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#608

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

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Editors

Editorial Office

Ruhr Economic Papers #608

Responsible Editor: Roland Döhrn

ISSN 1864-4872 (online) – ISBN 978-3-86788-705-2

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Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

http://dx.doi.org/10.4419/86788705
ISSN 1864-4872 (online)
ISBN 978-3-86788-705-2

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EU Structural Funds and Regional Income Convergence – A sobering experience

Abstract

The European Structural and Investment Funds (ESIF) are the prime instrument of EU regional policy. European policy makers place considerable hope into their growth stimulating funding measures to overcome current economic stagnation. Consequently, there is a strong need for credible evidence regarding the programs' effectiveness. Based on an empirical identification strategy linked to modern growth theory, we find that the disbursement of EU structural funds is negatively correlated with regional growth. Incorporating spatial dynamics and decomposing this correlation into a direct and a spatially-indirect component, it is particularly the latter which determines this "sobering" finding. Regarding the economics behind these results, the obtained negative spatial effect may reflect the role played by policy-induced spatial competition among neighboring regions. It could also highlight the backwardness in technological endowment and economic structures of highly funded regions. In any case, EU structural funding does not seem to contribute effectively to foster income convergence across regions.

JEL Classification: C21, R12, R58

Keywords: EU regional policy; Solow growth model; spatial spillovers; panel data

February 2016

1 Philipp Breidenbach, RWI; Timo Mitze, University of Southern Denmark, RWI, and RCEA; Christoph M. Schmidt, RWI, RUB, and CEPR London. *– We are grateful to Thomas Bauer, Roland Döhrn, Alfredo Paloyo, Nadine Riedel and Jens Südekum as well as participants of the RES Conference 2012, the ESF Exploratory Workshop on Fiscal Policy 2012, the ERSA 2011 and the IIPF 2012.* *– All correspondence to: Philipp Breidenbach, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: Breidenbach@rwi-essen.de*

1. Introduction

The European Structural and Investment Funds (ESIF) are one of most important supranational economic policy instruments of the European Union (EU). They aim at reducing disparities between the levels of development of the various regions as codified in Article 174 of the Treaty on the Functioning of the European Union. Throughout the last decades, the budgetary importance of the ESIF as part of the complex construction of EU regional policies has grown steadily. In the current financial framework period 2014-2020 for the first time in the EU's history the major share of funding – 450 out of 960 billion Euro – has been allotted to regional policies under the headings of "Cohesion" (€325 bn.) and "Competitiveness and Growth" (€125 bn.). Traditionally, the EU's common agricultural policy, which had been the heavyweight of EU funding over the last decades (European Council 2015).

Given the persistence in economic differences between regions and countries within the EU and the disappointing pace of economic recovery after the great recession of 2007/08 and the subsequent "Euro" debt crisis, there is a vivid debate among politicians and scientific scholars regarding the actual impact of the EU funding on regional economic performance. Yet, the distinct non-experimental nature of funding programs has made it difficult to credibly identify their causal effects on growth. Correspondingly, the range of approaches devoted to the empirical analysis of funding effects has led to a wide spectrum of conclusions about the actual impacts of the ESIF, reporting both positive and negative effects of EU regional policy. The importance of a solid impact assessment is accentuated as proponents of these instruments place considerable hope in their potential to combat weak economic growth, even assigning a crucial role to them in the EU's current growth strategy.

How much emphasis is placed on stimulating investment as principal strategy of economic policy, is highlighted by the Commission's legislative proposal published in January 2015 for a new European Fund for Strategic Investment (ESFI), implemented by the European Investment Bank from mid-2015 to 2017. With a volume of about € 315 billion, the ESFI is expected to launch growth-stimulating investment projects in similar veins as the ESIF by supporting strategic investments in key areas such as infrastructure, education, research and innovation and risk finance for small businesses. However, despite their similarity in terms of policy goals, the two programs will be implemented through different financial instruments and can thus be expected complement one another.[2] Accordingly, accurate predictions about the potential effectiveness of this new stimulus package would have to be

[2] While the European Fund for Strategic Investment (EFSI) focuses on attracting private investors to economically viable projects with a substantial leverage effect, the European Structural and Investment Funds (ESIF) consists of grants (European Commission, 2015).

extrapolated from a reliable account of the actual effects of previous ESIF funding. They should not merely reflect a leap of faith, as in the current discussion.

To provide such an assessment, this contribution conducts a multitude of regression analyses to identify the link between EU funding through the ESIF and regional income convergence. We contribute to the literature by i.) offering an identification strategy with a close link to recent contributions in growth theory and the various transmission channels of funding, ii.) accounting for the spatial and temporal dynamics in the regional growth paths, and iii.) using de facto disbursed amounts awarded to 127 EU15 regions prior to the severe economic crisis of 2007/08 provided by EU commission's DG budget instead of the frequently applied funding commitments that have been found to be a poor proxy for actual payments. The use of pre-crisis data is motivated by the likely occurrence of severe structural breaks in economic time series, which may bias the regression results. In terms of the consistent use of the prevailing bureaucratic diction, the reader should note that –throughout the remainder part of this analysis– we refer to the term of Structural Funds (SF) rather than European Structural and Investment Funds (ESIF) as the official funds name for the time period of analysis until 2007.

Overall, our empirical results regarding the effect of EU SF-funding are disillusioning: We basically find no statistical evidence that funding is able to enhance the speed of income convergence for funded compared to non-funded regions. Most importantly, regions whose neighborhoods comprise a relatively high share of grant recipients display a significantly worse growth performance due to negative spatial interaction effects. These results may indicate a potential causal link in the sense that regions are enabled to poach input factors (such as investments) from neighboring regions once they are funded. Yet, they are also compatible with the presence of high structural and technological backwardness among the regions receiving the highest funding volumes. Actually, these regions might be persistently uncoupled in their development dynamics from the rest of the EU. Being consistent with earlier evidence on the existence of distinct geographically delineated convergence clubs in the EU (e.g., Ramajo et al. 2008), this possibility should be taken into account for the design of future regional development strategies.

The remainder of the paper is organized as follows: In the next section, we summarize the recent empirical literature regarding the effectiveness of EU SF-funding and discuss the conceptual issues underlying its empirical analysis. Section 3 outlines the institutional setup and describes the variables in the dataset, while Section 4 reports the empirical results together with a thorough discussion of the robustness of the funding effect with respect to the choice of the underlying spatial regime. Section 5 concludes the paper with an outline of the implications of our results for future European policy.

2. Conceptual Issues

Methodological Approaches to regional policy evaluation

Of the numerous publications concerned with the role of the EU regional policy for growth and development, only a few apply rigorous quantitative evaluation approaches that have the potential to thoroughly address the difficult task of identifying their causal effects on regional growth (for literature surveys see, e.g., Persson et al. 2012, Mohl and Hagen 2009 and Dall'erba et al. 2006). As Gripaios et al. (2008) argue in the context of EU regional policy evaluation, it is particularly difficult to establish a reasonable counterfactual situation from which the causal impact can be assessed. Furthermore, the identification is made even more cumbersome by the occurrence of policies overlapping at the supranational, national and regional levels. Finally, researchers have to cope with rather poor data quality for EU-wide funding analyses on the regional level (Mohl and Hagen 2009).

Recent empirical contributions have responded to these obstacles by using innovative methodological approaches. Generally, two different methodological streams of research, namely the structural and the experimentalist approach, have recently gained importance in the field of policy evaluation (Holmes 2010). While the latter approach has been mainly promoted through microeconometric evaluation studies in the field of labor economics, the structural approach has been devised in modern macroeconomic analyses. Regarding empirical applications of the (quasi-)experimentalist approach, Mohl and Hagen (2008), Becker et al. (2012) and Mitze et al. (2015) use a generalized propensity score approach to estimate the impact of regional policy instruments on GDP growth. In a similar vein, Becker et al. (2010) apply a regression discontinuity approach.

These approaches are promising, since they emphasize the importance of controlling for self-selection into treatment, the possible endogeneity of the policy variable, and the unknown functional form of the empirical model. Yet, they also face some shortcomings: For example, the generalized propensity score approach in Becker et al. (2012) and Mitze et al. (2015) only examines the effectiveness of different funding intensities for the funded regions and not the effectiveness of funding per se. Moreover, Mitze (2014) and Mitze et al. (2015) conclude that in regional data settings, regional heterogeneity and the presence of spatial dependence across regions may result in a suboptimal selection of statistical twins needed to proxy the counterfactual situation.

In contrast, structural approaches transform theoretical models into testable functional forms. They trace the path by which the initial policy stimulus translates into changes of the outcome variable, with the aim of interpreting the value of the empirical parameters within models of growth theory (for literature surveys see, e.g., Rickman 2010 and de la Fuente 2002). Arbia et al. (2008) discuss the impact of the researchers' specification choice on the model predictions in a neoclassical convergence equation, thereby emphasizing that different functional specifications may imply quite different convergence concepts. Nevertheless, with recently established methodological developments in the field of panel and spatial econometrics, this strategy remains the mainstream approach.

In panel regression models driven by mutual space-time dynamics, the specification and interpretation becomes quite complex if the focus lies on the effect of a specific policy variable. Mohl and Hagen (2010), among others, show that it is necessary to control for global spatial spillover effects since regional growth levels strongly depend on the performance of neighboring regions. Alecke et al. (2013) additionally demonstrate that local spatial spillovers may also characterize transmission channels, and allowing for interaction effects between the policy variable and the controls might be essential for drawing a complete picture of regional policy effects. In our work, these issues will be accounted for in the specification of the empirical model used for estimation purposes.

Convergence, transitory dynamics and spatial links in empirical growth models

In the implementation of the structural approach to regional policy evaluation, the neoclassical Solow-type growth framework marks a suitable starting point. All of our proposed econometric specifications will rely on extensions of this model. To test for income convergence, the basic model can be stated as (Barro 1991, Tondl 2001)

$$\Delta y_{i,T} = \frac{\ln(y_{i,T}) - \ln(y_{i,0})}{T} = \alpha + \beta \ln(y_{i,0}) + u_{i,T} \, , \tag{1}$$

where $\Delta y_{i,T}$ is the growth rate of GDP per capita (y) over the period [$0; T$] for a set of $i=1,\dots,N$ regions. In the empirical application the coefficients α and $\beta=(1-e^{-\theta t})/T$ are unknown parameters to be estimated. The implicit parameter θ is the average regional rate of convergence towards steady state income. The error term, $u_{i,T}$ is assumed to be homoscedastic, non-correlated and normally distributed.

The main motivation for using the concept of neoclassical growth and convergence as a framework is that it allows controlling for the region's initial income level as a proxy for its 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 ($\beta<0$).[3] Hence, this basic model addresses a very special case of structurally homogenous regions, as it implies that regions

[3] However, this 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 $\beta=(1-\psi)(g + n + \delta)$, where ψ is the output elasticity of capital, g is technological progress, n is population growth and δ is the capital depreciation rate (Mankiw et al. 1992: 422).

(unconditionally) converge to a common steady-state income level and that transitory differences in region's per capita income growth rate are solely based on initially heterogeneous endowment with physical capital.

A basic solution to overcome this implausible assumption might be the inclusion of fixed effects in a panel data framework, which can account for time-persistent regional differences, implying conditional regional convergence. Neglecting these potential determinants would clearly lead to an omitted variable bias (Islam 1995). Beside such "catch-all" fixed effects, the Mankiw-Romer-Weil (MRW-) convergence specification (Mankiw et al. 1992) addresses the importance of human capital for economic growth.

$$\Delta y_{i,t} = \alpha_i + \beta \ln(y_{i,t-1}) + \sum_{k=1}^{K} \varphi_k \ln(x_{i,t-1,k}) + \lambda_t + u_{i,t} \,. \tag{2}$$

In the panel context the dependent variables is specified as $\Delta y_{i,t} = \ln(y_{i,t}) - \ln(y_{i,t-1})$ with the time dimension being $t=1,\ldots,T$. Fixed effects for regions (α_i) and years (λ_t) are included and in addition to human capital, the set of time-varying regional controls $x_{i,t,k}$ contains information the current stock of investments, and the size of the population and the labor force (see, e.g., Mohl and Hagen 2010).

Following Acemoglu (2009), we rearrange the model into a regression equation in levels of variables, which allows estimating equation (2) as a dynamic panel data model. Given that $\Delta y_{i,t} = \ln(y_{i,t}) - \ln(y_{i,t-1})$, rearranging the estimation equation only affects the coefficient of $y_{i,t-1}$ ($\delta=\beta+1$), while leaving the coefficients for the set of regional controls unchanged (Tondl 2001). The equation can be written as:

$$\ln(y_{i,t}) = \alpha_i + \delta \ln(y_{i,t-1}) + \sum_{k=1}^{K} \varphi_{1,k} \ln(x_{i,t-1,k}) + \lambda_t + u_{i,t}. \tag{3}$$

Standard OLS or fixed-effects models (FEM) will lead to biased estimates in the regression coefficients for equation (3), since $y_{i,t-1}$ is correlated with the model's error term u_{it} (see Nickell 1981, Baltagi 2008). Beside analytical or bootstrap-based approaches aiming to correct for the bias of the standard FEM parameter estimates (Kiviet 1995, Everaert and Pozzi 2007, Bruno 2005), the most widely used approaches of dealing with this kind of endogeneity typically applies instrumental variable (IV) and generalized methods of moments (GMM) based estimation techniques (Arellano and Bond 1991, Blundell and Bond 1998).[4]

[4] While the first generation of IV/GMM-models used transformations in first differences, latter extensions also account for the information in levels, when setting up proper estimators. A commonly applied estimation tool is the so-called system GMM estimator (thereafter, SYS-GMM) by Blundell and Bond (1998) as weighted average of first difference and level GMM

In this paper, we mainly focus on the application of the system GMM (SYS-GMM) estimator proposed by Blundell and Bond (1998). This is motivated by its high degree of flexibility in order to derive consistent instruments, which not only account for the endogeneity of the autoregressive parameter in the dynamic panel data model of equation (3) but also other forms of model misspecification. Moreover, we follow Roodman (2009) in controlling for large instrument collection in the SYS-GMM approach and test instrument validity ex post. Estimators with an analytical bias correction in the autoregressive parameter (Kiviet, 1995) are used as a sensitivity check in order to test for the degree of potential misspecifications of SYS-GMM.[5]

As Everaert and De Groot (2015) point out, the recent panel data literature has shifted its attention from the focus on the consistent specification of the models' temporal dynamics to the account of cross-sectional or spatial dependence. In fact, taking regions as isolated islands (equation 3) is an over-simplistic assumption (Acemoglu 2009). Eckey and Koesfeld (2005), De Castris and Pellegrini (2012) as well as Alecke et al. (2013), among others, have shown that disregarding the spatial effects associated with regional subsidies may lead to a substantial bias in the overall empirical assessment of the policy.

Specifically, Ertur and Koch (2007) and Fischer (2010) augment the neoclassical growth model-framework to capture space-related technological interdependencies across regions. Recent advantages in the specification and estimation of (dynamic) spatial econometric models have made the handling of these interdependencies feasible by means of weighting observations based on information about the spatial proximity of sample regions (see, for instance, LeSage and Pace 2009, Elhorst 2012). Augmented in this spirit, we can derive a Spatial Cross-regressive Model (SCM) based on the MRW-approach in equation (4) as

$$\begin{aligned}\ln(y_{i,t}) = \alpha_i + \delta \ln(y_{i,t-1}) + \sum_{k=1}^{K} \varphi_{1,k} \ln(x_{i,t-1,k}) + \\ \sum_{k=1}^{K} \varphi_{2,k} \sum_{j=1}^{N} w_{ij} \ln(x_{j,t-1,k}) + \lambda_t + u_{i,t},\end{aligned} \tag{4}$$

where w_{ij} is the respective standardized element of the (*NxN)*-spatial weighting matrix **W** representing spatial linkages between region *j* an region *i* with the following properties: The matrix is non-negative, non-stochastic and finite, individual elements respect the conditions $0 \leq w_{ij} \leq 1$, $w_{ij} = 0$, if $i=j$, and the standardization implies $\sum_{j=1}^{N} w_{ij}=1$ for $j=1,...,N$.

estimation. 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).

[5] The latter may particularly stem from the so-called "many" and/or "weak instrument" problem associated with SYS-GMM estimation given that the number of instruments grows as the sample size increases.

A more complex spatial dynamics additionally allows for the inclusion of a spatial lag of the dependent variable in a Spatial Durbin Model (SDM) specification as

$$\ln(y_{i,t}) = \alpha_i + \beta \ln(y_{i,t-1}) + \rho \sum_{j=1}^{N} w_{ij} \times \ln(y_{j,t-1}) + \sum_{k=1}^{K} \varphi_{1,k} \ln(x_{i,t-1,k}) + \sum_{k=1}^{K} \varphi_{2,k} \sum_{j=1}^{N} w_{ij} \ln(x_{j,t-1,k}) + \lambda_t + u_{i,t}, \tag{5}$$

where the parameter ρ measures the spatial connectivity of a region's output level to the neighboring regions, which is included as a "catch all" term for spatial dependence. For standardized weighting matrices ρ is bound to take values between $-1 \leq \rho < 1$ (Fischer and Wang 2011). We apply spatial extensions of the SYS-GMM approach, which make use of consistent moment conditions for the instrumentation of the spatial lag coefficient (ρ) of the endogenous variable (see Kukenova and Monteiro 2009, Elhorst 2012 as well as Bouayad-Agha and Vedrine 2010).[6]

Accounting for policy instruments

The notion of (un-)conditional convergence among European regions is, in fact, the main motivation for a growth-oriented, allocative EU regional policy, in particular with regard to the Convergence Funding. Thus, it is somewhat unfortunate that the assessment of income convergence and the role of regional policy therein, is pursued rather ad hoc in most studies, both in terms of variable selection and model specification. By contrast, we aim at estimating different growth models that account for the different transmission channels from policy input to economic outcomes.

To account for these transmission channels, we extend the empirical growth models in two dimensions: First, we consider model specifications, where the policy variable enters in an "additive" way as an explicit regressor in the set of regional control variables. Second, we model the transmission channels from policy input to economic outcomes in a "multiplicative" way based on the use of interaction terms for the working of the policy conditionally on lagged outcome levels and the region's income distance to long-run steady state income.

Most empirical work augments the growth equation by policy variables in a log-linear additive style by simply including a policy variable measuring the input of funding ($sf_{i,t}$) to the set of controls $x_{i,t,k}$. Mohl and Hagen (2010), for instance, propose the following augmented model specification:

[6] By means of Monte Carlo simulations, Kukenova and Monteiro (2009) have shown 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. As for the case of the non-spatial, time dynamic model specification in equation (3), the spatially augmented regression approaches can either be estimated by IV/GMM-based approaches or by (Quasi-)Maximum Likelihood (see Elhorst 2012, for an overview).

$$\ln(y_{i,t}) = \alpha_i + \delta \ln(y_{i,t-1}) + \sum_{k=1}^{K} \varphi_k \ln(x_{i,t-1,k}) + \sum_{m=1}^{M} \gamma_m \ln(sf_{i,t-m}) + \lambda_t + u_{i,t}\ , \qquad (6)$$

where the entries $sf_{i,t-m}$ are the respective SF payments per capita in period t-m. This distributed-lag specification as shown in equation (6) accounts for a wide range of transmission channels from the policy input to the outcome variable over time. One example is public infrastructure investments, which are expected to gradually phase in and induce growth only after some time has expired since installation (see, e.g., Bradley 2006).

However, even the joint consideration of the M parameters γ_m (equation 6) as temporally distributed funding effects is prone to underestimate the "comprehensive" effect of funding as it ignores that the SF may work by leveraging private investments which are included in the set of controls $\sum_{k=1}^{K} x_k$ (Mohl and Hagen 2009). Thus, these private investments form a "bad control" variable as described by Angrist and Pischke (2008) since they constitute an outcome of the SF funding themselves, a problem which is mostly disregarded in the literature (Mohl and Hagen 2009). Consequently, the pure SF effect captured by the parameters γ_m in equation 6, ignoring further channels, marks a lower bound of the true funding effect.

To derive a more encompassing estimate of this effect, we would need to account for the effect of SF-funding volume spent on private investments. Unfortunately, there is no information on the precise split of funding into investment-projects and other funding provision, preventing us from separating other funding items from the physical capital investments. However, despite being unable to observe the share of SF devoted to investments, we aim to obtain a more realistic estimate by the formulation of an auxiliary regression model as

$$\ln(inv_{i,t}) = \tilde{\alpha}_i + \eta \ln(sf_{i,t}) + \kappa \ln(y_{i,t-1}) + \tilde{\lambda}_t + \tilde{u}_{i,t}. \qquad (7)$$

The above auxiliary model explains the level of private investments in each period by incorporating regional and time fixed effects, the contemporaneous funding ($sf_{i,t}$)[7] and lagged GDPpc ($y_{i,t-1}$). Inserting equation (7) into the main model (equation (6)) leads to an alternative estimation specification as

[7] Since investments are typically associated with contemporaneous funding, and there is no convincing theoretical concept for a link between past funding and recent investments, the lag structure is ignored in this auxiliary estimation.

$$\ln(y_{i,t}) = \tilde{\tilde{\alpha}}_i + \delta \ln(y_{i,t-1}) + \kappa \ln(y_{i,t-2}) + \sum_{k=1}^{K \notin inv} \varphi_k \ln(x_{i,t-1,k})$$
$$+ \tilde{\tilde{\gamma}}_1 \ln(sf_{i,t-1}) + \sum_{m=2}^{M} \gamma_m \ln(sf_{i,t-m}) + \tilde{\tilde{\lambda}}_t + \tilde{\tilde{u}}_{i,t}. \tag{8}$$

The time and regional fixed effects now combine unobserved explanatory factors from both equations, and the same holds for the error term $\tilde{\tilde{u}}_{i,t}$. More importantly, the coefficient of the one-period lagged SF-funding ($\tilde{\tilde{\gamma}}_1 = \gamma_1 + \varphi_{inv} \times \eta$) now comprises the immediate effect of funding on regional growth and its induced effect via private investments, which together make up the "comprehensive" funding effect. The reader should note, however, that the estimated conditional correlation between private investments and SF funding in equation (7) does not describe a causal effect of funding effects on investments for several reasons with the most straightforward being that SF-funding volumes and private investments are both prone to be driven by the unobserved regional investment climate.[8]

Thus, in terms of causal inference, η (and therefore also $\tilde{\tilde{\gamma}}_1$) is likely to be upward biased and may only provide an upper bound of the true funding effect. Furthermore, the share of private investments which is not explained by the controls of the auxiliary model (equation (7)) forms – by definition – an omitted variable bias in the subsequent estimation of the GDPpc (equation (8)). Thus, in the following, equation (8) is rather seen as robustness tests which can reveal a potential bias in the benchmark additive model (equation 6).

Another sort of bias may be related to the assumed functional form of the growth equation. The additive specification of the funding variable implicitly assumes that SF-funding influences long-run steady-state income differences. While this argument may hold for public infrastructure or human capital investments, it is unreasonable for the case of private investment subsidies, which – according to neoclassical growth theory – may only have a transitory effect on the path of income growth to long-run steady state level. In other words, these aids do not improve regional pre-conditions to reach higher prosperity level but they speed up the process to reach an unchanged steady-state level. Substantial shares of funding are rather spent for such subsidies which merely improve the utilization of existing resources of production. To account for the possibility that SF only influence the

[8] This holds true in particular, since almost every investment is eligible for funding in highly funded regions. Thus, a higher funding is also the consequence of increasing investment incentives.

speed of convergence towards a steady-state, one might include interaction terms of the (lagged) policy variable and lagged income (Brambor et al. 2005) as[9]

$$\begin{aligned} \ln(y_{i,t}) &= a_i + d\ln(y_{i,t-1}) + \sum_{k=1}^{K} c_k \ln(x_{i,t-1,k}) + \gamma \ln(sf_{i,t-1}) \\ &+ \xi\left[\ln(y_{i,t-1}) \times \ln(sf_{i,t-1})\right] + \lambda_t + u_{i,t}. \end{aligned} \tag{9}$$

One could extend the specification as outlined above. To include the indirect effects of funding on investments by specifying the effect of SF-funding as $\tilde{\tilde{\gamma}}_1 = \gamma_1 + \varphi_{inv} \times \eta$ (equation (8)). In the following, we will refer to the basic specification (equation (6)), though. The explicit inclusion of an interaction term between the policy variable and lagged income levels can be motivated as follows: SF-related investment subsidies basically aim at reducing the user costs of capital and thus affect regional differences in the marginal return of capital in favor of funded regions (Alecke et al. 2013). 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 the speed of convergence. In equation (9) the coefficient ξ for the interaction term $\ln(y_{i,t-1}) \times \ln(sf_{i,t-1})$ reveals if funding tends to enhance the speed of convergence in funded regions on the path towards long-run steady state income.[10]

Finally, to address the issue of cross-sectional dependence, we extend the latter by means of including spatial lags of the lagged outcome variable and the set of regressors as proposed in the previous subsections. Along these lines, we augment our basic specification (equation (6) in two different ways. The space-time-dynamic specification of the additive regression model can be specified according to[11]

$$\begin{aligned} \ln(y_{i,t}) &= a_i + d\ln(y_{i,t-1}) + \rho \sum_{j=1}^{N} w_{ij} \ln(y_{j,t-1})) + \sum_{k=1}^{K} c_{1,k} \ln(x_{i,t-1,k}) \\ &+ \sum_{k=1}^{K} c_{2,k} \sum_{j=1}^{N} w_{ij} \ln(x_{j,t-1,k}) + \gamma_1 \ln(sf_{i,t-1}) + \gamma_2 \sum_{j=1}^{N} w_{ij} \ln(sf_{j,t-1}) + \lambda_t + u_{i,t}. \end{aligned} \tag{10}$$[12]

[9] While the lag structure of the policy variable is not shown in these conceptual equations, our estimations consider the structure as in equation (4), though with a varying number of lags included. For ease of presentation we only present the one period lagged multiplicative interaction term here.

[10] Moreover, equation (9) presents the special case of a more general regime-switching model between funded and non-funded regions, which relaxes the assumption of homogeneous regression parameters. By contrast, a heterogeneous slope coefficient approach would test for different long-run convergence clubs for the set of funded and non-funded regions (see Durlauf and Johnson 1995, Durlauf 2001).

[11] With respect to the included time and spatial lags of the endogenous variables in equation (10), we can distinguish between space-time-recursive, space-time simultaneous and space-time dynamic specifications (see Anselin et al. 2008). In the following, we restrict our analysis to the space-time dynamic model, which includes a time lag of the dependent variable and its spatial lag.

[12] For ease of reading, the lag structure (t-m) of funding in the additive spatial model is not shown here but included in the estimations.

where γ_1 indicates the *direct effect* of SF-funding as $\left(\partial y_{i,t}/\partial sf_{i,t-1}\right)$ and γ_2 indicates the spatial *indirect effect* of SF-funding resulting from a response of income levels in region *i* due to a change in SF-funding in region *j* as $\left(\partial y_{i,t}/\partial sf_{j,t-1}\right)$. These effects then gives the overall impact of SF-funding on the output level of region *i* as $\left(\partial y_{i,t}/\partial sf_{t-1}\right)$.

The alternative regression specification as a spatially extended interaction model based on equation (9) turns out to be a bit more complex in its notation since the direct interaction term $\left(\ln(sf_{i,t-1}) \times \ln(y_{i,t-1})\right)$ will have to be interacted with $\left(\mathrm{w}_{ij} \times \ln(sf_{j,t-1})\right)$. The coefficient of this interaction term (ξ_3) then describes how much the region's speed of convergence is influenced by the amount of funds allocated to its spatial neighborhood. It is thus able to capture any spatial crowding-in or crowding-out effects of regional policy. The full regression equation becomes

$$\begin{aligned}
&\ln(y_{i,t}) = a_i + d\ln(y_{i,t-1}) + \rho\sum_{j=1}^{N} w_{ij}\ln(y_{j,t-1}) + \sum_{k=1}^{K} c_{1,k}\ln(x_{i,t-1,k}) + \\
&\sum_{k=1}^{K} c_{2,k}\sum_{j=1}^{N} w_{ij}\ln(x_{j,t-1,k}) + \gamma_1\ln(sf_{i,t-1}) + \gamma_2\sum_{j=1}^{N} w_{ij}\ln(sf_{j,t-1}) + \\
&\xi_1\sum_{j=1}^{N} w_{ij}\ln(sf_{j,t-1})\times\ln(sf_{\mathrm{i},t-1}) + \xi_2[\ln(y_{i,t-1})\times\ln(sf_{i,t-1})] + \\
&\xi_3\sum_{j=1}^{N} w_{ij}(\ln(sf_{j,t-1})\times[\ln(y_{i,t-1})\times\ln(sf_{\mathrm{i},t-1})]) + \lambda_t + u_{i,t}.
\end{aligned} \tag{11}$$

The overall intention of our different model specifications comprising equation (6) to equation (11) is to derive a robust measure of the effect of SF funding by providing a range of estimates of the marginal effect of the SF-policy variable ($\ln(sf_{i,t-1})$) on regional income growth, which reflects the variegated nature of actual transmission channels of SF funding.[13] Since marginal policy effects based on interaction models cannot be derived directly from the estimation output, the computation of the effects according to equation (6) equation (11) is summarized in the appendix (Table A.1). [14]

3. Funding framework, data and the spatial setup

With a respective volume of € 213, € 347 and € 450 billion in the three consecutive multiannual financial framework periods covering the years 2000 to 2020, regional policy has become the largest

[13] The presentation of the marginal effect can be easily extended to the case of multiple lags in the funding variable as specified in equation (5).

[14] For ease of presentation in the remaining figures and tables, we use the matrix notation when referring to the spatial weighting matrix **W**.

budgetary item of the EU. Although the goal system of regional policy has been adapted over the course of time, e.g., to align it with the EU2020 strategy, its main purpose still centers around the support of economically handicapped regions, predominantly by: i) the provision of physical investment grants to the private business sector, ii) fostering human capital accumulation and iii) supporting investments into local public infrastructure. More recently, especially support for small and medium-sized enterprises, for instance, through research and development (R&D) projects, has been added to the agenda in order to create growth and jobs, tackle climate change and energy dependence, as well as reduce poverty and social exclusion as the main high-level goals of the EU2020 strategy.

For the period of analysis from 1994 to 2007, Structural Funds have been allocated to three major objectives and a broader class of minor ones.[15] Throughout this analysis, we focus on the effectiveness of "Convergence" payments (or "Objective 1" in old terminology for the financial framework period 2000-2006), which explicitly target income convergence by stimulating growth in lagging regions. Regions with a GDPpc below 75 % of the EU average are eligible for funding which is mainly financed through the European Regional Development Fund (ERDF) and the European Social Fund (ESF).[16] Representing about two third of total SF-funding, "Convergence" payments are by far the largest item of the EU Structural Funds (Mohl and Hagen 2010). Moreover, in contrast to other funding, its legislative framework has stayed nearly unchanged for the three included funding periods.

Furthermore, Convergence has a clearly measurable policy goal in terms of fostering regional income convergence. This is not the case for other objectives which pursue quantitatively less well-defined goals like gender equality, environmental improvements etc. In addition, Convergence funding follows a clear definition of regional standards for claiming payments. That is, regions meeting the funding prerequisite of realizing a GDPpc below 75 % of the EU average are eligible for receiving payments, irrespective of their current GDP growth or any form of growth expectations. This reduces the potential problem of reverse causality for analyzing the impact of funding on income growth.

Data about funding disbursements are taken from the commission's annual report on the structural funds for the years 1994-1999 (European Commission, 1995 to 2000) and from on-site access at the EU Directorate-General for Budget (DG Budget) for the years 2000-2007.[17] These provide infor-

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[15] In addition to "Convergence", EU regional policy focuses on "Regional Competitiveness and Employment" and "European Territorial Cooperation".

[16] Detailed information on funding, funding schemes and the provision of funds can be found under: http://ec.europa.eu/regional_policy/how/index_en.cfm,

[17] 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 (committed funding has to be disbursed two years after the end of the funding period at latest) we know that all commitments from 1999 have to be paid out in 2001 at latest. Having no further information on the actual spending behavior, we equally spread differ-

mation on real payments. Annual commitments which are widely utilized in literature have major weaknesses since they do not exert any effect themselves and recent debates have shown that these commitments differ by far from the effectively disbursed money.

We estimate our model specifications for a set of 127 regions in the EU15-area over the period 1997-2007, ignoring the time span after 2007 which is heavily plagued by effects of the economic crisis. Data from 1993 onward are included to construct the lag structures of funding. Since the NUTS2 regions are the relevant unit for funding eligibility, this regional delineation is used whenever possible. Though, due to limited data availability in some cases we have to rely on higher levels of aggregation. This leads to a sample of 127 regional entities.[18]

Table 1: Data overview and stylized facts

Variable	Measured as	Mean	Std. Dev.
Income (GDPpc)	GDP per capita (in PPP)	21537.31	8328.19
Structural Funds Intensity (SF)	"Convergence" payment per capita (in €)	39.53	67.18
Investment intensity	Gross fixed capital formation in manufacturing per capita (in €)	2063.92	18250.86
Human capital	Workforce in technical-jobs and science in relation to the whole employment (in %)	10.45	3.64
Labor Force Participation	Employment in relation to the whole population (in %)	45.07	4.87
Population Growth	Annual change of the population level (in %)	1.00	0.01

Note: Variables enter the estimations their logarithmic values (except the population growth). *Source:* All economic variables are taken from Eurostat (2010) regional database, data on Structural Funds payments are obtained from DG Budget unit A.2.

As described in the previous section, regional output is measured in terms of GDP per capita at purchasing power parity (PPP) as dependent variable. The major explanatory variables, private investment and human capital accumulation, are measured as the stock of gross fixed capital in manufacturing and the workforce in science and in technical jobs. All control variables are calculated in per capita values. Furthermore, we control for labor force participation (LFS) and population growth rates. The funding variable is also defined in per capita-terms. For empirical estimation, we use all

ences between the sum of commitments and payments for the year 1999 on the actual spending for the subsequent years 2000 and 2001.

[18] Regions from the New Member States of the union are not taken into account for several reasons. Data availability is worse for those regions, they were not member of the EU since the beginning of observation time and there is no information about provisions from other EU-schemes before the access to the union. A detailed list of all regions covered in the regression exercise is given in the appendix.

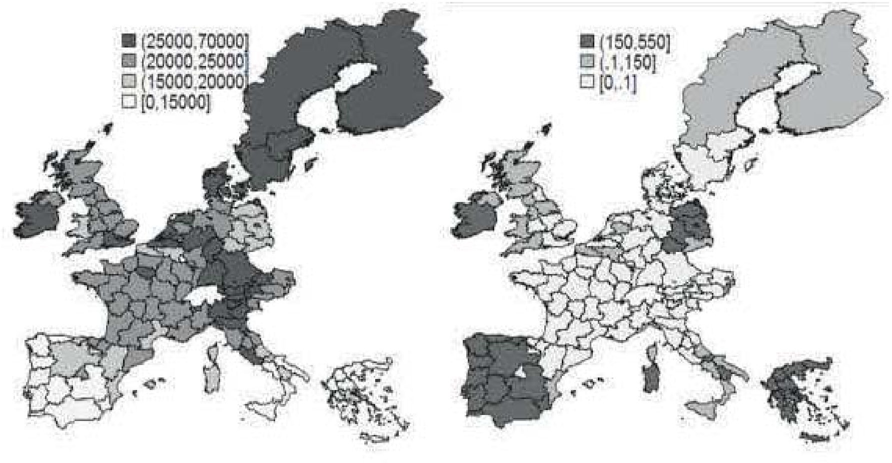
variables in their logarithmic transformations except population growth. An overview of variable definitions and summary statistics is given in Table 1.

Figure 1 provides an overview on the spatial distribution of GDPpc in the EU15 (left map) and the "Convergence" SF-funding intensity per capita (right map). It becomes apparent that "Convergence" SF-Funding concentrates on low-income regions, as intended. The figure also reveals that, on average, regions enjoying a high funding intensity tend to have neighbors which are also heavily supported and furthermore, that the poor regions are spatially clustered in the same way. These maps give a first impression for the importance of spatially augmented specifications which are utilized in the course of this analysis.

To account for spatial heterogeneity and for the potential role of spatial spillovers originating from mutual dependencies among the variables, we construct for each variable its spatial lag defined as weighted average of values in the neighborhood of region *i.* The literature does not offer clear guidance for the implementation of spatial variables, and the concrete design of the spatial weighting matrix **W** may have effects on the results (Stakhovych and Bijmolt 2009). We base our weighting matrix **W** on geographical distances between two regions *i* and *j* (d_{ij}).[19] Specifically, we use inverted distances between the regions' centroids to construct the distance parameter $w_{ij}=1/d_{ij}$ and provide robustness checks in terms of alternative distance measures.

[19] We use straight line distances from regional centroids to each other as reference point for the weight. Other possibilities would be street kilometers, driving time or economic integration measures for the distance. Instead of the centroids one could use distances from each capitol city.

Figure 1: Average GDP (left) and "Convergence" SF-funding (right)
Per capita values from 1994 - 2007



Source: Own map, data from Eurostat (2010), DG Budget unit A.2.

4. Empirical Results

Non-spatial estimation results

We begin estimating the linear additive model as commonly applied in analyses of regional policy. Starting with the basic setup outlined in equation (6) the results for the standard (uncorrected) FEM, a bias corrected fixed-effects model (FEMc) and SYS-GMM specifications are reported in Table 2. While the set of control variables remains unchanged, we vary the policy variable between a short-run one year lag specification and a longer-run with up to four lags.[20]

The first two columns report the results of the FEM benchmark specification. All coefficients show the theoretically expected signs and the lagged GDPpc, human capital and investment variables are statistically significant. The coefficient of the labor force participation and the population growth rate are insignificant. The included lagged GDPpc value has a coefficient of less than one, which corresponds with the neoclassical growth theory. The effects of the controls stay quite stable over all specifications reported in Table 2. The small coefficient of the lagged GDPpc indicates a rather high conditional convergence rate, but this estimates may suffer from potential endogeneity due to the dynamic character of the model.[21]

[20] For the latter case, Table 2 reports the summed SF-effect over all included lags.

[21] However, as Arbia et al. (2008) point out, depending on the chosen econometric method, the regression parameter has to be interpreted carefully. Note that for the FEM the implicit convergence rate is the adjustment process towards the region's own steady state and not towards a common per-capita income level.

Indeed, for the FEMc estimations reported in column (iii) an (iv) the coefficient increases to values between 0.925 and 0.931 implying a slower speed of convergence. For the remaining variables the results of the FEM and FEMc are very similar. Both models also report negative coefficients for the SF-funding variable. In the standard FEM specification, the funding effect is negative and significant (as well as in the corrected FEM specification with a one-year-lag structure). The funding effect in the four-year-lag specification, however, turns out to be statistically insignificant for the FEMc model. Similar results are found in the literature by Dall'erba and LeGallo (2008).

In the case of the SYS-GMM specification reported in column (v) and (vi), the statistical significance of the explanatory variables is less evident: While the investment variable stays significant, the human capital variable turns insignificant. The funding variable stays insignificant for all SYS-GMM specifications as well. Since these models rely on instruments, we put special attention to post-estimation tests for instrument validity, which is not rejected for our regression specifications by means of Hansen *J*- and *C*-tests as well as the Arellano and Bond (1991) test for autocorrelation in the residuals (AR2).[22]

As discussed in Section 2, the coefficient of the funding variable might be downward biased. Therefore, Table 2 presents the SF-funding effect obtained from a regression in the spirit of equation (8) which substitutes the original investment by a function of funding and lagged GDPpc. The funding coefficient from this estimation is highlighted in the line “comprehensive funding effect”. Since the estimate of this comprehensive effect does not differ from the previous results regarding exclusively the direct effect, the problem outlined in Section 2 does not seem to be substantial and we do not account for this specification in the following specification. [23]

[22] Table 2 reports the results of the Hansen *J*- and *C*-statistic (the latter is referred to as Diff-in-Hansen statistic in the table – both for the equation in levels in the SYS-GMM approach as well as to explicitly test the exogeneity of the instruments for the SF-funding variable). Here, we deliberately chose a small number of IV candidates based on a maximum lag length restriction of four periods as well as using collapsed instruments in order not to weaken the testing results (see Roodman 2009, Bowsher 2002). 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. Furthermore, we show the results for autocorrelation tests in the residuals (Roodman 2009).

[23] For ease of reading, the estimations derived from equation (9) are not presented in the text but in Table A.2 in the appendix.

Table 2: Non-spatial dynamic panel data estimations for GDP per capita

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	Fixed effect model (FEM)		Bias-corrected Fixed effect model (FEMc)		System-Generalized Method of Moments (SYS-GMM)	
Dep.Var.: ln(GDP per capita)	One lag	Four lags	One lag	Four lags	One lag	Four lags
$ln(GDPpc_{t-1})$	0.7839*** (0.0355)	0.7751*** (0.0345)	0.9314*** (0.0205)	0.9284*** (0.0213)	0.8534*** (0.0311)	0.8461*** (0.0339)
$ln(INV_{t-1})$	0.0031*** (0.001)	0.0026** (0.001)	0.0022 (0.0013)	0.0018 (0.0013)	0.0040*** (0.0013)	0.0032** (0.0013)
$ln(HC_{t-1})$	0.0508*** (0.0161)	0.0485*** (0.0158)	0.0384*** (0.0102)	0.0391*** (0.01)	0.0275* 0.0153	0.0192 (0.0138)
$ln(LFS_{t-1})$	0.0362 (0.0274)	0.0241 (0.0246)	0.0151 (0.0284)	0.0002 (0.0278)	-0.0176 (0.0367)	-0.0595 (0.0520)
$ln(POP_t)$	-0.1465 (0.2853)	-0.2468 (0.284)	-0.6661** (0.3291)	-0.6714** (0.3214)	0.0140** (0.0057)	0.0102** (0.0051)
$\boldsymbol{ln(SF_{t-1})}$	**-0.0016** **(0.0006)**		**-0.0017***** **(0.0005)**		**-0.0007** **(0.0006)**	
$\sum_{m=1}^{4} \boldsymbol{ln(SF_{t-m})}$		**-0.0012*** **(0.0007)**		**-0.0012** **(0.0135)**		**-0.0002** **(0.0006)**
No. of Groups	127	127	127	127	127	127
No. of Obs.	1211	1147	1211	1147	1211	1147
"Comprehensive" funding Effect as in equation (9)	-0.0015*** (0.0005)	-0.0010*** (0.0005)	-0.0019** (0.0006)	-0.0011* (0.0009)	-0.0007 (0.0005)	0.0001 (0.0006)
No. of instruments					15	15
Hansen J-statistic					22.15	18.63
Diff-in-Hansen for Lev. Eq.					8.77	7.36
Diff-in-Hansen for SF					1. 48	0.29
AR2					1.53	1.56
STMI	0.160***	0.175***	0.175***	0.166***	0.181***	0.195***

Note: ***,**,* denote significance at the 1 %-, 5 %- and 10 %-level. Robust and regionally clustered standard errors are reported in parentheses; SYS-GMM is computed as efficient two-step GMM estimation. Time fixed effects are included. STMI denotes the space-time Moran's I (Moran 1950) of the residuals and indicates that positive correlation of the residuals and the spatially weighted residuals of neighboring regions. *Source*: Eurostat (2010), DG Budget unit A.2.

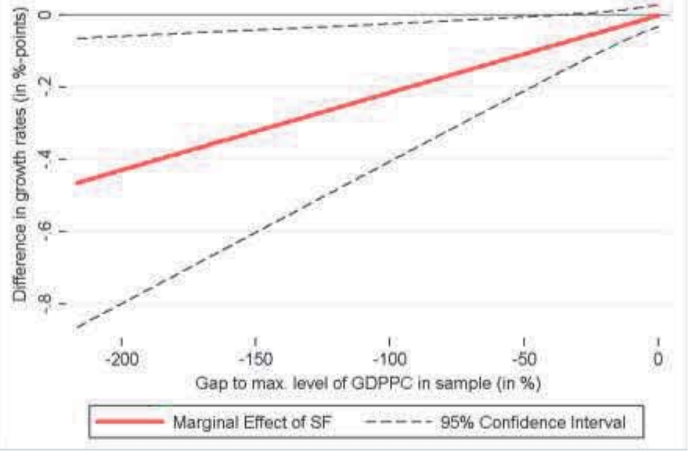
With regard to the interaction regression specification according to equation (10), it is necessary to go beyond the display of the traditional regression output in order to convey quantities of interest such as the marginal effect of an explanatory on the dependent variable.[24] Furthermore, standard statistical inference is not feasible here and regression outputs cannot be interpreted directly. The calculation of meaningful standard errors implies that further elements of the variance-covariance

[24] As we will show in the following, 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 funding growth effect conditional on the underlying initial income level or, alternatively, the region's gap to the maximum GDPpc.

matrix of the estimation system have to be used beside its main diagonal elements (see Table A.1 and Brambor et al. 2005 for details).[25]

In Figure 2, we plot the marginal growth effect (that is, change in the speed of convergence) of SF funding in percentage points (y-coordinate) conditional on the regions' GDP per capita gap to the long-run steady-state income level (x-coordinate).[26] As in Pfaffermayr (2009), we assume that all regions approach their steady state from below and set the "zero gap" equal to the maximum value of the income distribution in our sample. Additionally, based on the regression output for the SYS-GMM specification with a one-year lag structure for the SF-funding intensity, the figure reports a 95% confidence interval for the computed marginal effect and the underlying standard error.

Figure 2: Marginal effect of SF funding on regional growth conditional on regional income gaps to maximum level of GDP per capita in sample



Note: Results based on interaction model specification from Table A.3. For a calculation of marginal effect of SF funding see Table A.1 in the appendix. *Source:* Eurostat (2010), DG Budget unit A.2.

The distribution of the marginal effect conditional on the region's income gap in Figure 2 shows that the effect is statistically significant and negative; it tends to increase (in absolute terms) for regions with higher income gaps. In other words: The estimated marginal growth effect of SF-funding is lower in the poorest regions. In these bottom regions of the initial income distribution (gap to steady state), funding has a negative effect on GDPpc development, which is significant at the 5 %-level. The

[25] As Brambor et al. (2005) as well as Braumoeller (2004) point out, first, the inclusion of all constitutional terms is necessary to avoid running the risk of an omitted variable bias; second, meaningful marginal effects and standard errors cannot be read directly from output tables but have to be calculated separately.

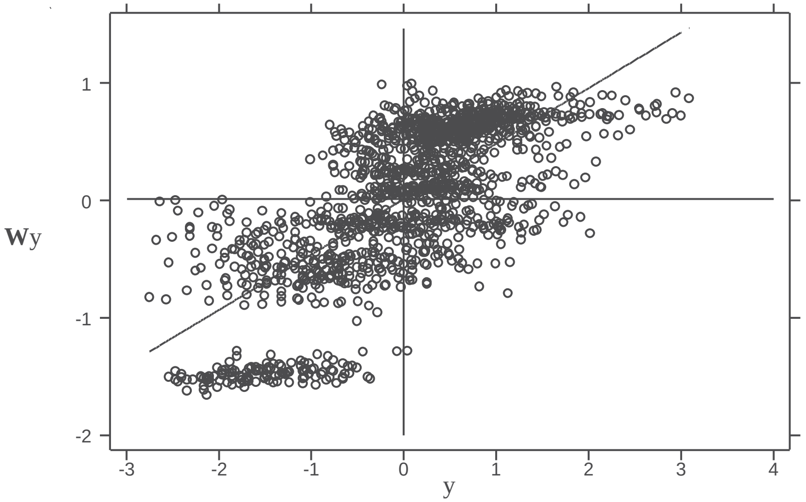
[26] Underlying regression results for the multiplicative interaction model can be found in Table A.2.

results thus support the negative findings from some specifications of the linear additive regression model. The obtained negative findings of Figure 2 are quite substantial (up to -0.5% percentage points). However, all these non-spatial effects are found to suffer from spatial correlations as the space-time version of Moran's *I* statistic (STMI, Moran 1950, Lopez et al. 2011) on the residuals in Table 3 suggest.

Incorporating spatio-temporal dynamics

To highlight the extent of spatial correlation, we plot the STMI for the GDP per capita in Figure 3, which shows a plain positive correlation. The upward sloping fitted regression line reflects the positive spatial dependence for GDP per capita with a value of STMI=0.473. High regional GDPpc values (normalized; x-coordinate) are linked to a higher GDPpc in their neighboring regions (y-coordinate) as defined by **W**.

Figure 3: Space-Time Moran's I (STMI) for GDP per capita



Source: Own calculations based on Eurostat (2010).

Given this strong indication of spatial association in the error terms (Table 2) and the dependent variable (Figure 3), we explicitly include spatial lags of the endogenous variable and the set of regressors including our SF-policy variable in the estimation approach. Nevertheless, the dynamic stability of the model has to be regarded when the spatial lag of the endogenous variable is included (see, e.g., Parent and LeSage 2010). We use a time-space dynamic specification, which restricts spatial lags of the endogenous variable also to enter with a one period time lag as proposed by Bouayad-Agha and Vedrine (2010). Since the SYS-GMM approach has shown quite satisfactory results in the non-spatial benchmark case and it is easy to translate this approach to spatial circumstances, we concentrate on the GMM estimation by means of applying spatially extended SpSYS-GMM estimators.[27]

The results (Table 3) show that the time lagged endogenous variables remain statistically significant and almost of equal size as in the non-spatial benchmark models. We do not find statistically significant coefficients for the time-spatial lag of the dependent variable in columns (i) and (ii). Therefore, we restrict the model in columns (iii) and (iv) into a local spillover model with $\rho=0$, ignoring this time-spatial lag. Compared to the non-spatial baseline estimations, the negative marginal effects of the region's direct funding intensity on per capita income vanish. For the short term time-space dynamic model we even get a small significant positive SF-funding coefficient. However, the spatial indirect funding effect is found to be negative, leading to a negative overall marginal effect of direct and indirect SF funding (according to the definition of marginal effects in spatially-extended models outlined in Table A.1).

The negative indirect effects thereby suggest that spatial spillovers have a major role in funding policies. The detriment of a region which is located beside a funded region can be explained by the reduction of investments which tend to shift towards the funded regions. Since the hypothetical pre-funding distribution of investment intensities formed a somehow efficient market outcome, the funding can be regarded as a distortion of this outcome. In this sense, funding only provides some rather small benefits in funded regions (shown by slightly positive direct effect) compared to the drawbacks for neighbors (shown by negative indirect effect). Overall, this leads to negative overall marginal effects of SF funding on regional GDP per capital growth.[28]

Alternatively, the results may hint at the existence of spatially clustered convergence-clubs (Quah 1993), which are formed because regions lag behind in their technological and structural development despite of their extraordinary funding. Since this backwardness may not be fully captured in the in the set of control variables (at least, there is no convincing regional indicator for structural backwardness), the negative spatial funding effect may reflect this lock-in effect in certain EU regions.

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[27] As before, we carefully test for IV validity, since the number of instruments grows fast when accounting for spatial lags. As shown in Table 4, the Hansen J-statistic does not reject instrument exogeneity. Further, there is no sign for remaining serial autocorrelation in the residuals as indicated by the Arellano and Bond (1991) test (AR2).

[28] The "comprehensive funding effect" – considering a potential funding effect via investments – has also been tested for the spatially augmented model is reported. This effect also remains negative and is not reported in the table but it is available upon request.

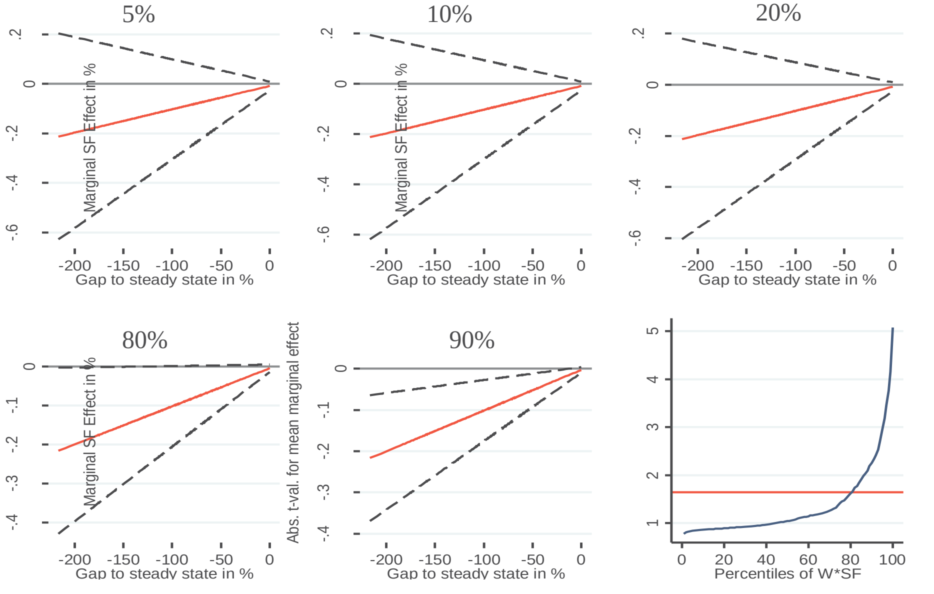
Table 3: Spatial dynamic panel data SpSYS-GMM-estimations for GDP per capita

	(i)	(ii)	(iii)	(iv)
Dep. Var.: *ln*(GDPpc)	Time-Space Dynamic SDM		Spatial Cross-Regressive (SCR)	
*ln(*GDPpc$_{t-1}$)	0.8892***	0.5880***	0.7679***	0.8270***
	(0.0740)	(0.0576)	(0.0296)	(0.0282)
*ln(*INV $_{t-1}$)	0.0099	0.0032	0.0062	0.0054***
	(0.0091)	(0.0022)	(0.0047)	(0.0013)
*ln(*HC $_{t-1}$)	0.0443**	0.1195***	0.0274**	0.0197
	(0.0174)	(0.0445)	(0.0126)	(0.0139)
*ln(*LFS $_{t-1}$)	-0.0249	-0.2999***	-0.0084	-0.0400
	(0.0369)	(0.0722)	(0.0375)	(0.0337)
*ln(*POP $_{t}$)	0.0077	0.0304***	0.0147**	0.0135*
	(0.0051)	(0.0070)	(0.0059)	(0.0075)
***ln(*SF $_{t-1}$)**	**0.0013***		**-0.0011**	
	(0.0008)		**(0.0010)**	
$\sum_{m=1}^{4} \boldsymbol{ln(SF_{t-m})}$		**-0.0015**		**0.0028****
		(0.0044)		**(0.0013)**
W × *ln(*GDPpc$_{t-1}$)	-0.0350	0.0876		
	(0.2469)	(0.1941)		
W × *ln(*INV t$_{t-1}$)	-0.0220	0.0109	0.0390**	-0.0670***
	(0.0314)	(0.0012)	(0.0177)	(0.0138)
W × *ln(*HC $_{t-1}$)	-0.2609*	0.0886	0.1359***	0.0005
	(0.1384)	(0.1271)	(0.0514)	(0.0846)
W × *ln(*LFS $_{t-1}$)	0.7858***	1.8821***	-0.5644**	1.0623***
	(0.2464)	(0.4786)	(0.2853)	(0.2275)
W × *ln(*POP $_{t}$)	0.0376	0.0355	-0.069*	0.0155
	(0.0292)	(0.0372)	(0.0359)	(0.0293)
W × ***ln(*SF $_{t-1}$)**	**-0.0158*****		**-0.0120*****	
	(0.0045)		**(0.0047)**	
$\sum_{m=1}^{4} \mathbf{W} \times \boldsymbol{ln(SF_{t-m})}$		**-0.0044**		**-0.0196*****
		(0.0075)		**(0.0058)**
Marginal effect (overall = direct + indirect)	**-0.0109*****	**-0.0167*****	**-0.0145****	**-0.0059**
of SF funding	**(0.0039)**	**(0.0048)**	**(0.0042)**	**(0.0067)**
No. of Obs.	1211	1147	1211	1147
No. of instruments	46	58	27	55
Hansen J-statistic	29.51 (22)	39.94 (31)	35.99	33.03
Diff-in-Hansen for Lev. Eq.	9.86	21.38 (16)	14.62	18.44
Diff-in-Hansen for SF	4.69	9.04	1.07	0.89
AR2	1.53	0.69	0.98	1.63

Note: ***,**,* denote significance at the 1 %-, 5 %- and 10 %-level. 127 regional groups. Time effects included in all estimations. Robust and regionally clustered standard errors are given in parentheses. The SpSYS-GMM is computed as efficient two-step GMM estimation. For a calculation of marginal effect of SF funding see Table A.1 in the appendix. *Source:* Eurostat (2010), DG Budget unit A.2.

We can get further insights into the role played by spatial spillovers by estimating the spatially augmented interaction model specification. In line with Figure 2, Figure 4 plots the marginal effect of SF-funding on the region's convergence rate as a function of the region's own income gap to steady state and the 5 %-, 10 %-, 20 %-, 80 %- and 90 %-percentiles of spatially weighted funding intensities in neighboring regions. While the solid lines indicate the marginal growth effects of SF-funding, the dashed lines show the 95 %-confidence intervals. For low to moderate levels of indirect SF-funding, the marginal effect turns out to be insignificant (Figure 4). However, the effect becomes significant for the 80 % and 90 % percentile of the spatial lag of SF-funding. This threshold (at around the 80 % percentile) is also emphasized by the lower right graph, plotting the associated *t*-values (one-sided) for a test of the statistical significance of mean marginal SF-funding effect (averaged over the regions' gap to maximum GDP per capital level) for each percentile of the distribution of the spatial lag of SF-funding as conditioning factor.

Figure 4: Marginal effect of SF funding on regional growth conditional on regional income gaps and spatially weighted SF-funding intensities in neighboring regions

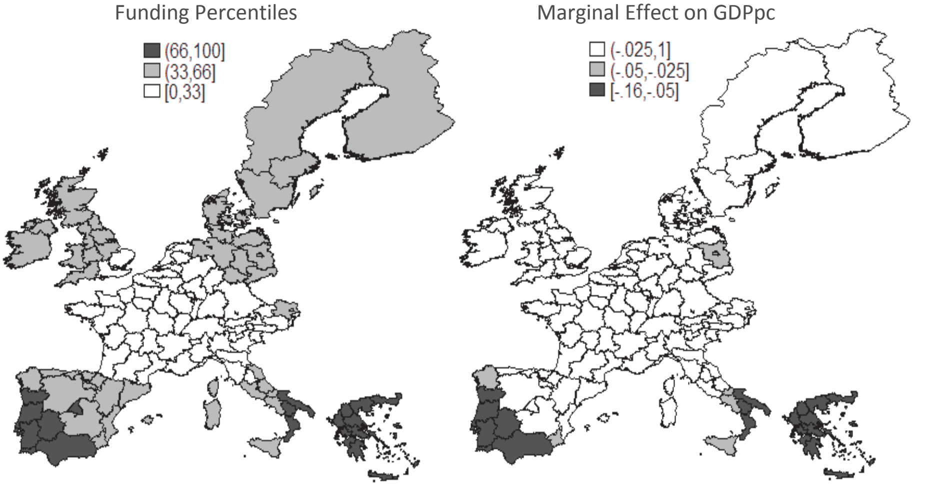


Note: Spatially weighted SF-funding intensities are displayed for selected percentiles of the variable's distribution. The lower right figure shows the results of a t-test for the statistical significance of the mean marginal SF-funding effect (averaged over the regions' gap to maximum GDP per capital level) for each percentile of the distribution. Results based on spatial interaction model specification from Table A.3. Dashed lines provide the 95 % confidence interval. For a calculation of marginal effect of SF funding see Table A.1 in the appendix. *Source:* Eurostat (2010), DG Budget unit A.2.

The results of the spatial interaction model suggest that the negative effects of spatial funding are caused by the regions with the highest share of spatial funding intensity. This hints at the existence of negative spillover effects which form deprived convergence clusters. In similar veins, Pfaffermayer (2009) reports such findings for positive spillovers. He states that these spillovers are expected to be higher, the more advanced the neighboring regions are. Our findings provide evidence for the hypothesis that the spatial funding serves as a proxy for structural backwardness of such macro clusters which tend to characterize all the regions within these convergence-clubs.

Moreover, this conclusion is supported by a graphical illustration (Figure 5) which shows that the regions causing the negative overall effect are spatially clustered (right map). As Figure 4 already reported, the maps also reveal that the negative effect mainly stems from the highest funded regions. These regions are particular located in southern Europe. Thus, these results provide similar evidence as earlier contributions such as Ederveen et al. (2006) who particularly refer to the importance of the institutional setup in funded regions as a condition for funding effectiveness. Our results may also hint at the importance of the backwardness in terms of technological endowment and economic structures as factors which deprive these regions and which should be compensated to improve funding effectiveness.

Figure 5: Neighborhood Funding intensity (left) and Overall Funding Effect (right)



Note: Results based on spatial interaction model results from Table A.3. The darker colors indicate more negative effects of direct and indirect funding. *Source:* Eurostat (2010), DG Budget unit A.2.

Robustness checks

In this section, we aim at testing the robustness of our results for alternative spatial weighting matrices given that the choice of the latter may crucially determine the models ability to account for cross-sectional dependence in the data. Since the literature does not offer clear guidance with respect to the design for **W**, we use three different weighting schemes as alternative specification for the reference case of inverted distances. The first alternative substitutes the original linear distance by squared values (putting more weight on close neighbors). In the second specification the k nearest neighbors are regarded as neighbors, independent from their absolute distance. As a standard value from the literature we choose $k = 10$.[29] As a third specification, we choose a "Placebo" weighting matrix with randomly generated weights[30], which is just introduced as a control and should deliver insignificant results.

Table 4: Robustness Checks for spatial interaction models

	Funding Variable	Inverted Distances	Squared Inverted Distances	Binary Matrix (k=10)	Random Matrix
(i)	$\mathbf{W} \times ln(SF_{t-1})$	-0.0146*** (0.0041)	-0.0243*** (0.0056)	-0.0193*** (0.0029)	0.00004 (0.0408)
(ii)	$\sum_{m=1}^{4} \mathbf{W} \times ln(SF_{t-m})$	-0.0119** (0.0054)	-0.0146*** (0.0049)	-0.0227*** (0.0039)	0.0067 (0.0407)
(iii)	$\mathbf{W} \times ln(SF_{t-1})$	-0.0142*** (0.0053)	-0.0120** (0.0049)	-0.0140*** (0.0041)	0.0068 (0.0236)
(iv)	$\sum_{m=1}^{4} \mathbf{W} \times ln(SF_{t-m})$	-0.0094** (0.0039)	-0.0169*** (0.0037)	-0.0147*** (0.0035)	-0.0376 (0.0314)

Note: ***,**,* denote significance at the 1 %-, 5 %- and 10 %-level. Standard errors are given in parentheses. Complete regression tables can be obtained from the authors upon request. *Source:* Eurostat (2010), DG Budget unit A.2.

The point estimates of our SF-policy variable in Table 4 show quite similar regression coefficients and statistical significance levels for the three constructions of **W** and the expected insignificant result for the randomized weighting matrix in the last column. The robustness checks do not give any hint that our results crucially depend on the chosen spatial weighting matrix underlying the validity of the results.

[29] We standardize the weighting matrix for estimation; therefore the values of w_{ij} are equal to *1/k* or 0. Although this procedure is chosen in different studies (e.g., Ertur and Koch 2007 or Mohl and Hagen 2010), it has the major shortcoming that region *j* can be flagged as neighbor for region *i* while it is not linked in the other direction. This can be the case when region *i* is located on a coast line or when the further neighbors of region *j* are smaller regions.

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

5. Conclusion

In this paper we have analyzed the effectiveness of EU regional policy as an allocative instrument in fostering per capita income convergence among EU15 NUTS2 regions. The policy variables in focus are the “Convergence” payments within the EU Structural Funds. These payments are exogenous to regional growth expectations, pursue a clearly attributable policy goal and have been governed by a consistent legislative framework over the three considered funding periods, facilitating a quantitative impact analysis over a rather long funding period. Applying different empirical models derived from (spatial) growth theory, we estimate the link between “Convergence” SF-payments and regional GDP per capita evolution for 127 regions throughout the sample period 1997-2007. We put a particular focus on the proper specification and interpretation of the SF-related policy variable in each regression approach as well as on capturing the role of spatial spillovers.

Encompassing the full range of potential transmission channels from the policy stimulus onto our outcome variable, the results indicate that the funding does not foster income growth in lagging regions over and above the average income convergence rate in the EU. While we partly obtain empirical evidence for a statistically significant negative marginal funding effect in our non-spatial benchmark case, the augmented estimations, capturing cross-sectional dependence among EU regions, particularly show that this effect is driven by the spatially-indirect funding component.

We motivate the revealed negative link between regional growth and spatial funding intensities with two possible explanations: Basically, regional SF-funding, mainly implemented through investment subsidies, might induce a competition (poaching) effect among neighboring regions for potential regional investors. Following this argumentation, the negative spatial effects, found in the estimations, can be interpreted as causal effects. In this case, policy needs to consider the extent of spatial competition in future funding schemes and implement mechanisms which prevent such poaching behavior.

Besides, we found that the negative effect is mainly driven by those funded regions with the relatively high funding intensities in their spatial neighborhood, thus forming larger macro-regions of high SF-funding. In this context, the intensity of direct and spatially-indirect SF-funding can be interpreted as an indicator for (structural or technological) backwardness which is not captured in the controls. Earlier findings in the literature confirm this. Accordingly, the results suggest that substituting necessary fundamental and long-lasting structural reforms by enormous funding-based and short-termed investment plans to overcome the poor economic growth performance of these macro-regions in Europe will not lead to success.

The EU commission should be very careful in offering such growth programs, as in particular the southern European regions seem to suffer from the structural backwardness and are caught in persistent growth traps. Taken together, the "Convergence" SF-funding currently fails in its allocative goal to foster income convergence. Looking at the growing importance of EU regional policy within the enlarged EU-28 as highlighted by the intended European Fund for Strategic Investment, these considerations should be taken seriously when designing new funding priorities and associated regulations in order to obtain long-lasting growth stimuli in the key areas of regional policy including, education, research and innovation, as well as risk finance for small businesses.

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Appendix

Table A.1: Computation of average marginal SF policy effects

	Additive	Multiplicative
Non-spatial	Eq.(7): $\frac{\partial \Delta y_{i,t}}{\partial \ln(sf_{t-1})} = \gamma$	Eq.(10): $\frac{\partial \Delta y_{i,t}}{\partial \ln(sf_{t-1})} = \gamma + \left(\xi \times \ln(y_{t-1})\right)$
Spatial	Eq.(11): <u>Local spillover model (SCM, *ρ=0*)</u> $\frac{\partial \Delta y_{i,t}}{\partial \ln(sf_{t-1})} = \underset{\text{Direct}}{\gamma_1} + \underset{\text{Indirect}}{\gamma_2}$	Eq.(12): <u>Local spillover model (SCM, *ρ=0*)</u> $\frac{\partial \Delta y_{i,t}}{\partial \ln(sf_{t-1})} = \gamma_1 + \gamma_2 + \left[\xi_1 \times \left(\mathbf{W} \times \ln(sf_{i,t-1})\right)\right] + \left(\xi_2 \times \ln(y_{i,t-1})\right) + \left[\xi_3 \times \left(\ln(y_{i,t-1})\right) \times \left(\mathbf{W} \times \ln(sf_{i,t-1})\right)\right]$
	Eq.(11): <u>Global spillover model (SDM, *ρ≠0*)</u> $\frac{\partial \Delta y_{i,t}}{\partial \ln(sf_{t-1})} = \frac{1}{N} z' S_{sf}(\mathbf{W}) z$ with: $S_{sf}(\mathbf{W}) = \left(I_N - \rho \mathbf{W}\right)^{-1} \left(\underset{\text{Direct}}{\gamma_1 I_N} + \underset{\text{Indirect}}{\gamma_2 \mathbf{W}}\right)$	Eq.(12): <u>Global spillover model (SDM, *ρ≠0*)</u> $\frac{\partial \Delta y_{i,t}}{\partial \ln(sf_{t-1})} = \frac{1}{N} z' S_{sf}(\mathbf{W}) z$ with: $S_{sf}(\mathbf{W}) = \left(I_N - \rho \mathbf{W}\right)^{-1} \begin{pmatrix} \gamma_1 I_N + \gamma_2 \mathbf{W} + \xi_1 \times \left(\mathbf{W} \times \ln(sf_{i,t-1})\right) \\ + \xi_2 \times (\mathbf{W} * \ln(y_{i,t-1})) + \xi_3 \times \left(\ln(y_{i,t-1})\right)\left(\mathbf{W} \times \ln(sf_{i,t-1})\right) \end{pmatrix}$

Note: I_N is a (*N x N*)-identity matrix, *z* is a (*N x 1*)-vector of ones. For details on the computation of the global spatial multiplier see Pace and LeSage (2009). Details on the computation of standard errors for the marginal effects in the multiplicative case are given in Brambor et al. (2005).

Table A.2: Detailed results for "comprehensive" SF-funding effect according to equation (9)

Dep.Var.: *ln*(GDP per capita)	(i) Fixed effect model (FEM) One lag	(ii) Four lags	(iii) Bias-corrected Fixed effect model (FEMc) One lag	(iv) Four lags	(v) System-Generalized Method of Moments (SYS-GMM) One lag	(vi) Four lags
ln($GDPpc_{t-1}$)	0.6979*** (0.0337)	0.7885*** (0.0314)	0.8276*** (0.0205)	0.9298*** (0.0213)	0.8099*** (0.0352)	0.8841*** (0.0410)
ln(HC_{t-1})	0.0464*** (0.0134)	0.0459*** (0.0153)	0.0379*** (0.0102)	0.0376*** (0.01)	0.0266** (0.0134)	0.0253 (0.0163)
ln(LFS_{t-1})	0.1033** (0.0445)	0.0258 (0.0244)	0.0875 (0.0284)	0.0003 (0.0278)	0.0914* (0.0502)	0.0799 (0.0602)
ln(POP_t)	-0.3687 (0.3028)	-0.4127 (0.2578)	0.0403** (0.3291)	-0.7136** (0.3214)	0.0180*** (0.0061)	0.0120*** (0.0046)
***ln*(SF_{t-1})**	**-0.0015*** (0.0005)**		**-0.0019*** (0.0005)**		**-0.0007 (0.0005)**	
$\sum_{m=1}^{4} \boldsymbol{ln(SF_{t-m})}$		**-0.0010* (0.0005)**		**-0.0010 (0.0135)**		**-0.0002 (0.0006)**
No. of Groups	127	127	127	127	127	127
No. of Obs.	1371	1256	1371	1256	1211	1147
No. of instruments					16	16
Hansen *J*-statistic					35.26***	27.11**
Diff-in-Hansen for Lev. Eq.					12.52*	11.18
Diff-in-Hansen for SF					32.63	3.08
AR2					2.75***	2.11**

Note: ***,**,* denote significance at the 1 %-, 5 %- and 10 %-level. Standard errors are given in parentheses; SYS-GMM is computed as efficient two-step GMM estimation. *Source:* Eurostat (2010), DG Budget unit A.2.

Table A.3: Regression results for multiplicative interaction models

Dep. Var.: ***ln(*GDPpc$_t$)**	SYS-GMM	SpSYS-GMM
*ln(*GDPpc$_{t-1}$)	0.8872*** (0.0158)	0.7975*** (0.0621)
*ln(*INV$_{t-1}$)	0.0033*** (0.0011)	0.0012 (0.0021)
*ln(*HC $_{t-1}$)	-0.0355*** (0.0136)	0.001 (0.0118)
*ln(*LFS $_{t-1}$)	-0.0003 (0.034)	0.021 (0.0548)
*ln(*POP $_t$)	0.7405 (0.463)	0.009* (0.0045)
*ln(*SF $_{t-1}$)	-0.0233** (0.0094)	0.0009** (0.0004)
W × *ln(*GDPpc$_{t-1}$)		0.4026* (0.2172)
W × *ln(*INV t$_{t-1}$)		0.0351* (0.0181)
W × *ln(*HC $_{t-1}$)		-0.3944*** (0.1159)
W × *ln(*LFS $_{t-1}$)		0.3121 (0.2745)
W × *ln(*POP $_t$)		-0.0438 (0.0293)
W × *ln(*SF $_{t-1}$)		-0.0245*** (0.0035)
*ln(*GDPpc$_{t-1}$) x *ln(*SF $_{t-1}$)	0.0021** (0.0009)	0.0010*** (0.0002)
*W*ln(*SF $_{t-1}$) x *ln(*SF $_{t-1}$)		00.0009 (0.0011)
*ln(*GDPpc$_{t-1}$) x (**W** × *ln(*SF $_{t-1}$))		0.0004 (0.0003)
(**W** x *ln(*SF $_{t-1}$)) x *ln(*SF $_{t-1}$)* *ln(*GDPpc$_{t-1}$)		0.0001 (0.0001)
No. of Groups	127	127
No. of Obs.	1216	1216
Hansen J-statistic	23.46	45.30*
AR2	1.49	1.54

Note: ***,**,* denote significance at the 1 %-, 5%- and 10 %-level. Standard errors are given in parentheses; SYS-GMM and SpSYS-GMM are computed as efficient two-step GMM estimation. *Source:* Eurostat (2010), DG Budget unit A.2.

Table A.4: List of EU regions in sample

BE1	Brussel	FR62	Midi-Pyrenees
BE2	Flanders	FR63	Limousin
BE3	Wallonia	FR71	Rhone-Alpes
DK0	Denmark	FR72	Auvergne
DE1	Baden-Württemberg	FR81	Languedoc-Roussillon
DE2	Bavaria	FR82	Provence-Alpes Cote d'Azur
DE3	Berlin	FR83	Corse
DE4	Brandenburg	IE0	Ireland
DE5	Bremen	ITC1	Piemonte
DE6	Hamburg	ITC2	Valle d'Aosta
DE7	Hesse	ITC3	Liguria
DE9	Lower Saxony	ITC4	Lombardia
DE8	Mecklenburg-Western Pomerania	ITD1	Bolzano
DEA	North Rhine-Westphalia	ITD2	Trento
DEB	Rhineland-Pfalz	ITD3	Veneto
DEC	Saarland	ITD4	Friuli-Venezia Giulia
DED	Saxony	ITD5	Emilia-Romagna
DEE	Saxony-Anhalt	ITE1	Toscana
DEF	Schleswig-Holstein	ITE2	Umbria
DEG	Thuringia	ITE3	Marche
GR11	Makedonia-Thraki	ITE4	Lazio
GR12	Kentriki Makedonia	ITF1	Abruzzo
GR13	Ditiki Makedonia	ITF2	Molise
GR14	Thessalia	ITF3	Campania
GR21	Epiros	ITF4	Puglia
GR22	Ionia Nisia	ITF5	Basilicata
GR23	Ditiki Ellada	ITF6	Calabria
GR24	Sterea Ellada	ITG1	Sicilia
GR25	Peloponnisos	ITG2	Sardegna
GR30	Attiki	LU0	Luxemburg
GR41	Voreio Aigaio	NL1	North Netherlands
GR42	Notio Aigaio	NL2	East Netherlands
GR43	Kriti	NL3	West Netherlands
ES11	Galicia	NL4	South Netherlands
ES12	Asturias	AT11	Burgenland
ES13	Cantabria	AT12	Niederösterreich
ES21	Basque Country	AT13	Wien
ES22	Navarre	AT21	Kärnten
ES23	Rioja	AT22	Steiermark
ES24	Aragon	AT31	Oberösterreich
ES30	Madrid	AT32	Salzburg
ES41	Castile-Leon	AT33	Tirol
ES42	Castile-La Mancha	AT34	Vorarlberg
ES43	Extremadura	PT11	North
ES51	Catalonia	PT15	Algarve
ES52	Vealencia	PT16	Centre

ES53	Balearic Islands	PT17	Lisbon and the Tagus Valley
ES61	Andalusia	PT18	Alentejo
ES62	Murcia	FI	Finland
ES63/64	Ceuta and Mellila	SE1	Stockholm
ES70	Canary Island	SE2	South-West Sweden
FR10	Ile de France	SE3	North Sweden
FR21	Champagne-Ardenne	UKC	North Esat England
FR22	Picardie	UKD	North West England
FR23	Haute-Normandie	UKE	Yorkshire and the Humberlands
FR24	Centre	UKF	East Midlands
FR25	Basse-Normandie	UKG	West Midlands
FR26	Bourgogne	UKH	East of Enland
FR30	Nord Pas de Calais	UKI	Greater London
FR41	Lorraine	UKJ	South East England
FR42	Alsace	UKK	South West england
FR43	Franche-Comte	UKL	Wales
FR51	Pays de la Loire	UKM	Scotland
FR52	Bretagne	UKN	Northern Ireland
FR53	Poitou-Charentes		
FR61	Aquitaine		