In year 2000, the Italian unemployment rate was 8.4 percent for men, 14.9 percent for women, 31.1 percent for younger workers (aged less than 25 years), and 8.4 percent for the rest of the working-age population. In Spain, it was 10 percent for men, 20.6 percent for women, 25.5 percent for younger workers and 12.2 percent for the rest of the working-age population (respectively 5.6 percentage points lower and 3.8 percentage points higher than the corresponding Italian rates).

In both countries, labor market conditions differ considerably across regions. In Italy, the unemployment rate in year 2000 was around 4 percent in the North-Eastern regions,[4] but close to 24 percent in the Southern regions.[5] In Spain, it was below 5 percent in Navarra and Balears, but around 25 percent in the Southern regions.[6]

Panels a) and b) of Figures 1 and 2 show the age profile of the quarterly flow into employment by gender for Italy and Spain respectively. The flow is expressed as a percentage of the non-employed population, and therefore corresponds to the exit rate $M/(U+O)$ from non-employment. The rate is further decomposed in order to separately identify those who move from unemployment from those who move from out of the labor force. Data have been smoothed using a simple centered

[2] The rotation scheme of the Italian LFS implies that each individual is interviewed only twice during the period October 1999–October 2000. Thus, the Italian pooled dataset contains transitions of different individuals. This is not true for the Spanish pooled dataset, where a sizeable part of the pooled sample (around 42 percent) is observed for all the 5 waves taking place between October 1999 and October 2000, 29 percent is observed 4 times, 21 percent is observed 3 times, and 9 percent is observed 2 times.

[3] We do not consider the effects of the new European Commission regulation 1897/2000 regarding the definition of unemployment. The new definition is more restrictive than the usual ILO definition, because people merely registered at employment offices are now considered as non-active job seekers. As a consequence, these people are excluded from the unemployment pool. So far, Spain is the only country of the European Union that has adopted this regulation (see Garrido & Toharia 2003 for a discussion).

[4] Trentino A.A., Veneto, Friuli V.G., and Emilia R.

[5] Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia and Sardegna.

[6] Andalusia, Canarias, Extremadura, Murcia and Ceuta y Melilla.

moving average of the age-specific rates. In Spain, exit rates from non-employment initially increase with age, reach a peak around age 35 for men and 26 for women, and then decrease. The Italian data reveal a similar pattern, but with a weaker relationship between age and the female exit rate from non-employment.

As in many other countries (see for example Clark & Summers 1979, Burda & Wyplosz 1994, and Jones & Riddell 1999), both in Italy and Spain a sizeable part of the quarterly flow into employment consists of people initially recorded as out of the labor force. In Spain, this flow is particularly important for women older than 35 years of age. In Italy, it amounts on average to nearly half the total flow for men and to about 70 percent for women. Thus, in both countries, the study of the matching process must take into account also movements from out of the labor force.

In general, an observed transition from inactivity to employment masks two transitions, one from inactivity to job seeking and one from job seeking to employment. These transitions are not observed because we only know an individual's working condition at fixed points in time one quarter apart from each other. However, our estimates of the number of matches M and the number of job seekers S must somehow take them into account. In this paper, we measure M by the number of people who are without a job at time t and find employment before time $t+1$. Similarly, we measure S by the sum of those who search and find employment (i.e. M) and those who search but do not find employment (i.e. those who are unemployed at $t+1$).

According to the ILO definition, people without a job are recorded as unemployed if they have undertaken at least one search action during the 30 days preceding the reference period. However, because we are considering job matches that take place during a quarter, consistency between flow and stock data requires that we include in the pool of job seekers those recorded as inactive at time $t+1$ because their last search action occurred 2 or 3 months before time $t+1$. The Italian and Spanish data provide a measure of this larger stock of job seekers. In fact, unlike other labor force surveys, the Italian data report for non-employed people the number of months passed since the last search action. It is therefore easy to identify those who made at least one search step during the previous 2–3 months. On average, they amount to nearly 20 percent of total unemployment. The Spanish LFS does not allow us to derive such measure, but only to identify those who have not undertaken any search step during the previous 30 days because they are waiting for the results of previous efforts. On average, they represent around 2 percent of total unemployment.

Panels c) and d) of Figures 1 and 2 show the ratio $S/(U+O)$, which is a direct estimate of search intensity. They also show the ratio M/S, which is a direct estimate of the probability of finding employment during a quarter. According to these non-parametric estimates, average male search intensity in Spain increases with age up to age 28–30, and then decreases. At its peak, search intensity is around 70 percent. In Spain, women aged 26 have the largest probability of participating to an application round and, at this peak, search intensity is around 50 percent. Compared with Spain, the age profile of search intensity of Italian men is shifted towards older ages. Moreover, at the peak, search intensity is almost 10 percentage points lower than in Spain. Search intensity for Italian women is even lower and equals 30 percent at the peak. Thus, the Italian labor market is characterized by a higher share of non-employed people who decide to stay out of the labor market.

In both countries, the estimated hazard rate h is around 30 percent on average (around 35 percent for men and 25 percent for women). In Spain, the age-profile of h decreases by age, especially for men. In Italy, it is instead U-shaped, the minimum being reached between 22 and 28 years of age. This is a peculiar feature of the Italian labor market, where people with secondary education, who amount to around 60 percent of the total population of this age group, tend to search more intensively but have less job opportunities than other groups in the population (see Viviano 2002). In both countries, older people have a lower probability of participating to an application round but a relatively higher probability of finding employment.

4 Results

The literature on the matching function typically assumes that the labor market is segmented, for example by skills, regions or travel-to-work-areas (see for example Coles & Smith 1996). As a consequence, market tightness θ and search intensity s need not be the same for different labor market segments. In this paper, we allow both θ and s to be functions of regional labor market characteristics and socio-demographic characteristics of a person (gender, age, schooling attainments). Because θ can only take non-negative values and s must lie between 0 and 1, the following specifications are adopted

$$\theta_i = \theta(X_i) = \exp(\beta^\top X_i) \tag{5}$$

and

$$s_i = s(Z_i) = \frac{\exp(\gamma^\top Z_i)}{1 + \exp(\gamma^\top Z_i)}, \tag{6}$$

where β and γ are vectors of unknown parameters and X_i and Z_i, with $X_i \neq Z_i$, are vectors containing personal characteristics and regional labor market characteristics. For parsimony, both X_i and Z_i only contain the main effects and exclude interactions between personal characteristics and regional labor market characteristics.

More precisely, the vector X_i contains three indices of regional labor market conditions. The first is the fraction of workers who worked more hours than usual during the reference period. The second is the average number of extra hours worked during the reference week. The third is the regional separation rate at time t, that is, the number of people moving from employment to non-employment between time t and time $t+1$ divided by total employment at time t. The first two variables capture the effects of labor demand shock, while the third reflects structural labor market characteristics.[7] Under the assumption that urban agglomeration may affect frictions (see for example Coles & Smith 1996), X_i further includes a dummy variable equal to 1 if the region of residence contains a big city (one with more than 1,000,000 inhabitants). To take into account possible seasonal effects and unobserved regional characteristics, the vector X_i also contains seasonal dummies and area dummies (different in the two countries). Finally, X_i contains a set of dummies for gender (female dummy), age (four age groups: 16–24, 25–34, 35–44 and 45+) and educational attainments of a person (three levels: primary, secondary and tertiary education following the ISCED classification).

In addition to the dummies for gender, age and educational attainments, the vector Z_i contains the position of a person within the household (single and living alone, household-head, spouse of the head, other household member), self-reported work status (job seeker, student, other condition), past work experience, and a set of dummies for the type of non-employment status (ILO unemployed, job seeker but not in the 4 weeks before the survey, not job seeker) and the search method used. It also includes labor market characteristics, as described by the regional separation rate and the dummy for a large city in the region of residence.[8]

The model parameters β and γ have been estimated by maximizing the sample log-likelihood $L(\beta, \gamma) = \sum_i \ln \ell_i(\beta, \gamma)$, where ℓ_i is of the form (4), with θ and s specified as in (5) and (6).[9] After selecting the non-employed persons aged between 16 and 64, the Italian and Spanish samples consist of 116,853 and 165,798 observations respectively. Because of the rotation scheme, large part of the Spanish sample consists of repeated observations for the same person. So, for Spain, estimated standard errors are derived from the the "sandwich" estimate of the asymptotic variance

[7] In the two countries the separation rate depends on the characteristics of employment in a given segment. For example, in both countries the separation rate is highly correlated with the fraction of temporary workers.

[8] Under the assumption that individuals are unable to adjust immediately to aggregate shocks, the current value of variables which are highly correlated with the business cycle, such as the fraction of workers who worked more hours than usual during the reference period and the average number of extra hours worked during the reference week, should not help predict search intensity.

[9] The sample log-likelihood has been maximized using the Newton-Raphson optimization method provided by the `ml` command in Stata 7.0, with numerical first and second derivatives, and with starting values of the parameters set equal to zero. For both countries, convergence is always achieved after 5 iterations.

matrix, under the assumption that observations on the outcome variable are independent between persons but not within.

Table 2 reports estimates of the β and γ coefficients associated, respectively, with market tightness and search intensity. The baseline case is a man aged 25–34, not at school, with secondary education, living with his parents in the Southern part of Italy (Area 4), [10] or Spain (Area 5),[11] not in a big city, with past work experience, who sougth actively for a job during the previous four weeks by sending applications and *curricula*. Regional separation rates, fraction of overtime workers and average extra hours worked are all expressed as deviations from the country specific means. For both countries, our estimates indicate significant differences in market tightness between men and women, and across age groups, educational levels and geographical areas. In Italy, market tightness is higher for people with tertiary education, while in Spain it is higher for people with primary education only. In both countries, market tightness is negatively related to the separation rate, the fraction of overtime workers and the average extra hours worked during the reference week. Finally, the matching rate is lower in regions with a big city, as found also by Coles & Smith (1996) for England and Wales.

Search intensity is higher for men, for people aged 25-34 and for people with higher educational attainments. As expected, search intensity is also affected by household background variables, labor market conditions at time t and the type of search methods used, with similar impact on both Italian and Spanish job seekers.

Table 3 reports average predicted search intensity and market tightness. For each individual in the sample, predicted values are computed by keeping household background variables, previous labor market condition, and regional labor market characteristics at their average, but allowing gender, age group, educational attainment and region of residence to vary across individuals. Predicted values are then averaged over gender, age group, educational attainment and geographical area.[12] We do so in order to isolate the "pure" effect of variation across this second set of variables. The table also provides the average value of a number of features of the matching process, namely the hazard rate, the search duration (the inverse of hazard rate), the vacancy duration (the inverse of the probability V/M that a vacancy is filled), the elasticity to unemployment η_U, and the elasticity to vacancy η_V. These indicators unable us to interpret labor market dynamics underlying the unemployment rates of the two countries. For example, a higher intensity implies that a rela-

[10] Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, and Sardegna.
[11] Andalusia, Canarias, Extremadura, Murcia, and Ceuta y Melilla.
[12] Averages are weighted using the probability weights provided by each survey.

tively higher share of population searches for a job. Thus, it can increase the unemployment rate. However, when search intensity is associated with a high enough market tightness, the final effect on the unemploymnet rate can be of any sign.

In Italy, average estimated search intensity is equal to 28.6 percent, that is, 28.6 percent of the non-employed population carries out some search action during each quarter (see Table 3). Average search intensity is higher for men, for people aged 25–34, and for more educated persons. It also varies considerably by geographical area, and is higher in the Southern part of the country (Area 4).[13] In Italy, average market tightness is equal to 44.5 percent, that is, about 45 vacancies are available for every 100 job seekers. Large differences can be found by gender and age group, with older people facing a tighter market than younger workers (64.0 versus 35.5 percent). Market tightness is slightly higher for people with lower educational attainment than for people with secondary education (44.5 versus 39.5). There are striking differences across regions, however. In the North-Eastern part of the country (Area 2), estimated market tightness is equal to 82.5 percent, almost twice the national average.

Thus, our results suggest that differences in the male and female unemployment rates cannot be imputed to search intensity, which is higher for men than for women, but to differences in market tightness, which is more than 10 percentage points higher for men. Our estimates suggest also that the Italian youth unemployment is not due to lower search intensity, that for this group is close to the national average, but to the fact that market tightness is 6 percentage points lower than the average. Finally, the high unemployment rate of the Southern regions is due not only to lower market tightness (20.8 percent), but also to higher search intensity (8 percentage points higher than the average).

In Spain, average estimated search intensity is equal to 35.3 percent, a value that is remarkably higher than in Italy. As in Italy, search intensity is above average for men, more educated people and in the Southern regions (Area 5).[14] In Spain, however, market tightness is lower than in Italy (28.6 versus 44.5 percent) and differences among socio-demographic groups are smaller. Market tightness is higher for men than for women (33.7 versus 23.5 percent), while the differences across education levels are relatively small. Unlike Italy, market tightness decreases with age, being highest among people aged 16–24 (37.3 percent) and lowest among people aged 45+ (23 percent). This partly explains why the Spanish youth unemployment rate is lower than the Italian one. In the Eastern regions of Spain (Area 2), θ is only 8 percentage points higher than the national average,

[13] Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, and Sardegna.
[14] Andalusia, Canarias, Extremadura, Murcia, and Ceuta y Melilla.

while for the other regions the differences are negligible. Finally, as in Italy, in the Southern regions (Area 5), the high unemployment rate is a combination of a larger pool of applying job seekers and a lower market tightness.

In both countries, and for almost all the segments of the labor market that we consider, the job creation rate is quite small compared to the pool of applying job seekers. On average, the matching technology is characterized by a low elasticity to unemployment. The estimated values are .230 for Italy and .113 for Spain, close to the estimates of Burda and Wyplosz (1994). Because of a higher market tightness, average search duration is lower in Italy than in Spain (3.4 quarters versus 3.9 quarters). Vacancy duration, on the other hand, is about one quarter in both countries. Our estimates suggest that, both in Italy and Spain, labor market dynamics is mainly driven by the demand side of the market. This result does not hold for all geographical areas, however. In the North-Eastern part of Italy (Area 2), where θ is 82 percent, search duration is equal to only 1.8 quarters, while the elasticity to unemployment is around .488. Therefore, at least in Italy, notable supply effects can be found at the regional level.

5 Conclusions

This paper proposes a simple method that allows estimating relevant features of a macro matching function from data on individual labor market transitions. This method has two main advantages. First, it enables us to derive a measure of market tightness even when data on vacancies are not available or their quality is poor. Second, it gives us a way of modelling and estimating the probability that a non-employed person enters the labor market at a given time. Given the particular specification of the matching function, we can decompose individual transition probabilities in two parts, one influenced by individual search intensity, and one determined by the characteristics of the matching technology.

Because of the high degree of harmonization of European labor force surveys, the proposed estimation method can be applied to obtain comparable information on matching technology in several European countries. As an illustration, this paper focuses on Italy and Spain. In both countries, unemployment is a very persistent phenomenon, unevenly distributed between men and women, among age groups, and across regions.

Our results suggest that, both in Italy and Spain, the process of job creation does is not heavily influenced by the supply side of the market. Differently from the findings of macro models for other European countries, the average elasticity to unemployment is quite low, and the matching rate appears to be driven mainly by the vacancy creation process.

Some sizeable supply effect can be found in Italy at the regional level. In the North-Eastern part of this country, the estimated elasticity to unemployment is near to .50, not far from the elasticities generally estimated for many other low-unemployment countries.

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Table 1: Labor force participation rates, employment rates and unemployment rates in year 2000.

	Men	Women	Aged ≤ 24	Aged > 24	Total
			Labor force participation rates		
Italy	67.0	46.2	37.7	64.4	59.7
Spain	78.4	51.5	46.8	69.4	64.8
			Employment rates		
Italy	73.2	39.2	27.4	59.1	53.1
Spain	70.6	40.9	34.9	61.1	55.6
			Unemployment rates		
Italy	8.4	14.9	31.1	8.4	10.9
Spain	10.0	20.6	25.5	12.2	14.2

Table 2: Market tightness and search intensity: Estimated coefficients and p-values (for simplicity, the coefficient for the seasonal dummies are not reported). Area 1 consists of Piemonte, Lombardia, Liguria in Italy, and Cantabria, La Rioja, Navarra, Pais Vasco in Spain. Area 2 consists of Trentino A.A., Veneto, Friuli V.G., Emilia R. in Italy, and Aragon, Catalunia, Comunidad Valenciana, Balears in Spain. Area 3 consists of Toscana, Umbria, Marche, Lazio in Italy, and Asturias, Galicia in Spain. Area 4 consists of Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna in Italy, and Castilla La Mancha, Castilla y Leon, Madrid in Spain. Area 5 consists of Andalusia, Canarias, Extremadura, Murcia, Ceuta y Melilla in Spain.

	Market tightness				Search intensity			
	Italy		Spain		Italy		Spain	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Constant	-1.92	.00	-1.22	.00	2.17	.00	2.56	.00
Women	-.28	.00	-.36	.00	-.13	.00	-.12	.00
Age 16-24	.07	.05	.23	.00	-.13	.00	-.05	.11
Age 35-44	.34	.00	-.16	.00	-.13	.00	-.30	.00
Age 45+	.66	.00	-.24	.00	-.96	.00	-1.15	.00
Tertiary education	.22	.00	.01	.66	.24	.00	.50	.00
Primary education	.12	.00	.09	.00	-.20	.00	-.13	.00
Single living alone					.03	.69	-.07	.30
Household head					.08	.08	-.40	.00
Spouse of head					-.48	.00	-.69	.00
Student					-1.36	.00	-.67	.00
Other					-1.91	.00	-1.42	.00
No past experiences					-.25	.00	-.82	.00
Unempl: Asked friends					.56	.00	.29	.00
Unempl: Public recruitment					.06	.31	.07	.45
Unempl: Public employment office					.12	.01	.89	.00
Unempl: Set up a self-employment					-.10	.70	0.00	1.00
Not searching at time t, but before					-1.52	.00	-1.25	.00
Not searching at time t					-2.67	.00	-3.13	.00
Area 1	.84	.00	-.04	.38	-.01	.75	.01	.78
Area 2	1.23	.00	.35	.00	.07	.09	.10	.01
Area 3	.55	.00	-.18	.00	.06	.09	.10	.02
Area 4			.03	.51			-.03	.41
Region with a big city	-.45	.00	-.06	.16	-.02	.39	-.08	.03
Separation rate	-1.71	.19	-1.45	.15	2.87	.00	1.28	.16
Fraction of overtime workers	-2.18	.13	-19.43	.00				
Average extra hours worked	-.04	.13	.02	.07				

Table 3: Matching technology estimates. Area 1 consists of Piemonte, Lombardia, Liguria in Italy, and Cantabria, La Rioja, Navarra, Pais Vasco in Spain. Area 2 consists of Trentino A.A., Veneto, Friuli V.G., Emilia R. in Italy, and Aragon, Catalunia, Comunidad Valenciana, Balears in Spain. Area 3 consists of Toscana, Umbria, Marche, Lazio in Italy, and Asturias, Galicia in Spain. Area 4 consists of Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna in Italy, and Castilla La Mancha, Castilla y Leon, Madrid in Spain. Area 5 consists of Andalusia, Canarias, Extremadura, Murcia, Ceuta y Melilla in Spain.

	Search intensity (%)	Market tightness (%)	Hazard rate (%)	Search duration (quarters)	Vacancy duration (quarters)	Elasticity to S (%)	Elasticity to V (%)
Italy	28.6	44.5	36.0	3.39	1.16	23.0	77.0
Men	35.0	50.4	39.3	3.01	1.19	26.9	73.1
Women	22.3	38.5	32.7	3.76	1.11	19.0	81.0
Age 16-24	27.3	35.5	31.1	3.88	1.09	17.0	83.0
Age 25-34	41.4	32.7	29.2	4.16	1.08	15.0	85.0
Age 35-44	41.2	45.8	37.4	3.11	1.16	24.3	75.7
Age 45+	4.6	64.0	46.3	2.40	1.29	35.6	64.4
Tertiary ed.	41.6	49.4	38.7	3.07	1.19	26.1	73.9
Secondary ed.	24.0	39.5	33.1	3.73	1.12	19.6	80.4
Primary ed.	20.3	44.5	36.1	3.36	1.15	23.1	76.9
Area 1	23.5	42.4	37.3	2.82	1.12	23.6	76.4
Area 2	24.3	82.5	56.2	1.82	1.43	48.8	51.2
Area 3	30.1	32.1	30.0	3.57	1.06	14.4	85.6
Area 4	36.7	20.8	20.4	5.33	1.01	5.0	95.0
Spain	35.3	28.6	27.3	3.93	1.04	11.3	88.7
Men	44.3	33.7	31.5	3.30	1.06	15.9	84.1
Women	26.4	23.5	23.0	4.56	1.02	6.7	93.3
Age 16-24	22.3	37.3	34.2	3.03	1.08	19.3	80.7
Age 25-34	58.1	29.3	28.0	3.73	1.04	11.8	88.2
Age 35-44	50.6	24.9	24.2	4.32	1.02	7.8	92.2
Age 45+	10.3	23.0	22.6	4.65	1.02	6.3	93.7
Tertiary ed.	46.4	28.2	26.9	3.97	1.04	10.9	89.1
Secondary ed.	31.0	27.0	25.9	4.13	1.03	9.9	90.1
Primary ed.	28.7	30.7	28.9	3.68	1.05	13.2	86.8
Area 1	41.4	27.0	26.0	4.06	1.03	9.8	90.2
Area 2	35.3	36.7	33.7	3.11	1.08	18.8	81.2
Area 3	35.4	24.1	23.5	4.50	1.02	7.3	92.7
Area 4	28.0	28.0	26.9	3.93	1.03	10.7	89.3
Area 5	36.6	27.1	26.1	4.05	1.03	9.9	90.1

Figure 1: Flow into employment, search intensity and hazard of exit into employment. Italy.

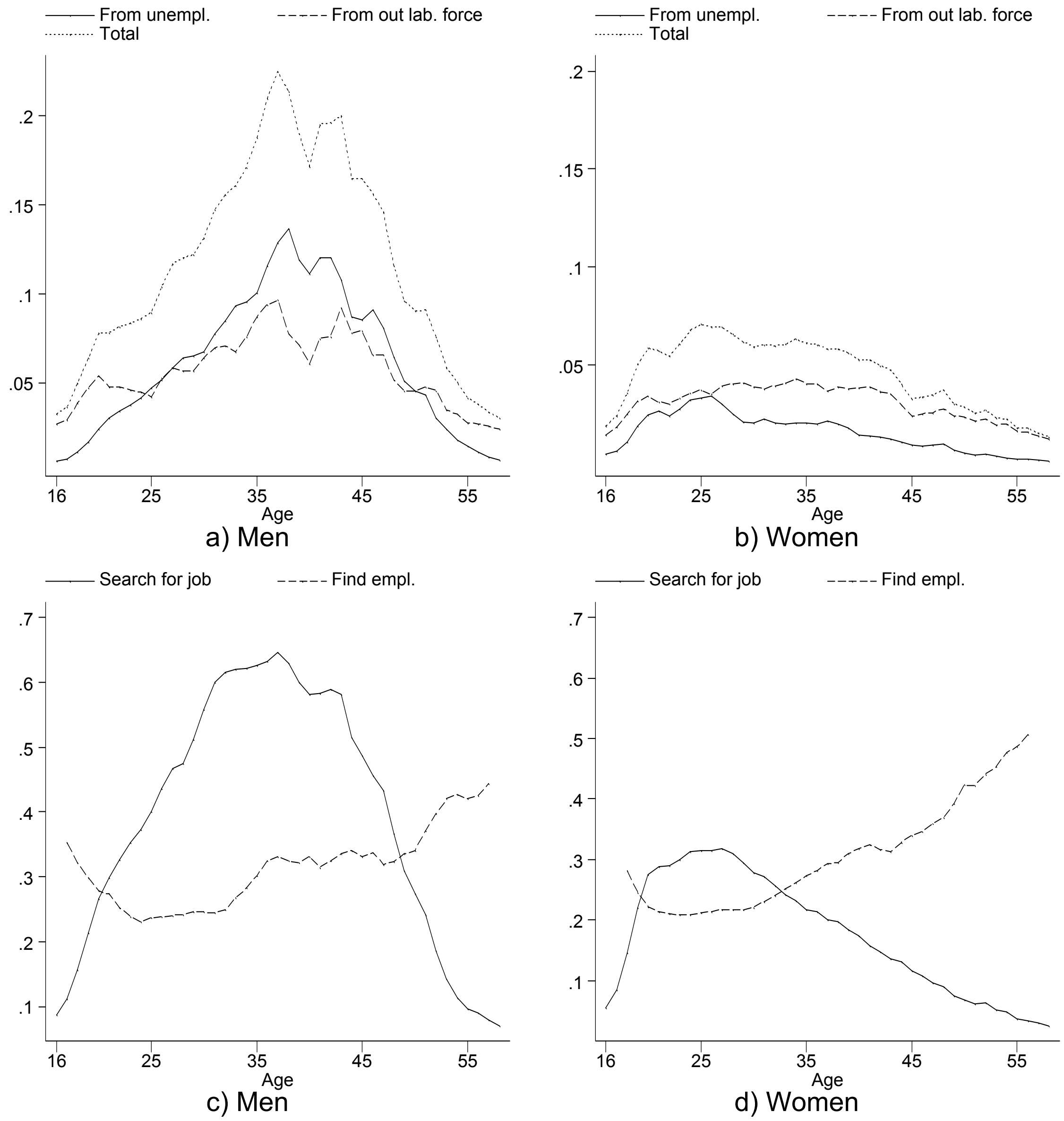

Figure 2: Flow into employment, search intensity and hazard of exit into employment. Spain.