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Agglomeration and Growth: Evidence from the Regions of Central and Eastern Europe

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Agglomeration and Growth: Evidence from the Regions of Central and Eastern Europe

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Abstract

This paper examines the empirical relationship between agglomeration and economic growth for a panel of 48 Central and Eastern European regions from 1995 to 2006. By agglomeration, we mean the within-regional concentration of aggregate economic activity, which we measure using the “topographic” Theil index developed by Brülhart and Traeger (2005). The transitional growth specification of Mankiw, Romer and Weil (1992) is augmented with this index and estimated using panel data methods that account for endogeneity and spatial dependence. Our empirical analysis provides evidence of a positive effect of agglomeration as measured by the topographic Theil index on long-run income levels. A one standard-deviation increase in agglomeration is estimated to raise steady-state income per capita by 15%. While this effect is sizeable, it also implies a trade-off between regional development and within-regional equality for Central and Eastern Europe.

Keywords: Agglomeration, regional growth, Central and Eastern Europe, spatial econometrics, panel data econometrics

JEL Classification: C23, R11, R12, P25

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1 Introduction:

The relationship between agglomeration, i.e. the spatial concentration of economic activity within countries or regions, and economic growth has been of long-standing scholarly interest in economics. Economic historians have observed a positive correlation between the two during the industrial revolution in Europe in the 19th century, when a marked rise in economic growth was accompanied by increasing concentration of economic activity in urban centres and industrial clusters.¹ Similar developments in China since the late 1970s are a more modern example. In urban and development economics, agglomeration also plays an important role. For example, Williamson (1965) suggests that in countries that are at an early stage of economic development, growth is relatively fastest in a few more prosperous and better-endowed “growth pole” regions such as urban and industrial agglomerations, so that rising income levels during the catch-up phase are associated with rising regional disparities.²

Recently, a number of theoretical contributions have provided a unified framework for analysing the relationship between agglomeration and growth, by integrating two strands of economic theory that had proceeded along separate lines until then: endogenous growth theory and the new economic geography initiated by Krugman (1991a), which analyses the distribution of economic activity in space. This recent research predicts a two-way relationship, whereby agglomeration is conducive to growth, and growth also leads to agglomeration.

In this paper, we investigate the link between the agglomeration of economic activity and economic growth at the level of European regions. While the empirical evidence that exists on this issue for Europe has mostly been concerned with Western Europe, we focus on the regions of Central and Eastern Europe (CEE), where there are good reasons to expect this relationship to be strong.

First, economic activity is more concentrated in CEE than in Western Europe, especially around the national capitals. For example, Landesmann and Römisch (2006) calculate that the regional dispersion of GDP per capita, measured by the coefficient of variation, averaged at 0.47 since the mid-1990s across the CEE regions when calculated both at NUTS-2 and NUTS-3 level, while the values for Western European regions were 0.29 and 0.38 respectively. Repeating the exercise without the capital regions, the dispersion across CEE falls markedly and is much closer to that for Western Europe, which declines only slightly. In part, this comparatively larger disparity between the capital regions and the rest of the CEE countries is a legacy of the centrally planned economic system of the Soviet Union, which favoured the capital cities as national centres of political

¹See Martin and Ottaviano (2001), who cite Hohenberg and Lees (1985).

²For more advanced countries, the “Williamson hypothesis” predicts the opposite, so that regional disparities fall as income rises further above a certain level. Overall, we may thus observe an inverted U-shaped relationship between a country’s income level and regional inequality.

administration, education and transport infrastructure.

Second, economic growth in CEE has been quite substantial since about 1995, and it exceeded growth in Western Europe by several percentage points during the first half of the 2000s. While the initial phase of transition to a market-based economic system that followed the disintegration of the Soviet Union in 1989/1990 involved severe recessions in most countries, by the mid-1990s output recovered and growth returned. Until the late 1990s, interruptions due to fiscal, currency or banking crises occurred in several countries, but from about 2000 onwards, growth rates accelerated and reached annual averages of 5.5% and more in the Baltics, Bulgaria and Romania, and 3-5% on average in the remaining CEE countries.³

Third, recent evidence suggests that economic growth in CEE has gone hand-in-hand with an increase in the pronounced regional concentration of economic activity that already characterised the CEE countries at the beginning of transition. This trend has mainly been the result of exceptionally strong growth in certain prosperous and highly agglomerated regions, coupled with a weaker performance of lagging regions (Römisch 2003, Paas and Schlitte 2007). In addition, empirical work on growth in the enlarged European Union since the mid-1990s has tended to find convergence occurring across all EU countries, as well as across CEE regions when convergence in the absolute form is tested for, but *divergence* across CEE regions when country-specific effects are introduced (e.g. Niebuhr and Schlitte 2004 and 2008, European Commission 2004). That is, while the poorer CEE countries are catching up to the richer EU-15, and catch-up and the concomitant reduction in income disparities is also taking place *across* the regions of different CEE countries, disparities *within* CEE countries have been rising. This combination of declining between-country disparities and increasing within-country disparities also points to the existence of a few regions which grow exceptionally fast and in which an increasingly large share of economic activity concentrates over time, while other regions cannot keep pace.

There are two types of highly agglomerated CEE regions that have grown more strongly than most other regions. On the one hand, the capital regions were better able to adjust to the massive structural changes induced by the transition than regions that had specialised in agriculture or industry under central planning, since compared to the latter, the capitals had maintained a more diversified economic structure. Moreover, the capitals have had access to a better educated labour force and they have been more successful in attracting foreign direct investment (FDI). The rise of the modern services sector is also most advanced in the capitals. By contrast, some rural and formerly heavy industry-based regions have not fully recovered from the severe slumps they experienced during transition and register below-average growth rates (e.g. Jasmand and Stiller 2005, Horvath 2000).

On the other hand, regions bordering Western Europe benefited from the shift in their relative geo-economic location brought about by the fall of the Iron Curtain. Their position

³Landesmann and Römisch (2006) pp.1-2.

changed from being relatively remote from their national economic centres to having the closest access to the large Western European market, a position of considerable advantage during the advancing trade integration of the CEE countries with the West. Correspondingly, economic activity in the border regions has increased, while eastern CEE regions have generally not performed as well. For example, their proximity to the West made the border regions an attractive destination for manufacturing FDI (e.g. the automotive clusters in western Slovakia and western Hungary). Several studies, for example Resmini (2003) and Niebuhr (2008), find that border regions in CEE experienced above-average growth rates in the 1990s.

The main contribution of this paper is to investigate the relationship between agglomeration and (short-run) economic growth for the regions of the ten CEE accession countries. We draw on a panel of 48 NUTS-2 regions over the period from 1995 to 2006. Consistent with the recent empirical literature on agglomeration and growth, we use the term “agglomeration” to refer to the concentration of *aggregate* economic activity within regions, that is, we do not consider the spatial concentration of individual industries.

Compared to much of the existing research for Western European regions, our measure of agglomeration has an important advantage. We use the “topographic” Theil index developed by Brülhart and Traeger (2005) to measure the concentration of total employment across NUTS-3 subregions within each CEE NUTS-2 region. This index allows the distribution of aggregate economic activity to be compared to the distribution of NUTS-3 region areas within each NUTS-2 region. The topographic Theil index differs from so-called “absolute” concentration indices that have been employed in some previous studies on agglomeration and regional growth in Western Europe, which measure concentration relative to the uniform distribution of economic activity across regions.

We estimate a transitional growth specification in the spirit of Mankiw, Romer and Weil (1992), which we augment with our measure of agglomeration, similar to other empirical studies on the topic. We make use of panel data estimators that allow us to deal with several estimation issues that may arise from the presence of unobserved region-specific fixed effects and the dynamic nature of our model, endogeneity of explanatory variables, and spatial dependence in our regional dataset.

In our empirical analysis, we find evidence of a statistically significant positive effect of agglomeration on transitional growth for our panel of CEE regions that is robust across estimation methods and models. In addition, the size of the long-run effect of agglomeration on income is economically significant. These results suggest that in terms of the Williamson hypothesis, the regions of Central and Eastern Europe as a whole are still at a stage where encouraging the geographic concentration of economic activity is growth-enhancing. However, since higher within-region concentration may also entail greater within-region inequality, policy makers could face a trade-off between economic growth and regional cohesion.

The remainder of this paper is organised as follows. The next two sections give an exposition of the recent theoretical literature linking agglomeration and economic growth and review the existing empirical literature. Section 4 outlines our modelling approach and estimation strategy. Section 5 describes the data and variables including our agglomeration measure. Section 6 presents and discusses the results, and section 7 concludes.

2 Theoretical Links between Agglomeration and Growth:

The recent theoretical literature on the agglomeration-growth nexus combines elements from the endogenous growth models of Romer (1990) and Grossman and Helpman (1991) with a new economic geography framework in the spirit of Krugman (1991a) or Venables (1996). A common theme of this literature is a mutually beneficial relationship between agglomeration and growth. Since the models are similar, we focus on two early protagonists, Martin and Ottaviano (1999, 2001), and comment briefly on the contributions by Baldwin and Forslid (2000), Baldwin, Martin and Ottaviano (2001), Fujita and Thisse (2003) and Baldwin and Martin (2004).

All agglomeration-and-growth models share the same general set-up. As in new economic geography, there are two regions that are initially identical. There are also the two standard sectors: a perfectly competitive sector producing a homogeneous good under constant returns to scale (e.g. agriculture), and a monopolistically competitive sector producing varieties of a horizontally differentiated good under increasing returns to scale as in Dixit and Stiglitz (1977) (e.g. manufacturing). The homogeneous good can be costlessly traded between regions. It serves as the numeraire and is produced in both regions using only immobile labour as an input. The differentiated good faces “iceberg” transport costs such that a fraction of the good “melts away” in trade. Each firm in the monopolistically competitive sector produces only one variety of the good using labour which may or may not be mobile between regions, depending on the model. Firms in this sector are free to locate in either region. Consumers have Cobb-Douglas preferences over the homogeneous good and a constant elasticity of substitution (CES) aggregate of varieties of the differentiated good.

In addition, a perfectly competitive R&D sector is introduced that operates as in Romer (1990) or Grossman and Helpman (1991). In Martin and Ottaviano (1999, 2001) and Fujita and Thisse (2003), it invents blueprints for new varieties of the differentiated good which are then patented, while in Baldwin and Forslid (2000), Baldwin et al. (2001) and Baldwin and Martin (2004), it produces capital (physical, human or knowledge capital). In both cases, it is the source of growth, which takes the form of growth in the number of varieties of the differentiated good or in the stock of capital. The production of new ideas (or capital goods) in the R&D sector is proportional to the stock of existing knowledge (capital) because knowledge spillovers make every innovation accessible to the entire research

community. Hence, as the output of the R&D sector rises, the marginal productivity of the input (e.g. researchers) employed in the sector rises, or equivalently, the marginal cost of producing a given innovation falls. The accumulation of knowledge therefore does not run into diminishing returns, which makes sustained long-run economic growth possible. A fixed cost of one unit of the R&D sector's output - a patent or a unit of capital - is required by the monopolistically competitive sector to produce each variety. In some of the models, the R&D sector is mobile across regions in that its output can be costlessly traded, while in others, it is immobile.

In Martin and Ottaviano (2001), the R&D sector is mobile and its only input is the same CES aggregate of varieties of the differentiated good that is produced by the monopolistically competitive manufacturing sector and demanded by consumers. Similar to the new economic geography models of Venables (1996) and Krugman and Venables (1995), this creates vertical linkages between the two sectors, which generate the process of cumulative causation that eventually results in the agglomeration of economic activity in one of the two regions.⁴ In order to isolate this channel, the model assumes that manufacturing labour is immobile, thus abstracting from the mechanism that brings about agglomeration in the seminal Krugman (1991a) model.

The R&D sector's use of differentiated goods as inputs in the innovation process means that part of the overall demand for the manufacturing sector's output comes from the R&D sector. To realise economies of scale and to minimise transport costs, manufacturing firms thus have an incentive to concentrate production in the region where a larger share of the R&D sector is located, that is, where expenditure on their products is higher.⁵ This constitutes a demand linkage between the two sectors. If the growth rate of the economy increases, which means that the R&D sector invents new varieties at a faster rate and therefore requires more of the differentiated good as an input, more manufacturing firms will choose to move to the region with the larger share of researchers, thereby raising the geographic concentration of manufacturing. As a result, the demand linkage makes the geographic agglomeration of manufacturing firms in a region a positive function of the rate of growth.

In turn, the cost of inputs in the R&D sector depends on the price of the differentiated goods produced by the manufacturing sector. To save on transport costs, the R&D sector thus has an incentive to locate in the region where more manufacturing firms are located, which represents a cost linkage between the sectors. If the geographic concentration of manufacturing increases as more firms move to a region, the cost of innovation in the research sector declines, which raises the rate of growth as new researchers enter the R&D

⁴The Venables and Krugman-Venables models assume vertical linkages between firms *within* the monopolistically competitive sector, so that the analogy is not exact.

⁵This implies the "home market effect" introduced by Krugman (1980), according to which the region with the larger share of demand for a good has a more than proportionately larger share of production of that good.

sector until profits return to zero. The cost linkage therefore makes the economy's growth rate a positive function of the geographic agglomeration of manufacturing.

Overall, the combination of the two linkages implies that an initial situation where both regions are symmetric - in that they have equal shares of the manufacturing and research sectors - is only a stable equilibrium if the growth rate of the economy is zero.⁶ In this case, the research sector is not active, so that the linkages that make agglomeration and growth mutually reinforcing processes do not operate. If growth is positive, however, a small disturbance to the symmetric equilibrium sets in motion a cumulative process that leads to both rising economic growth and the agglomeration of the R&D and manufacturing sectors in one region.⁷ In the stable equilibrium with positive growth, the R&D sector is entirely concentrated in one region, but manufacturing is less than fully agglomerated. This is because as the economy grows and new varieties are created only in the region in which the research sector is located, the increasing competition in manufacturing in that region induces a steady flow of some firms to the other region, which has no innovation activity.

In Martin and Ottaviano (2001), the linkage effects that foster agglomeration and growth are pecuniary externalities that result from market interactions between the manufacturing and research sectors. In all other models, the technological externalities in the form of knowledge spillovers that exist in the R&D sector, and in particular their potentially localised nature, also play an important role in linking agglomeration and growth. The main input in the research sector is now labour, so that input-output linkages with the manufacturing sector, as in Martin and Ottaviano (2001), are absent.

Martin and Ottaviano (1999) distinguish between a situation where knowledge spillovers within the R&D sector are global, in that they extend costlessly to both regions, and one where they are local, so that they benefit only their region of origin. In the first case, the invention of a new variety in the research sector of one region reduces the marginal cost of R&D in both regions, so that the cost of R&D in each region depends on the total number of existing varieties (which equals the number of monopolistically competitive firms) in the global economy.⁸ By contrast, in the second case, a new variety or firm lowers the marginal cost of R&D only in the region where it was created, so that the cost of R&D in each region depends on the number of varieties or firms in that particular location.

Martin and Ottaviano (1999) show that when R&D knowledge spillovers are localised, the agglomeration of manufacturing firms is beneficial to economic growth. With localised

⁶In equilibrium, the growth rate and each region's share of manufacturing firms are constant.

⁷Consider, for instance, the defection of one manufacturing firm from one region to the other. As the cost of innovation is now lower in the latter region, this region attracts all research activity, which raises the demand for manufacturing output in that region, inducing more firms to move in. This further lowers the cost of innovation, attracting new researchers into the R&D sector until profits are driven back to zero, raising the growth rate in the process. Manufacturing firms continue to move in until profits in the sector are equalised across regions.

⁸This assumption is made in Martin and Ottaviano (2001).

knowledge spillovers, a greater concentration of manufacturing firms in a region lowers the marginal cost of R&D, which raises the growth rate by attracting more researchers into the sector. On the other hand, when knowledge spillovers are global, growth is independent of agglomeration, since in this case, the presence of an additional firm lowers the cost of R&D equally everywhere, no matter where the firm is located.

When spillovers are localised, the R&D sector - which is mobile in this model - has an incentive to concentrate all of its activity in the region where a larger share of the manufacturing sector is located, because the cost of research is lower there (a cost linkage between the sectors). Hence, if one of the two regions has an exogenously given higher number of firms at the outset, the R&D sector will end up fully agglomerated in this region. However, there is no further linkage that would give the manufacturing sector an incentive to locate near researchers as in Martin and Ottaviano (2001), and labour is assumed to be immobile. Overall therefore, no cumulative process arises in this model that would lead to the concentration of manufacturing activity in one location, as is the case in the other models.

In Fujita and Thisse (2003) and Baldwin and Forslid (2000), agglomeration raises the growth rate via the same cost linkage as in Martin and Ottaviano (1999) when knowledge spillovers in the research sector are localised. Both models build on Krugman (1991a), where labour mobility is the mechanism that leads to the complete agglomeration of economic activity in one region. Finally, Baldwin et al. (2001) and Baldwin and Martin (2004) show that when the R&D sector is immobile, growth also fosters agglomeration, in addition to the positive effect of agglomeration on growth that arises when knowledge spillovers are localised.

3 Previous Empirical Evidence:

There is a small empirical literature investigating the relationship between the agglomeration of aggregate economic activity and the evolution of European regional incomes that is motivated by the theoretical models outlined above. In an early contribution, Sbergami (2002) uses a “Barro-style” transitional growth specification to investigate the effect on national GDP growth of the geographic concentration of employment in manufacturing industries across NUTS-1 regions within six EU countries. She uses panel data from 1984 to 1995 and employs three different indices to measure industrial concentration: the “locational” Gini coefficient, the Theil index and a concentration index derived from Krugman (1991b). For two of these three indices, she obtains a significant negative coefficient, which suggests that greater dispersion rather than agglomeration of manufacturing industries is beneficial for (short-run) growth. The author’s own interpretation is that if it is the spatial distribution of R&D activity that matters for growth, and if the distribution of R&D differs from that of manufacturing industries, then the latter may not be very informative.

The following papers consider agglomeration at the level of the aggregate economy instead of the industry level, in contrast to Sbergami (2002). Crozet and Koenig (2008) estimate a convergence specification augmented with the log-difference of their measure of agglomeration, so that the *growth rate* of agglomeration affects long-run income levels. They consider the NUTS-1 regions of 14 Western European countries from 1980 to 2000. Agglomeration is measured alternatively by the standard deviation and a Theil index of per-capita GDP across NUTS-3 regions within each NUTS-1 region. Crozet and Koenig find a positive and significant coefficient for the full sample, which results also when agglomeration is proxied by the standard deviation of GDP density (GDP per km²) instead of GDP per capita. However, when the coefficient on agglomeration is allowed to differ between the richer northern and the poorer southern regions of Western Europe, it turns out that the positive relationship only holds for the former. For the less developed southern regions, changes in the growth rate of agglomeration have no significant effect.

Bosker (2007) examines the relationship between agglomeration and transitional growth for the NUTS-2 regions of 16 Western European countries from 1977 to 2002. Because of data limitations, he does not consider the sub-regional agglomeration of economic activity but employment density (employment per km²) at the NUTS-2 level. However, density measured at the aggregate regional level does not capture the distribution of economic activity across sub-regional units and is therefore not an adequate gauge of the *within*-regional concentration of economic activity that we are interested in.⁹ Bosker augments Mankiw et al.'s (1992) convergence specification with employment density and estimates the equation on panel data by OLS as well as maximum likelihood when introducing a spatial lag of the dependent variable. From his preferred results that control for region- and period-specific fixed effects, he concludes that a region's employment density has a significant negative effect on its (short-run) rate of growth for his sample.

Finally, Brühlhart and Sbergami (2009) conduct a comprehensive country-level analysis of the subject. Their empirical specification is a "Barro-style" transitional growth model with a large number of control variables. For a world-wide sample of about 100 countries and a sample of 16 Western European countries since 1960, the relationship between subnational agglomeration and country-level growth is estimated using cross-section OLS and panel system-GMM techniques. Agglomeration is measured both by variables that capture urbanisation, such as the share of a country's population that lives in cities or in the largest city, and by Brühlhart and Traeger's (2005) "topographic" Theil index of employment concentration across NUTS-2 regions within EU countries.¹⁰

⁹Sbergami (2002) illustrates that aggregate employment density and indices of within-region concentration do not necessarily measure the same thing and may even yield conflicting outcomes: large countries (in terms of area) in her sample register both low levels of employment density and high values of her agglomeration indices.

¹⁰The urbanisation variables serve as agglomeration proxies chiefly in the world-wide sample, where information on the distribution of employment across subnational regions is not readily available for many countries.

Brülhart and Sbergami (2009) specifically investigate the Williamson hypothesis, for which they find supportive evidence: across samples and methods, agglomeration fosters transitional growth in poorer countries, while for countries with per-capita incomes above about 10 000 U.S. dollars (12 300 U.S. dollars for the Western European sample) in 2006 prices, agglomeration is detrimental to growth.¹¹ For more advanced countries, the negative effects associated with the concentration of economic activity, such as congestion externalities and greater competition, therefore appear to outweigh the positive effects. Since compared to Western Europe, the CEE countries in our sample are relatively poor, Brülhart and Sbergami's results seem consistent with the positive relationship between agglomeration and transitional growth that we conjecture for the CEE regions.

Overall, the existing empirical evidence appears to be neither exhaustive nor conclusive. In particular, the use of different agglomeration measures and data at different spatial scales makes it difficult to compare the results of these contributions and to draw more general conclusions. The only other paper that considers NUTS-2 regions as we do, Bosker (2007), employs an agglomeration measure that is not ideal. In addition, to the best of our knowledge, the case of the Central and Eastern European regions has so far not been studied in depth.

4 Empirical Framework:

4.1 Baseline Model Specification:

Since the theoretical literature on agglomeration and growth is based on endogenous growth theory, it predicts an effect of agglomeration on the economy's long-run equilibrium growth rate via an effect on the rate of technological progress. However, the empirical studies presented above invariably make use of the Barro- and Mankiw-Romer-Weil (henceforth also MRW) versions of the neoclassical framework that model short-run growth along a transition path to the long-run equilibrium, where growth is constant and exogenous. To keep our results comparable, we base our analysis on Mankiw et al.'s (1992) convergence specification, which we augment with our measure of agglomeration.¹²

The Mankiw et al. (1992) model of growth in the neighbourhood of the steady state may be appropriate for the CEE countries from the mid-1990s onwards, when they were beginning to leave the upheavals of economic regime change behind. During our sample period, their growth process could be characterised as adjustment towards a long-run equi-

¹¹The cutoff income levels correspond roughly to the GDP per capita of Brazil or Bulgaria for the world-wide sample and of Spain for the Western European sample.

¹²We refer to the simple version of Mankiw et al.'s (1992) specification that does not include human capital.

librium driven by the accumulation of physical capital.¹³ In contrast to Western Europe, for the CEE regions such transitional or “catch-up” growth is likely to have dominated variation in long-run growth rates - as measured, for instance, by total factor productivity growth rates - which may be more difficult to identify in this paper. We also regard the available time series on gross fixed capital formation for the CEE regions to be too short and, for the initial years, too unreliable for the calculation of physical capital stocks required to construct TFP indices.

Our baseline specification for the log-level of income per capita of region i in year t is the following dynamic model:

$$\ln y_{it} = \gamma \ln y_{i,t-1} + \theta_1 \ln s_{it} + \theta_2 \ln(n_{it} + g + \delta) + \theta_3 \text{agglom}_{it} + u_{it}, \quad (1)$$

where s_{it} is the regional fraction of output that is saved or invested at time t , n_{it} and g are the growth rates of labour and technology, and δ is the depreciation rate of the capital stock. u_{it} is a mean-zero error term.

The term agglom_{it} represents our measure of agglomeration. The theoretical discussion in section 2 suggests that this variable should have a positive effect on the long-run growth rate as given by the rate of technological progress. On the other hand, our MRW-type specification in equation (1) implies that greater agglomeration of economic activity raises growth in the short run, so that we expect θ_3 to be positive. However, we may still be able to gain some indication of the importance of agglomeration in the long run from its effect on long-run income levels, measured as $\frac{\theta_3}{1-\gamma}$.

Other explanatory variables of interest in the context of CEE regional growth are human capital, R&D and FDI. As emphasised by endogenous growth models, for example, the first two are key drivers of technological progress by fostering own innovation as well as the imitation of knowledge developed at the technological frontier. Similarly, FDI may be regarded as an important channel of technology transfer for countries behind the frontier. FDI inflows into the CEE countries since the mid-1990s have been substantial, and especially secondary educational attainment rates are high in comparison to Western Europe. However, data on FDI are generally unavailable at the regional level, and regional R&D and human capital series for CEE are available only patchily and cover few years. By employing region-specific fixed effects in estimation (see below), on the other hand, we are at least able to capture permanent differences in human capital, R&D and FDI between the CEE regions.

¹³For example, Arratibel et al. (2007) find that the share of investment in GDP was high in the CEE countries compared to Western Europe over our sample period. Moreover, growth accounting exercises such as in European Commission (2004) suggest that capital accumulation contributed significantly to output growth in these countries since 1995.

4.2 Estimation Methods:

To estimate equation (1), we use the panel data framework, which allows controlling for unobservable region-specific fixed effects that are time-invariant and may be correlated with other explanatory variables, such as physical geography and economic institutions. We therefore write u_{it} in equation (1) as

$$u_{it} = \mu_i + \eta_t + v_{it},$$

where μ_i are region-specific fixed effects and η_t represent unobserved period-specific effects that are common to all regions but vary over time, such as macroeconomic shocks. v_{it} is a mean-zero disturbance.

In dynamic models like (1) with the error term defined as above, the presence of both region-specific fixed effects and a lagged dependent variable implies that the pooled OLS (POLS) estimator is inconsistent. Similarly, the within-groups (WG) estimator is likely to be inconsistent if the number of time periods T in the panel is small (Nickell 1981). Bond (2002) notes that the bias in the POLS and WG estimates of the coefficient on the lagged dependent variable, γ in our case, is likely to be in opposite directions - upward in the case of OLS and downward for WG.

When the number of cross-sectional units N in the panel is large, the first-differenced (FD-GMM) and system-GMM (S-GMM) estimators developed by Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) may provide consistent estimates of model (1). Both first-difference the equation and use lagged levels dated $t - 2$ and earlier as instruments for the first-differenced equations (FD-GMM) and lagged first differences as instruments in the levels equations (S-GMM). When the series used in estimation are highly persistent, the instruments employed by FD-GMM may be weak and the S-GMM estimator may be preferred.

However, since our cross-sectional sample size, $N = 48$, is relatively small, we do not focus on GMM estimation in this paper. Instead, we adopt the following strategy to deal with the region-specific fixed effects. We primarily estimate model (1) using within groups (WG), assuming that our time dimension is large enough for any inconsistencies of the Nickell (1981) type not to be important. Then, we investigate the sensitivity of the WG results to allowing for $T = 11$ to be too short to avoid these inconsistencies, by using a modified version of the FD- and S-GMM estimators.

With this modification, we attempt to minimise finite-sample bias in the GMM estimates that may result from a large number of instruments relative to the cross-sectional sample size (“overfitting”). It consists of restricting our instrument set in two ways. First, the maximum lag length of the endogenous variables used as instruments in the first-differenced equations is limited to three. In addition, the size of the instrument matrix is reduced by stacking the instruments available per variable for each time period into a

single column, as in standard two-stage least-squares, rather than generating a separate column for each time period and lag available for that time period, as in panel GMM. This approach may therefore be more appropriately referred to as “parsimonious” or “restricted” GMM.

When testing the validity of the instruments, we pay particular attention to the additional instruments for the equations in levels employed by S-GMM. Blundell and Bond (2000) show that for the lagged first difference of the dependent variable to be a valid instrument, one condition is that the model we specify for $\ln y_{it}$ has generated this variable for long enough before the start of the sample period for the influence of the true initial conditions to vanish. For our application to Eastern Europe since 1995 however, this argument could be considered less compelling. For example, the structural changes associated with economic transition may have radically altered the process generating income per capita from 1989/1990 onwards.

A second estimation issue that we may face is contemporaneous correlation of the explanatory variables in equation (1) with v_{it} due to e.g. simultaneity. For example, the theoretical models in section 2 describe growth and agglomeration as joint processes that reinforce each other, so that $agglom_{it}$ may be endogenous. In addition, this could be the case for the share of output that is invested, s_{it} , and for the growth rate of labour, n_{it} , if we allow for inward or outward migration to take place in response to shocks to regional output. We therefore check the robustness of our results to treating each of the explanatory variables as endogenous and instrumenting them with their own time lags.

A third estimation issue that may be present in our setup is spatial dependence or spatial autocorrelation between the regional observations in our dataset. This arises in situations where observations across cross-sectional units are not independent but correlated with outcomes at other points in geographical space. Spatial dependence may be of the “substantive” type, i.e. the result of economically meaningful interactions between spatial units which form part of the model of interest, or of the “nuisance” type, resulting from measurement issues associated with the underlying spatial data that lead to spatially correlated measurement error. In both cases, spatial dependence that remains unaccounted for in estimation manifests itself in spatially correlated regression residuals.

However, the consequences for the model parameter estimates differ between the two. In the substantive case, if the values of e.g. the dependent variable at neighbouring locations - its “spatial lag” - are relevant to the model (which is then called *spatial lag model*) but omitted, the standard POLS estimator is biased and inconsistent. In the nuisance case, usually represented by means of a spatial lag in the error term (*spatial error model*), POLS parameter estimates remain unbiased and consistent but are no longer efficient, and the estimated standard error are biased and inconsistent.

Spatially lagged variables are operationalised by means of an $N \times N$ spatial weight matrix \mathbf{W} with typical element w_{ij} , which defines the nature and strength of spatial in-

teraction between locations i and j . We use a weight matrix based on inverse squared distances between the capitals of the CEE NUTS-2 regions, which is a common choice in the literature. That is, we define $w_{ij} = 1/d_{ij}^2 \forall i \neq j$, where d_{ij} is the great-circle distance between the capitals of regions i and j . By convention, $w_{ii} = 0$ and \mathbf{W} is row-standardised.

In this paper, we follow the standard approach in the empirical spatial econometrics literature and first test for spatial autocorrelation in the residuals of our OLS and WG estimates of model (1). Upon finding evidence of significant residual spatial dependence of the substantive type, we estimate two alternatives to model (1) that augment it with spatially lagged dependent and explanatory variables respectively. In addition, we tackle potential remaining spatial error autocorrelation by estimating our standard errors in a way that is robust to the presence of cross-section correlation. Overall, our main interest remains with the coefficient on $agglom_{it}$.

In addition to model (1), which can be rewritten as

$$\ln y_{it} = \gamma \ln y_{i,t-1} + \mathbf{x}_{it}\boldsymbol{\theta} + \mu_i + \eta_t + v_{it}$$

with \mathbf{x}_{it} a (1×3) row vector of the explanatory variables $\ln s_{it}$, $\ln(n_{it} + g + \delta)$, and $agglom_{it}$ and $\boldsymbol{\theta}$ a (3×1) vector of coefficients, we estimate the following models:

$$\ln y_{it} = \gamma \ln y_{i,t-1} + \rho \sum_{j=1}^N w_{ij} \ln y_{jt} + \mathbf{x}_{it}\boldsymbol{\theta} + \mu_i + \eta_t + v_{it} \quad (2)$$

$$\ln y_{it} = \gamma \ln y_{i,t-1} + \mathbf{x}_{it}\boldsymbol{\theta} + \sum_{j=1}^N w_{ij} \mathbf{x}_{jt}\boldsymbol{\phi} + \mu_i + \eta_t + v_{it} \quad (3)$$

where $\boldsymbol{\phi}$ is another (3×1) vector of coefficients. Model (2) could be called a dynamic spatial lag model and model (3) a dynamic spatial cross-regressive model, except that these specifications usually assume *iid* errors. The only assumption that we make on the error term v_{it} is that it is serially uncorrelated with mean zero, that is, we allow for cross-section correlation of a general form in v_{it} .

Models (2) and (3) can be estimated by straightforward extension of the methods that we employ to address the first two estimation issues discussed previously in this section. Following our approach to the presence of region-specific fixed effects in model (1), we initially use the WG estimator for models (2) and (3). In model (2), the spatially lagged dependent variable is treated as endogenous with respect to v_{it} , due to the two-directional nature of the neighbour relation in space, where each location is its neighbour's neighbour. Consequently, we adopt an instrumental variables approach to estimating model (2), using as instruments the time lags of $\sum_{j=1}^N w_{ij} \ln y_{jt}$ and, following Kelejian and Robinson (1993), the spatially lagged explanatory variables $\sum_{j=1}^N w_{ij} \mathbf{x}_{jt}$, which we treat as exogenous throughout this paper. Given this, model (3) raises no particular estimation issues.

Analogous to the a-spatial case, WG may be inconsistent due to the presence of both a

time-lagged dependent variable and region-specific fixed effects in a panel with a moderately short time dimension. As suggested by Kukenova and Monteiro (2009), this problem may be remedied also in the spatial case by applying the S-GMM estimator described above. The spatially lagged dependent variable would again be treated as endogenous and instrumented as above. Monte Carlo simulations in Kukenova and Monteiro (2009) indicate that using S-GMM for spatial dynamic panel data models such as model (2) dominates a range of other estimators regarding unbiasedness and consistency. It also performs well in terms of efficiency, particularly when additional endogenous explanatory variables are considered. We use our parsimonious version of the estimator.

5 Data and Variables:

The data we use in this paper come from the 2008 edition of the Cambridge Econometrics (CE) European Regional Database, which provides information on the CCE regions from 1990 to 2006, and from Eurostat. We measure regional income per capita y_{it} as regional gross value added (GVA) divided by population. GVA is given at constant prices in 2000 euros in the CE database, which we adjust for cross-country price-level differences using national purchasing power standard (PPS) exchange rates, which are national purchasing power parities defined relative to the EU average. The saving rate s_{it} is constructed as the share of gross fixed capital formation, also expressed in PPS-adjusted 2000 euros, in total regional GVA. The growth rate of the labour force n_{it} is proxied with the growth rate of the total population. As is common in the literature, we set $g + \delta$ equal to 0.05 for all regions and years.¹⁴ To construct our agglomeration index, we use data on regional area from the Eurostat Regional Statistics database together with employment series from CE.

We begin our empirical analysis in the year 1995 and disregard the period from 1990 to 1994. Economic data for Central and Eastern Europe during the early transition period until the mid-1990s are generally believed to be unreliable and not comparable to later years, as a result of considerable measurement problems raised by the momentous changes in economic systems at the time (Eckey et al. 2009, Tondl and Vuksic 2003).

Our sample comprises 48 NUTS-2 regions from the ten CEE countries.¹⁵ For Estonia, Latvia, Lithuania and Slovenia, where no subdivision at NUTS-2 level exists, we use country-level data instead. Since we measure agglomeration for each region across its NUTS-3 sub-regions, we drop three CEE regions (one Czech, two Polish) which are not further subdivided into NUTS-3 regions. This is also the case for three further regions: the Czech capital Prague and the region it is embedded in, Central Bohemia, and the

¹⁴In line with results from Eckey, Dreger and Türck (2009), who find that values for g and δ computed for most CEE countries over the period 1995 to 2004 are higher than for the EU-15, we varied our figure from 0.05 to 0.10 and 0.15. However, this made no significant difference to the results.

¹⁵The regions in the sample are from Bulgaria (6 NUTS-2 regions), the Czech Republic (6), Estonia (1), Latvia (1), Lithuania (1), Hungary (7), Poland (14), Romania (8), Slovenia (1) and Slovakia (3).

Slovakian capital Bratislava. We merge the first two with each other and the third with its neighbour Western Slovakia. In contrast to the regions we drop, Prague and Bratislava are unambiguously surrounded by one neighbouring region, so that aggregating them appears natural and preferable to dropping them, given our relatively small cross-sectional sample size. The resulting aggregates also satisfy Eurostat’s population thresholds for NUTS-2 regions.

Appendix A provides a list of all regions in the sample and the number of their respective NUTS-3 sub-regions. Variable summary statistics are provided in Appendix B.

5.1 Measuring Agglomeration:

Our focus in this paper is on the concentration of aggregate economic activity across NUTS-3 regions within each CEE NUTS-2 region. Following Krugman (1991b), one approach to measuring the geographic distribution of economic activity has been to adapt indices used in the income inequality literature. Examples include the “locational” Gini coefficient based on the Balassa index of revealed comparative advantage, the Theil index, the coefficient of variation, and an index suggested by Krugman (1991b) based on the relative mean deviation. The Herfindahl index has also been a popular choice. All indices can be constructed as measures of concentration (of economic activity in given geographical areas) or specialisation (of geographical areas in particular activities). We are interested in the former.

Choosing an appropriate measure of the spatial concentration of economic activity across regions raises a number of empirical challenges. Combes, Mayer and Thisse (2008) outline six desirable properties that an ideal index of spatial concentration should satisfy. The first two are only relevant for industry-level data and therefore do not apply. The third and fourth are that the index should be comparable across spatial scales and unbiased with respect to arbitrary changes in the spatial classification. Fifth, it should be defined relative to a well-established benchmark distribution under which geographic concentration is assumed to be zero. And sixth, it should be amenable to significance testing. Of these criteria, all inequality indices mentioned above meet only the fifth, and sometimes the sixth.¹⁶

5.1.1 The Modifiable Areal Unit Problem:

Problems with satisfying the third and fourth criteria are related to the well-known Modifiable Areal Unit Problem (MAUP). This is a source of bias in statistical measures that are based on geographical units, in the sense that these measures are sensitive to the way in which the units are organised. It arises from the partition of continuous heterogeneous

¹⁶See Combes et al. (2008) pp. 256-266.

space into discrete regions, and it is more acute when the latter are, like the NUTS regions, based on administrative rather than economic principles.

The MAUP has two components. The first is that the value taken by a statistical measure like an index of spatial concentration depends on the scale of spatial aggregation considered, since different scales imply different levels of heterogeneity of economic activity within regions (scale problem). For example, the degree of concentration within NUTS-1 regions measured across NUTS-2 regions is likely to differ from that measured across NUTS-3 regions. Consequently, the concentration index is not comparable across spatial scales as required by criterion three. In the case of the NUTS, this problem is compounded by the heterogeneity of region sizes that exists within each classification band.

The second component of the MAUP is that at a given spatial scale, the value taken by an index of spatial concentration depends on the way the boundaries are drawn between regions (zone problem). This is because changing the boundaries leads to an artificial reallocation of economic activity between regions, thus altering the degree of concentration measured within or across them, while the underlying distribution of economic activity remains the same. As a result, the concentration index is not unbiased with respect to arbitrary changes in the spatial classification and therefore does not satisfy criterion four. In this context, a problem with the NUTS is that the administrative basis of the classification makes arbitrary boundaries that cut through economically integrated areas more likely.

One approach to addressing the scale problem that has been taken in the literature is to check the robustness of the results to using alternative levels of aggregation. However, since our main unit of analysis are NUTS-2 regions, for which only one further subdivision (NUTS-3) exists, this route is not open to us.¹⁷ To minimise the zone problem, some authors attempt to get as close as possible to measuring the true distribution of economic activity by using a geographical classification that is based on economic rather than administrative criteria. An example is the use of local labour market areas (e.g. Travel to Work Areas in the United Kingdom or Local Labour Systems in Italy), which are defined, via daily commuting patterns, such that a majority of the resident population in an area also works in that area. Data at this level of detail are not yet available from Eurostat.¹⁸

None of the empirical papers reviewed in section 3 use a measure of concentration that overcomes the MAUP. Our strategy for dealing with it relies on the fact that we control for time-invariant region-specific fixed effects in estimation. If the bias in our agglomeration

¹⁷Eurostat has developed a classification system at the sub-NUTS-3 level called “LAU”, for Local Administrative Units. There are two LAU levels, of which the lower (most disaggregated) consists of municipalities in many countries. Currently, LAU-level data available from Eurostat are limited to area and population for 2009 and 2010.

¹⁸Eurostat does provide data on so-called “larger urban zones” and “metropolitan regions”, which are functional urban areas defined by taking into account commuting from surrounding territories and can thus be considered labour market areas. However, these data cover only cities and do not exhaust the geographical territory of the countries we study.

measure that arises from the MAUP does not vary over time, it will be eliminated by the within-groups and GMM estimators that we use.

5.1.2 The Benchmark Distribution:

With regard to the fifth criterion, three main distributions have typically been chosen as the benchmark in the literature. The first is the uniform distribution, so that the concentration of economic activity is assumed to be zero if the latter is uniformly distributed across the regions, irrespective of their geographic or economic size. Under the null hypothesis of no concentration, each region therefore has the same share of total activity, and any deviation from this even distribution would result in a positive value of the concentration index. However, this may not be a very meaningful way to measure concentration given the irregular distribution of region areas and endowments. Indices that use the uniform distribution as their benchmark have been labelled “absolute” concentration indices.

An alternative that seems economically more relevant, but is only applicable when measuring concentration at the industry level, is to use the distribution of aggregate economic activity across the regions as the benchmark.¹⁹ Such indices are called “relative” concentration indices. Under the null of no concentration, the distribution of activity in an industry matches that of total economic activity across the regions. Consequently, the index takes a positive value if a given industry is geographically more concentrated than the economy as a whole.

Finally, a variant of relative concentration is the concept of “topographic” concentration introduced by Brühlhart and Traeger (2005). The benchmark here is the distribution of the geographical areas of the regions, so that zero concentration obtains if the distribution of economic activity matches that of the regions’ land mass. We choose an index in this class, which allows us at least to control for variations in the size of NUTS region areas when measuring agglomeration. In particular, we follow Brühlhart and Sbergami (2009) in using the topographic Theil index developed in Brühlhart and Traeger (2005).

The Theil index belongs to the family of generalised entropy measures of inequality. These have the advantage over the Gini and Krugman indices mentioned above that they are easily decomposable into inequality within and between constituent subgroups.²⁰ In addition, Brühlhart and Traeger (2005) have proposed bootstrap-based significance tests for their Theil index, so that it satisfies Combes et al.’s (2008) criterion six.

Our agglomeration measure differs from those considered in Bosker (2007), Crozet and Koenig (2008), and partly in Sbergami (2002). The latter employs relative versions of the

¹⁹When assessing the concentration of aggregate economic activity, as we do, this approach would imply comparing the distribution of the latter with itself, which is meaningless.

²⁰This decomposition would be interesting if we computed concentration, say, across *all* CEE NUTS-3 regions. Then overall concentration could be decomposed into concentration within and between countries or within and between NUTS-2 regions, for instance. However, we are primarily interested in concentration *within* NUTS-2 regions, so that the decomposition is less relevant.

Gini and Krugman indices, but an absolute Theil index. The measures used by Crozet and Koenig (2008) are also absolute. Bosker (2007) proxies agglomeration of NUTS-2 regions with aggregate employment density at the NUTS-2 level. As discussed in section 3, this approach does not capture the *within*-regional distribution of economic activity.

5.1.3 The Topographic Theil Index:

Brühlhart and Traeger’s (2005) topographic Theil index for the concentration of aggregate economic activity across NUTS-3 regions within each CEE NUTS-2 region is given by the following expression (dropping time subscripts for simplicity):

$$T_i^T = \sum_r \frac{E_{ri}}{\sum_r E_{ri}} \ln \frac{E_{ri}/A_{ri}}{\sum_r E_{ri}/\sum_r A_{ri}} \quad (4)$$

where $r = 1, \dots, R$ is the set of NUTS-3 subregions within each NUTS-2 region i , E_{ri} is total employment in NUTS-3 region r pertaining to NUTS-2 region i , and A_{ri} is the total area of NUTS-3 region r . By rewriting the Theil index in equation (4) as

$$T_i^T = \sum_r \frac{E_{ri}}{E_i} \ln \frac{E_{ri}/E_i}{A_{ri}/A_i}, \quad (5)$$

it is easily seen that this index weights the share of each NUTS-3 region in the corresponding NUTS-2 region’s total employment by the share of that NUTS-3 region in the NUTS-2 region’s total area. This reflects the zero-concentration benchmark of the topographic Theil index, which is the distribution of the NUTS-3 region areas within each NUTS-2 region. If NUTS-3 regional employment is distributed in line with these regions’ land area, the topographic Theil index takes the value zero. If a NUTS-3 region has a greater share of a NUTS-2 region’s employment than of its area, the index takes a positive value. The topographic Theil index reaches its upper bound when all employment within a NUTS-2 region is concentrated in the NUTS-3 region with the smallest area. In this case, the index takes the value $\ln(A_i/A_{si})$, where s is the smallest NUTS-3 region within NUTS-2 region i .²¹ By standardising the value of the index for each NUTS-2 region by its theoretical maximum as given by this expression, the comparability of the index across NUTS-2 regions may be enhanced.²²

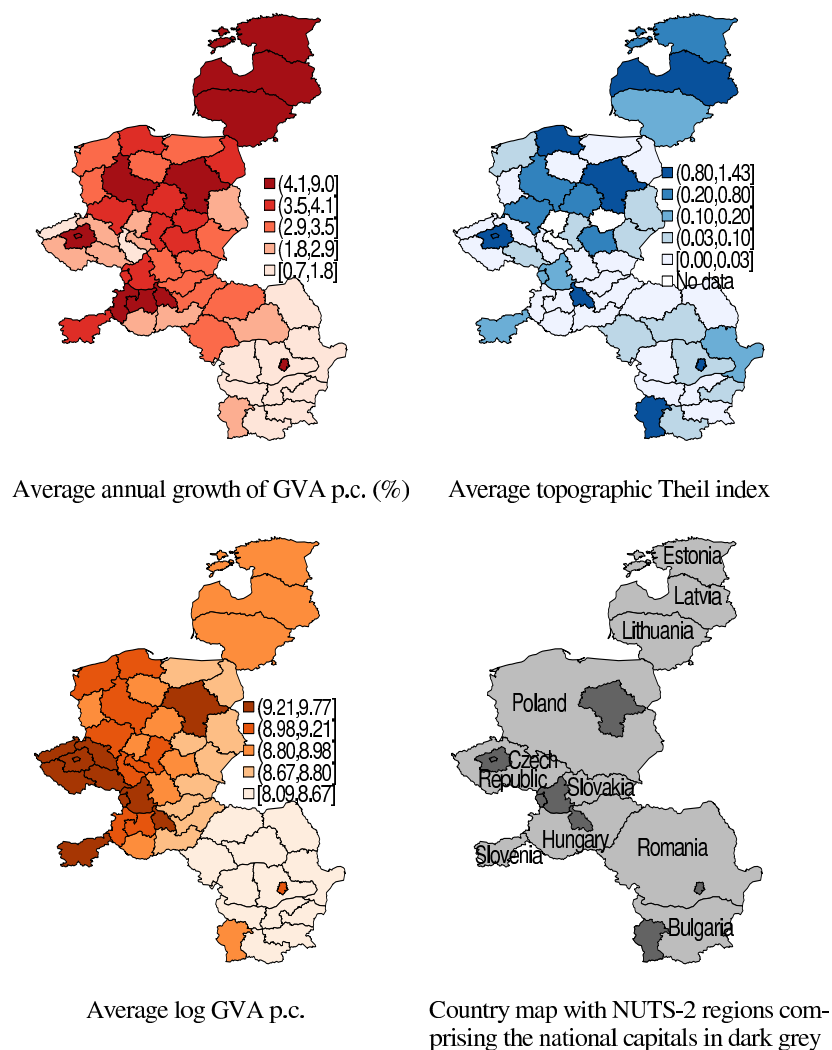
We use total employment as our measure of economic activity in the NUTS-2 and NUTS-3 regions. At the regional level, most empirical studies on concentration have chosen data on either value added or employment. Some authors prefer the latter because of the absence of data on price level differences between regions within countries, and almost all papers reviewed in section 3 consider employment. To measure regional areas, we use data on total area in km² from the Eurostat Regional Statistics database.

²¹See Bickenbach and Bode (2008) p.21.

²²This is currently work in progress.

Figure 1 illustrates the distribution of some key variables of interest - the growth rate of per-capita income, the topographic Theil index, and the log-level of per-capita income - across the CEE NUTS-2 regions in average values over our sample period. To ease interpretation, the figure also provides a country-level map of the area with those NUTS-2 regions where the countries' capital cities are located shaded in dark grey (bottom right).

Figure 1: Variable Distribution across CEE NUTS-2 Regions, 1995-2006



The top left-hand map shows that income growth was highest in the Baltic countries and in the capital regions of the Czech Republic, Hungary, Poland and Romania. The maximum was attained by Latvia, which grew at a rate of 9% per annum, with Estonia and Lithuania following closely behind. Fast-growing non-capital regions were Western and Central Transdanubia in Hungary, Greater Poland province and several other regions in Poland. On the other hand, growth rates were lowest on average in most Bulgarian regions

and in the non-capital regions of Romania, where output shrank over the first half of our sample period, in some cases at annualised rates of 5%.

The top right-hand map displays the spatial distribution of the topographic Theil index. In each country, by far the highest values of the index are registered by the capital regions. The Romanian capital region Bucharest-Ilfov has, at 1.43, the highest average value over our sample period. Other highly scoring regions are the capital regions of Poland, Hungary and the Czech Republic, for which the index averages between 1.25 and 1.33. Employment in Latvia as a whole is also highly concentrated relative to the distribution of NUTS-3 region areas. At the other end of the spectrum, employment is geographically dispersed relative to NUTS-3 region areas in many non-capital NUTS-2 regions of Bulgaria, the Czech Republic, Hungary, Slovakia and Romania. Overall, within-regional concentration of economic activity as measured by our Theil index is unevenly distributed across the CEE NUTS-2 regions: while a few regions are very agglomerated, many are not.

The bottom left-hand map of Figure 1 depicts the average log-level of income per capita over our sample period. This map clearly demonstrates that a west-east gradient in per-capita income levels exists in Eastern Europe: except for the Baltic countries and the capitals of Poland, Bulgaria and Romania, the further a region is from Western Europe, the poorer it is. The particularly strong performance of border regions in the Czech Republic, Slovakia, Hungary, and in Slovenia is also evident from Figure 1.

6 Estimation Results and Discussion:

In this section, we present estimates of models (1), (2) and (3) for our balanced panel of 48 Eastern European NUTS-2 regions over the period from 1995 to 2006. As outlined in section 4.2, we first focus on the within-groups estimator under the assumption that our time dimension, $T = 11$, is long enough for problems associated with Nickell bias not to matter much. In this framework, we test for spatial dependence and examine the robustness of the results to treating the explanatory variables as endogenous. Finally, we allow for the time dimension to be short enough for Nickell bias to be important and use our “parsimonious” GMM estimators to address it. Overall, we compare the results obtained in all cases for our main variable of interest, $agglom_{it}$, to investigate whether they are stable across estimation methods and models. Throughout, a full set of time dummies in all regressions captures period-specific fixed effects that are common to all regions.

Table 1 reports results for model (1) using pooled OLS and within groups. In columns (i) and (iii), we first present estimates of Mankiw et al.’s (1992) baseline transitional growth specification. In both columns, the estimated coefficients on $\ln s_{it}$ and $\ln(n_{it} + g + \delta)$ are correctly signed and most are highly significant. This provides some initial evidence that capital accumulation and possibly population growth may play an important role for long-run regional incomes in the CEE regions. The significant estimates of the coefficient on

the lagged dependent variable $\ln y_{i,t-1}$, $\hat{\gamma}$, also indicate that convergence to region-specific long-run paths for per-capita income levels is taking place for our sample of CEE regions.

Table 1: Model (1) - Pooled OLS and Within Groups

Dependent variable:	(i)	(ii)	(iii)	(iv)
$\ln y_{it}$	POLS	POLS	WG	WG
$\ln y_{i,t-1}$	0.996*** (0.008)	0.987*** (0.008)	0.654*** (0.057)	0.638*** (0.060)
$\ln s_{it}$	0.044** (0.017)	0.040** (0.017)	0.076*** (0.020)	0.080*** (0.020)
$\ln(n_{it} + g + \delta)$	-0.018*** (0.004)	-0.017*** (0.004)	-0.009 (0.006)	-0.009 (0.006)
$agglom_{it}$		0.022*** (0.005)		0.145** (0.054)
LR $agglom_{it}$		1.635 (1.038)		0.401*** (0.126)
AB-AR(1)	0.75 (0.454)	0.59 (0.558)	0.17 (0.862)	0.30 (0.764)
AB-AR(2)	2.02 (0.044)	1.63 (0.103)	1.11 (0.267)	1.04 (0.297)
Moran's I		10.60 (0.000)		3.88 (0.000)
LM-Error		3.23 (0.073)		4.65 (0.031)
Robust LM-Error		0.29 (0.592)		0.28 (0.596)
LM-Lag		71.69 (0.000)		6.55 (0.011)
Robust LM-Lag		68.75 (0.000)		2.71 (0.100)
Adjusted R^2	0.984	0.985	0.990	0.990
Time Dummies	Yes	Yes	Yes	Yes
Observations	528	528	528	528
Number of Regions	48	48	48	48

Notes: Standard errors, reported in parentheses, are robust to heteroskedasticity and cross-section correlation (Huber-White standard errors clustered on years); ***, **, and * indicate significance at the 1%, 5% and 10% levels; AB-AR(1) and AB-AR(2) are Arellano and Bond's (1991) tests of first- and second-order residual serial correlation, asymptotically standard normal under the null of no serial correlation, p-values in parentheses.

Moran's I test of spatial autocorrelation of general form is asymptotically standard normal under the null of no spatial autocorrelation.

LM-Error and LM-Lag are LM tests of spatially autoregressive errors and a spatially lagged dependent variable respectively, asymptotically $\chi^2(1)$ under the null of no spatial dependence of the specified form; robust versions allow for presence of spatial dependence of the form not tested for, also asymptotically $\chi^2(1)$ under the null of no spatial dependence of the specified form; p-values in parentheses for all spatial tests.

However, the estimate of $\hat{\gamma}$ in column (i) is not significantly different from 1, and the implied speed of convergence differs dramatically between OLS and WG specifications. Column (i) suggests a slow speed of 0.4% per year, which is consistent with other empirical studies on convergence for CEE regions using OLS (e.g. Paas and Schlitte, 2007).²³ In the

²³The annual speed of convergence is calculated as $\hat{\beta} = -(\ln \hat{\gamma})/\tau$, where $\tau=1$ in our annual setup in this

presence of region-specific fixed effects, we would expect the OLS estimate of γ to be biased upwards and the implied speed of convergence to be biased downwards. When using the WG estimator in column (iii) however, it rises to 42% per year.

This high number could be due to several factors. One is downward bias in $\hat{\gamma}$ of the Nickell (1981) type, which we investigate below. Other possible reasons may be related to the particular sample period in this paper, or to specifics of the CEE growth experience we do not capture. These possibilities represent an avenue for future research, so our estimates of the speed of convergence in this paper should be regarded as preliminary.

In columns (ii) and (iv), we augment the baseline MRW specification with our agglomeration index. In addition to the short-run coefficient on $agglom_{it}$, $\hat{\theta}_3$, we report the long-run coefficient, denoted by LR $agglom_{it}$.²⁴ While the short-run coefficient may be interpreted as a measure of the impact of a given increase in agglomeration on growth in transition to the steady-state path, the long-run coefficient provides an estimate of the effect of a permanently higher level of agglomeration on the long-run level of per-capita income. Both coefficients are positive in columns (ii) and (iv), and except for the long-run effect in column (ii), they are highly significant.

The size of the long-run coefficient in column (iv) suggests that this effect is also economically important. The point estimate of 0.401 implies that an increase in agglomeration - in our case, in the geographic concentration of NUTS-2 regional employment relative to the distribution of NUTS-3 regional areas - by one standard deviation²⁵ raises a region's steady-state level of income per capita by about 17%. In fact, this result remains fairly robust across estimation methods and models in the remainder of this section. Controlling for region-specific fixed effects, as we do in column (iv) and all following tables, ensures that this effect is not driven by the capital city regions, which feature so prominently in Figure 1. Preliminary estimates using a version of the topographic Theil index that is standardised by its maximum for each NUTS-2 region also indicate very similar results.

The estimates of the other coefficients change little when moving from the baseline specification in column (i) to introducing $agglom_{it}$ in column (ii), and similarly when moving between columns (iii) and (iv). The annual speed of convergence implied by the OLS estimate of γ in column (ii) is 1.3%, compared to 45% when using WG in column (iv). Taking the latter at face value suggests that regional long-run per-capita income levels should adjust rapidly to a change in the level of agglomeration. Finally, Arellano and Bond's (1991) serial correlation tests detect no evidence of first- or second-order serial correlation in the residuals of the OLS and WG estimates in columns (ii) and (iv).

paper.

²⁴The long-run coefficient is computed as $\frac{\hat{\theta}_3}{1-\hat{\gamma}}$. Standard errors are obtained using the delta method.

²⁵The standard deviation of $agglom_{it}$ is 0.428, see Table B.1 in the Appendix. As an illustration, this is roughly equivalent to the difference in the Theil index between the most agglomerated Polish region Masovia, which comprises the capital Warsaw, and the second-most agglomerated Polish region Pomerania, home to Gdansk, one of the country's largest metropolitan areas.

To investigate the implications of spatial dependence for the results in Table 1, we first present tests of spatial autocorrelation in the residuals of the pooled OLS and WG estimates of model (1) in columns (ii) and (iv). We use standard tests from the spatial econometrics literature, Moran’s I and the Lagrange multiplier tests of spatial error and lag dependence, as well as their robust versions proposed by Anselin, Bera, Florax and Yoon (1996).²⁶

The Moran’s I tests in columns (ii) and (iv) indicate significant spatial autocorrelation in the residuals of model (1). The LM tests provide some guidance to the choice between including a spatially lagged dependent variable or a spatially autoregressive error process as the appropriate model for capturing the spatial dependence in the data. In both columns (ii) and (iv), the LM-Lag test statistic is more significant than the LM-Error statistic. Moreover, the Robust LM-Lag test is significant, although only marginally in column (iv), while the Robust LM-Error test is not. That is, there is strong evidence of an omitted spatial lag even if we allow for spatial error autocorrelation, but there is no evidence of spatial error autocorrelation once we allow for the presence of a spatial lag. This suggests that model (1) augmented with a spatially lagged dependent variable - i.e. model (2) - is the preferred specification, and that our estimates of model (1) in Table 1 may be inconsistent.

In Table 2, we therefore next consider model (2). As an alternative way to control for spatial autocorrelation, we also present results for model (3), which augments model (1) with spatially lagged explanatory variables.

Column (i) reproduces column (iv) of Table 1, i.e. our WG estimates of model (1), for comparison. In column (ii), we report WG estimates of model (2), where we treat the spatially lagged dependent variable $\sum_j w_{ij} \ln y_{jt}$ as endogenous and instrument it using two-stage least-squares.²⁷ Potential candidates for valid and informative instruments for this variable are its own time lags as well as the exogenous spatially lagged explanatory variables $\sum_j w_{ij} \ln s_{jt}$, $\sum_j w_{ij} \ln(n_{jt} + g + \delta)$ and $\sum_j w_{ij} agglom_{jt}$, or $\sum_j w_{ij} \mathbf{x}_{jt}$ for short, as explained in section 4.2.

When using the time lag of the spatially lagged dependent variable, $\sum_j w_{ij} \ln y_{j,t-1}$, as an instrument together with the spatially weighted explanatory variables, the Hansen test rejects the validity of this instrument set at the 5% level.²⁸ Therefore, in column (ii), we present estimates of model (2) using only the $\sum_j w_{ij} \mathbf{x}_{jt}$ as instruments, which the Hansen test does not reject at the 5% level. The AB-AR tests also point to an absence of serial correlation in the model residuals. The Kleibergen and Paap (2006) test indicates that the equation is identified, so that our instruments are likely informative, that is, correlated

²⁶We implement the tests for residual spatial autocorrelation using Jeanty’s (2010) `anketest` command for Stata.

²⁷We refer to this estimator as “two-stage least-squares within groups” (2SLS-WG) henceforth. All 2SLS estimation was carried out using Stata command `ivregress` as well as Baum, Schaffer and Stillman’s (2010) command `ivreg2` for Stata. WG estimates were obtained in this setup by including a full set of region dummies.

²⁸The p-value of the test is 0.019.

with $\sum_j w_{ij} \ln y_{jt}$.

Table 2: Models (1), (2), (3) - Within Groups and Two-Stage Least-Squares

Dependent variable:	(i)	(ii)	(iii)
$\ln y_{it}$	Model 1	Model 2	Model 3
	WG	2SLS-WG	WG
$\ln y_{i,t-1}$	0.638*** (0.060)	0.544*** (0.060)	0.639*** (0.065)
$\sum_j w_{ij} \ln y_{jt}$		0.694*** (0.125)	
$\ln s_{it}$	0.080*** (0.020)	0.047* (0.024)	0.044 (0.027)
$\ln(n_{it} + g + \delta)$	-0.009 (0.006)	-0.010* (0.006)	-0.007 (0.005)
$agglom_{it}$	0.145** (0.054)	0.160*** (0.045)	0.177** (0.056)
$\sum_j w_{ij} \ln s_{jt}$			0.122*** (0.017)
$\sum_j w_{ij} \ln(n_{jt} + g + \delta)$			-0.016* (0.008)
$\sum_j w_{ij} agglom_{jt}$			0.168 (0.281)
LR $agglom_{it}$	0.401*** (0.126)	0.350*** (0.075)	0.491*** (0.108)
AB-AR(1)	0.30 (0.764)	1.22 (0.223)	-0.28 (0.783)
AB-AR(2)	1.04 (0.297)	1.33 (0.185)	0.21 (0.835)
Hansen J		5.06 (0.080)	
Kleibergen-Paap rk		56.13 (0.000)	
Hausman		26.82 (0.000)	
Moran's I	3.88 (0.000)	-0.93 (0.351)	3.43 (0.001)
LM-Error	4.65 (0.031)	0.43 (0.510)	0.26 (0.608)
Robust LM-Error	0.28 (0.596)		1.84 (0.176)
LM-Lag	6.55 (0.011)		4.11 (0.043)
Robust LM-Lag	2.71 (0.100)		5.68 (0.017)
Time Dummies	Yes	Yes	Yes
Observations	528	528	528
Number of Regions	48	48	48

Notes: See notes to Table 1. Hansen J is the Hansen (1982) test of m overidentifying restrictions, asymptotically $\chi^2(m)$ under the null that the overidentifying restrictions are valid; Kleibergen-Paap rk is the Kleibergen and Paap (2006) test of the null that the equation is underidentified (LM version); Hausman is the robust regression-based version of the Hausman (1978) test used to test the null hypothesis that $\sum_j w_{ij} \ln y_{jt}$ is exogenous; p-values in parentheses for these three tests.

Instruments used in in column (ii) are $\sum_j w_{ij} \ln s_{jt}$, $\sum_j w_{ij} \ln(n_{jt} + g + \delta)$ and $\sum_j w_{ij} agglom_{jt}$.

Further, we report a Hausman test on the difference between the coefficient on the spatially lagged dependent variable $\sum_j w_{ij} \ln y_{jt}$ estimated by 2SLS-WG (column (ii)) and by WG treating the variable as exogenous (not shown).²⁹ According to the p-value of the test, the null hypothesis of no significant difference between these coefficient estimates - or equivalently, of zero correlation between the spatially lagged dependent variable and the model errors - is rejected. This suggests that $\sum_j w_{ij} \ln y_{jt}$ should indeed be considered endogenous.

Judging from Moran's I and the LM-Error test in column (ii), there is no evidence of remaining spatial autocorrelation in the residuals. Model (2) therefore appears to deal successfully with the spatial dependence present in our data. The coefficient estimate on the spatially lagged dependent variable ($\hat{\rho}$) in column (ii) is sizeable and highly significant. Its positive sign implies that a given increase in income per capita in a region's near neighbours as defined by our choice of \mathbf{W} also raises that region's own level of income per capita. Being located close to high-income regions is thus beneficial for a region's economic performance, which may be interpreted as evidence of positive spillovers emanating from high-income regions.

In column (iii) by contrast, the residual spatial autocorrelation tests show that model (3) does not fully capture the spatial correlation in the data. In particular, the LM-Lag test and its robust counterpart indicate a preference for a model that includes a spatially lagged dependent variable. We therefore conclude that of our two alternative spatial models, model (2) is a more suitable extension of model (1) for the purpose of allowing for spatial dependence.

The short- and long-run coefficients on our main variable of interest, $agglom_{it}$, are positive and significant in all three columns of Table 2. This supports our finding in Table 1 of a positive effect of agglomeration as measured by the topographic Theil index on short-run growth and steady-state income for our sample of CEE regions. Moreover, the point estimates all lie within each other's 95% confidence intervals across the three specifications. In column (ii), a one standard-deviation increase in agglomeration raises regional per-capita income by 15% in the long run, compared to our previous estimate of 17% in column (i) and 21% in column (iii). The implied annual speed of convergence in column (ii) is 61%.

The parameters on the remaining variables that are common to all three models also do not differ substantially across the columns. They are correctly signed and in model (2), they are all significant at least at the 10% level. In model (3), the coefficients on the investment share and the population growth rate are not significant, while their spatially lagged versions are. This is again suggestive of spillover effects between neighbouring regions in our sample. Thus, the results in column (iii) imply that a higher rate of capital

²⁹We use the regression-based version of the test, as outlined in Wooldridge (2002) for instance. It is asymptotically equivalent to the original Hausman (1978) test.

accumulation in surrounding regions raises a region's own income level, while faster population growth in nearby regions lowers it. The spatially lagged agglomeration index is insignificant. However, when considering our estimates of model (2), it seems that the spatially lagged explanatory variables in model (3) exert their influence on regional income mainly through their effect on spatially lagged income, rather than independently.

In sum, Table 2 suggests that our conclusions regarding the effect of agglomeration on income and growth are robust to accounting for spatial dependence. Consequently, we now move on to exploring the potential endogeneity of the explanatory variables \mathbf{x}_{it} , i.e. of $\ln s_{it}$, $\ln(n_{it} + g + \delta)$ and $agglom_{it}$. Due to the presence of significant spatial correlation in the residuals of model (1), we focus on model (2) for the remainder of this section.

In Table 3, column (i) contains the 2SLS-WG estimates of model (2) from the previous table. In columns (ii) to (iv), each of the \mathbf{x}_{it} is treated as endogenous in turn. As instruments, we use the first time lag of all \mathbf{x}_{it} , that is, $\ln s_{i,t-1}$, $\ln(n_{i,t-1} + g + \delta)$ and $agglom_{i,t-1}$, in addition to the $\sum_j w_{ij} \mathbf{x}_{jt}$ from above. To be valid, they must be uncorrelated with the error term v_{it} , which in turn must be serially uncorrelated. In all columns, the Hansen test of overidentifying restrictions does not reject the validity of our instrument set at the 5% level, and the AB-AR tests also provide no evidence of serial correlation in the residuals. From the Kleibergen-Paap test, we conclude that each equation is identified, albeit more marginally so in column (iii).

To test whether the \mathbf{x}_{it} can be individually considered uncorrelated with the error terms in columns (ii) to (iv), we implement Difference Hansen tests between these models and the benchmark model in column (i). Based on our instrument set, the tests indicate that each variable can be treated as exogenous, and we therefore continue to do so henceforth. Although the informativeness of our instruments for $\ln(n_{it} + g + \delta)$ could be questioned, there are few signs of bias and imprecision, which may arise as a consequence of weak instruments, in column (iii). Since alternative instruments are not easy to come by, we also continue to treat $\ln(n_{it} + g + \delta)$ as exogenous.

Nevertheless, the estimated short- and long-run effects of agglomeration on per-capita income in columns (ii) to (iv) remain positive, generally significant, and similar to - albeit slightly below - our tentatively preferred WG estimates in column (i). The long-run effect of a one standard-deviation increase in agglomeration on income in the last three columns is in the region of 11% to 13%, compared to 15% in the first. The estimates of γ in columns (ii) to (iv) suggest that implied speeds of convergence remain broadly similar to column (i) but decline slightly.

Table 3: Model (2) - Endogeneity of Explanatory Variables

Dependent variable:	(i)	(ii)	(iii)	(iv)
$\ln y_{it}$	2SLS-WG	2SLS-WG	2SLS-WG	2SLS-WG
Endogenous variables:	$\Sigma_j w_{ij} \ln y_{jt}$ and:	$\ln s_{it}$	$\ln(n_{it} + g + \delta)$	$agglom_{it}$
$\ln y_{i,t-1}$	0.544*** (0.060)	0.568*** (0.075)	0.579*** (0.074)	0.580*** (0.074)
$\Sigma_j w_{ij} \ln y_{jt}$	0.694*** (0.125)	0.903*** (0.156)	0.638*** (0.157)	0.640*** (0.163)
$\ln s_{it}$	0.047* (0.024)	-0.007 (0.023)	0.025 (0.020)	0.025 (0.021)
$\ln(n_{it} + g + \delta)$	-0.010* (0.006)	-0.008 (0.005)	-0.015 (0.009)	-0.008 (0.005)
$agglom_{it}$	0.160*** (0.045)	0.111** (0.046)	0.124*** (0.047)	0.113 (0.074)
LR $agglom_{it}$	0.350*** (0.075)	0.256*** (0.084)	0.293*** (0.086)	0.270* (0.163)
AB-AR(1)	1.22 (0.223)	0.59 (0.552)	0.34 (0.734)	0.42 (0.677)
AB-AR(2)	1.23 (0.185)	1.08 (0.282)	1.22 (0.221)	1.24 (0.217)
Hansen J	5.06 (0.080)	6.92 (0.140)	8.99 (0.061)	9.05 (0.060)
Kleibergen-Paap rk	56.13 (0.000)	39.11 (0.000)	9.38 (0.095)	63.86 (0.000)
Hausman/Dif-Hansen	26.82 (0.000)	1.62 (0.203)	0.00 (0.980)	0.01 (0.922)
Time Dummies	Yes	Yes	Yes	Yes
Observations	528	480	480	480
Number of Regions	48	48	48	48

Notes: See notes to Tables 1 and 2. Hausman, used in column (i), is the robust regression-based version of the Hausman (1978) test of the null hypothesis that $\Sigma_j w_{ij} \ln y_{jt}$ is exogenous; Dif-Hansen, used in columns (ii)-(iv), is the Difference Hansen test of the null hypothesis that each \mathbf{x}_{it} is exogenous; p-values in parentheses.

Instruments used in columns (i)-(iv) are $\Sigma_j w_{ij} \ln s_{jt}$, $\Sigma_j w_{ij} \ln(n_{jt} + g + \delta)$ and $\Sigma_j w_{ij} agglom_{jt}$. Additional instruments employed in each of columns (ii)-(iv) are $\ln s_{i,t-1}$, $\ln(n_{i,t-1} + g + \delta)$ and $agglom_{i,t-1}$.

In Table 4, we investigate our final estimation issue, the possible bias in the WG estimates given our time dimension $T = 11$. We contrast the familiar 2SLS-WG estimates of model (2) in column (i) with “parsimonious” FD- and S-GMM estimates in columns (ii) to (v). Following the discussion of the results in Table 3, we treat the right-hand side variables \mathbf{x}_{it} as exogenous. Thus, we include them in the instrument set for the first-differenced equations in columns (ii) to (v) in the same form as they appear in these equations, that is, as $\Delta \mathbf{x}_{it}$. Similarly, the exogenous spatially lagged explanatory variables enter this instrument set in first differences, as $\Delta \Sigma_j w_{ij} \mathbf{x}_{jt}$. Further, we include temporally lagged

levels of the dependent variable $\ln y_{it}$ dated $t - 2$ and $t - 3$.

As additional instruments for the equations in levels in column (iii), we use $\Delta \mathbf{x}_{it}$, $\Delta \sum_j w_{ij} \mathbf{x}_{jt}$ and $\Delta \ln y_{i,t-1}$. In column (iv), we examine the validity of $\Delta \ln y_{i,t-1}$, which may be called into question in light of the major transformation experienced by Eastern European economies during transition, by excluding it from the instrument set for the levels equations. In column (v), we do the same for $\Delta \sum_j w_{ij} \mathbf{x}_{jt}$. For both first-differenced and levels equations, the instruments available for each variable for all time periods are stacked into a single column in order to limit the number of instruments relative to the number of cross-sectional units.³⁰

In column (ii), some of the parsimonious FD-GMM estimates exhibit typical symptoms of weak instruments. For instance, the coefficient on the lagged dependent variable is substantially smaller than the baseline WG estimates in column (i) - which, if anything, we may suspect to be biased downwards - and the standard errors of the coefficients on $\ln y_{i,t-1}$, $\sum_j w_{ij} \ln y_{jt}$ and $agglom_{it}$ are considerably higher. This points to potential gains from using (parsimonious) S-GMM.

In column (iii), the Hansen and Difference Hansen tests neither reject the validity of our instruments for the first-differenced equations nor of the full set of additional instruments that we use for the levels equations (“Dif-Hansen, all levels IVs”). Also, the AB-AR tests detect significant negative first-order serial correlation in the first-differenced residuals, as expected, but no second-order serial correlation.

Some parameter estimates in column (iii) differ substantially from column (i). In particular, the coefficient on the lagged dependent variable is now considerably higher than the corresponding WG estimate. It implies an annual speed of convergence of 23% compared to 61% per year in column (i). However, if some of the additional instruments for the equations in levels are invalid, which may be the case for $\Delta \ln y_{i,t-1}$ for reasons outlined above, the estimate of γ in column (i) could be biased upwards. To test this, we carry out Difference Hansen tests between the model in column (iii) and those in columns (iv) and (v).

For $\Delta \ln y_{i,t-1}$, the test (“Dif-Hansen, $\Delta \ln y_{i,t-1}$ ”) clearly indicates that this instrument cannot be considered uncorrelated with the region-specific fixed effects. By contrast, the validity of the $\Delta \sum_j w_{ij} \mathbf{x}_{jt}$ is not rejected in column (v). These conclusions are congruent with the Difference Hansen tests of all additional instruments for the levels equations taken together (“Dif-Hansen, all levels IVs”) in the last two columns, which reject the validity of the instrument set containing only $\Delta \mathbf{x}_{it}$ and $\Delta \ln y_{i,t-1}$, but not of that containing $\Delta \mathbf{x}_{it}$ and $\Delta \sum_j w_{ij} \mathbf{x}_{jt}$.

On the basis of these instrument validity tests, the estimates in column (iv) appear to be the most reliable of all parsimonious GMM models in Table 4. A minor flaw is the

³⁰We implement this by using the option “ivstyle” instead of “gmmstyle” for the instruments in Roodman’s (2009) `xtabond2` command for Stata.

absence of strong evidence of first-order serial correlation in the residuals, but perhaps more importantly, there is also no strong evidence of second-order serial correlation.

Table 4: Model (2) - Parsimonious GMM

Dependent variable:	(i)	(ii)	(iii)	(iv)	(v)
$\ln y_{it}$	2SLS-WG	FD-GMM	S-GMM	S-GMM	S-GMM
Levels IV-set:			Full	Excl.	Excl.
				$\Delta \ln y_{i,t-1}$	$\Delta \Sigma_j w_{ij} \mathbf{x}_{jt}$
$\ln y_{i,t-1}$	0.544*** (0.060)	0.408** (0.177)	0.793*** (0.117)	0.510*** (0.196)	0.962*** (0.210)
$\Sigma_j w_{ij} \ln y_{jt}$	0.694*** (0.125)	0.469* (0.242)	0.170 (0.171)	0.529** (0.232)	0.093 (0.350)
$\ln s_{it}$	0.047* (0.024)	0.020 (0.016)	0.036** (0.017)	0.017 (0.014)	0.028 (0.021)
$\ln(n_{it} + g + \delta)$	-0.010* (0.006)	-0.001 (0.002)	-0.003 (0.002)	-0.003 (0.002)	-0.003 (0.003)
$agglom_{it}$	0.160*** (0.045)	0.281** (0.118)	0.092* (0.048)	0.170** (0.069)	0.042 (0.064)
LR $agglom_{it}$	0.350*** (0.075)	0.475** (0.231)	0.448** (0.191)	0.347*** (0.091)	1.101 (4.889)
AB-AR(1)	1.22 (0.223)	-1.31 (0.191)	-1.94 (0.052)	-1.49 (0.136)	-1.92 (0.055)
AB-AR(2)	1.23 (0.185)	1.41 (0.159)	1.60 (0.109)	1.48 (0.139)	1.55 (0.120)
Hansen J		1.61 (0.657)	11.53 (0.318)	5.93 (0.747)	11.28 (0.127)
Dif-Hansen, all levels IVs			10.36 (0.169)	4.55 (0.603)	10.48 (0.033)
Dif-Hansen, $\Delta \ln y_{i,t-1}$				5.60 (0.018)	
Dif-Hansen, $\Delta \Sigma_j w_{ij} \mathbf{x}_{jt}$					0.25 (0.969)
Time Dummies	Yes	Yes	Yes	Yes	Yes
Observations	528	432	480	480	480
Number of Regions	48	48	48	48	48
Number of Instruments		17	25	24	22

Notes: See notes to Table 1. GMM estimators are two-step estimators; GMM standard errors are robust to heteroskedasticity and serial correlation (clustered on regions), and they are corrected for small-sample bias as suggested by Windmeijer (2005); Hansen J and Dif-Hansen are the Hansen (1982) and Difference Hansen tests of overidentifying restrictions, p-values in parentheses.

Columns (ii)-(v): Instruments used for the first-differenced equations are $\ln y_{i,t-2}$, $\ln y_{i,t-3}$, $\Delta \Sigma_j w_{ij} \ln s_{jt}$, $\Delta \Sigma_j w_{ij} \ln(n_{jt} + g + \delta)$, $\Delta \Sigma_j w_{ij} agglom_{jt}$, $\Delta \ln s_{it}$, $\Delta \ln(n_{it} + g + \delta)$ and $\Delta agglom_{it}$.

Column (iii): Additional instruments used for the levels equations are $\Delta \ln y_{i,t-1}$, $\Delta \Sigma_j w_{ij} \ln s_{jt}$, $\Delta \Sigma_j w_{ij} \ln(n_{jt} + g + \delta)$, $\Delta \Sigma_j w_{ij} agglom_{jt}$, $\Delta \ln s_{it}$, $\Delta \ln(n_{it} + g + \delta)$ and $\Delta agglom_{it}$.

Column (iv): $\Delta \ln y_{i,t-1}$ is excluded from the instruments used for the levels equations in column (iii).

Column (v): $\Delta \Sigma_j w_{ij} \ln s_{jt}$, $\Delta \Sigma_j w_{ij} \ln(n_{jt} + g + \delta)$ and $\Delta \Sigma_j w_{ij} agglom_{jt}$ are excluded from the instruments used for the levels equations in column (iii).

All instruments are implemented as “ivstyle” instruments in Roodman’s (2009) `xtabond2` command for Stata.

The parsimonious S-GMM estimates in column (iv) are quite similar to the 2SLS-WG estimates in column (i) that we have focused on so far. In particular, both short- and long-run coefficients on $agglom_{it}$ are almost identical, with a long-run effect of a one standard-deviation increase in agglomeration on regional income of around 15%.³¹ Further, the implied speed of convergence and the role of the spatially lagged dependent variable are very similar, while the estimated coefficients on the other explanatory variables in column (iv) are not dramatically different from those in column (i). This supports the view that the length of the time dimension in our panel may not be a source of important bias in our WG estimates, especially regarding the long-run effect of agglomeration, so that the results in column (i) remain our preferred estimates overall.

To summarise, for our sample of CEE regions, the preferred results point to sizeable benefits of agglomeration for long-run income that appear to manifest themselves quickly. Whether they are due to pecuniary externalities or to localised knowledge spillovers in the research sector, as in the theoretical models discussed in section 2, these benefits suggest that a strategy of fostering the geographic concentration of economic activity within regions, e.g. by encouraging the formation of industrial clusters, holds considerable promise for regional growth in Eastern Europe. On the other hand, the benefits of agglomeration may come at the cost of greater within-region inequality, which implies that policy makers could have to trade off fostering regional growth on aggregate against achieving a balanced development of different areas within regions. Martin (1999) has noted this trade-off in the context of EU policy. Ultimately, it makes the European Union’s goals of growth, as expressed in the Lisbon and Europe 2020 Strategies, and catch-up of its least developed regions, highlighted by the convergence objective of EU regional policy, appear to conflict for Central and Eastern Europe.

7 Conclusion:

This paper studies the effect of agglomeration on economic growth for a panel of 48 NUTS-2 regions from Central and Eastern Europe over the period 1995 to 2006. Although a body of theory has recently emerged that analyses this relationship, empirical work has remained scarce and focused on Western Europe. Since both growth and the geographic concentration of economic activity have been high in Central and Eastern Europe, we fill a gap in the existing literature by considering a set of regions that is of particular interest for the topic under investigation.

In addition, our measure of agglomeration, which is defined in this paper as the spatial concentration of aggregate employment within regions, differs from some others that have been employed in the recent empirical literature on agglomeration and growth. We use the topographic Theil index of Brühlhart and Traeger (2005), which measures the distribution

³¹It is worth noting that in column (iii), this long-run effect is, at 19%, also not radically different.

of total employment across the NUTS-3 subregions of each NUTS-2 region relative to the distribution of the NUTS-3 region areas within each NUTS-2 region. In contrast to so-called absolute concentration indices, we are thus able to account at least for differences in region areas when measuring agglomeration. Finally, we use panel data estimation methods that allow us to address the presence of region-specific fixed effects, the possible endogeneity of explanatory variables and spatial correlation in the data.

Our empirical analysis provides evidence that agglomeration has a positive effect on short-run economic growth that is both statistically and economically significant. We show that this result is fairly robust across alternative estimation methods. Our preferred estimate of the long-run coefficient on agglomeration implies that in Eastern Europe, a NUTS-2 region that is more agglomerated by about one standard deviation of the Theil index - roughly equivalent to the difference between the two most agglomerated Polish regions - benefits from a 15% increase in steady-state income per capita.

We therefore conclude that encouraging agglomeration in Central and Eastern European regions could contribute substantially to raising their prosperity in the long term. However, while this may be true for the CEE NUTS-2 regions on aggregate, a further increase in their already high levels of geographic concentration of economic activity - and thus plausibly of income and wealth - may also raise important issues of intra-regional equity.

One limitation of the empirical analysis in this paper and in the existing empirical literature is a gap to the theoretical models on agglomeration and growth. To be fully consistent with these, one would need to examine the effect of agglomeration on the *long-run* rate of growth, i.e. on the growth rate of total factor productivity. The construction of reliable TFP indices for CEE regions will, however, require longer time series than are currently available, since for the calculation of capital stocks, reliable initial-period investment data are essential.

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Appendices

A List of Regions

Country	Code	Region Name (NUTS-3)	Country	Code	Region Name (NUTS-3)
Bulgaria	BG31	North West (5)	Poland	PL11	Lodz Province (3)
	BG32	North Central (5)		PL12	Masovia Province (5)
	BG33	North East (4)		PL21	Lesser Poland Province (3)
	BG34	South East (4)		PL22	Silesia Province (4)
	BG41	South West (5)		PL31	Lublin Province (3)
	BG42	South Central (5)		PL32	Subcarpathia Province (2)
Czech Republic	CZ01+	Prague+		PL34	Podlasie Province (2)
	CZ02	Central Bohemia (2)		PL41	Greater Poland Province (5)
	CZ03	South West (2)		PL42	West Pomerania Province (2)
	CZ04	North West (2)		PL43	Lubusz Province (2)
	CZ05	North East (3)		PL51	Lower Silesia Province (4)
	CZ06	South East (2)		PL61	Kuyavia-Pomerania Province (2)
	CZ07	Central Moravia (2)		PL62	Warmia-Masuria Province (3)
				PL63	Pomerania Province (3)
Estonia	EE00	Estonia (5)	Romania	RO11	North West (6)
Latvia	LV00	Latvia (6)		RO12	Centre (6)
Lithuania	LT00	Lithuania (10)		RO21	North East (6)
				RO22	South East (6)
Hungary	HU10	Central Hungary (2)		RO31	South (7)
	HU21	Central Transdanubia (3)		RO32	Bucharest-Ilfov (2)
	HU22	Western Transdanubia (3)		RO41	South West (5)
	HU23	Southern Transdanubia (3)	RO42	West (4)	
	HU31	Northern Hungary (3)	Slovenia	SI00	Slovenia (12)
	HU32	Northern Great Plain (3)		Slovakia	SK01+
HU33	Southern Great Plain (3)	SK02			Western Slovakia (4)
		SK03	Central Slovakia (2)		
			SK04	Eastern Slovakia (2)	

Notes: The number of NUTS-3 sub-regions for each NUTS-2 region is given in parentheses. NUTS-2 regions comprising the national capitals are given in bold font. For Estonia, Latvia, Lithuania and Slovenia, NUTS level 2 coincides with the country level.

B Summary Statistics

Table B.1: Summary Statistics

Variable		Mean	Std. Dev.	Min.	Max.	Observations
y_{it}	overall	7843	3115	2720	22322	$N = 576$
	between		2906	3305	17765	$n = 48$
	within		1192	3697	12401	$T = 12$
$\Delta \ln y_{it}$	overall	0.034	0.054	-0.336	0.262	$N = 528$
	between		0.018	0.007	0.090	$n = 48$
	within		0.051	-0.315	0.240	$T = 11$
s_{it}	overall	0.240	0.067	0.038	0.473	$N = 576$
	between		0.054	0.075	0.342	$n = 48$
	within		0.040	0.114	0.415	$T = 12$
n_{it}	overall	-0.003	0.005	-0.050	0.011	$N = 528$
	between		0.004	-0.018	0.003	$n = 48$
	within		0.004	-0.039	0.007	$T = 11$
$agglom_{it}$	overall	0.263	0.428	0	1.466	$N = 576$
	between		0.431	0	1.430	$n = 48$
	within		0.031	0.042	0.385	$T = 12$

Table B.2: Correlation Matrix

	$\ln y_{it}$	$\Delta \ln y_{it}$	$\ln s_{it}$	$\ln(n_{it} + g + \delta)$	$agglom_{it}$
$\ln y_{it}$	1				
$\Delta \ln y_{it}$	0.2395***	1			
$\ln s_{it}$	0.3400***	0.2556***	1		
$\ln(n_{it} + g + \delta)$	0.1164***	-0.0330	0.2787***	1	
$agglom_{it}$	0.4133***	0.2482***	0.2505***	0.0684	1

Notes: *** indicates significance at the 1% level.