Estimating a spatial matching function for disabled people: evidence from Italy

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Abstract

This paper proposes a spatial matching function for disabled people using a panel of 20 Italian regions covering the period 2006-2011. In particular, we implement a static model, via the Spatial Durbin Model (SDM), and a dynamic model, via Generalized Method of Moments system (GMM-system). According to the results, there is a *congestion effect* among disabled unemployed people in the regional labour market, due to an excess of unemployed disabled people compared to available vacancies.
Moreover, the negative sign of the spatial lag of vacancies shows that: the discomfort caused by the spatial and qualitative heterogeneity of the labour supply of disabled people; the low mobility of disabled people; the presence of vacancies that are almost never jobs for the disabled people; and job expectations too high led by a more functional labour market in the neighboring regions, reduce the efficiency of the domestic matching process.
The positive sign of the spatially lagged dependent variable reveals the presence of positive spatial spillovers. Furthermore, our results suggest that dynamic rather than static modelling is appropriate for estimating the matching function for disabled people.

Keywords: *Disabled People, Public Policy, Non-Labour Market Discrimination, Empirical Matching, Spatial Dependence, Regional Unemployment.*

JEL: *J14, J48, C21, C23, R12.*

<u>**Preliminary draft**</u>

1.Introduction

This paper aims to evaluate the ability of Law 68/99 to promote the employment of disabled people in terms of the matching process between unemployment and vacancies, and therefore we propose to analyze this Law from a macroeconomic perspective. In particular, we estimate the structure of the matching technology from 2006 to 2011, the only years for which all the data needed to estimate the model are available The matching function focuses on frictional unemployment, and describes a functional relationship between the inflow into new jobs and its determinants,; in particular, the available stocks of job searchers and vacancies (for a survey see Petrangolo and Pissaridies, 2001). Given that Law 68/99 aims at improving the matching between unemployed disabled people and disabled worker-searching firms, both in terms of number of matches and of duration of unemployment, the matching framework seems the natural starting point for a macroeconomic evaluation. Our work is based on data related to only disabled people (new matches, vacancy stocks and unemployment stocks).

In Italy, Law 68 of March 12, 1999 (from now on Law 68/99) aims at the regulation and promotion of the employment of persons with disabilities. Law 68/99 is fully embedded in the complex process of reform of services for the Italian labour market which has been occurring since 1997. This law has contributed significantly to the employment of disabled people, and consequently to their social inclusion (Orlando and Patrizio 2006). More specifically, it pivots on the concept of "targeted employment", so that the employment of disabled people is based on quotas of compulsory hiring, but also on a careful assessment of their residual ability, on providing, where necessary, training courses, internship and business mentoring, and on special three sided employment contracts.

To our knowledge, there are only few studies on Law 68/99 in macroeconomic terms, namely, the studies by Agovino and Rapposelli (2011; 2012, 2013), who investigate the ability of Italian regions to efficiently coordinate the various actors involved in the employment of disabled people according to Law 68/99 in order to reach the matching between demand and supply of jobs for disabled people. However, none of these studies applies the methodology based on the matching framework.

The variables of the labour market are related in space. When we exclude spatial correlation, and we assume cross-sectional independence between observation units, we obtain biased and inefficient estimates. In the empirical literature on the matching function, there are few contributions that consider the spatial effects. Burgess and Profit (2001), Hynninen (2005), Fahr and Sunde (2001b, 2006a, 2006b) introduce spatial interactions in the matching function by exogenous variables lagged in space (the regressors). This approach has been criticized by Lottman (2012) because it does not adequately capture the spatial autocorrelation in the data. In particular, Lottman (2012) proposes to estimate a model that includes also the spatial error term in addition to the spatial lag of the dependent variable, in order to overcome this problem; in this way she overcomes the problem of cross-sectional dependence in the residuals.

In summary, in this paper we propose to investigate whether new jobs for disabled people (matches) are spatially correlated, and if the market conditions in the neighboring regions are relevant in the process of creation of new jobs for disabled people within the region where by market conditions we mean levels of new matches, vacancies stocks and unemployment stocks. In particular, we estimate a spatial Durbin model (SDM) for panel data and to overcome the problem of spatial dependence in the residuals, we also check for the presence of spatial correlation in the error term. In addition, we control for the dynamics of the labour market, introducing in the SDM a time lag of the dependent variable, and applying a GMM-system estimator to control for endogeneity problems arising from both the spatial and the temporal lag of the dependent variable.

The paper is organized as follows. Section 2 presents the basic matching model, Section 3 reviews the methodology, Section 4 presents the data set, Section 5 is dedicated to the estimation results. Section 6 gives the conclusions.

2.Matching function and limits of the empirical analysis

The standard model of the matching function assumes the existence of a homogeneous set of workers and vacancies. The matching process can be seen as a black box (Petrongolo and Pissarides, 2001), which is usually represented in the empirical literature through a Cobb-Douglas specification (Burda, 1993; Stevens, 2007):

$$M = AU^{\beta_1}V^{\beta_2} \quad (1)$$

where M is the ($NTx1$) vector of the flow of matches, and A describes the augmented matching productivity (see Fahr and Sunde, 2004); in particular, changes in value of A capture changes in the geographic and skill characteristics of workers and jobs or other differences between the two, as well as differences in search behavior among job searchers (Broersma and Van Ours, 1999). U and V denote the ($NTx1$) vectors of unemployment and vacancies stocks.

In the empirical literature equation (1) is estimated considering the logarithms:

$$lnM = lnU\beta_1 + lnV\beta_2 + \alpha + \mu_i + \nu_t + \varepsilon \quad (2)$$

where μ_i is a regional fixed effect, ν_t is the time fixed effect, and ε represents the ($NTx1$) vector of errors which are assumed to be *i.i.d.* across i and t with zero mean and constant variance σ^2.

This specification of the matching function follows the hypothesis of random matching approach; this approach, defined *stock-stock approach*, assumes that agents are matched randomly at any point in time, regardless of the duration of the research. This approach is opposed to another one defined *stock-flow approach*, which assumes that the unemployed have complete information about possible jobs. Either they find a job instantaneously or they wait until new vacancies arrive on the market. Consequently, the *stock-flow approach* does not only take into account stocks but also inflows into unemployment and vacancies (Lottman, 2012). The *stock-stock approach* has been widely criticized (see Coles and Smith, 1998; Gregg and Petrongolo, 2005; Petrongolo and Pissarides, 2001; Fahr and Sund, 2009), because it implicitly assumes an undirected, random underlying search process leading to matches between homogeneous unemployed and homogeneous vacancies.

In our case, we will refer to the *stock-stock approach* due to the unavailability of data of inflows on the unemployed disabled people and vacancies specifically for disabled people. The choice of *stock-stock approach* represents a first limit of our analysis.

Another limitation, highlighted by the empirical literature is represented by the choice of the dependent variable, in particular, the variable used to measure the match tends to exclude the figure of employed job searchers. In many empirical studies this variable is omitted due to its unavailability (Broersma and Van Ours, 1999). Many studies use total hires as a proxy of the number of matches. In fact, hires include not only the unemployed who find a job but also the flow of persons out of the labour force into a job, and the flow of employed workers who are looking for another job.

As a result, the matching concerns the vacancies and of all job seekers and we no longer have the matching of vacancies and unemployed job seekers. . In particular, Broersma and Van Ours (1999) conclude that it is important to distinguish between employed looking for jobs and unemployed looking for a job, as not taking into account this distinction produces a biased estimate of the parameters of the matching function. This distinction is relevant when we consider the spatial lag of vacancies among the regressors of the matching function. In particular, Fahr and Sunde (2002, 2003) find that the sign of the coefficient of spatially lagged vacancies depends on the type of dependent variable used: the effect is positive for all hires and hires that were already employed, while it is negative for unemployment outflows into employment.

In our case we cannot get information on the construction of the matching variable for disabled people; the ISFOL data does not explain whether the variable matching includes total hires (the hires that were already employed and unemployment outflows into employment) or only unemployment outflows into employment; therefore, the sign of the spatial lag of vacancies will allow us to identify the type of dependent variable that we are using.

Another issue is the temporal aggregation of data (Hynninen, 2005). Since the matching function describes a process continuous in time, the use of data referring to discrete time introduces a problem of bias in the estimate of the parameters of the matching function. In particular, a greater aggregation of data will result in a greater bias (Burdett et al., 1994); therefore, it is advisable to use highly disaggregated data over time (monthly, quarterly). In fact, data with high temporal frequency are rarely available, especially when evaluating a matching function for disabled workers. In

our case, as in other empirical work on the matching function, we have no data with frequency less than annual.
A final issue is due to the aggregation of spatial data (Hynninen, 2005; Kano and Ohta, 2005). The spatial aggregation of data was discussed and rejected by the empirical literature, and it is preferred to work on disaggregated data at the level of local labour markets (Burgess and Profit, 2001; Coles and Smith, 1996; Ilmakunnas and Pesola, 2003; Hynninen, 2005). Spatially disaggregated data are justified by the idea that the aggregate economy is a collection of distinct and heterogeneous spatially labour markets who suffer themselves from many frictions. Spatially disaggregated data allow to examine the spatial aspects of the matching function and the weight of the interactions between the different local labour markets within an economy. On the basis of these considerations, many scholars have enriched the basic matching function with the spatial lag of regressors (unemployment, vacancies) with the objective to evaluate spillovers between different local labour markets (Burda and Profit, 1996; Burgess and Profit, 2001; Ilmakunnnas and Pesola, 2003). In our study, spatial disaggregation at regional level is the highest available.
We can summarize in the following three points the limitations in the estimation of the matching function:

1. unavailability of the single components of the matching variable (the unemployed who find a job, the flow of persons out of the labor force into a job, and the flow of employed workers who are looking for another job);
2. lack of regressors (unemployed and vacancies) expressed in terms of flow;
3. lack of disaggregated data in time and space.

Due to all these limitations the results of empirical studies on the matching function should be interpreted with caution (Anderson and Burgess, 2000; Fahr and Sunde, 2001a).

3. Spatial model specification

The specification of our *static* matching function is represented by a spatial Durbin model (SDM), which, in addition to the spatial lag of the dependent variable and the regressors, also checks for the presence of a spatial process in the error term[1].
The SDM is specified in the following way:

$$lnM = \lambda WlnM + lnU\beta_1 + lnV\beta_2 + WlnU\theta_1 + WlnV\theta_2 + \alpha + \mu_i + \nu_t + \varepsilon$$

[1] Lottman (2012) after implementing the SDM, without checking for a spatial process in the error term, finds that the residuals are characterized by spatial correlation. This result suggests that the model with only exogenous variables lagged in the space, partially capture the spatial autocorrelation in the data. Consequently, it is relevant to consider the spatial process also in terms of error.

$$\varepsilon = \rho W \varepsilon + \eta \tag{3}$$

where M is a ($NTx1$) vector of matches, U and V are the ($NTx1$) vectors of the unemployment and vacancy stocks, respectively; μ_i is a spatial fixed effect, and ν_t is the time fixed effect. W is the non-stochastic (NxN) spatial weights matrix. In our case we use a binary spatial weights matrix; in particular, when two regions are neighbors, i.e. they share a common border, the corresponding entry in the matrix is one and zero otherwise. The elements on the main diagonal are zero by construction, since a region cannot be contiguous to itself. The spatial weights matrix is row standardized so that neighbouring variables are weighted averages of the values in neighbouring regions (Anselin, 1988). Lottman (2012) criticizes the use of a binary contiguity matrix because not sufficient to fully capture the spatial relationships among the geographical units, on the contrary she suggests using a matrix that takes into account commuting between different local labour markets. In the case of geographical units such as provinces, local labour markets, or smaller geographical units, it is justified to use a matrix that takes into account the phenomenon of commuting (commuting that takes place within a region); in the case of larger geographical units (such as regions) it does not seem reasonable to think of a commuting to work that goes beyond neighboring regions; for this reason in our case a binary contiguity matrix seems justified, as it takes into account commuting between adjacent regions. In addition, it is difficult to think about a matrix that takes into account commuting in the case of the disabled people. The matrix of binary contiguity is preferable, in the case of disabled workers, to the one that takes into account commuting among distant regions, for the following two reasons[2]:

- disabled people are not readily available to mobility (Raia, 2006). Disabled people by their nature are obviously not very mobile, as they are often dependent on their family, and their medical care is also linked to their residence[3].
- Disabled people looking for work through Law 68/99 must register in the employment centers of residence, therefore migration following cyclical unemployment is unlikely.

[2] The binary contiguity matrix, in the case of disabled people who find work thanks to Law 68/99, gives us a measure of the influence that the policies of contiguous regions have on the policies of a given region. In particular, we expect that the implementation of Law 68/99 in a given region does not exhaust its effects in the region itself, but also produces its effects in the neighboring regions; and viceversa.

[3] The choice of family doctor is simultaneously with the enrollment in the National Health Service. To enroll in the National Health Service, one must go to the Local Health Unit's administrative offices of the territory of residence. Only in the case where citizens is domiciled in that territory for a period longer than three months and for reasons of health, study or work, it is possible temporary enrollment (with a term not exceeding to 1 year and renewable) in a Local Health Unit other than one the municipality of residence. The citizen, assisted by the territorial jurisdiction Local Health Unit, who wants to enroll in a Local Health Unit that belongs to another municipality can only do so when the municipalities are geographically neighboring, and after the presentation of a specific documentation, which will be assessed by the Committee of General Practitioners.

β and θ are respectively ($Kx1$) vector of slope parameters to be estimate, λ is a spatial autoregressive parameter that measures the magnitude of interdependence across regions, and α is the intercept.
η represents the ($NTx1$) vector of errors which are assumed to be *i.i.d.* across *i* and *t* with zero mean and constant variance σ^2. A spatial error term implies that a shock introduced in a given region not only affect the matching of the region where it was generated, but it will produce its effect also on the matching of neighboring regions (Rey e Montouri, 1999). Examples of this process in the case of the labour market are regional shocks such as changes in the governments of the regions or the closure of a production site.
Indeed, in empirical implementation, we can conduct several specification tests to examine whether the SDM model can be simplified into spatial lag model, spatial error model, or an OLS model. In particular, in empirical analysis, the likelihood ratio (LR) tests can be used to test such restrictions. Imposing the restriction $\theta = -\lambda\beta$ in the SDM yields a spatial error model, while if the restriction $\theta = 0$ is imposed, it leaves us with the spatial lag model. In addition, if $\lambda = 0$, an OLS model with spatial on the regressors arises.
Equation (3) can be estimated with the maximum likelihood estimation techniques (see Elhorst and Fréret, 2009).

3.2 Dynamic model specification

The objective of the *dynamic* specification is to capture the temporal dynamics of the matching process. In order to capture this dynamic, we will enrich the SDM with the time lag of the dependent variable. In particular, the model that we estimate is the following:

$$lnM = \lambda WlnM + \phi TlnM + lnU\beta_1 + lnV\beta_2 + WlnU\theta_1 + WlnV\theta_2 + \alpha + \mu_i + \nu_t + \varepsilon$$
$$\varepsilon = \rho W\varepsilon + \eta$$
(4)

where T is an ($NTxNT$) matrix with ones on the lower first-minor diagonal, i.e. at coordinates ($N+1, 1$), ($N+2, 2$),…, ($Nt, Nt-1$), and zeros elsewhere. *TlnM* is thus a typical first-order temporal lag, with ϕ as its coefficient (see Hays et al., 2009).
The estimation of a model with temporally and spatially lagged dependent variables introduces the problem of distortion due to endogeneity. One way to overcome this problem is the use of an instrumental variables procedure applied to a dynamic model of panel data. In particular, we refer to a GMM estimator that uses the dynamic properties of the data to generate proper instrumental variables (Arellano e Bond, 1991; Arellano and Bover, 1995)[4].

[4] We use a set of instrument variable $L(lnU, lnV, WlnU, WlnV, W^2lnU, W^2lnV, T^2lnM)^4$, that is, regressing WlnM on $L(lnU, lnV, WlnU, WlnV, W^2lnU, W^2lnV)$ and *TlnM* on $L(lnU, lnV, WlnU, WlnV, W^2lnU, W^2lnV, T^2lnM)$; where, with W^2 we indicate the second-order binary contiguity matrix (Anselin, 1988). In the case of temporally lagged dependent

The GMM estimator allowsto control for weak endogeneity by using the instrumental variables, which consist of appropriate lagged values of the explanatory variables. To deal with the fact that measurement errors are likely to be determined not only by random errors but by specific and persistent characteristics of each region, we use the GMM-system (Arellano e Bover, 1995; Blundell e Bond, 1998) that combines into a single system the regression equation in both differences and level. The GMM-system estimator allows to control for unobserved region-specific effects that are potentially correlated with the explanatory variables.
Since the consistency of the parameters obtained by means of the GMM estimator depends crucially on the validity of the instruments, we consider two specification tests: the Sargan test of overidentifying restrictions, which tests the null hypothesis of overall validity of the instruments used and the test for serial correlation of the error term, which tests the null hypothesis that the differenced error term is first and second order serially correlated. Failure to reject the null hypothesis of no second-order serial correlation implies that the original error term is serially uncorrelated and the moment conditions are correctly specified.

4. Data

We use yearly data on unemployment, vacancies and matches for disabled people for the period from 2006 until 2011. This data is provided by ISFOL (Institute for the Development of Vocational Training for Workers) at regional level. Although Law 68/99 came into force in 1999, ISFOL provides the regional details on unemployment, vacancies and matches for disabled people only from 2006 onwards (Ministry of Employment, 2006-2007, 2008-2009, 2010-2011). In addition, the unavailability of data prior to 1999 does not allow to implement an analysis of the effectiveness on Law 68/99.
The match variable is a flow variable and is defined on the basis of job placement as defined by Article 7 of Law 68/99 (rules on compulsory recruitment). ISFOL does not specify whether the match variable includes also the employed disabled people who are looking for a job, in addition to the unemployed disabled people who find a job. Since job placement for disabled people is based on enrollment to employment centers, it is natural to think that after a job placement the disabled person is deleted from the list of unemployed people with disabilities looking for work; a new enrollment means that the disabled person is unemployed again and therefore the match variable only include the outflows into employment of unemployed disabled people. The match variable also includes the disabled people hired in firms which by law are not obliged to do so, and are hired via the agreement[5] (Article 11, paragraphs 1 and 4, agreements and agreements for work integration).

variable, we use as additional instrument the temporal lag of second order of dependent variable ($T^2 lnM$) (see Hsiao, 2003)

[5] Through the agreements, signed by the interested parties (workers, employers, provincial offices for the employment of disabled workers and authorities that promote the labour integration), it is possible to define a personalized program of interventions to overcome barriers related to the inclusion in the workplace. The agreements are the tool by which

The unemployment variable is a stock variable and concerns disabled people enrolled in job centers at the 31st of December. In this case, ISFOL does not make a distinction between the unemployed looking for employment and the unemployed who are not looking for a job; for this reason, the variable of unemployment will be distorted upwards.

The vacancies variable is a stock variable and is defined by art. 3 of Law 68/99 (compulsory recruitment, reserve shares). The public and private employers are obliged to have among their employees workers with disabilities, in proportion to the size of the firm (Article 3 of Law 68/999). In particular, the employer is obliged to have a reserve shares of:

- one disabled worker if the firm has a number of employees ranging from 15 to 35;
- two disabled workers if the number of employees ranges from 36 to 50;
- 7% of workers if the number of employees is more than 50.

The reserve share that is not filled (vacancies) allows to determine the stock of vacancies. ISFOL data do not allows to distinguish between vacancies in the public and in the private sector. In our analysis we consider separately the vacancies in the public and in the private sector.

In calculating the match, unemployment and vacancies variables are also included people who are not disabled but fall into the categories provided by ex art. 18[6], for this reason the variables are biased upwards; since the share of these people is modest, the distortion is very small and has little influence on the variables.

Table 1 shows the summary statistics of our panel data over time and considering the absolute values. The match shows on average a decreasing trend and reaches its minimum in 2009, a year after the economic crisis (we go from 1,744 in 2006 to about 1,168 match in 2009), we observe a small upturn in the last two years. We record a regional variability in the match variable that exceeds 1,000 units. The unemployment stock increase steadily during 2006 until 2010 while decreasing in 2011. The summary statistics show strong regional variation in the unemployment stocks with values for the standard deviation of more than 40,000. Finally, we observe that the vacancies stocks in the public sector is significantly lower than the one in the private sector; on average the vacancies stocks in the public sector shows an increasing trend until 2010, while in 2011 it shows a significant reduction. The vacancy stock in the private sector shows on average a cyclical pattern until 2009, from 2009 onwards shows a downward trend. The regional variation in terms of vacancy stock reaches its peak in 2009 (1,020.176), in the case of public vacancies, and in 2008 (5,052.85), in the case of vacancies in the public sector.

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the law seeks to promote the integration targeted, through a gradual labour integration of people with disabilities, aimed at the achievement of the employment obligations.

[6] Orphans and surviving spouses of people who died (or became disabled) for reasons of work, war or service.

Table 1: yearly summary statistics of unemployment stocks, vacancy stocks and matches of disabled people at regional level (2006-2011).

Variables	2006	2007	2008	2009	2010	2011
Matches:						
Min	95	72	71	45	50	0
1st quartile	815	684	670	505.5	506	103.5
Median	1,278.5	1,215	1,121	834	932	893.5
Mean	1,744.95	1,694.1	1,576.2	1,167.9	1,341.684	1,279.15
3rd quartile	2,389.5	2,414	2,057	1,731	1,900	1,941
Max	6,876	6,082	7,113	4,330	4,834	5,233
Standard deviation	1,637.058	1,503.999	1,653.093	1,090.529	1,272.542	1,470.754
Unemployed stocks:						
Min	513	487	423	455	532	0
1st quartile	7,821	7,951.5	8,291.5	8,541	9,304	624
Median	18,908.5	25,831.5	24,212.5	24,028.5	30,107	17,811.5
Mean	35,401.3	39,255.85	38,811.65	37,996.15	42,082.74	34,399.95
3rd quartile	39,147.5	45,205.5	45,421	45,324	53,616	38,042.5
Max	156,890	164,567	164,744	166,571	141,044	148,188
Standard deviation	45,084.96	46,877.31	44,350.87	44,041.37	45,068.31	46,043.93
Public vacancy stocks:						
Min	0	2	3	8	0	0
1st quartile	24.5	155	114	140.5	121	0
Median	230	360.5	318	387	393	90.5
Mean	492.3	541.65	616.85	735.9	729.3	437.2
3rd quartile	696.5	787.5	982.5	705.5	759	704.5
Max	2,843	1,828	2,403	3,721	3,484	2,520
Standard deviation	691.3511	505.3383	671.7023	1,020.176	964.9898	707.7927
Private vacancy stocks:						
Min	0	18	11	11	0	0
1st quartile	288	270.5	226	265	207	17.5
Median	1,537.5	1,342	941	976.5	675	382
Mean	3,028.85	2,727.45	3,246.15	2,656.2	2,619.947	1,442.35
3rd quartile	3,555	3,171.5	2,834	2,274.5	2,095	1,411
Max	15,947	12,945	18,074	16,424	15,927	14,551
Standard deviation	4,128.774	3,654.743	5,052.85	4,327.353	4,515.305	3,247.097

5. Empirical results

In this section we present the results of the econometric estimations. Because of the multicollinearity problems between public and private vacancies, we implement two separate estimates: an estimate with only public vacancy stocks and one with only private vacancy stocks.
Firstly, we estimate the static matching specification (column 1, Table 2 for public vacancy stocks; column 2, Table 2 for the private vacancy stocks); finally, we estimate the dynamic matching model (column 3, Table 3 for public vacancy stocks; column 4, Table 3 for private vacancy stocks).
As regards the static estimates (see columns 1 and 2, Table 2), we observe that the Hausman test rejects the null hypothesis, and leads us to prefer the fixed to the random effects model. Furthermore, we perform a likelihood ratio test (LR) in order to investigate whether the SDM can be reduced to spatial lag or error model, The LR

results ($p<0.05$ for both null hypotheses: $\theta=0$ and $\theta= -\lambda\beta$) indicate that the SDM can be properly applied to describe the matching function for disabled people.

As suggested by the matching theory, the estimated elasticities of both stock variables are positive (unemployment and vacancies). In particular, in the case of public vacancy stocks, the elasticity of matches on unemployment equal to 0.5954, this means that un increase of unemployment stock by 1% results in an increase of matching by 0.5954%. The public vacancy stocks is not significant, and this highlights the lack of importance of the public sector in the matching process for workers with disabilities. In addition, the spatial lag of the unemployed stock is significant and has a negative sign. The negative sign seems to capture a cyclical effect: a higher unemployment rate in neighboring regions, indicating a worse economic situation, reduces the number of matches. Therefore, an economic contraction has the effect of both reducing new hires and of increasing the number of layoffs; in this case, the number of available vacancies contracts, as according to Law 68/99 companies affected by particular conditions, such as layoffs, are temporarily exempted from the recruitment of disabled persons. This result suggests congestion effects due to an excess of unemployed disabled people compared to reduced available vacancies. The economic contraction does not limit its effect to the region where it has originated and produces its effects in neighboring regions as well (contagion effect).

The spatial lag of the public vacancy stock is not significant, therefore has no effect on the local matching process. In contrast, the spatial lag of the dependent variable is significant and has a positive sign; this reveals the presence of spatial spillovers through which regions "do better" if neighboring regions experience high creation rates of new jobs. It 's interesting to note that the parameter associated with the spatial error term is significant and has positive sign: a random shock introduced in a given region not only affect the match of disabled workers in the same region where it is generated, but it also produces its effect on the match of neighboring regions (Montouri and Rey, 1999).

Using the definition of elasticity, $\beta_1 = (\delta M/M)/(\delta U/U)$, it is possible to define the marginal effect $(\delta M/\delta U)$, that indicates the number of additional matches produced if the stock of unemployed increases by one unity. The interpretation is the same for other regressors. We verify that the greatest marginal effect is produced by the spatial lag of the dependent variable, followed by the spatial lag of unemployed stock; in particular, the creation of one new job in neighboring regions has the effect of increasing the "home matches" by 13 units of disabled workers; moreover, if the unemployed stock of contiguous regions increases by one, the number of "home matches" is reduced by about 6 units.

In the case of the model that considers the private vacancy stocks among the regressors (Table 2, column 2), both stock variables are significant and have the expected positive sign. In particular, the elasticity of matches on unemployment equals 0.5542, this means that an increase of unemployment stock by 1% results in an increase of matching by 0.5542%. The elasticity of matches on private vacancy

stocks is 0.1193. Also in this case the spatial lag of the unemployed stock is negative and significant, while the spatial lag of the vacancy stock is not significant. The spatially lagged dependent variable and the spatial error term are positive and significant. Also in this case, the greatest marginal effect is produced by the spatial lag of the dependent variable, followed by the spatial lag of unemployed stock, although the size of the effect is smaller compared with the results of the previous regression. In particular, the creation of a new job in contiguous regions has the effect of increasing the "home matches" by 8 units of disabled workers; in addition, if the unemployed stock of contiguous regions increases by one, the number of "home matches" is reduced by about 3 units.
This result is due to the significance of the parameter associated with the private vacancy stock that appears to be a relevant variable in the matching process; the significance of this variable reduces the impact of the spatial lag of the dependent variable and the spatial lag of the stock of unemployed.

Regarding the dynamic model, we observe that the estimated elasticities of both stock variables, for both models, are positive and significant (columns 3 and 4, Table 3). The public vacancy stock is now significant, the elasticity of private vacancy stock is greater than the one of the public sector (0.0916 and 0.0239 respectively). The spatial lag of unemployed stock is significant and has negative sign, the impact is greater in the case of the private sector.
The spatial lag of the vacancy stock is significant and with a negative sign for both models, with a greater effect in the case of private vacancy stocks (-0.0190 and -0.0039, respectively). This result is in line with Fahr and Sunde' work (2002, 2003), which decomposes the match variable and distinguish between individuals who were unemployed before successfully matching, and previously employed job switchers. The authors find that the sign associated with the coefficient of the spatial lag of the vacancy stock depends on the type of dependent variable used: the effect is *positive* for all those hired and for those hired who were already employed, while it is *negative* for unemployment outflows into employment. There are several causes that justify the negative sign of the spatial lag of the vacancy stock. In particular:

- the discomfort caused by the spatial and qualitative heterogeneity of the labour supply of disabled people jointly with the low mobility of disabled people (Raia, 2006). In particular, the presence of areas with a high probability of job placement and the reduced presence of disabled people willing to work and areas where the opposite happens poses the problem of mobility of workers. Mobility itself normally reduces the matching process and that in the case of disabled people it is particularly acute, both for the personal and the institutional reasons we have discussed above.
- Raia (2006) also observes that vacancies are almost never jobs for the disabled people, but they could even be a sign of the inability of contiguous regions to implement the matching between the demand and supply of labor. In particular, a large part of the labour demand in the industrial sector, which

theoretically provide more jobs, is often hostile to disabled workers, and it often requires positions and tasks not compatible with reduced work capacity. In addition, the public and private service sectors do not show a particularly active demand for labour. Consequently, an increase in the stock of vacancies in neighboring regions is not necessarily an indicator of good performance of the labour market in these regions, with the effect of leaving many vacancies.

— If we interpret the negative sign as an indicator of the ability of contiguous regions to create new jobs, we can think that more jobs imply more variety of work. The variety slows the domestic matching process because disabled people looking for work are influenced in their choices by more attractive job prospects coming from neighboring regions. This encourages local disabled people not settle for the first job offered they receive, as their job expectations rise. This negative effect is reinforced by the difficulty of mobility of disabled people.

In addition, it is important to conclude that the negative sign of the vacancy stock allows us conclude that in the case of disabled people, the dependent variable is made up of unemployed disabled people outflows into employment (Fahr and Sunde, 2002, 2003).

The spatial lag of the dependent variable is still positive for both models but with reduced impact, this result also applies to the spatial error term. Finally, we observe that the temporally lagged dependent variable is significant and has positive sign, with a greater impact in the case of the private vacancies stocks. This result implies that an increase in the number of matches during the previous period has a positive effect on the matches of the current period. A change in the size of the impact of the regressors is due to the introduction of the time lag of the dependent variable; without this variable the other regressors only caught a part of its effect.

Information-theoretic criteria such as Akaike’s Information Criteria (AIC) (Akaike, 1973) and Bayesian Information Criteria (BIC) (Schwarz, 1978) are increasingly being used to address model selection problems; in particular, a model that minimize AIC and BIC criteria is selected. In our case, the dynamic model minimizes the AIC, BIC criteria and maximizes the Log-likelihood criteria. The fourth model achieves the best compromise between data fitting and parsimony; the model with the private stock vacancies (column 4).

The Sargan test, which allows to verify the validity of the instruments, does not reject the null hypothesis and this confirms the validity of the instruments used. In addition, there is no evidence of first and second-order serial correlation (the null hypothesis is not rejected); consequently, the GMM estimator is consistent. In particular, the consistency of the GMM estimator requires that there is no serial correlation of the second order in the differenced error term.

Table 2: Estimates of matching functions using the spatial static panel model.

Dependent variable: ***lnM***	**Public vacancy stocks (1)**	**Private vacancy stocks (2)**
WlnM (*spatial autocorrelation into the matching function***)**	0.1337**	0.1213**
	(2.53)	(2.08)
lnU	0.5954***	0.5542***
	(21.00)	(15.38)
lnV_public	0.0498	
	(1.59)	
lnV_private		0.1193**
		(2.33)
WlnU	-0.0662*	-0.0636*
	(-1.81)	(-1.85)
WlnV_public	-0.0224	
	(-1.45)	
WlnV_private		-0.0096
		(-0.40)
Wε (*spatial error term***)**	0.1338**	0.1214**
	(6.384)	(4.340)
Constant	0.1639	0.0806
	(0.49)	(0.25)
Log-like	-54.8467	-54.0920
Akaike Information Criterion	0.1697	0.1676
Bayesian Information Criteria	0.2092	0.2065
LR test on θ=0	[0.0133]	[0.0023]
LR test on θ=-λβ	[0.0218]	[0.0058]
Hausman test of fixed versus random effects model	42.50***	54.28***
	(0.000)	(0.000)

*Notes: t-statistics are in parentheses; p-value are reported in brackets; ***, ** and * indicate coefficients that are significant at 1%, 5% and 10%, respectively.*

Table 3: Estimates of matching functions using the spatial dynamic panel model.

Dependent variable: ***lnM***	**Public vacanciy stocks (3)**	**Private vacancy stocks (4)**
WlnM (*spatial autocorrelation into the matching function***)**	0.0786***	0.0650***
	(5.35)	(4.03)
TlnM (*first-order temporal lag into the matching function***)**	0.0461**	0.0678**
	(2.63)	(2.49)
lnU	0.7585***	0.5515***
	(52.35)	(25.91)
lnV_public	0.0239***	
	(4.07)	
lnV_private		0.0916***
		(3.37)
WlnU	-0.0659***	-0.0812***
	(-5.74)	(-9.55)
WlnV_public	-0.0039***	
	(-2.85)	
WlnV_private		-0.0190***
		(-3.01)
Wε (*spatial error term***)**	0.0787***	0.0766***
	(28.644)	(7.384)
Constant	0.0211	-0.1150
	(0.73)	(-3.01)
Log-like	73.1480	74.0110
Akaike Information Criterion	0.0156	0.0147
Bayesian Information Criteria	0.0187	0.0157
Sargan overidentification test	[0.6328]	[0.8351]
AR(1): serial correlation of first order	[0.360]	[0.490]
AR(2): serial correlation of second order	[0.713]	[0.498]

*Notes: t-statistics are in parentheses; p-value are reported in brackets; ***, ** and * indicate coefficients that are significant at 1%, 5% and 10%, respectively.*

6. Conclusions

In this paper, we estimate a spatial matching function for disabled people. Four our empirical analysis we use the ISFOL panel dataset for Italian regions over the period 2006-2011. In order to capture the dynamics on labour markets, we use not only a static modeling but also a dynamic model specification. Our results show that the dynamic model better captures the data structure than the static one.

Results show that the spatial lag of unemployment has a negative impact on matches. This result reflects the business cycle effect: higher levels of unemployment in other regions represent a proxy of a contraction in the economy, that spreads also in the neighboring regions reducing their matching process. In particular, an economic contraction has the effect of reducing new hires and of increasing the number of layoffs; in this case, according to Law 68/99 companies affected by particular conditions, such as layoffs, are temporarily exempted from the recruitment of disabled persons. This result suggests congestion effects; due to an excess of unemployed disabled people and to a contraction of available vacancies.

The negative sign of the spatial lag of vacancies shows that:

1. the discomfort caused by the spatial and qualitative heterogeneity of the labour supply of disabled people;
2. the low mobility of disabled people;
3. the presence of vacancies that are almost never jobs for the disabled people;
4. and job expectations too high

led by a more functional labour market in the neighboring regions, reduce the efficiency of the domestic matching process.

The spatial lag of the dependent variable is positive, highlighting positive spatial spillovers, involving that regional policy activities have wider consequences. In particular, a local matching shock is not limited to one region but has also effects on neighboring regions. As a result, regional policies aiming to facilitate the process of matching of disabled workers have effect not only in the region where the policy has been implemented, but also involve contiguous regions.

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