Employment Segmentation, Labour Mobility, and Mismatch: Spain, 1987-1993[1]

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Abstract

In this paper we analyse the matching process in the Spanish labour market taking into account some of its institutional peculiarities. In particular, we estimate a matching function from a panel of occupational groups and Spanish regions for the 1987-93 period, allowing for workers' mobility across regions and occupations, and controlling for the workers' turnover generated by the high incidence of …xed-term employment contracts. We …nd that i) there is some mobility across workers' occupations within the same region, ii) workers mobility across regions is rather low, and iii) the number of hires is highly correlated with the proportion of …xed-term employment workers. The estimation of these matching functions allows us to build two alternative mismatch measures. The …rst one is obtained taking the distance along the diagonal, from the origin to the aggregate Beveridge curve. It shows that frictional mismatch increased during the 1991-1993 recession. The second mismatch index measures the incidence of reallocation shocks on the dispersion of the unemployment/vacancy ratio across labour market segments. According to this measure, the incidence of reallocation shocks was the highest during the last recession in 1992-1993.

JEL Codes: J41, J64.

1 Introduction

During the last decade, the emphasis of the economic analysis of the labour market has shifted from the understanding of stocks to the understanding of ‡ows. A new approach, the so-called "‡ow approach", has become a standard way of looking at the performance of labour markets. Under this view, workers and …rms are under continuous turnover: workers move among three stages, inactivity, employment and unemployment, while jobs are destructed, and vacancies are created and, then, …lled with workers. An essential building block of this approach is the matching function which represents the matching mechanism which relates the two parts of the market, workers in search for a job and un…lled job vacancies. The matching function is supposed to collect all the characteristics of the search process of both individuals to …nd a job, and …rms to …ll vacancies. A well-known representation of the aggregate matching function is the so-called Beveridge curve, which relates vacancy and unemployment rates.

Within this general approach, some researchers have assumed that matching mechanisms in the labour market can be represented by an aggregate matching function, much in the same spirit of the aggregate production function representing the production possibilities of the whole economy. Some examples of empirical matching functions at the aggregate level can be found in Blanchard and Diamond (1989), for the US, Jackman, Pissarides and Savouri (1990), for the OECD, Antolín (1994), for Spain, and Bell (1997), for France, Great Britain and Spain. Furthermore, from the estimation of aggregate matching functions, some researchers have attempted to construct measures of mismatch, that is, the distance between the characteristics of labour supplies and labour demands, and of workers' search e¤orts. These measures of mismatch are often related to institutional peculiarities of the labour markets which may determine workers' search e¤orts, like, for instance, the replacement rate and duration of unemployment bene…ts, the tax wedge, and expenditures on training and other "active" labour market policies.

This literature is not free of criticisms, though. First, there is the issue of the adequacy of measures of aggregate mismatch, many of them lacking theoretical foundations. A good measure of aggregate mismatch should be consistent with the aggregation of measures of mismatch along several dimensions (skills, regions, etc.) and micro-markets, whatever might be the appropriate segments of the labour market to be considered. Secondly, there

are data availability problems, as it is not always easy to get reliable data on hires and vacancies. Finally, there is some discussion about the correct speci…cation of the matching function, whether constant returns to scale should be imposed on any speci…cation and which institutional features of the labour market to use as determinants of workers' search e¤orts.[1]

There are however other labour market institutions which, without directly a¤ecting workers' search intensity, may have some implications for the correct speci…cation of the aggregate matching function. An example of labour market institutions which could make the matching function to behave di¤erently across countries, is the regulation of employment contracts. In some European countries, this regulation has produced a "dual labour market", with some workers enjoying high employment protection (high …ring jobs) and workers under "atypical" employment contracts, facing much higher turnover rates and a low probability of transition to permanent employment. Empirical estimation of aggregate matching has not taken into account the worker turnover caused by the dual structure of some European labour markets, which is not matched by a similar job turnover. In dual labour markets, it is very plausible that a given number of workers are successively matched with the same job, providing an appearance of a very dynamic market when, in fact, the rates of job creation and job destruction may be low.

This paper attempts to …ll some gaps in the previous discussion. We …rst discuss the properties of some measures of mismatch. Then, using disaggregated data by Spanish regions and occupational groups, we estimate matching functions, allowing for workers mobility across regions and occupations, and controlling for the incidence of …xed-term employment contract, which yields high turnover rates. Finally, we use our estimations to evaluate the evolution of the proposed mismatch measures. The structure of the paper is as follows. Section 2 provides some background on economic and institutional characteristics of the Spanish labour market, and reviews recent work on Spanish matching functions. Section 3 discusses conceptual issues on the measurement of mismatch. In section 4, we describe our data sources, pinpointing some drawbacks of available data. In section 5 we present some estimations of matching functions in which we allow for some mobility across labour markets segments, include heterogeneity across regions and occupations, and control for the turnover caused by …xed-term

[1] Blanchard and Diamond (1989) …nd that the US aggregate matching function has constant returns to scale. This property is also found by van Ours (1992) for the Dutch matching function. However, Smith (1992), for Australia, and Bell (1997), for France, …nd matching functions with decreasing returns to scale. Bell (1997) also …nds that the Spanish and the British matching functions present increasing returns to scale.

employment contracts. In section 6 we analyse the evolution of the resulting mismatch measures. Finally section 7 concludes and proposes some new lines of research.

2 The Spanish labour market: Some background

The Spanish labour market displays some interesting peculiarities: i) it is the labour market with the highest unemployment rate in the OECD (about 20% nowadays, and a similar average for the last decade), ii) the incidence of Spanish unemployment is uneven (unemployment is higher among women, youths, unskilled workers, and in certain regions like Andalusia, Extremadura, and Canary Islands) and unemployment di¤erentials are persistent), iii) there is a strong employment segmentation between employees hired under permanent contracts and employees hire under …xed-term contracts (about 34% of employees), iv) there seemingly is a highly intense matching process (in 1996 there were more than 8.5 million hires out of a labour force of 16 millions), and v) despite seemingly high turnover rates, there is a high proportion of long-term unemployed (about 50% of unemployed have been searching for a job during one year and over). Thus, Spanish unemployment is very high, persistent, and unevenly distributed. On the other hand, employment is segmented between permanent employees, who enjoyed high employment protection, and …xed-term employees, who can be easily dismissed. The duration of …xed-term employment contract has been limited, so that after some period (normally three years) the employer ought to either rehire the worker under a permanent contract or dismiss it. This limitation has resulted in increasing ‡ows into and out of employment for workers with …xed-term employment contracts, who have very low rehiring rates as permanent employees.

Most analysts seem to agree that the persistent nature of Spanish unemployment cannot be understood without persistent e¤ects from shocks to unemployment. For instance, a recent paper by Dolado and Jimeno (1997) shows that the evolution of the Spanish unemployment rate over the last 25 years can be modelled by a simple labour market model in which there is full hysteresis and, hence, transitory shocks have permanent e¤ects on unemployment. However, what is the main element in the transmission mechanism of shocks which produces such a long-lasting e¤ects is an open question. In principle, there are some culprits: employment inertia arising from high …ring costs, insider e¤ects in wage determination, and outsiders' low ability to compete for new job vacancies.

One reason why outsiders may not be able to …ll new vacancies is that they do not have the skills required by employers and, thus, there is some mismatch between labour demand and labour supply. This contrasts, however, with the high workers' turnover rates that …rms seen to be willing to face. Another likely source of persistence, both of the aggregate unemployment rate and of regional unemployment di¤erences, is the immobility of labour across regions (see Jimeno and Bentolila, 1998). Biased technological progress, and skills speci…cities combined with long unemployment spells and pure reallocation shocks, plus low mobility across segments of the labour market, may also help to explain unemployment di¤erences across workers' occupational groups.[2]

Thus, whatever its causes, mismatch between labour demand and labour supply quali…es to be one of the culprits of Spanish unemployment persistence, and has been subject to scrutiny. Bentolila and Dolado (1991) computed some indexes of regional mismatch (dispersion of both absolute and relative unemployment rates around the national average) and found that the absolute mismatch index (see Layard, Nickell and Jackman, 1991) has been declining since the late 1970s, and that the relative index had no signi…cant trend. Leaving aside conceptual issues about what these indexes are really measuring, it can be concluded that it is di¢cult to explain the increasing trend in Spanish unemployment from the evolution of mismatch indexes. However, as shown by Entorf (1995), in a context in which the national unemployment rate seems to behave like a unit root process, there are no reasons to expect some correlation between these mismatch indexes and aggregate unemployment. Dolado and Gómez (1996) have estimated unemployment-vacancy relationships (what is known as Beveridge curves) across Spanish regions with the goal of identifying aggregate shocks and reallocation shocks in regional evolutions. They have found that, at the aggregate level, the Beveridge curve seems to have move outwards since the beginning of the seventies until the mid-eighties, and since then, aggregate shocks seem to drive unemployment and vacancies in counterclockwise moves around a stable Beveridge curve. The outwards movement of the Beveridge curve can be interpreted as a reduction of the e¤ectiveness of the matching process. They also group Spanish regions in three categories: i) regions where aggregate shocks seem to be the main driving force of unemployment and vacancies (Aragon, Baleares, Catalonia, Madrid, Navarra and La Rioja); ii) regions where both aggregate shocks and an outwards movement of the Beveridge curve are behind the unemployment-vacancy dynamics (Asturias, Cantabria, Castilla and León, Castilla-La Mancha, Valencian Community,

[2] In fact, as documented by García, Jimeno and Toharia (1995), there has been a very pronounced change in the occupational composition of Spanish employment in recent years.

Galicia, Murcia, and the Basque Country), and iii) regions where reallocation shocks have played a major role: (Andalusia, Extremadura and Canary Islands). This estimation of unemployment-vacancy relationships at the regional level are performed under the assumption of local labour markets (that is, only unemployed and vacancies in the region enter the matching function which represent the hiring process). Although it is well-known that inter-regional mobility in Spain is quite low and this may be a valid assumption as a starting point (see Jimeno and Bentolila, 1996), in order to identify the causes of mismatch it may be relevant to search for inter-regional di¤erences in this regard.

A mismatch dimension which has been less investigated is mismatch by occupations. As already mentioned, there has been a very pronounced occupational change in the Spanish economy in recent years (see García, Jimeno and Toharia, 1995) which has had di¤erent intensities across regions. At the same time, the incidence of …xed-term employment contract has surged (from about 18% in 1987 to about 32% in 1993). This observation calls for estimation of the matching function disaggregating across regions and occupations, as in Entorf (1996), allowing for inter-regional and inter-occupational workers' mobility, as we will do in the following sections.

However, despite low workers' mobility across regions and a seemingly high degree of mismatch between labour supply and labour demand, the Spanish labour market produces very high workers' turnover rates: nowadays, for a labour force of about 16 millions, there are more than 8.5 million hires per year. Hopenhayn and García-Fontes (1996), using data from the Social Security register, …nd that job separation rates and workers' ‡ows into employment increased signi…cantly after the liberalisation of …xed-term employment in 1984. However, these ‡ows may be due to job creation and job destruction (reallocation) and to workers' rotation on the same job position. García-Serrano and Malo (1997), using data from a panel of large Spanish …rms, …nd that workers' ‡ows are of similar magnitude to that of other European countries, but that job creation and job destruction rates are much lower. This suggests that the increasing workers' ‡ows into and out of employment are caused by higher workers' turnover rates on a relatively invariant number of job vacancies. Hence, any empirical analysis of the matching process in the Spanish labour market ought to take into account the incidence of …xed-term employment.

3 The matching function and the measurement of mismatch

The concept of mismatch refers to di¤erences between the composition of labour supply and the composition of labour demand by some relevant characteristics of the unemployed and un…lled job vacancies. Labour supply and labour demand may be distant in several dimensions: regions, skills, sectors, occupations, etc. Thus, there are three previous questions to any empirical study on this matter:

1. What is the relevant dimension to look for mismatch or, in other words, in which units is the aggregate labour market to be breakdown?

2. How is the distance between the composition of labour demand and the supply composition in each labour market subunit to be measured?

3. How the measures of mismatch in each unit of the labour market ought to be aggregated to obtain an index of mismatch?

In the empirical literature on labour mismatch, there are two main dimensions in which researchers have tried to identify distances between labour demand and labour supply. The …rst dimension is skill mismatch, which has to do with workers' human capital and abilities required by new job vacancies. The measurement of skill mismatch is performed using data on the educational and occupational levels of unemployed. The second main dimension of mismatch is the territorial one (regional mismatch), which has to do with the distance between the location of vacancies and the residence of the unemployed. Under this approach, several indexes of mismatch has been proposed in the literature. Among the most popular ones are the standars deviations of relative unemployment rates and of absolute unemployment di¤erences. In the regional dimension, these indexes are de…ned as follows:[3]

$$M^1 = \frac{1}{N_l}\sqrt{\sum_{i=1}^{N_l}\left(\frac{ur_i}{ur}\right)^2}: \tag{1}$$

$$M^2 = \frac{1}{N_l}\sqrt{\sum_{i=1}^{N_l}(ur_i - ur)^2}: \tag{2}$$

where ur_i stands for the unemployment rate in region i; and ur is the national unemployment rate. N_l represents the number of regions. The main

[3] These indexes are more troublesome to de…ne in the skill/occupational dimension as unemployment rate by skills/occupations are not well de…ned.

shortcoming of these measures is that they dismissed the demand side of the labour market (which is irrelevant only under the assumption that job vacancies are uniformly distributed across segments).

We will analyse mismatch combining both the regional and the skill/occupational dimensions. To do so, we will breakdown the aggregate labour market by occupations and regions and estimate matching functions in each unit of the labour market. We now turn now to specify this representation of the aggregate labour market.

3.1 The matching function and the measurement of mismatch

We take the aggregate labor market as segmented across occupations and regions. Let H_{ijt}, S_{ijt} and V_{ijt} represent hires, active labour suppliers and job vacancies opened in occupation j in region i during period t: As usual in the matching literature, we assume that hires in each segment depend on active labour suppliers and job vacancies, through the following matching function:

$$H_{ijt} = e^{(\acute{}_i + \mu_j + ,_t)} \; (S_{ijt})^{½} (V_{ijt})^{¹} : \tag{3}$$

The matching function is supposed to be time-dependent and speci…c to an occupation and to a region. Parameters ½ and ¹ are supposed to be strictly positive and strictly smaller than one, implying that the matching function is increasing in both arguments and concave. In order to be homogeneous of …rst degree, ½ + ¹ must be equal to one. For simplicity, we assume that both parameters are equal across segments. The e¢ciency parameters $\acute{}_i$, μ_j and $,_t$ should add up to a negative number.[4]

At this stage, we can state some general considerations related to the mismatch problem using equation (3):

1. Frictional Mismatch. Under constant returns to scale, if in a particular segment of the labour market labour suppliers and vacancies

[4] In general, it is assumed that a matching function m(S; V) must be smaller than the min fS; V g, for obvious reasons. A Cobb-Douglas speci…cation does not check this property for all pair fS; V g; but it can be interpreted as a log-linear approximation of a more general functional form. In any case, with a Cobb-Douglas speci…cation, the constant term must be smaller than one. In the estimation, however, vacancies, job searchers and hires are not measured in the same units, implying that this condition does not necessarily hold.

are equal, $S_{ij} = V_{ij}$ (a situation equivalent to a market clearing condition), there would be some frictional unemployment associated to the transaction technology, which will be given by the following expression:

$$M^F_{ijt} \equiv \frac{S_{ijt} - H_{ijt}}{S_{ijt}} = 1 - e^{-(\alpha_i + \mu_j + \gamma_t)} > 0. \tag{4}$$

The mismatch measure, M^F, can be obtained from the Beveridge curve, taking the distance along the diagonal, from the origin to the curve.[5] This way of measuring mismatch requires the estimation of the constant term of the corresponding matching function. Notice that if $\alpha_i = \mu_j = 0$, $M^F_{ijt} = M^F_t$ for all the segments in the labour market. Otherwise, an aggregate measure should be constructed from the micro data.

2. **Allocation Mismatch.** When the different segments of the labour market face idiosyncratic shocks and there is no perfect mobility of jobs and workers, unemployment could come from reasons other than frictional mismatch. In this case, the ratio S_{ijt}/V_{ijt} becomes an indicator of the gap between supply and demand. If there were perfect mobility across segments, $S_{ijt}/V_{ijt} = S_t/V_t$, i..e., the relation between job suppliers and vacancies would be the same across segments. In this case, an aggregate measure of mismatch could be[6]

$$M^A = \sqrt{\sum_{ij} \left(\frac{S_{ij}}{S} - \frac{V_{ij}}{V} \right)^2}. \tag{5}$$

To better understand it, notice that the ratio $\frac{V_{ij}}{S_{ij}}$ measures the slope of the straight line crossing the origin and the Beveridge curve at the observed point $\{S_{ij}; V_{ij}\}$. For each segment, we measures, on the Beveridge curve, the distance between the individual pair $\{S_{ij}; V_{ij}\}$ and the aggregate pair $\{S; V\}$.

Periods of very important reallocation shocks (i.e., idyosincratic shocks with very different employment consequences) should imply relatively high values of the allocation mismatch measure. Moreover, persistence on this measure depends crucially on labour market mobility.

[5] This measure is similar to the one proposed by Sneessens and Drèze (1986) in a quantity rationing framework.

[6] If the number of suppliers and vacancies in each segment of the labour market were known, then this measure of mismatch could be computed without estimation of the matching function.

3.2 Labor mobility across labor market segments

To make empirically implementable the matching function in equation (1), we ...rst need to de...ne the concept of active labour supplier. As standard in the matching literature, we could exclude in-the-job search and include only unemployed as active labour suppliers. Our matching function is speci...ed at the regional/occupational level and there plausibly is mobility across regions and occupations. Thus, we consider active labour suppliers to be those unemployed in the corresponding segment of the labour market, U_{ijt}, and some unemployed workers from other occupations within region i, U_{it}, and from other regions within occupation j, U_{jt}, that may be actively searching for a job in the labour market segment ij. Under this assumption,

$$S_{ijt} = U_{ijt} + \bar{}\frac{U_{it}}{N_J} + \circ\frac{U_{jt}}{N_I}: \tag{6}$$

where N_J and N_I represent the number of occupations and regions respectively. Implicitly, we assume that all ij unemployed workers are active in the ij segment of the labor market, even if a proportion of them are also active in other segments. Notice that if we aggregate over all labour market units, the aggregate number of job searchers become:

$$S_t = (1 + \bar{} + \circ)\, U_t:$$

The parameters $\bar{}$ and $\circ$ are measures of the number of markets, other than its own segment of the labor market, visited by the mean unemployed worker in its own region and its own occupation respectively. In this sense, they are indicators of intra-regional (or inter-occupational) and intra-occupational (or inter-regional) mobility respectively. Notice that the greater $\bar{}$ and $\circ$ are, the less persistent allocation mismatch will be.

Taking a log-linear approximation to equation (6), we can writte down the matching function (3) in the following terms:

$$h_{ijt} = (\acute{}_i + \mu_j + \text{¸}_t) + \text{½}\,¢\,\pm\,[u_{ijt} + \bar{}u_{it} + \circ u_{jt}] + {}^1¢\,v_{ijt}: \tag{7}$$

Lowercase letters denote the logarithm of the corresponding variable. The parameter $\pm$ comes from the log-linear approximation of equation (6) and it can be shown that $\pm = 1/(1 + \bar{} + \circ)$. This speci...cation would allow us to estimate the relevant matching parameters. There are some restrictions which can be tested:

1. In case of constant returns to scale, $\text{½} + {}^1 = 1$:

2. If labour market segments are isolated from each other, then there is neither regional nor occupational mobility, and, thus, ¯ = ° = 0: Otherwise, ¯ or ° or both should be strictly possitive.

3.3 Fixed-term and permanent jobs

As commented above, the Spanish labour market is segmented between permanent jobs and ...xed-term jobs. Fixed-term jobs have a limited maximum duration, so that when the employment spell reaches this limit, the employee has either to be promoted to permanent employee or ...red. This causes a very high labour turnover in same jobs, as employers do not renew the employment contracts of ...xed-term employees and substitute them for a di¤erent employee instead. In the rest of this section, we study the implications of this institutional nature for the analysis of matching functions.

Let us assume that there are two types of jobs (permanent and temporary) with di¤erent matching processes. Unfortunately, we have no separate information on hires, job searchers and vacancies for permanent and ...xed-term employees. Thus, we use the proportion of ...xed-term employees to approximate this situation. Letting ¿ be the proportion of ...xed-term employees, we assume that the joint matching process of temporary and permanent jobs can be represented by

$$h_{ijt} = (\acute{}_i + \mu_j + \text{¸}_t + \text{®} \cdot \text{¿}_{ijt}) + \text{½} \cdot \pm [u_{ijt} + \bar{}u_{it} + \text{°}u_{jt}] + \text{¹} \cdot v_{ijt}: \quad (8)$$

Equation (8) will be the basic speci...cation for our empirical analysis below. Note that the constant term in the regression is a measure of the e¢ciency in the matching process. It may be time-varying and depend on the ratio of ...xed-term employees in the segment ij of the labour market. This dependence of hires on the ratio of ...xed-term employees is mainly a composition e¤ect arising from di¤erent degrees of e¢ciency between the matching function of ...xed-term employees and that of permanent employees. Thus, the parameter $\acute{}_i + \mu_j + \text{¸}_t$ represents the e¢ciency of the permanent matching process and the parameter ® measures the di¤erence on e¢ciency between the matching of ...xed-term and permanent employees.

4 The data

The estimation of matching functions is often subject to problems of data reliability. The problems arises from two sources. First, it is di¢cult to have a good proxy of the stock of job vacancies available at a given time. For some countries, vacancies rates are proxied by help-wanted indexes (see, for

instance, Abraham, 1987). In other countries, there are public employment agencies which keep registers of job o¤ers and hires. From data collected by these registers, some researchers have constructed proxies for the stock of vacancies and the number of hires. Alternatively, other researchers have measured the number of hires from either the ‡ows out of unemployment which are available from Labour Force Surveys. This measure brings together ‡ows from unemployment into employment with ‡ows from unemployment into inactivity.

Since we want to estimate matching functions at the regional/occupational level, we need proxies for the stocks of job vacancies and the number of hires disaggregated by regions and occupations. Given data availability constraints, we are compelled to proxy the number of hires from the ‡ows into employment provided by Spanish Labor Force Survey (LFS, hereafter).[7] Thus, hires are measured as the entrants to employment during the last year. This has the advantage over ‡ows out of unemployment of not confusing hires with transitions from unemployment to inactivity. The number of unemployed by regions and occupations is taken from the same source. LFS data are available since 1964. However, only since 1987 there is information on the characteristics of the previous job of the unemployed. We have individual data on the employment status of residents in the 17 Spanish regions (Autonomous Communities). We consider 82 occupational groups (which correspond to the two-digit classi…cation of the Clasi…cación Nacional de Ocupaciones, 1974). The classi…cation of occupations was changed in 1994, so that our sample period spans from 1987 to 1993. We also can compute the proportion ratio of …xed-term employees for each region and occupation.

As for vacancies, we use the number of hires provided by the National Employment O¢ce (Instituto Nacional de Empleo, INEM). This o¢ce keeps a register of job o¤ers and the resulting hires, whose main data are published in Estadística de Empleo (Employment Statistics). This source provides the number of job o¤ers registered at the employment o¢ce, which are immediately available and still vacant at the end of the relevant period (one month), which we will take as a proxy for vacancies rates. This data set is disaggregated by regions and by occupations (10 occupational groups). As pointed out by Antolín (1994), this measure of vacancies is biased downwards, since not all job o¤ers are intermediated by the National Employment Agency. He proposes a method to correct this bias, which when performed on regional data boils down to the application of a correction factor of roughly 2.5 on the o¢cial vacancy series. We have used both the original and the corrected series for the estimation of matching functions at the regional/occupational

[7] We use the LFS of the second quarter of each year.

level. Since the results do not change signi…cantly, we choose to report the results from using the original vacancy series on job o¤er un…lled at the end of each month, disaggregated by regions and occupations.

The three key variables are not measured in the same unit. Our measure of hires is a good approximation of the corresponding annual ‡ow. Our measures of labour suppliers and vacancies, however, are approximated by the stock of unemployed workers and un…lled vacancies at a given moment of time. Fortunately, changes in units only a¤ect the constant term. However, it is important to notice that the constant term could be non negative, as theoretically required.

Our data on hires, unemployment and vacancies are plotted in Figures 1 to 3, grouping the 17 Spanish regions in three groups as in Dolado and Gómez (1996) for exposition purposes. Figure 1 shows that our sample period, 1987-93, covers roughly a complete cycle: the number of hires increases in 1987-90/1 and falls in 1992-93. This is con…rmed by unemployment evolutions (see Figure 2): unemployment rates fall form 1987-91 and then increase markedly in 1992-93. However, vacancy rates (see Figure 3) show a decreasing trend throughout most of the period, with some few exceptions.

5 The results

Our base estimating equation is equation (8) above: the (log) number of hires for region i and occupation j depends on …xed-term employment rates, the (log) number of unemployed, and the (log) number of vacancies. We start by restricting this speci…cation to the case ¯ = ° = 0, i.e., those in which the relevant number of job searchers is the corresponding number of unemployed in the own segment. Results are reported in the …rst and second columns of Table 1. The equation is estimated by OLS allowing for regional and occupational …xed e¤ects (…rst column). According to these results, the elasticities of hires to unemployment and vacancies are similar and rather low (about .12). Fixed-e¤ects and time e¤ects are rather signi…cant. Furthermore, the proportion of …xed-term employment is also very signi…cant, being the corresponding semi-elasticities above unity. Across regions, Catalonia and Madrid have signi…cantly higher constant terms. Across occupations, o¢ce personnel (oc3), commercials (oc4), waiters and hotels personnel (oc5), specialized manual workers (oc8), and non-specialized manual workers (oc9) have the highest coe¢cients. After substituting time dummies for the aggregate unemployment rate (column 2), we …nd that the aggregate unemployment rate is non-signi…cant, while the rest of coe¢cient do not change much.

Figure 1. Hires as % of unemployed by Spanish regions (1987-93)

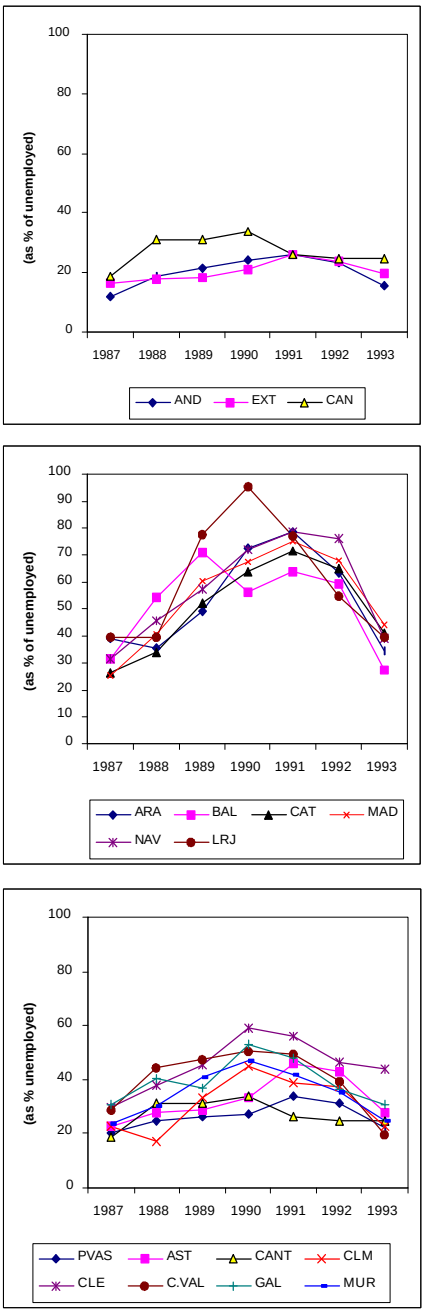


Figure 2. Unemployment rates by Spanish regions (1987-93)

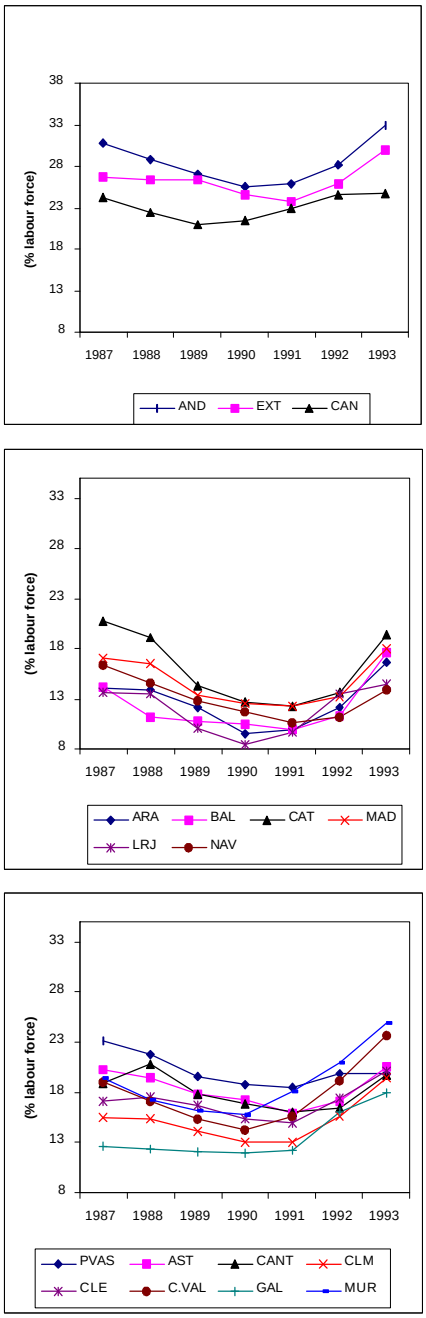
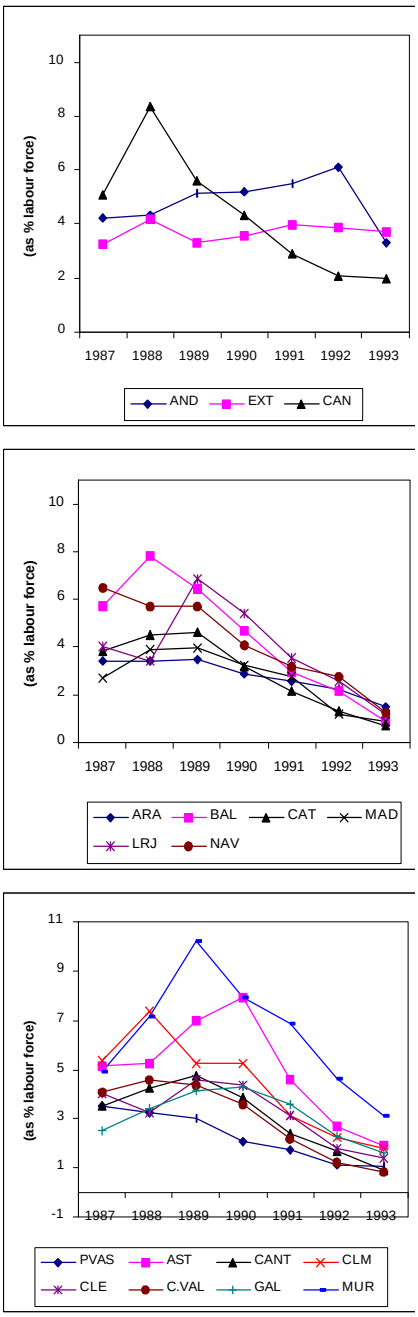


Figure 3. Vacancy rates by Spanish regions (1987-93)



The specification of the matching function in colums 1 and 2 assumes workers' immobility across regions and occupations ($\beta = \gamma = 0$). As we want to test this hypothesis, in alternative specifications of the matching function, we substitute region and occupational dummies by the number of unemployed in the region and the number of unemployed in the same occupation in other regions (in logs). These two variables turn out to be quite significant (see columns 3 and 4 of Table 1), with coefficients of around .45 and .25, respectively, which, given the coefficient of u_{ij}, implies values of β around 2 and γ around 1. Thus, there seems to be significantly more occupational mobility (2 over 9) than regional mobility (1 over 16). In columns 5 and 6 of Table 1, we impose the constraint of constant returns to scale in the matching function, without significant changes in the results. The elasticity of hires with respect to vacancies is around .15, which is much lower than estimates obtained form the estimation of aggregate matching functions from time series data. The semi-elasticity of hires with respect to the proportion of fixed-term employment in each segment of the labour market is around .5 but barley significant. Finally, the coefficient of time dummies suggests a raise in matching efficiency from 1988 to 1990 and a fall after 1991.

In Tables 2 to 4 we report similar set of results to check for robustness. First (see Table 2), we include the first lag of the endogenous variable to control for serial correlation of the residuals, which is quite evident from the set of results in Table 1. The estimates from this specification do no differ qualitatively: the elasticities with respect to unemployed and vacancies are close to those in Table 1 and the implicit estimates of β and γ are, again, around 2 and 1. Then, we use as regressors lag values of the (log) number of unemployed and of vacancies. Whether current of lag values of these regressors should be included is a question of the timing assumption. Since we are using annual data, it seems quite obvious that current values are better candidates as regressors in the matching function. However, given the high degree of persistence of Spanish unemployment, we include lag values as regressor (see Table 3) to find, again, similar qualitative results. Finally, in Table 4, we report the results from IV estimation to control for a plausible endogeneity bias. We obtain less efficient estimates, a higher elasticity of hires with respect to unemployed in the same region and occupation (around .4), and lower implicit estimates for regional and occupational mobility (β and γ).

Overall, we interpret the whole set of results as indicating the existence of: i) constant returns to scale in the aggregate matching function, ii) a high correlation of hires and the proportion of fixed-term employment workers, iii) some mobility across occupations, iv) a lower mobility across regions, and v) a high degree of serial correlation in the matching process coming from the

high workers' turnover rate, which, in turn, is due to the dual nature of the labour market arising from the segmentation of employment between permanent and fixed-term employees.

6 Mismatch measures

The previous set of results are to be used to compute the two mismatch indexes defined in Section 3.1. The first index is computed from the aggregate Beveridge curve and measures shifts upwards or downwards of the unemployment/vacancy relationship (see the definition of M^F in equation (4)). This index can be understood as an aggregate change in the matching efficiency of the economy. The second index is related to the dispersion of the unemployment/vacancy ratio across labour market segments. This index can be understood as a measure of allocation mismatch (see the definition of M^A in equation (5)). We will compare the evolution of these two indexes to that of traditional mismatch indexes as the absolute or relative dispersion of unemployment rates across regions.

In the first panel of Figure 4, we plot the indexes of mismatch based on the relative and absolute dispersion of unemployment rates M^1 and M^2, as defined in equations (1) and (2), where regions stand for the 17 Spanish Autonomous Communities[8]. The absolute dispersion of regional unemployment rates shows an increasing, but not very pronounced, trend since 1998. This contrasts whit the evolution of the aggregate unemployment rates which decreased during the 1987-91 period, to surge in the recesion of 1992-93. As for relative dispersion of regional unemployment rates, it follows a pattern that mirrors that of the aggregate unemployment rates: increasing in 1987-91, when the aggregate unemployment rate was falling, and decreasing in 1992-93, when the aggregate unemployment rate surged. Thus, from these indexed, no clear conclusions on the sources and relevance of mismatch can be drawn.

In the second panel we plot the frictional mismatch index M^F.[9] Since the estimated coefficient for the temporary/permanent ratio is non significantly different from zero when we allow for mobility (see columns 4 and 6 in Tables 1 to 3), the constant term becomes very similar across segments on the labour market and it is essentially given by the time dummy, λ_t. As a consequence, the mismatch index M^F is approximately equal across segments and it represents relatively well the aggregate situation. Contrary to the unemployment

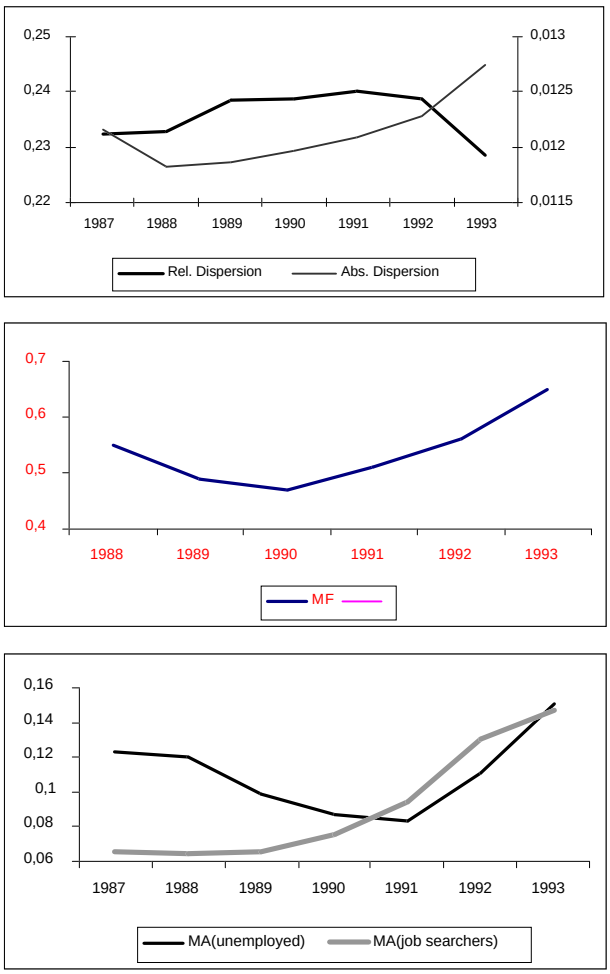
[8] Weighted dispersions show the same pattern that measures M^1 and M^2 in Figure 4.

[9] It was computed following estimation (6) in Table 1.

dispersion measures, this index of mismatch shows a significant increase after 1990, implying that the Beveridge curve moved out during the last recession.

Finally, as explained below, under a disaggregated approach different segments of the labour market could be eventually situated over different points on the Beveridge curve. The allocation mismatch M^A, gives us a measure of dispersion around the average vacancies/job suppliers ratio, where regions stand for the 17 Spanish Autonomous Communities and occupations stand for 10 occupational groups. The third panel of Figure 4 shows the evolution of this index for two alternative measures of labour suppliers: unemployed workers in the corresponding segment of the labour market and our more general measure given by equation (6), with $\beta = 2$ and $\gamma = 1$. For both measures of job suppliers it shows an increase of allocation mismatch after 1991, implying that reallocations due to negative idiosyncratic shocks has had a negative effect on unemployment.

Figure 4. Measures of mismatch (Spain, 1987-93)



7 Concluding remarks

In this paper we have estimated matching functions for the Spanish labour market taking into account some of its institutional peculiarities and using a panel of regions and occupations for the 1987-93 period. In particular, we have allowed for workers' mobility across regions and occupations, and controled for the workers' turnover generated by the high incidence of fixed-term employment contracts. We find that i) the elasticities of hires to unemployed and vacancies are close to .85, for unemployed, and .15 for vacancies (which suggests the existence of constant returns to scale), ii) a high correlation of hires and the propotion of fixed-term employment, iii) workers mobility across regions is rather low, iv) there is some mobility across workers' occupations within the same region, and v) the number of hires shows a high degree of serial correlation. Our estimates boils down to the existence of constant returns to scale in the aggregate matching function, and relative (im)mobility of workers: during the year and on average, each unemployed seems to be searching for a job in one region other than their own region of residence (out of 16 regions) and less than two occupational groups other than their own (out of 9 occupational groups considered).

The proposed mismatch measures show that, during the last recession the Beveridge curve of the representative segment of the labour market moved out, implying that the efficiency of the matching process was reduced. At the same time, there was an increase in the allocation mismatch (i.e., a greater dispersion of the position of each segment on the Beveridge curve), which gives some evidence in favor of the reallocation process associated to recessions, as in Caballero and Hammour (1996).

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Table 1. Estimates of the matching function. Dependent variable: h_{ij}.

	(1)	(2)	(3)	(4)	(5)	(6)
Const.	6.05 (.62)	6.79 (1.77)	6.84 (4.43)	-3.35 (1.15)	6.88 (1.55)	-1.89 (.23)
u_{ij}	.12 (.04)	.11 (.04)	.24 (.04)	.25 (.05)	.27 (.04)	.28 (.04)
v_{ij}	.12 (.05)	.09 (.05)	.15 (.04)	.17 (.04)	.16*	.17*
(%) $temp_{ij}$	1.10 (.36)	1.71 (.34)	.46 (.46)	.04 (.46)	.66 (.40)	.29 (.40)
u_j			.24 (.08)	.25 (.08)	.16 (.03)	.16 (.03)
u_i			.48 (.07)	.46 (.07)	.41 (.04)	.39 (.04)
u_t		-.02 (.10)	-.70 (.14)	–	-.61 (.12)	–
REGIONS:	$\hat{A}^2_{16}$ = 237:1	$\hat{A}^2_{16}$ = 255:13				
Aragon	-.88 (.16)	-.92 (.16)				
Asturias	-1.28 (.16)	-1.29 (.16)				
Baleares	-1.37 (.18)	-1.41 (.17)				
Canarias	-1.00 (.14)	-1.06 (.13)				
Cantabria	-1.87 (.27)	-1.93 (.26)				
Castilla-La Mancha	-.84 (.15)	-.90 (.15)				
Castilla y León	-.53 (.11)	-.55 (.11)				
Cataluña	.45 (.13)	.45 (.13)				
Com. Valenciana	-.07 (.10)	-.10 (.10)				
Extremadura	-1.52 (.17)	-1.58 (.17)				
Galicia	-.40 (.14)	-.39 (.14)				
Madrid	.24 (.24)	.29 (.24)				
Murcia	-1.54 (.16)	-1.62 (.15)				
Navarra	-1.60 (.19)	-1.67 (.18)				
País Vasco	-.73 (.13)	-.74 (.13)				
La Rioja	-2.04 (.24)	-2.13 (.24)				
TIME:	$\hat{A}^2_{5}$ = 27:7			$\hat{A}^2_{5}$ = 81:9		$\hat{A}^2_{5}$ = 94:5
1989	.18 (0.08)			.29 (.08)		.28 (.08)
1990	.32 (0.08)			.41 (.07)		.39 (.07)
1991	.34 (0.09)			.42 (.09)		.41 (.09)
1992	.32 (0.10)			.15 (.10)		.17 (.10)
1993	.21 (0.10)			-.17 (.12)		-.12 (.11)
OCCUPATIONS:	$\hat{A}^2_{9}$ = 278:3	$\hat{A}^2_{9}$ = 266:3				
OC1	.05 (.09)	.05 (.09)				
OC2	-.42 (.29)	-.48 (.28)				
OC3	.77 (.11)	.76 (.10)				
OC4	.96 (.11)	.94 (.11)				
OC5	1.00 (.12)	.95 (.12)				
OC6	.12 (.19)	.08 (.19)				
OC7	.27 (.14)	.18 (.13)				
OC8	.78 (0.10)	.74 (.10)				
OC9	1.14 (0.12)	1.03 (.12)				

OLS-Fixed e¤ects estimation. *Restricted to constant returns to scale.
Heterokedasticity and serial correlation robust standard errors in parenthesis.

Table 2. Estimates of the matching function. Dependent variable: h_{ij}

	(1)	(2)	(3)	(4)	(5)	(6)
Const.	4.13 (.63)	6.35 (1.32)	6.43 (.96)	-1.23 (.73)	6.45 (.96)	-.79 (.18)
$h_{ij;\,i\,1}$	0.32 (.07)	.34 (.07)	.52 (.05)	.51 (.06)	.52 (.05)	.51 (.05)
u_{ij}	.08 (.03)	.07 (.03)	.12 (.03)	.12 (.03)	.13 (.03)	.13 (.03)
v_{ij}	.09 (.05)	.07 (.04)	.08 (.03)	.08 (.03)	.07*	.09*
(%) $temp_{ij}$	.73 (.29)	1.02 (.32)	.11 (.25)	-.003 (.25)	.17 (.26)	.07 (.24)
u_j			.09 (.05)	.10 (.05)	.07 (.02)	.07 (.02)
u_i			.22 (.05)	.22 (.05)	.21 (.03)	.20 (.03)
u_t		-.15 (.09)	-.53 (.08)	–	-.51 (.07)	–
REGIONS:	$\hat{A}^2_{16}$ = 56:7	$\hat{A}^2_{16}$ = 58:3				
Aragon	-.60 (.13)	-.61 (.13)				
Asturias	-.88 (.19)	-.87 (.18)				
Baleares	-.90 (.19)	-.90 (.18)				
Canarias	-.67 (.13)	-.68 (.13)				
Cantabria	-1.24 (.24)	-1.24 (.23)				
Castilla-La Mancha	-.53 (.13)	-.55 (.13)				
Castilla y León	-.35 (.09)	-.34 (.09)				
Cataluña	.29 (.10)	.28 (.09)				
Com. Valenciana	-.07 (.07)	-.08 (.07)				
Extremadura	-1.03 (.18)	-1.03 (.18)				
Galicia	-.28 (.11)	-.26 (.10)				
Madrid	.20 (.15)	.23 (.14)				
Murcia	-1.04 (.18)	-1.05 (.18)				
Navarra	-1.11 (.19)	-1.11 (.19)				
País Vasco	-.52 (.11)	-.51 (.11)				
La Rioja	-1.36 (.25)	-1.37 (.25)				
TIME:	$\hat{A}^2_{5}$ = 18:4			$\hat{A}^2_{5}$ = 53:3		$\hat{A}^2_{5}$ = 63:0
1989	.11 (0.09)			.11 (.10)		.11 (.10)
1990	.18 (0.07)			.15 (.07)		.15 (.07)
1991	.15 (0.09)			.08 (.08)		.08 (.08)
1992	.14 (0.10)			-.04 (.07)		-.04 (.07)
1993	.02 (0.10)			-.26 (.08)		-.25 (.08)
OCCUPATIONS:	$\hat{A}^2_{9}$ = 82:9	$\hat{A}^2_{9}$ = 84:3				
OC1	.04 (.06)	.04 (.06)				
OC2	-.21 (.21)	-.23 (.21)				
OC3	.52 (.12)	.51 (.11)				
OC4	.63 (.14)	.60 (.13)				
OC5	.66 (.15)	.61 (.13)				
OC6	.07 (.13)	.05 (.13)				
OC7	.15 (.12)	.11 (.11)				
OC8	.53 (0.11)	.49 (.10)				
OC9	.76 (0.16)	.68 (.13)				

OLS-Fixed e¤ects estimation. *Restricted to constant returns to scale.
Heterokedasticity and serial correlation robust standard errors in parenthesis.

Table 3. Estimates of the matching function. Dependent variable: h_{ij}						
	(1)	(2)	(3)	(4)	(5)	(6)
Const.	4.22 (.66)	6.86 (1.22)	4.09 (.94)	-1.09 (.66)	-6.27 (1.31)	-.58 (.19)
$h_{ij;\ i\ 1}$	0.32 (.07)	.33 (.07)	.52 (.05)	.50 (.06)	.53 (.07)	.49 (.07)
$u_{ij\ i\ 1}$	.12 (.04)	.11 (.04)	.13 (.04)	.14 (.04)	.06 (.05)	.09 (.05)
$v_{ij\ i\ 1}$	.05 (.05)	.05 (.05)	.08 (.03)	.08 (.02)	.11*	.21*
(%) $temp_{ij}$	.73 (.33)	.98 (.32)	.13 (.25)	-.01 (.26)	.27 (.32)	-.10 (.33)
$u_{j\ i\ 1}$			.07 (.04)	.08 (.04)	.03 (.02)	.04 (.02)
$u_{i\ i\ 1}$			.21 (.05)	.22 (.05)	.17 (.04)	.17 (.04)
u_t		-.19 (.08)	-.35 (.06)	–	-.51 (.07)	–
REGIONS:	$\hat{A}^2_{16}$ = 57:6	$\hat{A}^2_{16}$ = 58:5				
Aragon	-.60 (.13)	-.59 (.14)				
Asturias	-.86 (.18)	-.84 (.18)				
Baleares	-.88 (.18)	-.87 (.18)				
Canarias	-.67 (.13)	-.67 (.13)				
Cantabria	-1.26 (.23)	-1.23 (.22)				
Castilla-La Mancha	-.53 (.13)	-.53 (.13)				
Castilla y León	-.35 (.09)	-.34 (.09)				
Cataluña	.29 (.09)	.28 (.09)				
Com.Valenciana	-.09 (.06)	-.09 (.06)				
Extremadura	-1.04 (.17)	-1.03 (.17)				
Galicia	-.26 (.10)	-.25 (.10)				
Madrid	.21 (.14)	.23 (.14)				
Murcia	-.99 (.19)	-1.00 (.19)				
Navarra	-1.11 (.19)	-1.10 (.19)				
País Vasco	-.53 (.11)	-.52 (.11)				
La Rioja	-1.35 (.26)	-1.34 (.26)				
TIME:	$\hat{A}^2_5$ = 18:4			$\hat{A}^2_5$ = 42:9		$\hat{A}^2_5$ = 84:7
1989	.08 (0.09)			.04 (.10)		.14 (.12)
1990	.17 (0.07)			.14 (.08)		.38 (.09)
1991	.11 (0.08)			.05 (.09)		.46 (.09)
1992	.12 (0.07)			.05 (.08)		.63 (.10)
1993	-.05 (0.08)			-.21 (.08)		.41 (.10)
OCCUPATIONS:	$\hat{A}^2_9$ = 90:2	$\hat{A}^2_9$ = 87:4				
OC1	.05 (.06)	.05 (.06)				
OC2	-.27 (.20)	-.24 (.20)				
OC3	.48 (.12)	.48 (.11)				
OC4	.57 (.13)	.57 (.13)				
OC5	.61 (.14)	.58 (.14)				
OC6	.003 (.13)	.01 (.13)				
OC7	.07 (.09)	.05 (.12)				
OC8	.48 (0.11)	.47 (.10)				
OC9	.69 (0.15)	.63 (.14)				

OLS-Fixed e¤ects estimation. *Restricted to constant returns to scale.
Heterokedasticity and serial correlation robust standard errors in parenthesis.

Table 4. Estimates of the matching function. Dependent variable: h_{ij}				
	(1)	(2)	(3)	(4)
Const.	-1.62 (.48)	4.54 (1.64)	-.14 (.17)	6.60 (1.44)
$h_{ij;\ i\ 1}$	.57 (.02)	.79 (.15)	.65 (.08)	.64 (.09)
u_{ij}	.09 (.02)	.00 (.13)	.13 (.07)	.16 (.09)
v_{ij}	.11 (.04)	.08 (.03)	.07¤	.07¤
(%) $temp_{ij}$	-.55 (.33)	-.16 (.36)	-.42 (.34)	-.68 (.45)
u_j	.15 (.07)	.06 (.05)	.03 (.02)	.02 (.01)
u_i	.24 (.06)	.11 (.05)	.12 (.03)	.11 (.02)
u_t		-.36 (.11)		-.37 (.07)
TIME:	$\hat{A}^2_5$ = 70:86		$\hat{A}^2_3$ = 68:6	
1989	.10 (.06)			
1990	.10 (.05)			
1991	.12 (.05)		-.08 (.06)	
1992	-.03 (.04)		-.15 (.05)	
1993	-.30 (.05)		-.32 (.07)	
Sargan test	$\hat{A}^2_{42}$ = 61:46	$\hat{A}^2_{51}$ = 65:24	$\hat{A}^2_{26}$ = 37:6	$\hat{A}^2_{26}$ = 42:5
m_1	-1.78	-2.38	-.8	-.91
m_2	.38	-1.43	-1.4	-1.51

IV estimation. *Restricted to constant returns to scale.
Instruments for u_{ij}, v_{ij}, $temp_{ij}$, $h_{ij\ i\ 1}$: Lags of given variables
Heterokedasticity and serial correlation robust standard errors in parenthesis.