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DOES GLOBALIZATION AFFECT REGIONAL GROWTH? EVIDENCE FOR NUTS-2 REGIONS IN EU-27

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Abstract

We analyze the influence of newly constructed globalization measures on regional growth for the EU-27 countries between 2001 and 2006. The spatial Chow-Lin procedure, a method constructed by the authors, was used to construct, on a NUTS-2 level, complete regional data for exports, imports and FDI inward stocks, which serve as indicators for the influence of globalization, integration and technology transfers on European regions. The results suggest that most regions have significantly benefited from globalization measured by increasing trade openness and FDI. In a non-linear growth convergence model, the growth elasticities for globalization and technology transfers decrease with increasing GDP per capita. Furthermore, the estimated elasticity for FDI decreases when the model includes a higher human capital premium for CEE countries and a small significant growth enhancing effect accrues from the structural funds expenditures in the EU.

Keywords

Regional Globalization Measures, EU Integration (Structural Funds), Regional Growth Convergence Models, Foreign Direct Investment (FDI)

I. Introduction

Globalization is a combination of phenomena observed to affect people's lives in an economic, political as well as in a social way (see for example Keohane and Nye, 2000). The term 'globalization' arose in social sciences in the 1960s, but has been mostly used since the mid 1980s. While classical and new theories of international trade (Ricardo, 1817; Stolper and Samuelson, 1941; Melitz, 2003) clearly indicate the efficiency gains of

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market integration, the phenomenon of globalization is often criticized in that it favor the rich and harm the poor. However, most empirical studies find significant positive growth effects of commonly used globalization indicators at the national level and some studies highlight the role of factors needed to reap the benefits of growth, like human capital endowment (see Dreher, 2006).

Only a few studies deal with globalization at the regional level in the EU, mainly because the (latent) variable globalization can be best proxied at a national level where more global information can be gathered. One reason is that globalization forces have to be separated from EU integration forces and technological progress, especially transfers into new member states. The idea of this paper is to first construct on a regional level and then use these indicators on globalization, EU integration and technology transfers in a regional convergence model to explain GDP growth per capita. The aim is to get some empirical evidence as to what type of influence factors are important at the regional level in the EU at the turn of the century.

In this paper, we extend the analysis of globalization to the NUTS-2 regions of the 27 countries of the European Union (EU-27). Under economic globalization, we define increasing economic integration and interaction between countries. Using the definition of Clark (2000) whereas globalization is *the process of creating networks of connections among actors at multi-continental distances, mediated through a variety of flows including people, information and ideas, capital, and goods*, straightforward economic measurements would include trade flows, investment flows and knowledge spillovers. The growth effects of those indicators have been extensively studied at the national level and they are increasingly studied on the regional level.

For example, Badinger and Tondl (2005) investigate the growth implications of trade as a channel of technology and knowledge transmission embodied in the traded goods. They concluded that trade is especially important for closing the technological gap between high and low income regions. Tondl and Vukcis (2007) investigated the role of foreign direct investment (FDI) in the catching up process of Eastern Europe. According to them, FDI was a major growth determinant for Eastern Europe during the second half of the 1990s. They also find that the regional innovative capability, measured by human capital, is an important factor for technology transfer. Gonzales-Rivas (2007) estimated the impacts of trade openness on regional inequality for Mexico. The results suggest that regions with lower education but also regions with higher income and better infrastructure benefit from the opening of trade, implying mixed results of the effects on regional inequality.

The importance of regional innovation for the economic performance has been found in Paci and Pigliaru (2001) or Maurseth (2001) using patent data. Other studies suggest that knowledge spillovers crucially depend on the geographic distance (see for example, Fischer and Varga, 2003; Fischer et al., 2006; Fischer and Griffith, 2008). Besides the international technology and knowledge transfer through FDI and trade, the spatial proximity at the regional level seems to be an important factor explaining the personal inter-linkages of human capital in research and development. However, the decreasing importance of geographical distance due to decreasing transport prices and the Internet should also have led to increasing international knowledge spillovers. Such spillovers are expected to be strongest in those regions with sufficient underlying research infrastructure and human capital.

Given these previous results from the literature, this paper aims at extending the findings of regional impacts of globalizing forces by applying new data on regional globalization indicators. A recently developed method by the authors permits predicting regionally unavailable data like trade and FDI. The method extends the interpolation method for time series data of Chow and Lin (1971) to the spatial dimension. A detailed description for the spatial Chow-Lin method is given in Polasek et al. (2010) and Polasek and Sellner (2010). In short, the spatial Chow-Lin procedure uses the relationship between a dependent variable that is only measured at a more aggregate regional level (i.e. national exports of a country) and independent variables that are measured at a more disaggregate regional level (i.e. regional Gross Value Added) to predict the dependent variable at the disaggregate regional level.

We propose the spatial Chow-Lin method to derive predictions for trade flows and FDI inward stocks for the NUTS-2[3] regions of the EU-27. As stated above, trade and FDI are expected to increase regional growth by providing new technology to the region and by expanding the market, which should lead to more intense competition, the reduction of inefficiencies and economies of scale. Within a regional growth regression framework, we test the newly constructed measures for their implications of growth and convergence for a sample of 259 NUTS-2 regions between 2001 and 2006.

The paper is structured as follows: Section II gives a short overview of regional growth determinants commonly used in the growth convergence literature. In section III, we motivate the analysis of globalization at the regional level and discuss extensions of the basic regional convergence model by human capital, traffic infrastructure and newly constructed measures of **GL**obalization, **IN**tegration and **T**echnology transfers (abbreviated by GLINT). The empirical model is then derived in section IV and the results of the linear and non-linear (also called 'interaction') convergence model are given in section V. A final section concludes.

II. Determinants of Regional Growth

As in the empirical applications of national growth regressions, the factors that might explain regional growth are numerous, a problem that became known as the 'open-endedness' of growth theories (see Brock and Durlauf, 2001). Finding the right choice of variables might be very difficult and led to the use of procedures like Bayesian Model Averaging (BMA) to overcome model uncertainty (see Cuaresma et al., 2009, for a regional growth application). However, according to economic theory, some determinants are believed to be important for economic growth, both for the regional and national level.

The neoclassical growth theory mainly mentions the growth factor physical capital accumulation (see Kaldor, 1961). Regions with less capital stock are growing faster as they further accumulate capital until they reach an equilibrium growth path that is only influenced by exogenous technological progress. Within this neoclassical theory, a convergence

[3] Nomenclature of Territorial Units for Statistics.

mechanism is expected to drive growth in the poorer regions. Even though convergence forces helped poorer regions to catch up (see Cuaresma et al., 2009; Tondl, 1999) to some extent, there is also evidence that some rich regions diverge from the rest (see Fischer and Stirböck, 2006; Fischer and Stumpner, 2008, for club convergence[4]). Endogenous growth theory explains this behavior by accounting for technological progress that is expected to be more rapid in regions that provide the required endowments.

Such endowments include, for instance, human capital (see Lucas, 1988) that has been revealed as a regional growth factor in several studies so far (see for example Brunow and Hirte, 2009; Fischer et al., 2009). The existence of a well-trained labor force is important for own innovations but also for the adaption of imported external technologies and knowledge. Another important factor in this respect is the regional shape of the research and development sector. Sufficient scientific public and private infrastructure and R&D funds influence the innovation outcome significantly, often measured by the number patents in the empirical literature, and the productivity of the regions (see Sterlacchini, 2008; Bronzini and Piselli, 2009).

In addition to the internal endowments of a region, external technology and knowledge can impact the innovative potential of a region. Tondl and Vuksic (2007) found that FDI was far more important for growth in CEE (Central and Eastern European) countries than the general investment of a region. Besides new technology and techniques that are brought to a country by FDI, the knowledge embodied in the organizational capital of the firms and the skills that are acquired by the workforce might create spillovers to locally integrated firms or neighboring regions.

Another channel for external technology transmission is international trade (see Rivera-Batiz and Romer, 1991; Rivera-Batiz and Xie, 1993). By importing goods, the technology embodied in the products is imported as well. Additionally, higher returns on own innovation investment can be expected from larger sales markets (economies of scale), stimulating own research efforts. Finally, the pro-competitive effect of the open markets forces entrepreneurs to reduce inefficiencies and close the productivity gap. Empirical evidence for this hypothesis is given in Badinger and Tondl (2005) for EU regions.

Finally, the regional endowment with public capital stock is often mentioned as a growth factor in the literature (see Aschauer, 1989). Public infrastructure investment in transport and communication can be seen as a public good that is part of the production and distribution process of an economy. Particularly less developed regions are expected to benefit from investment in infrastructure (see Puga, 2002). The empirical results of regional models are, however, mixed in this respect. For example, Berechman et al. (2006) accounted for lagged effects and found significant positive effects of infrastructure for US states and at a county level. By contrast, Petrakos et al. (2007) and Capello (2007) do not find significant effects of infrastructure for European regions.

[4] Club convergence is the phenomena whereby regions converge to different steady states depending on their endowment, capabilities or cumulative causation.

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III. Regional Economic Globalization

As Capello and Fratesi (2009) showed in a globalization simulation analysis, the expected regional impacts vary depending on the regions' ability to absorb external shocks and translate them into economic growth. They simulated the effects of different strategic behaviors of the BRIC[5] countries on the Old and New Member States of the EU. For the regional predictions they employ the MASST model (see Capello et al., 2007), which distributes the growth effects of a national sub-model to the regions via a regional shift factor. This shift factor depends on the endowment of the regions, whereas regions with higher innovative capabilities reap more benefits of national growth.
These interesting insights about the impacts of an international (or global) phenomenon at the regional level motivated the following analysis. The main challenge is that, firstly, the phenomenon of globalization incorporates various different aspects, even when concentrating only on economic globalization (as, for example, defined by Dreher, 2006) as in this study. Secondly, globalization is not directly observable at the regional level and for an empirical analysis we need proxy variables. Consequently, we first have to define the concept of globalization, integration and technology (to which we will refer briefly as GLINT variables) and then show how to construct measures at the regional level.

Measures for Globalization, Integration and Technology Transfers (GLINT)

Most empirical studies for a cross-section of countries proxy economic globalization by flow data and measures based on them: trade flows, financial flows, capital flows or innovation flows, (see Dreher, 2006). We follow this literature and analyze globalization effects by three GLINT variables: a general globalization variable via trade, a technological transfer variable via FDI, and a regional integration variable measured by the EU structural funds expenditures.

With X (M) denoting exports (imports), our first globalization measure is the variable trade openness (TO), which is defined by the share of exports and imports in GDP[6]:

$$TO_t \equiv \frac{(X_t + Mt)}{GDP_t}, \quad t = 1, ..., T.$$

As motivated by Tondl and Vuksic (2007), we include the FDI inward stock as percentage of GDP ($\overline{TEC}$) to measure the regions exposure to technology transfers:

[5] Brazil, Russia, India and China.
[6] Following Badinger and Tondl (2005), we also tested for the different channels of growth stimuli through trade by accounting for the imports and exports as percentage of GDP separately. Higher import shares might be associated with higher degree of technological spillovers Coe and Helpman (1995), while higher exports shares are associated with a pro-competitive trade effect already discussed above. The results for these estimations are not reported in this paper, as we did not find evidence for these proposed effects of trade at the regional level.

$$TEC_t \equiv \frac{FDI_t^{IS}}{GDP_t}, \quad t = 1, ..., T,$$

with FDI^{IS} being the FDI inward stock of a region.

Our third measure is intended to capture the economic integration effects of regions within the EU. The EU integration effect can be realized across regions through a bundle of channels. Notaro (2002) gives an overview on the effects of market integration on competition and efficiency. To summarize, most studies find positive incentives to increase efficiency if competition increases. This is due to the decreased moral hazard coming from optimized information, reputation effects as productivity shocks are assumed to be the same across an industry, and the remainder is attributed to managerial ability, increased worker effort, either because of rent sharing or increased productivity through R&D (in which case the results are rather mixed). Market integration is also said to have a positive effect on firms' productivity through a 'Darwinistic' survival effect. Efficient firms are supposed to stay in the market and grow, while inefficient firms with higher costs exit the market. The underlying theory assumes common random cost distributions that are known by each firm, but the true costs for one firm is not known, as it is randomly drawn. The lower the true costs of the entering firm the higher the probability it will stay. Opening up foreign markets is supposed to shift the critical value of costs towards zero.

As we lack data that is suitable to capture regional economic integration effects of the EU, we include the EU structural funds expenditures. It can be expected that the funds help lagging regions in the setting up of new enterprises and assist them in entering the internal market, for example through export aids. A lot of recent literature exists on the GDP and employment growth impacts caused by the structural funds expenditures. For example, Cappelen et al. (2003), Puigcerver-Penalver (2007) and Becker et al. (2008) find significant impacts on GDP growth. However, Becker et al. (2008) fails to establish significant employment effects and Dall'erba and Gallo (2007) finds that the different objectives do not impact the way they are designed for. Cappelen et al. (2003) and Puigcerver-Penalver (2007) also find different impacts with respect to the period the funds are received.

In order to account for the relative importance of the structural funds (SF) received by a region, we divide the total regional structural funds expenditure SFEXP[7] by regional GDP and use the indicator (SF):

$$SF \equiv \frac{SFEXP}{GDP}. \tag{1}$$

[7] Basically, the structural funds of the EU consist of the following four funds: European Regional Development Funds (ERDF), European Social Fund (ESF), European Agricultural Guidance and Guarantee Fund (EAGGF) and Financial Instrument for Fisheries Guidance (FIFG). For a more detailed description of the included sub-funds, see the Appendix.

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Construction of the Regional GLINT indicators

Of the above proposed indicators to measure economic globalization, only the structural funds expenditures are observable at the regional level. NUTS-2 data on exports, imports and FDI inward stocks are not available for the regions of the EU-27. Previous studies have used either national values (see Gonzales-Rivas, 2007) or created ad-hoc measures of regionalized variables (see Badinger and Tondl, 2005). To construct the regional GLINT measures related to the globalization process, we use the recently developed spatial Chow-Lin data interpolation method (see Polasek et al., 2010).

Within the Chow-Lin method, the aggregate (national) relationship between our variables of interest (trade, FDI) and explanatory factors is used to predict the regional (NUTS-2) values for those variables, using the explanatory factors, which must be observable at the regional level. In a first step, the relationship between the missing disaggregate and the aggregate observable variables is established in an econometric framework. For this step, it is important to find regionally available explanatory factors that account for a large part of the variation in the data and that are responsible to influence the variable to be regionalized (interpolated) on theoretical and empirical grounds. The second step consists of a prediction using the estimated coefficients and regional explanatory factors (or indicators), adding an estimate of the residuals to ensure that the sum of the regional values add up to the national value.

Depending on the variable to be completed at the disaggregated level, different econometric models might be considered. In the economic literature, trade and FDI flows are often modeled using a origin-destination spatial (gravity-type) interaction model (see Zwinkels and Beugelsdijk, 2010). However, as even national data on bilateral flows of FDI turn out to be incomplete, a simple cross-sectional model might also be considered. A detailed description for the spatial Chow-Lin method is given in Polasek et al. (2010) for non-flow and in Polasek and Sellner (2010) for flow models (spatial interaction models). In the following, we briefly describe the essentials of the estimated models used within the spatial Chow-Lin interpolation procedure, while a more detailed description of the variables used and estimation results can be found in the Appendix.

Our first globalization measure is the trade openness of a region, defined by the share of imports and exports in GDP. Given our aim to find a measure for globalization, this certainly covers intra and extra EU-27 trade flows of the regions of the EU-27. As the data coverage and quality differs between intra and extra EU-27 flows, we estimated separate models for the two flows.

Given a richer data set, we constructed a flow model for the intra EU-27 trade flows using the population, GDP and employment in the manufacturing sector of the origin and destination region, the value added share that is associated with the sectoral trade flow and the employment in trade of the origin region (the choice of indicators basically followed Murat Celik and Guldmann, 2007) as explanatory variables. We estimated the model for six different sectors using data between 1999 and 2006, where the data were fully available via Eurostat's external trade database. As a distance measure for the spatial model, we used Euclidean distances between the centroids of the countries. The detailed estimation results are given in Table 8 in the Appendix.

For the extra EU-27 trade flows, we applied a non-flow Chow-Lin model; as there are numerous trading partners, involving substantial amount of data from different sources, such a model would be computationally too demanding and require large computing power and additional programming work that is beyond the scope of this study. As explanatory variables we used GDP, population and the GVA (gross value added) of sectors that can be expected to require or provide goods from the respective sectoral classification of the trade data. For each sector, two panel models were estimated, one for the exports and one for the imports. The Tables 10 to 11 in the Appendix show the results for the industry specific panel estimations in detail.

For the FDI inward stocks, the data did not allow us to estimate a flow model nor differentiate between sectors for a sufficiently large sample. Therefore we applied a non-flow model for the periods 1995–2006, including the variables area and GDP, efficiency wage (compensation per employee/average labor productivity), share of tertiary educated active population, patents per million inhabitants, the lagged GDP growth rate, GDP per capita, the investment rate and GVA shares of key sectors for FDI (financial services, business services, high-tech manufacturing). The choice of the variables was motivated by Narula and Wakelin (1998); Hatzius (2000); Noorbakhsh and Paloni (2001); di Giovanni (2005). The estimation results for the FDI inward stocks are given in Table 12 in the Appendix.

The estimated coefficients from Tables 8 to 12 were then used along with the corresponding NUTS-2 indicators to predict the regional values of the dependent variables.

IV. The Estimation of Regional Convergence Models

This section introduces the class of regional growth models and the estimation procedures.

The basic regional growth model

The starting point is the Cobb-Douglas production function augmented by human capital

$$Y = AK^{\alpha}L^{\beta}H^{\gamma}, \tag{2}$$

where Y is GDP, K is the total physical capital stock, L is employment, H is the stock of human capital and the constant A can be interpreted as production technology or 'Solow residual'. Assuming constant returns to scale ($1 = \alpha + \beta + \gamma$) and replacing employment by the population times the participation rate ($POP * PART$) we get

$$Y = AK^{\alpha}(POP * PART)^{\beta}H^{\gamma}. \tag{3}$$

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Dividing equation (3) by population POP, taking logs and differences of the form $\Delta \ln y = \ln y_{2006} - \ln y_{2001}$ yields

$$\Delta \ln y = \Delta \ln A + \alpha \Delta \ln k + \beta \Delta \ln PART + \gamma \Delta \ln h, \tag{4}$$

and lower case letters indicate per capita variables (e.g. $y = GDP/POP$).

In their BMA study on regional growth factors, Cuaresma et al. (2009) found that a convergence variable is an important factor in the growth model. Thus, we include the log of the GDP per capita at the beginning of our growth period to control for that. Finally, since regions can be expected to interact with neighboring regions via unobserved trade, worker or knowledge flows we allow for a spatial lag term in our specification. Also note that not accounting for spatial dependence in the error terms might severely bias the estimates from an econometric point of view (see LeSage and Pace, 2009).
Therefore, our basic or cross-sectional benchmark model for analyzing globalization effects is

$$\begin{aligned} \Delta \ln y &= c + \alpha \Delta \ln k + \beta \Delta \ln PART + \gamma \Delta \ln h + \kappa \ln y \\ &+ \rho W \Delta \ln y + \Delta \ln A + \epsilon, \end{aligned} \tag{5}$$

with c being the common intercept and ϵ being an i.i.d. disturbance term; ρ denotes the spatial correlation (of the lagged dependent variable) and W is the $N \times N$ row-normalized spatial weight matrix, respectively, describing the spatial neighborhood of the $N = 259$ NUTS-2 regions in the regional model. For simplicity, we use a first order contiguity matrix, weighting all regions that are contingent to another with the same factor (queen contiguity matrix).
In contrast to the model of Lucas (1988), i.e. relating the growth of knowledge to the growth of economies, Romer (1990) argues that the existing stock of knowledge in an economy is an important factor for growth. Such a stock is empirically often measured by the variable ‘R&D capital stock’, which is not sufficiently available at the regional level given our sample. Thus, we approximate the existing knowledge stock by the stock of human capital (h_h for tertiary and h_m for secondary education) in a region. We test within the basic growth model, whether the specification of Romer or Lucas yields better results, and then we will adopt the better model.

Regional Growth Model Extensions

Following recent empirical literature on regional growth, we extend the basic growth model by a set of exogenous regressors that describe the technological capabilities and other factors that potentially influence the growth of a region. These additional factors will be discussed in the remainder of this section and are tested for their empirical validity by adding them to the basic growth model.

First, as in Paci and Pigliaru (2001) and Maurseth (2001), we include as a proxy variable of the innovation process the regional patent activity ($PATENTS$). Note that this variable is troublesome for a few reasons. First, patents themselves cannot be expected to have a direct economic impact; it might rather be that the application of patents turn into an increase in productivity. Other variables that might approximate the innovation process, like $R\&D$ expenditure or personnel, are not available for all regions in our sample period. Second, we explore whether public infrastructure in transport and communication has an impact on regional growth, particularly in less developed regions (see for example Puga, 2002). To measure the stock of communication infrastructure we use the share of Internet users (IU) per country, taken from Eurostat. As measures of regional transport infrastructure (TI) for the EU-27, we employ the potential accessibility measures for air, rail, road and multi-modal transports taken from the EU supported ESPON project. We test different functional forms for the transport infrastructure, including quadratic terms, and interact them with the income per capita (y) at the beginning of period to test for non-linearities that might occur (see Puga, 2002).
In a third step, we include in the basic model the newly constructed regional (GLINT) measures on globalization, technology and integration, as described above. We like to find out whether regions that are more exposed to globalization are responsible for higher growth rates or if the process of opening-up is connected to regional growth. As a proxy variable, we use the total trade openness (TO), as defined above.
Our technology proxy, the regional FDI inward stocks in percentage of GDP denoted by $\overline{TEC}$ proxies technology transfers into a region and is measured either by the average level or as average growth rates over the five year period. Again, we interact this measure with the regional income per capital level, building up on the results of Badinger and Tondl (2005) and Tondl and Vuksic (2007).
To approximate the effects of EU integration on regional growth, we used the structural funds expenditures for the period 2000–2006 of the EU (SF) measured as percentage of the regional GDP. Note that by taking into account all structural funds objectives and the pre-accession aids (for this funds period this covers the 12 New Member States), all regions of the European Union are affected by the funds expenditures (and not just the objective 1 regions).

V. Growth Model Estimation for EU-27 Regions

Due to data availability in Eurostat, we estimate a spatial cross-sectional model (see equation 5) covering the period 2001–2006. We use the following notation: $\Delta \ln y_t$ stands for the average yearly growth of the y variable over the period 2001–2006. A detailed description of the data set and the included NUTS-2 regions can be found in the Appendix. As in the approach of Tondl and Vuksic (2007), we use as a proxy variable for human capital both the share of secondary and upper-secondary (h_m) or tertiary (h_h) educated economically active population, in a region. Unfortunately, these indicators contain many outliers. Some outliers and erratic observations are modeled by the estimation algorithm as we use a Bayesian heteroscedastic SAR model with a hierarchical (chi2) prior for the variance inflation factors (see Geweke, 1993) in the error term. For all our coefficients, we choose flat priors with mean 0 and variance $1e + 12$.

Extending the basic model by Human Capital

As we can see from Table 1, model 2 with initial shares of human capital (h_h and h_m, in column 2) seems to explain more of the variance within the estimation period than the model with growth rates (in column 1). The growth rates of human capital (in column 1) enter negatively and are highly statistically significant. This may be due to the fact that our estimation period covers more recent years, where the level of human capital of more advanced regions of the Old Member States was nearly saturated and the growth rates have been low. In the New Member States, regions start with rather low levels of human capital but experience higher growth. Our estimation period might, however, be too short to detect the effects of newly formed human capital. Including both, levels and growth rates, does not substantially improve the fit of the model (measured by R^2) and the coefficients on the growth rates are insignificant (see column 3). We, therefore, prefer the model with the levels rather than the growth rates of human capital, because all coefficients are significant and have the expected sign and size.

Table 1: Human Capital and Regional Growth – Bayesian SAR Estimation Results

Model	(growth rates)		(levels)		(both)	
Variable	(1)		(2)		(3)	
c	0.030	***	0.004		0.000	
	(0.004)		(0.004)		(0.005)	
$\Delta \ln PART$	0.455	***	0.610	***	0.620	***
	(0.054)		(0.053)		(0.053)	
$\Delta \ln k$	0.232	***	0.260	***	0.261	***
	(0.028)		(0.024)		(0.026)	
$\Delta \ln h_h$	−0.085	***			0.010	
	(0.021)				(0.023)	
$\Delta \ln h_h m$	−0.125	***			0.038	
	(0.028)				(0.033)	
h_h (high)			0.054	***	0.058	***
			(0.008)		(0.009)	
h_m (medium)			0.036	***	0.040	***
			(0.004)		(0.005)	
$\ln y$	−0.008	***	−0.009	***	−0.009	***
	(0.001)		(0.001)		(0.001)	
ρ	0.484	***	0.303	***	0.288	***
	(0.051)		(0.051)		(0.053)	
No. Obs. (Vars.)	259	(7)	259	(7)	259	(9)
R^2 (adj. R^2)	0.677	(0.670)	0.783	(0.779)	0.787	(0.782)
No Draws (Omissions)	25000	(5000)	25000	(5000)	25000	(5000)

*Significance at the 1, 5 and 10% level is denoted by ***, ** and *, respectively. Standard errors are in parenthesis.*

Looking at the residuals of the MCMC procedure for the estimated models of Table 1, we found that the heteroscedastic model still hints at several regions as large outliers. After including dummy variables for Romania, the Romanian region 'Bucuresti-Ilfov', the Greek region 'Sterea Ellada' and 'Cyprus', we also tried to include a capital city dummy (like in Capello (2007); Tondl and Vuksic (2007); Cuaresma et al. (2009)), because city regions tend to grow faster than rural regions. For brevity, we do not report all the estimation results for the dummy variables.

Extending the basic model by Patents and Internet access

As a next step, we test the technological and infrastructure variables within our outlier corrected growth regression framework. First, we included the share of Internet users in the year 2001, the log of the patents per million inhabitants ($lnPATENTS$) and the growth rates of patents ($\Delta lnPATENTS$) as proxies for the technological output of a region[8]. We see no significant influence of this variable. Column 2 and 3 in Table 2 show the results for the variable patents per million inhabitants. We only find a barely significant, very small and negative coefficient for the logged level variable. This result is not surprising, as this indicator describes the innovative output of a region with respect to research and development. As there is no plausible reason to believe that the whole benefit of such an effort should be realized in the same region, we can not expect much from this indicator.

[8] Including the share of Internet users (INTERNET) reduces our sample from 259 regions to 251 as we do not have data in the regions of Denmark, Estonia, Cyprus, Latvia, Lithuania, Luxembourg, Malta and Slovenia.

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Table 2: Technological Indicators and Growth – Bayesian SAR Estimation Results

Model	(Internet)		(Patents)		(Patents growth)	
Variable	(1)		(2)		(3)	
c	-0.00003		-0.002		0.002	
	(0.004)		(0.005)		(0.004)	
$\Delta \ln PART$	0.595	***	0.642	***	0.646	***
	(0.053)		(0.049)		(0.050)	
$\ln k$	0.233	***	0.237	***	0.247	***
	(0.026)		(0.025)		(0.024)	
h_h (high)	0.051	***	0.055	***	0.052	***
	(0.008)		(0.007)		(0.007)	
h_m (medium)	0.037	***	0.041	***	0.038	***
	(0.004)		(0.004)		(0.004)	
$\ln y$	-0.008	***	-0.007	***	-0.009	***
	(0.001)		(0.002)		(0.001)	
INTERNET	-0.003					
	(0.007)					
$\ln PATENTS$			-0.001	*		
			(0.001)			
$\Delta \ln PATENTS$					0.0004	
					(0.004)	
ρ	0.337	***	0.275	***	0.280	***
	(0.052)		(0.051)		(0.052)	
No. Obs. (Vars.)	251	(14)	259	(14)	259	(14)
R^2 (adj. R^2)	0.812	(0.804)	0.826	(0.819)	0.825	(0.818)
No Draws (Omissions)	25000	(5000)	25000	(5000)	25000	(5000)

*Significance at the 1, 5 and 10% level is denoted by ***, ** and *, respectively. Standard errors are in parenthesis.*

Extending the basic model by traffic accessibility

In a further step to include infrastructure in the regional convergence model, we test the ESPON accessibility indicators for their potential to improve the growth model. ESPON uses a variable that captures the quality (the potential accessibility as defined by ESPON) rather than the quantity (like road or rail km) of transport infrastructure. The ESPON accessibility indicator is available for road, rail, air, sea and multi-modal and all sub-indicators are highly correlated with each other, resulting in rather similar estimation results when we used them in a extended convergence model. We, therefore, only report the results of the multi-modal accessibility indicator that contain all four modes of transportation. The results are shown in Table 3.

Table 3: Transport Infrastructure (Multimodal-Access) models: Bayesian SAR Estimation Results

Model	(linear)		(quadratic)		(GDP inter.)		(CEE inter.)	
Variable	(1)		(2)		(3)		(4)	
c	0.004		0.088	*	−0.038	*	0.015	**
	(0.008)		(0.064)		(0.028)		(0.008)	
$\Delta \ln PART$	0.642	***	0.646	***	0.623	***	0.600	***
	(0.051)		(0.050)		(0.052)		(0.053)	
$\Delta \ln k$	0.247	***	0.244	***	0.243	***	0.234	***
	(0.024)		(0.023)		(0.024)		(0.025)	
h_h	0.053	***	0.050	***	0.056	***	0.058	***
	(0.007)		(0.008)		(0.008)		(0.007)	
h_m	0.038	***	0.039	***	0.038	***	0.036	***
	(0.004)		(0.004)		(0.004)		(0.004)	
$\ln y$	−0.009	***	−0.008	***	0.006		−0.008	***
	(0.001)		(0.001)		(0.009)		(0.002)	
Acc. Multi-modal	−0.001		−0.039	*	0.009		−0.003	**
	(0.002)		(0.029)		(0.007)		(0.002)	
(Acc. Multi-modal)^2			0.004	*				
			(0.003)					
$\ln y^*$ (Acc. Multi-m.)					−0.004	*		
					(0.002)			
CEE*(Acc. Multi-m.)							0.015	***
							(0.004)	
CEE Dummy							−0.059	***
							(0.019)	
ρ	0.278	***	0.289	***	0.282	***	0.267	***
	(0.053)		(0.052)		(0.053)		(0.052)	
No. Obs. (Vars.)	258	(14)	258	(15)	258	(15)	258	(15)
R^2	0.828		0.833		0.835		0.842	
adj. R^2	0.821		0.825		0.827		0.833	
No Draws	25000		25000		25000		25000	
No Omissions	5000		5000		5000		5000	

*Significance at the 1, 5 and 10% level is denoted by ***, ** and *, respectively. Standard errors are in parenthesis.*

Including just the log of the multi-modal accessibility indicator has no significant effect on growth of GDP per capita[9]. As discussed before, there is reason to believe that the marginal growth enhancing effects of infrastructure might diminish, so we include a quadratic term in the equation (see column 2).

Interestingly, the coefficient of accessibility becomes significant at the 10% level and remains negative, while the quadratic term is positive and significant. The reason why we cannot find the expected diminishing marginal returns might be reflected by the choice

[9] Note that the sample shrinks to 258 regions, because the ESPON indicator does not report the accessibility of the Canary Islands.

of the variable. As we have a qualitative indicator of transport infrastructure, the effects seem to turn positive after a certain accessibility level is reached. However, the weak significance levels of the indicators is still unsatisfactory. We, therefore, test whether the effects differ with respect to the income level of the region considered. In columns 3 and 4 of Table 3, we therefore interact the variable with GDP per capita and a Central and Eastern Europe (CEE) dummy variable. Both models suggest that accessibility is mainly a convergence factor for low income regions. This is seen from the negative interaction term (see column 3) and the positive interaction term (see column 4). Also note that the coefficient on the initial GDP per capita turns insignificant (see column 3), and the coefficient of the dummy variable for the CEE countries is negative and significant (see column 4). Thus, taking into account the accessibility of the low income regions explains most of the convergence process.

Linear and Non-Linear Extensions by GLINT Variables

Now we turn to the impact of the variables of interest in this study, the GLINT variables, to see if they can add to the explanation of regional growth in Europe. Prior to the empirical analysis, it is useful to formulate some beliefs about the functional form the GLINT globalization and integration variables that augment the basic convergence growth model. The studies of Badinger and Tondl (2005) and Tondl and Vuksic (2007) both used the stock measure of trade flows and FDI stocks respectively, in percent of GDP averaged over the growth period. We are open to the functional form, i.e. in what way to include either the average levels or the growth rates of the GLINT variables into the convergence model. The best results in terms of significance of the coefficients were obtained by including the growth of trade openness (denoted by $\Delta \ln TO$), the average stock of FDI inward stock in percent of GDP (denoted by $\overline{TEC}$) and the structural funds expenditures between 2000 and 2006 in percent of average GDP (denoted by SF). Furthermore, we found out that we obtain only significant results for the GLINT variables when we include them in a non-linear way in the basic convergence model, like in Gonzales-Rivas (2007). The idea is to emphasize the regional convergence process by making the GLINT elasticities level dependent using interaction terms as regressors, and, therefore, we call this extension of the basic model ‘Interaction Convergence Model’.

The SAR estimation results of the ‘Interactive Convergence Model’ are shown in Table 4. Besides the direct coefficients of the estimation, we also report the total effects – including additionally the spatial feedbacks or indirect effects – calculated according to LeSage and Pace (2009).

Table 4: Linear and Interaction Convergence Models with GLINT Variables – Bayesian SAR Estimation Results for EU Regions

Model	(linear)		(3 interactions)		(2 interactions)	
Variable	(1)		(2)		(3)	
c	−0.001		−0.023	***	−0.021	***
	(0.004)		(0.008)		(0.006)	
$\Delta \ln PART$	0.638	***	0.624	***	0.621	***
	(0.053)		(0.052)		(0.050)	
$\Delta \ln k$	0.243	***	0.206	***	0.222	***
	(0.023)		(0.026)		(0.024)	
h_h (high)	0.053	***	0.055	***	0.053	***
	(0.008)		(0.008)		(0.008)	
h_m (medium)	0.040	***	0.036	***	0.039	***
	(0.005)		(0.005)		(0.005)	
$\ln y$	−0.008	***	−0.001		−0.002	
	(0.001)		(0.003)		(0.002)	
$\Delta \ln TO$	−0.002		0.198	***	0.232	***
	(0.025)		(0.075)		(0.071)	
$\ln y * \Delta \ln TO$			−0.075	***	−0.086	***
			(0.027)		(0.025)	
$\overline{TEC}$	0.001		0.020	**	0.024	***
	(0.002)		(0.009)		(0.009)	
$\ln y * \overline{TEC}$			−0.006	**	−0.007	***
			(0.003)		(0.003)	
SF	0.010		−0.007		0.024	***
	(0.009)		(0.042)		(0.009)	
$\ln y * SF$			0.015			
			(0.017)			
Capital City	0.007	***	0.005	***	0.007	***
	(0.002)		(0.002)		(0.002)	
ρ	0.279	***	0.282	***	0.289	***
	(0.052)		(0.052)		(0.051)	
Total Effects						
$\Delta \ln TO$	−0.003		0.278	***	0.328	***
$\ln y * \Delta \ln TO$			−0.105	***	−0.122	***
$\overline{TEC}$	0.001		0.028	**	0.033	***
$\ln y * \overline{TEC}$			−0.009	**	−0.010	***
SF	0.014		−0.010		0.034	***
$\ln y * SF$			0.021			
No. Obs. (Vars.)	259	(15)	259	(18)	259	(17)
R^2 (adj. R^2)	0.832	(0.823)	0.845	(0.834)	0.842	(0.832)
No Draws (Omissions)	25000	(5000)	25000	(5000)	25000	(5000)

*Significance at the 1, 5 and 10% level is denoted by ***, ** and *, respectively. Standard errors are in parenthesis.*

The linear convergence model, given in column 1, includes the GLINT globalization variables in a spatial regression model (linear means: not interacting with initial GDP per capita). Surprisingly, we see only insignificant coefficients for the three GLINT variables and the coefficients on trade openness TO have negative signs. Note that the total effects

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(given at the bottom of Table 4), including the direct effect of the variable and the indirect effect through the spatial autoregressive framework, always exceed the estimates, because we find a positive significant spatial autocorrelation in the sample period. As there is reason to believe that globalization impacts regions differently according to their initial income level (a similar result for the productivity GAP was found in Badinger and Tondl (2005)), we interact the GLINT variables trade, FDI and EU integration with the initial GDP per capita ($\ln y$) variable. This specification corresponds to the assumption, that the convergence process within the EU-27 is driven by forces of globalization[10].

The second column of Table 4 shows the estimates of this 'Interactive Convergence Model'. It can be seen that interacting with the initial GDP per capita, the coefficients of trade openness (TO) and FDI inward stock (TEC) in percent of GDP impacted positively on the growth of GDP per capita between 2001 and 2006. Now, the positive GLINT effects are diminishing with rising initial GDP per capita.

These estimation results favor the hypothesis that globalization through trade and foreign direct investment acts as a (non-linear) convergence factor for less economically developed regions within the EU-27. Moreover, these estimation results indicate that increasing economic integration explains most of the convergence among those regions, as the coefficient of the unconditional convergence term ($\ln y$) decreases substantially in size and turns insignificant. Both, the coefficients of the structural funds variable (SF) and the interaction term with SF variable are insignificant at conventional confidence levels. Because the (SF) variable is a variable that is aimed at less developed regions in the EU, the inclusion of the interaction term with GDP per capita into the 'Interactive Convergence Model' is superfluous. Removing the interaction term of the structural funds measures ($\ln y * SF$) yields the results shown in column 3 of Table 4. The coefficient on the integration measure now turns highly significant and increases by a factor of 2.4 compared to the linear model in column 1. The estimation of this EU integration elasticity means that an increase in structural funds of 1 per cent of regional GDP leads to a growth of 0.024 per cent.

[10] We also tested for the non-linear nature in other variables like the share of Internet users and the number of patents per million inhabitant, both variables that turned out insignificant in the prior analysis. However, we failed to find evidence for non-linearities with respect to initial income per capita, human capital or differing effects for capital city or CEE regions for those variables. Including those non-linearities led to similar results concerning the ranking of winners and losers.

Interpretation of GLINT Elasticities in the 'Interaction Convergence Model'.

In the 'Interactive Convergence Model', the elasticities are a linear function of the interaction variable, the log GDP per capita level. The individual elasticities for the 3 GLINT variables are

$$\begin{aligned} \partial y/\partial \Delta \ln TO &= (\beta_{TO} + \beta_{TO,INT} * \ln y) * \Delta \ln TO \\ \partial y/\partial \overline{TEC} &= (\beta_{TEC,INT} * \ln y) * \overline{TEC} \\ \partial y/\partial SF &= \beta_{SF} * SF. \end{aligned} \tag{6}$$

A graphical representation of the level dependent elasticities is given in Figure 1. We see that the coefficients of trade openness (TO) and FDI ($\overline{TEC}$) cannot be interpreted as elasticities as in the linear convergence model but depend in the 'Interactive Convergence Model' on GDP per capita. Figure 1 shows the effect of a 1 percent increase of those measures, given a distinct level of income. For the computation of the elasticities (equation 6) we used the coefficients of column three in Table 4. The estimates of the structural funds expenditures SF imply constant (SF) elasticities (SF^2) with respect to GDP per capita[11]. From Figure 1 we see that the trade (∂TO) elasticity and the FDI ($\partial\overline{TEC}$) elasticity are decreasing functions of $\ln y$ and change the sign around a certain GDP per capita threshold. All regions below this threshold value potentially benefit from changes in TO or $\overline{TEC}$, while all regions above might not see a direct benefit[12].

[11] In models not reported in this paper, we tried different specifications for the structural funds measure. Most interestingly, we found a significant negative quadratic term for the funds, indicating a peak at 30 percent funds in percent of GDP and negative funds effects for 60 percent and over. However, as the sample maximum is 60 percent – for the Greek region 'Voreio Aigaio', we decided against this.

[12] Note that a possible evaluation target of regional EU politics could be an elasticity curve of GLINT variables that has negative slope but is rather flat and close to zero for rich regions.

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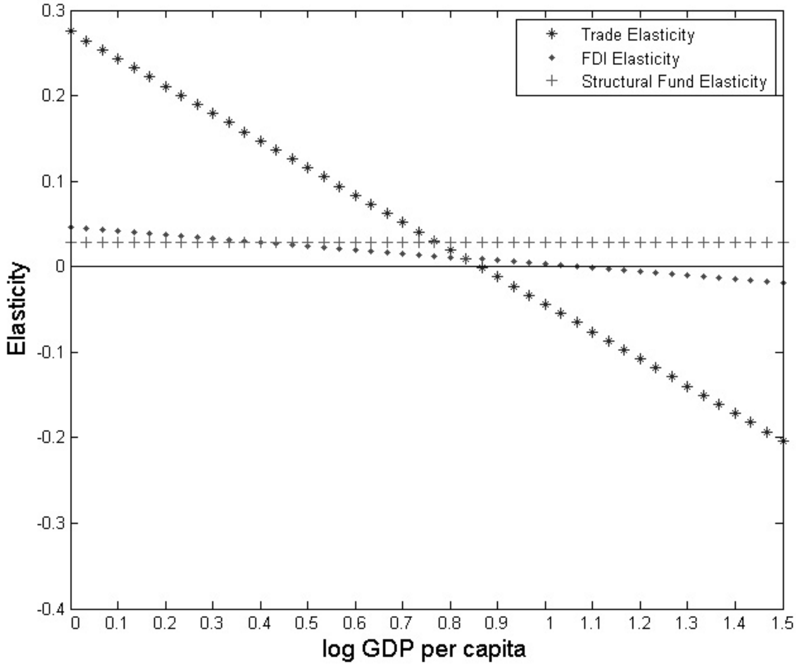
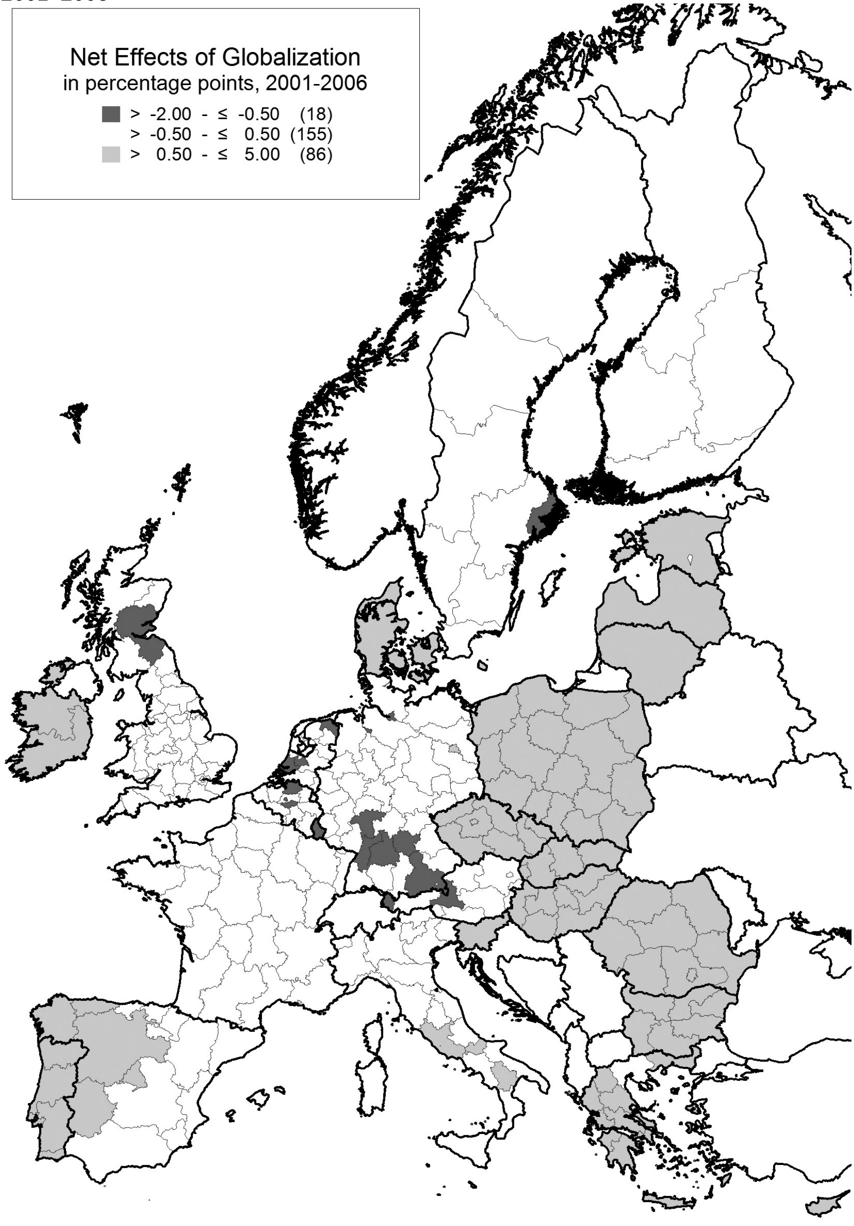
Figure 1: GDP per Capita Dependent Elasticities: Contribution of Trade, FDI and Structural Funds



The map in Figure 2 shows the sum of all three globalization measures (GLINT) based on the 'Interaction Convergence Model' of the lower panel of column three in Table 4. In addition to the directly estimated coefficients in the model (which includes indirect spatial feedback effects), we sum all the interaction terms with GDP per capita (indexed by INT), so that the total (non-linear) globalization effect on regional growth of all the GLINT variables is calculated by

$$\begin{aligned} \overline{GLINT} &= (\beta_{TO} + \beta_{TO,INT} * \ln y) * \Delta \ln TO \\ &+ (\beta_{TEC} + \beta_{TEC,INT} * \ln y) * \overline{TEC} \\ &+ \beta_{SF} * SF. \end{aligned} \tag{7}$$

Figure 2: Net Impacts of Globalization (GLINT) Variables on GDP per Capita Growth, 2001–2006



The total GLINT effects in Figure 2 are given in percentage points, and we have clustered the regions into 3 groups: the globalization winners with a growth bonus between 0.5 and 4 percentage points, the globalization losers with a negative impact of 0.5 or more percentage points and regions that were basically unaffected by globalization forces through the GLINT variables during the estimation period. The number next to the legend shows the number of regions (from a total of 259) falling into these 3 groups. We see that almost two thirds of the regions have not been strongly affected by the GLINT globalization forces between 2001 and 2006. The winners are the New Member States of the EU, Greece, Portugal, Western Spain, Northern Ireland and Southern Italy. Clearly, as the interaction convergence model implies, these regions are found all on the lower end of GDP per capita scale in 2001. According to these 3 classes, only 14 regions can be identified as net losers of globalization, because they started already at a high initial GDP per capita level, and these are mostly German, Dutch, Belgian and Austrian regions[13]. Note that these regions are large cities like Vienna, Munich, Frankfurt, Brussels, Amsterdam, Stockholm and Helsinki. These cities might not really be losers at the end of the day, since some of them enjoy the capital bonus (dummy variable: 'Capital City') of about 0.7 percentage points of growth in our model might overcome these distributional losses (via GLINT) by other aggregation forces that we could not quantify and have not yet taken care of.

Figure 3 displays the boxplot distribution of the net impacts of the globalization indicators according to the MCMC draws of the coefficients. This is the (posterior) estimated contribution of the GLINT variables in the interaction convergence model. The distribution is obtained by inserting the MCMC sample into the definition of the sum of the GLINT contribution in (7). The distribution of the total GLINT effects have been ordered and gives answers to 2 questions: which regions have significant positive (negative) GLINT contributions and which regions are the most volatile with respect to GLINT contributions. For the first question, we rank the regions according to the median of the (posterior) GLINT contributions and for the second question, we rank the regions according to the interquartile range (IQR) to rule out any effects due to outliers in the sampling distribution. We see that there are more GLINT distributions that lie on the positive side than on the negative side. That means that, looking at the total GLINT effects, there are more regions that are winners than losers. But the majority of regions might experience either positive or negative effects of the 3 GLINT contributions. If it comes to the volatility of these total GLINT influences, we see no clear correlation with the median GLINT effects. It seems that volatility across regions follows different influences and this effect needs more attention for future regional growth modeling. Different modeling strategies might have to be taken into account to find out if the volatile responses of regions to globalization influences can be explained.

[13] Luxembourg, Bruxelles, Prov. Antwerpen, Prov. Brabant Wallon, Stuttgart, Karlsruhe, Oberbayern, Bremen, Hamburg, Darmstadt, Groningen, Utrecht, Noord-Holland, Zuid-Holland, Wien, Salzburg, Vorarlberg, Etelä-Suomi, Stockholm and Inner London.

Figure 3: MCMC Distribution of GLINT effects ($\overline{GLINT}$) on GDP per capita growth, 2001–2006

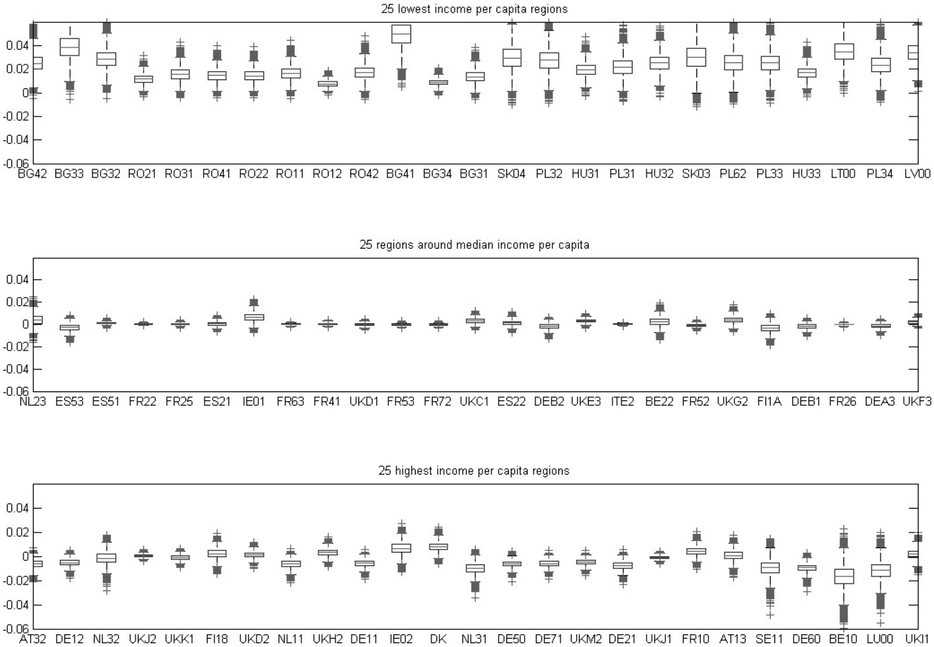
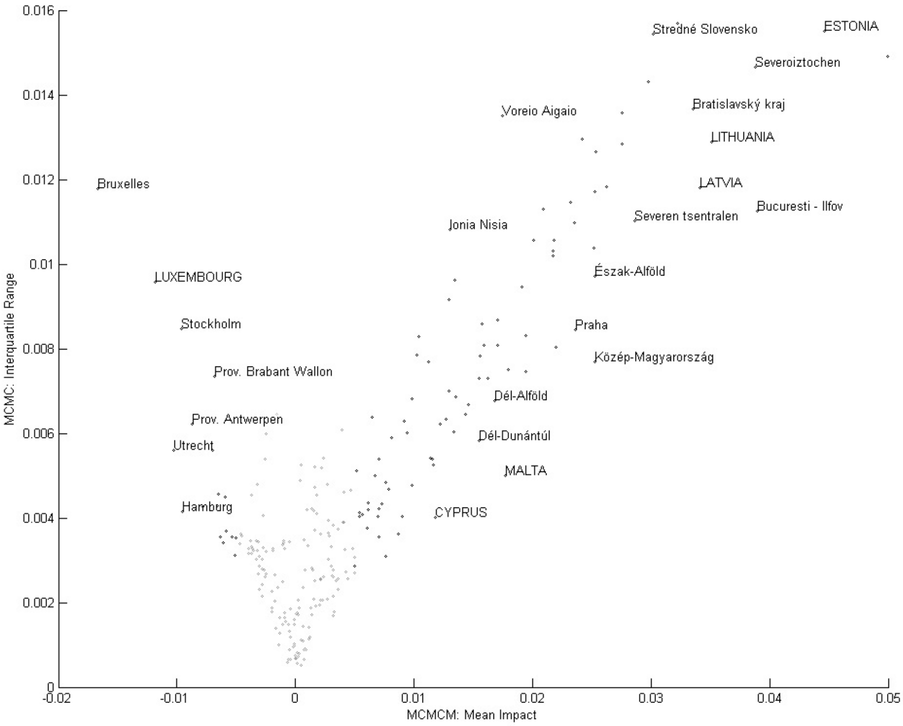


Figure 4 can be seen as a risk analysis of the total GLINT contributions. Points colored in dark (light) indicate the GLINT losers (winners) of figure 2. Most of the growth rates and the volatility of the GLINT contributions are small, concentrate around the zero vortex and form a triangular cone. But some growth rates can become large and are associated with larger dispersions from the growth rate distribution. The positive branch is larger than the negative branch, both in terms of the size of the mean and the IQR. This can be seen as good news, since more regions will benefit and the size of the effects are larger for the regions in the positive branch. The fact that many regions cluster around the vortex is not too surprising, since GLINT effects are not expected to be the largest effects in a regional growth model that is exposed to many heterogeneous influences.

Next we extend the GLINT effect to a 'GLINT+' effect by including the capital city dummy. The rational behind this is that the richest regions in Europe are capital city dummies and they experience a growth-bonus. Since the GLINT effects show that the losers are the rich regions which are mostly capital cities, can this negative effect be off-set by the capital city dummy: Thus we compute the 'GLINT+' variable by just adding the capital city dummy.

$$\overline{GLINT^{+}} = \overline{GLINT} + D_{CapitalCity} \tag{8}$$

Figure 4: GLINT Scattergram: A Cone formed by Median vs. Interquartile Range (IQR) of the GLINT Effects Distribution



Now we can compare the GLINT with the $\overline{GLINT^{+}}$ results in Figures 4. Note that the number of losing and winning regions does not change too much. Also the box-plots for the richest and poorest regions seem to have not a smoother appearance than for the GLINT summary. How can this happen? One reason is that adding the capital dummy increases the correlation structure in the estimation process that does not lead to smoother predictions of the $GLINT^{+}$ variable if we add all effects together. Certainly more research is needed to explore this rough prediction phenomenon which might also stem partly from the non-linear interaction model.

Sensitivity analysis

To check the sensitivity of the estimation results of the interaction convergence model, we performed three sensitivity checks, which are shown in Table 5. The estimates in column 1 were estimated using the feasible generalized spatial two-stage least squares (2SLS) estimator proposed by Kelejian and Prucha (1998) with a contiguity matrix for the spatial error component (with parameter λ). We see that the implications of the interaction convergence model do not change, though the interaction terms and the structural funds measure are estimated less precisely. Next, we include a Central and Eastern European (CEE) dummy, to check whether our results are driven by a growth bonus of the New Member States. The coefficient of the CEE dummy is positive and significant at a ten percent level. Nevertheless, all GLINT globalization measures have a significantly estimated coefficient, with the coefficient of trade openness being slightly smaller.

Table 5: Interactions in the Globalization Model: Sensitivity and Model Checks for the 'Interactive Convergence Model'

Model	(2SLS)		(CEE)		(CEE interact.)	
Variable	(1)		(2)		(3)	
c	−0.005		−0.026	***	−0.024	***
	(0.004)		(0.008)		(0.008)	
$\Delta \ln PART$	0.641	***	0.629	***	0.684	***
	(0.057)		(0.051)		(0.068)	
$CEE * \Delta \ln PART$					−0.166	*
					(0.110)	
$\Delta \ln k$	0.221	***	0.212	***	0.196	***
	(0.025)		(0.025)		(0.036)	
$CEE * \Delta \ln k$					0.000	
					(0.054)	
h_h (high)	0.046	***	0.053	***	0.049	***
	(0.010)		(0.008)		(0.008)	
$CEE * h_h$					0.073	**
					(0.032)	
h_m (medium)	0.036	***	0.036	***	0.034	***
	(0.006)		(0.005)		(0.005)	
$CEE * h_m$					0.007	
					(0.012)	
$\ln y$	−0.004	*	0.001		0.000	
	(0.002)		(0.003)		(0.003)	
$\Delta \ln TO$	0.236	***	0.209	***	0.208	***
	(0.091)		(0.073)		(0.082)	
$\ln y * \Delta \ln TO$	−0.073	**	−0.078	***	−0.076	***
	(0.032)		(0.026)		(0.029)	
$\overline{TEC}$	0.021	***	0.022	***	0.008	
	(0.008)		(0.009)		(0.010)	
$\ln y * \overline{TEC}$	−0.006	**	−0.007	***	−0.003	
	(0.003)		(0.003)		(0.003)	
SF	0.017	*	0.030	***	0.027	***
	(0.009)		(0.010)		(0.010)	
CEE Dummy			0.006	*	−0.007	
			(0.004)		(0.010)	
ρ	0.169	**	0.284	***	0.284	***
	(0.078)		(0.051)		(0.051)	
λ	0.500	**				
	(0.253)					
No. Obs. (Vars.)	259	(18)	259	(18)	259	(22)
R^2 (adj. R^2)	0.864	(0.856)	0.844	(0.834)	0.847	(0.834)
No Draws (Omissions)			25000	(5000)	25000	(5000)

*Significance at the 1, 5 and 10% level is denoted by ***, ** and *, respectively. Standard errors are in parenthesis.*

The third column (CEE interactions) shows the results when different factor elasticities for Old and New Member States are considered. We extend the GDP interaction model with another 4 interaction variables, but now we also interact the CEE dummy with the 4 factor variables h_h, h_m, $\Delta \ln PART$ and $\Delta \ln k$. Except for the elasticity of tertiary human capital (h_h) and an only marginally significant difference for the participation rate, there do not seem to be significant differences in the factor shares and the explanatory power of the 'double interaction model'. However, the coefficient of our measure of technological globalization – the FDI inward stock per capita – decreases to about half the size and is now insignificant. This might be an indication that the higher elasticity of tertiary human capital in the CEE countries is connected to the FDI proxy variable and thus to the technology transfer effect after the fall of the iron curtain.
Finally, an additional model including interactions of the FDI measure with the educational variables, shows significant interactions of FDI with higher education (h_h). The results for this model are not reported here, as the coefficient on the lower-order FDI term is insignificant. This result might be due to the fact, that co-linearities are commonly present when using numerous interaction terms (see Brambor et al., 2006). Additionally, our FDI measure was constructed using information about the educational level of the regions. Nevertheless, our results seem plausible in view of the finding in Tondl and Vuksic (2007) that FDI stocks foster growth in CEE countries, when combined with sufficient human capital endowment.

VI. Conclusion

This paper investigates the impact of 3 types of globalization variables, trade openness, EU integration and technology transfer (briefly abbreviated as GLINT variables) on the regional growth on GDP per capita in Europe. The model covers most of the NUTS-2 regions of the EU-27 states for a five year period with the best available data. A recently developed method – the spatial Chow-Lin procedure – has been applied to construct regional indicators of the GLINT variables, resulting in data predictions on a regional level for trade openness (the global indicator) and FDI inward stocks (the technology indicator) based on data available on a country level in the EU. We tested these newly constructed indicators on globalization, integration (approximated by the structural funds expenditures in percent of GDP) and technology transfers within a cross-sectional spatial growth regression model between 2001 and 2006.
The lesson learned is: explaining the impact of globalization on growth in the EU using a regional model is a highly complex non-linear regression problem. By estimating an 'Interaction Convergence Model' to allow for GDP dependent convergence elasticities, we found evidence that the effects of the GLINT indicators differ with respect to the economic prosperity of the EU-27 regions, favoring less developed regions. The 'Interaction Convergence Model' shows that the convergence process in European regions follows non-linear processes and is exposed to heterogenous and also heteroskedastic influences. This insight is per se not surprising, because a regional model has to cover diverse regional effects, but it shows that a rather simple interaction with convergence terms can explain these effects for GLINT variables (but not for others) on a regional level.

This empirical result throws new light on the importance of the European economic integration process in addition to the economic convergence process that is triggered by the recent globalization process and ongoing technological transfers for the regions within the EU-27. Furthermore, we found that the effects of the globalization indicator (i.e. trade openness) is higher than for the technology transfers (proxied by the inward FDI variable). Further, a sensitivity analysis points to an interdependence between FDI inward stocks and the human capital endowment of a region.
Additionally, we found evidence that the structural funds expenditures (the EU integration proxy variable) impacted positively on per capita income growth during the first 5 years in this century. Future work has to determine if the non-linear nature of the convergence process is a transient feature or if the non-linearity is due to some omitted regional variables that cannot be measured at the present time. Many panel studies at the country level have shown that economic convergence or non-convergence is quite difficult to explain by currently available variables, estimation techniques and models. This study has at least shown that measuring convergence on a regional level is a difficult task. The regional perspective adds another dimension to the problem and might rather contribute to exploring how to discriminate between convergence and divergence forces at a regional level.

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Annex A: Data and Regional Sample

Data Description

Y .... real GDP in 2000 prices, taken from Cambridge Econometrics Regional Database.

K .... real capital stock in 2000 prices, estimated using a perpetual inventory method: $K_t = K_{t-1}(1 - \delta) + I_t$. Investment I_t are taken from Cambridge Econometrics Regional Database. The initial capital stock was constructed by $K_{1980} = I_{1980}/(g_{i,1980-2006} + \delta)$ (see Griliches, 1980), with $g_{i,1980-2006}$ being the average annual investment growth rate.

POP .... population in 1,000 persons (Cambridge Econometrics).

$PART$... participation rate $PART = EMP/POP$ (Cambridge Econometrics).

h .... human capital measured as the share of economically active population with tertiary education, taken from Eurostat (some values interpolated by time means or NUTS-1 values).

Pat...... number of patent applications per million inhabitants, taken from Eurostat (some values interpolated by time means or NUTS-1 values).

IU ...... share of Internet users in the population, taken from ESPON.

TI....... potential accessibility measures by air, rail, road and multi-modal, taken from ESPON.

X, M.... regional trade flows predicted by the spatial Chow-Lin method (see Polasek et al., 2010; Polasek and Sellner, 2010). National values taken from Eurostat external trade statistics. Documentation of variables used and estimation results is available from authors upon request.

FDI .... regional FDI inward stocks predicted by the spatial Chow-Lin method (see Polasek et al., 2010; Polasek and Sellner, 2010). National values taken from Eurostat external trade statistics, WIIW database on Foreign Direct Investment in Central-, East- and South-East Europe and the FDI statistics of the IMF. Documentation of the variables used and estimation results are available from authors upon request.

SF ...... the structural funds expenditure for the periods 1994–1999 and 2000–2006 have been taken from the 'Regional Policy – Inforegio' homepage of the EU Commission http://ec.europa.eu/regional policy/funds/prord/prord en.htm. Data on pre-accession aids have been taken from ESPON. The period 1994–1999 includes the objectives 1, 2, 5b and 6, as well as the non-objective funds RECHAR II, REGIS II, RESIDER II, RETEX II, SME, URBAN and KONVER II. Period 2000–2006 includes the Objectives 1, 2 and 3, national programs, multi-regional programs, the non-objective funds URBAN II, and the pre-accession aid. Multi-regional and national programs have been divided evenly among the regions in the country affected.

Regional Sample

Table 6: Included NUTS-2 Regions, 2006 Classification

		Regions			Regions
1	DK00	Denmark	131	ITC3	Liguria
2	EE00	Estonia	132	ITC4	Lombardia
3	CY00	Cyprus	133	ITD1	Prov. Aut. Bolzano-Bozen
4	LV00	Latvia	134	ITD2	Prov. Aut. Trento
5	LT00	Lithuania	135	ITD3	Veneto
6	LU00	Luxembourg	136	ITD4	Friuli-Venezia Giulia
7	MT00	Malta	137	ITD5	Emilia-Romagna
8	SI00	Slovenia	138	ITE1	Toscana
		Belgium	139	ITE2	Umbria
9	BE10	Bruxelles	140	ITE3	Marche
10	BE21	Prov. Antwerpen	141	ITE4	Lazio
11	BE22	Prov. Limburg (B)	142	ITF1	Abruzzo
12	BE23	Prov. Oost-Vlaanderen	143	ITF2	Molise
13	BE24	Prov. Vlaams Brabant	144	ITF3	Campania
14	BE25	Prov. West-Vlaanderen	145	ITF4	Puglia
15	BE31	Prov. Brabant Wallon	146	ITF5	Basilicata
16	BE32	Prov. Hainaut	147	ITF6	Calabria
17	BE33	Prov. Liège	148	ITG1	Sicilia
18	BE34	Prov. Luxembourg (B)	149	ITG2	Sardegna
19	BE35	Prov. Namur			**Hungary**
		Bulgaria	150	HU10	Közép-Magyarország
20	BG31	Severozapaden	151	HU21	Közép-Dunántúl
21	BG32	Severen tsentralen	152	HU22	Nyugat-Dunántúl
22	BG33	Severoiztochen	153	HU23	Dél-Dunántúl
23	BG34	Yugoiztochen	154	HU31	Észak-Magyarország
24	BG41	Yugozapaden	155	HU32	Észak-Alföld
25	BG42	Yuzhen tsentralen	156	HU33	Dél-Alföld
		Czech Republic			**Netherlands**
26	CZ01	Praha	157	NL11	Groningen
27	CZ02	Střední Čechy	158	NL12	Friesland
28	CZ03	Jihozápad	159	NL13	Drenthe
29	CZ04	Severozápad	160	NL21	Overijssel
30	CZ05	Severovýchod	161	NL22	Gelderland
31	CZ06	Jihovýchod	162	NL23	Flevoland
32	CZ07	Střední Morava	163	NL31	Utrecht
33	CZ08	Moravskoslezko	164	NL32	Noord-Holland
		Germany	165	NL33	Zuid-Holland
34	DE11	Stuttgart	166	NL34	Zeeland
35	DE12	Karlsruhe	167	NL41	Noord-Brabant
36	DE13	Freiburg	168	NL42	Limburg (NL)
37	DE14	Tübingen			**Austria**
38	DE21	Oberbayern	169	AT11	Burgenland
39	DE22	Niederbayern	170	AT12	Niederösterreich
40	DE23	Oberpfalz	171	AT13	Wien
41	DE24	Oberfranken	172	AT21	Kärnten
42	DE25	Mittelfranken	173	AT22	Steiermark
43	DE26	Unterfranken	174	AT31	Oberösterreich
44	DE27	Schwaben	175	AT32	Salzburg
45	DE30	Berlin	176	AT33	Tirol

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Table 6 – continued from previous page

		Regions			Regions
46	DE41	Brandenburg-Nordost	177	AT34	Vorarlberg
47	DE42	Brandenburg-Südwest			**Poland**
48	DE50	Bremen	178	PL11	Lodzkie
49	DE60	Hamburg	179	PL12	Mazowieckie
50	DE71	Darmstadt	180	PL21	Malopolskie
51	DE72	Gießen	181	PL22	Slaskie
52	DE73	Kassel	182	PL31	Lubelskie
53	DE80	Mecklenburg-Vorpommern	183	PL32	Podkarpackie
54	DE91	Braunschweig	184	PL33	Swietokrzyskie
55	DE92	Hannover	185	PL34	Podlaskie
56	DE93	Lüneburg	186	PL41	Wielkopolskie
57	DE94	Weser-Ems	187	PL42	Zachodniopomorskie
58	DEA1	Düsseldorf	188	PL43	Lubuskie
59	DEA2	Koln	189	PL51	Dolnoslaskie
60	DEA3	Münster	190	PL52	Opolskie
61	DEA4	Detmold	191	PL61	Kujawsko-Pomorskie
62	DEA5	Arnsberg	192	PL62	Warminsko-Mazurskie
63	DEB1	Koblenz	193	PL63	Pomorskie
64	DEB2	Trier			**Portugal**
65	DEB3	Rheinhessen-Pfalz	194	PT11	Norte
66	DEC0	Saarland	195	PT16	Centro
67	DED1	Chemnitz	196	PT17	Lisboa
68	DED2	Dresden	197	PT18	Alentejo
69	DED3	Leipzig	198	PT15	Algarve
70	DEE0	Sachsen-Anhalt			**Romania**
71	DEF0	Schleswig-Holstein	199	RO11	Nord-Vest
72	DEG0	Thüringen	200	RO12	Centru
		Greece	201	RO21	Nord-Est
73	GR11	Anatoliki Makedonia, Thraki	202	RO22	Sud-Est
74	GR12	Kentriki Makedonia	203	RO31	Sud-Muntenia
75	GR13	Dytiki Makedonia	204	RO32	Bucuresti-Ilfov
76	GR14	Thessalia	205	RO41	Sud-Vest Oltenia
77	GR21	Ipeiros	206	RO42	Vest
78	GR22	Ionia Nisia			**Slovakia**
79	GR23	Dytiki Ellada	207	SK01	Bratislavský kraj
80	GR24	Sterea Ellada	208	SK02	Zapadné Slovensko
81	GR25	Peloponnisos	209	SK03	Stredné Slovensko
82	GR30	Attiki	210	SK04	Východné Slovensko
83	GR41	Voreio Aigaio			**Finland**
84	GR42	Notio Aigaio	211	FI13	Itä-Suomi
85	GR43	Kriti	212	FI18	Etelä-Suomi
		Spain	213	FI19	Länsi-Suomi
86	ES11	Galicia	214	FI1A	Pohjois-Suomi
87	ES12	Principado de Asturias			**Sweden**
88	ES13	Cantabria	215	SE11	Stockholm
89	ES21	Pais Vasco	216	SE12	Östra Mellansverige
90	ES22	Comunidad Foral de Navarra	217	SE21	Sydsverige
91	ES23	La Rioja	218	SE22	Norra Mellansverige
92	ES24	Aragón	219	SE23	Mellersta Norrland
93	ES30	Comunidad de Madrid	220	SE31	Övre Norrland
94	ES41	Castilla y León	221	SE32	Småland med öarna

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Table 6 – continued from previous page

		Regions			Regions
95	ES42	Castilla-la Mancha	222	SE33	Västsverige
96	ES43	Extremadura			**United Kingdom**
97	ES51	Cataluña	223	UKC1	Tees Valley and Durham
98	ES52	Comunidad Valenciana	224	UKC2	Northumberland, Tyne and Wear
99	ES53	Illes Balears	225	UKD1	Cumbria
100	ES61	Andalucia	226	UKD2	Cheshire
101	ES62	Región de Murcia	227	UKD3	Greater Manchester
102	ES63	Ciudad Autónoma de Ceuta (ES)	228	UKD4	Lancashire
103	ES64	Ciudad Autónoma de Melilla (ES)	229	UKD5	Merseyside
104	ES70	Canarias (ES)	230	UKE1	East Riding and North Lincolnshire
		France	231	UKE2	North Yorkshire
105	FR10	Île de France	232	UKE3	South Yorkshire
106	FR21	Champagne-Ardenne	233	UKE4	West Yorkshire
107	FR22	Picardie	234	UKF1	Derbyshire and Notting-hamshire
108	FR23	Haute-Normandie	235	UKF2	Leicestershire, Rutland and Northants
109	FR24	Centre	236	UKF3	Lincolnshire
110	FR25	Basse-Normandie	237	UKG1	Herefordshire, Worcestershire and Warks
111	FR26	Bourgogne	238	UKG2	Shropshire and Staffordshire
112	FR30	Nord-Pas-de-Calais	239	UKG3	West Midlands
113	FR41	Lorraine	240	UKH1	East Anglia
114	FR42	Alsace	241	UKH2	Bedfordshire, Hertfordshire
115	FR43	Franche-Comté	242	UKH3	Essex
116	FR51	Pays de la Loire	243	UKI1	Inner London
117	FR52	Bretagne	244	UKI2	Outer London
118	FR53	Poitou-Charentes	245	UKJ1	Berkshire, Bucks and Oxfordshire
119	FR61	Aquitaine	246	UKJ2	Surrey, East and West Sussex
120	FR62	Midi-Pyrénées	247	UKJ3	Hampshire and Isle of Wight
121	FR63	Limousin	248	UKJ4	Kent
122	FR71	Rhône-Alpes	249	UKK1	Gloucestershire, Wiltshire and North Somerset
123	FR72	Auvergne	250	UKK2	Dorset and Somerset
124	FR81	Languedoc-Roussillon	251	UKK3	Cornwall and Isles of Scilly
125	FR82	Provence-Alpes-Côte dAzur	252	UKK4	Devon
126	FR83	Corse	253	UKL1	West Wales and The Valleys Ireland
		Ireland	254	UKL2	East Wales
127	IE01	Border, Midlands and Western	255	UKM2	North Eastern Scotland
128	IE02	Southern and Eastern Italy	256	UKM3	Eastern Scotland
		Italy	257	UKM5	South Western Scotland
129	ITC1	Piemonte	258	UKM6	Highlands and Islands
130	ITC2	Valle dAosta/Vallée dAoste	259	UKN0	Northern Ireland

Source: Eurostat

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Annex B: Estimations for Data Disaggregation

Intra EU-27 Trade Flows

As the trade flows are available in a different classification (SITC Rev. 3), the product codes have been aggregated to match the existing NACE Rev. 1.1 classification of Gross Value Added. As shown in Table 7 the analysis covers six sectoral aggregates.

Table 7: Sector Classification and Correspondence for Intra EU-27 Trade

Sector No.	NACE Rev. 1.1 Code	SITC Rev. 3 Code	Sector Name
1	DA	0, 1, 4	Food and Beverages and Tobacco
2	DB+DC	26, 65, 84, 85	Textiles and Clothing
3	DF+DG+DH	27, 3, 5	Fuels, Chemicals, Rubber and Plastic Products
4	DL	75, 76, 77	Electronics
5	DM	78, 79	Transport Equipment
6	all other D	all other	other Manufacturing

We model the flows from an origin region i to a destination region j by a gravity model as follows:

$$\begin{aligned} y_{ijt} &= \alpha + \beta_i X_{it} + \beta_j X_{jt} + \delta D_{ij} + \epsilon_{ijt} \\ & \forall i \neq j, \quad i,j = 1,\ldots,N, \quad t = 1,...,T, \end{aligned} \tag{9}$$

where y_{ijt} is the logarithm of the trade flow from country (region) i to country (region) j in the year t. X_{it} (X_{jt}) is the logarithm of the matrix containing the origin (destination) specific factors and D_{ij} is a matrix element that includes the bilateral impedance factor distance. The regression coefficients are given by α, β, δ and u_{ij} being an iid disturbance term. In empirical applications, gross domestic product GDP (or gross value added GVA), population or GDP per capita are usually used as supply and attraction factors of the countries (regions).

Empirical evidence and theoretical considerations suggest to disaggregate trade with respect to product groups when estimating a gravity model. For example, distinguishing between differentiated and homogeneous products permits us to model different income elasticities (see Feenstra et al. (1998)). Empirical studies (see for example Baldwin et al. (2005), Flam and Nordström (2006) or Sargento (2007)) found significantly different coefficient estimates between product groups. Another interesting feature is the differentiation in the distance parameter, which might be higher for heavy goods of low value and lower for high technology goods. However, it should be kept in mind that even when disaggregating trade, the resulting product groups are still rather aggregated. Nevertheless, by differentiating between sectors or product groups, we are able to add additional information to the sample. This is especially important for the consecutive spatial Chow-Lin

disaggregation procedure, which produces more heterogeneous results among the regions the more information we add to the model and the more the regions differ in their gross value added (GVA) structures with respect to manufacturing industries.
The estimation results of are given in Table 8. We have used a Bayesian procedure[14] to estimate the coefficients. For the heteroskedastic residual ϵ_{it} in this procedure we make the following distributional prior assumptions:

$$\begin{aligned} \epsilon_{it} &= \mathcal{N}[0, \sigma^2 V], \quad V = diag(v_1, v_2, \ldots, v_n), \quad \sigma^2 = \Gamma(s_*^2, n_*); \\ r/v_i &= \chi^2(r)/r, \quad r = \Gamma(m, k), \quad i = 1, \ldots, n, \quad \beta = \mathcal{N}[b_*, H_*]. \end{aligned}$$

Overall, the estimation results show quite satisfying fits with adjusted R^2 of above 0.7 for each industry regression. We found that trade decreases with increasing population of the origin region in five out of six industries, and the effect is economically and statistically significant throughout all industries. The coefficient on the population of the destination region is expected to be significant and positive, because 'D-population' is a proxy of the demand of the destination region. The GDP coefficients for the origin and destination regions are both positive and statistically significant in all six industries.
The Gross Value Added (GVA) of the specific industry of the origin country is also always positive and significant. The employment in trade of the origin country as a proxy, for the inner-national transport promoting distribution network is significant and positive as expected in four out of six industries (see Murat Celik and Guldmann, 2007). The coefficients on manufacturing employment of the origin country is only negative and significant as expected in the industry 'Chemicals'. In the three other industries, where it was used to approximate intermediate demand in the origin region, the coefficient is significant and the sign is positive. By contrast, the approximation of the intermediate demand of the destination country is significant and negative in three out of four industries, a result that is not supported by our expectations either.
The impact of distance varies between industry from -1.14 (for Electronics) to -1.64 (for Chemicals). Perishables and goods that are expensive to transport ('Food', 'Chemicals' and 'Transport Equipment') show stronger distance impacts than goods in the industries 'Textiles', 'Electronics' and 'Manufacturing'.

[14] MCMC estimation for the Bayesian heteroscedastic linear models (see Geweke, 1993).

Table 8: Estimation Results for Intra EU-27 Trade Flows

	Food	Textiles	Chemicals	Electronics	Transport Equ.	other Manufacturing
constant	−9.20 ***	−13.03 ***	−15.58 ***	−9.55 ***	−10.66 ***	−11.04 ***
	(0.42)	(0.37)	(0.48)	(0.48)	(0.68)	(0.33)
POP origin	−1.14 ***	−0.35 ***	1.32 ***	−1.40 ***	−1.87 ***	−0.56 ***
	(0.10)	(0.09)	(0.12)	(0.12)	(0.16)	(0.09)
POP destination	0.06 ***	0.31 ***	1.07 ***	0.22 ***	0.38 ***	0.24 ***
	(0.03)	(0.03)	(0.08)	(0.08)	(0.11)	(0.06)
GDP origin	0.13 ***	0.26 ***	0.10 **	0.34 ***	0.56 ***	0.32 ***
	(0.04)	(0.03)	(0.06)	(0.05)	(0.06)	(0.05)
GDP destination	0.75 ***	0.69 ***	0.57 ***	0.82 ***	0.94 ***	0.78 ***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
GVA industry origin	1.36 ***	0.56 ***	0.84 ***	0.92 ***	0.81 ***	0.79 ***
	(0.06)	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)
EMP trade origin	0.75 ***	0.70 ***	−0.12	0.75 ***	0.76 ***	−0.19 ***
	(0.11)	(0.10)	(0.10)	(0.11)	(0.15)	(0.08)
EMP manu origin			−1.06 ***	0.36 ***	0.90 ***	0.61 ***
			(0.08)	(0.09)	(0.12)	(0.07)
EMP manu destination			−0.79 ***	−0.09	−0.40 ***	−0.11 **
			(0.07)	(0.07)	(0.10)	(0.05)
distance	−1.55 ***	−1.22 ***	−1.64 ***	−1.14 ***	−1.62 ***	−1.29 ***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
Observations	5476	5534	5569	5569	5569	5569
No. Variables	8	8	10	10	10	10
R^2 adjusted	0.729	0.759	0.785	0.799	0.745	0.846
No. Draws	5000	5000	5000	5000	5000	5000
No. Omissions	500	500	500	500	500	500
Prior mean – all vars	0	0	0	0	0	0
Prior std. – all vars	1000	1000	1000	1000	1000	1000

*Significance at the 1, 5 and 10% level is denoted by ***, ** and *, respectively. No fixed or random effects are included. Standard errors are in parenthesis.*

Extra EU-27 Trade Flows

As explained in the paper, we use a non-flow spatial Chow-Lin model (see Polasek and Sellner, 2008) for the 'external EU-27' flows. We have estimated the total 'extra EU-27' exports and imports of the EU-27 countries for different sectors of the economy using total external export or import data of the respective EU regions.

The data has also been taken from Eurostat and Cambridge Econometrics, but involves a different sectoral breakdown (see Table 9). Some industries coincide with the industrial breakdown already used for the intra EU-27 trade flows. However, the 'Textiles and Clothing' industry appears in 'other manufactured goods', 'Electronics' is included in 'Machinery and transport equipment', and additionally we have the product groups 'Raw Materials', 'Mineral Fuels' and 'other Commodities'. The last product group contains commodities and transactions that are not classified elsewhere, like postal packages, coins or gold.

Table 9: Sector Classification and Correspondence for Extra EU-27 Trade

Product Groups	SITC Rev. 3
A: Food and Beverages and Tobacco	0, 1
B: Raw materials	2, 4
C: Mineral fuels, lubricants and related materials	3
D: Chemicals and related products, n.e.s.	5
E: Other manufactured goods	6, 8
F: Machinery and transport equipment	7
G: Commodities and transactions, not classified elsewhere in the SITC	9

As we have now have a rougher product classification, we use as potential attraction factors for exports and imports GDP, population and sectoral information on Gross Value Added (GVA) of different sectors (all variables in logs). The models are chosen on grounds of R^2 statistics and plausibility of the industries concerned. The Tables 10 to 11 show the results for the industry panel estimations in detail. Except for the import equation for 'other commodities not classified in the SITC', the R^2 statistics are satisfying.

Exports are mostly determined by the sectoral GVA in the corresponding sector (see 'Food, Beverages and Tobacco' or 'Chemicals' for example). For some sectors the GVA of 'Distribution' exerts a negative impact on exports, which can be interpreted as the final demand of the origin region (i.e. the size of the internal trade sector of an economy). The same interpretation can be made for the 'Construction' and 'Hotels and Restaurants' sector and for the industries 'Food', 'Mineral Fuels' and 'Raw Materials', where the sectoral GVA can be interpreted as the intermediate demand of the origin region.

Table 10: Estimation Results for Extra EU-27 Exports

	A		B		C		D		E		F		G	
c	−0.564		−2.059	**	−11.415	***	−1.701	**	−1.439	***	0.996	**	−17.448	***
	(0.895)		(1.038)		(1.247)		(0.774)		(0.406)		(0.488)		(1.447)	
GDP	0.332		0.452	*	3.787	***	0.758	***	0.703	***	0.405	***	5.277	***
	(0.303)		(0.337)		(0.451)		(0.256)		(0.143)		(0.060)		(0.544)	
POP	−0.521	***	−0.669	***	0.536	***	−0.130	**	−0.187	***	−0.466	***	−0.116	
	(0.132)		(0.158)		(0.131)		(0.063)		(0.044)		(0.057)		(0.115)	
GVA share in:														
Agriculture			0.838	***										
			(0.146)											
Mining,energy supply			1.149	***										
			(0.201)											
Total Manufacturing					−2.443	***								
					(0.416)									
Food, beverages and tobacco	1.743	***												
	(0.162)													
Textiles and leather etc.			−0.091						0.121	***				
			(0.087)						(0.040)					
Coke, refined petroleum, . . .					0.653	***	1.025	***						
					(0.208)		(0.087)							
Electrical and optical equ.											0.681	***		
											(0.049)			
Transport equipment											0.228	***		
											(0.059)			
Other manufacturing									0.776	***			0.372	*
									(0.074)				(0.248)	
Construction			−0.786	***	−1.486	***								
			(0.284)		(0.326)									
Market Services														
Distribution	−0.409						−0.734	***	−0.521	***			−4.408	***
	(0.339)						(0.207)		(0.127)				(0.465)	
Hostels and restaurants	−0.273	***												
	(0.082)													
adj. R^2	0.8527		0.8164		0.7067		0.8885		0.9298		0.9526		0.7621	
Number of draws	5000		5000		5000		5000		5000		5000		5000	
Number of omissions	500		500		500		500		500		500		500	
Prior mean – all vars	0		0		0		0		0		0		0	
Prior std. – all vars	1000		1000		1000		1000		1000		1000		1000	
Observations	216		215		207		216		216		216		190	

Table 11: Estimation Results for Extra EU-27 Imports

	A	B	C	D	E	F	G
c	−1.635 ***	−4.321 ***	−1.960 *	−1.009	−3.120 ***	−0.033	−13.815 ***
	(0.444)	(0.556)	(1.178)	(0.795)	(0.379)	(0.536)	(1.703)
GDP	0.529 ***	0.870 ***	−0.006	−0.063	0.995 ***	0.571 ***	3.792 ***
	(0.162)	(0.196)	(0.399)	(0.334)	(0.093)	(0.182)	(0.644)
POP	−0.052	0.297 ***	0.162 **	0.187 ***	0.104 **	−0.200 ***	0.522 ***
	(0.099)	(0.098)	(0.095)	(0.059)	(0.053)	(0.055)	(0.174)
GVA share in:							
Agriculture	−0.267 ***	0.022		−0.051			
	(0.080)	(0.100)		(0.067)			
Mining, quarrying and energy supply			0.406 ***				
			(0.173)				
Total Manufacturing							
Food, beverages and tobacco	1.102 ***						
	(0.121)						
Textiles and leather etc.		0.214 ***			−0.075 **		
		(0.063)			(0.044)		
Coke, refined petroleum, . . .			−0.363 ***	0.380 ***			
			(0.094)	(0.059)			
Electrical and optical equipment						0.377 ***	
						(0.051)	
Transport equipment						−0.089 *	
						(0.064)	
Other manufacturing					−0.103		
					(0.083)		
Construction		−0.432 **	0.475 ***				
		(0.203)	(0.193)				
Market Services							
Distribution	−0.476 ***			0.210 *			−3.201 ***
	(0.169)			(0.139)			(0.635)
Hotels and restaurants	0.055						
	(0.059)						
Transport and communications			0.416 *			0.156	
			(0.263)			(0.209)	
adj. R^2	0.9171	0.869	0.8732	0.9318	0.9325	0.9119	0.5298
Number of draws	5000	5000	5000	5000	5000	5000	5000
Number of omissions	500	500	500	500	500	500	500
Observations	216	216	208	216	216	216	190

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The import equations are displayed in Table 11. We see that either population or GDP of a region is positively and significantly linked to imports. A region's own production of certain product groups is mostly negatively related to specific import groups[15]. However, sometimes the coefficients are opposite and/or insignificant[16].

FDI Inward Positions

As the bilateral data on FDI flows for the EU-27 contains a lot of gaps, we model the total FDI inflows to the countries of the EU-27. The model we suggest is close to the one of Noorbakhsh and Paloni (2001), modeling inward FDI flows only by the characteristics of the receiving country. Contrary to Noorbakhsh and Paloni (2001), our depending variable is the inward FDI stock of a given country and not the inflows. Besides size measures such as area and GDP, we include an approximation to efficiency wage, human capital, technological structure, past GDP growth, GDP per capita, total investments and the GVA of financial and business services, real estate and business services, manufacturing in electronics and manufacturing of transport equipment.

GDP (GDP) and area ($AREA$) are used to control for the size effects of the receiving country. Bigger countries are expected to receive more absolute FDI inward flows but less relative to GDP (the latter was found in Gao, 2004).

Hatzius (2000) found that labor-intensive FDI might favor countries with lower wages. However, FDI may also flow to high wage countries, because of the demand for highly skilled labor and a higher productivity (see UNCTAD, 1999). As a measure of wage, taking this facts into account, we therefore divided the compensation per employee (as an approximation to unit labor costs) by the average labor productivity (Gross Value Added per employee) of the manufacturing sector[17] ($EFFWAGE^{Manu}$). We further include technology and human capital measures in our specification to additionally control for skills (as motivated by Narula and Wakelin, 1998). The technological structure is measured using patent applications per million of population (PAT). Human capital is approximated using the share of tertiary educated active population ($TERTEDU$).

Higher past GDP growth rates are expected to attract FDI as found in previous studies for less developing countries (see Root and Ahmed, 1979; Scheider and Frey, 1985; Torrisi, 1985). GDP per capita ($GDPPC$) is included to test whether poorer or richer countries attract more FDI apart from factors relating to wages and skills. Gao (2004) found that the receiving countries GDP per capita is negatively related to the inward flow. We also test if total national investments ($INVEST$) serves as a complement or substitute for FDI.

Finally, we include sectoral information in the form of GVA shares in our model. First, the GVA of financial services (GVA^{Fin}) is included to control for the financial structure

[15] See, for example, GVA 'Coke and Petroleum' for Mineral Fuels, 'Textiles and Leather' for other Manufacturing, 'Transport equipment' for Machines and transport equipment or the national distribution network 'GVA Distribution' for other Commodities.

[16] See for example GVA in 'Food and Beverages' for the imports of food and beverages or 'Coke and refined Petroleum' for the imports of 'Chemicals'.

[17] We chose the manufacturing sector as the reasons for FDI changed over time from resource-based motives (until 1960), over the exploitation of cheap labor for manufacturing (until 1980) to technology-intensive manufacturing (after 1980) (see Noorbakhsh and Paloni, 2001).

of a country and to test whether foreign investors seek regions where complementing services for production and financing are heavily represented[18]. In line with the skill and high-technology manufacturing seeking hypothesis of FDI, we further include the GVA shares of the high-tech manufacturing and services sectors, which according to the sectoral classification of the NUTS-2 data would be real estate and business services (GVA^{Bus}), manufacturing in electronics (GVA^{Elec}) and manufacturing of transport equipment ($GVA^{TranEqu}$).

Data on FDI inward stocks has been taken from the Eurostat[19] database and complemented by the wiiw[20] database on Foreign Direct Investment in Central-, East- and South-East Europe and the FDI statistics of IMF[21]. The data are available between 1995 and 2006. Average yearly exchange rates have been used to convert the currencies to current euros. Prior to 2002, only data for the Belgium-Luxembourg Economic Union (BLEU) are available. To generate the data for Belgium and Luxembourg, this data has been divided by the sum of the countries after 2002 using the average shares of each country. The FDI stock data have been deflated using the GDP deflators used by Cambridge Econometrics. All other data is taken from Cambridge Econometrics and Eurostat.

We included all variables in the logs and estimated a Bayesian heteroscedastic panel (as for the intra EU-27 trade flows) between 1999 and 2006. As Luxembourg receives an enormous amount of FDI given the size of the country, we included a Luxembourg dummy ($DumLux$) to control for this effect:

$$\begin{aligned}
\log FDI_{it} &= \alpha_1 + \alpha_2 DumLux + \beta_1 \log GDP_{it} + \beta_2 \log AREA_i \\
&+ \beta_3 \log GDPPC_{it} + \beta_4 \log INVEST_{it} + \beta_5 \Delta GDP_{it-1} \\
&+ \beta_6 \log EFFWAGE_{it}^{Manu} + \beta_7 \log PAT_{it} \\
&+ \beta_8 \log TERTEDU_{it} + \beta_9 \log GVA_{it}^{Fin} + \beta_{10} \log GVA_{it}^{Bus} \\
&+ \beta_{11} \log GVA_{it}^{Elec} + \beta_{12} \log GVA_{it}^{TranEqu} + \epsilon_{it}.
\end{aligned} \tag{10}$$

The estimation results are given in Table 12. The full model is given in the first column. The coefficient on GDP per capita is negative, indicating that poorer countries attract more FDI inward flows. Another support for this hypothesis is the negative significant coefficient of efficiency wages. The dummy variable for Luxembourg has the expected sign and is highly significant. The size of a country measured by its area has a negative impact on FDI as in Gao (2004). Larger countries account for comparatively less FDI inward stocks, though the GDP coefficient is positive. The lag of GDP growth is positive as expected but not statistically significant.

The measures for technological capability and human capital have positive signs and are significant. National investments seem to be complement foreign investments. Higher GVA shares of financial services and manufacturing in transport equipment also contribute

[18] This indicator was motivated by the financial market variable in di Giovanni (2005).
[19] See http://epp.eurostat.ec.europa.eu/portal/page/portal/eurostat/home.
[20] See http://www.wiiw.ac.at/.
[21] See http://www.imf.org/external/data.htm.

Table 12: CL Estimation of FDI inward stocks

Variables	Model 1		Model 2		Model 3	
Intercept	7.083	***	7.701	***	7.811	***
	(0.877)		(0.698)		(0.680)	
Dummy Lux.	1.915	***	1.949	***	1.922	***
	(0.245)		(0.241)		(0.240)	
GDP	1.074	***	1.060	***	1.067	***
	(0.055)		(0.053)		(0.054)	
$AREA$	−0.324	***	−0.317	***	−0.313	***
	(0.043)		(0.041)		(0.042)	
$GDPPC$	−0.439	***	−0.389	***	−0.391	***
	(0.152)		(0.141)		(0.143)	
$INVEST$	1.026	***	1.055	***	1.075	***
	(0.209)		(0.204)		(0.205)	
ΔGDP_{it-1}	0.687					
	(1.526)					
$EFFWAGE^{Manu}$	−1.108	***	−1.131	***	−1.093	***
	(0.155)		(0.156)		(0.149)	
PAT	0.151	**	0.109	**	0.095	**
	(0.073)		(0.057)		(0.056)	
$TERTEDU$	0.868	***	0.858	***	0.870	***
	(0.106)		(0.103)		(0.103)	
GVA^{Fin}	0.245	**	0.230	**	0.256	**
	(0.121)		(0.117)		(0.112)	
GVA^{Bus} & Bus. Serv.	−0.243					
	(0.248)					
GVA^{Elec}	−0.084	*	−0.049			
	(0.065)		(0.057)			
$GVA^{TranEqu}$	0.546	***	0.537	***	0.500	***
	(0.072)		(0.072)		(0.058)	
adj. R^2 (No Obs)	0.9450	(216)	0.9452	(216)	0.9454	(216)
No of draws (omissions)	15000	(1500)	15000	(1500)	15000	(1500)
Prior mean (std), all vars	0	(1000)	0	(1000)	0	(1000)

to higher inward stocks. The coefficient on the share of real estate and business services is not significant, maybe due to the fact that only parts of the much smaller business services component of this sector aggregate is defined as high-tech. The coefficient on the share of GVA in manufacturing of electronics is marginally significant and negatively signed.

The second column of Table 12 shows the results without the insignificant variables of column 1. We see an improvement in the fit of the regression and the coefficient on the GVA share of manufacturing in electronics is now insignificant. We thus further exclude this regressor to derive our favored specification in column 3.