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## Do EU structural funds promote regional employment? Evidence from dynamic panel data models

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**WORKING PAPER SERIES**

**NO 1403 / DECEMBER 2011**

**DO EU STRUCTURAL  
FUNDS PROMOTE  
REGIONAL  
EMPLOYMENT?**

**EVIDENCE FROM  
DYNAMIC PANEL  
DATA MODELS**

by Philipp Mohl  
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# DO EU STRUCTURAL FUNDS PROMOTE REGIONAL EMPLOYMENT? EVIDENCE FROM DYNAMIC PANEL DATA MODELS

by Philipp Mohl<sup>1</sup>  
and Tobias Hagen<sup>2</sup>

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## Abstract

Despite its rather broad goal of promoting “economic, social and territorial cohesion”, the existing literature has mainly focused on investigating the Cohesion Policy’s growth effects. This ignores the fact that part of the EU expenditures is directly aimed at reducing disparities in the employment sector. Against this background, the paper analyses the impact of EU structural funds on employment drawing on a panel dataset of 130 European NUTS regions over the time period 1999-2007. Compared to previous studies we (i) explicitly take into account the unambiguous theoretical propositions by testing the conditional impact of structural funds on the educational attainment of the regional labour supply, (ii) use more precise measures of structural funds for an extended time horizon and (iii) examine the robustness of our results by comparing different dynamic panel econometric approaches to control for heteroscedasticity, serial and spatial correlation as well as for endogeneity. Our results indicate that high-skilled population in particular benefits from EU structural funds.

*Keywords:* EU structural funds, dynamic panel models, spatial panel econometrics, regional employment effects

*JEL classification:* R11, R12, C23, J20

## Non-technical summary

The largest part of the EU budget—more than one third of total EU expenditures and corresponding to 380 billion euros—is spent on EU Cohesion Policy for the Multiannual Financial Framework from 2007–2013. Despite its rather general focus on promoting “economic, social, and territorial, cohesion among Member States” (Art. 3(3) TEU), the investigation of the impact of Cohesion Policy has mainly concentrated on the policy’s growth effects.

However, the employment effects are key to understanding regional income disparities, since income differences are, per definition, based on differences in the labour productivity and/or employment level, among other factors. In addition, parts of the EU expenditures (in particular Objective 2 payments) are directly aimed at reducing disparities in the employment sector. Nevertheless, only a few papers have analysed the employment effects of this policy field and the overall empirical results are inconclusive. Moreover, from a theoretical perspective, higher expenditures on EU funding do not necessarily increase the total employment level. Instead, its impact depends on whether structural funds are used as capital subsidies or as human capital investment and it is subject to the educational attainment of the population. Furthermore, to the extent that structural funds payments have short-term business cycle effects, the employment effect may be low for economies with a positive output gap and a tight labour market situation. All in all, the net effect on total employment is an empirical question.

This question is addressed in this paper, analysing the impact of EU structural funds on employment with a panel dataset of 130 European regions over the time period 1999–2007. Our empirical results confirm the theoretical predictions as total structural funds have no significant positive impact on the regional employment level. However, we find evidence that structural funds may be interpreted as capital subsidies and are only conditionally effective. These funds have a significant positive impact on the total employment level in regions with a low share of low-skilled population, and have a negative effect in the case of a high share of low-skilled population.

Our results have policy implications for the setup of future Multiannual Financial Frameworks. It becomes evident that EU funding lacks a clear concept on how to promote employment in the medium- to long-run. Our results indicate that the high-skilled population in particular benefits from EU structural funds payments. As a consequence, a strategy should define objectives which are clearly measurable and allow for an ex-post assessment of this policy field. This, in turn, would contribute to a more effective policy.



# 1 Introduction

The largest part of the EU budget—more than one third of total EU expenditures and corresponding to 380 billion euros—is spent on EU Cohesion Policy for the Multiannual Financial Framework from 2007–2013. Despite its rather general focus on promoting “economic, social, and territorial, cohesion among Member States” (Art. 3(3) TEU), the current literature on the effectiveness of EU funding has mainly focused on the question whether EU aid has promoted economic growth and convergence (for a survey see Esposti and Bussoletti, 2008; Hagen and Mohl, 2011b).

However, the employment effects are key to understanding regional income disparities (measured, e.g. as GDP per capita), since income differences are, per definition, based on differences in the labour productivity and/or employment level, among other factors. In addition, parts of the EU expenditures (in particular Objective 2 payments) are directly aimed at reducing disparities in the employment sector. Nevertheless, only a few papers have analysed the employment effects of this policy field. While earlier contributions find positive employment effects from the European Regional Development Fund for EU regions in the 1988-1993 period (Busch, Lichtblau, and Schnabel, 1998) and for firms in northern and central Italy (Bondonio and Greenbaum, 2006), the recent evidence is rather disillusioning; suggesting that there are no positive employment effects for EU countries (Heinemann, Mohl, and Osterloh, 2009) or regions (Dall’erba and Le Gallo, 2007; Becker, Egger, and von Ehrlich, 2010). By contrast, Bouvet (2005) finds a positive effect of EU aid on employment growth in a sample of eight EU Member States between 1975 and 1999.<sup>1</sup> One drawback in the literature is the poor data availability of EU funding. The annual reports on structural funds published by the European Commission (1995, 1996a,b, 1997, 1998, 1999, 2000) only

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<sup>1</sup>Apart from the studies cited, there is a growing literature which analyses more general labour market effects at the regional level in Europe, e.g. studies on the determinants of unemployment (Basile and de Benedicits, 2008) or labour force participation rates (Elhorst and Zeilstra, 2007).

comprise regional commitments / payments for the 1994–1999 period. Unfortunately, since 2000, these reports have only consisted of aggregate data at the country level. As a consequence, no paper has analysed the employment effects using regional structural funds payments post 1999.

There are at least four theoretical arguments why EU funding is not unambiguously associated with positive total employment effects. First, structural funds payments increase the employment level if they lead to human capital investment (for example, from the European Social Fund); however, if they are used as capital subsidies (for example, investment grants for firms or business start-ups), the employment effects will be inconclusive. On the one hand, structural funds payments reduce capital costs, which leads to more output and employment (scale effect). On the other hand, reduced capital costs increase relative costs of labour, which may cause (low-skilled) labour to be substituted by capital (substitution effect). According to the “capital-skill-complementary hypothesis” (Griliches, 1969), the demand for skilled labour increases with decreasing capital costs, while the demand for unskilled labour decreases with diminishing capital costs. Second, the employment effects are inconclusive if structural funds payments have a positive effect on technological progress. According to the “skill-based technological change hypothesis” (Berman, Bound, and Griliches, 1994), technological progress may lead to an increase of the relative demand for high-skilled labour, and thus to a decrease in demand for low-skilled labour. Third, in order to induce a positive employment effect, the regional labor supply must match with the additional demand for high-skilled labour. Fourth, short-term business cycle effects might impede employment growth. If Cohesion Policy was associated with a positive aggregate demand stimulus and if the economy was characterised by a positive output gap and a tight labour market situation, Cohesion Policy would not promote employment growth but would lead to an overheating of the economy, implying an acceleration of price and wage inflation. As indicated by Kamps, Leiner-Killinger, and Martin (2009) this could be in particular the case for the eastern European Member States,

which joined the EU in 2007 and exhibited high growth rates.

All in all, the net effect on total employment is theoretically unclear ex ante and, hence, an empirical question which is addressed in this paper. We evaluate the impact of EU structural funds on employment with a panel dataset of 130 European NUTS regions over the time period of 1999-2007. Compared with previous studies we explicitly take into account the unambiguous theoretical propositions by investigating the conditional impact of structural funds on the educational attainment. Moreover, we are, to the best of our knowledge, the first who analyse this research question with more precise measures of EU funding by distinguishing between Objective 1, 2 and 3 payments and for an extended time period using data from the Multiannual Financial Framework 2000-2006. Finally, we examine the robustness of our results by comparing different dynamic panel econometric approaches, highlighting specific methodological problems, controlling for heteroscedasticity, serial and spatial correlation, as well as for endogeneity.

Our results indicate that structural funds in total have no significant positive impact on the regional employment level. However, we find some evidence that structural funds are conditionally effective and may be interpreted as capital subsidies. They have a significant positive impact on the employment level in regions with a low share of low-skilled population, whereas they have a negative effect on the employment level in the case of a high share of low-skilled population. This implies that the high-skilled population in particular benefits from EU structural funds payments.

The outline of this paper is as follows. We start in Section 2 with a discussion of the econometric specification. This is followed by a presentation of the empirical results in the light of the methodological challenges in Section 3. Finally, Section 4 concludes.

## 2 Econometric specification

### 2.1 Baseline panel approach

Our estimation of the employment effects of structural funds payments is based on a reduced-form approach including the implications of both a labour demand model as well as a labour supply model. We define employment (*emp*) as the regions' total employment per population aged 15 to 65 in order to account for the substantial differences in the size of the regional labour markets in Europe.

From a theoretical point of view, structural funds payments may affect employment through the channel of labour demand by increasing the endowment of private and public capital in the region. This raises the marginal product of labour, the output level, and thus, *ceteris paribus*, labour demand. A second transmission channel is an increase in the technological progress which may affect total labour demand positively or negatively, as discussed in the introduction.

Our baseline specification is defined as follows:<sup>2</sup>

$$\begin{aligned} emp_{i,t} = & \beta_0 + \beta_1 emp_{i,t-1} + \beta_2 comp.emp_{i,t-1} + \beta_3 pop.young_{i,t-1} + \\ & + \beta_4 low\ skilled_{i,t-1} + \beta_5 market\ potential_{i,t-1} + \beta_6 grr_{i,t-1} + \\ & + \beta_7 union\ density_{i,t-1} + \beta_8 sf_{i,t-1} + \mu_i + \lambda_t + u_{i,t} \end{aligned} \quad (1)$$

where the subscript  $i = 1, \dots, 130$  denotes the region and  $t$  indicates the time index of our sample for the time period of 1999–2007. Note that all independent variables are lagged and expressed in log terms. We estimate a dynamic panel data model by including the lagged employment variable in order to deal with the sluggish adjustment process (Nickell, 1987).

Moreover, we consider a number of region-specific control variables. We have to proxy the regional wage level by the compensation of employees in

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<sup>2</sup>Note that we also tested for a non-linear relationship between structural funds and employment. Our findings, which are available upon request, show that there is no evidence for a non-linear relation.

the manufacturing sector (*comp.emp*) due to data availability. Note that the regional wage level is endogenous with respect to the regional employment level which has to be taken into account in the estimation strategy (Topel, 1986).

The percentage share of the population aged under 15 (*pop.young*) is added as a proxy for two unobserved variables which are relevant for the quantity and quality of regional labour supply, namely (i) the amount of experience in the labour market (human capital) and (ii) the effect of having young children (Elhorst, 2003). We control for the share of population with low levels of education (*low skilled*), since the demand for low-skilled workers decreases according to the hypothesis of skill-based technological change cited above. Hence, an increase in (high-skilled) labour demand may not raise employment in regions with a high share of low-skilled people, due to mismatch problems. Moreover, we follow Basile and de Benedicis (2008) for our definition of *market potential*. This measure accounts for both the size of the regional market and its position relative to other regional markets. It is calculated as the sum of GDP of region  $i$  and the weighted GDP of the neighbouring regions, while the latter is weighted with its squared geographical distance between the centroids of the countries (the coordinates of the regional centroids are available upon request).

Furthermore, the scope of the regions in promoting employment is constrained by national labour market institutions. As a consequence, we take into account the level of benefits (Holmlund, 1998) by including the gross replacement rate (*grr*). In addition, we control for *union density* since higher union density could strengthen the bargaining position of the union, resulting in higher wage demands and/or a more compressed wage structure (Scarpetta, 1996; Nickell and Layard, 1999; Blau and Kahn, 1999; Nickell, Nunziata, and Ochel, 2005).

Moreover, we included the employment protection indicator of the OECD to account for employment protection laws following the literature by Lazear (1990). We also considered indicators measuring the structure of the econo-



mies, such as the share of regional employment in the agricultural/industrial sector. However, the latter variables—the employment protection indicator and the share of industry structure in regional employment—are not statistically significant, so we excluded them from our final specifications.

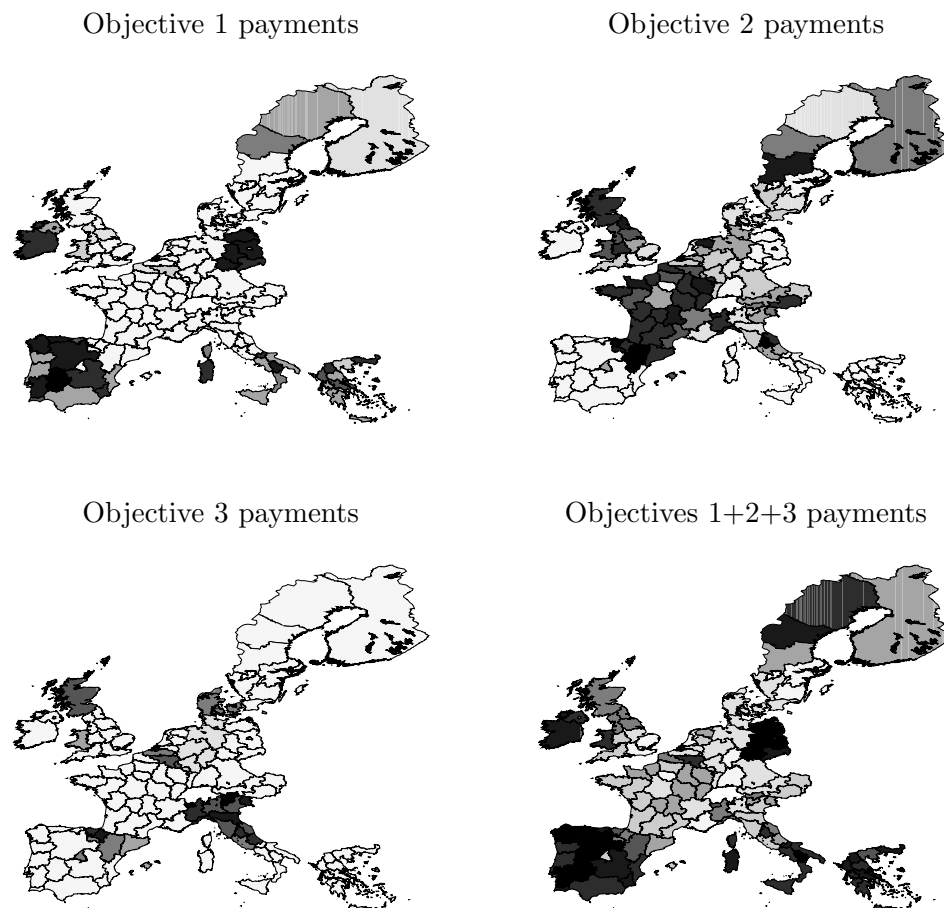
The main variable of interest is the structural funds variable (*sf*). Table 4 clarifies that total structural funds can be classified into three different objectives. Around two-thirds of total structural funds payments are allocated to regions with a GDP lower than 75% of the EU average. This Objective 1 funding has the primary goal to promote development in less prosperous regions. The remaining part is spent without a clear allocation scheme on regions in structural decline (Objective 2) and to support education, training and employment policies (Objective 3). For our empirical analysis we draw on a dataset, which has, to the best of our knowledge, only been used by Mohl and Hagen (2010) in the context of the evaluation of economic growth effects of EU funding. This dataset includes precise measures of EU structural funds by distinguishing between Objective 1, 2 and 3 payments over the time period of 1999-2007.

To present an overview of the regional distribution of the structural funds, Figure 1 shows the quantile maps displaying the distribution of the funds over nine intervals by assigning the same number of values to each of the nine categories in the map. The payments are expressed as a share of population and are displayed as averages over the entire time period of observation. The darker the area, the higher the share of that region's payments of structural funds per capita. The figures show that Ireland, Eastern Germany, Greece, Southern Italy and Spain benefit most from Objective 1 payments, whereas France, the UK, Northern Spain and Sweden show particularly high gains from Objective 2 and Objective 3 payments, respectively.

We are not only interested in analysing the employment impact of total regional structural funds payments, we are also keen on distinguishing between Objective 1, 2 and 3 payments. For this reason we start with specifications including the total sum of Objective 1+2+3 payments and then



**Figure 1:** Quantile maps, averages 1999–2006



*Notes:* Own illustration. The payments of structural funds do not include multiregional funding programmes. The darker the area, the higher the relative share of regions' payments of structural funds per capita.

continue by investigating the impact of each single Objective. It could be argued that structural funds projects, such as infrastructure investment, only become effective after some time lag. Thus, we follow Mohl and Hagen (2010) and analyse the impact of time lags in greater detail: We start our empirical analysis by excluding any structural funds variable before gradually adding the lagged structural funds variables; beginning with a lag of one year and ending up with a specification comprising structural funds with lag of up to four-years ( $sf_{i,t-j}$  with  $j = 1, \dots, 4$ ).

Due to multicollinearity the coefficients and standard errors of the structural funds variable cannot be interpreted if the variable is included into the regression with several lags. As a consequence, we calculate the sum of structural funds coefficients ( $\sum_{j=1}^J sf_{i,t-j}$ ) corresponding to the short-run elasticity (Obj. short-term elast. (size)) and then use a simple Wald test to determine whether the short-run elasticity is statistically different from zero (Obj. short-term elast. (p-value)). As our estimation specification displayed in equation (1) equals a dynamic approach, it is more convincing to interpret the long-term impact of the structural funds. We do so and list its size (Obj. long-term elast. (size)) and significance level (Obj. long-term elast. (p-value)) in the regression output tables. The estimated long-term elasticity could be used to show that a one per cent increase of structural funds (per capita) leads to a rise of the regional employment level by  $X\%$ .

Moreover, we provide a more parsimonious specification and control for both country- and region-fixed effects by subtracting the annual country mean from each of the variables instead of including dummy variables (Bond, Hoeffler, and Temple, 2001). For variables (union density, gross replacement rate) or countries (Denmark, Ireland and Luxembourg) where region-specific variables are not available, we subtract the annual EU mean. For illustrative purposes, the transformed employment level for Bavaria in year  $t$  is computed by subtracting the German employment level in year  $t$ , whereas in the case of Ireland, which only consists of one NUTS region, we subtract the EU mean of year  $t$ .

Furthermore, in order to avoid losing observations, we replace missing entries of the compensation per employee variable with zero and include a dummy variable which is equal to 1 if the variable contains a missing entry (for a similar approach see Fitzenberger, Kohn, and Wang, 2011). The dummy variable is never statistically significant and thus not displayed in the regression output tables. Finally,  $u_{i,t}$  is the i.i.d. error term of the specification. Table 1 gives an overview of the precise definitions and data sources of the variables used. The correlation matrix and the summary statistics are displayed in Tables 2 and 3.

## 2.2 Spatial panel approach

The results of our baseline panel regression approach might be influenced by regional spillover effects, which have been neglected so far, resulting in biased estimates. In our sample of 130 European regions, the regions which are located next to each other might disclose a stronger spatial dependence than regions at a greater distance to one another.

In order to take these considerations into account, we apply spatial econometric techniques, using a  $N \times N$  weight matrix ( $W$ ) containing information about the connectivity between regions. Its diagonal consists of zeros, while each  $w_{ij}$  specifies the way region  $i$  is spatially connected to region  $j$ . To standardise the external influence upon each region, the weight matrix is normalised so that the elements amount to one. We follow the approach by Le Gallo and Ertur (2003) and Ertur and Koch (2006) and use a weight matrix consisting of the  $k$ -nearest neighbours computed from the distance between the centroids of the NUTS regions.<sup>3</sup> This weight matrix is based purely on geographical distance, which has the big advantage that exogeneity

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<sup>3</sup>We use the Matlab toolbox “Arc\_Mat” (LeSage and Pace, 2004) to determine the centroids of the polygons (regions) expressed in decimal degrees. These are converted to latitude and longitude coordinates and are available upon request. The  $x$  nearest neighbours of each region are then calculated with the help of the Spatial Statistics Toolbox 2.0 (Pace, 2003).

of geographical distance is unambiguous. It is defined as follows:

$$W(k) = \begin{cases} w_{ij}^*(k) = 0 & \text{if } i = j \\ w_{ij}^*(k) = 1 & \text{if } d_{ij} \leq d_i(k) \text{ and } w_{ij}(k) = w_{ij}^*(k) / \sum_j w_{ij}^*(k) \\ w_{ij}^*(k) = 0 & \text{if } d_{ij} > d_i(k) \end{cases}$$

where  $w_{ij}^*$  is an element of the unstandardised weight matrix  $W$  and  $w_{ij}$  is an element of the standardised weight matrix,  $d_i(k)$  is the smallest distance of the  $k^{th}$  order between regions  $i$  and  $j$  so that each region  $i$  has exactly  $k$  neighbours.<sup>4</sup>

Generally, the inclusion of a spatially lagged dependent variable into a panel fixed effects model generates an endogeneity problem because the spatially weighted dependent variable is correlated with the disturbance term (Elhorst, 2010). In order to control for this simultaneity, the following results are based on a quasi-maximum likelihood estimator for spatial dynamic panel models as proposed by Yu, de Jong, and Lee (2008). This model foresees spatially-weighted coefficients for both the lagged and the contemporaneous employment level. Apart from the inclusion of the spatial weight variables, the selection of variables remains the same as in equation (1), so we estimate the following model:

$$\begin{aligned} emp_{i,t} = & \beta_0 + \lambda W emp_{i,t} + \rho W emp_{i,t-1} + \gamma emp_{i,t-1} + \beta_2 comp.emp_{i,t-1} + \\ & + \beta_3 pop.young_{i,t-1} + \beta_4 low\ skilled_{i,t-1} + \beta_5 market\ potential_{i,t-1} + \\ & + \beta_6 grr_{i,t-1} + \beta_7 union\ density_{i,t-1} + \beta_8 sf_{i,t-j} + \mu_i + \lambda_t + u_{i,t} \end{aligned} \quad (2)$$

Unfortunately, it is currently not feasible to estimate a spatial lag model and to control simultaneously for endogeneity of the other independent variables, for example with a (system) GMM approach. The reason for this

<sup>4</sup>For example, for  $k = 10$  the elements of the row / column vector of the weight matrix ( $W$ ) for the region “Region de Bruxelles-capitale” (be) are all zeros with the exception of the ten nearest neighbours (be2, be3, fr10, fr21, fr22, fr30, fr41, nl2, nl3 and nl4) whose elements are 0.1.

is that introducing a spatial weight matrix creates a non-zero log-Jacobian transformation from the disturbances of the model to the dependent variable, while the system GMM procedure by Blundell and Bond (1998) is based on the assumption of no Jacobian term involved.<sup>5</sup>

### 2.3 Panel approach with interaction term

As indicated in the introduction, it is not clear from a theoretical perspective whether EU funding is indeed associated with higher employment levels. According to the capital-skill-complementary hypothesis (Griliches, 1969) and the skill-based technological change hypothesis (Berman, Bound, and Griliches, 1994) the demand for skilled labour increases with decreasing capital costs, while the demand for unskilled labour decreases with diminishing capital costs. Hence, it might be argued that structural funds are only conditionally effective depending on the regional education level. In order to test this conditionality, we include an interaction term in the model of equation (1) and estimate the following specification:

$$\begin{aligned}
 emp_{i,t} = & \beta_0 + \beta_1 emp_{i,t-1} + \beta_2 comp.emp_{i,t-1} + \beta_3 pop.young_{i,t-1} + \\
 & + \beta_4 low\ skilled_{i,t-1} + \beta_5 market\ potential_{i,t-1} + \beta_6 grr_{i,t-1} + \\
 & + \beta_7 union\ density_{i,t-1} + \beta_8 sf_{i,t-1} + \beta_9 sf_{i,t-1} \times low\ skilled_{i,t-1} + \\
 & + \beta_{10} high\ skilled_{i,t-1} + \mu_i + \lambda_t + u_{i,t}
 \end{aligned}
 \tag{3}$$

To interpret this model, we calculate the marginal effects of structural funds on the employment level, which consists of the first derivative of the above regression model (for a general overview on interaction models see Braumoeller, 2004; Brambor, Clark, and Golder, 2006). This implies that we have to evaluate the marginal effects at different values of *low skilled*. In doing so, we take into account that the low-skilled variable is only defined over a certain interval, and we calculate the marginal effects for a set of

<sup>5</sup>We thank James LeSage for his helpful advice.

percentiles ( $5^{th}$ ,  $10^{th}$ ...,  $95^{th}$ ) between the minimum and the maximum of the variable *low skilled*. In contrast to plotting the marginal effects over evenly spaced values between the minimum and maximum of the *low skilled* variable, the use of percentiles has the advantage that it illustrates the frequency distribution of the variable and thus enables a more meaningful interpretation of the marginal effects. In addition, we indicate the level of uncertainty regarding the marginal effects by plotting the lower and upper bound of the 95% confidence intervals. The details of the calculations are described in the appendix in Section B.

### 3 Econometric results

From an econometric point of view, the investigation of employment effects of EU funding poses several methodological challenges. First, the empirical results might be biased due to simultaneity: the allocation criteria of the structural funds are likely to be correlated with the dependent variable employment since its allocation depends, *inter alia*, on the regional unemployment rate and the employment structure. Second, regional employment variables might be influenced by regional spillover effects, as structural funds payments may increase one region's employment which, in turn, may affect neighbouring regions' employment positively or negatively. Finally, the estimation results might strongly depend on the choice of the econometric approach.

#### 3.1 Baseline panel approach

We start with checking all specifications for autocorrelation using the test proposed by Wooldridge (2002) (Table 5). As the Wooldridge test clearly rejects the null hypothesis of no first-order autocorrelation, standard errors are specified to be robust not only to heteroskedasticity but also to serial



correlation as proposed by Newey and West (1987).<sup>6</sup> We find a positive and strongly significant impact of the lagged dependent variable. The size and significance level of the coefficient hardly change, irrespective of how many lags of the structural funds variable are included. As expected, our wage variable (*comp.emp*) shows a negative coefficient, which is, however, not significant. A high share of young population and of low level education leads to a statistically significant reduction of the employment level. Moreover, the regional market potential has a positive and significant impact on the employment level. Both variables measuring labour market regulations at the national level—the gross replacement rate and the union density—are not statistically significant.

The main variable of interest is the structural funds variable. Table 5 reveals that the total Objective 1+2+3 payments are not statistically significant. One reason for this might be that the estimation results are biased due to endogeneity of the structural funds variable, since the employment structure is one criterion for the allocation of structural funds. In order to deal with this issue, the literature has suggested two kinds of external instrument variables. Dall’erba and Le Gallo (2008) instrument structural funds payments by the regions’ distance to Brussels, arguing that the spatial distribution of structural funds payments follows a centre-periphery pattern. Bouvet (2005) uses partisan affinity as an instrument for structural funds. However, while the first set of instruments shows no variation over time at all, the time variation of variables related to political affinity is low and in some regions even zero. Thus, their effect on structural funds payments is absorbed once regional fixed effects are controlled for, rendering them unsuitable for a panel fixed effects approach.

As a consequence, we address the problem of endogeneity by basing the identification on internal instruments via a system GMM estimator (Blun-

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<sup>6</sup>As a robustness check, we used the estimation procedure proposed by Prais-Winsten and Driscoll and Kraay (1998). The results hardly change and they are available upon request.

dell and Bond, 1998). We assume that lagged employment, compensation per employee, education, market potential and structural funds payments are endogenous. The standard errors are finite-sample adjusted following Windmeijer (2005). When using the system GMM estimator the number of instruments grows quadratically with  $T$ . Too many instruments can overfit the instrumented variables (Roodman, 2009), reduce the power properties of the Hansen test (Bowsher, 2002) and lead to a downward-bias in two-step standard errors (Windmeijer, 2005). In order to guarantee a parsimonious use of instruments, we follow Mehrhoff (2009) and limit the number of instruments by using the ‘collapse’ option Roodman (2009). As a robustness check we also increased the number of instruments in the system GMM regressions; however, the results hardly differ.

Given this parsimonious specification, the estimation results show that the Hansen test of overidentifying restrictions is not statistically significant, i.e. the null hypothesis which states that the instruments are not correlated with the residual cannot be rejected (Table 5). We also report the p-values for the tests of serial correlation. These tests are based on first-differenced residuals and we expect the disturbances  $u_{i,t}$  not to be serially-correlated in order to yield valid estimation results. The regression output in Table 5 shows no second-order serial correlation (AR(2) (p-value)). For most variables, the size and significance level are comparable to the results of the previous regressions. The use of the system GMM estimator slightly increases the size of the coefficients of the lagged dependent variable, while the market potential variable is no longer statistically significant. Above all, the Objective 1+2+3 variable is still not statistically significant.

Even though the total payments of structural funds have no significant impact, it cannot be ruled out that sub-parts of the EU funding significantly affect the employment level. As a consequence, we re-run our regression model using more precise measures of structural funds, distinguishing between Objective 1, 2 and 3 payments. The results show that the size of the coefficients of the Newey and West specifications are in line with the results

of the more aggregated analysis (Table 6). In particular, the coefficients of the disaggregated structural funds variable are not statistically significant. Switching to the system GMM estimator again slightly increases the size of the coefficients of the lagged dependent variable (Table 6). Moreover, the short- and long-term elasticities of Objective 1 payments now show jointly statistically significant negative coefficients when the structural funds variable is included with more than one lag, while Objective 3 payments have a significantly positive coefficient when more than two lags are included.

As mentioned above, the most likely channel through which structural funds affect employment is an increase in the regional capital endowment, which leads to an increase of the marginal product of labour, the output level, and, *ceteris paribus*, the labour demand, given a matching labour supply. When estimating the effect of EU funding on employment, some part of the causal effect might be, at least in an indirect way, absorbed by the inclusion of the market potential. For this reason we replace our proxy for the output level and define *market potential 2* for region  $i$  as the weighted GDP of the neighbouring regions, thereby excluding the GDP of region  $i$ . The reduced-form approach including the regions' output level may be interpreted as being based on a 'conditional labour demand model', the estimation strategy without the regions' output level as being based on an 'unconditional labour demand model'.

In line with the results of described above, the size and significance level of the independent variables hardly change.<sup>7</sup> In particular, our indicator measuring market potential is still positive and the total structural funds variable is not significant. We also estimated the model using the disaggregated structural funds variables. The size and significance levels remain broadly unchanged except that the Objective 3 variable is no longer statistically significant.

The use of the *market potential 2* variable is still associated with the potential problem of regional spillover effects. As a consequence, we drop

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<sup>7</sup>The detailed regression results are available upon request.

the market potential variable and re-run the regressions. Table 7 reveals that the results of the independent variables broadly remain unchanged and that the structural funds variable is still not statistically significant. Switching to the disaggregated analyses shows that Objective 1 payments partly show a negative and significant coefficient, while Objective 3 funding has a jointly significant positive impact if the structural funds variable is included with more than one lag.

## 3.2 Spatial panel approach

The estimation of a spatial panel model requires the definition of a spatial weight matrix. We start our regression analysis with a very low value for the indicator measuring the closeness; assuming that the spillover effects are limited to the four closest regions ( $k = 4$ ). Table 8 reveals that the contemporaneous spatial weight matrix ( $\gamma$ ) has a positive and strongly significant coefficient, while the lagged spatial weight matrix ( $\rho$ ) has a negative and statistically significant coefficient. This implies that spillover effects seem to have an immediate positive cross-regional effect, boosting the employment level before they turn negative. This negative impact may be explained by migration and commuting, i.e. people tend to move or commute to the neighbouring regions if economic differences of the regional labour market persist, resulting in negative employment effects in the origin region.

Apart from the spillover effect, the results show that the significance levels of the coefficients are broadly comparable with the non-spatial regressions. The size of most coefficients is slightly reduced as some of the causal relationship can be explained by regional spillover effects. The lagged dependent variable still has a strong positive impact on the employment level. A high share of young population and low levels of education have a significantly negative effect. Market potential promotes the regional employment, and the coefficients of union density and the gross replacement rate are not statistically significant.

As regards the structural funds variable, Table 8 reveals that total struc-

tural funds now seem to have a jointly negative impact if more than two lags are included. Using more disaggregated structural funds data, we find a small negative impact of Objective 3 payments (Table 9). The results do not change when switching to the model excluding the market potential variable (Tables 8, 9).

As some papers claim that the regression results are very sensitive to the choice of the weight matrix (LeSage and Fischer, 2008; LeSage and Pace, 2010), we also estimate our regression model for various spatial weight matrices, i.e. we use different parameters of  $k$ , an inverse euclidean ( $W.dist$ ) and an inverse squared euclidean ( $W.dist2$ ) distance weight matrix. Table 10 shows that with a larger coefficient of the weight matrix the coefficients of the contemporaneous and lagged weight matrices rise. However, the increases are limited to a certain range, and the size and significance levels of the other independent variables are not substantially affected. Irrespective of the choice of the matrix, the weight coefficients are statistically significant at the 1% level. Furthermore, the size and significance levels of the other independent variables hardly change with a different weight matrix.

### 3.3 Panel approach with interaction term

Finally, we investigate whether structural funds are conditionally effective depending on the education levels of the working age population, i.e. the skill-level of labour supply. For this purpose, we estimate an interaction model using the structural funds and the low-skill variable in an interaction framework. Unlike the remaining independent variables, the low-skilled variable is only available from the year 1999 onwards, so we restrict our estimation to three lags only.

The results displayed in Table 11 show that the lagged dependent variable is still strongly significant, while the statistical significance of the remaining coefficients is reduced. The coefficient of the interaction term tells us how the marginal effect varies according to values of low education, while its significance level tests whether low education (linearly) conditions the effect

of structural funds on employment (and vice versa). However, as indicated above, it is more convincing to base the interpretation on the calculation of the marginal effects.

We graph the marginal effects of the short- and long-term elasticities for varying values of the education variable, starting with the total structural funds (top left panel) and followed by Objective 1 (top right panel), Objective 2 (bottom left panel) and Objective 3 (bottom right panel) payments (Figure 2). The straight line displayed in the graphs represent the marginal effect of structural funds surrounded by 95% confidence intervals. The marginal effects of structural funds are a linear function of *low skilled*. Moreover, the coefficients displayed in Table 11 indicate the impact of structural funds when *low skilled* is zero, while the interaction coefficient gives our estimate of the slope of the marginal effect line.

Figure 2 shows that the marginal effects of structural funds and our confidence regarding the marginal effects vary with values of *low skilled*. Moreover, the marginal effects of total structural funds payments clearly show a negative slope. The total structural funds payments have a positive impact on the employment level in regions with a low share of low-skilled population, while they have a negative impact in regions with a high share of low-skilled population. These insights are particularly valid for the marginal effects of the long-term elasticities of Objective 1+2+3 and of Objective 1 payments. As regards Objective 2 payments, the slope of the marginal effects depends on the number of lags and the confidence intervals point to no significant impact. Finally, the marginal effects of the Objective 3 payments have a slight negative slope but do not turn negative.

These results are still valid when switching to the model excluding market potential and when including the high-skilled variable as an additional independent variable. Moreover, the results hardly change when estimating a dynamic spatial panel interaction model in the model including or excluding market potential.<sup>8</sup> Finally, we estimate our interaction model by replacing

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<sup>8</sup>The estimation results are not displayed in their entirety due to space constraints but



the variable measuring educational attainment. We interact the structural funds variable with an indicator measuring the share of high-skilled population. Figure 3 illustrates that this leads to a positive linear effect, implying that structural funds have a positive impact on the employment level in regions with a high share of high-skilled population, whereas they negatively affect the employment level in regions with a low share of high-skilled population.

## 4 Conclusions

While the current literature on the effectiveness of EU funding has primarily concentrated on the investigation of the economic growth effects, the aim of this paper is to evaluate their employment impact. From a theoretical perspective higher expenditures on EU funding do not necessarily lead to higher total employment levels. Instead, its effectiveness depends, in particular, on whether structural funds payments are used as capital subsidies or as human capital investment and it is subject to the educational attainment of the population as well as to the labour market tightness. The paper contributes to the literature by (i) investigating the relevance of the inconclusive theoretical prediction via the estimation of interaction effects, (ii) analysing more precise measures of EU aid over an extended time period and (iii) applying dynamic (spatial) panel techniques, controlling for heteroscedasticity, serial and spatial correlation, as well as for endogeneity. In particular, using a spatial dynamic panel approach, we find that regional spillovers do have a significant impact on the regional employment level irrespective of which Objective and time lag is analysed.

In line with the theoretical predictions, we find no clear evidence that

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are available upon request. We also estimated the regression model with various spatial weight matrices in order to check the robustness of the results. The empirical evidence, which is available upon request, shows that the spatial panel interaction model does not depend on the choice of the spatial weight matrix.

EU funding promotes employment. Instead, structural funds payments seem to be used as capital subsidies: they have a statistically positive impact on employment in regions with a low share of low-skilled population, and they have a negative impact on the employment level in regions with a high share of low-skilled population. Broadly summarising, we find that a one per cent increase of total structural funds payments leads to a positive (negative) impact on the regional employment by approximately 0.05% in regions with a high (low) share of skilled population. These results seem to be mainly driven by Objective 1 funding, which corresponds to the largest part of total structural funds payments.

Apart from the theoretically-founded explanation, a statistically insignificant, or even negative, impact of structural funds payments can be explained by at least four factors: First, in contrast to Objective 1 payments, Objective 2 and 3 payments are not solely based on clear criteria. Hence, there is room for political bargaining and/or side payments so that politically motivated projects are financed rather than economically efficient and growth-increasing projects. Second, *de jure* the structural funds payments have to be co-financed. However, recent panel studies using country data provide evidence that some crowding out of national public investment may take place (Hagen and Mohl, 2011a). This, in turn, might have a negative impact on the regional GDP. Third, Cohesion policy could be ineffective with regard to human capital investment. Finally, a positive employment effect due to additional labour demand driven by a short-term aggregate demand stimulus is only possible if the quality and quantity of labour supply suffices. This may not be the case in periods of positive output gaps, for example, in the new East-European member states.

The results have policy implications for the setup of future Multiannual Financial Frameworks. It becomes evident that EU funding lacks a clear concept on how to promote employment in the medium- to long-run. Our results indicate that the high-skilled population in particular benefits from EU structural funds payments. As a consequence, a strategy should define

objectives which are clearly measurable and allow for an ex-post assessment of this policy field. This, in turn, would contribute to a more effective policy.

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# Appendix

## A Description of the dataset

The European regions are classified by the European Commission into three different groups called “Nomenclature des unités territoriales statistiques” (NUTS). These units refer to the country level (NUTS-0) and to three lower subdivisions (NUTS-1, NUTS-2 and NUTS-3), which are classified according to the size of population. Our dataset consists of both NUTS-1 and NUTS-2 regions. In order to guarantee the highest degree of transparency, this section lists the abbreviations of the NUTS codes in brackets following the classifications of the European Commission (2007).

The choice of the NUTS level follows the data availability of structural funds payments. Generally, we try to use data on NUTS-2 level whenever possible. This is the case for France, Greece, Italy, Portugal, Spain, and Sweden. However, in case of Germany we have to use NUTS-1 level because the annual reports do not contain more detailed information. Moreover, in some countries there is no clear-cut distinction in the sense that in the annual reports the structural funds are partly allocated to the NUTS-1 and partly to the NUTS-2 level. Finally, the annual reports of structural funds for 1995 and 1996 (European Commission, 1996b, 1997) for some countries only contain data at the NUTS-1 level. As a consequence, we chose the NUTS-1 level for Austria, Belgium, Finland, the Netherlands, and the United Kingdom.

For Denmark and Luxembourg subdivisions do not exist, so that NUTS-0, NUTS-1 and NUTS-2 codes are the same. We regard these cases as NUTS-2 regions. In Ireland the labels of NUTS-0 and NUTS-1 are identical, so that we classify Ireland as a NUTS-1 region. Please note that we do not consider the overseas regions of France (Départments d’outre-mer (fr9) consisting of Guadeloupe (fr91), Martinique (fr92), Guyane (fr93) and Réunion (fr94)), Portugal (Região Autónoma dos Açores (pt2, pt20), Região Autónoma da Madeira (pt3, pt30)), and Spain (Canarias (es7, es70)). As a consequence, our dataset consists of the following 130 NUTS-1 and NUTS-2 regions, for which we have structural funds payments:

**Belgium** (3 NUTS-1 regions): Région de Bruxelles-capitale (be1), Vlaams Gewest (be2), Région Wallonne (be3);

**Denmark** (1 NUTS-2 region): Denmark (dk);

**Germany** (16 NUTS-1 regions): Baden-Württemberg (de1), Bayern (de2), Berlin (de3), Brandenburg (de4), Bremen (de5), Hamburg (de6), Hessen (de7), Mecklenburg-Vorpommern (de8), Niedersachsen (de9), Nordrhein-Westfalen (dea),

Rheinland-Pfalz (deb), Saarland (dec), Sachsen (ded), Sachsen-Anhalt (dee), Schleswig-Holstein (def), Thüringen (deg);

**Greece** (13 NUTS-2 regions): Anatoliki Makedonia, Thraki (gr11), Kentriki Makedonia (gr12), Dytiki Makedonia (gr13), Thessalia (gr14), Ipeiros (gr21), Dytiki Ellada (gr23), Ionia Nisia (gr22), Sterea Ellada (gr24), Peloponnisos (gr25), Attiki (gr30), Voreio Aigaio (gr41), Notio Aigaio (gr42), Kriti (gr43);

**Spain** (16 NUTS-2 regions): Galicia (es11), Principado de Asturias (es12), Cantabria (es13), País Vasco (es21), Comunidad Foral de Navarra (es22), La Rioja (es23), Aragón (es24), Comunidad de Madrid (es30), Castilla y León (es41), Castilla-La Mancha (es42), Extremadura (es43), Cataluña (es51), Comunidad de Valenciana (es52), Illes Balears (es53), Andalucía (es61), Región de Murcia (es62), Ciudad Autónoma de Ceuta (es63), Ciudad Autónoma de Melilla (es64);

**France** (22 NUTS-2 regions): Île de France (fr10), Champagne-Ardenne (fr21), Picardie (fr22), Haute-Normandie (fr23), Centre (fr24), Basse-Normandie (fr25), Bourgogne (fr26), Nord-Pas-de-Calais (fr30), Lorraine (fr41), Alsace (fr42), Franche-Comté (fr43), Pays-de-la-Loire (fr51), Bretagne (fr52), Poitou-Charentes (fr53), Aquitaine (fr61), Midi-Pyrénées (fr62), Limousin (fr63), Rhône-Alpes (fr71), Auvergne (fr72), Languedoc-Roussillon (fr81), Provence-Alpes-Côte d'Azur (fr82), Corse (fr83);

**Ireland** (1 NUTS-1 region): Irland (ie);

**Italy** (21 NUTS-2 regions): Piemonte (itc1), Valle d'Aosta/Vallée d'Aoste (itc2), Liguria (itc3), Lombardia (itc4), Provincia autonoma Bolzano (itd1), Provincia autonoma Trento (itd2), Veneto (itd3), Friuli-Venezia Giulia (itd4), Emilia-Romagna (itd5), Toscana (ite1), Umbria (ite2), Marche (ite3), Lazio (ite4), Abruzzo (itf1), Molise (itf2), Campania (itf3), Puglia (itf4), Basilicata (itf5), Calabria (itf6), Sicilia (itg1), Sardegna (itg2);

**The Netherlands** (4 NUTS-1 regions): Noord-Nederland (nl1), Oost-Nederland (nl2), West-Nederland (nl3), Zuid-Nederland (nl4);

**Luxembourg** (1 NUTS-1 region): Luxembourg (lu);

**Austria** (3 NUTS-1 regions): Ostösterreich (at1), Südösterreich (at2), Westösterreich (at3);

**Portugal** (5 NUTS-2 regions): Norte (pt11), Algarve (pt15), Centro (P) (pt16), Lisboa (pt17), Alentejo (pt18);

**Finland** (2 NUTS-1 regions): Manner-Suomi (fi1), Åland (fi2);

**Sweden** (8 NUTS-2 regions): Stockholm (se11), Östra Mellansverige (se12), Småland med öarna (se021), Sydsverige (se22), Västsverige (se23), Norra Mellansverige (se31), Mellersta Norrland (se32), Övre Norrland (se33);

**UK** (12 NUTS-1 regions): North East (ukc), North West (ukd), Yorkshire and the Humber (uke), East Midlands (ukf), West Midlands (ukg), East of England (ukh), London (uki), South East (ukj), South West (ukk), Wales (ukl), Scotland (ukm), Northern Ireland (ukn).

## B Descriptive statistics and regression results

Table 1: Variables and data sources

Variable	Definition	Source
Emp	Employment ( <i>reg_lfe2enace</i> ) over total population between 15 and 64 years ( <i>reg_d2avg</i> )	
Comp. emp	Compensation of employees in the manufacturing sector in million of Euro ( <i>reg_e2rem</i> )	
Pop. young	Share of population aged 15 and below ( <i>reg_d2jan</i> ) over total population	
Low-skilled	Share of population aged 15 and over whose highest level of education is pre-primary, primary and lower secondary education – levels 0-2 according to the International Standard Classification of Education (ISCED) 1997 ( <i>reg_lfsd2pedu</i> )	Eurostat Regio statistics (the official Eurostat codes are listed in parentheses)
High-skilled	Share of population aged 15 and over whose highest level of education is tertiary education – levels 5-6 according to ISCED (1997) ( <i>reg_lfsd2pedu</i> )	
Market potential	Sum of GDP ( <i>reg_e2gdp</i> ) of region <i>i</i> and GDP of all other regions <i>k</i> , weighted by the square of the Euclidean distance from region <i>i</i> to region <i>k</i> $market\ potential_{i,t} = GDP_{i,t} + \sum_k (GDP_k / d_{ik}^2)$ .	
Market potential 2	GDP of all other regions <i>k</i> , weighted by the square of the Euclidean distance from region <i>i</i> to region <i>k</i> $market\ potential2_{i,t} = \sum_k (GDP_k / d_{ik}^2)$ .	
grr	Gross replacement rate, which measures the average of the gross unemployment benefit replacement rates for two earnings levels, three family situations and three durations of unemployment divided by 100. The original data are for every second year and have been linearly interpolated.	OECD, database on unemployment benefit entitlements and replacement rates
Union density	Trade union density	OECD
SF pc Obj. 1	Objective 1 payments per capita in Euro	Data for 1999 are from the European Commission (2000); Data for the period 2000–2006 were accessed at the European Commission in Brussels on 24/25 November 2007
SF pc Obj. 2	Objective 2 payments per capita in Euro	
SF pc Obj. 3	Objective 3 payments per capita in Euro	
SF pc Obj. 1+2+3	Objectives 1+2+3 payments per capita in Euro	

Table 2: Correlation matrix

	Emp.	Comp. emp.	Pop. young	Low-skilled	Grr	Union density
Emp.	1					
Comp. emp.	0.4411	1				
Pop. young	0.1267	0.3352	1			
Low-skilled	-0.3511	-0.7035	-0.2066	1		
Grr	0.3549	0.6781	0.2533	-0.4792	1	
Union density	0.3767	0.6633	0.3282	-0.5468	0.6657	1
Market potential	0.0298	0.0821	0.097	0.2428	-0.0713	-0.0632
Market potential 2	0.3388	0.1172	0.0789	-0.3231	-0.0269	-0.0304
SF pc Obj. 1	-0.403	-0.452	-0.2357	0.2999	-0.3702	-0.3348
SF pc Obj. 2	0.0757	0.1218	0.0103	-0.088	-0.0196	0.1219
SF pc Obj. 3	0.0663	-0.1118	-0.2965	0.1362	-0.0372	-0.0018
SF pc Obj. 1+2+3	-0.4062	-0.4644	-0.2778	0.3121	-0.406	-0.3284
	Market potential	Market potential 2	SF pc Obj. 1	SF pc Obj. 2	SF pc Obj. 3	SF pc Obj. 1+2+3
Market potential	1					
Market potential 2	-0.0431	1				
SF pc Obj. 1	-0.144	-0.0851	1			
SF pc Obj. 2	0.1441	-0.0935	-0.3468	1		
SF pc Obj. 3	0.0923	0.1068	-0.2243	0.2284	1	
SF pc Obj. 1+2+3	-0.1092	-0.1047	0.9637	-0.0989	-0.088	1



**Table 3:** Summary statistics

Variable		Mean	Std. dev.	Minimum	Maximum	Observations
Emp.	overall	0.6334	0.0833	0.2456	0.8398	N = 1142
	between		0.0803	0.3669	0.8253	n = 130
	within		0.0244	0.5121	0.7119	T = 8.7846
Comp. emp.	overall	24,377.8	8,389.6	5,899.5	47,353.4	N = 961
	between		8,585.8	7,504.2	47,080.6	n = 130
	within		1,490.1	15,193.8	30,414.2	T = 7.3923
Pop. young	overall	0.1608	0.0261	0.1000	0.2340	N = 1163
	between		0.0257	0.1034	0.2249	n = 130
	within		0.0054	0.1408	0.1888	T = 8.9462
Low-skilled	overall	0.4443	0.1789	0.0911	0.8746	N = 1163
	between		0.1669	0.1557	0.8352	n = 130
	within		0.0671	0.0133	0.6447	T = 8.9462
Grr	overall	0.3127	0.1012	0.1207	0.6107	N = 1168
	between		0.0986	0.1329	0.5166	n = 130
	within		0.0238	0.1954	0.4068	T = 8.9846
Union density	overall	0.2779	0.1813	0.0782	0.8063	N = 1106
	between		0.1775	0.0813	0.7705	n = 130
	within		0.0124	0.2151	0.3193	T = 8.5077
Market potential	overall	155,565.6	109,534.1	22,697.7	606,570.4	N = 1032
	between		109,565.2	24,062.4	595,974.7	n = 129
	within		8,641.8	78,995.9	207,308.0	T = 8
Market potential 2	overall	78,719.1	37,566.6	16,052.9	282,920.6	N = 1032
	between		37,495.7	16,687.0	257,092.1	n = 129
	within		3,855.2	43,116.4	104,547.6	T = 8
SF pc Obj. 1	overall	44.2765	71.8250	0.0000	408.1175	N = 1169
	between		63.0015	0.0000	272.1494	n = 130
	within		34.9174	0.0000	280.3748	T = 8.9923
SF pc Obj. 2	overall	10.2749	16.8297	0.0000	300.6687	N = 1170
	between		11.9288	0.0000	67.8109	n = 130
	within		11.9129	0.0000	243.1328	T = 9
SF pc Obj. 3	overall	2.5094	6.3707	0.0000	51.3384	N = 1170
	between		5.6338	0.0000	33.4844	n = 130
	within		3.0106	0.0000	23.9043	T = 9
SF pc Obj. 1+2+3	overall	57.0718	66.9904	0.0000	408.1175	N = 1169
	between		56.0263	0.0000	272.1494	n = 130
	within		37.0368	0.0000	298.6794	T = 8.9923

**Table 4:** Definition of the structural funds variables by Objective, 1994–2006

Definition	1994-1999	Definition	2000-2006
	share of total SF		share of total SF
<b>Obj. 1:</b> To promote the development and structural adjustment of regions whose development is lagging behind the rest of the EU	67.6%	<b>Obj. 1:</b> Supporting development in the less prosperous regions	69.7%
<b>Obj. 6:</b> Assisting the development of sparsely-populated regions (Sweden & Finland only)	0.5%		
<b>Obj. 2:</b> To convert regions seriously affected by industrial decline	11.1%	<b>Obj. 2:</b> To support the economic and social conversion of areas experiencing structural difficulties	11.5%
<b>Obj. 5b:</b> Facilitating the development and structural adjustment of rural areas	4.9%		
<b>Obj. 3:</b> To combat long-term unemployment & facilitate the integration into working life of young people & of persons exposed to exclusion from the labour market	10.9%	<b>Obj. 3:</b> To support the adaptation and modernisation of education, training & employment policies in regions not eligible under Obj. 1	12.3%
<b>Obj. 4:</b> To facilitate the adaptation of workers to industrial changes and to changes in production systems			

Source: European Commission.

Table 5: Reduced-form employment model including market potential: Objectives 1+2+3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Newey and West (1987)				Two-step system GMM					
Emp. per wp. (t-1)	0.469*** (4.063)	0.469*** (4.060)	0.468*** (4.095)	0.466*** (4.077)	0.467*** (4.083)	0.593*** (6.738)	0.594*** (7.799)	0.664*** (9.635)	0.718*** (9.830)	0.737*** (11.21)
Comp. emp. (t-1)	-0.00329 (-0.241)	-0.00331 (-0.242)	-0.00237 (-0.175)	-0.00252 (-0.185)	-0.00252 (-0.185)	-0.00392 (-0.0596)	-0.00529 (-0.112)	-0.0349 (-0.779)	-0.0303 (-0.852)	-0.0301 (-0.711)
Pop. young (t-1)	-0.156*** (-4.381)	-0.155*** (-4.361)	-0.157*** (-4.399)	-0.158*** (-4.384)	-0.158*** (-4.383)	-0.113*** (-2.386)	-0.120** (-3.072)	-0.0858* (-2.174)	-0.0817* (-2.157)	-0.0812* (-2.163)
Low-skilled (t-1)	-0.0749* (-2.010)	-0.0750* (-2.012)	-0.0725* (-1.990)	-0.0724* (-1.995)	-0.0724* (-1.991)	-0.0632 (-1.762)	-0.0696* (-2.326)	-0.100** (-2.658)	-0.0701 (-1.694)	-0.0645 (-1.745)
Grr (t-1)	0.000342 (0.0362)	0.000346 (0.0366)	0.000199 (0.0203)	0.000155 (0.0157)	0.000172 (0.0175)	-0.000719 (-0.125)	0.00163 (0.317)	0.00247 (0.416)	0.00173 (0.348)	0.000825 (0.197)
Union density (t-1)	0.00410 (0.128)	0.00405 (0.126)	0.00542 (0.168)	0.00609 (0.187)	0.00599 (0.183)	-0.00230 (-0.580)	-0.00231 (-0.571)	-0.00119 (-0.302)	-0.00195 (-0.466)	-0.00195 (-0.627)
Market potential (t-1)	0.122* (2.449)	0.123* (2.472)	0.105* (2.063)	0.100 (1.946)	0.0999 (1.945)	0.0542 (1.062)	0.0483 (1.337)	0.0416 (0.951)	0.0309 (1.164)	0.0360 (1.377)
SF pc Obj. 1+2+3 (t-1)	0.000177 (0.0968)	0.000437 (0.240)	0.000451 (0.248)	0.000453 (0.249)	0.000451 (0.248)	0.000451 (0.248)	-0.00236 (-0.436)	-0.00258 (-0.523)	-0.00486 (-0.991)	-0.00519 (-1.074)
SF pc Obj. 1+2+3 (t-2)			-0.00337* (-2.045)	-0.00336* (-2.040)	-0.00337* (-2.057)			7.94e-05 (0.0396)	0.000337 (0.124)	3.91e-05 (0.165)
SF pc Obj. 1+2+3 (t-3)				-0.00147 (-0.941)	-0.00149 (-0.945)				0.000787 (0.387)	0.000542 (0.316)
SF pc Obj. 1+2+3 (t-4)					0.000237 (0.214)				0.00213 (1.269)	0.00213 (1.269)
Constant	-0.117** (-2.599)	-0.117** (-2.598)	-0.100 (-1.436)	-0.0970 (-1.358)	-0.0960 (-1.350)	0.00213 (0.790)	0.00226 (0.842)	0.00233 (0.869)	0.00169 (0.830)	0.00139 (0.796)
Obj. 1+2+3 short-term elast. (size)			-0.00303 (-0.00303)	-0.00437 (-0.00437)	-0.00417 (-0.00417)			-0.00250 (-0.00250)	-0.00374 (-0.00374)	-0.00248 (-0.00248)
Obj. 1+2+3 short-term elast. (p-value)			0.153	0.103	0.144			0.599	0.545	0.634
Obj. 1+2+3 long-term elast. (size)		0.000334 (0.923)	-0.00571 (-0.00571)	-0.00819 (-0.00819)	-0.00783 (-0.00783)		-0.00582 (-0.00582)	-0.00743 (-0.00743)	-0.0133 (-0.0133)	-0.00942 (-0.00942)
Obj. 1+2+3 long-term elast. (p-value)			0.152	0.105	0.154		0.666	0.607	0.519	0.618
Wooldridge AR(1) (p-value)	0	0	0	0	0					
AR(1) (p-value)						0.00243	0.00168	0.000473	0.000342	0.000273
AR(2) (p-value)						0.248	0.246	0.265	0.278	0.300
Hansen (p-value)						0.422	0.455	0.449	0.392	0.645
No. of instruments						33	41	49	57	65
No. of observations	959	959	959	959	959	129	129	129	129	129
No. of regions	129	129	129	129	129	129	129	129	129	129

Notes: In columns (1) to (5) standard errors are calculated according to Newey and West (1987), t-statistics are reported in parentheses. In columns (6) to (10) z-statistics are listed in parentheses applying the two-step system GMM estimator as proposed by Blundell and Bond, 1998). The lagged dependent variable, compensation per employee, low-skilled, market potential and the structural funds variables are assumed to be endogenous. We instrument the endogenous variables with both its lags and its differenced lags and use the "collapse" option. Standard errors are corrected using the approach by Windmeijer (2005). \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

Table 6: Reduced-form employment model including market potential: Objectives 1, 2, 3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Newey and West (1987)				Two-step system GMM				
Emp. per wp. (t-1)	0.469*** (4.063)	0.467*** (4.026)	0.468*** (4.045)	0.467*** (4.034)	0.468*** (4.040)	0.588*** (8.791)	0.629*** (11.39)	0.670*** (14.18)	0.677*** (16.92)
Comp. emp. (t-1)	-0.00329 (-0.241)	-0.00368 (-0.268)	-0.00336 (-0.244)	-0.00363 (-0.263)	-0.00352 (-0.255)	-0.0503 (-1.049)	-0.0760* (-1.973)	-0.0587* (-1.208)	-0.0509 (-1.190)
Pop. young (t-1)	-0.156*** (-4.381)	-0.154*** (-4.296)	-0.151*** (-4.154)	-0.151*** (-4.053)	-0.150*** (-4.003)	-0.104* (-2.532)	-0.0658 (-1.657)	-0.0471* (-2.069)	-0.0258 (-0.960)
Low-skilled (t-1)	-0.0749* (-2.010)	-0.0746* (-1.988)	-0.0722 (-1.946)	-0.0707 (-1.900)	-0.0720 (-1.885)	-0.0947*** (-2.688)	-0.103*** (-3.439)	-0.0746 (-1.754)	-0.0635 (-1.657)
Grr (t-1)	0.000342 (0.0362)	0.000384 (0.0409)	0.000125 (0.0130)	0.00167 (0.0172)	0.00228 (0.0236)	-0.00180 (-0.266)	-0.000712 (-0.114)	-0.00277 (-0.322)	-0.00155 (-0.322)
Union density (t-1)	0.00410 (0.128)	0.00417 (0.130)	0.00542 (0.166)	0.00593 (0.180)	0.00570 (0.173)	-0.00237 (-0.547)	-0.00239 (-0.608)	-0.00218 (-0.534)	-0.00161 (-0.335)
Market potential (t-1)	0.122* (2.449)	0.125* (2.502)	0.119* (2.346)	0.116* (2.288)	0.115* (2.255)	0.0599 (1.272)	0.0359 (1.191)	0.0215 (1.055)	0.0196 (1.145)
SF pc Obj. 1 (t-1)	0.000650 (0.452)	0.000650 (0.452)	0.00156 (1.058)	0.00150 (1.058)	0.00143 (1.018)	-0.00394 (-0.866)	-0.00416 (-1.266)	-0.00692 (-1.539)	-0.00632 (-1.784)
SF pc Obj. 1 (t-2)			-0.00363* (-2.140)	-0.00389* (-2.336)	-0.00398* (-2.311)				-0.00216 (-0.888)
SF pc Obj. 1 (t-3)				-0.00244 (-0.177)	-0.000316 (-0.222)				0.000920 (0.0882)
SF pc Obj. 1 (t-4)					0.000579 (0.389)				0.000953 (0.635)
SF pc Obj. 2 (t-1)		-0.00116 (-0.603)	-0.00198 (-1.049)	-0.00192 (-1.049)	-0.00185 (-0.948)	0.000992 (0.204)	0.00399 (0.535)	0.00813 (1.043)	0.00527 (0.804)
SF pc Obj. 2 (t-2)			0.00105 (0.726)	0.00120 (0.833)	0.00114 (0.766)		0.000819 (0.266)	0.000518 (0.126)	0.000460 (0.149)
SF pc Obj. 2 (t-3)				-0.00181 (-1.195)	-0.00174 (-1.170)			-0.00134 (-0.542)	-0.000178 (-0.0922)
SF pc Obj. 2 (t-4)					0.000365 (0.264)				0.00164 (1.132)
SF pc Obj. 3 (t-1)		0.00131 (0.662)	0.00191 (0.946)	0.00178 (0.891)	0.00209 (1.026)	0.00546 (0.692)	0.00994 (0.535)	0.00998 (1.570)	0.0180** (2.641)
SF pc Obj. 3 (t-2)			-0.000654 (-0.378)	-0.000836 (-0.498)	-0.000665 (-0.400)		-0.00367 (-0.971)	-0.000984 (-0.196)	-0.00177 (-0.304)
SF pc Obj. 3 (t-3)				0.000586 (0.368)	0.000751 (0.469)			0.00455 (1.547)	0.00384 (1.192)
SF pc Obj. 3 (t-4)					-0.00119 (-0.779)				-0.00374 (-1.027)
Constant	-0.117** (-2.599)	-0.122** (-3.089)	-0.114** (-2.891)	-0.113 (-1.567)	-0.112 (-1.561)	0.00259 (0.882)	0.00254 (0.767)	0.00171 (0.738)	0.000849 (0.368)
Obj. 1 short-term elast. (size)				-0.00264	-0.00228		-0.00649	-0.00786	-0.00665
Obj. 1 short-term elast. (p-value)				0.337	0.417		0.0194	0.0169	0.0594
Obj. 1 long-term elast. (size)		0.00122	-0.00390	-0.00495	-0.00429		-0.0175	-0.0238	-0.0206
Obj. 1 long-term elast. (p-value)		0.657	0.358	0.347	0.433		0.00929	0.0115	0.0456
Obj. 2 short-term elast. (size)			-0.000936	-0.00254	-0.00209		0.00481	0.00628	0.00719
Obj. 2 short-term elast. (p-value)			0.654	0.232	0.390		0.419	0.176	0.164
Obj. 2 long-term elast. (size)		-0.00218	-0.00176	-0.00477	-0.00393		0.00241	0.0130	0.0190
Obj. 2 long-term elast. (p-value)		0.545	0.545	0.201	0.366		0.842	0.435	0.194
Obj. 3 short-term elast. (size)			0.00126	0.00153	0.000987		0.00628	0.0135	0.0164
Obj. 3 short-term elast. (p-value)			0.614	0.600	0.764		0.610	0.152	0.0265
Obj. 3 long-term elast. (size)		0.00246	0.00237	0.00287	0.00185		0.0133	0.0169	0.0410
Obj. 3 long-term elast. (p-value)		0.504	0.613	0.602	0.763		0.486	0.613	0.129
Wooldridge test AR(1) (p-value)	0	0	0	0	0				
AR(1) (p-value)						0.000676	0.000236	7.59e-05	5.49e-05
AR(2) (p-value)						0.238	0.217	0.208	0.226
Hansen (p-value)						0.858	0.466	0.255	0.340
No. of instruments						57	81	105	129
No. of observations	959	959	959	959	959	959	959	959	959
No. of regions	129	129	129	129	129	129	129	129	129

Notes: In columns (1) to (5) standard errors are calculated according to Newey and West (1987), t-statistics are reported in parentheses. In columns (6) to (9) z-statistics are listed in parentheses applying the two-step system GMM estimator as proposed by (Blundell and Bond, 1998). The lagged dependent variable, compensation per employee, low-skilled, market potential and the structural funds variables are assumed to be endogenous. We instrument the endogenous variables with both its lags and its differenced lags and use the "collapse" option. Standard errors are corrected using the approach by Windmeijer (2005). \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

Table 7: Reduced-form employment model excluding market potential

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Obj. X = Obj. 1+2+3					Obj. X = Obj. 1				
Emp. per wp. (t-1)	0.622*** (5.997)	0.606*** (8.186)	0.692*** (10.110)	0.756*** (10.31)	0.832*** (14.90)	0.639*** (6.133)	0.613*** (9.324)	0.670*** (12.25)	0.692*** (14.60)	0.704*** (15.67)
Comp. emp. (t-1)	0.0223 (0.476)	0.0347 (0.740)	-0.00402 (-0.108)	-0.0313 (-1.046)	-0.0255 (-0.861)	0.0203 (0.463)	-0.00679 (-0.202)	-0.0575 (-1.846)	-0.0508 (-1.315)	-0.0467 (-1.315)
Pop. young (t-1)	-0.0569 (-1.482)	-0.0775* (-2.427)	-0.0461 (-1.479)	-0.0497 (-1.688)	-0.0317 (-1.494)	-0.0695 (-1.560)	-0.0689 (-1.941)	-0.0283 (-0.825)	-0.0250 (-1.114)	-0.00977 (-0.332)
Low-skilled (t-1)	-0.111* (-2.317)	-0.0953*** (-2.767)	-0.130*** (-2.610)	-0.0943* (-2.144)	-0.107* (-2.569)	-0.102* (-2.228)	-0.0894** (-2.751)	-0.117*** (-2.904)	-0.0937* (-2.207)	-0.0707 (-1.738)
Grr (t-1)	0.00311 (0.552)	0.00269 (0.457)	0.00360 (0.566)	0.00149 (0.302)	0.00177 (0.462)	0.00228 (0.420)	0.00161 (0.250)	0.00105 (0.178)	-0.00261 (-0.523)	-0.00202 (-0.401)
Union density (t-1)	-0.00139 (-0.349)	-0.000934 (-0.236)	0.000473 (0.121)	-0.000602 (-0.142)	0.000793 (0.252)	-0.00183 (-0.445)	-0.00238 (-0.625)	-0.00185 (-0.479)	-0.00158 (-0.401)	-0.000769 (-0.150)
SF pc Obj. X (t-1)		-0.00272 (-0.503)	-0.00142 (-0.296)	-0.00616 (-0.889)	-0.00565 (-0.873)	-0.000499 (-1.268)	-0.000499 (-1.268)	-0.00306 (-0.901)	-0.00875 (-1.862)	-0.00722 (-1.686)
SF pc Obj. X (t-2)			0.000630 (0.314)	-0.000688 (-0.207)	-0.00105 (-0.404)			-0.00182 (-1.036)	-0.00102 (-0.416)	-0.00164 (-0.759)
SF pc Obj. X (t-3)				-0.000274 (-0.129)	-0.000463 (-0.262)			0.00183 (0.806)	0.00126 (0.558)	0.00126 (0.558)
SF pc Obj. X (t-4)					0.00188 (0.985)			0.00138 (0.778)	0.00138 (0.778)	0.00138 (0.778)
SF pc Obj. 2 (t-1)						0.00126 (0.232)	0.00126 (0.232)	0.00418 (0.541)	0.00677 (0.980)	0.00601 (0.980)
SF pc Obj. 2 (t-2)								0.000695 (0.207)	-0.000772 (-0.203)	0.000554 (0.173)
SF pc Obj. 2 (t-3)									-0.00129 (-0.563)	-0.000418 (-0.198)
SF pc Obj. 2 (t-4)									0.00148 (0.953)	0.00148 (0.953)
SF pc Obj. 3 (t-1)							0.00796 (0.914)	0.0156* (2.309)	0.0127* (1.998)	0.0194* (2.157)
SF pc Obj. 3 (t-2)								-0.00425 (-1.046)	-0.000469 (-0.104)	-0.00249 (-0.386)
SF pc Obj. 3 (t-3)									0.00503 (1.447)	0.00445 (1.385)
SF pc Obj. 3 (t-4)									-0.00454 (-0.952)	-0.00454 (-0.952)
Constant	0.00293 (0.993)	0.00261 (0.876)	0.00291 (0.937)	0.00207 (1.101)	0.00189 (1.031)	0.00254 (0.869)	0.00267 (1.019)	0.00333 (1.156)	0.00167 (0.724)	0.00129 (0.531)
Obj. X short-term elast. (size)				-0.000786 (-0.00712)	-0.00528 (-0.380)			-0.00488 (-0.120)	-0.00795 (-0.243)	-0.00623 (-0.124)
Obj. X short-term elast. (p-value)				0.361	0.380			0.120	0.0243	0.124
Obj. X long-term elast. (size)		-0.00690 (-0.617)	-0.00255 (-0.861)	-0.0292 (-0.308)	-0.0314 (-0.318)		-0.0129 (0.184)	-0.0148 (-0.0778)	-0.0258 (-0.0145)	-0.0210 (-0.0870)
Obj. X long-term elast. (p-value)				0.308	0.318			0.0778	0.0145	0.0870
Obj. 2 short-term elast. (size)								0.00488	0.00471	0.00763
Obj. 2 short-term elast. (p-value)								0.396	0.206	0.121
Obj. 2 long-term elast. (size)							0.00326 (0.820)	0.0148 (0.415)	0.0153 (0.226)	0.0257 (0.154)
Obj. 2 long-term elast. (p-value)								0.0173	0.0173	0.0168
Obj. 3 short-term elast. (size)								0.123	0.0260	0.00881
Obj. 3 short-term elast. (p-value)								0.0343	0.0561	0.0566
Obj. 3 long-term elast. (size)							0.0205 (0.349)	0.121	0.0208	0.00314
Obj. 3 long-term elast. (p-value)								8.16e-05	6.07e-05	4.83e-05
AR(1) (p-value)	0.00251	0.00139	0.000290	0.000288	0.000139	0.00207	0.000398	0.00207	0.00471	0.00763
AR(2) (p-value)	0.251	0.250	0.274	0.293	0.332	0.255	0.234	0.205	0.205	0.232
Hansen (p-value)	0.200	0.171	0.258	0.206	0.226	0.174	0.491	0.436	0.346	0.280
No. of instruments	26	34	42	58	58	26	50	74	98	122
No. of observations	964	964	964	964	964	964	964	964	964	964
No. of regions	130	130	130	130	130	130	130	130	130	130

Notes: In columns (1) to (5) standard errors are calculated according to Newey and West (1987). t-statistics are reported in parentheses. In columns (6) to (9) z-statistics are listed in parentheses applying the two-step system GMM estimator as proposed by (Blundell and Bond, 1998). The lagged dependent variable, compensation per employee, low-skilled, market potential and the structural funds variables are assumed to be endogenous. We instrument the endogenous variables with both its lags and its differenced lags and use the "collapse" option. Standard errors are corrected using the approach by Windmeijer (2005). \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

**Table 8: Spatial panel model: Objective 1+2+3**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Reduced-form employment model including market potential					Reduced-form employment model excluding market potential				
$\gamma$	0.34154***	0.34157***	0.34173***	0.3381***	0.33821***	0.35114***	0.35093***	0.34989***	0.34537***	0.34563***
$\rho$	-11.8197	-11.8221	-11.8487	-11.7104	-11.6907	-12.2548	-12.2495	-12.2401	-12.0608	-12.0516
Emp. per w.p. (t-1)	-0.22456***	-0.22542***	-0.2276***	-0.22404***	-0.22412***	-0.23212***	-0.23312***	-0.23459***	-0.23023***	-0.23042***
Comp. emp. (t-1)	(-5.1052)	(-5.1214)	(-5.1768)	(-5.1011)	(-5.1005)	(-5.2817)	(-5.3028)	(-5.3482)	(-5.2515)	(-5.2543)
Pop. young (t-1)	0.38197***	0.38197***	0.38197***	0.38197***	0.38197***	0.38197***	0.38197***	0.38197***	0.38197***	0.38197***
Low-skilled (t-1)	-11.3023	-11.3033	-11.31	-11.3159	-11.316	-11.3032	-11.3049	-11.3123	-11.3185	-11.3186
Grr (t-1)	-0.01255	-0.012424	-0.011004	-0.010827	-0.010841	-0.009644	-0.009546	-0.008308	-0.008318	-0.008371
Union density (t-1)	(-0.73969)	(-0.73231)	(-0.64912)	(-0.63959)	(-0.64038)	(-0.56861)	(-0.56295)	(-0.49082)	(-0.49225)	(-0.49532)
Market potential (t-1)	-0.18847***	-0.19002***	-0.19126***	-0.19172***	-0.19161***	-0.18125***	-0.18357***	-0.18582***	-0.18671***	-0.18643***
SF pc Obj. 1+2+3 (t-1)	(-4.3752)	(-4.4003)	(-4.4349)	(-4.4511)	(-4.4445)	(-4.206)	(-4.2476)	(-4.3069)	(-4.3342)	(-4.3244)
SF pc Obj. 1+2+3 (t-2)	-0.043752**	-0.043146**	-0.040268**	-0.039195**	-0.039277**	-0.048713**	-0.04775**	-0.043891**	-0.042463**	-0.042674**
SF pc Obj. 1+2+3 (t-3)	(-2.0353)	(-2.0042)	(-1.8692)	(-1.8214)	(-1.8215)	(-2.2723)	(-2.232)	(-2.0412)	(-1.9771)	(-1.9834)
SF pc Obj. 1+2+3 (t-4)	0.0020002	0.0020406	0.0022363	0.0023245	0.0023232	0.0031164	0.0031432	0.0032223	0.0032439	0.0032355
Obj. 1+2+3 short-term elast. (p-value)	-0.15657	-0.15975	-0.17536	-0.18255	-0.18245	-0.24349	-0.24504	-0.25239	-0.25452	-0.25387
Obj. 1+2+3 long-term elast. (p-value)	0.012178	0.01226	0.012716	0.013553	0.013549	-0.001901	0.0093358	0.010231	0.01132	0.01132
Sum $ \gamma + \rho + \rho $	-0.42196	-0.42486	-0.44141	-0.47111	-0.47097	(-0.43053)	-0.32308	-0.35485	-0.3932	-0.39322
No. of regions	0.15636**	0.15343**	0.13591**	0.12651**	0.12627**					
	-2.2736	-2.2232	-1.9558	-1.8181	-1.8115					
	(-0.009578)	(-0.0062332)	(-0.0056028)	(-0.0056063)	(-0.0056063)					
	(-0.50043)	(-0.3249)	(-0.29243)	(-0.29261)	(-0.29261)					
		-0.0034714**	-0.0032124**	-0.0032201**	-0.0032201**					
		(-1.9207)	(-1.7742)	(-1.7739)	(-1.7739)					
		-0.0030335**	(-1.7652)	(-1.7652)	(-1.7652)					
		-0.059439	-0.067253	-0.067253	-0.067253					
		-0.0009578	-0.0040948	-0.0068063	-0.0068063					
		-0.50043	0.12457	0.029199	0.050505					
		-0.0014547	-0.0062204	-0.010283	-0.010162					
		0.63715	0.045153	0.00093857	0.0010769					
	0.94807	0.94896	0.95129	0.94441	0.94429	0.96523	0.96601	0.96645	0.95756	0.95802
	130	130	130	130	130	130	130	130	130	130

Notes: The spatial dynamic panel estimator uses a quasi-maximum likelihood estimator applying the Matlab routine *sur-panel.jh'ai* by Yu, de Jong, and Lee (2008). t-statistics are reported parentheses; \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

Table 9: Spatial panel model: Objective 1, 2, 3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Reduced-form employment model including market potential				Reduced-form employment model excluding market potential			
$\gamma$	0.337*** (-11.6425)	0.33722*** (-11.6595)	0.33746*** (-11.7298)	0.34609*** (-12.0723)	0.34714*** (-12.0977)	0.34677*** (-12.0952)	0.34689*** (-12.1556)	0.35502*** (-12.501)
$\rho$	-0.23042*** (-5.231)	-0.23468*** (-5.309)	-0.24356*** (-5.5465)	-0.22012*** (-5.0069)	-0.23835*** (-5.4153)	-0.24171*** (-5.4708)	-0.25018*** (-5.6974)	-0.22565*** (-5.1329)
Emp. per w.p. (t-1)	0.38197*** (-11.3309)	0.38197*** (-11.3468)	0.38197*** (-11.4942)	0.38197*** (-11.5887)	0.38197*** (-11.3346)	0.38197*** (-11.351)	0.38197*** (-11.4966)	0.38197*** (-11.5918)
Comp. emp. (t-1)	-0.010529 (-0.62117)	-0.009244 (-0.54578)	-0.008821 (-0.52601)	-0.010644 (-0.63909)	-0.007605 (-0.44871)	-0.006396 (-0.37782)	-0.005928 (-0.48886)	-0.008137 (-0.48886)
Pop. young (t-1)	-0.20562*** (-4.7044)	-0.20722*** (-4.7243)	-0.19759*** (-4.5362)	-0.19394*** (-4.476)	-0.19823*** (-4.5319)	-0.20029*** (-4.6355)	-0.19039*** (-4.3723)	-0.18719*** (-4.3201)
Low-skilled (t-1)	-0.043395*** (-2.0201)	-0.040953*** (-1.893)	-0.046785*** (-2.1718)	-0.042372*** (-1.9737)	-0.048301*** (-2.2532)	-0.044929*** (-2.0789)	-0.050513*** (-2.3459)	-0.045677*** (-2.1292)
Grr (t-1)	0.0025073 (-0.19674)	0.0026931 (-0.21176)	0.0019783 (-0.1571)	0.002664 (-0.21317)	0.0036454 (-0.28549)	0.0037598 (-0.29511)	0.0030686 (-0.24323)	0.0036533 (-0.29191)
Union density (t-1)	0.010906 (-0.37865)	0.010813 (-0.37606)	0.010265 (-0.36049)	0.0067268 (-0.23796)	0.0078653 (-0.27263)	0.0081114 (-0.28167)	0.0075839 (-0.2659)	0.004229 (-0.14943)
Market potential (t-1)	0.16151** (-2.3461)	0.15407** (-2.2311)	0.15611** (-2.279)	0.14119** (-2.0701)	0.14119** (-2.0701)	0.14119** (-2.0701)	0.14119** (-2.0701)	0.14119** (-2.0701)
SF pc Obj. 1 (t-1)	0.0016257 (-0.82966)	0.0023661 (-1.1745)	0.0032246 (-1.601)	0.0031731 (-1.5836)	0.0012348 (-0.63082)	0.0020178 (-1.0022)	0.002893 (-1.4366)	0.0028602 (-1.4286)
SF pc Obj. 1 (t-2)								
SF pc Obj. 1 (t-3)								
SF pc Obj. 1 (t-4)								
SF pc Obj. 2 (t-1)	-0.001663 (-0.84348)	-0.002241 (-1.1037)	-0.009181 (-1.5575)	-0.002844 (-1.399)	-0.001702 (-0.86099)	-0.002253 (-1.1071)	-0.003192 (-1.5588)	-0.002835 (-1.3916)
SF pc Obj. 2 (t-2)								
SF pc Obj. 2 (t-3)								
SF pc Obj. 2 (t-4)								
SF pc Obj. 3 (t-1)	-0.0063922** (-1.8847)	-0.0061241** (-1.7881)	-0.005091 (-1.4952)	-0.0057013* (-1.6708)	-0.0063799** (-1.8761)	-0.0062015** (-1.8064)	-0.005196 (-1.5224)	-0.0057941* (-1.6947)
SF pc Obj. 3 (t-2)								
SF pc Obj. 3 (t-3)								
SF pc Obj. 3 (t-4)								
Obj. 1 short-term elast. (size)		-0.001124 (-0.07026)	-0.001835 (-0.13127)	-0.001004 (-0.074863)	-0.001004 (-0.074863)	-0.001805 (-0.13127)	-0.00267 (-0.19535)	-0.001594 (-0.11594)
Obj. 1 short-term elast. (p-value)		0.002452 (0.43369)	0.001696 (0.39138)	0.001535 (0.63704)	0.0018914 (0.55187)	0.002763 (0.39879)	0.004088 (0.21287)	0.002471 (0.45364)
Obj. 1 long-term elast. (size)		-0.002207 (-0.16144)	-0.002484 (-0.18114)	-0.002309 (-0.1742)	-0.002309 (-0.1742)	-0.002548 (-0.18415)	0.0019875 (0.14528)	-0.002732 (-0.20273)
Obj. 2 short-term elast. (size)		-0.002509 (-0.18114)	-0.003329 (-0.24535)	-0.003532 (-0.2538)	-0.003532 (-0.2538)	-0.003901 (-0.283)	0.0030432 (0.2271)	-0.004235 (-0.3188)
Obj. 2 long-term elast. (size)		0.42563 (0.30485)	0.42563 (0.30485)	0.42563 (0.30485)	0.42563 (0.30485)	0.42563 (0.30485)	0.42563 (0.30485)	0.42563 (0.30485)
Obj. 2 long-term elast. (p-value)		0.00029 (0.059633)	0.00029 (0.059633)	0.00029 (0.059633)	0.00029 (0.059633)	0.00029 (0.059633)	0.00029 (0.059633)	0.00029 (0.059633)
Obj. 3 short-term elast. (size)		-0.009641 (-0.076133)	-0.013979 (-0.10695)	-0.012104 (-0.09246)	-0.009772 (-0.07507)	-0.0064811 (-0.05234)	0.1028 (0.014078)	-0.007436 (-0.05234)
Obj. 3 short-term elast. (p-value)		0.076133 (0.94938)	0.013979 (0.96298)	0.012104 (0.94818)	0.009772 (0.96746)	0.013583 (0.97044)	0.014078 (0.97044)	0.01529 (0.96263)
Obj. 3 long-term elast. (size)		0.94938 (0.94938)	0.94938 (0.94938)	0.94938 (0.94938)	0.94938 (0.94938)	0.94938 (0.94938)	0.94938 (0.94938)	0.94938 (0.94938)
Obj. 3 long-term elast. (p-value)		130 (130)	130 (130)	130 (130)	130 (130)	130 (130)	130 (130)	130 (130)
Sum $ T + \rho + p $		130	130	130	130	130	130	130
No. of observations		130	130	130	130	130	130	130
No. of regions		130	130	130	130	130	130	130

Notes: The spatial dynamic panel estimator uses a quasi-maximum likelihood estimator applying the Matlab routine *sar\_panel\_jhaz* by Yu, de Jong, and Lee (2008). t-statistics are reported parentheses; \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

**Table 10:** Size of the estimated spatial coefficients for different weight matrices ( $W$ )

Obj. $W$	sf not included			sf up to 1 lag			sf up to 2 lags			sf up to 3 lags			sf up to 4 lags		
	$\lambda$	$\rho$	$\gamma$	$\lambda$	$\rho$	$\gamma$	$\lambda$	$\rho$	$\gamma$	$\lambda$	$\rho$	$\gamma$	$\lambda$	$\rho$	$\gamma$
W2	0.32856	-0.1865	0.38197	0.32413	-0.18943	0.38197	0.32482	-0.19205	0.38197	0.32448	-0.19767	0.38197	0.33392	-0.17771	0.38197
W3	0.34154	-0.22456	0.38197	0.337	-0.23042	0.38197	0.33722	-0.23468	0.38197	0.33746	-0.24356	0.38197	0.34609	-0.22012	0.38197
W4	0.37156	-0.34118	0.53699	0.36791	-0.34606	0.54398	0.36716	-0.34877	0.53999	0.36603	-0.35288	0.52999	0.37292	-0.32835	0.51296
W5	0.38225	-0.38921	0.56596	0.37802	-0.39406	0.57	0.37788	-0.39841	0.56397	0.37713	-0.40448	0.55296	0.38320	-0.38017	0.53499
W6	0.38957	-0.45783	0.60199	0.38465	-0.46014	0.59195	0.385	-0.46692	0.58998	0.3847	-0.47585	0.57598	0.3915	-0.448	0.56698
W7	0.38546	-0.49458	0.602	0.38096	-0.49693	0.60196	0.38017	-0.50066	0.585	0.38017	-0.51256	0.575	0.38776	-0.48332	0.567
W8	0.37296	-0.50608	0.59696	0.36857	-0.50748	0.59099	0.36812	-0.51292	0.591	0.36687	-0.51266	0.56696	0.37688	-0.49287	0.55698
W9	0.36686	-0.51819	0.59398	0.36322	-0.52285	0.60295	0.36245	-0.52942	0.5895	0.36123	-0.53723	0.57899	0.37179	-0.50432	0.576
W10	0.36616	-0.56535	0.58698	0.36247	-0.57089	0.59299	0.36141	-0.57675	0.59097	0.35926	-0.58485	0.56697	0.37104	-0.55318	0.56397
W11	0.3632	-0.5758	0.589	0.35949	-0.58131	0.59398	0.35832	-0.58506	0.589	0.35657	-0.59123	0.56996	0.36768	-0.56659	0.557
W12	0.36044	-0.58417	0.60098	0.356	-0.59104	0.60599	0.35409	-0.5927	0.587	0.35255	-0.60396	0.568	0.36373	-0.56673	0.56499
W13	0.35468	-0.57504	0.61299	0.34913	-0.58129	0.60198	0.34858	-0.58531	0.60397	0.34682	-0.59689	0.583	0.35775	-0.55863	0.57
W14	0.34763	-0.58281	0.60298	0.34214	-0.58981	0.59196	0.34156	-0.59462	0.59594	0.33854	-0.59996	0.56499	0.35126	-0.56369	0.54796
W15	0.34088	-0.56878	0.61199	0.33552	-0.57599	0.606	0.33453	-0.57942	0.59497	0.33263	-0.58849	0.585	0.34595	-0.54928	0.57199
W.dist	0.34763	-0.58281	0.60298	0.34214	-0.58981	0.59196	0.34156	-0.59462	0.59594	0.33854	-0.59996	0.56499	0.35126	-0.56369	0.54796
W.dist2	0.37963	-0.67363	0.71899	0.37576	-0.6856	0.70098	0.37627	-0.69549	0.706	0.37476	-0.70408	0.68798	0.38238	-0.66052	0.671
Obj. $W$	sf not included			sf up to 1 lag			sf up to 2 lags			sf up to 3 lags			sf up to 4 lags		
W2	0.32856	-0.1865	0.38197	0.32853	-0.18699	0.38197	0.32833	-0.1879	0.38197	0.32844	-0.18469	0.38197	0.32447	-0.1847	0.38197
W3	0.34154	-0.22456	0.38197	0.34157	-0.22542	0.38197	0.34173	-0.2276	0.38197	0.3381	-0.22404	0.38197	0.33821	-0.22412	0.38197
W4	0.37156	-0.34118	0.53699	0.37175	-0.34237	0.54299	0.37158	-0.3437	0.54497	0.36842	-0.33965	0.54999	0.36809	-0.33899	0.54397
W5	0.38225	-0.38921	0.56596	0.38259	-0.3913	0.57298	0.38222	-0.39189	0.57397	0.37909	-0.38781	0.57195	0.37933	-0.38805	0.57399
W6	0.38957	-0.45783	0.60199	0.38936	-0.45883	0.59698	0.38917	-0.46041	0.59796	0.3866	-0.45642	0.60199	0.38631	-0.45616	0.60096
W7	0.38546	-0.49458	0.602	0.38511	-0.49515	0.59599	0.38539	-0.49798	0.60598	0.38233	-0.49289	0.59797	0.38259	-0.49353	0.61098
W8	0.37296	-0.50608	0.59696	0.37285	-0.50681	0.59498	0.3734	-0.51314	0.59497	0.37147	-0.51093	0.60598	0.37055	-0.51004	0.59398
W9	0.36686	-0.51819	0.59398	0.36725	-0.51999	0.60498	0.36813	-0.52801	0.61095	0.36588	-0.52541	0.611	0.36531	-0.52526	0.611
W10	0.36616	-0.56535	0.58698	0.36669	-0.56725	0.60195	0.36705	-0.57349	0.60299	0.36466	-0.5707	0.59599	0.36406	-0.57073	0.596
W11	0.3632	-0.5758	0.589	0.36329	-0.57664	0.594	0.36388	-0.58273	0.60396	0.36158	-0.58031	0.598	0.36079	-0.58046	0.59696
W12	0.36044	-0.58417	0.60098	0.36034	-0.58487	0.603	0.3603	-0.58825	0.60498	0.35834	-0.5859	0.61096	0.35717	-0.58539	0.60297
W13	0.35468	-0.57504	0.61299	0.35454	-0.57547	0.61295	0.35433	-0.57913	0.60799	0.35195	-0.57747	0.60296	0.35107	-0.57762	0.59997
W14	0.34763	-0.58281	0.60298	0.34718	-0.58234	0.59499	0.34737	-0.58815	0.598	0.34503	-0.58702	0.59497	0.3442	-0.58805	0.59497
W15	0.34088	-0.56878	0.61199	0.34054	-0.56834	0.60597	0.34082	-0.57492	0.611	0.33852	-0.57399	0.60997	0.33768	-0.57473	0.60894
W.dist	0.34763	-0.58281	0.60298	0.34718	-0.58234	0.59499	0.34737	-0.58815	0.598	0.34503	-0.58702	0.59497	0.3442	-0.58805	0.59497
W.dist2	0.37963	-0.67363	0.71899	0.37934	-0.67385	0.71098	0.37944	-0.67817	0.70899	0.37699	-0.67499	0.72197	0.37616	-0.67349	0.70497

Notes: The spatial dynamic panel estimator uses a quasi-maximum likelihood estimator applying the Matlab routine *sar-panel\_ghai* by Yu, de Jong, and Lee (2008). Irrespective of which weight matrix is used, all indicators are statistically significant at the 1% level. The coefficients refer to equation (2) and correspond to  $W emp_{i,t}$  ( $\lambda$ ),  $W emp_{i,t-1}$  ( $\rho$ ) and  $emp_{i,t-1}$  ( $\gamma$ ).

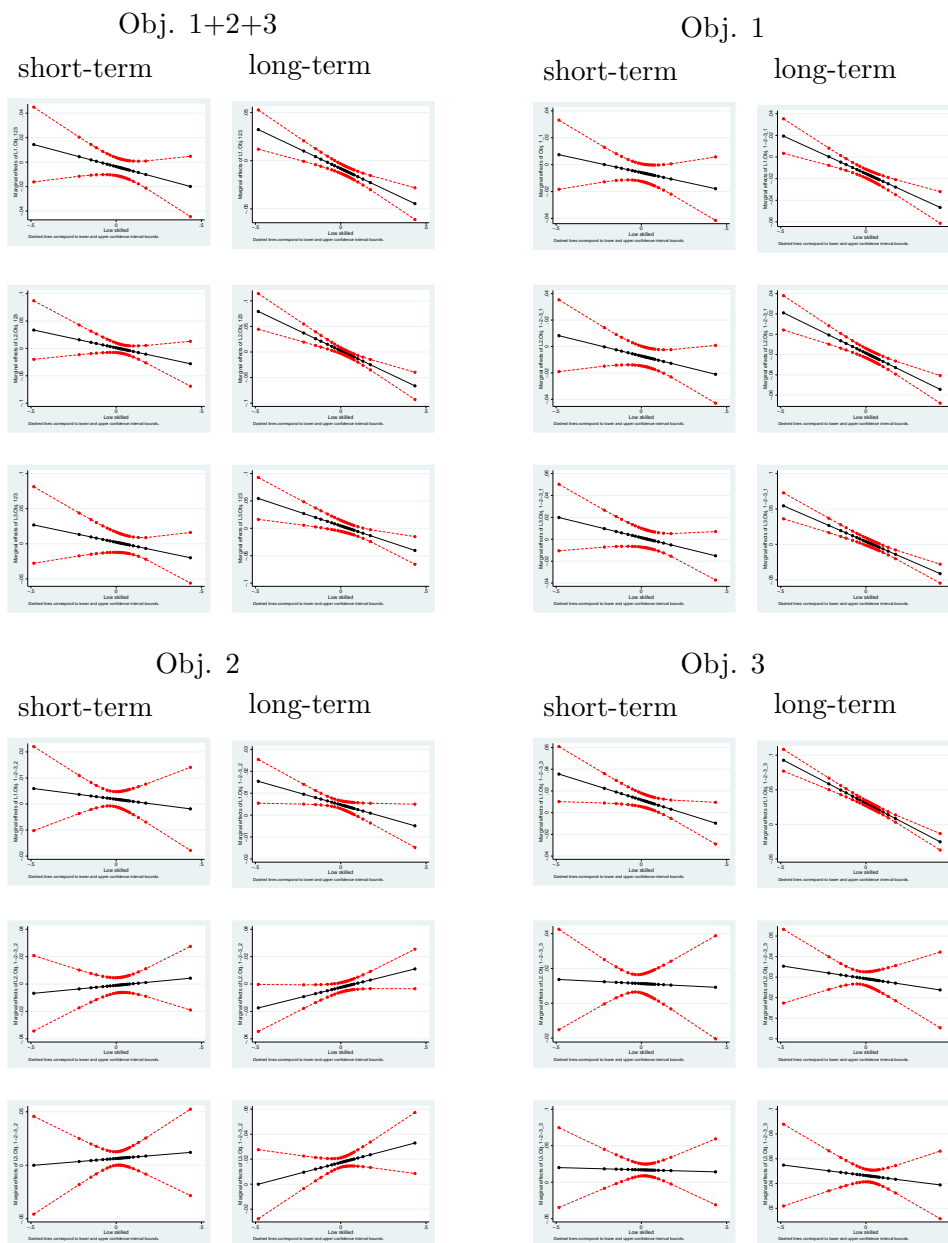


**Table 11:** Interaction model: Objectives 1+2+3

	(1)	(2)	(3)	(4)
Emp. per wp. (t-1)	0.611*** (6.164)	0.588*** (5.010)	0.545*** (7.929)	0.727*** (9.349)
Comp. emp. (t-1)	0.0417 (1.083)	0.0722 (1.450)	0.0967** (2.880)	0.103 (1.893)
Pop. young (t-1)	-0.0626 (-1.452)	-0.0670 (-1.444)	-0.0912* (-2.526)	-0.0430 (-0.988)
Grr (t-1)	0.00407 (0.691)	0.00219 (0.478)	0.00608 (0.870)	0.00190 (0.236)
Union density (t-1)	-0.00178 (-0.489)	-0.000570 (-0.131)	-0.00189 (-0.500)	-0.00253 (-0.551)
SF pc Obj. 1+2+3 (t-1)	-0.00325 (-0.687)	-0.00137 (-0.283)	-0.000596 (-0.140)	-0.00301 (-0.670)
SF pc Obj. 1+2+3 x Low-skilled (t-1)	-0.0684 (-1.507)	-0.0562 (-1.342)	-0.0213 (-0.437)	-0.0411 (-0.686)
Low-skilled (t-1)	0.156 (1.161)	0.189 (1.303)	0.200 (1.292)	0.347 (1.054)
SF pc Obj. 1+2+3 (t-2)		0.000102 (0.0476)	-0.00113 (-0.462)	-0.000849 (-0.232)
SF pc Obj. 1+2+3 x Low-skilled (t-2)		-0.0116 (-0.458)	-0.0219 (-0.640)	-0.00415 (-0.0726)
Low-skilled (t-2)		-0.0587 (-0.621)	-0.108 (-0.887)	-0.358 (-1.187)
SF pc Obj. 1+2+3 (t-3)			0.000281 (0.117)	-0.000613 (-0.235)
SF pc Obj. 1+2+3 x Low-skilled (t-3)			-0.00939 (-0.684)	0.0205 (0.988)
Low-skilled (t-3)			0.0316 (0.588)	-0.0485 (-0.568)
SF pc Obj. 1+2+3 (t-4)				-0.00125 (-0.575)
SF pc Obj. 1+2+3 x Low-skilled (t-4)				0.00517 (0.287)
Low-skilled (t-4)				-0.0269 (-0.366)
Constant	0.0142 (0.903)	0.00712 (0.475)	0.00649 (0.357)	0.0221 (1.207)
Obj. 1+2+3 short-term elast. (size)		-0.00127	-0.00144	-0.00572
Obj. 1+2+3 short-term elast. (p-value)		0.788	0.784	0.294
Obj. 1+2+3 long-term elast. (size)	-0.00835	-0.00308	-0.00317	-0.0209
Obj. 1+2+3 long-term elast. (p-value)	0.510	0.783	0.784	0.266
AR(1) (p-value)	0.00115	0.00961	0.0189	0.00324
AR(2) (p-value)	0.246	0.606	0.186	0.411
Hansen (p-value)	0.606	0.560	0.358	0.200
No. of instruments	40	43	46	49
No. of observations	964	834	705	576
No. of regions	130	130	129	129

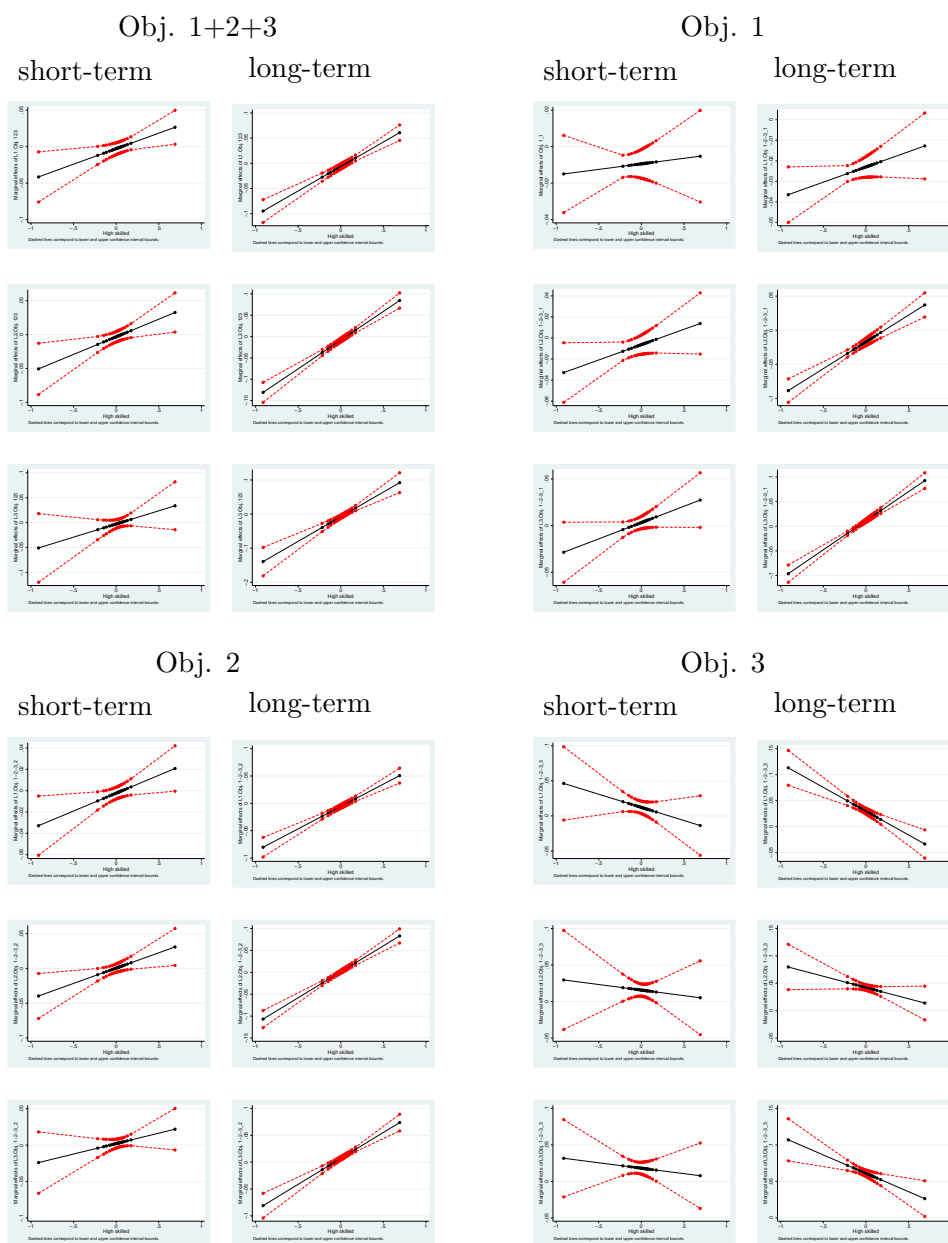
Notes: z-statistics are listed in parentheses applying the two-step system GMM estimator as proposed by (Blundell and Bond, 1998). The lagged dependent variable, compensation per employee, low-skilled, market potential and the structural funds variables are assumed to be endogenous. We instrument the endogenous variables with both its lags and its differenced lags and use the “collapse” option. Standard errors are corrected using the approach by Windmeijer (2005).  
\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

**Figure 2:** Marginal effects of structural funds on employment



*Notes:* The estimation results are based on the baseline specification Reduced-form employment model including market potential displayed in equation (3). The regressions are estimated using the two-step system GMM estimator proposed by Blundell and Bond (1998), while standard errors are corrected using the approach by Windmeijer (2005). The lagged dependent variable, compensation per employee, low-skilled, market potential and the structural funds variables are assumed to be endogenous. We instrument the endogenous variables with both its lags and its differenced lags and use the “collapse” option. The marginal effects are calculated for short-term and long-term elasticities as well as for one to up to three lags.

**Figure 3:** Marginal effects of structural funds on employment (Reduced-form employment model including market potential using the high skilled)



*Notes:* The estimation results are based on the baseline specification of the reduced-form employment model including market potential and interacting the structural funds variable with the share of high-skilled population. The regressions are estimated using the two-step system GMM estimator proposed by Blundell and Bond (1998), while standard errors are corrected using the approach by Windmeijer (2005). The lagged dependent variable, compensation per employee, high-skilled, market potential and the structural funds variables are assumed to be endogenous. We instrument the endogenous variables with both its lags and its differenced lags and use the “collapse” option. The marginal effects are calculated for short-term and long-term elasticities as well as for one to up to three lags.

## C Calculation of the interaction effects

We estimate an interaction model, interacting two variables, namely structural funds ( $sf$ ) and percentage share of low-skilled population ( $z$ ). The marginal effects are calculated by taking the first derivative of our specification listed in equation (3), i.e.:

$$\frac{\partial \widehat{emp}}{\partial sf} = \widehat{\beta}_{L1.sf} + \widehat{\beta}_{L1.sf \cdot z} \cdot z$$

where  $L$ . denotes the use of a lagged variable. The level of uncertainty regarding the marginal effects is indicated by the variance ( $Var$ ) of the marginal effects. If the marginal effects consists of two addends (as it is the case in the equation above), the variance of the short-term elasticity can be calculated as follows:

$$\begin{aligned} Var \left( \frac{\partial \widehat{emp}}{\partial sf} \right) &= Var(\widehat{\beta}_{L1.sf}) + z^2 Var(\widehat{\beta}_{L1.sf \cdot z}) + \\ &+ 2z Cov(\widehat{\beta}_{L1.sf}, \widehat{\beta}_{L1.z}) \end{aligned}$$

Generally, if the marginal effects consists of more than two addends, the variance can be approximated using the following Taylor rule,

$$\begin{aligned} Var(g(X, Y)) &\sim \left( \frac{\partial g(X, Y)}{\partial X} \right)^2 \cdot Var(X) + \left( \frac{\partial g(X, Y)}{\partial Y} \right)^2 \cdot Var(Y) + \\ &+ 2 \left( \frac{\partial g(X, Y)}{\partial X} \cdot \frac{\partial g(X, Y)}{\partial Y} \cdot Cov(X, Y) \right) \end{aligned}$$

where  $g(X, Y)$  stands for the function of the marginal effects. This implies that the long-term elasticity is calculated as:

$$\begin{aligned} Var \left( \frac{\partial \widehat{emp}}{\partial sf} \right) &= (Var(\widehat{\beta}_{L1.sf}) + z^2 Var(\widehat{\beta}_{L1.sf \cdot z}) + \\ &+ 2z Cov(\widehat{\beta}_{L1.sf}, \widehat{\beta}_{L1.z})) \cdot (1 - \widehat{\beta}_{L1.emp})^{-1} \end{aligned}$$

If the estimation equation includes the structural funds variable with up to two lags, the marginal effects are computed via the following expression:

$$\frac{\partial \widehat{emp}}{\partial sf} = \widehat{\beta}_{L1.sf} + \widehat{\beta}_{L2.sf} + z(\widehat{\beta}_{L1.sf \cdot z} + \widehat{\beta}_{L2.sf \cdot z})$$

The variance of the short-term elasticity is then defined as:

$$\begin{aligned}
\text{Var} \left( \frac{\partial \widehat{emp.}}{\partial sf} \right) &= \text{Var}(\widehat{\beta}_{L1.sf}) + \text{Var}(\widehat{\beta}_{L2.sf}) + z^2 \text{Var}(\widehat{\beta}_{L1.sf \cdot z}) + \\
&+ z^2 \text{Var}(\widehat{\beta}_{L2.sf \cdot z}) + 2 \text{Cov}(\widehat{\beta}_{L1.sf}, \widehat{\beta}_{L2.sf}) + \\
&+ 2 z \text{Cov}(\widehat{\beta}_{L1.sf}, \widehat{\beta}_{L1.sf \cdot z}) + 2 z \text{Cov}(\widehat{\beta}_{L1.sf}, \widehat{\beta}_{L2.sf \cdot z}) + \\
&+ 2 z \text{Cov}(\widehat{\beta}_{L2.sf}, \widehat{\beta}_{L1.sf \cdot z}) + 2 z \text{Cov}(\widehat{\beta}_{L2.sf}, \widehat{\beta}_{L2.sf \cdot z}) + \\
&+ 2 z^2 \text{Cov}(\widehat{\beta}_{L1.sf \cdot z}, \widehat{\beta}_{L2.sf \cdot z})
\end{aligned}$$

whereas the variance of the dynamic long-term elasticity is given by:

$$\begin{aligned}
\text{Var} \left( \frac{\partial \widehat{emp.}}{\partial sf} \right) &= (\text{Var}(\widehat{\beta}_{L1.sf}) + \text{Var}(\widehat{\beta}_{L2.sf}) + z^2 \text{Var}(\widehat{\beta}_{L1.sf \cdot z}) + \\
&+ z^2 \text{Var}(\widehat{\beta}_{L2.sf \cdot z}) + 2 \text{Cov}(\widehat{\beta}_{L1.sf}, \widehat{\beta}_{L2.sf}) + \\
&+ 2 z \text{Cov}(\widehat{\beta}_{L1.sf}, \widehat{\beta}_{L1.sf \cdot z}) + 2 z \text{Cov}(\widehat{\beta}_{L1.sf}, \widehat{\beta}_{L2.sf \cdot z}) + \\
&+ 2 z \text{Cov}(\widehat{\beta}_{L2.sf}, \widehat{\beta}_{L1.sf \cdot z}) + 2 z \text{Cov}(\widehat{\beta}_{L2.sf}, \widehat{\beta}_{L2.sf \cdot z}) + \\
&+ 2 z^2 \text{Cov}(\widehat{\beta}_{L1.sf \cdot z}, \widehat{\beta}_{L2.sf \cdot z})) \cdot (1 - \widehat{\beta}_{L1.emp})^{-1}
\end{aligned}$$

Finally, we take account of the lower and upper bound of the 95% confidence intervals, which can be calculated as follows:

$$\frac{\partial \widehat{emp.}}{\partial sf} \pm t_{df,p} \sqrt{\text{Var}(d \widehat{emp.} / d sf)},$$

using the inverse t-distribution function to create the multiplier.  $t_{df,p}$  is the critical value in a t-distribution and  $df$  stands for the degrees of freedom ( $n - k$ ), where  $n$  refers to the number of observations and  $k$  refers to the number or regressors, including the intercept, that produces a p-value at which hypothesis tests are to be made.

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