

# A spatiotemporal analysis of aggregate labour force behaviour by sex and age across the European Union

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**Abstract** This study investigates the causes of variation in age-specific male and female labour force participation rates using annual data from 154 regions across ten European Union member states for the period 1983–1997. Regional participation rates appear to be strongly correlated in time, weakly correlated in space and to parallel their national counterparts. An econometric model is designed consistent with these empirical findings. To control for potential endogeneity of the explanatory variables, we use an instrumental variables estimation scheme based on a matrix exponential spatial specification of the error terms. Many empirical studies of aggregate labour force behaviour have ignored population distribution effects, relying instead on the representative-agent paradigm. In order for representative-agent models to accurately describe aggregate behaviour, all marginal reactions of individuals to changes in aggregate variables must be identical. It turns out that this condition cannot apply to individuals across different sex/age groups.

**Keywords** Labour force participation · Aggregation · Serial dependence · Spatial dependence · Endogeneity

**JEL Classification** C21 · C23 · J21 · R23

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## 1 Introduction

According to Deaton (1992, p. vii), research into labour force behaviour has attracted microeconomists interested in household behaviour as well as macroeconomists for whom aggregate labour supply behaviour has always occupied a central role in explaining aggregate fluctuations. The former seek consistency in a variety of empirical evidence built around the theory of choice between consumption and working time, whereas the latter try to develop adequate empirical models to explain aggregate labour supply behaviour over space and time measured by labour force participation rates. Neither approach need necessarily complement the other, since the search for coherent foundations may not always be the most direct way to discover empirical regularities. Recently, Blundell and Stoker (2005) have reviewed specific solutions to bridge the gap between research at the individual and at the aggregate level.

The analytical thrust of this paper is to investigate the extent to which individuals may be lumped together for the purpose of a common treatment. To this end, the theory behind the labour force participation rate and its causal factors is summarised in Sect. 2. Aggregation across individuals or across groups of people is not allowed if their marginal reactions are significantly different from each other. In view of the results reported by those studies that have investigated both male and female participation rates (Lillydahl and Singell 1985; Fair and Dominguez 1991; Elhorst 1996a), it is safe to conclude that a distinction between sexes is preferable. Whether a further distinction between different age groups is also preferable is more difficult to say, since the empirical evidence is much older and mainly based on models without spatial and dynamic effects (Dernburg and Strand 1965; Barth 1968; Bowen and Finegan 1969; King 1978; Clark and Summers 1982).

To explain aggregate labour force behaviour, three empirical regularities need to be taken into account: (1) Regional participation rates tend to be strongly correlated in time, (2) Regional participation rates tend to parallel national participation rates, and (3) Regional participation rates tend to cluster in space. These empirical regularities have been documented in several studies (Adnett 1996, Chap. 7; Overman and Puga 2002; OECD 2005). In this study an econometric model is designed consistent with these empirical regularities. Although each of these problems has been dealt with separately, as we will show in Sect. 3, the combination has not. To take account of the empirical regularity that regional participation rates tend to cluster in space, we adopt a new approach. Instead of the commonly used first-order spatial autocorrelation model, we use matrix exponentials for spatially transforming the error term (MESS). This transformation is recently introduced by LeSage and Pace (2007) and opens the opportunity to use an estimation method partly based on instrumental variables and partly on maximum likelihood to control for potential endogeneity of the explanatory variables. In Sect. 4 participation rate equations are estimated for the total working-age population, for males, for females, and for both males and females in five different age categories using annual data from 154 regions across ten European Union member states for the period 1983–1997.

## 2 Theory

At a micro level, the decision to participate in the labour market is a dichotomous random variable with a value of 1 if the market wage rate exceeds the individual's reservation wage and 0 if it does not. The neoclassical formulation of this decision may be derived from a static model of choice between consumption and working time. A person is said to participate in the labour market if (s)he is employed or if (s)he is unemployed but available for work and actively seeking a job. This definition implies that both employed and unemployed people participate.<sup>1</sup> People who do not participate are inactive. If we start from regional data instead of individual data, the observed variable consists of a proportion  $L_j$  of individuals belonging to the working-age population in region  $j$  ( $j = 1, \dots, N$ ) who decide to participate.

Although the analysis of micro data is sometimes believed to be superior, we have one reason for keeping to aggregated data. The individual labour force decision often entails variables measured on a spatial level, notably the unemployment rate and the industry mix within the worker's home region. Since these variables do not vary across individuals within the same region, the disturbance term will be correlated across individual observations within the same region and consequently downwardly bias the standard errors of the coefficient estimates of these variables (Moulton 1990). One remedy is to take averages over individuals across regions and use these constructed regional averages as the units of observations in the regressions. Assuming that there is no correlation in the unobserved determinants of labour force behaviour across regions (an assumption which is rather restrictive and subject to discussion later in this paper), the residuals of these regressions are uncorrelated across observations and conventional standard error formulas are valid. The striking conclusion that the analysis of aggregate behaviour may actually be preferable to the usual microeconomic analysis when individual decisions are also driven by local variables has been regenerated by the literature on the wage curve (Blanchflower and Oswald 1994).

The transition from the micro level to the meso level for homogeneous groups is discussed in Pencavel (1986). Elhorst and Zeilstra (2007) extend this study by addressing the problem of heterogeneous population groups. Pencavel uses the concept of reservation wage, the individual's implicit value of time when on the margin between participating in the labour market and not participating. This reservation wage,  $w^*$ , depends on observable explanatory variables ( $X$ ) and unobservable explanatory variables ( $\varepsilon$ ). Suppose individuals of a particular population group ( $g$ ) have identical observable explanatory variables  $X_g$ , but different unobserved explanatory variables  $\varepsilon$ . Wages ( $w$ ) might vary between population groups and between regions, but (like  $X_g$ ) they do not vary within population groups within regions, i.e.  $w = w_g$ . Consequently, differences in reservation wages are caused by different values of the unobserved explanatory

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<sup>1</sup> Self-employed people also participate. Their wage rate may be approached by the shadow wage rate from the production part of a household production model (see Elhorst 1994).

variables  $\varepsilon$  only. Let  $f_g(w_g^*)$  be the density function describing the distribution of reservation wages across individuals of group  $g$  and  $F_g(w_g^*)$  the cumulative distribution function corresponding to the density function. This cumulative distribution function  $F_g(w)$  is interpreted as giving for any value of  $w_g$  the probability of the event  $w_g^* \leq w_g$ , that is, the proportion of individuals who offer positive hours of work to the labour market since the market wage rate exceeds their reservation wage. Then the labour force participation rate  $L_g$  of group  $g$  is the cumulative distribution of  $w_g^*$  evaluated at  $w_g^* = w_g$ , given  $X_g$  and a set of fixed but unknown parameters  $\beta_g$ ,

$$L_g(w_g, X_g, \beta_g) = F_g(w_g | X_g, \beta_g), \quad (1)$$

where the dependence of the labour participation rate of population *group*  $g$  has been made explicit on  $w_g$  and  $X_g$ . Functional forms of  $F_g$  most frequently used in applied research are the linear and the logit probability function. In theory, the linear probability function has an obvious defect in that it is not constrained to the interval  $[0,1]$  as a probability should. In practice, however, predictions outside the interval  $[0,1]$  hardly occur when the explanatory model of the model is reasonable ( $>0.75$ ). This also holds for males aged between 25 and 54, whose participation rate is most close to the upper bound.

Since different groups of people within each region have different observable explanatory variables  $w_g$  and  $X_g$ , the total labour force participation rate is determined by the sum of the group-specific cumulative density functions  $F_g(w_g | X_g, \beta_g)$  ( $g = 1, \dots, G$ ) weighted by the share of each population group in the total population of working age ( $a_g$ ). In mathematical terms

$$L_{\text{total}} = \sum_{g=1}^G a_g F_g(w_g | X_g, \beta_g). \quad (2)$$

From this equation it follows that there are two ways to deal with the problem of heterogeneous population groups. One way is to consider a limited number of regression equations for broad population groups and to correct for the composition effect of groups having different observable explanatory variables  $X$ . This approach has been followed by Elhorst and Zeilstra (2007). The other, more prevalent, way is to consider as many population groups as necessary to obtain within-group homogeneity and then to estimate a separate regression equation for each population group.

Generally, the extent to which the participation rate may be aggregated or must be disaggregated can be considered as offering two competing models to choose from. Supposing that the participation rate of two population groups can be explained, say  $A$  and  $B$ , or their joint participation rate can be explained, then the first model consists of two participation rate equations (using linear probability functions)

$$L_A = \frac{n_A}{N_A} = X_A \beta_A + \varepsilon_A, \quad L_B = \frac{n_B}{N_B} = X_B \beta_B + \varepsilon_B, \quad (3)$$

where  $n$  is the labour force,  $N$  is the population of working-age, and  $w$  is assumed to be part of  $X$ . The second model consists of one participation rate equation

$$L_{A+B} = \frac{n_A + n_B}{N_A + N_B} = X_{A+B}\beta_{A+B} + \varepsilon_{A+B}, \quad (4)$$

where  $L_{A+B} = W_A L_A + W_B L_B$  with  $W_A = N_A/(N_A + N_B)$  and  $W_B = N_B/(N_A + N_B)$ .  $\varepsilon_A$  and  $\varepsilon_B$  in (3), and  $\varepsilon_{A+B}$  in (Eq. 4), are independently and identically normally distributed error terms for all people with zero mean and variance  $\sigma_A^2$ ,  $\sigma_B^2$  and  $\sigma_{A+B}^2$ , respectively.

Starting from two participation rate equations of two different population groups and from  $X_A = X_B$ , it is possible to investigate whether the marginal reactions of two population groups are the same by testing the hypothesis  $H_0 : \beta_A = \beta_B$  against the alternative hypothesis  $H_1 : \beta_A \neq \beta_B$ . Note that the participation rate of every population group is taken to depend on the same set of explanatory variables. If one equation was to contain an explanatory variable that is lacking in the other and its coefficient estimate was statistically different from zero,  $H_0$  would have to be rejected in advance.

The so-called Chow test can be used to test the equality of sets of coefficients in two regressions, but this test is only valid under the assumption that the error variances of both equations equalise,  $\sigma_A^2 = \sigma_B^2$ . The empirical analysis to be discussed later in this paper reveals that this assumption is rather implausible; if the parameter vector  $\beta$  differs between two population groups, the error variance is different as well. Therefore, the Wald test is adopted here. Let  $\beta_A$  and  $\beta_B$  denote two vectors of  $k$  parameters, one for group  $A$  and one for group  $B$ , with covariance matrices  $V_A$  and  $V_B$ , then the Wald statistic

$$(\hat{\beta}_A - \hat{\beta}_B)'(V_A + V_B)^{-1}(\hat{\beta}_A - \hat{\beta}_B), \quad (5)$$

has a chi-squared distribution with  $k$  degrees of freedom under the null hypothesis that the estimates of  $\beta_A$  and  $\beta_B$  have the same expected value.

### 3 Stylised facts and econometric modelling

This study analyses regional participation rates in the European Union (number of regions of each country given in parenthesis): Belgium (9), Germany (29 regions in West<sup>2</sup> and five regions in East Germany), Greece (13), Spain (17), France (22), Italy (20), the Netherlands (12), Austria (9), Portugal (7), the UK (11). The basic data are taken from Eurostat's regional data file for the period 1983–1997. We have used the regional division of Eurostat at the NUTS 2 level, with the exception of the United Kingdom and East Germany, for which Eurostat only collects data at the NUTS 1 level.<sup>3</sup> The model that will be developed below starts with the existence of regional differences within countries. Consequently, Denmark, the Republic of Ireland and Luxembourg had to be eliminated from the analysis because they constituted a

<sup>2</sup> The urban region of Hamburg and the region of Schleswig–Holstein, as well as the urban region of Bremen and the region of Lüneburg have been consolidated into two new ones.

<sup>3</sup> In 1994, Eurostat also started collecting data at the NUTS 2 level in the UK, but these data have been converted to the original NUTS 1 level.

single region at the NUTS 2 level. Furthermore, it should be noted that the data set is incomplete because some countries became member states of the EU after 1983. A total of 1825 observations are available.

Table 1 describes the participation rate of the working-age population broken down by sex and age in 1986 and 1996. An inverse U-shaped relationship is apparent between the number of men and the number of women in the labour force, and their ages. The male participation rate is low in the 15–24 age category, it increases sharply in the 25–34 age category and it reaches its peak in the 35–44 age category. In the 45–54 age category the male participation rate begins to decline and in the 55–64 age category it falls off dramatically. The female participation rate in the 15–24 age category is also low. Again, it increases in the 25–34 age category but is less when compared to that of men, while it already starts to decrease in the 35–44 age category.

In this section we introduce three stylised facts and discuss their consequences for econometric modelling.

### 3.1 Regional participation rates tend to be strongly correlated in time

Table 2 describes the correlation coefficients of the male and female participation rates for observations made in single regions one year, seven years and 14 years apart. These correlation coefficients are large and diminish slightly over time. Frequently, the null hypotheses of no serial autocorrelation of the error term should a regional labour force participation rate equation be formulated in static form and estimated by OLS has to be rejected under these circumstances. One remedial reaction could be to re-estimate the model using methods that assume that the errors are generated by a first-order serial autoregressive process, but this approach has been severely criticised. Rather than improving an initial model when it appears to be unsatisfactory, Hendry (1995, Chap. 7) argued that it is better to start with a more general model containing a series of simpler models, nested within it as special

**Table 1** Participation rates broken down by sex and age in 1986 and 1996

| Category         | Mean 1986 | Mean 1996 |
|------------------|-----------|-----------|
| Males 15–24      | 55.4      | 46.4      |
| Males 25–34      | 94.7      | 91.6      |
| Males 35–44      | 97.0      | 95.9      |
| Males 45–54      | 92.6      | 90.7      |
| Males 55–64      | 57.8      | 49.0      |
| Males 15–64      | 79.0      | 76.3      |
| Females 15–24    | 46.9      | 39.7      |
| Females 25–34    | 63.8      | 72.1      |
| Females 35–44    | 60.0      | 70.4      |
| Females 45–54    | 50.4      | 59.4      |
| Females 55–64    | 24.5      | 25.1      |
| Females 15–64    | 49.6      | 54.7      |
| Population 15–64 | 64.1      | 65.5      |

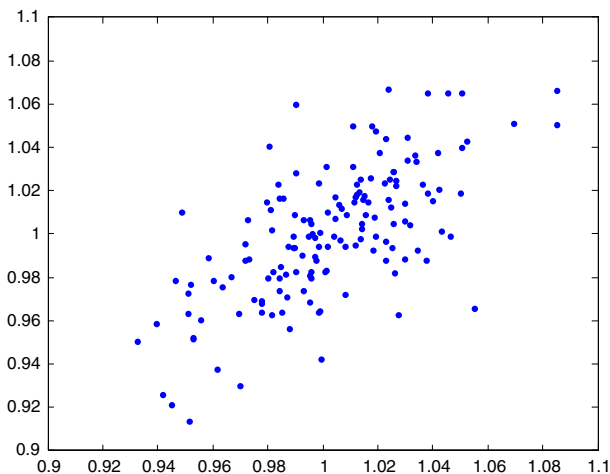
**Table 2** Correlation coefficients of participation rates over time

| Variables            | Correlation coefficients |         |          |
|----------------------|--------------------------|---------|----------|
|                      | 1 year                   | 7 years | 14 years |
| Male participation   | 0.88                     | 0.72    | 0.61     |
| Female participation | 0.95                     | 0.82    | 0.78     |

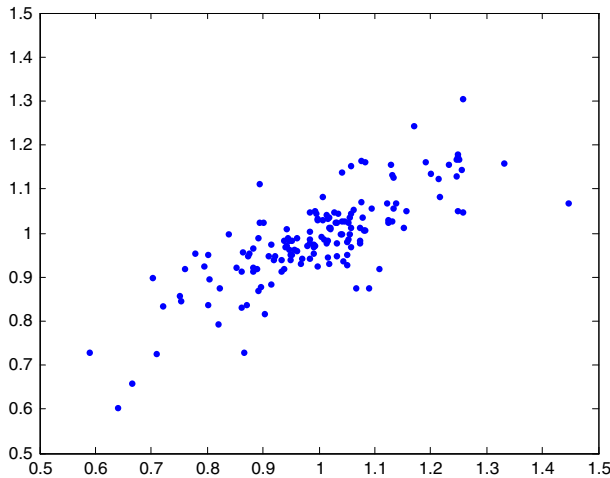
cases. The general model Hendry recommended as a generalisation of the first-order serial autocorrelation model for *time-series data* is the first-order serial autoregressive distributed lag model, a linear dynamic regression model in which the labour force participation rate  $L(t)$  is regressed on  $L(t-1)$  and the explanatory variables  $X(t)$  and  $X(t-1)$ .

### 3.2 Regional participation rates tend to parallel national participation rates

In addition, many studies have reported that regions tend to maintain their relative position over time (Adnett 1996, Chap. 7; Overman and Puga 2002; OECD 2005). One way to illustrate this is by looking at regional participation rates relative to their national counterparts over time. Figure 1 charts the results obtained for men and Fig. 2 the results obtained for women at the beginning and at the end of the observation period for the 154 regions in the sample (note the difference in scale). Both graphs, as well as the regression coefficient of almost 1 obtained by regressing the  $y$ -values on the  $x$ -values (without intercept), demonstrate that there is a tendency for regional participation rates to increase and decrease together in different regions along the national evolution of this variable over time. National fluctuations, in turn, are explained by labour market institutional background variables, such as wage



**Fig. 1** Regional male participation rate relative to its national counterpart at the beginning and the end of the observation period (regression without intercept:  $y = 1.002x$ ,  $t$ -value 508.80,  $R^2 = 0.33$ )



**Fig. 2** Regional female participation rate relative to its national counterpart at the beginning and the end of the observation period (regression without intercept:  $y = 1.009x$ ,  $t$ -value 145.76,  $R^2 = 0.62$ )

bargaining, social security, retirement and tax system, and by cultural and religious differences. All of these country-specific circumstances affect the level around which regional participation rates within one country vary. Not accounting for this country heterogeneity runs the risk of obtaining biased results.

There are three ways to deal with this finding in regression analysis. The first is to introduce a set of country dummy variables. The second is to take regional point differentials about the national participation rate, that is  $L_r - L_n$ , and to do the same for the explanatory variables. The third is to take regional participation-rate relativities, that is  $L_r/L_n$ , and to do the same for the explanatory variables. According to Molho (1983), the latter approach has the advantage that the estimated coefficients may be interpreted as directly relating regional variation in the explanatory variables to regional variation in the participation rates, whereas in the first two models no such direct interpretation is possible. This is because

$$E_{X_r/X_n}^{L_r/L_n} = \frac{\partial L_r/L_n}{\partial X_r/X_n} \frac{X_r/X_n}{L_r/L_n} = \frac{\partial L_r}{\partial X_r} \frac{X_r}{L_r} = E_{X_r}^{L_r}. \quad (6)$$

Thus, for example, if a variable changes over time in a fairly uniform manner across regions, then although that variable may affect participation rates regionally and nationally, it may not affect the regional distribution of participation rates. The most telling examples are the labour market institutional background variables. Since these variables do not differ significantly between regions within European countries, it is the integration of macroeconomic and regional economic research on participation that enables their evaluation. However, the problem this approach presents is that the number of institutional factors that can be included in such an analysis is often limited, given the lack of data across a large number of countries and at many different points in time. The analysis of regional participation relativities circumvents this data problem, with the observation that such an



integrated approach is an important subject for future research (see Elhorst and Zeilstra 2007). Another advantage is that regional participation rates relativities are much less cyclically variable than regional point differentials. Martin (1997) has proven that the dispersion of relative regional participation rates is equivalent to the dispersion of absolute regional participation rates divided by the national participation rate and therefore tends to be much smaller. A final advantage is that relative measures of variables are stationary. Stationary variables are a prerequisite for regression analysis (Greene 2003). Some series of observations over time only become stationary after being first-differenced  $d$  times. This kind of series is said to be integrated to the order of  $d$ . One way to find out whether a series is stationary is to test for the absence of a unit root. This is not necessary when using relative measures of variables because the compound fraction of a regional variable and its national counterpart is of the order of 0, even when these single variables are of a higher order of integration.

### 3.3 Regional participation rates tend to cluster in space

Table 3 reveals Moran's  $I$  deviating from its expected male and female participation rate values (and the  $t$  value of these statistics) in 1983, 1990, and 1997. The spatial weight matrix,  $W$ , used to describe the spatial arrangement of the regions in calculating Moran's  $I$  is a binary contiguity matrix. The results support the view that neighbouring values of male and female regional participation rates are more similar than those further apart.

Elhorst (2001) presented several dynamic models to analyse *space-time data*. One of the models that appeared to be acceptable when studying space-time data on regional labour force participation rates is Hendry's first-order autoregressive distributed lag model, discussed above, but then corrected for spatial autocorrelation. The best-known model to correct for spatial autocorrelation is the spatial error model for *cross-sectional data* (Anselin 1988). This model starts with a first-order spatial autoregressive process generating the error terms  $\varepsilon = \delta W\varepsilon + v$ , where the error terms  $\varepsilon$  and  $v$  are written in vector form,  $v \sim N(0, \sigma^2 I_N)$ ,  $W$  is a pre-specified spatial weight matrix of order  $N$  whose regularity conditions are spelled out in Lee (2004) and  $\delta$  is the spatial autocorrelation coefficient. Instead of this first-order spatial autocorrelation model, we adopt the use of matrix exponentials for spatially transforming the error term, a transformation recently introduced by LeSage and Pace (2007) and abbreviated to matrix exponential spatial specification (MESS). On

**Table 3** Moran's  $I$  of participation rates at three points in time

| Year | Male participation |           | Female participation |           |
|------|--------------------|-----------|----------------------|-----------|
|      | Moran's I-E(I)     | $t$ value | Moran's I-E(I)       | $t$ value |
| 1983 | 0.558              | 5.92      | 0.615                | 6.52      |
| 1990 | 0.643              | 8.05      | 0.647                | 8.11      |
| 1997 | 0.572              | 7.40      | 0.628                | 8.12      |

using matrix exponentials, the error term  $\varepsilon$  undergoes a linear transformation  $S\varepsilon_t = v_t$  with  $S$  defined as

$$S = e^{\delta W} = \sum_{q=0}^{\infty} \frac{\delta^q W^q}{q!}. \tag{7a}$$

Hence,

$$S = \varepsilon + \delta W\varepsilon + \frac{\delta^2}{2} W^2\varepsilon + \dots + \frac{\delta^7}{5040} W^7\varepsilon + \dots. \tag{7b}$$

The relationship between the spatial autocorrelation coefficient in a first-order spatial autocorrelation model ( $\delta_{SEM}$ ) and in MESS ( $\delta_{MESS}$ ) can be approximated by  $\delta_{SEM} \approx 1 - e^{\delta_{MESS}}$ , which implies that a negative estimate for  $\delta_{MESS}$  (e.g.,  $-0.25$ ) corresponds to a positive estimate for  $\delta_{SEM}$  (0.22).

MESS has the advantage that it does not require the numerical computation of a Jacobian term in transforming the estimation model from the error term into the dependent variable, because the Jacobian term equals zero

$$\text{Log}|S| = \log |e^{\delta W}| = \log |e^{\delta \times \text{trace}(W)}| = \log |e^{\delta \times 0}| = \log |1| = 0. \tag{8}$$

In addition to their paper, LeSage and Pace also published a MATLAB function on <http://www.spatial-econometrics.com> to estimate the parameters of the linear spatial lag model,  $SY = X\beta + \varepsilon$  and  $\varepsilon \sim N(0, \sigma^2 I_N)$ , by the method of maximum likelihood (ML). We have rewritten this function to estimate the parameters of a regression model (in general terms of)  $Y = X\beta + v$  with spatially autocorrelated error terms  $S\varepsilon = v$  and  $v \sim N(0, \sigma^2 I_N)$ . Since  $\varepsilon \sim N(0, \sigma^2 \Omega_\delta)$ , where  $\Omega_\delta = (SS')^{-1} = e^{-\delta W'} e^{-\delta W}$ , the log-likelihood function of this model is

$$\text{Log}L = -\frac{N}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} (Y - X\beta)' \Omega_\delta^{-1} (Y - X\beta), \tag{9}$$

which does not contain a Jacobian term, as shown in (Eq. 8). The ML estimators of  $\beta$  and  $\sigma^2$ , given  $\delta$ , can be solved from their first-order maximizing conditions

$$\beta_{ML} = (X' \Omega_{\delta_{ML}}^{-1} X) X' \Omega_{\delta_{ML}}^{-1} Y \quad \text{and} \quad \sigma_{ML}^2 = \frac{1}{N} (Y - X\beta_{ML})' \Omega_{\delta_{ML}}^{-1} (Y - X\beta_{ML}). \tag{10a}$$

Since the Jacobian term is zero, maximizing the log-likelihood with respect to  $\delta$  is equivalent to minimizing the residual sum of squares  $(Y - X\beta)' \Omega_\delta^{-1} (Y - X\beta)$ . LeSage and Pace (2007) show that the latter can be written as a  $2q - 2$  polynomial in  $\delta$ , as a result of which the first-order condition for  $\delta$  has  $2q - 3$  possible roots, where  $q$  is the maximum number of terms used in the calculation of  $S$  in (7). It has been decided to set  $q = 7$ , as the impact of eight or higher order terms appeared to be negligible.<sup>4</sup> The problem of finding all the roots has a well-defined mathematical solution. By looking at the second-order condition, they also find that the polynomial is strictly

<sup>4</sup> If  $W$  is a non-negative row-normalized matrix, it can have a maximum of 1 in any row. Hence, the magnitude of the elements in the powers of  $W$  does not grow with the power. Given the rapid decline in the coefficients in the power series, achieving a satisfactory progression with seven terms is feasible.

convex in  $\delta$ , as a result of which only one of these  $2q-3$  possible roots minimizes the residual sum of squares. This is the ML estimate of  $\delta$ , given  $\beta$  and  $\sigma^2$ , which we denote by

$$\delta_{ML} = \delta(\beta_{ML}, \sigma_{ML}^2). \tag{10b}$$

To obtain the maximum likelihood estimates of the parameters of the model numerically, these two constituent solutions are used in an iterative two-step procedure where  $\beta$  together with  $\sigma^2$  and  $\delta$  are alternately estimated until convergence occurs.

Another advantage of MESS, suggested as a subject for further investigation in LeSage and Pace (2007), is that a similar iterative two-step procedure can be used when some explanatory variables are endogenous instead of exogenous. In the empirical analysis we will introduce three explanatory variables that often are found to be endogenous: the wage rate (Fair and Dominguez 1991; Schmidt 1993; Blundell et al. 2003), the unemployment rate (Fleisher and Rhodes 1976), and the birth rate (Schultz 1981; Pott-Buter 1993). Endogeneity requires instrumental variable methods like two-stage least squares (2SLS) to obtain consistent parameter estimates.

Let  $Z$  denote a matrix of instrumental variables. Since we have a linear model (in general terms of)  $Y = X\beta + \varepsilon$ , with  $E(\varepsilon\varepsilon') = \sigma^2\Omega_\delta$ , and one or more endogenous  $X$  variables, we may estimate  $\beta$  by the (generalized) 2SLS estimator derived from the estimation criterion

$$Min_\beta (Y - X\beta)' \Omega_\delta^{-1} Z (Z' \Omega_\delta^{-1} Z)^{-1} Z \Omega_\delta^{-1} (Y - X\beta). \tag{11}$$

This (generalized) 2SLS estimator takes the form (Bowden and Turkington 1984, Chap. 3; Amemiya 1985, pp. 240–241)

$$\beta_{2SLS} = [X' \Omega_\delta^{-1} Z (Z \Omega_\delta^{-1} Z)^{-1} Z' \Omega_\delta^{-1} X]^{-1} X' \Omega_\delta^{-1} Z (Z' \Omega_\delta^{-1} Z)^{-1} Z' \Omega_\delta^{-1} Y, \tag{12a}$$

while

$$\sigma_{2SLS}^2 = \frac{1}{N} (Y - X\beta_{2SLS})' \Omega_\delta^{-1} (Y - X\beta_{2SLS}). \tag{12b}$$

Just as the ML estimator of  $\beta$  in (Eq. 10a), this estimator appears to require an estimate of  $\delta$  be in hand already, even though it is the object of estimation. A consistent and efficient estimator of  $\delta$  may be obtained by also minimizing the estimation criterion in (Eq. 11) with respect to  $\delta$ . Since the Jacobian term of the MESS transformation equals zero, and minimizing the overall sum-of-squared residuals is equivalent to maximizing the log-likelihood in (Eq. 9) as a result, it is easily seen that this estimator is identical to the ML estimator of  $\delta$ , where the ML estimators of  $\beta$  and  $\sigma^2$  are replaced by their 2SLS counterparts

$$\delta = \delta_{ML}(\beta_{2SLS}, \sigma_{2SLS}^2). \tag{12c}$$

These constituent solutions can again be used in an iterative two-step procedure where  $\beta$  together with  $\sigma^2$  and  $\delta$  are alternately estimated until convergence occurs.

### 3.4 Conclusion

Combining the extensions consistent with the empirical regularities within one framework, the econometric model to be estimated in the empirical analysis takes the form

$$\frac{L_r}{L_n}(t) = \tau \frac{L_r}{L_n}(t-1) + \frac{X_r}{X_n}(t)\beta_1 + \frac{X_r}{X_n}(t-1)\beta_2 + \varepsilon(t), \quad (13a)$$

$$\varepsilon(t) \sim N(0, \sigma^2 e^{-\delta W'} e^{-\delta W}) \quad (13b)$$

This model can be estimated by the 2SLS/ML procedure for a model with endogenous explanatory variables spelled out in (Eq. 9)–(Eq. 12c). The required generalization from cross-sectional to space-time data is straightforward.

Even though our estimation model is dynamic, it reproduces a static equation under equilibrium conditions. This can be seen from a reparameterizing of Eq. (13a) taken from Wickens and Breusch (1988), known as an equilibrium correction model (neglecting the error terms)

$$\begin{aligned} \frac{L_r}{L_n}(t) &= \frac{\tau}{1-\tau} \Delta \frac{L_r}{L_n}(t) + \frac{X_r}{X_n}(t) \frac{\beta_1 + \beta_2}{1-\tau} - \Delta \frac{X_r}{X_n}(t) \frac{\beta_2}{1-\tau} \\ &= \tau^* \Delta \frac{L_r}{L_n}(t) + \frac{X_r}{X_n}(t) \beta_1^* + \Delta \frac{X_r}{X_n}(t) \beta_2^*, \end{aligned} \quad (14)$$

where  $\Delta$  denotes the first-difference operator. This equation demonstrates that there still exists a static long-run equilibrium relationship between the dependent variable and the explanatory variables, but short-run dynamics of how equilibrium is approached are explicitly taken into account.  $\beta_1^*$  reflects the long-run response of  $L_r/L_n$  with respect to  $X_r/X_n$ , or of  $L_r$  with respect to  $X_r$  (see Eq. 6), while  $\beta_2^*$  reflects the short-run or immediate response of  $L_r/L_n$  to a change in  $X_r/X_n$  or of  $L_r$  to a change in  $X_r$ .

One might argue that time period fixed effects should also be included in (Eq. 13a) in order to prevent that trends along the observations over time, either linear or cyclical, might bias the actual cross-section relation between regions that we want to examine. However, since the regional variables are taken relative to their national counterparts, these trends have already been filtered out. Similarly, one might argue that regional fixed effects should be included to control for region-specific time-invariant variables. One problem is that regional fixed effects are likely to be correlated with the dependent variable lagged in time, introduced to account for serial dependence among the observations, thereby generating inconsistent parameter estimates (Baltagi 2005, Chap. 8). Solutions to this problem have been discussed in Elhorst (2005).<sup>5</sup> In this paper we report estimation results obtained by estimating (13) without controls for regional fixed effects and with controls for regional fixed effects. Baltagi (2005, pp. 200–201) has pointed out that the coefficient estimates of models without controls for regional fixed effects are

<sup>5</sup> Elhorst (2005) considered a first-order spatial autoregressive process generating the error terms. The likelihood function of the model when this first-order spatial autoregressive process is replaced by MESS can be obtained by substituting  $S$  in (Eq. 7) for the matrix  $B$  in his equation (11) on p. 94 (including the Jacobian terms).

based on both the cross-sectional variation among the regions at each point in time and the time-series variation of each region over time, whereas the coefficient estimates of models with controls for regional fixed effects are only based on the time-series component of the data. By considering the results of both models, we are able to verify whether the results are robust to the inclusion of regional fixed effects.

#### 4 Empirical analysis

We have estimated a regional labour force participation rate equation for the total working-age population, for males, for females, and for both males and females in five different age categories. The regional participation rate of each sex/age group is taken to depend on the wage rate, the unemployment rate, the industry mix, the population structure (approached in this paper by the birth rate) and the educational attainment of the population. A detailed description of these variables is given in the [Appendix](#), while a motivation for these variables is given below. Table 4 reports the standard deviation of these variables, which, just as the dependent variable, are taken relative to their national counterparts. This table shows that the standard deviation of the unemployment rate is more than 9 times as large as the standard deviation of the industry mix. Tables 5 and 6 report the long-run coefficient estimates of the explanatory variables [ $\beta_1^*$  in Eq. (14)]. The coefficients of the variables measured in percentages (unemployment rate, industry mix, education) present the shift in the participation rate measured on the interval 0–100% when these variables rise by one percentage point. The coefficient of the wage rate shows the shift in the participation rate when this variable rises by 1% and the coefficient of the birth rate when this variable rises by 1 person per 1000 population. For completeness, Tables 5 and 6 also report the coefficient of the lagged dependent variable  $\tau$  and the spatial autocorrelation coefficient  $\delta$ . The wage rate, the unemployment rate and the birth rate have been treated as endogenous explanatory variables. As instrumental variables, we used variables typically used in studies explaining the unemployment rate, the wage rate and the birth rate, such as demographic variables, amenities and sectoral employment shares. To test the joint hypothesis that the instruments are valid and that the model is correctly specified, the instruments that do not lie in  $X_t/X_N(t)$  or  $X_t/X_N(t-1)$  should have no ability to explain any variation in the participation rate. This test is taken from Davidson and

**Table 4** Standard deviation of explanatory variables

| Variables         | SD     |
|-------------------|--------|
| Wage rate         | 0.1002 |
| Unemployment rate | 0.3726 |
| Lower education   | 0.1588 |
| Medium education  | 0.1430 |
| Higher education  | 0.2188 |
| Birth rate        | 0.1583 |
| Industry mix      | 0.0400 |

**Table 5** Estimation results; long-run coefficient estimates

| Expl. var.               | Dependent variable: labour force participation rate (LFPR <sub><i>t</i></sub> ) |                  |                       |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
|--------------------------|---|------------------|-----------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
|                          | Men   |                  |                       |                  |                  |                  | Women            |                  |                  |                  |                  |                  |                  |
|                          | 15–64   |                  | 15–24                 |                  | 25–34            |                  | 35–44            |                  | 45–54            |                  | 55–64            |                  |                  |
| Wrate                    | 0.058<br>(1.78)   | 0.010<br>(0.10)  | 0.136(2.16)<br>(1.69) | 0.101<br>(1.69)  | 0.031<br>(2.41)  | 0.002<br>(0.38)  | 0.015<br>(0.89)  | 0.181<br>(2.27)  | 0.075<br>(0.85)  | 0.090<br>(1.29)  | 0.186<br>(2.81)  | 0.167<br>(1.88)  | 0.068<br>(0.40)  |
| Urate                    | -0.126<br>(6.61)  | -0.067<br>(7.77) | -0.196<br>(6.33)      | -0.145<br>(5.77) | -0.034<br>(6.89) | -0.022<br>(8.74) | -0.015<br>(2.47) | -0.092<br>(3.19) | -0.267<br>(5.75) | -0.172<br>(5.35) | -0.137<br>(5.42) | -0.134<br>(4.47) | -0.172<br>(2.80) |
| Educ-l                   | -0.148<br>(3.72)  | -0.066<br>(3.64) | -0.246<br>(3.34)      | -0.339<br>(4.15) | -0.031<br>(2.07) | -0.003<br>(0.46) | 0.005<br>(0.22)  | -0.072<br>(0.76) | -0.388<br>(3.41) | -0.070<br>(0.91) | -0.153<br>(2.07) | -0.249<br>(2.46) | -0.503<br>(2.37) |
| Educ-m                   | -0.075<br>(2.47)  | -0.047<br>(3.16) | -0.114<br>(2.04)      | -0.217<br>(3.44) | -0.010<br>(0.90) | 0.007<br>(1.30)  | 0.020<br>(1.12)  | -0.108<br>(1.40) | -0.289<br>(3.23) | 0.009<br>(0.15)  | -0.002<br>(0.03) | 0.060<br>(0.76)  | -0.463<br>(2.59) |
| Educ-h                   | 0.010<br>(0.47)   | 0.006<br>(0.58)  | 0.018(0.41)<br>(4.82) | -0.267<br>(4.82) | -0.011<br>(1.26) | 0.013<br>(3.12)  | 0.064<br>(3.93)  | 0.231<br>(3.35)  | -0.222<br>(3.20) | 0.049<br>(1.00)  | 0.049<br>(1.07)  | 0.088<br>(1.43)  | 0.196<br>(1.49)  |
| Brate                    | -0.025<br>(1.04)  | 0.061<br>(4.78)  | -0.172<br>(3.15)      | 0.079<br>(1.71)  | 0.013<br>(1.31)  | 0.003<br>(0.62)  | 0.045<br>(2.81)  | 0.419<br>(4.70)  | -0.009<br>(0.13) | -0.363<br>(4.32) | -0.338<br>(4.75) | -0.194<br>(2.70) | -0.086<br>(0.62) |
| Mix                      | 0.169<br>(1.99)   | 0.044<br>(1.06)  | 0.356(2.15)<br>(1.06) | -0.240<br>(1.36) | -0.168<br>(4.02) | -0.073<br>(4.18) | 0.006<br>(0.10)  | 0.829<br>(3.09)  | -0.313<br>(1.17) | -0.327<br>(1.74) | 0.134<br>(0.76)  | 0.647<br>(2.59)  | 2.081<br>(3.50)  |
| LFPR <sub><i>t</i></sub> | 0.882<br>(96.19)  | 0.796<br>(61.18) | 0.887<br>(107.61)     | 0.805<br>(55.26) | 0.744<br>(47.31) | 0.610<br>(32.57) | 0.811<br>(57.45) | 0.828<br>(60.22) | 0.840<br>(66.63) | 0.859<br>(73.73) | 0.849<br>(82.73) | 0.861<br>(98.90) | 0.872<br>(85.90) |
| $\delta$                 | -0.168<br>(3.08)  | -0.188<br>(3.11) | -0.181<br>(3.61)      | -0.226<br>(4.22) | -0.212<br>(3.70) | -0.340<br>(6.60) | -0.400<br>(7.75) | -0.216<br>(3.26) | -0.116<br>(2.03) | -0.198<br>(3.63) | -0.029<br>(0.55) | -0.011<br>(0.23) | -0.276<br>(5.33) |
| R <sup>2</sup>           | 0.918   | 0.944            | 0.910                 | 0.731            | 0.939            | 0.986            | 0.977            | 0.794            | 0.760            | 0.839            | 0.843            | 0.850            | 0.810            |
| Test instr.              | 14.17   | 14.61            | 17.99                 | 18.78            | 8.60             | 11.29            | 8.74             | 10.85            | 13.23            | 7.14             | 19.12            | 17.88            | 6.83             |

Notes: All variables are relative to their national counterparts. *t* Statistics are in parenthesis (absolute values). Coefficient estimates denote elasticities. Wrate, Urate and Brate have been treated as endogenous explanatory variables

MacKinnon (1993, pp. 232–237) and has a chi-squared distribution. The degrees of freedom are equal to the number of instruments that do not lie in  $X_t/X_N(t)$  or  $X_t/X_N(t-1)$ , which in our case is 8. The results of this test are reported in Table 5 and show that the hypothesis cannot be rejected for nine population groups at 5% significance (critical value 15.51), and cannot be rejected for any of the population groups at 1% significance (critical value 20.09).

We have tested the equality of the long-run coefficients of the explanatory variables for all crosswise combinations of population groups, a total of 78 pairs. The results are unambiguous. Even when allowing for 10 percent significance, the null hypothesis has to be rejected in 76 cases in Table 5 and in 77 cases in Table 6. Only female labour force behaviour in the successive age groups of 25–34 and 35–44, as well as 35–44 and 45–54 bear any resemblance to each other. In other words, marginal reactions of different population groups being identical is the exception rather than the rule. It follows from this finding that a sex and age-targeted labour market policy to promote labour force participation should be recommended. This issue will be returned to in the concluding section.

The coefficient estimate of lagged labour force participation ranges from 0.610 to 0.887 in Table 5 and from 0.473 to 0.718 in Table 6 and in all cases is highly significant. It indicates that labour force participation is habit persistent. The spatial autocorrelation coefficient is significant in 11 cases in both Tables 5 and 6 and ranges between  $-0.400$  and  $-0.011$ , which would correspond to (in reversed order) 0.011 and 0.330 in a first-order spatial autocorrelation model. The  $R$ -squared of the model without controls for regional fixed effects ranges from 0.73 to 0.94, partly due to the lagged dependent variable and the correction for spatial autocorrelation. These results nonetheless indicate that the explanatory power of the set of explanatory variables is large.

In accordance with the neo-classical economics argument, the participation rates appear to be positively related to the wage rate ( $Wrate$ ). The most widely used indicator of the wage rate in studies on regional labour force participation is gross average earnings over a certain time period (week, month and year). Some studies used income variables, but usually as proxies for the wage rate (see the references cited in Elhorst 1996b). In this study, data on manual and non-manual workers' average hourly earnings in manufacturing have been used, made available by the Eurostat Labour Costs Surveys. Although the wage rate is the most important explanatory variable from a theoretical point of view, the elasticity of the participation decision with respect to the wage rate appears to be rather small. In addition, the variation in the wage rate is relatively small (Table 4). In Table 5, the elasticity ranges from 0.002 to 0.181 with an average of 0.010 for men, and ranges from 0.068 to 0.186 with an average of 0.136 for women. Women are accordingly more responsive to wage changes than men. Young and older men, in their turn, are more responsive to wage changes than men in the prime-age groups. These elasticities only slightly change when controlling for regional fixed effects and are close to those reported by Pencavel (1986) and Killingsworth and Heckman (1986), who reviewed the extensive Anglo-Saxon literature on male and female labour supply. For males Pencavel registered elasticities which fall in the range of 0.2–0.4, and for females Killingsworth and Heckman registered elasticities, which fall in the range 0.05–0.25.

**Table 6** Estimation results; long-run coefficient estimates with controls for regional fixed effects

| Expl. var.                 | Dependent variable: labour force participation rate (LFPR <sub><i>t</i></sub> ) |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |                  |
|----------------------------|---|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
|                            | Men   |                  |                  |                  | Women            |                  |                  |                  | Women            |                  |                  |                  |                  |
|                            | Pop. 15–64  | 15–24            | 25–34            | 35–44            | 45–54            | 55–64            | 15–24            | 25–34            | 35–44            | 45–54            | 55–64            |                  |                  |
| Wrate                      | 0.015<br>(0.97)   | 0.008<br>(0.91)  | 0.062<br>(1.92)  | 0.013<br>(0.69)  | 0.016<br>(2.76)  | 0.009<br>(2.56)  | 0.001<br>(0.11)  | 0.232<br>(4.82)  | 0.000<br>(0.01)  | 0.080<br>(2.37)  | 0.100<br>(2.66)  | 0.013<br>(0.27)  | 0.169<br>(2.55)  |
| Urate                      | -0.033<br>(4.24)  | -0.025<br>(5.03) | -0.040<br>(2.49) | -0.004<br>(0.33) | -0.031<br>(2.38) | -0.008<br>(3.60) | -0.008<br>(1.52) | -0.100<br>(3.70) | -0.037<br>(1.58) | -0.012<br>(0.69) | -0.028<br>(1.33) | -0.018<br>(0.65) | -0.188<br>(4.49) |
| Educ-l                     | -0.164<br>(7.10)  | -0.043<br>(5.07) | -0.282<br>(6.06) | -0.257<br>(5.01) | -0.071<br>(3.50) | -0.018<br>(2.88) | -0.017<br>(1.14) | -0.079<br>(1.05) | -0.113<br>(1.91) | -0.110<br>(2.38) | -0.448<br>(7.10) | -0.203<br>(6.03) | -0.512<br>(4.36) |
| Educ-m                     | -0.105<br>(4.51)  | -0.025<br>(2.77) | -0.171<br>(3.66) | -0.107<br>(2.06) | -0.050<br>(2.44) | -0.025<br>(3.74) | -0.020<br>(1.19) | -0.068<br>(0.86) | -0.070<br>(1.12) | -0.080<br>(1.62) | -0.306<br>(4.81) | -0.108<br>(2.97) | -0.227<br>(1.85) |
| Educ-h                     | 0.028<br>(1.71)   | 0.011<br>(1.66)  | 0.057<br>(1.71)  | 0.157<br>(4.02)  | 0.086<br>(5.94)  | 0.017<br>(3.63)  | -0.010<br>(1.23) | 0.261<br>(4.42)  | 0.053<br>(1.15)  | 0.135<br>(3.76)  | 0.079<br>(1.81)  | 0.062<br>(2.38)  | 0.294<br>(3.27)  |
| Brate                      | 0.122<br>(5.19)   | 0.066<br>(7.19)  | -0.159<br>(3.49) | 0.408<br>(7.09)  | 0.108<br>(5.10)  | 0.018<br>(2.73)  | 0.022<br>(1.35)  | 0.163<br>(2.00)  | -0.191<br>(4.69) | -0.022<br>(0.46) | -0.130<br>(2.15) | -0.192<br>(2.43) | -0.174<br>(1.37) |
| Mix                        | 0.183<br>(3.32)   | -0.046<br>(2.08) | 0.655<br>(5.49)  | -0.282<br>(2.20) | -0.118<br>(2.36) | -0.009<br>(0.53) | -0.051<br>(1.85) | -0.204<br>(1.95) | 0.036<br>(0.23)  | 0.386<br>(3.21)  | 0.769<br>(4.86)  | 1.239<br>(5.87)  | 1.290<br>(4.18)  |
| LFPR <sub><i>t-1</i></sub> | 0.674<br>(27.18)  | 0.559<br>(19.21) | 0.718<br>(31.92) | 0.487<br>(14.38) | 0.639<br>(22.86) | 0.473<br>(13.74) | 0.489<br>(14.18) | 0.625<br>(22.22) | 0.496<br>(14.93) | 0.592<br>(21.13) | 0.682<br>(28.25) | 0.702<br>(30.21) | 0.586<br>(19.30) |
| $\delta$                   | -0.208<br>(5.43)  | -0.139<br>(3.14) | -0.240<br>(6.12) | -0.248<br>(7.11) | -0.218<br>(2.29) | -0.332<br>(7.84) | -0.362<br>(7.28) | -0.120<br>(2.97) | -0.056<br>(1.16) | -0.175<br>(3.89) | -0.175<br>(3.89) | -0.016<br>(0.28) | -0.206<br>(4.24) |

Notes: All variables are relative to their national counterparts. *t* Statistics are in parenthesis (absolute values). Coefficient estimates denote elasticities. Wrate, Urate and Brate have been treated as endogenous explanatory variables



A large number of studies have tried to find a relationship between labour force participation and *local* variables linked to individual places of work or residence. One of the most important local variables is the probability of being dismissed or of finding a job, which in turn depends on an area's labour demand conditions (see, for a theoretical exposition, Elhorst and Zeilstra 2007). These labour market conditions can be measured by the unemployment rate, the vacancy rate, job availability, the industry mix and the share of part-time employment in total employment. In an overview paper of regional labour market research on participation rates, Elhorst (1996b) found that 16 studies (out of 17) adopted the regional unemployment rate (Urate). Even though unemployed people count as participants in the labour market, almost all these studies found a negative relationship between the labour force participation rate and the regional unemployment rate. They explained this finding as evidence of the discouragement effect dominating regional labour force behaviour.<sup>6</sup> Our results largely corroborate the empirical evidence. The unemployment elasticity is negative and statistically different from zero for all population groups in Table 5, and negative for all population groups and statistically different from zero for seven population groups in Table 6. In addition, the variation in the unemployment rate is relatively large (Table 4). Therefore, it may be considered as further evidence that the discouragement effect dominates the labour market in the European Union. Furthermore, women appear to be more responsive to the discouragement effect than men, and young and older people to be more responsive than people in the prime-age groups.

Just like the unemployment rate, the industry mix is a local variable that can be traced back to an area's labour market conditions. The industry mix was first introduced in the seminal work by Bowen and Finegan (1969) and was meant to measure structural differences between metropolitan areas in the relative abundance of those jobs commonly held by females. Another variable that is of importance is the share of part-time work in total employment. This share has increased sharply during recent years. In the EU, the growth of the number of part-time jobs continued even during recessions. Before the 1990s, the growth of part-time work was particularly associated with the increase in the employment of women. The explanation is that working part-time permits women to combine working outside the household with their (perceived) obligations within the household. However, at the same time, there has also been a marked upward trend in the part-time employment of men. Between 1985 and 1997 the proportion of men employed part-time in the Union rose from 3.7 to 5.8%. This suggests that the trend towards working part-time of women is spreading to men, as a corollary perhaps of the shift in employment to the service industry. Our industry-mix variable (Mix) measures the predicted ratio of female employment to total employment within a region, the prediction being based on (1) the ratio of female employment to total employment within the agricultural, manufacturing and service sectors at the national level, each

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<sup>6</sup> In general, it is hypothesised that a negative value for the regional unemployment rate implies a net discouragement effect over the additional worker effect, and vice versa. Strictly speaking, however, the added-worker effect cannot exist in (1). Essentially, this is because at zero labour supply, increases in wages do not change income. Income effects could be brought in if labour supply were modelled as resulting from joint maximisation by individuals within a family.

sector further divided into full-time and part-time labour, and (2) the distribution of total employment among these industries and among full-time and part-time labour within each region (see the [Appendix](#) for a mathematical formulation). The industry mix reflects the extent to which the regional distribution of employment among industries and full-time and part-time labour is favourable to women.

As expected, women, especially in the higher age groups, benefit, while men, especially in the lower age groups, suffer from an industry mix favourable to women. This pattern emerges from the results reported in [Table 6](#), which are based on the time-series component of the data. When the cross-sectional variation between the regions is also utilized, the coefficient estimates for some population groups change sign, though only significant with respect to men in the highest age group of 55–64. One explanation that older men also benefit from an industry mix favourable to women might be that jobs in the services sector are less physically demanding. Over the period 1985–1997, the EU has experienced a fall in the share of employment in agriculture from 8.3 to 5.0%, in manufacturing from 34.4 to 29.6%, and an increase in the share of employment in services from 57.3 to 65.4%. Part-time employment of men has increased from 3.7 to 5.8% and of women from 28.1 to 32.5% during this period. By simulating the impact of these changes on the industry mix variable, it has been computed that this sectoral shift has caused a 1.2/1.3 percentage point increase and the expansion of part-time employment a 0.7/0.8 percentage point increase in the total labour force participation rate (the first number is based on the coefficient estimate in [Table 5](#) and the second number on the coefficient estimate in [Table 6](#)).

The better educated are often thought to be better off than the less well educated: (1) they possess skills more often in demand in an economy with burgeoning technological progress, (2) they are likely to conduct more efficient searches, (3) they are less prone to layoffs and thus exhibit more stable employment patterns, and (4) higher earnings enable women in particular to make individual arrangements for paid help for housework and childcare. We considered three variables measuring the educational attainment of the population: the percentage of people aged 25–59 having completed less than upper-secondary education (low skilled), upper-secondary education (medium skilled), and tertiary education (highly skilled). These variables are taken from several Eurostat issues of *Education across the European Union: Statistics and Indicators*. Since these variables have been taken relative to their national counterparts, they no longer sum up to a constant<sup>7</sup>, as a result of which neither of these variables needs to be dropped to avoid perfect collinearity.

The following picture emerges when looking at the estimation results of the educational variables for a particular population group. For illustration, we use the coefficient estimates obtained for the entire working age population in [Table 5](#). The coefficient of the highly skilled (0.010;  $t$  value 0.47) is greater than the coefficient of the medium skilled ( $-0.075$ ;  $t$  value 2.47), which in turn is greater than the coefficient of the low skilled ( $-0.148$ ;  $t$  value 3.72). This implies that if the percentage of the low skilled decreases by one percentage point to the benefit of the highly skilled, the participation rate will increase by  $0.010 - (-0.148) = 0.158$ .

<sup>7</sup> When these variables are not taken relative to their national counterparts, they sum up to 100%.

Similarly, if the percentage of the medium skilled decreases by one percentage point to the benefit of the highly skilled, the participation rate will increase by  $0.010 - (-0.075) = 0.085$ . Both increases are also significant, since the coefficients of the low and of the medium skilled are significantly smaller than zero and therefore also smaller than the coefficient of the highly skilled. If the percentage of the low skilled decreases by one percentage point to the benefit of the medium skilled, the participation rate also increases. However, this increase of  $-0.075 - (-0.148) = 0.073$  is not significant. Similar patterns are obtained for the other age groups or when using the coefficient estimates from Table 6. Only men and women aged under 25 deviate from this plausible model structure when utilizing both the cross-sectional component and the time-series component of the data (Table 5). The reason might be the following. If a country has reached a more advanced level of development, the number of people aged between 15 and 24 remaining in education after compulsory schooling tends to increase. For that purpose, these people generally have to move to the more densely populated regions, especially if they enrol at a university, as it is in these places that universities are located. Since people who remain in education are not available for the labour market, or at least to a lesser extent,<sup>8</sup> it follows that the participation rate of people aged under 25 will fall. This also explains why this effect disappears when utilizing the time-series component of the data only (Table 6).

One explanation why the difference between the highly and the medium skilled tends to be significant, whereas the difference between the medium and the low skilled is not might be that education is to be thought of as a necessary but not a sufficient condition for people to get a job. When new jobs are not forthcoming, that is, during an economic downturn or in backward regions, or when people are confronted with barriers to the labour market, like failure to find adequate childcare or care for the elderly, public transport systems in rural areas that are not adapted to the routine of work and discriminatory wages, education is not the key to better performance. This finding is in line with the OECD (1994, p. 127), which pointed out that there is little evidence to support an across-the-board increase in educational attainment. There seems to be a clear dividing line at higher education, below which labour market opportunities are worse than above it.

As the regional data file of Eurostat does not offer data on marital status and family structure at a regional level, the birth rate has been submitted as a proxy (Brate). The birth rate is defined as the number of births per 1000 population. In accordance with previous empirical work (Pott-Buter 1993; Jacobsen 1999), a higher birth rate appears to reduce the female participation rate, especially of women of childbearing and child-rearing age. On the other hand, this pattern is less pronounced when utilizing the time-series component of the data only. In both Tables 5 and 6, the birth rate also appears to have a positive and in many cases significant effect on the labour force participation rates of men. Generally, a higher birth rate is associated with a larger share of the population aged under 25. In other words, the younger the population the higher the male participation rates will be.

<sup>8</sup> Today, a higher number of youngsters combine education with part-time work, such that the transition from education to working life may in fact be a process rather than a straightforward change.

This appears to be the case in the island regions of Portugal, Spain, Italy and Greece, regions in Southern Italy, and in Northern Ireland.

## 5 Conclusions

The extent to which the labour force behaviour of different population groups may be lumped together for the purpose of a common treatment has been investigated in this paper. Recent empirical studies of aggregate labour force behaviour have ignored population distribution effects, relying instead on the representative-agent paradigm. In order for representative-agent models to accurately describe aggregate behaviour, all marginal reactions of individuals to changes in aggregate variables must be identical. We have found strong empirical evidence against this condition being applied for individuals across different sex/age groups.

Regional participation rates also appeared to be strongly correlated in time, weakly correlated in space and to parallel their national counterparts. An econometric model was designed consistent with these empirical findings. We expect that this type of model will also be beneficial to the analysis of related labour market issues like unemployment, employment growth, GRP growth, and the wage rate, as these variables exhibit similar properties. By using a specification to spatially transform the error term other than the familiar first-order spatial autocorrelation model, this model can also be extended to endogenous explanatory variables which often occur in regional labour market models. One suggestion for further research would be a Monte Carlo study that focuses on the small sample properties of the 2SLS estimator and a comparison of these properties with those of its GMM counterpart developed by Kelejian and Prucha (1999).

The European Council of EU leaders has set themselves targets of reaching an overall employment rate of 70%, of 60% for women and of 50% for older workers by 2010 (European Commission 2000). The model developed in this paper has brought more precision to our understanding of the labour force behaviour of different sex/age groups in the European Union at regional level. As the variables in the regression equations have been taken relative to their national counterparts, cyclical fluctuations have largely been eliminated. Consequently, we are in a position to judge which policy measures may have a permanent upward effect on labour force participation (and employment) from a regional perspective. A subject for further research is to find a specification consistent with the stylized facts reported in this paper that can also be used to simulate policy changes in region-invariant or macro variables (see Elhorst and Zeilstra 2007).

A policy aimed at stimulating labour supply by raising income from working through tax cuts is probably of no value. The impact of the wage rate is of so small an order of magnitude that this policy instrument has hardly any effect. A policy aimed at stimulating labour demand, contributing to more jobs and less unemployment, and especially to wage restraint, seems to be one of the best options to raise the labour force behaviour of the Union's population, particularly in those countries and those regions with above-average unemployment figures. This follows from the coefficient estimates of the unemployment rate based on both the cross-sectional

and the time-series component of the data (Table 5). If the unemployment rate were to decline by 5 percentage points, as in the European Commission's projection over 1999–2010 (European Commission 2000), the participation rate of the total working-age population would increase by 6.4% points, that of women by 9.8% points, that of young people by 9.7% points, and that of older people by 5.5% points. In other words, this policy would not only bring the European Council's targets much closer, it would also be of more help to vulnerable population groups, as opposed to people in the prime-age age groups whose participation rate would increase by "only" 3.9% points. We have one word of caution. When considering the coefficient estimates based on the time-series component of the data only (Table 6), these figures tend to fall by a factor of approximately 4.

We have found strong empirical evidence that a better educated population resulting in a relatively large increase in the percentage of highly skilled workers has an upward effect on labour force participation. However, it was also found that there is a dividing line at higher education below which labour market opportunities are worse than above it. This implies that a better educated population resulting in relatively more medium skilled workers is no guarantee for achieving better performance. This remark is lacking from the European Commission's (2002) advice to the European Council.

After the baby boom in the post-war period, women's labour force participation increased partly due to a declining birth rate. Now that the birth rate in most European countries is stabilising, this process will come to an end when the rise in female participation, which started in the younger age groups, also reaches the older age groups over time, unless further measures are taken to break down barriers to labour market entry for women with children. In view of the inverse relationship that still exists between the birth rate and women's labour force participation, it follows that making employment more accessible to women than it already is may help to further increase women's labour force participation. During the second half of the 1980s, the European Commission (2000) supported a wide variety of proposals to stimulate a greater sharing of family responsibilities. Among these proposals was the promotion of childcare systems (not only for pre-school-age children but also for school-age children since the mismatch between working hours and school hours is another common obstacle to women's access to the labour market), and parental and family leave. But in its advice to the European Council, the European Commission (2002) recorded that not many member states have taken action in these areas.

The European Commission has frequently stressed the relationship between job creation in the services sector and employment. Since 1980, services are the only area of activity in which there has been net job creation. The number of people employed in services increased (in 1996 the services sector accounted for 65% of total employment in the Union) while the number of people employed in agriculture and industry fell. Services, however, account for an even larger share of employment in the US (73%), suggesting that there is considerable scope for expansion in Europe. The results of our empirical analysis show weak evidence supporting this view. An economy that shifts to more employment in the services industry and to more part-time jobs has an upward effect on the labour force

participation rate of the working-age population as a whole, and on that of women in particular.

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## Appendix

### Definitions of variables

- *Labour force participation rate (%)*. Ratio of (self-)employed and unemployed people to total population of different sex and age groups.
- *Wage rate*. Average hourly earnings of manual and non-manual workers in manufacturing converted to 1990 ECU's with the help of Purchasing Power Parities and Consumer Price Indices developed by Eurostat. Source: Labour Costs Surveys 1984, 1988, 1992, and 1996, Eurostat, nuts1 regions. Data for intermediate years are computed by using national figures or by linear interpolation.
- *Unemployment rate (%)*. Ratio of unemployed people (harmonised unemployment) to active labour population (15–64). A person is considered unemployed if he/she is without work, currently available for work and seeking work, that is, if he/she has taken specific steps in a specified recent period to seek paid employment or self-employment.
- *Industry mix (%)*. Predicted ratio of female employment to total employment measured by

$$\text{Mix}^{r,f} = 100 * \sum_{s=1}^3 \sum_{j=1}^2 \frac{E_{s,j}^{r,m+f}}{E_{\text{total}}^{r,m+f}} \frac{E_{s,j}^{n,f}}{E_{s,j}^{n,m+f}},$$

where  $E$  = employment,  $s$  = sector (agriculture, manufacturing, and services),  $j$  = type of work (full-time and part-time),  $f$  = females,  $m$  = males,  $r$  = region and  $n$  = country. The first ratio at the right-hand side measures the share of (male and female) employment for a particular sector and a particular type of work in total employment within a region, and the second ratio measures the share of female employment for a particular sector and a particular type of work in (male and female) employment for that sector and that type of work within the country where the region is located.

- *Education*. Percentage of people aged 25–59 having lower, medium or higher education (Educ-l, Educ-m and Educ-h). Lower education is defined as less than upper-secondary education, medium education is defined as upper secondary education, International Standard Classification of Education (ISCED) 3, and higher education is defined as tertiary education, ISCED 5–7.
- *Birth rate*. Number of births per 1000 population per year.

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