Regional Convergence in Europe and the Role of Urban Agglomerations

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Using data for EU-27 NUTS 2 regions and major cities, we evaluate empirically the role of urban growth spillovers as a determinant of income dynamics at the regional level. We go beyond the empirically well documented static relationship between national income and productivity in urban agglomerations. We use spatial regression models to quantify the effect of city growth spillovers on neighboring regions and assess the interrelationship between urban and regional growth. Our results indicate that urban growth spillovers play an important role in explaining differences in per capita income growth across European regions: Strong income growth in urban agglomerations provides an additional growth bonus for neighboring regions. This effect is very homogeneous across regions in Western and Eastern Europe. Our results indicate that the industrial composition of the agglomeration also matters for regional growth: Regions hosting urban agglomerations with a relatively high specialization in the primary sector as well as in fuels and chemicals tend to experience lower rates of economic growth. Our study is particularly relevant for policymakers since it indicates a trade-off between fostering income convergence at the regional level on the one hand and spurring national growth on the other hand.

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1 Introduction

Empirical research on the determinants of economic growth at the regional level in Europe tends to find that regions that host a capital city systematically have higher income growth rates after controlling for other factors that affect economic growth. This is particularly true for regions in Central, Eastern and Southeastern European (CESEE)[2] countries (see Crespo Cuaresma et al., 2009). The aim of this paper is to shed light on the interrelationships between regions and urban agglomerations in the growth process in Europe at the level of NUTS 2 regions and to evaluate empirically the role of urban growth as an engine of economic growth and income convergence in Europe. The answer to this question is particularly relevant for policymaking since the quantification of the effect of urban agglomerations on economic growth at the regional (and national) level is a key piece of information to assess the efficiency of regional policy measures. If agglomerations are the source of important growth spillovers economic policy may face a trade-off between growth at the national level and equality in the spatial distribution of activity between and within regions of a given country. Our analysis is linked to two strongly related branches of the academic literature. On the one hand, we investigate the nature of the determinants of economic growth and income convergence at the regional level in Europe in a modelling framework which explicitly takes into account spatial spillovers. On the other hand, we specifically

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[2] *In the empirical part of this study, the CESEE region comprises the following countries: Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia.*

contribute to the empirical literature on agglomeration economies in the European context. We aim to answer questions such as whether urban characteristics are important determinants of growth at the regional NUTS 2 level, at which European cohesion policy is implemented. We also study the role that the sectoral composition of urban poles plays as a factor affecting regional economic growth and income convergence. We pay particular attention to differences between Western and Eastern regions of the EU and evaluate the scope of the spillovers which emanate from urban agglomerations for entire regions.

Concerning the first branch of literature, the process of regional income convergence in Europe as well as the effect that regional policy has had on economic growth have been studied in detail, and a number of empirical facts have been robustly identified. Regarding conditional income convergence, Barro and Sala-i-Martin (1991) estimated in a seminal contribution the annual speed of income convergence for European regions close to 2%. The role of structural funds has received a lot of attention in the empirical literature, but the mixed econometric evidence for the effectiveness of such policies is plagued with sample selection problems. Recently, Becker et al. (2008) used regression discontinuity methods to deal with the problem of sample selection and found evidence for growth effects in regions receiving structural funds.[3] On the other hand, convergence clusters or clubs have been identified by Canova (2004) and Corrado et al. (2005). Basile (2008) finds positive (nonlinear) effects of schooling for EU-15 regions, whereas the results in LeSage and Fischer (2007) indicate that industry diversity impacts negatively on European growth rates. As for CESEE, a thorough study identifying growth triggers in CESEE regions has been carried out by the European Commission (European Commission, 2004). On the one hand, the results point to decreasing income inequality between regions of different countries. On the other hand income inequality is shown to be increasing *within* CESEE countries. That is, regional divergence and convergence co-exist in Europe, a finding that is confirmed by the results in Szörfi (2007), who shows that in an early stage of catching-up, regional inequalities tend to increase.

The role of agglomerations has so far been relatively underrepresented in regional growth studies for the EU. There are empirical results for European NUTS 3 regions which confirm the existence of *static agglomeration economies* (see, for example, Ciccone, 2002), implying that urban poles tend to have higher levels of productivity. However, concerning effects on the growth rate of income per capita *(dynamic agglomeration economies),* the existing research has delivered ambiguous empirical results hitherto. Empirically, the existence of dynamic agglomeration economies implies that urban centers have an effect on national economic growth (or on income growth at subnational levels, which nest the geographical level at which cities are located), a phenomenon that is usually referred to as the Jacobs hypothesis (Jacobs, 1969). An example of the controversy testing this empirical fact is the discussion between Mario Polèse and Peter Taylor in *Urban Studies* (see Polèse, 2005, 2006, and Taylor, 2006a and 2006b).

There are several theoretical models that underpin the existence of such dynamic agglomeration economies (see Glaeser and Gottlieb, 2009, for an excellent

[3] *See Boldrin and Canova (2001) for a critical assessment of regional economic policies in the framework of empirical models of regional determinants of growth and income convergence.*

review of the literature). The theoretical literature on dynamic agglomeration externalities touches upon the effect that urban poles have on the main variables put forward by endogenous growth theory: ideas and human capital. Cities are considered to be centers which are particularly productive in the creation and transmission of new ideas (see, for example, Duranton and Puga, 2000). Likewise, the implementation of new or significantly improved products, processes and business practices largely takes place in urban areas (De Groot et al., 2008). In parallel, the complementarity of urban agglomeration and human capital plays an important role in expanding growth externalities that originated in urban poles. Thus, in the framework of endogenous growth theory with agglomeration economies, aggregate developments at the national level can depend on the performance of large agglomerations that act as growth poles (Thomas and Robins, 2005).

Some stylized facts underscore the importance of urban hubs for national developments. Looking at GDP levels, the proportion of GDP in urban agglomerations is impressive for some countries: In 2008, around 24% of the respective national GDP in Austria and Bulgaria was earned in the respective capital city; Budapest's GDP amounts to nearly 30% of the total Hungarian GDP. This reflects two trends: First, people tend to cluster in agglomerations, which in turn explains the large capital city share in total economic activity. Second, high-value products tend to be produced in urban areas, whereas manufacturing is largely located in backward regions. The sectoral structure of urban agglomerations thus determines to a high degree the regional industrial composition. An empirical investigation of the urban sectoral structure might therefore yield important insights for regional growth.

The aim of this contribution is to assess whether urban agglomerations in Europe generate growth spillovers in neighboring regions, thus offering empirical evidence for the existence of dynamic agglomeration economies. Crespo Cuaresma et al. (2009) investigate the robustness of regional growth determinants for European regions, concentrating on variables measured at the NUTS 2 level. Their analysis exploits information on more than 50 potential growth drivers, five of which are reported as robustly related to growth. The empirical analysis in Crespo Cuaresma et al. (2009) reaches the conclusion that human capital and income convergence (particularly in CESEE) are robust driving forces of income growth in Europe and that regions with capital cities have a growth bonus as compared to the rest of the regions in a country. In this study, we aim to open the black box behind this last result by examining in more detail the role of urban agglomerations and the characteristics that make them engines of regional growth, i.e. the potential existence of urban agglomeration economies. The paper is structured as follows: Section 2 introduces the measures of urban industrial composition, and section 3 presents the data and the econometric specification we employ. Section 4 summarizes the empirical results and section 5 concludes.

2 Urban Agglomerations in Europe: the Stylized Facts

Urban economics[4] concludes that specialization, diversity and competition shape urban growth in employment and productivity and hence economic growth. De Groot et al. (2008) surveys the bulk of the empirical literature on urban agglomerations,

[4] *Rosenthal and Strange (2003) provide an excellent overview of the economics of urban agglomeration.*

concluding that diversity and competition are conducive to the development of patents, innovations and productivity, while the results are mixed for specialization. A potential explanation is that industrial clusters tend to specialize in the whole production process and cannot compete with foreign firms that specialize in a certain stage of the production process (Thomas and Robins, 2005). The theoretical arguments concerning specialization and diversity imply that the concentration of economic activity in a few industries will enhance growth whenever agglomeration externalities work *within the same industry*. In the spirit of Marshall, Arrow and Romer, firms can benefit from firm clusters of the same industry because of labor market pooling, input sharing and knowledge spillovers. Agglomeration externalities can also work in an *inter*sectoral dimension ("urbanization economies"), where the growth bonus of specialization vanishes and a diversified city base is assumed to further spur growth. According to Jacobs (Jacobs, 1969) knowledge spillovers are assumed to work best *across* industries, and, consequently, variety and diversity of proximate industries enhance the innovation process that leads to urban and, ultimately, regional growth.

For the empirical analysis of the role of specialization within urban agglomerations, we start by analyzing statistical measures of industrial composition. Duranton and Puga (2000) propose indicators of overall specialization (ZI_i), overall diversity (DI_i) and sector specialization (location quotient, LQ_{ij}), defined respectively as

$$ZI_i = \max_j (s_{ij}) \qquad (1),$$

$$DI_i = (\sum_{j=1}^{m} s_{ij}^2)^{-1} \qquad (2),$$

$$LQ_{ij} = \frac{s_{ij}}{s_j} \qquad (3),$$

with the shares of economic activity of city *i* in sector *j* denoted by

$$s_{ij} = GVA_{ij} / \sum_{j=1}^{m} GVA_{ij} \, ,$$

where GVA is gross value added and the respective sector shares given by

$$s_j = \sum\nolimits_{i=1}^{n} GVA_{ij} / \sum_{i=1}^{n} \sum_{j=1}^{m} GVA_{ij}$$

for $i=1,....,n$ cities and $j=1,....,m$ sectors. The first two indicators are absolute measures of specialization/diversity, while relative measures indicate to what extent the distribution of economic activity among cities deviates from a reference structure (city system). However, as Aiginger and Davies (2004) argue, for drawing policy implications, absolute measures are of particular interest, since they assess the uneven distribution of industrial activity, and this matters most for industry shocks and, consequently, fluctuations of economic performance. Note that the *ZI* indicator has values in the [0,1] interval, whereas *DI* can take values in the range of 1 to *m*. Larger values of ZI (DI) imply more specialization (diversity). Besides the overall degree of specialization, it is also of interest in which sectors agglomerations specialize. This can be assessed by calculating location quotients. A value of $LQ_{ij} > 1$

indicates that city i's share in sector j is above that of the city system and thus indicates sector-specific specialization.

Table 1 below summarizes the industrial composition pattern in European cities at the beginning (1995) and the end (2007) of our sample period. The data for our empirical analysis stem from a harmonized city dataset which was set up by Cambridge Econometrics on behalf of the European Economic Research and Advisory Consortium (ERECO) in recent years. The database provides a comparable set of economic indicators for 62 large European cities (see the appendix for the list of cities included in the analysis).[5] With respect to the time dimension and structural detail (14 sectors), this data base goes well beyond all other sources available, and its completeness and topicality is guaranteed by continuous work on the database by national institutes. However, the scarcity of data at the level of "functional" urban regions and the problems of definition associated with this concept apply also here. To proxy functional urban regions, the database therefore collects information on those administrative regional entities which correlate most strongly with a functional delimitation of the city region in question. Data used therefore spread from the NUTS 1 (e.g. London) to the NUTS 3 level (most cities).[6]

Table 1

Descriptive Statistics of Specialization and Diversity Indicators in Europe

	Summary statistics 1995			Summary statistics 2007		
	Mean	*Min.*	*Max.*	*Mean*	*Min.*	*Max.*
ZI*	0.266	0.146 (Lisboa)	0.393 (Paris)	0.292	0.138 (Lisboa)	0.440 (Paris)
DI*	6.935	4.801 (Hamburg)	10.590 (Lisboa)	6.340	4.174 (London)	10.510 (Lisboa)
Agriculture, forestry and fishing	1.940	0.001 (Bucureşti)	14.500 (Lisboa)	1.742	0.046 (London)	11.920 (Lisboa)
Mining and energy supply	1.230	0.000 (Riga)	5.277 (Edinburgh)	1.255	0.000 (Riga)	4.205 (Sofiya)
Food, beverages and tobacco	1.258	0.000 (Riga)	4.919 (Bucureşti)	1.321	0.000 (Riga)	4.747 (Dublin)
Textiles and clothing	1.431	0.072 (Stockholm)	16.530 (Riga)	1.549	0.087 (Edinburgh)	12.070 (Riga)
Fuels, chemicals, rubber and plastic products	0.916	0.000 (Riga)	1.978 (Torino)	1.029	0.000 (Riga)	2.578 (Rouen Le Havre)
Electronics	0.964	0.000 (Riga)	2.888 (Budapest)	1.057	0.000 (Riga)	3.183 (Helsinki)
Transport equipment	0.893	0.000 (Riga)	3.369 (Birmingham)	1.009	0.000 (Riga)	3.291 (Stuttgart)
Other manufacturing	0.970	0.000 (Riga)	1.855 (Stuttgart)	1.066	0.000 (Riga)	2.715 (Plzeň)
Construction	1.145	0.562 (Bruxelles)	2.528 (Leipzig)	1.160	0.440 (Hamburg)	3.207 (Thessaloniki)
Wholesale and retail	1.100	0.731 (Brno)	1.923 (Warszawa)	1.125	0.535 (Thessaloniki)	2.036 (Poznań)
Hotels and restaurants	0.939	0.350 (Sofiya)	2.371 (Madrid)	0.878	0.317 (Warszawa)	2.630 (Athina)
Transport and communications	1.084	0.691 (Stuttgart)	2.328 (Riga)	1.067	0.531 (Stuttgart)	2.057 (Sofiya)
Financial services	0.910	0.275 (Brno)	1.927 (Sofiya)	0.832	0.171 (Brno)	1.984 (London)
Other market services	0.855	0.276 (Bucureşti)	1.357 (Paris)	0.866	0.337 (Lisboa)	1.363 (Paris)

Source: Authors' calculations.

* *ZI denotes the specialization index, DI a measure for diversity.*

[5] *We had to impute GVA (gross value added) figures for Warszawa, Krakow, Poznań and Wrocław instead of GDP figures. Due to a lack of data, the unemployment rate for Ljubljana for 1995 constitutes an average over the period 1990–93. Furthermore, the unemployment rate for Kobenhavn is set to the Danish national unemployment rate in 1995.*

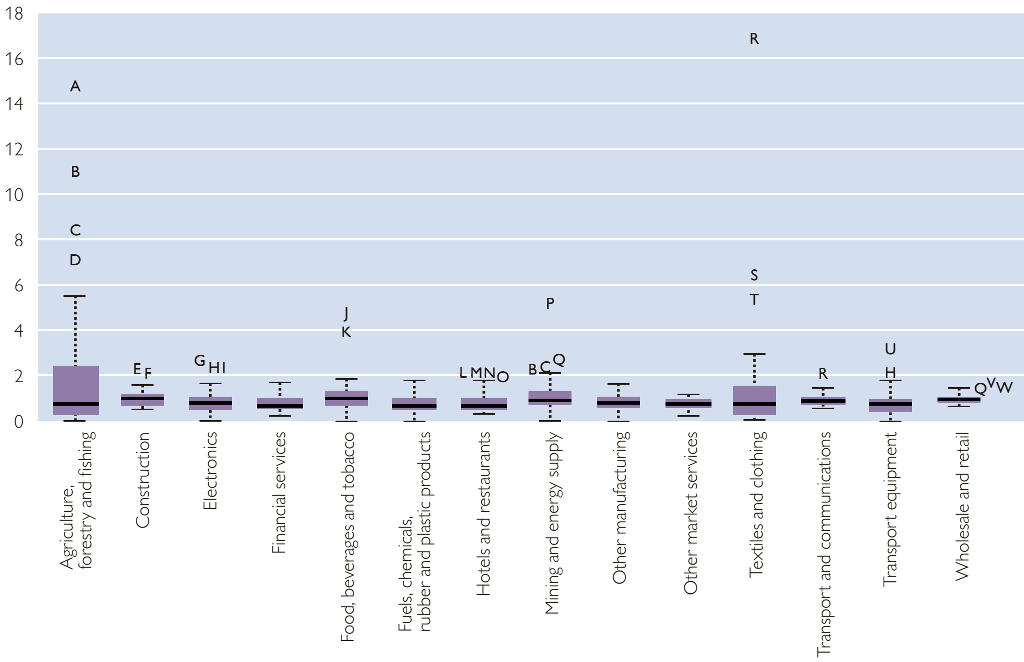
[6] *Note that for the NUTS 2 regions "ie02" and "nl33," the urban data set offers two agglomerations per region (Dublin and Cork for "ie02" and Amsterdam and Den Haag for "nl33"). In both cases we opted for the larger agglomeration, thus excluding Cork and Den Haag from the following descriptive and causal analysis. In the case of London, the urban variables have been assigned to the NUTS 2 region "ukl2" (Outer London), which is assumed to be the center of economic activity in London.*

The table reveals some stylized facts: In 1995, the degree of overall specialization was smallest in Lisbon, while Paris appeared to be the most specialized city. Diversity was most pronounced in Lisbon, while Hamburg showed the lowest level of the diversity indicator (DI). Regarding sector specific specialization, Riga, Brno and Bucharest appear frequently as outliers on both ends of the specialization spectrum. While Riga was the least specialized city in mining, food, fuels, electronics, transport equipment and other manufacturing, it was most specialized in textiles and clothing as well as in transport and communications. The figures for 2007 reveal a rather stable pattern for some cities: Lisbon and Paris continued to be the least and most specialized cities in Europe respectively. Lisbon was also the city with the most diversified industrial base in 2007.

Charts 1 and 2 present boxplots of the location quotient for 1995 and 2007. Some interesting features of the geographical structure of specialization patterns are visible in these graphs. Cities in peripherial countries tend to be specialized in primary sector activities, textiles and clothing as well as food, beverages and tobacco. This is not an exclusive feature of urban agglomerations in CESEE countries but is also visible in cities in Portugal and Ireland. Although some changes took place in the period from 1995 to 2007 in terms of specialization, the persistence of the location quotient differentials across European cities is high, and such specialization clusters tend to persist for the full period under analysis.

Chart 1

Boxplot of Location Quotient (1995)

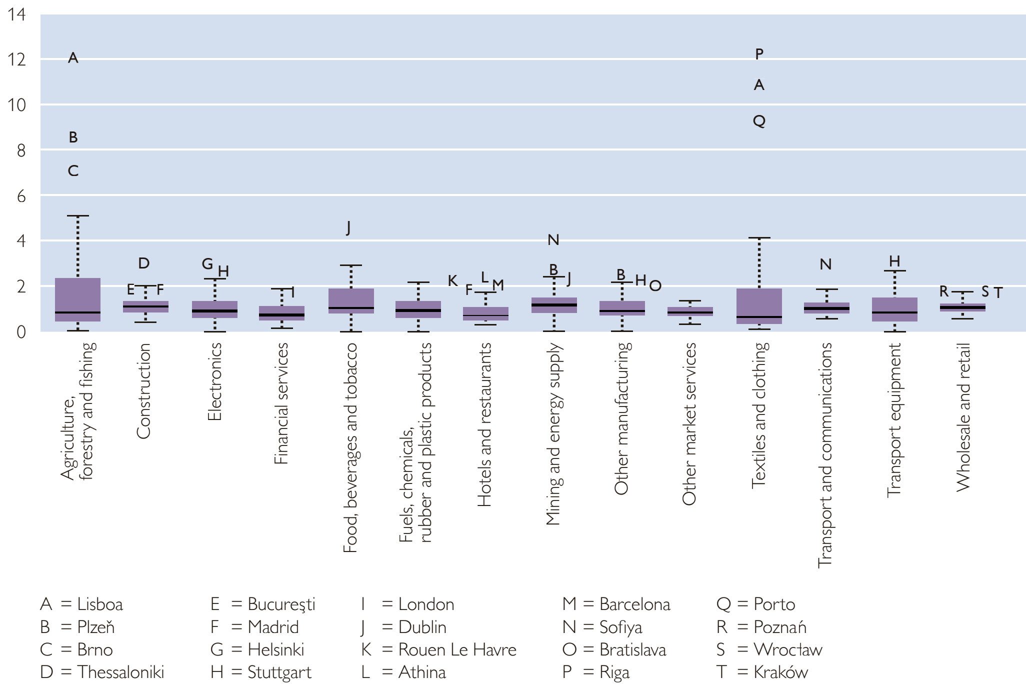


A = Lisboa
B = Plzeň
C = Brno
D = Vilnius
E = Leipzig
F = Dresden
G = Budapest
H = Stuttgart
I = Helsinki
J = București
K = Dublin
L = Madrid
M = Valencia
N = Barcelona
O = Athina
P = Edinburgh
Q = Wrocław
R = Riga
S = Lisboa
T = Porto
U = Birmingham
V = Warszawa
W = Kraków

Source: Authors' calculations.

Chart 2

Boxplot of Location Quotient (2007)



Source: Authors' calculations.

3 Econometric Specification and Data

The effects of urban variables on the regional growth process are estimated using a spatial error model (SEM) of the following form

$$y = \alpha \iota_N + X_k \beta_k + \varepsilon, \tag{4}$$

$$\varepsilon = \lambda W \varepsilon + u$$

where y is an N-dimensional column vector of growth rates of income per capita for N regions, α is the intercept term, ι_N is an N-dimensional column vector of ones, $X_k=(x_1 \ldots x_k)$ is a matrix whose columns are stacked data for k explanatory variables (both regional and urban) and $\beta_k=(\beta_1 \ldots \beta_k)'$ is the k-dimensional parameter vector corresponding to the variables in X_k. Our observation unit is a NUTS 2 region, and our dataset combines urban and regional characteristics. It should be noted that urban variables are only available for some, but not all of the regions, since sufficiently large urban agglomerations are not present in all regional units. For the remaining regions, the urban variables are filled with zero values (which is essentially the same as premultiplying the corresponding variable with a city dummy variable). This may cause multicollinearity problems among the urban variables, which need to be taken into account when it comes to interpreting the regression results. The above model constitutes a spatial regression model that parametrizes spatial correlation via the error term. The geographical structure in the data is specified via a weighting matrix W, and λ is a scalar that picks up the degree of spatial autocorrelation. Positive values of λ imply positive spatial correlation, leading to growth clusters in the data. The remaining error term u is then assumed to be an N-dimensional shock process that is free of spatial correlation with zero mean and a diagonal variance-covariance matrix $\Omega=\sigma^2 I_N$.

The use of a spatial regression model proves useful since the presence of spatial dependence is well documented in the applied regional convergence literature (see e.g. Niebuhr, 2001, Fischer and Stirböck, 2006, or Crespo Cuaresma and Feldkircher, 2010). Unmodelled spatial autocorrelation may lead to flawed inference (Anselin, 1988), and such a phenomenon may arise due to the economic interaction of countries, regions and cities such as the movement of capital, labor (commuting and migration) and goods (trade flows). Furthermore, locational characteristics, endowments and resources not being restricted to administrative borders can lead to similarity across areas which are close to each other. The resulting spatial correlation is typically parametrized by a weight matrix W, where we use two different variants thereof: an inverse distance matrix W_inv and distance band matrices W_db. The inverse distance matrix assigns a non-zero weight to each neighborhood observation in the sample, with the weights being a decreasing function of distance (smaller weights are given to regions that are far away from each other). Distance band matrices identify neighbors as those regions that are situated within a certain radius.[7] These regions are then assigned equal weights (we thus solely distinguish between neighbors and non-neighbors, with the latter receiving zero weights). We prefer an econometric specification using the SEM (spatial error model) instead of a spatial autoregressive structure (SAR model). On the one hand, statistical tests have indicated that the residuals are free of remaining spatial autocorrelation under the SEM model, so there is no empirically backed reason why one should prefer the SAR model over the SEM. On the other hand, an SAR specification would potentially mask (at least part of) the effect of urban spillovers in the spatial lag of the regional growth variable, thus making the model difficult to interpret.

Our regional dataset covers cross-sectional information on all 255 EU-27 regions,[8] and each income growth observation refers to the average annual growth rate in the period from 1995 to 2007, deflated using national consumer price data. Note that for the majority of the sample period, CESEE regions are yet not EU members. This implies that potential structural breaks related to formal EU membership play a negligible role in this dataset.[9] The regional dataset is complemented by an urban dataset covering information on 62 major European cities, which are listed in table 2. Besides data on employment, our urban dataset covers sectoral GVA for 14 industry sectors.[10] These data serve as proxy for size, wealth and the industrial composition of the respective agglomeration. All explanatory

[7] *The matrices are based on great circle distances between regions' centroids (i.e. economic centers, typically the regions' capital cities) measured in kilometers.*

[8] *See the data appendix in Crespo Cuaresma et al. (2009) for a detailed list of all the 255 regions.*

[9] *See Crespo Cuaresma et al. (2008) for an assessment of EU membership as a growth determinant at the national level.*

[10] *These sectors are agriculture, forestry and fishing, mining and energy supply, food, beverages and tobacco, textiles and clothing, fuels, chemicals, rubber and plastic products, electronics, transport equipment, other manufacturing, construction, wholesale and retail, hotels and restaurants, transport and communications, financial services, and other market services.*

variables (regional and urban) are measured at the beginning of the sample period so as to minimize potential endogeneity problems. To our knowledge, the combined dataset is the most comprehensive used hitherto in terms of the range of variables covered in the regional and urban dimension.

4 Empirical Results

We start by including in our model the growth determinants identified by Crespo Cuaresma et al. (2009) as being robust growth drivers, namely initial GDP per capita (income convergence) and the share of highly educated workers in the labor force (which is a proxy for human capital).[11] Crespo Cuaresma et al. (2009) furthermore show that regions situated in CESEE economies as well as those that host a country's capital city have significantly higher income growth rates. This is modelled by including binary variables which identify CESEE regions and capital cities. On top of this, even higher growth rates than those implied by these effects are found in CESEE capital city regions, which suggests that the interaction term of the two aforementioned variables should also be included as a covariate in the econometric model. Capital cities are a subset of our urban dataset, and the effect proposed in our model implies that there is a direct effect on economic growth through the hosting of the capital city and a potential indirect spillover from urban agglomerations in nearby regions. These five variables constitute our baseline regression model and are consequently enriched by certain categories of urban variables. The results of the estimations carried out are summarized in table 2.

We first test whether urban growth spills over to nearby regions after controlling for the regional growth determinants mentioned above. This implies that we test whether European agglomerations act as growth poles. We do this by constructing a spatial lag of the urban growth variable, that is each region's growth process is assumed to be influenced by a (distance-) weighted average of that of neighboring agglomerations. By concentrating on spatially lagged urban growth, we circumvent the potential endogeneity issues – both from an economic as well as an econometric perspective – that would arise in estimating the direct effect of the city on the region where it is located. Furthermore, since our model already imposes spatial autocorrelation through the structure of the error term, we are actually assessing empirically effects that are superimposed to the usual growth spillovers present in regional data. As a neighborhood structure we use an inverse distance matrix, which we multiply with the growth rate of income in the urban agglomeration. This implies that the closer agglomerations are located to the region in question, the more influential they are assumed to be in shaping the regional growth process. The first column in table 2 reveals that European cities are indeed growth engines for entire regions, with the respective coefficient being positive and significant. This implies that regions which are close to urban agglomerations whose income per capita is growing receive an extra growth bonus above the one which is being modelled by imposing spatial autocorrelation in the economic growth process at the subnational level.

In the next step, we look at urban characteristics and the role they play in shaping regional growth processes. We start by testing the two prominent urban

[11] *The source for income per capita is Eurostat, while the human capital data are sourced from Eurostat's Labour Force Survey.*

theories mentioned above: the Jacobs hypothesis stating that diversity (DI) in economic activity is key to superior economic performance and the Marshall-Arrow-Romer hypothesis advocating urban specialization (ZI). It should be stated that both theories are not mutually exclusive and can co-exist, therefore nothing prevents us from using both variables in the regression model. To our knowledge, the two theories have so far not been tested in this context, that is its consequences for regional growth are uninvestigated. We also have data for the industrial composition of regions themselves, although at a far less disaggregated level, but the results in Crespo Cuaresma et al. (2009) demonstrate that there is no robust empirical relationship between sectoral composition and regional growth for the NUTS 2 dataset used here. Column 2 of table 2 presents the results of the model which includes both variables (as explained above, these variables can be interpreted as the interaction between a dummy for urban agglomeration and the respective characteristic of the agglomeration) and reveals that none of the two urban sectoral composition measures is a significant factor when it comes to explaining differences in regional growth robustly.

It may be the case that the specialization indicators are simply too broad and that it is industrial specialization at the urban level that matters most to discern growth patterns at the regional level. We thus add the 14 location quotient variables which capture the degree of industry-specific specialization (columns 3 and 4 of table 2). Three variables turn out to be of empirical relevance: specialization in agriculture (whose partial correlation with economic growth at the regional level is negative), in food, beverages and tobacco (with a positive association) and in fuels, chemical and plastic products (which is negatively related to regional growth).

Finally, we add other urban factors unrelated to the industrial composition to control for size and employment. However, none of these controls survive standard significance tests. Our final specification is thus given in column 4 of table 2, incorporating 5 regional variables and 4 urban factors. Several aspects are worth mentioning: First, the identified variables are all robust determinants of regional growth. Regardless of which other factors are included, the sign and magnitude of the nine variables never change markedly. This is particularly relevant for the variable capturing the spillovers from urban to regional growth. Second, our explanatory variables cannot account for the full spatial autocorrelation present in the European growth process at the regional level. This is reflected in the existence of positive spatial autocorrelation in the residual, which in our case is captured through the spatial error structure; however, it would affect our estimates if the geographical structure of the data were not taken into account when parametrizing the model. This is evident from the last line in table 2, which reports the results on the spatial parameter λ and shows that a nonspatial regression model – provided in the last column of the table – would lead to flawed inference.[12] Third, our results are robust with respect to the specification of the spatial weight matrix (and thus the specification of the underlying pattern of economic interaction among regions/agglomerations).[13]

[12] *A Moran's I test on the regression residuals of a standard (nonspatial) linear regression offers significant evidence that spatial correlation is present in the data.*

[13] *The results are available from the authors upon request.*

Table 2

The Impact of Urban Growth on Regional Economic Growth

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6 (OLS)
Constant	0.105 ***	0.106 ***	0.092 ***	0.092 ***	0.093 ***	0.081 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Initial income per capita	–0.011 ***	–0.011 ***	–0.009 ***	–0.009 ***	–0.009 ***	–0.008 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share of highly educated workers	0.034 ***	0.035 ***	0.033 ***	0.029 ***	0.032 ***	0.031 ***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
CESEE dummy	0.005	0.004	0.005	0.005	0.004	0.006 **
	(0.098)	(0.123)	(0.080)	(0.055)	(0.138)	(0.018)
Capital city	0.007 ***	0.007 ***	0.004	0.006 ***	0.006 **	0.006 **
	(0.001)	(0.002)	(0.088)	(0.007)	(0.016)	(0.011)
CESEE dummy x capital city	0.024 ***	0.023 ***	0.018 ***	0.021 ***	0.020 ***	0.021 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spatially lagged city growth	1.709 ***	1.766 ***	1.818 ***	1.859 ***	1.989 ***	1.900 ***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
DI[1]	–	0.000	–	–	–	–
	–	(0.369)	–	–	–	–
ZI[1]	–	–0.007	–	–	–	–
	–	(0.520)	–	–	–	–
Agriculture, forestry and fishing	–	–	–0.001 **	–0.001 **	–0.001	–0.001 **
	–	–	(0.023)	(0.025)	(0.053)	–0.039
Mining and energy supply	–	–	–0.001	–	–	–
	–	–	(0.653)	–	–	–
Food, beverages and tobacco	–	–	0.007 ***	0.007 ***	0.007 ***	0.007 ***
	–	–	(0.000)	(0.000)	(0.000)	(0.000)
Textiles and clothing	–	–	0.000	–	–	–
	–	–	(0.521)	–	–	–
Fuels, chemicals, rubber and plastic products	–	–	–0.008 **	–0.007 ***	–0.006 **	–0.007 ***
	–	–	(0.012)	(0.000)	(0.002)	(0.000)
Electronics	–	–	–0.001	–	–	–
	–	–	(0.598)	–	–	–
Transport equipment	–	–	–0.002	–	–	–
	–	–	(0.383)	–	–	–
Other manufacturing	–	–	0.007	–	–	–
	–	–	(0.202)	–	–	–
Construction	–	–	–0.002	–	–	–
	–	–	(0.558)	–	–	–
Wholesale and retail	–	–	–0.003	–	–	–
	–	–	(0.490)	–	–	–
Hotels and restaurants	–	–	0.000	–	–	–
	–	–	(0.918)	–	–	–
Transport and communications	–	–	0.005	–	–	–
	–	–	(0.222)	–	–	–
Financial services	–	–	0.000	–	–	–
	–	–	(0.903)	–	–	–
Other market services	–	–	–0.003	–	–	–
	–	–	(0.535)	–	–	–
Population	–	–	–	–	0.001	–
	–	–	–	–	(0.309)	–
Share of economically active population	–	–	–	–	0.007	–
	–	–	–	–	(0.067)	–
Unemployment rate	–	–	–	–	0.000	–
	–	–	–	–	(0.184)	–
City income per capita	–	–	–	–	–0.001	–
	–	–	–	–	(0.198)	–
Lambda	0.516	0.510	0.704	0.687	0.668	–
Log-likelihood	860.558	860.994	880.57	877.078	880.183	875.507

Source: Authors' calculations.

*Note: P-values in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.*

[1] *ZI denotes the specialization index, DI a measure for diversity.*

So far we have identified urban growth spillovers to regions that are close to each other. A policymaker could be interested in the extent of the spillovers. Are they rather local phenomena, or does growth really spread far out? To answer this question we construct several distance band weight matrices with the radius ranging from 300 to 700 kilometers. A distance band matrix with a radius of 300 kilometers assumes that cities can influence regions that are up to 300 kilometres apart. Table 3 contains the estimation results. It can be seen that growth spillovers are significant for regions that are not more than 500 kilometers apart. The effect is furthermore sizable for such regions. An increase by 2 percentage points in the growth rate of a city (roughly the long-run mean growth rate in our sample) increases economic growth in a region which is up tp 500 kilometers away by 0.02 percentage points. This is roughly comparable to the effect found when increasing the share of tertiary educated workers by 0.67 percentage points in the respective region. Although the effect is modest for such growth rates, it is widespread and can be sizable for regions close to fast-growing urban poles.

Table 3

The Spatial Extent of Urban Growth Spillovers

	W_DB (300)	W_DB (400)	W_DB (500)	W_DB (600)	W_DB (700)
Constant	0.123 ***	0.130 ***	0.139 ***	0.131 ***	0.127 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Initial income per capita	–0.011 ***	–0.012 ***	–0.013 ***	–0.012 ***	–0.012 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share of highly educated workers	0.031 ***	0.030 ***	0.029 ***	0.030 ***	0.030 ***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
CESEE dummy	0.007 **	0.005	0.004	0.005	0.006 **
	(0.016)	(0.070)	(0.218)	(0.074)	(0.041)
Capital city	0.006 ***	0.007 ***	0.007 ***	0.007 ***	0.007 ***
	(0.004)	(0.002)	(0.001)	(0.002)	(0.004)
CESEE dummy x capital city	0.019 ***	0.019 ***	0.020 ***	0.019 ***	0.019 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Agriculture, forestry and fishing	–0.001 **	–0.001 **	–0.001 **	–0.001 **	–0.001 **
	(0.029)	(0.028)	(0.029)	(0.034)	(0.031)
Food, beverages and tobacco	0.007 ***	0.007 ***	0.007 ***	0.007 ***	0.007 ***
	(0.000)	(0.000)	–0.0004	(0.000)	(0.000)
Fuels, chemicals, rubber and plastic products	–0.007 ***	–0.007 ***	–0.007 ***	–0.007 ***	–0.007 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Spatially lagged city growth (300km)	0.002	–	–	–	–
	(0.781)	–	–	–	–
Spatially lagged city growth (400km)	–	0.008	–	–	–
	–	(0.177)	–	–	–
Spatially lagged city growth (500km)	–	–	0.010 **	–	–
	–	–	(0.037)	–	–
Spatially lagged city growth (600km)	–	–	–	0.005	–
	–	–	–	(0.199)	–
Spatially lagged city growth (700km)	–	–	–	–	0.002
	–	–	–	–	(0.502)
Average number of neighbors	18	28	41	55	69
Lambda	0.800	0.787	0.794	0.800	0.804
Log-likelihood	871.189	872.053	873.296	871.973	871.375

Source: Authors' calculations.

*Note: P-values in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.*

Table 4

Estimation Results for CESEE Specification

	Model 1	Model 2	Model 3	Model 4
Constant	0.091 ***	0.094 ***	0.092 ***	0.089 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Initial income per capita	–0.009 ***	–0.010 ***	–0.009 ***	–0.009 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Share of highly educated workers	0.029 ***	0.029 ***	0.029 ***	0.030 ***
	(0.001)	(0.001)	(0.002)	(0.001)
CESEE dummy	–0.006	0.004	0.005	0.004
	(0.550)	(0.117)	(0.072)	(0.211)
Capital city	0.006 ***	0.013	0.006 **	0.007 ***
	(0.009)	(0.121)	(0.016)	(0.004)
CESEE dummy x capital city	0.022 ***	0.022 ***	0.021 ***	0.016 ***
	(0.000)	(0.000)	(0.000)	(0.001)
Spatially lagged city growth	1.542 ***	2.031 ***	1.904 ***	2.149 ***
	(0.000)	(0.000)	(0.000)	(0.001)
Agriculture, forestry and fishing	–0.001 **	–0.001 **	–0.001 **	–0.001 ***
	(0.024)	(0.026)	(0.028)	(0.007)
Food, beverages and tobacco	0.008 ***	0.007 ***	0.007 ***	0.008 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Fuels, chemicals, rubber and plastic products	–0.007 ***	–0.006 ***	–0.007 ***	–0.006 **
	(0.000)	(0.000)	(0.008)	(0.026)
Spatially lagged city growth x CESEE dummy	1.341	–	–	–
	(0.243)	–	–	–
Spatially lagged city growth x capital city	–	–1.020	–	–
	–	(0.392)	–	–
City population	–	–	0.000	0.001
	–	–	(0.825)	(0.216)
Spatially lagged city growth x city population	–	–	–0.031	–0.276
	–	–	(0.818)	(0.096)
Spatially lagged city growth x city population x CESEE dummy	–	–	–	0.544
	–	–	–	(0.072)
City population x CESEE dummy	–	–	–	–0.003
	–	–	–	(0.218)
Lambda	0.637	0.713	0.693	0.634
Log-likelihood	877.742	877.439	877.104	880.303

Source: Authors' calculations.

*Note: P-values in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.*

The rather large extent of urban spillovers calls for further investigation. Is it large cities that are responsible for the far-reaching spillovers? Are only capital cities growth promoting? To which extent is there a different pattern for CESEE cities? To shed more light on these issues, we re-estimated the model including several interaction terms. The first column in table 4 shows the results separating the effects from CESEE cities. Surprisingly, there are no additional effects from agglomerations located in the CESEE region present in the data. The same holds true for capital cities, which are often assumed to be the center of economic activity in a country. Lastly, we test whether large cities and/or large cities in CESEE are causing the far-reaching spillovers. Again, there is no empirical evidence that supports parameter heterogeneity of the spillover effect across regions as defined by these factors. The urban agglomeration spillovers found are therefore not statistically different in Western and Eastern European regions. The link between urban and regional growth within regions, however, is significantly different in CESEE countries, where regions hosting capital cities have an overproportional growth bonus compared to their Western European counterparts.

5 Conclusions

The empirical analysis carried out in this study assesses the role of urban agglomerations as economic growth engines in Europe by analyzing the effect of economic growth at the city level on neighboring NUTS 2 regions. Our results indicate that urban growth spillovers play an important role in explaining differences in per capita income growth across European regions. Furthermore, we find that the sectoral structure of cities matters for explaining the link between urban and regional growth patterns. In particular, regions with urban agglomerations with a relatively high degree of specialization in the primary sector as well as in fuels and chemicals tend to experience lower rates of economic growth than other such regions where agglomerations display a different sectoral composition.

We move further from analyzing the direct effect of urban growth on income growth at the regional level to assess the role of spatial spillovers originated at the city level across regions. To this end, we concentrate on the spreading of growth impulses from an urban agglomeration in a given region to neighboring regions. Our results indicate that income growth in urban agglomerations affects neighboring regions and that this effect is homogeneous in the EU. This is not the case for the agglomeration effects found within regions hosting the capital city, which tend to be stronger in CESEE economies. It should be noted that since our model explicitly controls for inter-regional spatial dependence in the growth process in Europe, the effect from neighboring urban agglomerations constitutes an extra growth bonus above the standard growth spillovers which are usually modelled in studies related to regional growth.

The existence of such dynamic agglomeration economies bears several implications for regional policymakers: First, regional policy faces a trade-off between maximizing economic growth at the regional level and balancing income differentials within and between countries in Europe. This trade-off, however, is counterbalanced to a certain degree by positive growth spillovers from urban agglomerations to neighboring regions as identified by our empirical analysis. In order to optimize the distribution of economic wealth, regional policies should target an efficient allocation of economic activity (Ottaviano, 2003). Our empirical results identify urban agglomerations as growth engines and thus recommend that the geographical allocation of economic activity should be concentrated in major European cities in order to boost overall growth in Europe. Fostering growth in major European agglomerations would thus comply with the regional policy of the EU, which explicitly aims at improving the economic wellbeing of regions in the EU. Second, the flip side of this coin is that such a policy bears the risk of an increase in wealth divergence within Europe. The lion's share of the budget for regional policy is devoted to the so-called "convergence objective" covering Europe's poorest regions in terms of per capita GDP. This part of regional policy is geared to removing economic, social and territorial disparities across regions within the EU by enhancing economic growth and improving the regional competitiveness of lagging (peripheral) regions. Our results, however, show that positive growth spillovers of urban hubs can enhance growth in entire regions that are nearby. The effect of these growth spillovers loses significance with distance but is still powerful in the European context, where most regions are located close enough to urban agglomerations. The risk of increasing wealth divergence when allocating economic activity to urban agglomerations may thus – to a certain degree – be mitigated by positive urban growth spillovers.

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Appendix

Major European Cities included in the Dataset

#	City	#	City	#	City
1	Wien	22	Helsinki	43	Rotterdam
2	Bruxelles	23	Paris	44	Warszawa
3	Sofiya	24	Rouen Le Havre	45	Kraków
4	Praha	25	Lille	46	Poznań
5	Plzeň	26	Nantes	47	Wrocław
6	Brno	27	Toulouse	48	Porto
7	Ostrava	28	Lyon	49	Lisboa
8	Stuttgart	29	Montpellier	50	Bucureşti
9	München	30	Aix-Marseille	51	Stockholm
10	Berlin	31	Thessaloniki	52	Ljubljana
11	Hamburg	32	Athina	53	Bratislava
12	Frankfurt	33	Budapest	54	Manchester
13	Düsseldorf	34	Dublin	55	Leeds
14	Köln	35	Torino	56	Birmingham
15	Dresden	36	Milano	57	London
16	Leipzig	37	Bologna	58	Bristol
17	Kobenhavn	38	Roma	59	Cardiff
18	Tallinn	39	Vilnius	60	Edinburgh
19	Madrid	40	Riga	61	Glasgow
20	Barcelona	41	Utrecht	62	Belfast
21	Valencia	42	Amsterdam		