Evaluating EU Regional Policy: Many Empirical Specifications, One (Unpleasant) Result

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First draft: April 2011
NOT FOR CITATIONS

Abstract

Numerous studies have focused on the role played by EU regional policy, in particular objective 1 structural funding, in fostering growth and convergence among European regions. Why conducting another one? We argue that two facts are still lacking in the actual academic debate in order to get a sound empirical identification strategy and reliable results: First, one should take the theoretical underpinnings of regional growth models more serious, and second, a likewise careful account of the role of spatial dependence in the data is needed. Though research has increasingly become aware of the latter point, in empirical operationalization still the ad-hoc inclusion of a hardly interpretable 'catch-all' spatial lag term of the endogenous variable is the researcher's first choice. In this paper, we use the insights of new theoretical and empirical approaches aiming at directly quantifying interregional spillovers associated with the amount of funds granted to lagging regions and their geographical neighborhood. Testing various empirical model scenarios, our results all hint to the unpleasant conclusion that EU objective 1 structural funds show to have a no or even negative effects on regional growth for a sample of 127 NUTS2 regions within the EU15 over the decade 1997–2007.

JEL: C21, R12, R58

Keywords: EU Regional Policy, Neoclassical Growth, Spatial Spillover, Dynamic Panel Data

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1 Introduction

The analysis of EU Regional Policy is a delicate issue. Especially the EU structural funds (SF) as a major regional policy instrument have been subject to an extensive debate in academic and political spheres. With a volume of €213 billion in the funding period from 2000 to 2006 and a designated sum of €347 billion in the actual funding period up to 2013 it displays the second highest amount in the EU budget (Inforegio 2008). The goal of SF is to support handicapped regions by the provision of physical investment grants to the private business sector, human capital qualification schemes and local public infrastructure among others. Funding is split into three major objectives and a broader class of minor objectives. In this paper, we concentrate on the causal impact of objective 1 payments (or in new terminology objective "convergence"), which explicitly targets intra-EU income convergence by stimulation the growth performance in lagging regions.

Despite its political importance, only few studies thoroughly account for the difficult task of identifying the causal effects of funding by an appropriate identification strategy within a rigorous evaluation approach. In a recent literature survey, Dall'erba et al. (2007) show that only a dozen out of more than one hundred studies dealing with European regional policies, conduct a formal econometric estimation of the impact of structural funds on growth. For Gripaios et al. (2008) the reason for this is threefold: In first place, it is hard to establish a reasonable counterfactual situation from which the policy impact can be assessed. The identification of the causal effect of funding is furthermore hindered by the likely occurrence of overlapping (supranational, national and regional) policies as well as, finally, the poor data quality for EU-wide analyses.

Nevertheless, those empirical studies conducted so far, increasingly show a high degree of innovativeness and professionalism in dealing with the likely pitfalls of analysing regional growth and convergence processes in the EU linked to the notion of funding. Two streams have basically evolved. Being aware of the problems associated with the descriptive approach typically employed in regional economics, these new attempts rely heavily on structural or experimentalist research designs in order to address the problems raised by Gripaios et al. (2008) and to identify the quantitative impacts of policy changes (Holmes 2010). While the latter school has been mainly promoted through microeconometric based evaluation studies in the field of labor economics, the structural approach has been elaborated mainly in modern macroeconomic analysis and aims at estimating empirical models closely tied to a theoretical benchmark in order to interpret the value of the empirical parameters or set theory-guided identification restrictions (see Rickman 2010 for an overview).

Regarding its empirical application for EU regional policy analysis, Mohl and Hagen (2008) as well as Becker et al. (2010a) use a generalized propensity score model to estimate the impact of structural funds on GDP growth. In similar veins, Becker et al. (2010b) apply a regression discontinuity approach to the same empirical question. Although on the one hand these experimentalist models are very didactic in terms of stressing the severe consequences of biases stemming from self-selection into treatment and right-hand-side endogeneity of the policy variable and typically involve less assumptions about the parametric form of the model, on the other hand, given their translation from (microeconometric) labour market research they also face some shortcomings: For example, the generalized propensity score approach in Becker et al. (2010a) can only discriminate among the effectiveness of structural fund payments for the subset of beneficiary regions. No comparison can be made regarding the growth performance of non-funded regions.

Moreover, given the long history of national and supranational regional policy schemes, it is disputable whether these methods are effective in balancing pre-treatment differences among the analysed regions as necessary condition for the isolation of the causal effect of funding. Typically, the pre-treatment period is chosen on the basis of ad-hoc considerations or simply taken as first year of observations available, irrespective of whether the policy programme is already operating at this point of time or not. Of course, for a system of interrelated regions not only in space, but also in the space-time dimension these shortcomings do not come as a surprise. Given the institutional design of the EU regional policy which makes funding itself a function of economic characteristics such as regional GDP, (although desirable) it is rather impossible to find non-funded regions as comparison group for the funded counterparts, which face the same characteristics except their treatment status.[1]

As an alternative point of departure, theoretical models and their conforming empirical operationalizations may help to form concrete testable expectations about the likely impact and transmission mechanisms from the policy stimulus to changes in the outcome variable (see, e.g., de la Fuente 2000 for an survey). Together with recently established methodological advances in the field of panel and spatial econometrics, this may be seen as a promising road ahead and, in fact, is the mainstream approach taken by scholars for EU regional policy assessment. Arbia et al. (2008), for instance, carefully discuss the topic of the estimators' choice on the model predictions in a neoclassical convergence equation setting. The authors find that the revealed convergence parameter remains rather stable over a range of different estimators; however, careful interpretation of obtained parameter has to be done since different specifications may imply quite different concepts of convergence. Careful specification and interpretation has also be taken seriously if a policy variable is added to the regression exercise and/or an explicit notion is given to the role of space. Regarding the latter, Mohl and Hagen (2010) show by means of various panel data approaches that it is necessary to control for spatial spillover effects, which confirms earlier results that regional growth significantly depends on the performance of

[1] Similar arguments holds for the violation of the stable-unit-treatment assumption in a system of interrelated regions, where funding is expected not only to affect the own region's economic performance but spills over to neighboring regions.

neighboring regions.

For theoretical underpinnings, most of the empirical approaches rely on the Solow-type neoclassical growth model framework and test for the so called β–convergence implying that poor regions grow faster than their richer counterparts. Convergence among European regions is in fact a necessary condition for EU regional policy – and in particular Objective 1 structural funds – to work. However, rather than testing the empirical implications of the theoretical model in most studies variable selection turns out to be rather eclectic borrowing from different theoretical concepts and the specification of the empirical model is thus rather ad hoc. This is especially true when it comes to the inclusion of policy variables. In the following, we thus aim at estimating different growth models guided by neoclassical growth theory that carefully accounts for theoretical predictions regarding the expected transmission channels from policy input to economic outcome effects.

Among the crucial aspects dealt with is the question whether it is reasonable to assume that the EU structural funds have an effect on the region's steady-state growth rate or are rather expected to solely alter the speed of adjustment towards their equilibrium value. As will be shown, accounting for either of these transmission channels implies different empirical operationalizations of the neoclassical growth model. The same holds for the inclusion of spatial spillover variables. Using a broad set of different empirical specifications allows us to give a more robust answer whether Objective 1 structural fund payments have let to a higher growth performance of funded regions throughout the period 1997–2007. Our results are however disillusioning: We either find insignificant or even negative policy effects, which raise doubts regarding the effectiveness of EU regional policy. The latter results are particularly driven by negative spatial spillovers. That is, regions with a high share of grant recipients in their neighborhood show to have a significant worse growth performance compared to regions with a technologically advanced neighborhood. Besides confirming the theoretical predictions of spatialized Solow growth models, these findings hint at the existence of difference geographical convergence clubs for the EU as already identified by earlier scholars (see, e.g., Ramajo et al. 2008).

The remainder of the paper is organized as follows. The next section briefly presents the underlying theoretical model and proposes different scenarios in order to estimate the likely effect of the structural funds on output growth. Section 3 then presents the database, while section 4 reports the empirical results for the aspatial and spatial models, as well findings of robustness checks. Section 5 concludes the paper.

2 Convergence, transitory dynamics and spatial linkages

2.1 Growth model specifications

In this section, we first outline the neoclassical Solow-Swan-type growth framework that serves a vehicle for our empirical identification approach. The model is then augmented to account for spatial spillovers in order to capture the mutual interdependence among European regions.

Starting point is the linearized version of the neoclassical growth model as (Mankiw et al. 1992, Tondl 2001)

$$g_{i,T} = \frac{ln\,(y_{i,T}) - ln\,(y_{i,0})}{T} = a + b \times ln\,(y_{i,0}) + \epsilon_{i,T}, \tag{1}$$

where $g_{i,t}$ is the growth rate of GDP per capita (y) in region i over the period $[0, T]$. The cross-sectional dimension is $i = 1, \ldots, N$. The coefficients a and $b = (1 - e^{-\beta t})/T$ have to be estimated. The implicit parameter β is the average regional rate of convergence towards steady state income, $\epsilon_{i,T}$ is the error term, which is assumed to be homoskedastic, non-correlated and normally distributed. In analyzing income convergence, special attention is devoted to the interpretation of the coefficient b. The main motivation for using the concept of neoclassical growth and convergence as formal model framework is that it allows us to control for different initial income levels which serve as proxies for the region's initial capital endowment. Given decreasing marginal returns to capital, initial income levels are then expected to be negatively correlated with the growth rate of the regional economy. That is, if $b < 0$, convergence forces are at work. However, $b < 0$ is not a sufficient condition for unconditional convergence to occur. Besides, the convergence rate β should be in accordance with its theoretically expected value, where β can be derived as $\beta = (1 - \alpha)(g + n + \delta)$, and α is the output elasticity of capital, g is technological progress, n is population growth and δ is the capital depreciation rate (Tondl 2001).

In this setup, the fundamental ingredient of convergence analysis is the idea of the existence of a transitory income path common to all regions, which exhibits declining growth rates towards the path to the steady-state income. Or, in other words, initially poor regions are expected to grow faster the more remote they are with respect to steady-state income. Besides the assumption of diminishing marginal products in capital and labor, the model also assumes that the level of technology is exogenous as well as that returns to scale for capital and labor are constant in the production function (see, e.g., Tondl 2001 for details). Assumptions i.) to iii.) together imply that regions will converge to a common steady-state income level, meaning that convergence is unconditional. The only reason why regions show differences in their per capita income growth rate is the initially heterogeneous endowment with capital. In the long run, with constant population only a rise in the exogenously determined technology level leads to changes in the steady-state income.

Relaxing the strong assumption of homogeneity in the long-run technology level leads to a different model prediction also known as conditional convergence. Here regions face identical growth rates in steady-state. Nevertheless, their income levels may differ due to differences in the technology level, where the latter are typically treated as ‘catch all’ parameter for different kinds of potential driving factors of regional long-run development such as the regional knowledge stock, human capital, and public infrastructure. Neglecting these potential steady state determinants clearly leads to an omitted variable bias (Islam, 1995). Ways to get around with these problems typically involve two modifications of the approach in eq.(1): First, in order to account for time-constant steady state effects, panel data specifications of the convergence equation have been estimated which allow for the inclusion of time-fixed region specific dummy variables. Second, to control for time-varying determinants, variables derived from new growth theory models have been included. The latter models mainly motivate the role played by human capital, public infrastructure and R&D investments among other factors in driving the regions long-run steady state income level.

In its panel data specification eq.(1) can be written as

$$g_{i,t} = ln\left(y_{i,t}\right) - ln\left(y_{i,t-1}\right) = a_i - b \times ln\left(y_{i,t-1}\right) + \delta'\mathbf{X} + F_t + u_{i,t}, \quad \text{t=(1,...,T)}, \tag{2}$$

where a_i is a set of region specific dummies, $\mathbf{X}$ is a vector of further time-varying control variables such as the regional knowledge stock, human capital, and public infrastructure, F_t is a set of time dummies to control for common time-specific effects and $u_{i,t}$ is the model's error terms. The difference to the cross-sectional specification in eq.(1) is that panel data estimation uses several observation in time and thus parameter estimates such as $b = (1 - e^{-\beta})$ are derived from a much richer set of information than cross-sectional analyses.

Using eq.(2) as basic setup, we will now develop four extensions in order to conduct the policy evaluation and to quantify the impact of objective 1 structural funds payments on regional GDP per capita growth. These are summarized in Table 1.

Table 1: Regression design (cases) for objective 1 structural funds impact analysis

(**I**) Aspatial linear additive	(**III**) Spatial linear additive
(**II**) Aspatial multiplicative interaction	(**IV**) Spatial multiplicative interaction

2.2 Case I: Aspatial linear additive model

Most of the empirical work augments the neoclassical growth equation by policy variables in a simple linear additive fashion by simply adding a variable measuring the structural funds input $SF_{i,t}$ to the vector of control variables $\mathbf{X}$. We will refer to this as case I in the following.

To measure the policy impact from objective 1 structural funds in this setup, two alternative variable specification are typically employed. Regions eligible for receiving objective 1 subsidies can either be identified by a binary dummy variable, which takes a value of one if the region has received subsidies for the period of analysis and zero otherwise. Alternatively, total objective 1 spendings normalized by size or a regional performance indicator (such as population for the former, total employment or regional GDP for the latter) can be used, which result in a measure for the funding intensity of the policy scheme.[2] Mohl and Hagen (2010), for instance, propose the following augmented model specification

$$g_{i,t} = a_i - b \times ln\,(y_{i,t-1}) + \delta'\mathbf{X} + \sum_{j=1}^{M} \gamma_j \times ln\,(SF_{i,t-j}) + F_t + u_{i,t}, \tag{3}$$

where $\sum_{j=1}^{N} ln\,(SF_{i,t-j})$ is the sum of lagged structural funds payments per total population over lags 1 to M. The advantage of this distributed lag specification over the inclusion of contemporaneous or simply one period lagged structural funds payments is that the notion of time lags in the transmission channel from the policy input to the outcome variable of interest can be better addressed. One example is public infrastructure, which are expected to fade in only after a certain time period of installation (see, e.g., Bradley et al. 2006). Although the approach in eq.(3) thus already accounts for the importance of time-consuming adjustment processes in the analysis of the structural funds impact, the chosen specification nevertheless rests on the strong assumption that the SF payments actually influence long-run steady state income differences among funded and non-funded regions rather than their temporary dynamics towards steady-state. While this argument may partially hold for provision of public infrastructure or human capital investments, in the light of the growth theoretical underpinnings it is a rather unreasonable assumption for the case of private investment aid, which still account for a large fraction of overall objective 1 structural funds payments.[3]

2.3 Case II: Aspatial multiplicative interaction model

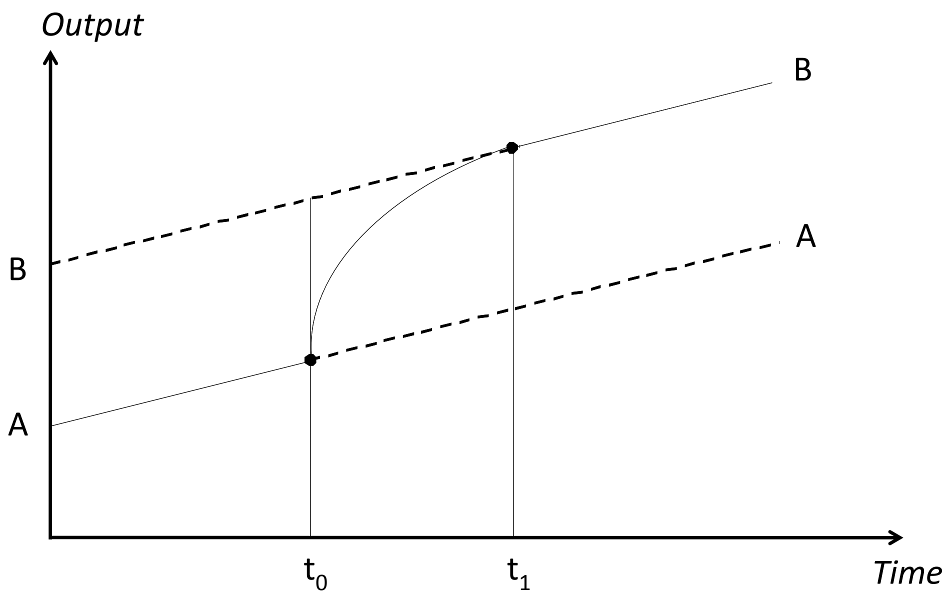
For investment subsidies the neoclassical growth model basically predicts that a permanent increase in the economy's investment rate leads to a temporary increase in the economic growth rates with a permanent shift of the economy's steady-state income level. Focusing on a graphical presentation of the model's dynamic properties (for technical details see Tondl 2001, Favero 2001), Figure 1 shows a region's long-run (or steady-state) growth path AA as a function of exogenously determined technical progress. In time period t_0, the investment rate is perma-

[2] As De Castris and Pellegrini (2010) point out, the use a simple flag to single out regions with or without policy funding may not be adequate if there is a high variability across regions in terms of the amount if subsidies.

[3] For the funding period 2000–2006, ERDF objective 1 commitments to the private sector (Category 1 Productive Environment) account up to 91 % of all ERDF objective 1 commitments in Austria, 85 % in Belgium, 79 in Sweden, 75 % in Finland and about 50 % in the UK, Netherlands and Germany. The total ERDF volume for this period was 101 billion. For further details see Sweco (2008).

nently increased (e.g., via an investment subsidy scheme). As the figure shows, this leads to a temporary increase in the economy's growth rate between time period t_0 and t_1. However, the more the economy converges towards its new path BB in t_1, this effect fades out. Nevertheless, there is a permanent level effect resulting in a higher steady-state growth path BB with a higher output (productivity) level as a result of increased investment activity. For economic policy, it is important that this level effect is only permanent if the increase in the investment rate is long lasting. Otherwise, the economy would return to the long run path AA.

Figure 1: Effect of a Permanent Increase in the Physical Investment Rate



Translating the theoretical model predictions into an empirically testable form is done by case II of our impact analysis. Here, objective 1 structural funds payments are only expected to influence the speed of convergence of the regional economy towards its steady-state. We operationalize this transmission channel by including an interaction term defined as the policy variable times initial (or in the case of panel data: lagged) income according to $(ln(SF_{i,t-1}) \times ln(y_{i,t-1}))$. As Brambor et al. (2005) point out, in order to adequately measure the marginal effect of funding conditional on these two exogenous variables, $ln(SF_{i,t-1})$ and $ln(y_{i,t-1})$ have to be included as constitutional terms in the regression framework as:[4]

$$g_{i,t} \quad = \quad a_i - b \times ln\,(y_{i,t-1}) + \delta'\mathbf{X} + \gamma_1 \times ln\,(SF_{i,t-1}) \qquad (4)$$

[4] For ease of presentation we only present the one period lagged multiplicative interaction term here. However, in the empirical analysis we will also account for higher order lags.

$$+\xi \times (ln(SF_{i,t-1}) \times ln(y_{i,t-1})) + F_t + u_{i,t},$$

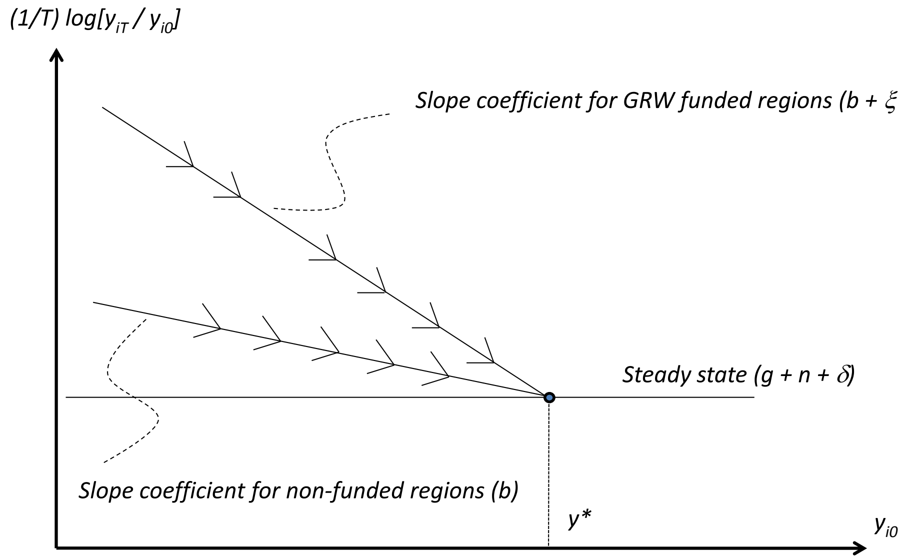
The use of the interaction term in the convergence equation can be motivated as follows: As shown above, the convergence rate β is determined by the output elasticity of capital, as well as population growth and capital depreciation rate, respectively. This fixed relationship, however, only holds for a closed economy. For regional analysis, the latter assumption does not seem plausible since we can expect a high mobility of capital among interrelated regional units. The introduction of (incomplete) capital mobility in the neoclassical growth model framework can then be done conditional on the initial income level, so that the value of the convergence rate β additionally captures the effect of capital mobility. To be more precise, the convergence rate β can now be formulated as $\beta = (1-\alpha)(g+n+\delta+\omega)$, where the additional term ω reflects the elasticity of external capital supply.

Thus, as long as ω is non-zero, taking capital mobility into account, it obviously increases β. As Schalk & Untiedt (1996) point out, the basic assumption for this transmission channel to work is that the external capital influx is determined by regional differences in the marginal return of capital. Yet, it is precisely the goal of investment subsidies to reduce the user cost of capital and thus to affect regional differences in the marginal return of capital in favor of supported regions (Alecke et al. 2011). Not accounting for this policy-induced change in the regional rate of return to physical investment in poor regions would result in a biased estimation of β. A negative regression coefficient for the interaction term ξ implies that the speed of convergence for supported regions is enhanced. However, one has to be aware that in the case of multiplicative interaction models statistical significance cannot be inferred directly from the regression output.[5] The total convergence rate can then be measured as $(b+\xi) = (1-e^{-\beta})$.

The theoretically expected relationship between initial income and the SF policy effect is shown graphically in figure 2. A negative coefficient ξ for the interaction term implies that, for each initial income level below the steady-state (y^*), funded regions show a higher speed of convergence in the growth/initial income-diagram relative to non-funded regions. The intersection of convergence curves for funded and non-funded regions marks the steady-state income level, where regions uniformly grow by $(g+n+\delta)$, driven by the constant rate of growth of technology (g), population growth (n), and the capital depreciation rate (δ). In fact, eq.(4) represents a special case of a more general empirical setup, which relaxes the assumption of homogeneous regression parameters between funded and non-funded regions in eq.(4). This would lead to a fully interacted switching-regime model specification and would imply testing for significantly different long-run convergence clubs for the set of funded and non-funded regions (see Durlauf and Johnson 1995, Durlauf et al., 2001).

[5]Instead, one has to compute the standard error as $\sigma = \sqrt{var(b) + var(\xi) + 2 \times cov(b\xi)}$ (see Brambor et al. 2005).

Figure 2: Regional policy induced change in slope coefficient of convergence equation



2.4 Case III: Spatial linear additive model

So far, we have treated the region's growth rate as being independent from its environment. This may be an over simplistic regression design. Recent contributions in the field of regional science have pointed to the empirical relevance of spatial dependencies in the analysis of income growth and convergence as well as spatial spillovers from regional policy instruments (see, e.g., Morena and Trehan, 1997, Fingleton, 2001). This also led to various reformulations of the neoclassical growth model to properly account for spatial effects. Ertur and Koch (2007) as well as Fischer (2010), for instance, augment the neoclassical framework to capture spatial spillovers by endogenizing the constant region-specific technology parameter a_i from eq.(2) to account for spatially related technological interdependencies. The model basically assumes that the region i's technology level is a function of the technology level from regions in the direct proximity of region i. Alternatively, Egger and Pfaffermayr (2006) as well as Pfaffermayr (2009) propose a spatial Solow growth model which assumes spillovers rising from learning effects in course of capital accumulation in the spirit of Quah (1993).

The proposed production function of the latter type of models implies that the total factor productivity of a specific region is positively related to the level of development of surrounding regions as measured by their spatially weighted ratio of capital to efficiency units of labor. Hence, spatial spillovers between any two regions decrease with the distance between them and – at a given distance – they are the higher the more advanced the neighboring regions are

(Pfaffermayr, 2009). Building on these theoretical extensions, we can derive a linear empirical operationalization for the spatial Solow model as

$$g_{i,t} = a_i - b \times ln\left(y_{i,t-1}\right) + \rho \times (\mathbf{W} * ln(y_{j,t-1})) + \delta'\mathbf{X} + \sum_{j=1}^{N} \gamma_j \times ln\left(SF_{i,t-j}\right) + F_t + u_{i,t}, \quad (5)$$

where $\mathbf{W}$ is a $N \times N$ weighting matrix linking lagged income levels $y_{j,t-1}$ for the sample observations $j \neq i$ to information about the j's region spatial proximity with respect to region i. The parameter ρ measures the strength of spatial spillovers and for $\rho = 0$ the derived steady state is identical to that one derived for the traditional Solow model. Pfaffermayr (2009) additionally shows that for the spatial Solow model the speed of convergence varies across regions and depends not only on β but also the strength of spillovers. The author shows that the lower the absolute value of the gap in initial income of a region's neighbors, the more the region can learn and the higher are spatial spillovers. Ignoring interregional spillovers may lead to an estimation bias if all regions approach to their steady state income levels from below.

Recent contributions have shown that a similar bias may not only occur for the estimation of β but also the impact of the policy stimulus. Eckey & Koesfeld (2005) and Alecke et al. (2011), for instance, have shown that disregarding the likely spatial effects associated with German regional private investment subsidies may lead to a substantial bias in the overall empirical assessment of the policy effect. To measure the latter effect properly, the authors propose a spatially augmented regression approach that does also incorporate further spatial lags of the set of right-hand-side regressors. The main message from the authors' analysis is that, although finding a positive direct effect for supported regions, negative indirect effects partly or entirely offset the positive effect. Similarly, spatial crowding out effects of private sector investment grants are also reported in De Castris and Pellegrini (2010) for Italian regions. Taking into account these findings, we may further augment the model to

$$\begin{aligned} g_{i,t} \;=\; & a_i - b \times ln\left(y_{i,t-1}\right) + \rho \times (\mathbf{W} * ln(y_{j,t-1})) + \delta_1'\mathbf{X} + \delta_2'(\mathbf{W} * \mathbf{X}) \\ & + \sum_{j=1}^{N} \gamma_{1,j} \times ln\left(SF_{i,t-j}\right) + \sum_{j=1}^{N} \gamma_{2,j} \times (\mathbf{W} * ln(SF_{i,t-j})) + F_t + u_{i,t}, \end{aligned} \quad (6)$$

Note that here the policy variable is present twice, first by its level values and also by its spatial lagged values with coefficients γ_1 and γ_2, respectively. The specification in eq.(6) serves as case III of our impact evaluation exercise for objective 1 structural funds payments. As De Castris and Pellegrini (2010) point out, one restricting element of the above model framework is that the empirical measurement of the spatial effect is affected by a spatial identification problem: That is, the spillover effect generated by the policy incentives should be disentangled from the spatial attraction across neighboring areas that cannot be attributed to incentives. By means of factor restrictions the authors then test whether the spatial spillover effect measured by $\gamma_{2,j}$ is equal to the spatial spillover effects induced by the covariates. If this equality holds, the policy spillover effects have to be attributed entirely to the general pattern of spatial autocorrelation across areas and not to specific policy effects.

2.5 Case IV: Spatial multiplicative interaction model

Although this regression approach has a very rich set of explanatory regressors, again one may argue that the empirical specification of the growth equation according to eq.(6) lacks to account of the dynamic effect of interregional spillovers along the convergence path towards steady state. Upon our knowledge, only very few empirical studies try to do so. One exception is Ramajo et al. (2008), who use a spatially augmented multiplicative interaction model to analyse convergence among EU regions during the period 1981 to 1996. However, the authors do not have information with respect to the size of the policy stimulus and simply distinguish funded and non-funded regions by means of their membership in one of the four Cohesion countries (Greece, Ireland, Portugal and Spain). This identification strategy may be problematic since many of factors (social, economic, institutional etc.) rather than EU policy may be influential in driving growth rate differences between the Cohesion-country group and the rest of the European regions. Also, the latter regions have also received structural funds payments over the observation period, which makes causal identification even harder. By using actual amounts of structural funds payments in a spatially augmented multiplicative interaction model, we try to circumvent this identification problem.

In order to incorporate the spatial effect on the region's speed of convergence, we do so by conditioning the policy effect on a second modifying variable in the regression design. Here we use the amount of objective 1 payments to neighboring regions. Taking up the argumentation from Pfaffermayr (2009) we expect that with an increasing amount of funds allocated to neighboring regions the growth performance of region i ceteris paribus decreases since the learning effects from having more technology-advanced regions around diminish. Also, this variable may capture the spatial crowding out effects observed from regional policy grant schemes in Eckey and Kosfeld (2005) as well as De Castris and Pellegrini (2010). The full regression equation then becomes

$$\begin{aligned} g_{i,t} \;=\;& a_i - b \times ln\,(y_{i,t-1}) + \rho \times (\mathbf{W} * ln(y_{i,t-1})) + \delta_1'\mathbf{X} + \delta_2'(\mathbf{W} * \mathbf{X}) \\ &+\gamma_1 \times ln\,(SF_{i,t-1}) + \gamma_2 \times (\mathbf{W} * ln(SF_{i,t-1})) + \phi_1 \times (ln(SF_{i,t-1}) \times (\mathbf{W} * ln(SF_{i,t-1}))) \\ &+\phi_2 \times (ln(SF_{i,t-1}) \times ln(y_{i,t-1})) + \phi_3 \times (\mathbf{W} * ln(SF_{i,t-1})) \times ln(y_{i,t-1})) \\ &+\tau \times (ln(SF_{i,t-1}) \times (\mathbf{W} * ln(SF_{i,t-1})) \times ln(y_{i,t-1})) + F_t + u_{i,t}, \end{aligned} \tag{7}$$

As for the regression approach in eq.(4), in order not to run the risk of obtaining an omitted variable bias, all individual and higher order constitutive terms have to be included in the specification. The main parameter of interest, τ, thus measures the region's speed of convergence conditional on the amount of own funding for region i as well as the amount of funds allocated to the neighborhood of i. However, again we have to be aware that this multiplicative interaction effect model deserves a careful statistical interpretation. Before we turn to the empirical estimation and interpretation of the outlined cases I to IV, we first give a brief overview of the dataset employed and present some stylized facts.

3 Institutional setup, data and stylized facts

The SF are the main instruments of the EU regional policy and are intended to support handicapped regions by the provision of physical investment grants to the private business sector, human capital qualification schemes as well as local public infrastructure. The funding is split into three major objectives, among them the objective 1 payments (or in the new terminology of EU-funds the objective "convergence"). Objective 1 payments are provided to promote growth in lagging regions whose GDP per capita is below 75 % of the EU average and are mainly issued through the European Regional Development Fund (ERDF) and the European Social Fund (ESF).

For the focus of our study, there are some strong arguments to concentrate on the narrow definition of objective 1 payments instead of looking at the effectiveness of all objectives. First of all, the legislative framework and selection criteria for objective 1 regions have stayed nearly unchanged for the three analysed funding periods 1994–1999, 2000–2006 and 2007–2013. This does not hold for the other objectives. Furthermore, objective 1 payments are the most prominent SF instrument making up two third of the entire SF budget. Moreover, objective 1 payments have a clear measurable policy goal in terms of fostering regional income convergence and have a clear definition of regional standards for claiming Objective 1 payments. That is, regions with a GDP per capita (thereafter GDPpc) below 75 percent of the EU average are eligible for receiving objective 1 payments, irrespective of their current GDP growth or any form of growth expectations. This should reduce the potential problem of reversed causality for analyzing the impact of objective 1 payments on income growth.

Data about funding payments are taken from the commission's annual report on the structural funds for the years 1994 to 1999 (European Commission, 1996 to 2000) and from on-site access at the DG Budget for the years 2000 to 2007.[6] We need to make some assumptions regarding actual financial payments for the period 1994–1999, since there is a difference between the sum of commitments and the sum of payments for this period. By the $N + 2$ rule we know

[6] We concentrate on information about real payments because it seems to be unrealistic that there is an effect merely arising from the commitment of grants.

that all commitments from 1999 have to be paid out in 2001 at latest. Therefore, we equally spread differences between the sum of commitments and payments for the year 1999 on the actual spendings for the subsequent years 2000 and 2001. Having no further information on the actual spending behavior, this seems for us to be the best way for handling this matter.

We estimate our model specifications for a set of 127 EU15 regions over the period 1997–2007. Our outcome variable of interest is the annual growth rate of GDPpc. As mentioned before, the included set of regressors are mainly considered to control for economic differences and therefore allowing individual steady-state levels. We explicitly control for regional differences in four key variables: i.) physical capital accumulation, ii.) the share of human capital, iii.) the region's labor participation and iv.) annual population's growth. Capital accumulation is measured in terms of the investment intensity as gross fixed capital formation in manufacturing relative to GDP. Since it is rather hard to find high-quality data for human capital at the EU regional level, we proxy the latter by the share of human resources in science and technology in total employment.

We also include the labor participation rate defined as employed persons per total population among the set of regressors in order to cancel out regional differences in productivity (GPD per employed persons) and GDPpc. And finally we control for regional population growth to wipe out these effects in the variation of our left hand side variable. Especially for regions with strongly varying population growth rates, this latter effect may complicate the isolation of the causal effect of objective 1 funding on GDPpc growth. For empirical estimation, we use all variables in their logarithmic transformations. An overview of variable definitions and summary statistics is given in Table 2. We use the disaggregated NUTS 2 whenever possible; however, due to poor data availability especially for the structural funds, in some cases we have to rely on higher levels of aggregation. Eventually, this leads to a sample of 127 regional entities. A detailed list of all regions covered is given in the appendix.

4 Econometric Approach and Results

4.1 Dynamic Panel Data Estimation

Choosing the proper estimation technique for our various regression designs is a challenging issue since we need to account both for time as well as spatial dynamics in a panel data framework. However, we can strongly benefit from recent advantages in estimating dynamic panel data processes as well as their spatial augmentations. To briefly develop the underlying estimation strategy, we rewrite the standard panel data specification of our neoclassical growth model in terms of a general dynamic panel data model (in log-linear specification) as

$$y_{i,t} = \alpha_0 + \alpha_1 y_{i,t-1} + \sum_{j=0}^{k} \beta_j' \mathbf{X}_{i,t-j} + \mu_i + \eta_t + \nu_{i,t}, \tag{8}$$

Table 2: Variable definitions and descriptive statistics

Variable	**Definition**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Income ($GDPpc$)	GDP per capita (in Euro)	21537.31	8328.19	6900	78100
Capital Stock changes (INV)	GFCF in manufacturing relative to GDP (in %)	0.1259	1.1543	0.0001	0.4117
Human capital (HC)	Human Resources in Science & Technology per total employment (in %)	0.2311	0.0675	0.0604	0.4216
Labor Force Participation (LFS)	Ratio between total employment and population	0.4507	0.0487	0.1788	0.5747
Population Growth Rate (POP)	Annual change in population level (in %)	1.0041	0.0063	0.9867	1.0383
Structural Funds Payment (SF)	Objective 1 ("convergence") payment per capita (in Euro)	39.5331	67.1766	0	475.5377

Source: All economic variable are taken from Eurostat (2010) regional database, data on structural Funds payments are obtained from DG Budget, unit A.2.

where the dependent variable is now specified in level terms as $y_{i,t}$ and the coefficient α_1 can be related to our b from above according to $\alpha_1 = 1 - b$. In this general setup μ_i present the unobservable individual effects, η_t are time-fixed effects and $\nu_{i,t}$ is the remainder error term.

In the recent literature there are numerous contributions on how to estimate a dynamic model of the above type consistently and efficiently. One specific problem to deal with is the inclusion of a lagged dependent variable in the estimation equation and its built-in correlation with the individual effect: That is, since y_{it} is a function of μ_i, also $y_{i,t-1}$ is a function of μ_i and thus $y_{i,t-1}$ as right-hand side regressor in eq.(8) is likewise correlated with the combined error term. Even in the absence of serial correlation of ν_{it} this renders standard λ-class estimators such as OLS, the fixed effects model (FEM) and random effects model (REM) inconsistent (see Nickel 1981 or Baltagi 2008 for an overview).

Besides analytical and bootstrap-based approaches aiming to correct for the bias of the FEM (Kiviet 1995, Everaert and Pozzi 2007), the most widely applied approaches of dealing with this kind of endogeneity typically applies instrumental variable (IV) and generalized methods of moments (GMM) based techniques. While the first generation of models used transformations in first differences, latter extensions also account for the information in levels, when setting up proper estimators. A common tool is the system GMM estimator (thereafter, SYS-GMM) by Blundell & Bond (1998) as weighted average of first difference and level GMM. The joint determination of data in first differences and levels mainly helps to increase the efficiency of the latter method compared to earlier specifications solely relying on first differenced data (Arellano and Bond 1991). In this paper, we mainly focus on the SYS-GMM estimator and use non-IV alternatives such as the corrected FEM as further references in order to detect severe misspecifications among the IV based approaches. Regarding the latter, we also carefully account for the 'many' and/or 'weak instrument' problem typically associated with GMM estimation, since the instrument count grows as the sample size T rises.

Given its very flexible form, subsequently also extensions of the GMM approach have been proposed, which make use of consistent moment conditions for the instrumentation of the spatial lag coefficient of the endogenous variable (see Kukenova and Monteiro 2009, Mitze 2010 as well as Bouayad-Agha and Vedrine 2010). Kukenova and Monteiro (2009) have also shown, by means of Monte Carlo simulations, that the spatial dynamic SYS-GMM model exhibits satisfactory finite sample properties. We use various sets of instruments for the spatial extension of the SYS-GMM approach. Besides, for the case of the multiplicative interaction models in case II and case IV we also have to be aware the standard statistical inference is not feasible and regression outputs cannot be interpreted per se. As Brambor et al. (2005) as well as Braumoeller (2004) point out, besides the inclusion of all constitutional terms to avoid running the risk of an omitted variable bias, it is essential to calculate substantively meaningful marginal effects and standard errors. Moreover, the analysis should not interpret constitutive terms as if they are unconditional marginal effects since this is only true for a very restrictive case (namely when all further variables used to calculate the interaction term are zero). The calculation of meaningful standard errors implies that further elements of the variance-covariance matrix of the estimation system have to be used besides it main diagonal elements (see Brambor et al. 2005 for details). We will account for these aspects in the following.

4.2 Empirical results: Case I and II

We start estimating the linear additive model (case I) as most commonly applied evaluation approach for regional policy effectiveness of EU structural funds. We estimate different model specifications starting from the basic setup outlined in eq.(3). The results for the standard fixed effects model (FEM), a bias corrected version of the latter (FEMc) and SYS-GMM-models are reported in Table 3. While the set of economic control variables remains unchanged in all specifications, for the policy variable we allow the lag structure to vary between a short-run single lag specification and a medium-run one to four lag specification. For the latter case, Table 3 reports the joint effect of funding computed based on the delta method. Next to objective 1 funding intensities we also test for the significance of a binary dummy which takes values of one if the region was funded in the last period and zero otherwise. All equations include time common effects and for the case of the SYS-GMM model we also include country level dummies.[7]

[7] Due to the time-invariance the country-specific effects are cancelled out in the FEM and FEMc.

Columns I to III in Table 3 report the results in the FEM benchmark model. All control-variables show the theoretically excepted coefficient sign and are tested to be statistically significant. The only exception is the population growth rate, which turns out to be insignificant. However, physical investments, human capital and the labor participation rate have a positive impact on GDPpc evolution. The included lagged GDPpc value has a coefficient of less than 1, which accords to the neoclassical theory and proofs stationarity of the variable. From the regression output we can also calculate the implicit convergence-speed to the individual steady state levels. Taking column II as an example, our estimates imply a very high speed of convergence of about 24 % per year.

However, as Arbia et al. (2008) point out, depending on the chosen econometric method, a careful interpretation of the regression parameter has to be done. First, given the FEM setup we have to keep in mind that the implicit speed is the adjustment process towards the region's on steady state and not towards a common long-run level. Moreover, the rather unrealistically higher convergence speed may stem from an estimation bias in the estimation of the lagged variable as mentioned above. Indeed, for the FEMc model the speed of convergence reduces significantly to values between 5 and 6 %. For the remaining variables the output of the FEM and FEMc are nevertheless very similar. Both models also report negative coefficients for the funding variable in per capita terms as well as binary dummy specification. While the results are significant for the single lag specification, they are tested insignificant for the cumulated one to four period lag effect.

Table 3: Dynamic panel data estimation results for per capita GDP

Dep. Var.: $ln(GDPpc_t)$	I	II	III	IV	V	VI	VII	VIII	IX
	FEM	FEM	FEM (D)	FEMc	FEMc	FEMc (D)	SYS-GMM	SYS-GMM	SYS-GMM (D)
$ln(GDPpc_{t-1})$	0.7959***	0.7851***	0.7952***	0.9486***	0.9361***	0.947***	0.877***	0.807***	0.889***
	(0.0331)	(0.0322)	(0.0332)	(0.0183)	(0.019)	(0.0183)	(0.0305)	(0.0599)	(0.0324)
$ln(INV_{t-1})$	0.0027***	0.0022**	0.0028***	0.0025*	0.0019	0.0025**	0.0012*	0.0043***	0.0012*
	(0.0009)	(0.0008)	(0.0009)	(0.0013)	(0.0013)	(0.0013)	(0.0006)	(0.0016)	(0.0006)
$ln(HC_{t-1})$	0.0318**	0.0377**	0.0320**	0.0225**	0.0284***	0.0227**	0.038***	0.0254**	0.041***
	(0.0147)	(0.0144)	(0.0344)	(0.0103)	(0.0103)	(0.0104)	0.0111	(0.0129)	(0.0121)
$ln(LFS_{t-1})$	0.0915***	0.0840**	0.0911***	0.0532**	0.0471*	0.0527	0.0107***	-0.3108	0.1192***
	(0.0341)	(0.0329)	(0.0344)	(0.0269)	(0.0268)	(0.0269)	(0.0388)	(0.1938)	(0.0435)
$ln(POP_t)$	-0.0940	-0.2461	-0.0849	-0.5398	-0.6830*	-0.5301	0.835	-0.6118	0.4752
	(0.2792)	(0.2624)	(0.2789)	(0.355)	(0.3517)	(0.3552)	(0.5924)	(0.4148)	(0.6699)
$ln(SF_{t-1})$	-0.0014**		-0.0259**	-0.0015***		-0.0282***	-0.0022***		-0.041***
	(0.0005)		(0.0116)	(0.0005)		(0.0094)	(0.0004)		(0.0075)
$ln(SF_{t-1})$ to $ln(SF_{t-4})$ (joint)		-0.0009			-0.0009			-0.0054**	
		(0.0006)			(0.0007)			(0.0026)	
No. Of Groups	127	127	127	127	127	127	127	127	127
No. Of Obs.	1216	1052	1052	1216	1052	1216	1216	1052	1216
Time Effects	22.29***	23.18***	22.58***	416.68***	64.73***	47.10***	39.66***	74.37***	370.49***
Hansen J-statistic							29.42*	12.98	26.16*
Diff-in-Hansen for Lev. Eq.							6.22	8.80*	5.73
Diff-in-Hansen for SF							6.21	8.16	3.97
AR2							1.68*	1.38	1.70*
STMI	0.180***	0.187***	0.181***	0.102***	0.105***	0.102***	0.158***	0.133***	0.146***

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level. Robust standard errors in brackets. D = Dummy variable specification. AR2 is the Arellano& Bond (1991) test for serial autocorrelation in the twice lagged residuals, STMI is the residual based space-time Moran's I statistic based on Lopez et al. (2010).

Also in the case of the SYS-GMM specification, most economic variables are estimated to be statistically significant for reasonable confidence levels and in concordance with economic theory. The objective 1 funding variable is negative and significant for both, the single lag specification as well as the augmented lag model. Since the SYS-GMM model relies on IV regression, we put special attention to post-estimation testing of IV validity. Table 3 thus reports the results of the Hansen J-statistic. Here, we deliberate chose a small number of IV candidates based on a maximum lag length restriction of 4 periods as well as using collapsed instruments in order not to weaken the testing results (see Roodman 2009; Bowsher 2002). As the results show, we do not get any evidence for correlation between the selected instruments and the model's error term. Based on a Diff-in-Hansen test, isolating a subset of instruments, we also explicitly check whether the use of the level equation in the SYS-GMM approach may cause trouble and whether the internal instruments for the policy variable can be regarded as exogenous. In both cases instrument exogeneity cannot be rejected at the 5 % level.

Taking this first empirical evidence, we then move on to the case of the multiplicative interaction model (case II). As already argued above, here it is nearly necessary to go beyond the traditional regression output in order to convey quantities of interest such as the marginal effect of an explanatory variable on the endogenous one. As we will show in the following, often a graphical presentation of the effect together with reasonable confidence intervals may help to illustrate the intended point of interest, especially if the conditioning variables are continuous as for our case of the objective 1 structural funds growth effect conditional on the underlying initial income level or, alternatively, the region's gap to long-run steady-state level.

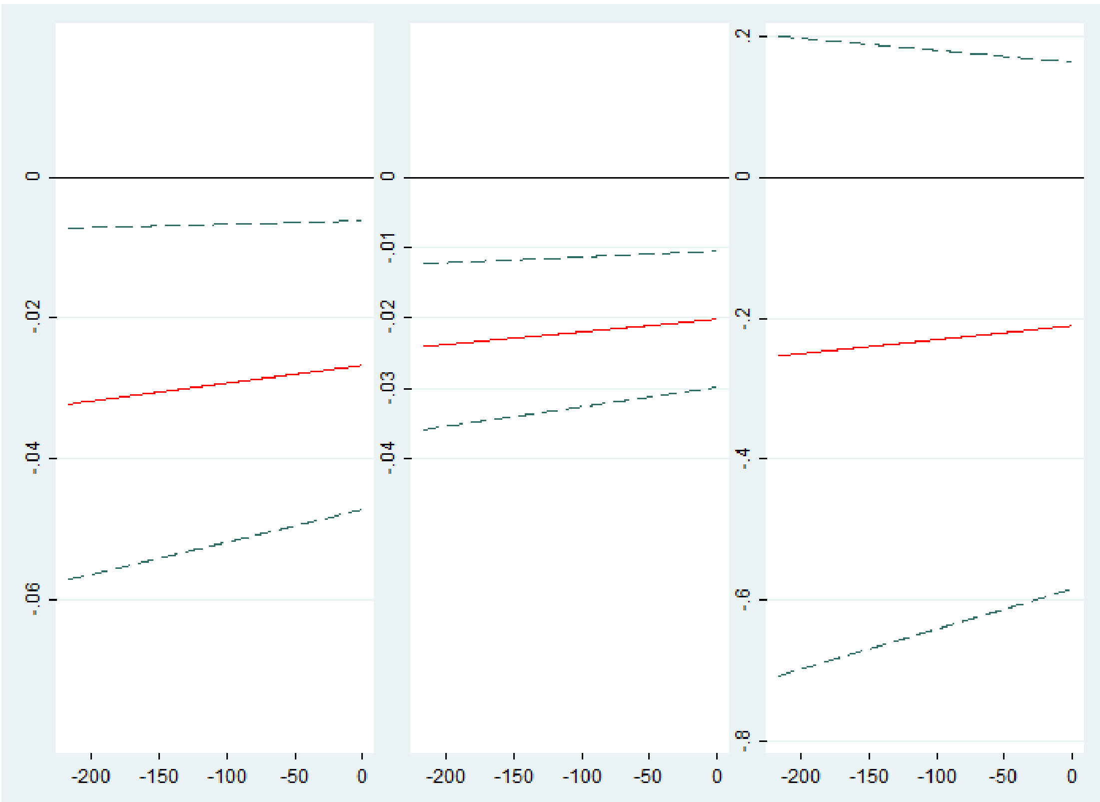
To identify the quantify of the additional growth impulse of the policy incentive multiplicative interaction model from eq.(4), we take the difference in the convergence rate between funded and non-funded regions as $\xi = (1 - e^{-\beta_{net} T})/T$, solve for β_{net} and then use the obtained coefficient to measure the difference in the speed of convergence conditional on the gap to steady-state income as

$$\Delta_n y_{i,t} = \beta_n \times (y^*_{i,t} - y_{i,t}). \tag{9}$$

$\Delta_n y_{i,t}$ measures the marginal effect of objective 1 funding conditional on the region's gap at time period t to the long-run steady-state level (in percentage points). Using this relationship based on the regression results for the multiplicative interaction model according to eq.(4), we can plot the distribution of the additional growth impulse of public support conditional on the observed empirical variance of labor productivity. The resulting policy effects together with a 95 % confidence interval are shown in Figure 3 for the FEMc and SYS-GMM using funding intensities (left and center graph, respectively) as well as the SYS-GMM model using the 0/1 flag indicator for being funded or not funded (right graph). The x-axis in Figure 3 plots the income gap to the steady-state level, as in Pfaffermayr (2009) we assume that all region approach their steady state from below and set the zero gap equal to the maximum value of the income distribution in our sample.

The y-axis plots the marginal growth effect of the objective 1 structural funds in percentage points. The displayed distribution of the marginal effects relative to the income gap in Figure 3 shows that the effect is negative for all three specifications and is rather constant for different income gaps. While the effect is insignificant for the dummy variable approach, it turns out significant when using funding intensities. The estimated marginal effect is about 2–3 percentage points smaller relative to the growth rate of non-funded regions for a similar projected income position. The results thus support the negative findings from the linear additive regression model. Additionally, it shows that the lower growth performance of funded regions holds to be almost constant for the plotted range differences from steady state income. This indicates, that no strong movements towards a common steady state take place and that different convergence clubs are formed. The underlying regression results for the multiplicative interaction model can be found in the appendix (see Table A1).

Figure 3: Marginal growth effect of objective 1 structural funds conditional on regional income gaps



Note: Left = FEMc estimates (XII), center = SYS-GMM (XIV), right = SYS-GMM with SF dummy (XV). Dashed lines are 95 % confidence intervals according to Brambor et al. (2005).

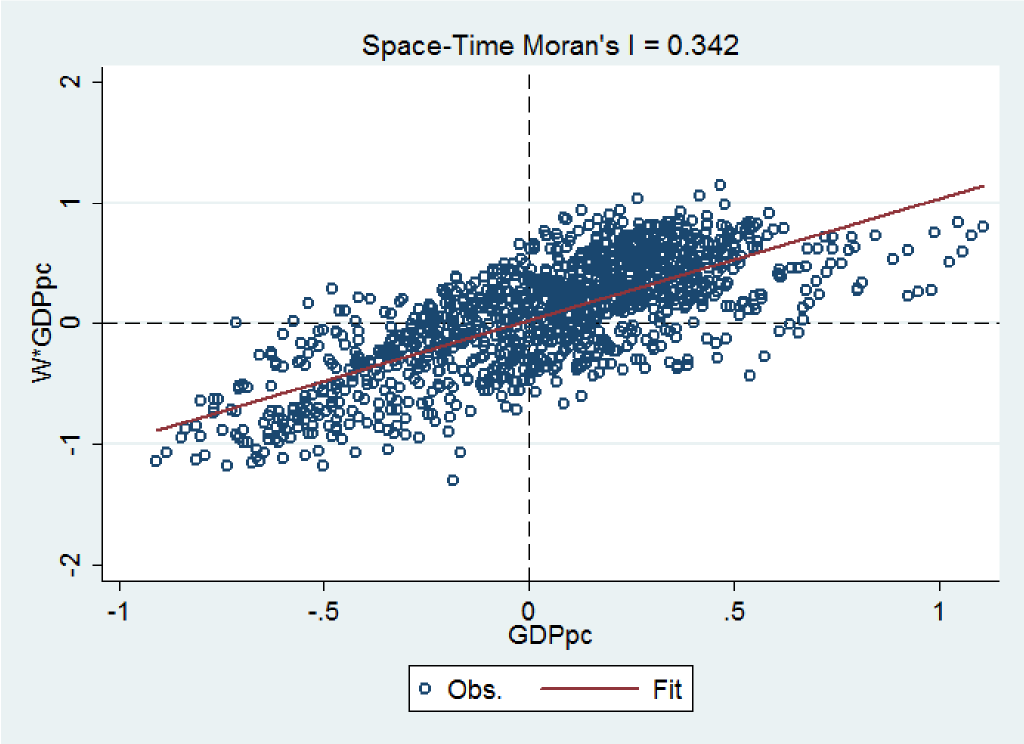
4.3 Extension to modelling spatial dynamics: Case III and IV

One shortcoming of the above regressions is the disregard of spatial interdependence among the variables. To account for the potential role of spatial spillovers originating from mutual dependences among the variables, we now construct for each variables its spatial lag defined as weighted average of values in the neighborhood of region i, where we use geographical distances as weighting factors. The construction of a spatial weighting matrix $\mathbf{W}$ based on geographical distances basically needs two modelling decisions to be taken: At the first stage one has to decide whether the geographical centriod or the region's capitol city is taken as point of measurement. At the second stage the distances have to be transformed, in standard procedures this is done by the inverted distance or the squared inverted distance. Alternatively one can employ a k-nearest neighbor approach, which use geographical information to identify neighbors in a first step and then condense these information to a dummy variable if region j belongs to the k-nearest neighbors of region i and 0 otherwise. A standard value is $k = 10$, which allows a spatial effect to exist with the 10 next neighbors, but no influence of the further regions. Since the estimation results may crucially depend on the chosen underlying spatial weighting scheme, use robustness checks to test the sensitivity of our results to changes in the weighting scheme. As default we use inverted distances to construct $\mathbf{W}$. Data about capitol cities come from Inforegio (2009), the distances between the capitol locations are calculated with latitudes and longitudes by WGS84 system.

As first check for the relevance of space in our regional dataset, we estimate the space-time version of Moran's I statistic (STMI) for our outcome variable GDPpc as recently proposed by Lopez et al. (2010). The resulting Figure 4 is easy to interpret: Using a scatter plot for a standardized variable $\breve{y}$ (with $\breve{y} = [y - \bar{y}]/sd(y)$) against its average neighbors $\breve{y}^s$ the distribution of observations in the four quadrants around the mean of $\breve{y}$ and $\breve{y}^s$ captures a picture of the spatial association of the variable y. If there is no spatial clustering the individual values of y^s should not systematically vary with y. On the contrary, for positive spatial association observations above (below) the means of y should correlate with high (low) values for y^s. Fitting a regression line to this scatter plot its slope coefficient shows the value for Moran's I correlation given the original variable y and the weighting matrix W^*. The clearly upwards sloping regression curve indicates a clear spatial connection of the regional GDPpc values. This spatial correlation needs to be considered in the further estimations. Similar spatial correlations are also detected for the set of regressors and for the residuals of the aspatial regression models. Here the STMI results in the last row of Table 3 clearly hint at the need of estimating spatially extended models to avoid a estimation bias stemming from cross-sectionally correlated residuals.

For cases III and IV we thus explicitly allow for spatial spillovers from the endogenous variable and the set of regressors including our SF policy variable. We start with a specification

Figure 4: Graphical presentation of Moran's I for per capita GDP



only containing spatial lags of the right hand side regressors and then also include a spatial lag of the dependent variable in columns XVIII and XIX of Table 4. The latter inclusion nevertheless has to be done carefully, in order not to affect the dynamic stability of the model (see e.g. Parent & LeSage, 2009). We use a time-space dynamic specification, which restricts spatial lags of the endogenous variable also to enter with a one period time lag (Bouayad-Agha & Vedrine 2010). Since the SYS-GMM approach has shown satisfactory results in the aspatial benchmark case and is easy to be applied to spatial circumstances, we concentrate on this specification in the following. The regression results are reported in Table 4. The results show that the time lagged endogenous variables remain statistically significant and of almost equal size as in the aspatial benchmark model. However, we do not find significant coefficients for the spatial lag of the dependent variable.

The spatial lags of the exogenous variables mostly turn out significant. Here, the investment intensity in neighboring region shows positive spillover effects on GDPpc in region i, while a higher labour force participation rate in neighboring regions has the opposite effect. We can also see from Table 4 that the negative total effect of objective 1 fundings mostly stems from its spatial spillover part, while the direct effect is estimated to be insignificant. Again, we carefully test for IV validity, since the number of instruments growth by the inclusion of spatial lags. As shown, the Hansen J-statistic does not reject instrument exogeneity for reasonable confidence intervals. There is no sign for remaining serial autocorrelation in the residuals as indicated by the Arellano & Bond (1991) test (denoted AR2). Finally, we could reject the null hypothesis that the spatial pattern in our policy variable is entirely attributable to a common spatial trend (see De Castris & Pellegrini 2010 for details).

Table 4: Model estimates by Spatial SYS-GMM)

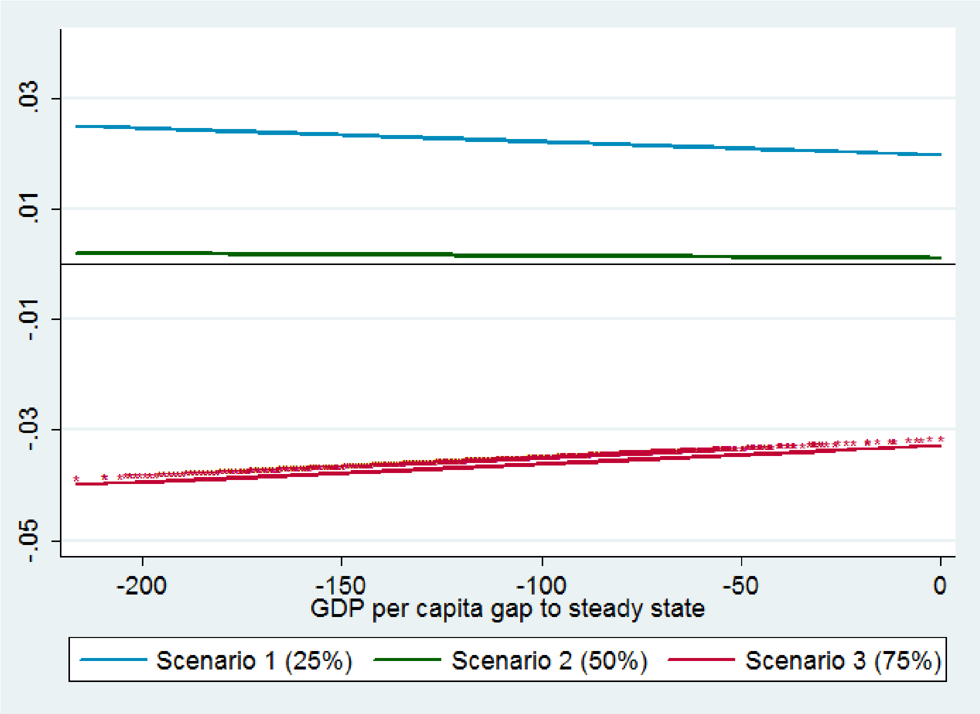
Dep. Var.: $ln(GDPpc_t)$	XVI SpSYS-GMM	XVII SpSYS-GMM	XVIII SpSYS-GMM	XIX SpSYS-GMM
$ln(GDPpc_{t-1})$	0.7816***	0.7976***	0.8930***	0.8626***
	(0.0716)	(0.0538)	(0.0679)	(0.0585)
$ln(INV_{t-1})$	-0.0091*	-0.0020	-0.0113***	-0.0075***
	(0.0051)	(0.0017)	(0.0033)	(0.0028)
$ln(HC_{t-1})$	0.0372*	0.0332*	0.0090	0.0274*
	(0.0203)	(0.0199)	(0.0119)	(0.0155)
$ln(LFS_{t-1})$	0.0360*	0.0927*	0.0467*	0.0783
	(0.0214)	(0.0538)	(0.0245)	(0.0232)
$ln(POP_t)$	-0.0126	-0.2264	-0.7215	0.9924
	(0.2909)	(0.4532)	(0.9126)	(0.6504)
$ln(SF_{t-1})$	0.0002		-0.0002	
	(0.0012)		(0.0009)	
$ln(SF_{t-1})$ to $ln(SF_{t-4})$ (joint)		0.0019		-0.0001
		(0.0022)		(0.0008)
$(\mathbf{W} * ln(GDPpc_{t-1}))$			0.3212	0.0306
			(0.2363)	(0.2479)
$(\mathbf{W} * ln(INV_{t-1}))$	0.1018***	0.0699***	0.0962***	0.0527***
	(0.0301)	(0.0115)	(0.0185)	(0.0155)
$(\mathbf{W} * ln(HC_{t-1}))$	0.1702	0.1827	-0.3107**	-0.1078
	(0.2068)	(0.1368)	(0.1518)	(0.1696)
$(\mathbf{W} * ln(LFS_{t-1}))$	-0.5931	-1.3381***	-1.7738***	-1.0545**
	(0.6033)	(0.4703)	(0.4866)	(0.4906)
$(\mathbf{W} * ln(POP_t))$	-3.3985	-2.1742	-0.8967	-4.5573
	(2.1001)	(3.9481)	(3.0395)	(5.2325)
$(\mathbf{W} * ln(SF_{t-1}))$	-0.0178**		-0.0236***	
	(0.0071)		(0.0074)	
$(\mathbf{W} * ln(SF_{t-1}))$ to $(W * ln(SF_{t-4}))$ (joint)		-0.0411***		-0.0343***
		(0.0157)		(0.0787)
No. Of Groups	127	127	127	127
No. Of Obs.	1216	1052	1216	1052
Time Effects	121.98***	241.08***	179.02***	153.50***
Hansen J-statistic	21.70*	28.17	24.21	25.59
AR2	0.89	0.33	0.57	0.52
Common factor test for W*SF (p-value)			(0.00)	(0.00)

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level. Standard errors in brackets. SpSYS-GMM as efficient two-step estimation. Common factor test according to De Castris & Pellegrini (2010). For details see text.

As a final specification test, we compute the results of the spatially augmented multiplicative interaction term model. This case IV may give further insights with respect to the role played by spatial spillovers from other funded regions in the neighborhood of region i. Since the graphical presentation involving two modifying variables (the initial income gap as in the aspatial specification as well as the amount of objective 1 funding for spatial neighbors) may become confusing, for the latter variable we plot three scenarios. These are the marginal effect of objective 1 funding to i on GDPpc in i conditional on its difference to steady state income i.) for a low level of funds received in the neighborhood (25 % percentile), ii.) a medium level (50 % percentile) and iii.) a high level of funding in neighborhood regions (75 % percentile). The results are shown graphically in Figure 5.

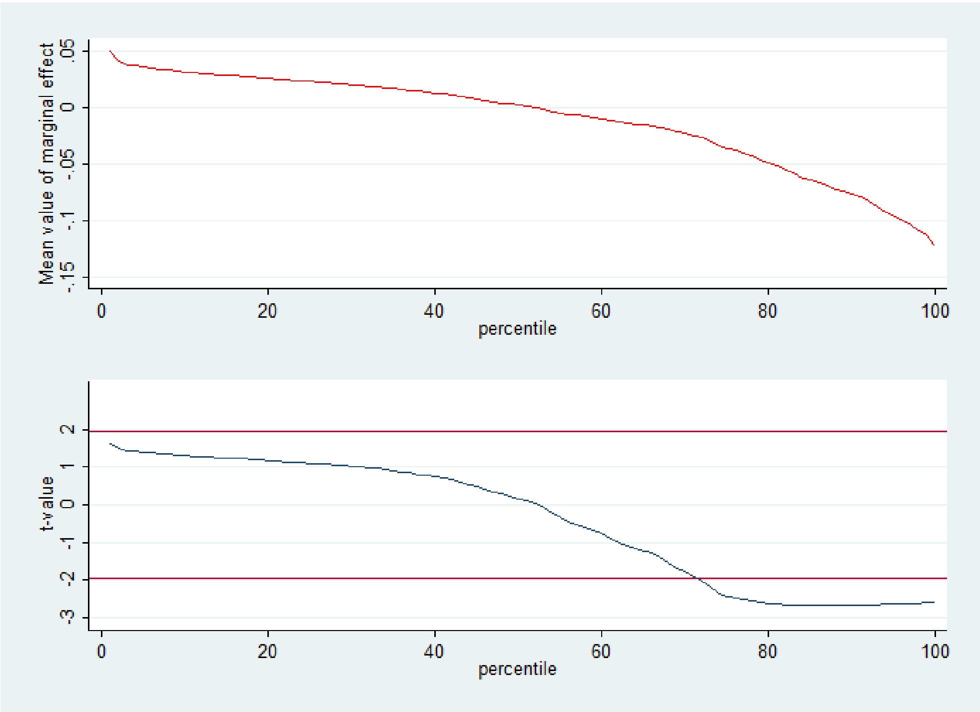
The figure shows, that for regions dominated by a neighborhood with a high share of funding, the resulting economic growth performance is significantly worse off. For the medium scenario (50 % percentile) the effect is almost inexistent, while for those regions in the geographical proximity of less intensively funded regions Figure 5 shows even a positive, albeit insignificant effect. Since the estimated marginal effects are rather constant across different income gaps, we additionally plot the mean effect for each percentile of the spatial lag of the policy variable. The results in Figure 6 show that the effect is statistically significant and negative for neighborhoods characterized by a high share of objective 1 funding roughly above 75 %. These latter results confirm the theoretical expectations from the spatially augmented Solow growth models that positive spillovers are the higher the more advanced the neighboring regions are and vice versa (Pfaffermayr 2009). In this sense, the share of objective 1 funding in the spatial neighborhood can be interpreted as an indicator for technological backwardness. The result also supports our interpretation from above that funded and non-funded regions form separate convergence clubs, where lagging regions hold back each other. EU regional policy by means of objective 1 fundings seems to have no effect on fostering income convergence among EU15 regions.

Figure 5: Marginal policy effect conditional on regional income gaps and spatial spillovers from funding



Note: Starred lines indicate significance.

Figure 6: Significance bounds for mean marginal effect of objective1 payments



Note: Upper and lower bounds for t-value are based on the 5 % significance level.

4.4 Robustness checks

In this section, we aim at testing the validity of the above results for alternative spatial weighting matrices. As Stakhovych & Bijmolt (2009) have recently shown by means of Monte Carlo simulations, the actual choice of $\mathbf{W}$ may indeed significantly impact on the regression results. Since the empirical literature does not offer clear guidance with respect to the design for $\mathbf{W}$, we use three different schemes as comparison for the reference case of inverted distances. The first alternative employs squared values of the original distance elements when constructing inverted distance weights, and thus puts a much higher value on close neighbors.

As a second specification, we use a condensed binary k-nearest neighbor matrix with a critical cut-off number of $k = 10$ as commonly used in other studies (see Ertur & Koch 2006 or Mohl & Hagen 2010). Matrix elements take a value of one if region j belongs to the 10 nearest neighbors of region i and is 0 otherwise. We standardize the matrix for the estimation therefore the values are equal to $1/k$ instead of 1.[8] As a third specification, we choose a randomly generated matrix.[9] We expect that spatial lags constructed from this matrix turn out to be insignificant. Estimation results for the point estimates of our policy variable are displayed in Table 5. The table shows that only for the randomly generated weighting matrix the effects turn indeed out to be insignificant as expected apriori. For the other specification the results are absolutely in line with our benchmark specification, underlying the validity of the regression results from above.

Table 5: Robustness Checks for spatial regression model in Table 4

Column		Inverted Distances	Squared inverted distances	Binary Matrix (k=10)	Random Matrix
XVI	$(\mathbf{W} * ln(SF_{t-1}))$	-0.0178**	-0.011***	-0.0096***	0.00004
		(0.0071)	(0.0044)	(0.003)	(0.0408)
XVII	$(\mathbf{W} * ln(SF_{t-1,t-2,t-3,t-4}))$	-0.0411***	-0.0165***	-0.0138***	0.0067
		(0.0157)	(0.0061)	(0.0044)	(0.0407)
XVIII	$(\mathbf{W} * ln(SF_{t-1}))$	-0.0236***	-0.0069**	-0.0045**	0.0068
		(0.0074)	(0.0034)	(0.0017)	(0.0236)
XIX	$(\mathbf{W} * ln(SF_{t-1,t-2,t-3,t-4}))$	-0.0343***	-0.0066	-0.0071	-0.0376
		(0.0787)	(0.0051)	(0.0045)	(0.0314)

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level. Standard errors in brackets.

[8] This matrix might be asymmetric; there is the possibility that region j belongs to the closest k neighbors of region i but not the other way around. This problem concerns mainly peripheral regions of the EU15.

[9] This matrix is symmetric and has random number obtained from the Stata routine TRUERND written by Radyakin (2011).

5 Conclusion

In this paper we have analysed the effectiveness of EU regional policy in fostering income convergence among EU15 regions. The policy variable in focus are objective 1 (or "convergence") payments. Since these funds have a clearly attributable policy goal and have a consistent legislative framework over the last three funding periods, a formal impact analysis can be conducted. Using different empirical models derived from growth theory, we are able to estimate the effect of objective 1 payments on regional GDP per capital evolution for 127 EU regions throughout the sample period 1997–2007. We put particular attention to correctly specify and interpret the policy variable in the regression approach as well as capture the role played by spatial spillovers. This leads us to a total of for different empirical cases, which are estimated either in a linear additive fashion or based on a multiplicative interaction model. All specifications employ modern methods for the analysis of dynamic panel data models.

Capturing the full range of potential transmission channels from the policy impact on our outcome variable, the results ultimately all hint to the unpleasant conclusion that EU Objective 1 structural funds show to have no or even negative effects on regional growth in the EU15. Our results also show that in particular the spatial components in the model play an important role in the decomposition of this negative effect. We are able to confirm recent theoretical contributions on the spatial Solow growth model indicating that negative spatial spillovers are the higher the less advanced the neighboring regions are. In this sense, the share of objective 1 funding in the spatial neighborhood can be interpreted as an indicator for technological backwardness. The results also hint at earlier findings in the literature that funded and non-funded regions form separate convergence clubs, where lagging regions hold back each other. EU regional policy by means of objective 1 fundings seems to have no effect on fostering income convergence among EU15 regions.

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Appendix

A.1 Regression Results for Multiplicative Interaction Models

Table A1: Estimation results of aspatial and spatial multiplicative interaction models

				Case II			Case IV
Dep. Var.: $ln(GDPpc_t)$	X FEM	XI FEM (D)	XII FEMc	XIII FEMc (D)	XIV SYS-GMM	XV SYS-GMM (D)	XX SpSYS-GMM
$ln(GDPpc_{t-1})$	0.7760***	0.7280***	0.9332***	0.9483***	0.8548***	0.8399***	0.9028***
	(0.0175)	(0.0214)	(0.0193)	(0.017)	(0.0203)	(0.0464)	(0.0547)
$ln(INV_{t-1})$	0.0023**	0.0025**	0.0021*	0.0028**	0.0006	0.002***	-0.0022*
	(0.0011)	(0.0011)	(0.0013)	(0.0013)	(0.0007)	(0.0007)	(0.0012)
$ln(HC_{t-1})$	0.0270***	0.0281***	0.0198*	0.0237**	-0.0054	0.0176	0.0432***
	(0.0083)	(0.0083)	(0.0103)	(0.0104)	(0.0127)	(0.0118)	(0.0123)
$ln(LFS_{t-1})$	0.1004***	0.1000***	0.0590**	0.0551**	0.0965***	-0.0253	0.0549**
	(0.023)	(0.0231)	(0.0269)	(0.0274)	(0.0375)	(0.0506)	(0.0245)
$ln(POP_t)$	0.1203	0.1241	-0.3749	0.3911	-0.1758	0.3619	1.237*
	(0.2554)	(0.2563)	(0.3562)	(0.356)	(0.2299)	(0.6439)	(0.6996)
$ln(SF_{t-1})$	-0.0385***	-0.6587***	-0.0266**	-0.0636	-0.0211***	-0.2106	-0.1319**
	(0.0064)	(0.1213)	(0.0104)	(0.0405)	(0.0049)	(0.1908)	(0.0521)
$ln(GDPpc_{t-1}) \times ln(SF_{t-1})$	0.0037***	0.0636***	0.0025**	0.0002	0.0019***	0.01977	0.0142***
	(0.0006)	(0.1217)	(0.001)	(0.0002)	(0.0005)	(0.0188)	(0.0054)
$(\mathbf{W} * Y)_{t-1}$							-0.4411**
							(0.1915)
$(\mathbf{W} * ln(INV_{t-1}))$							0.0353***
							(0.0086)
$(\mathbf{W} * ln(HC_{t-1}))$							-0.2411**
							(0.1204)
$(\mathbf{W} * ln(LFS_{t-1}))$							0.0755
							(0.3919)
$(\mathbf{W} * ln(POP_t))$							-2.2843
							(2.575)
$(\mathbf{W} * ln(SF_{t-1}))$							-0.0910
							(0.06)
$(\mathbf{W} * ln(SF_{t-1})) \times ln(SF_{t-1})$							-0.0157**
							(0.0068)
$(\mathbf{W} * ln(SF_{t-1})) \times ln(GDPpc_{t-1})$							0.0090
							(0.0061)
$(\mathbf{W} * ln(SF_{t-1})) \times ln(SF_{t-1}) \times ln(GDPpc_{t-1})$							0.0017**
							(0.0007)
No. Of Groups	127	127	127	127	127	127	127
No. Of Obs.	1216	1216	1216	1216	1216	1216	1216

Note: ***, **, * = denote significance levels at the 1%, 5% and 10% level. Standard errors in brackets.

A.2 List of Regions