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Published online: 10 Oct 2016.

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Regional labour force participation across the European Union: a time–space recursive modelling approach with endogenous regressors

Solmaria Halleck Vega[a,b] and J. Paul Elhorst[b]

ABSTRACT

Regional labour force participation across the European Union: a time–space recursive modelling approach with endogenous regressors. *Spatial Economic Analysis*. Although there is an abundant regional labour market literature taking a spatial perspective, only a few studies have explored extending the analysis of labour force participation with spatial effects. This paper revisits this important issue, proposing a time–space recursive modelling approach that builds on and appraises Fogli and Veldkamp's methodology from 2011 and finding for the United States that participation rates vary with past values in nearby regions. Major shortcomings in their study are corrected for, including stationarity and the control for endogenous regressors other than the time and space–time-lagged dependent variable using system generalized method of moments (GMM). The paper also highlights interaction effects among explanatory variables for the first time in this context. Using a panel of 108 regions across the European Union over 1986–2010, the results for total, male and female participation rates throw a new light on the socio-economic relevance of different determinants. Importantly, characteristics in neighbouring regions play a significant role, and neglecting endogeneity is found to have serious consequences, underlining increased attention on the specification and estimation of spatial econometric models with endogenous regressors.

KEYWORDS
Labour force participation, European Union regions, dynamic spatial panels, endogenous regressors

摘要

欧盟的区域劳动力参与：具内生迴归因素的时空递迴模型方法.*Spatial Economic Analysis*. 尽管有众多的区域劳动市场文献採取空间视角，但却仅有少数研究探讨以空间效应扩展劳动力参与的分析。本文重探此一重要的议题，提出以2011年佛格利（Fogli）与费尔德肯普（Veldkamp）的方法论为基础并对其进行评估之时空递迴模式化方法，发现美国的参与率随着过去的数值，在邻近的区域中有所差异。本文运用系统广义矩（GMM），修正这些研究的主要劣势，包括恆定和控制除了时间及时空迟滞依赖变因之外的内生迴归因素。本文亦在此脉络中首次强调解释性变因之间的互动效应。运用欧盟自1986年至2010年间一百零八个区域的面板，男性与女性的总参与率之结果，对于不同决定因素的社经相关性提出新的解释。重要的是，邻近区域的特徵扮演了显着的角色，而忽略内生性则发现具有严重的后果，凸显出对于具有内生迴归因素的空间计量经济模型之说明与评估的关注已有所增加。

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RÉSUMÉ

Le taux d'activité régional à travers l'Union européenne: une modélisation récursive espace-temps avec régresseurs endogènes. *Spatial Economic Analysis*. Bien qu'il y ait une documentation riche au sujet du marché du travail régional qui l'aborde du point de vue spatial, rares sont les études qui examinent comment pousser plus loin l'analyse des effets spatiaux sur le taux d'activité. Ce présent article réexamine cette importante question, proposant une modélisation récursive espace-temps qui développe et évalue la méthodologie de Fogli et Veldkamp datant de 2011 qui constate que les taux d'activité aux États-Unis varient en fonction des valeurs récentes des régions voisines. Employant la méthode des moments généralisée (MMG), on corrige d'importantes lacunes de leur étude, y compris la stationnarité et le contrôle pour les régresseurs endogènes hormis la variable dépendante retardée dans l'espace et dans le temps. Pour la première fois dans ce contexte, l'article souligne aussi les effets d'interaction entre les régresseurs. À partir d'un panel de 108 régions à travers l'Union européenne entre 1986 et 2010, les chiffres globaux des taux d'activité masculins et féminins éclaircissent sous un nouveau jour l'importance socioéconomique des divers déterminants. Surtout, les caractéristiques des régions voisines jouent un rôle non-négligeable, et il s'avère que ne pas faire attention à l'endogénéité a de graves conséquences, ce qui souligne l'attention accrue prêtée à la spécification et à l'estimation des modèles économétriques spatiaux avec régresseurs endogènes.

MOTS CLÉS

participation de la population active régions de l'Union européenne, panneaux spatiaux dynamiques, régresseurs endogènes

RESUMEN

Participación regional de la población activa en la Unión Europea: un enfoque de modelo recursivo tiempo–espacio con regresores endógenos. *Spatial Economic Analysis*. Aunque existen abundantes publicaciones sobre el mercado laboral regional con una perspectiva espacial, solo en unos pocos estudios se ha intentado ampliar con efectos espaciales el análisis de la participación de la población activa. En este artículo revisamos esta cuestión importante proponiendo un enfoque de modelo recursivo tiempo–espacio que valora y se basa en la metodología de Fogli y Veldkamp de 2011, donde se observó que en los Estados Unidos los niveles de participación varían con valores previos en regiones cercanas. Corregimos importantes deficiencias en su estudio, entre ellas la estacionalidad y el control de regresores endógenos que no sean la variable que depende del tiempo y el espacio–tiempo retrasado mediante el método generalizado de momentos (GMM). También se destacan los efectos de interacción entre las variables explicativas por primera vez en este contexto. A partir de un panel de 108 regiones de toda la Unión Europea para el periodo entre 1986 y 2010, los resultados para el nivel de participación total, de mujeres y de hombres, aportan un enfoque nuevo sobre la relevancia socioeconómica de los diferentes determinantes. Pero lo más importante es que las características en las regiones vecinas desempeñan un importante papel y observamos que ignorar la endogeneidad tiene graves consecuencias, subrayando la creciente atención a la especificación y estimación de los modelos econométricos espaciales con regresores endógenos.

PALABRAS CLAVE

participación de la población activa, regiones de la Unión Europea, paneles espaciales y dinámicos, regresores endógenos

1. INTRODUCTION

Increasing labour market participation is a main aim of the Europe 2020 Integrated Guidelines. However, there is concern regarding discouragement effects due to the persistence of the crisis (European Commission, 2013; ILO, 2015). While the unemployment rate is one of the most analyzed economic indicators, a caveat is that it can understate the weakness of the labour market. If people face bleak employment prospects and forgo entering the labour market, these decisions show up as lower participation rates rather than higher unemployment rates (Blanchard, 2006). Investigating causes of variation in participation thus allows for a distinctive perspective on the state of the labour market.

Labour market indicators show a high degree of heterogeneity across countries, as well as between regions within countries (Elhorst, 2003; OECD, 2011). Another key observation is that regions are not isolated economies due to factor mobility (European Commission, 2014). Dealing with interaction effects among agents is the topic covered by spatial econometrics (e.g., Arbia & Prucha, 2013). It is thus not surprising that there exists an abundant regional labour market literature taking a spatial perspective, especially on unemployment and wage differentials (e.g., Molho, 1995; Elhorst et al., 2007; Patacchini & Zenou, 2007; Baltagi et al., 2012).

In stark contrast, only a few studies have extended the analysis of labour force participation with spatial effects, with details provided later. The focus has been on endogenous interaction effects or correlated effects using the spatial autoregressive (SAR) or spatial error (SEM) models, which has also been predominant in the spatial econometrics literature, especially prior to 2007 (Elhorst, 2010). In this paper, we revisit this important issue proposing a time–space recursive modelling approach that builds on and appraises a recent interesting study by Fogli & Veldkamp (2011) (hereafter FV) where they find that participation rates vary with past participation rates in nearby regions using decennial data for females over 1940–2000 at the US county level.

In its basic form, the time–space recursive model regresses the dependent variable (Y_t) on the dependent variable lagged in time (Y_{t-1}) and on the dependent variable lagged in both space and time (WY_{t-1}), where W describes the spatial arrangement of the areal units in the sample. Although rarely used in applied settings, it can be useful to study spatial diffusion phenomena, which is the topic of FV. LeSage & Pace (2009, ch. 7) refer to this model as a classic spatiotemporal (partial adjustment) model and show that a process with high temporal dependence and low spatial dependence may nonetheless imply a long-run equilibrium with high spatial dependence. Korniotis (2010) uses the model to explain consumption growth in US states over 1966–98.

Certainly, including the spatial lag of the dependent variable, either at time t or $t − 1$, can be questioned. Motivations for interaction effects resulting in different spatial specifications is a key issue addressed in the next section. Based on substantive grounds and inspired by interesting papers appraising spatial econometrics in *Journal of Regional Science* (Partridge et al., 2012) and reaction (Halleck Vega & Elhorst, 2015), we highlight including interaction effects among explanatory variables in the time–space recursive model for the first time in this context. Notably, the coefficient estimates of these interaction effects are the indirect (spillover) effects, defined as the marginal impacts of changes to explanatory variables in a particular region on the dependent variable values in other regions. Conversely, the coefficient estimates in the SAR model are not the marginal impacts, requiring further calculations derived from the reduced form of the model, while spillovers are set to zero by construction in the SEM. Previous participation rate studies have hence not assessed spillovers. We note, nonetheless, that interpretation of coefficient estimates in spatial models and the use of indirect effects as a more valid basis for testing whether spillovers are significant has only recently received more attention (LeSage & Pace, 2009; Elhorst, 2010).

Major shortcomings in FV are also addressed. We find that their model is not stationary, pointing to misspecification problems. Other serious shortcomings are the use of the Arellano & Bond (1991) generalized method of moments (GMM) approach that is weak on data with persistent series, the exclusion of the unemployment rate, and the treatment of wage and other potentially endogenous variables as exogenous. To overcome these limitations, we make sure the stationarity condition is satisfied, include the unemployment rate as a key indicator of uncertainty, and apply system GMM to control for endogenous regressors other than the time and space–time-lagged dependent variable. This crucial issue is not usually dealt with in previous studies and more generally in the spatial econometrics literature, though, importantly, it is receiving growing attention (e.g., Fingleton & Le Gallo, 2008; Drukker et al., 2013).

To gain more insight on increasing labour market participation, the model is estimated for total, male and female participation rates using panel data over 1986–2010 for 108 regions across eight European Union (EU) countries. Since the marginal reactions to the explanatory variables tend to be different, a gender distinction is made (Cahuc & Zylberberg, 2004; Elhorst, 2008; Mameli et al., 2014). In addition to regional variables, national factors are included as they can impact the performance of the labour market (Blanchard & Wolfers, 2000; Boeri & van Ours, 2013). We also control for time-period and region-specific fixed effects. The results throw new light on the socio-economic relevance of different factors and, consistent with the conceptual framework, make clear that the characteristics of neighbouring regions play an important role in determining participation rates. Moreover, the finding that neglecting endogeneity has serious consequences on the results underlines increased attention in the literature on the specification and estimation of (dynamic) spatial econometric models with endogenous regressors.

This analysis builds upon the previous work of Halleck Vega & Elhorst (2014) in which the same data were used to estimate a system of equations, known as the Blanchard and Katz model, and in which the unemployment rate, labour force participation rate and employment growth rate are estimated as a function of their lagged values in space, time, and in both space and time. This paper follows a different route. It considers a single-equation model rather than a system to analyze the labour force participation rate, but instead tests whether and also finds strong empirical evidence in favour of the hypotheses that the unemployment rate, wage rate, employment growth rate and their spatially lagged values are endogenous. In addition, it controls for socio-economic and institutional background variables, which are lacking in Halleck Vega & Elhorst (2014).

The paper is structured as follows. Section 2 outlines the basic time–space recursive model, conceptual framework motivating spatial effects with reference to previous studies, and extension of the model highlighting other relevant determinants of participation rates. Section 3 describes the data, followed by the estimation strategy, specification checks and empirical results in Section 4. The final section provides concluding thoughts.

2. Methodology

2.1. Basic model

The basic time–space recursive model takes the form:

$$Y_t = \tau Y_{t-1} + \eta W Y_{t-1} + X_t \pi + \mu + \alpha_t \iota_N + \varepsilon_t, \tag{1}$$

where Y_t denotes an $N \times 1$ vector consisting of one observation of the labour force participation rate for every region ($i = 1, \ldots, N$) in the sample at a particular point in time ($t = 1, \ldots, T$). X_t is an $N \times K_1$ matrix of exogenous explanatory variables (e.g., socio-economic characteristics) associated with the $K_1 \times 1$ parameter vector π.[1] The spatial weights matrix W is a non-negative $N \times N$ matrix describing the spatial arrangement of the regions in the sample, where W is row normalized and diagonal elements are set to zero since no region can be viewed as its own

neighbour. A vector or matrix with subscript $t-1$ denotes its serially lagged value; and a vector or matrix pre-multiplied by W denotes its spatially lagged value. τ and η are the parameters associated with the lagged dependent variable and the space–time lagged dependent variable, where η is referred to as the lagged SAR coefficient. If $\eta \geq 0$, the stationarity condition requires $|\tau| < 1 - \eta$, while if $\eta < 0$, the model is stable when $|\tau| < 1 - \eta r_{\min}$, where $r_{\min}$ is the most negative purely real eigenvalue of W after this matrix is row normalized. $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})^T$ is a vector of independently and identically distributed disturbance terms whose elements have zero mean and finite variance σ^2. $\mu = (\mu_1, \ldots, \mu_N)^T$ is a vector with spatial fixed effects; and α_t is the coefficient of a time-period fixed effect, one for every year (except one to avoid perfect multicollinearity); while ι_N is an $N \times 1$ vector of ones. The control for time-specific effects is crucial since most variables tend to increase and decrease together in different regions over time; if not accounted for, η might be overestimated (Lee & Yu, 2010).

2.2. Previous studies and motivations for spatial effects

The time–space recursive model outlined above is hardly used in applied studies, though it can be useful to study spatial diffusion phenomena (Anselin et al., 2008; LeSage & Pace, 2009). This is also reflected in recent studies (shown in Table 1) extending the analysis of participation rates with spatial effects where the focus has been on the SEM or SAR model.[2] Whereas the SEM does not require a theoretical framework which can make it problematic on substantive grounds (Fingleton & Lopez-Bazo, 2006; Franzese & Hays, 2007), an SAR model does and implies that a region's participation rate is directly affected by participation rates in neighbouring regions.

As Anselin (2006, p. 6) states, the SAR model is generally conceptualized as representing the empirical counterpart to an equilibrium solution of strategic interaction or a spatial reaction function. This can be seen to be: $y_i = R(y_{-i}, x_i)$ where y_i is the level of decision variable y of agent i; y_{-i} reflects a function of the decision variables chosen by other agents; x_i is a vector of exogenous characteristics of i; and R is a linear functional form. Although the model can be applied to a representative

Table 1. Regional labour force participation studies with spatial effects

Study	Regions	Population	Period	Specification
Möller & Aldashev (2006)	Germany; NUTS-3	Male, female	1998	SAR, SEM
Elhorst & Zeilstra (2007)	European Union; NUTS-1 and -2	Male, female	1983–97; annual	SEM
Elhorst (2008)	European Union; NUTS-2	Total, male, female	1983–97; annual	SEM (MESS)
Cochrane & Poot (2008)	New Zealand; LMAs	Total	1991–2006; quinquennial	SAR, SEM
Falk & Leoni (2010)	Austria; districts	Female	2001	SEM
Liu & Noback (2011)	Netherlands; municipalities	Female	2002	SEM
Fogli & Veldkamp (2011)	United States; counties	Female	1940–2000; decennial	TSR

Note: NUTS, Nomenclature of Territorial Units for Statistics; the official hierarchical classification used by EUROSTAT divided from most to least aggregated: NUTS-1 to NUTS-3. LMAs, labour market areas; classification details are given in the text. The working-age population groups analyzed: total, males and females. Details on further population distinctions, such as marital status, and specifications are provided in the text. Specification: SAR, spatial autoregressive model; SEM, spatial error model; MESS, matrix exponential spatial specification; and TSR, time–space recursive model.

agent for a region, it is not clear whether the choice to participate in the labour market directly depends on neighbours' choices. In a social learning framework (e.g., Goyal, 2009, ch. 5):

$$y_{it} = R(y_{it-1}, y_{-it-1}, x_i),$$

yielding model (1). A way to view the paper by FV, which uses this latter model, is that information diffusion can change preferences, i.e., a gradual dynamic and spatial evolution exists. People require time to gather information, creating a delay in the decision-making process, and hence spatial dependence takes time to manifest itself (Elhorst, 2001; Anselin et al., 2008).

Since participation rates tend to be strongly correlated over time, most spatial panel data studies in Table 1 are dynamic, but simultaneous spatial dependence is assumed. Nevertheless, in some settings, such as this one, it is more intuitive that spatial dependence arises from a diffusion process working over time rather than taking place simultaneously (LeSage & Pace, 2009, ch. 7). FV focus on married women with children, where the idea is that initially participation rates rise slowly, but eventually, as information accumulates and uncertainty about maternal employment on children is resolved, participation flattens out and spatial dependence among local participation rates falls back. This 'S'-shaped spatial diffusion process is modelled via equation (1).

The general hypothesis that proximity to regions with higher participation rates leads to more information exchange, raising participation rates in nearby regions (cf. Moretti, 2011) can certainly be questioned. There is much debate on whether neighbourhood effects on even a small geographical scale exist, so that information exchange is most likely not the primary mechanism behind spatial dependence in regional labour force participation.[3] In fact, there has been more attention in the literature on the difficulty to justify endogenous interaction effects (e.g., Arbia & Fingleton, 2008; Partridge et al., 2012). McMillen (2012) critiques the overuse of the SAR (and SEM) as a quick fix for nearly any model misspecification issue related to space. Also, as demonstrated by Elhorst (2010), an important limitation of the SAR model is that the ratio between the marginal impacts of changes to explanatory variables in a region on the dependent variable values in other regions (spillover effect) and own region (direct effect) is the same for every explanatory variable, which is unlikely to hold in many applied settings. Also of great significance, as demonstrated by Corrado & Fingleton (2012), is that the empirical evidence in favour of a spatially lagged dependent variable can be misleading, since it may be picking up the effects of interaction effects among explanatory variables erroneously omitted from the model.

2.3. Extension of the model

Taking all the above on board, it is very interesting and germane to consider other determinants of participation decisions that may lead to more flexibility and insight on spillover mechanisms. Blanchard & Katz's (1992) seminal paper provides a solid foundation for these spillovers. Their theoretical framework assumes that regions produce different bundles of goods and that labour and firms are mobile across regions, and consists of four equations covering short-run labour demand, wage setting, labour supply and long-run effects of labour demand. For reasons of space, a detailed exposition can be referred to in Elhorst (2003). The key labour market variables in their model are participation, wage, unemployment and employment growth rates. We treat these variables as endogenous, for reasons discussed shortly. Most studies (Table 1), except for Elhorst & Zeilstra (2007) and Elhorst (2008), treat all explanatory variables as exogenous. Also significant is that even though Blanchard & Katz (1992) account for regional heterogeneity, their model does not explicitly incorporate spatial interaction effects.

Nevertheless, due to the high degree of heterogeneity in labour market conditions across regions, people might search for jobs and work elsewhere if the relative situation is better than in their region of residence. The observation that participation rates cannot be explained by only local conditions is also acknowledged in previous studies (Elhorst, 1996) (Table 1). The

Organisation for Economic Co-operation and Development's (OECD) (2009, p. 101) conclusion that neighbouring regions' performance influences the performance of any other region is pertinent as well, but very general. We highlight interaction effects among the key labour market variables for the first time in this context, so that wage, unemployment and employment growth rates in both the own region and neighbouring regions may be significant determinants of participation rates.

The time–space recursive model extended with interaction effects among explanatory variables and allowing for some variables to be endogenous other than the time and space–time lagged dependent variable takes the form:

$$Y_t = \tau Y_{t-1} + \eta W Y_{t-1} + Z_t \beta + W Z_t \theta + X_t \pi + \mu + \alpha_t \iota_N + \varepsilon_t, \tag{2}$$

where Z_t is an $N \times K_2$ matrix of endogenous explanatory variables; and the $K_2 \times 1$ vectors β and θ are parameters of the corresponding endogenous variables. The other variables and parameters are defined as in model (1). Since the model does not contain a simultaneous spatial lag of the dependent variable, the coefficients β and π denote short-term direct effects of a change in Z or a change in X on the dependent variable Y within a region, while the coefficients θ denote short-term spillover effects of a change in Z in one region on Y in any of the other regions. These spillovers are local in nature, i.e., arising only from a region's neighbourhood set. Global spillovers would arise from regions not belonging to this set if simultaneous spatial dependence is allowed for (Anselin, 2003; LeSage & Pace, 2011). However, this is counterintuitive in this setting, since it would imply that people do not require time to gather information from regions to which they are not connected.

The straightforward interpretation of the spillovers is one of the advantages of considering interaction effects among the explanatory variables (Elhorst, 2014). Another advantage is that no prior restrictions are imposed on the ratio between the spillover effect and the direct effect. Furthermore, LeSage and Pace (2009, section 7.2, with $\phi = 1$ and $\gamma = 0$ in their model) show that the long-term marginal effects of the expected value of the dependent variable with respect to the kth explanatory variable Z_k in unit 1 up to unit N take the form:

$$\left[\frac{\partial E(Y_t)}{\partial z_{1kt}} \cdots \frac{\partial E(Y_t)}{\partial z_{Nkt}} \right] = \left(I_N - \frac{\eta}{1-\tau} W \right)^{-1} \left(I_N \frac{\beta_k}{1-\tau} + W \frac{\theta_k}{1-\tau} \right). \tag{3}$$

This expression explains LeSage and Pace's finding that weak spatial dependence (small η) and strong time dependence (large τ) may eventually lead to strong spatial dependence in the long-term since η is divided by $1 - \tau$. A similar expression as in (3) applies to the control variables X; β_k needs to be replaced by π_k, while $\theta_k = 0$ since WX variables have not been included. Since W is row normalized, the long-term direct and spillover effects simplify to respectively (Small & Steinmetz, 2012, eq. 13c):

$$\frac{\beta_k (1 - \tau)}{(1 - \eta(1 - \tau))} = \frac{\beta_k}{1 - \tau - \eta} \text{ and } \frac{\theta_k (1 - \tau)}{(1 - \eta(1 - \tau))} = \frac{\theta_k}{1 - \tau - \eta}, \tag{4}$$

indicating that the long-term direct and spillover effects can be obtained from their short-term counterparts by multiplying them by the factor $1/(1 - \tau - \eta)$.

Before moving on to the empirical analysis, it is germane to briefly provide some more details on the labour market indicators and control variables. Building on the neoclassical theory of labour supply where a choice is made between consumption and leisure, the wage rate is decisive since the participation rate corresponds to the proportion of people whose reservation wage does not exceed the current wage (e.g., Cahuc & Zylberberg, 2004). Since people may also respond to regional wage differentials, it is also relevant to test whether wage spillovers exist via model (2). Finally, we control for endogeneity of the wage rate as higher participation can reduce wages due to the larger labour supply that it implies (Blundell et al., 2003; Acemoglu et al., 2004; Elhorst, 2008).

The unemployment rate provides an indication of the probability of securing a job and is included in most studies except for FV. A negative (positive) effect is referred to as the discouraged (additional) worker effect. Mincer's (1966) view that a negative association may reflect out-migration of people seeking work in other regions due to higher local unemployment is pertinent. Greenwood (2014) points out that unemployment reflects a situation in which the opportunity cost of migrating is lower and the incentive to find work outside the own region is higher. Unemployment conditions in other regions can thus serve as an impetus or deterrent to search or take a job elsewhere. We control for endogeneity of the unemployment rate since it is simultaneously determined with the participation rate (Fleisher & Rhodes, 1976). Whereas the effect of participation on unemployment should be positive *ceteris paribus* (if more people supply labour holding labour demand constant, the number of unemployed must increase), most studies have found that a negative effect dominates (Elhorst, 2003).

Employment growth is also simultaneously determined with participation, though not included in previous regional participation rate studies; a notable exception is Gordon & Molho (1985). However, many multiple equations studies, to begin with Blanchard & Katz (1992), do take participation to depend on employment growth. While unemployment reflects a mismatch in labour supply and demand, employment growth reflects labour demand. Changes in participation rates have been shown to be the main adjustment mechanism to demand shocks in European regional labour markets (Decressin & Fatás, 1995; Gács & Huber, 2005). Furthermore, job growth can encourage more people to enter the labour market (Elhorst, 2003; Partridge, 2001).[4] People may also respond to job opportunities in other regions, which makes employment growth spillovers potentially very relevant too, and here, migration may play an important role (Partridge & Rickman, 2003). Higher participation can also encourage job growth, known as 'people cause jobs' (Muth, 1971; McDonald & McMillen, 2011; Partridge & Rickman, 2003). Here, migration may also play an important role since people can stimulate demand for products, thus creating new jobs through migration. Accordingly, we control for endogeneity of the employment growth rate.

Socio-economic and institutional control variables are population density, educational attainment, the percentage share of the younger population which has the advantage that it may also reflect a higher birth rate (Elhorst, 2003; Mameli et al., 2014), active labour market policies (ALMP), employment protection legislation (EPL), unemployment benefits (UB) and early retirement (ER). These policy variables constitute a central part of the EU's 2020 employment strategy. ALMP are programmes to assist the unemployed to find work and activate non-participants. EPL aims to improve employment conditions, but can reduce incentives for firms to hire workers and/or create jobs (Boeri & van Ours, 2013). Yet, the effect is not clear-cut as it might be more costly for firms to lay off workers. In line with standard job search theory, the reservation wage increases with the UB level; due to lower search intensity, a rise in UB increases unemployment duration, with a negative impact on participation (Heijdra & van der Ploeg, 2002). In contrast, substantial benefits could induce labour market entry even in the absence of a desire to search for a job (Elhorst & Zeilstra, 2007). They can also encourage the unemployed to continue job search. ER covers assistance facilitating the full or partial early retirement of the elderly assumed to have low probability of finding a job or whose retirement facilitates the placement of the unemployed or people from another target group.

3. Data

The empirical analysis is based on panel data covering 108 NUTS-2 regions across eight EU countries over 1986–2010. The countries (number of regions) are Belgium (9), Denmark (1), France (21), West Germany (28), Italy (20), Luxembourg (1), the Netherlands (12) and Spain (16).[5] These regions are depicted in Figure 1, which shows the variation in participation rates for the most recent year and the starting year. Figure 2 graphs the evolution of the average
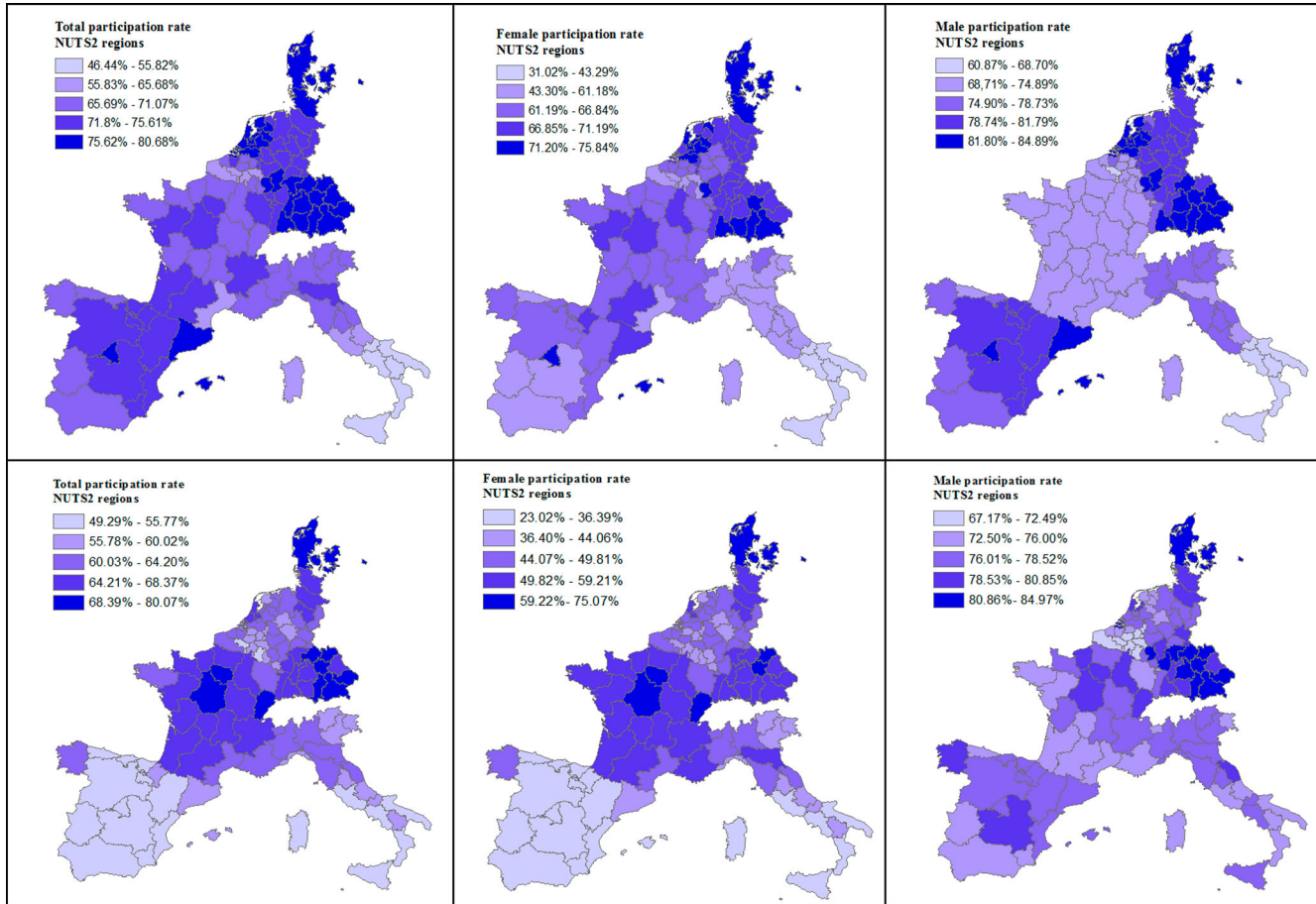
Figure 1. Regional labour force participation rates: first row: 2010, second row: 1986.
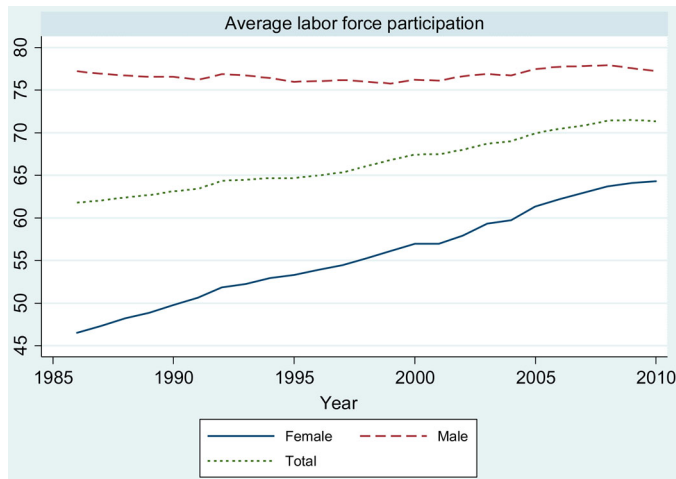
Figure 2. Evolution of regional labour force participation rates over time.

rates. Over this 25-year period, female participation rates increased from an average of 46.5% in 1986 to 64.3% in 2010, which is more than 0.6% each year, while male participation rates remained almost the same: 77.2% in 1986 compared with 77.3% in 2010.

Data are from the Labor Force Survey in EUROSTAT's regional database. For the labour force participation rate (*LFP*), we take the ratio of the total labour force and the working age (15–64 years) population. Female and male participation rates are calculated likewise, but for their respective cohorts. The unemployment rate (*UNEMP*) is the ratio of the unemployed and the number of people in the labour force. The employment growth rate (*EMP*) is calculated as the logarithm of the ratio of the number of people employed in period t and the number of people employed in period $t-1$. Regional education and demographic data is also from EUROSTAT. We take the percentage of people aged 25–64 years who have earned higher levels of education (*EDUC_H*), and percentage share of the population aged 15–24 years to the total working age population (*YOUNG*). From the Cambridge Econometrics European regional database, wage is defined as the logarithm of average compensation levels per employee in euros (*WAGE*) and population density (*DENS*) is the logarithm of total inhabitants per square kilometre. *ALMP*, *UB*, and *ER* are defined as the spending levels on these measures as a percentage of gross domestic product (GDP) from the OECD's Labor Market Statistics. *EPL* is an index from a scale of 0 (least stringent) to 6 (most restrictive), measuring regulations and costs involved in dismissing and hiring workers on fixed-term or temporary work contracts; data are from the OECD updated by Venn (2009).[6] Descriptive statistics and the correlation matrix between the variables are available in Tables A1 and A2 in the supplemental data online.

4. Results

Table 2 reports the time–space recursive model (2) results. Following the conceptual framework in Section 2, if regions are more accessible to each other, this provides a greater opportunity for interaction in terms of social learning (information diffusion) and labour mobility. Accordingly, W is specified with elements $w_{ij} = 1$ if regions are contiguous, and zero otherwise. Even though increased integration among EU member states might make national borders less relevant, it is still realistic to consider the various barriers (e.g., social and political) between countries. For this reason, the model is also estimated with elements $w_{ij} = 1$ if regions are contiguous but located in the same country only. The results of this alternative run are made available in Table A3 in the

Table 2. Time–space recursive model estimation results

Dependent variable: Labour force participation rate at time t (LFP_t)

	Total			Male			Female		
	POLS	LSDV	GMM-SYS	POLS	LSDV	GMM-SYS	POLS	LSDV	GMM-SYS
LFP_{t-1}	0.965	0.843	0.845	0.926	0.741	0.875	0.961	0.838	0.928
	(128.91)	(48.39)	(15.80)	(98.88)	(40.95)	(25.05)	(161.46)	(60.06)	(28.19)
$W \times LFP_{t-1}$	0.018	0.020	0.019	−0.002	0.011	0.014	0.018	0.019	0.004
	(3.08)	(4.18)	(2.88)	(−0.14)	(1.03)	(0.96)	(3.16)	(3.29)	(0.36)
$UNEMP_t$	0.001	0.112	−0.048	−0.017	0.081	−0.226	0.027	0.206	−0.049
	(0.08)	(4.14)	(−0.80)	(−1.38)	(2.12)	(−3.72)	(1.82)	(6.56)	(−0.71)
$W \times UNEMP_t$	−0.004	0.014	0.210	−0.005	0.019	0.212	−0.007	0.007	0.165
	(−0.34)	(0.57)	(3.05)	(−0.34)	(0.50)	(3.22)	(−0.40)	(0.22)	(1.84)
EMP_t	0.186	0.169	0.179	0.243	0.212	0.248	0.290	0.265	0.360
	(15.85)	(10.79)	(3.69)	(14.15)	(13.37)	(2.86)	(17.21)	(13.80)	(5.58)
$W \times EMP_t$	0.033	0.019	−0.059	0.002	−0.005	−0.203	0.018	0.014	−0.112
	(2.16)	(1.05)	(−0.90)	(0.10)	(−0.26)	(−2.24)	(0.86)	(0.57)	(−1.07)
$WAGE_t$	−0.001	−0.030	−0.055	−0.003	−0.029	−0.018	−0.001	−0.037	−0.060
	(−1.52)	(−4.66)	(−2.96)	(−2.40)	(−3.69)	(−1.28)	(−0.59)	(−4.61)	(−2.30)
$W \times WAGE_t$	0.005	0.039	0.073	0.007	0.052	0.009	0.009	0.046	0.077
	(3.28)	(4.80)	(3.33)	(3.62)	(6.14)	(0.80)	(3.82)	(4.49)	(2.81)
$EDUC\_H_t$	0.019	0.086	0.143	0.018	0.044	0.047	0.024	0.099	0.137
	(3.58)	(5.15)	(3.38)	(2.92)	(2.29)	(1.71)	(3.50)	(4.48)	(3.17)
$YOUNG_t$	−0.029	−0.104	−0.168	−0.013	−0.135	0.015	−0.096	−0.323	−0.204
	(−2.46)	(−4.15)	(−3.78)	(−0.89)	(−4.58)	(0.36)	(−5.91)	(−9.96)	(−2.78)

DENS$_t$	0.002	0.055	0.047	0.008	0.071	0.028	−0.002	0.071	0.046
	(0.56)	(5.50)	(2.67)	(2.27)	(5.91)	(2.34)	(−0.58)	(4.16)	(2.35)
ALMP$_t$	−0.001	0.001	0.008	−0.004	−0.005	0.002	−0.001	−0.007	0.001
	(−1.12)	(0.41)	(1.75)	(−3.18)	(−2.53)	(0.59)	(−0.65)	(−2.88)	(0.16)
UB$_t$	0.001	−0.004	−0.008	0.002	−0.007	−0.001	0.002	−0.004	−0.006
	(2.72)	(−4.56)	(−3.64)	(2.68)	(−5.43)	(−0.43)	(3.13)	(−4.57)	(−1.75)
ER$_t$	−0.005	−0.005	−0.027	−0.006	−0.002	−0.010	−0.006	−0.010	−0.020
	(−4.80)	(−2.33)	(−3.00)	(−4.72)	(−0.63)	(−2.35)	(−4.74)	(−3.14)	(−1.64)
EPL$_t$	−0.001	0.001	0.001	−0.002	−0.001	−0.003	0.001	0.002	0.001
	(−0.40)	(0.62)	(0.50)	(−2.19)	(−0.85)	(−1.85)	(0.38)	(2.01)	(0.44)
R^2	0.978	0.962		0.930	0.867		0.981	0.964	
Hansen			0.12			0.14			0.11
Diff-Hansen			0.84			0.67			0.37
AR(2)			0.31			0.53			0.01

Note: Time-period fixed effects are included in all specifications; region-specific fixed effects are controlled for in LSDV and GMM-SYS estimates. *t*-Statistics are reported in parentheses. The number of observations is 2415 for all models. Hansen is the test of over-identifying restrictions; Diff-Hansen tests the instruments for the equation in levels. AR(2) is the test for second-order serial correlation in the first-differenced residuals; *p*-values are reported.

supplemental data online.[7] Before interpreting the outcomes, it is appropriate first to provide some background on the estimation strategy and specification checks.

4.1. Estimation strategy and specification checks

The pooled ordinary least squares (POLS) and least-squares dummy variable (LSDV) estimates are included only for comparison purposes since these estimators are biased and inconsistent (Baltagi, 2013). The most serious cause for concern is that Y_{t-1} is correlated with μ and thus with the error term; note this also applies to WY_{t-1}, since it is a linear combination of Y_{t-1}. To control for endogenous regressors other than Y_{t-1} and WY_{t-1}, a system GMM is applied (Blundell & Bond, 1998). This alternative strategy to Arellano & Bond's (1991) difference GMM approach is apposite since τ is close to unity, and using the latter approach would result in large finite sample biases. GMM-SYS results are two-step estimates with heteroskedasticity consistent standard errors using the finite sample correction method developed by Windmeijer (2005).[8] Taking up the notation in model (2):

$$Z_t = (UNEMP_t, EMP_t, WAGE_t)$$
$$X_t = (EDUC\_H_t, YOUNG_t, DENS_t, ALMP_t, UB_t, ER_t, EPL_t).$$

The time and space–time lagged participation rate, and local and neighbouring labour market indicators based on theoretical developments in Section 2 are treated as endogenous variables, which we denote by:[9]

$$\check{Z}_t = (Y_{t-1},\ WY_{t-1}, Z_t, WZ_t).$$

To evaluate the validity of the instruments, the Hansen test of over-identifying restrictions and serial correlation test are carried out. If excessive moment conditions are used, the power of the Hansen test can decline in finite samples (Kiviet, 1995; Bowsher, 2002). We thus reduce the lag depth and apply each moment condition to all available periods, resulting in the moment conditions:

$$E(\textstyle\sum_t \Delta X_t \Delta \varepsilon_t) = 0,\ t = 3, \ldots, T$$
$$E(\textstyle\sum_t \check{Z}_{t-i} \Delta \varepsilon_t) = 0, i = 2, \ldots, 10;\ t = 3, \ldots, T$$

that should hold for the estimator to be consistent. In system GMM, the following additional moment conditions:

$$E(\textstyle\sum_t \Delta \check{Z}_{t-1} \varepsilon_t) = 0,\ t = 3, \ldots, T$$

should also hold. The validity of these instruments is appraised using the Hansen difference, also known as the C test (Hayashi, 2000). The full instrument set also includes the time-period fixed effects. Another important issue that should be noted is the potential weak instrument problem for the GMM-SYS estimator explained by Bun & Windmeijer (2010). In particular, GMM estimators might be susceptible to finite sample bias when the variance of the unobserved heterogeneity term (σ_μ^2) and the variance of the idiosyncratic disturbance term (σ_ε^2) are not similar; that is, the bias increases with increasing variance ratio (vr), where:

$$vr = \sigma_\mu^2 / \sigma_\varepsilon^2.$$

Thus, comparing these two variances can provide insight; we find they are relatively small, especially for the male and female participation rates.[10] Comparison with the POLS and

Table 3. Time–space recursive model estimation results using eight-year time intervals

Dependent variable: LFP_t			
	Total	**Male**	**Female**
	GMM-SYS	**GMM-SYS**	**GMM-SYS**
LFP_{t-1}	0.763	0.391	0.758
	(5.20)	(2.45)	(8.77)
$W \times LFP_{t-1}$	0.144	0.155	0.110
	(2.58)	(0.89)	(2.91)
$UNEMP_t$	−0.353	−0.322	−0.313
	(−1.16)	(−0.96)	(−1.03)
$W \times UNEMP_t$	0.706	0.649	0.903
	(2.48)	(1.51)	(2.59)
EMP_t	0.277	0.390	0.313
	(3.13)	(2.85)	(2.76)
$W \times EMP_t$	0.300	−0.084	0.106
	(0.67)	(−0.15)	(0.25)
$WAGE_t$	−0.162	−0.184	−0.214
	(−3.51)	(−1.89)	(−4.40)
$W \times WAGE_t$	0.285	0.365	0.410
	(3.16)	(3.46)	(4.19)
$EDUC\_H_t$	0.232	0.341	0.371
	(2.42)	(1.99)	(3.12)
$YOUNG_t$	−0.352	−0.352	−0.665
	(−1.85)	(−1.85)	(−3.58)
$DENS_t$	0.169	0.182	0.175
	(3.13)	(2.62)	(2.91)
$ALMP_t$	−0.024	−0.061	−0.033
	(−1.42)	(−1.67)	(−1.45)
UB_t	−0.010	−0.024	−0.016
	(−1.39)	(−2.36)	(−1.86)
ER_t	−0.091	−0.112	−0.140
	(−2.73)	(−3.53)	(−4.94)
EPL_t	−0.011	−0.033	−0.018
	(−1.97)	(−2.91)	(−2.45)

Note: Time-period fixed effects are included; the number of observations is 310 for all specifications; *t*-statistics are reported in parentheses.

LSDV estimates, as discussed in the following section, can also be useful as it provides some indication of whether there is a finite sample bias, which might be due to weak instruments.

First and essentially, the stationarity condition $|\tau| < 1 - \eta$ is satisfied for all the estimated specifications (Table 2; and see Table A3 in the supplemental data online). The Hansen test of

over-identifying restrictions and the C test reveal that we cannot reject the null that the instruments and residuals are uncorrelated for the total, male and female specifications, where $\chi^2(72)$ = 86.18, $\chi^2(72)$ = 84.92, $\chi^2(64)$ = 78.25 and $\chi^2(8)$ = 4.19, $\chi^2(8)$ = 5.76, $\chi^2(8)$ = 8.73 (p-values are in Table 2). Moreover, we cannot reject the null of zero second-order serial correlation for the total and male equations (m_2 = 1.01, p = 0.31 and m_2 = 0.63, p = 0.53).[11] For females, the null is rejected (m_2 = 2.70, p = 0.01) and thus we test for third-order serial correlation and cannot reject the null (m_3 = −0.83, p = 0.406). Accordingly, lags of the endogenous variables starting from $t − 3$ instead of $t − 2$ are used for the female equation.[12]

4.2. Interpretation of outcomes

In line with previous studies using panel data (Table 1) and reflecting that participation rates are strongly correlated over time, the coefficient estimate for the lagged labour force participation rate $LFP_{t−1}$ is large, positive and significant across all models.[13] Comparing the results from the different estimators, it can be seen that this coefficient in the GMM-SYS results is between the LSDV and POLS results, which tend to be biased downwards and upwards, respectively. The focus is therefore on the GMM-SYS results in Table 2, unless stated otherwise. Results shown in Table A3 in the supplemental data online using the alternative W taking into account national borders are qualitatively similar for most determinants, but for some there are interesting differences that we will discuss.

In stark contrast to FV's finding for US counties, we find almost no evidence that participation rates also vary with past participation rates in nearby regions across EU member states. Although the coefficient estimate of $W \times LFP_{t−1}$ is statistically different from zero and equal to 0.019 for the total participation rate, it is rather small. Furthermore, the corresponding coefficients for both males and females are small as well as insignificant; respectively, 0.014 and 0.004 with t-values of 0.96 and 0.36. FV find a value of 0.527, significant at the 1% level for women. Although long-run effects are not discussed in their study, the picture remains in our case when considering their long-term counterparts, which according to equation (4) yields 0.014/(1 − 0.875) = 0.112 and 0.004/(1 − 0.928) = 0.056. Further note that the long-term counterparts of the short-term direct and spillover effects, to be discussed shortly, can be obtained by multiplying these effects by $1/(1 − \tau − \eta)$, which take the values of 7.35, 9.01 and 14.71 for the total, male and female participation rate respectively.[14] Since τ dominates η in terms of both magnitude and significance level, the significance levels of the long-term effects are comparable with those of the short-term effects. This finding for $W \times LFP_{t−1}$ indicates that information diffusion is not the primary mechanism behind spatial dependence in regional labour participation rates across the EU, confirming questions of interest raised in Section 2.2.

An intriguing issue is what can explain this dissimilar outcome. It could partly be due to the different spatial and time span, and type of data being used. FV use decennial data of married women over the period 1940–2000 for US counties, while we use annual data of all women aged 15–64 over the period 1986–2010 for EU NUTS-2 regions. Yet, we have no reason to believe that these differences are decisive since the increase in female labour force participation in their dataset is comparable with ours. They observe an increase of around 30–50 percentage points – depending on which part of the female labour force is being considered – over a 60-year period, while we observe an increase of 20 percentage points over a 25-year period; an increase furthermore that has not yet flattened out, which could be because the increase in Europe came later than in the United States. NUTS-2-level regions are also approximately comparable with the US county level (Anselin et al., 2010).

Nevertheless, as FV stress the geographic nature of information transmission using decennial data, an interesting question is whether taking a longer interval affects the estimation results, especially for $W \times LFP_{t−1}$. Table 3 (and Table A4 in the supplemental data online) reports the GMM-SYS results using eight-year time intervals over the period 1986–2010.[15] The results

show that the magnitude of LFP_{t-1} is lower, while the magnitude of $W \times LFP_{t-1}$ is higher and becomes significant for both the female and the total participation rate as a result of this. Thus, we do find empirical evidence that proximity to regions with higher participation can help raise participation rates in nearby regions, but it is much less strong than in FV. For females in particular, we find a coefficient estimate of 0.110 versus 0.527 and a t-value of 2.91 versus 5.53. The conclusion must be that the dissimilarity in outcomes can be better explained by serious shortcomings in FV's study.

First, FV (see their table 2) find that the response coefficient τ of the lagged dependent variable Y_{t-1} is 0.916 and η of the dependent variable lagged both in space and time WY_{t-1} is 0.570. Consequently, the sum of these two coefficients is greater than 1, i.e., the stationarity condition requiring that $|\tau| < 1 - \eta$ is not satisfied, pointing to misspecification problems that have not been identified in their study. In addition, unlike previous regional participation rate studies, the unemployment rate is omitted by FV, which leaves out a key indicator of uncertainty. The wage rate is included, but along with other control variables is treated as exogenous, which is also the case in most previous studies (Table 1). Another notable dissimilarity is that the Arellano & Bond (1991) GMM approach is used instead of GMM-SYS, where the former estimator is known to be weak on data with short and persistent series. Finally, it should be emphasized that model (2), unlike model (1) specified in FV, includes the spatially lagged explanatory variables $W \times UNEMP_t$, $W \times EMP_t$ and $W \times WAGE_t$. We highlight these interaction effects for the first time in this context. Consistent with the theoretical and empirical rationale outlined in Section 2.3, most of the short-term spillover effects of these labour market determinants are significant; consequently, the coefficient estimate of $W \times LFP_{t-1}$ may pick up these effects when these variables are erroneously omitted from the model (Corrado & Fingleton, 2012).

We now turn in more detail to the direct and spillover effects of these labour market variables, primarily focusing on the results in Table 2, with some interesting comparisons in Table A3 in the supplemental data online. Furthermore, note that the results in Table 3 seem to be greater in magnitude, but this is due to the longer time interval. When multiplying the point estimates in Table 3 by $1/(1 - \tau - \eta)$ (see equation 4), we obtain 2.20 for the male and 7.57 for the female participation rate. These numbers are respectively 4.1 and 1.9 times smaller than the values 9.01 and 14.71 we found when using annual data. Therefore, when we observe marked differences between the tables in terms of magnitude, sign or significance level, we will refer to them explicitly.

Starting with the unemployment rate, for males there is a strong discouraged worker effect, which is in accordance with most previous studies (e.g., Elhorst & Zeilstra, 2007). In particular, a 1 percentage point increase in the unemployment rate in region i reduces the male participation rate in that region by 0.226% points (t-value = −3.72). This effect seems to be less pertinent in determining female participation rates, as well as in aggregate. In contrast, the spillover effect ($W \times UNEMP_t$) is positive and significant for total, male and female participation rates. This implies that people may indeed change their participation decision and migrate to nearby regions in search of more promising opportunities. This is consistent with arguments discussed in Section 2.3, including the relevance of the high degree of unemployment differentials across EU regions. An interesting finding from Table A3 in the supplemental data online is that unemployment spillovers are smaller in magnitude, suggesting that confining borders can be a barrier in facilitating labour market adjustments from shocks such as the recent crisis.

We emphasize that the control for endogeneity is crucial here. If the unemployment rate is treated as exogenous as in the LSDV estimates (see also Table 2), the conclusion is completely different, pointing towards a significant additional worker effect for all groups. Also noteworthy is that the spillover effect is insignificant in that case, whereas it is highly significant for all groups when endogeneity is properly controlled for. Finally, it is interesting to note that these results change when using data over eight-year time intervals (Table 3). Then, females appear to be

more responsive to neighbouring labour market conditions, in terms of magnitude and significance level. Apparently, both males and females are responsive, but males act earlier.

The direct effect of the employment growth rate turns out to be one of the most significant variables, both when using annual data and data over eight-year time intervals. As highlighted in Section 2.3, the generation of more jobs can encourage more people to enter the labour force. In particular, it is found that a 1 percentage point rise in the employment growth rate increases total, male and female participation rates by 0.179, 0.248 and 0.360 percentage points in the short-term, respectively. By contrast, employment growth spillovers appear to be limited; almost all coefficients in all tables are small and insignificant implying that people are less responsive in their participation decisions to job opportunities in other regions than to unemployment. It may indicate that unemployment reflects a situation in which the opportunity cost of migrating is lower; unemployment rates may also be more readily observable, as a result of which there is more reaction to these differentials as revealed in the significant unemployment spillover effects across all groups. A notable exception, nonetheless, is for males where the employment spillovers are quite large and significant. A 1 percentage point increase in the employment growth rate in region i reduces the male participation rate in region j by 0.203 percentage points (t-value = −3.72); the effect is smaller (−0.129; t-value = −1.98) when accounting for national borders despite the move for increased integration in the EU. This result is intuitive since in- and out-migration is limited to regions within a particular country.

The direct effect of the wage rate appears to be negative rather than positive. One explanation is that it is measured by compensation levels per employee, which consist not only of wages and salaries but also of employers' social contributions, thereby more reflecting the supply side (labour costs to employers) than the demand side of the labour market. This is an issue that has been identified in more labour force participation studies (Elhorst & Zeilstra, 2007), as well as New Economic Geography (NEG) studies (Bosker et al., 2010; Fingleton, 2011). By contrast, the wage spillover effect is significant for the total and female participation rates when using annual data, and for all groups when using data over eight-year time intervals. This result, together with the unemployment spillover, indicates that wage increases in neighbouring regions can raise participation in the own region due to out-of-region commuting, whereas employment growth in neighbouring regions cannot. It shows that the willingness to accept a job offer in a neighbouring region increases if it pays better, partly to compensate the commuting costs, but not if it is an equivalent job. It is one of the explanations why local changes in the participation rate have been found to be the most important adjustment mechanism to demand shocks in European regional labour markets. Interestingly, distinguishing between neighbours in the same country versus neighbouring countries changes the direct and spillover impacts explaining total participation rates. The direct effect of wage is positive, in line with theory, and the wage spillover is negative, which implies that people may be more willing to migrate if the region is located within their own country.

Finally, turning to the socio-economic and institutional controls, population density is positive and significant for all groups, which is in accordance with the agglomeration economies and thick labour market literature. For especially female and total participation rates, demographic composition and education are significant determinants.[16] The magnitude of the percentage share of the younger population is greatest for the female participation rate with a value of −0.204 (t-value = −2.78), which may also reflect the impact of a higher birth rate. Regarding the effect of education, it is 0.137 (t-value = 3.17) and is more pronounced for females than the 0.047 (t-value = 1.71) for males. This reflects that regions with a higher educated population possess skills that are more in demand by firms, that people with higher education are likely to conduct more efficient searches and are less prone to layoffs in an economy with continuous technological change, and that higher education also corresponds with greater task complexity

and work autonomy increasing the intrinsic value of work (Elhorst, 2003; OECD, 2013; European Commission, 2014).

The policy variables of the EU's 2020 employment strategy tend to have the expected sign and in many cases are also significant, despite that they change gradually over time making it difficult to find significant parameter estimates. ALMP can be especially pertinent in times of economic downturn such as the recent crisis when discouragement effects are prevalent. Though it has a positive effect, it is not significant for males and females, and weakly significant (10% level) for the total participation rate. The negative and highly significant association of UB and the total rate, and weakly significant association with the female rate, is in line with standard job search theory (Heijdra & van der Ploeg, 2002). Similarly, ER has a negative effect for all groups, which reflects that these retirement decisions tend to be irreversible and cause permanent declines in the labour force (Boeri & van Ours, 2013). EPL is significant only in the male participation rate equation, with a negative association. Although theoretically the direction of the impact is not clear-cut, the negative effect is consistent with the reasoning that despite the aim of EPL to enhance workers' welfare, it can discourage firms from hiring and/or creating jobs. The negative effects of EPL become more pronounced, also in the total and female participation rate equations when using data over eight-year time intervals.

5. CONCLUSIONS

Although empirical evidence of spatial dependence in regional labour markets is well established in the literature, there are only a few studies extending the analysis of participation rates with spatial effects. This study revisits this issue to better understand spillover mechanisms behind spatial dependence in regional participation rates across the EU. This is especially pertinent in light of the recent crisis and concerns on prevailing discouragement effects.

The proposed time–space recursive modelling approach builds on and appraises FV's recent methodology and finding for the United States that participation rates vary with past participation rates in nearby regions. Major shortcomings in their study are addressed and corrected for, including assuring that the models are stationary, appropriately controlling for endogenous regressors other than the time and space–time-lagged dependent variable, and highlighting the theoretical and empirical relevance of including interaction effects among explanatory variables for the first time in this context. This stands in stark contrast to previous regional labour force participation studies that have focused on endogenous or correlated effects.

Using a panel of 108 regions across the EU over 1986–2010, the results for total, male and female participation rates show that key labour market characteristics in neighbouring regions play a very important role in determining regional labour force participation across the EU. Also significantly, it is found that appropriately controlling for endogeneity is crucial as not doing so can have serious consequences on the economic and policy conclusions drawn. This underlines the growing attention in the literature on specifying and estimating (dynamic) spatial (panel data) models in the presence of additional endogenous regressors.

ACKNOWLEDGEMENT

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at 10.1080/17421772.2016.1224374

NOTES

1. Details of relevant determinants are provided in section 2.3, as well as the issue of potential endogeneity.
2. Elhorst (1996) provides a comprehensive overview of earlier studies. Elhorst (2008) considers spatial dependence in the disturbances, but uses a matrix exponential spatial specification (MESS) of the error terms (LeSage & Pace, 2009, ch. 9), which is advantageous in terms of estimation method flexibility which can be based on a mix of both instrumental variables (IV) and maximum likelihood (ML). Elhorst & Zeilstra (2007) use a hierarchical model; while Liu & Noback (2011) use a structural equation model. We have opted for a single-equation approach, as in all other studies shown in Table 1. In future work, it would be interesting to investigate a hierarchical model with the exogenous regional determinants treated as variables with random coefficients across countries and an extension of the single-equation time–space recursive model to a simultaneous model.
3. We thank a referee for constructive comments on this issue.
4. In this respect, the issue that unemployment and non-employment are increasingly less distinctive, especially in the United States, deserves more attention at the regional level. People who are not officially part of the labour force can still be informally quite active, joining when employment opportunities rise. We thank a referee for bringing this to our attention. Although beyond the scope of this paper, it would be insightful to investigate this issue comparing, for example, recent US labour market developments to those of the EU.
5. The Canary Islands are not included since they are among the outermost regions of the EU and we wanted to have as close as possible an unbroken study area. Brussels, Flemish Brabant and Walloon Brabant are combined; the urban regions of Hamburg and Bremen are joined with Schleswig-Holstein and Lüneburg, respectively.
6. For Luxembourg, EPL data are not available from 1986 to 2007.
7. We thank the referees for their suggestions on this point.
8. The correction is based on estimating the difference between the finite sample and the usual asymptotic variance of the two-step GMM estimator. Although two-step estimates use a more valid weighting matrix that does not assume homoskedasticity, there is a tendency of downward bias of the asymptotic standard errors in small samples. The fact that the two-step approach uses a weighting matrix that depends on estimated parameters causes extra variation.
9. As noted by the referees, education and policy could also potentially be endogenous. By taking the difference between the J-statistic with suspect variables treated as endogenous and the J-statistic with the variables treated as exogenous, we failed to reject that they are orthogonal to the error term. For education, test results for total, male and female participation rates are $\chi^2(1)$ = 1.05 (p = 0.31), $\chi^2(1)$ = 0.76 (p = 0.38), and $\chi^2(1)$ = 2.14 (p = 0.14); and for institutions, $\chi^2(4)$ = 3.01 (p = 0.56), $\chi^2(4)$ = 2.44 (p = 0.65), and $\chi^2(4)$ = 3.65 (p = 0.46). An explanation could be that these variables change gradually and policy is set at the national level, so that regional participation rates have no or very limited feedback effects.

10.   The values for each of the specifications are: for total, $\sigma^2_\varepsilon = 0.0001$, $\sigma^2_\mu = 0.00013$, $vr \approx 1.27$; for males, $\sigma^2_\varepsilon = 0.00017$, $\sigma^2_\mu = 0.00022$, $vr \approx 0.13$; and for females, $\sigma^2_\mu = 0.0001$, $\sigma^2_\mu = 0.0001$, $vr \approx 0.45$.

11.   The test statistic is denoted m_2, as in Arellano & Bond (1991). Since the test is applied to the residuals in differences, negative first-order serial correlation is expected. For total, males and females, $m_1 = -6.84$, $m_1 = -7.32$ and $m_1 = -7.41$, all with $p < 0.0001$.

12.   These findings are similar using the alternative W; for females, $m_3 = -0.85$, $p = 0.397$ (see Table A3 in the supplemental data online).

13.   As noted by a referee, this outcome could also potentially cover the effects of other factors correlated with the lagged participation rate and thus should be taken with some caution.

14.   Note that the magnitude of this overall multiplication factor is averaged out over the signs, magnitudes and significance levels of the coefficients of all variables, making comparisons between the three models difficult.

15.   We also used decade-long intervals, but starting with $T = 3$ and then losing two periods due to the inclusion of the lagged dependent variable and first-differencing resulted in too few observations and infeasible results.

16.   Overall, the results shown in Table A3 in the supplemental data online are quite similar, but for education the estimates are insignificant for all groups. One problem may be that it is positively correlated with other explanatory variables (cf. Elhorst & Zeilstra, 2007).

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