GEOGRAPHY, COST-OF-LIVING, AND DETERMINANTS TO ECONOMIC GROWTH: A STUDY OF THE SWEDISH REGIONS, 1911-1993

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Geography, Cost-of-Living, and Determinants to Economic Growth: A Study of the Swedish Regions, 1911-1993*.

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Abstract

This paper analyses determinants to economic growth with a spatial perspective using data on the Swedish counties for the period 1911-1993. We find that the county growth rate of income per capita is strongly related to the growth rate of income per capita in contiguous counties regardless of what explanatory variables are included in the regressions. We also find empirical evidence of geographical spillovers through the income per capita and market size in contiguous counties. In addition, we find that population density and population age structure impact the growth rate of income per capita only when incomes are not adjusted for regional differences in cost-of-living. When correctly adjusting for such differences, which rarely occur in the growth literature that uses regional data, the growth effects of these variables disappear. The regressions also show that the estimated growth effect of net in-migration is negative and statistically significant.

Keywords: Spatial econometrics; Spillovers; Economic Growth; PPP-adjustment; Agglomeration; Population Age Structure; Migration
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1. Introduction

During the past fifteen years a large number empirical studies have investigate determinants to economic growth (see e.g. Durlauf and Quah, 1999, and Temple, 1999). However, as noted by e.g. Temple (1999), these studies typically make an assumption of independent observations. In other words, they assume that the growth rate in different locations are independent of each other. Some deviations from this assumption do, however, exist: Moreno and Trehan (1997) which is a country study; Montouri and Rey (1999) who use the US-states data set. Further, Armstrong (1995), and Chattrerji and Dewhurst (1996) takes geography into account when analysing Great Britain and López *et al* (1999) apply a spatial approach when studying convergence dynamics across European regions.

When theoretically analysing geographical spillovers, Alfred Marshall (1920) argued that the decision of where to locate industrial activities is affected by three different categories of returns to agglomeration. Briefly, he argued for (1), knowledge spillovers that loosely speaking are in the air, (2), forward and backward linkages (today formalised in the new economic geography literature)[1] and, (3), labour market pooling. For the first and second, distance is implicitly involved whereas the size of cities are central for the latter.

In the theoretical growth literature, technological spillovers are present in some models (see, e.g., Barro and Sala-i-Martin; 1995, Ch. 8 for a leader follower model, and Aghion (1999) for technology transfer models). Reasons to believe that knowledge is to some extent locally bounded are put forward as five 'stylised facts' by Dosi (1988), and further developed by Feldman (1994a, 1994b) and Baptista and Swann (1998). Finally, there exists a growing literature that focuses on the spatial dimension of economic growth; some recent examples are Amiti (1998) and Hanson (1998) who focus on the concentration of industrial activities in Europe and the US, respectively. In a recent book by Marjolein (2000) some theoretical modelling (and a brief survey) of knowledge spillovers across space is presented.

This paper is a regional growth study on the twenty-four Swedish Counties for the period 1911-1993. By taking geography as well as other determinants to economic growth into account, this paper substantially extends the unconditional convergence study by Persson (1997).

When analysing spatial interdependency in regional income per capita growth rates, we find robust and significant evidence for spatially autocorrelated growth rates; that is, growth rates in one county are found to be dependent on growth rates in contiguous counties. We also find additional channels of geographical growth spillovers, these are, the income per capita, and the market size in contiguous counties. These channels are also investigated by Moreno and Trehan (1997), and by Montouri and Rey (1999). (The latter do, however, only

[1] See e.g. Krugman, Fujita and Venables (1999).

investigate the income per capita channel.) In sum, we find evidence for both income and market size spillovers but, due to collinearity, it is hard to distinguish between them.

The data set collected by Alan Heston and Robert Summers attempt to control for differences in price levels across countries. In regional studies it is rare that incomes are PPP-adjusted. In contrast, this paper uses regional incomes that are adjusted for regional differences in cost-of-living (see Persson, 1997). In view of the fact that regional growth studies typically do not adjust regional incomes for regional price differences, this paper reports regression results based on both non-adjusted and cost-of-living adjusted incomes.

An interesting result that appears is that age structure, which is often not taken into account in empirical growth studies included in convergence studies, is correlated with the regional cost of housing. In particular, we find the share of population older than 65 and younger than 15 years to be negatively related to the economic growth rate when the non-adjusted income data are used but insignificant when the cost-of-living adjusted income data is used. Moreover, we find that agglomeration, measured by population density, has a positive effect on the growth rate of income per capita only for the unadjusted income data. Obviously, population density is correlated with the cost-of-living. Among the control variables, only the net migration rate is found to have a (negative) robust impact on per capita income growth independently whether income is PPP-adjusted or not.

The contributions in this paper include: (I) a thorough investigation of the largely ignored spatial dependence; (II) an analysis of the spatial pattern of growth spillovers through income and market size; (III) an analysis that based on income data that are both adjusted and non-adjusted for regional differences in the cost-of living.

The paper is organised as follows. In section 2 we describe the data and perform an exploratory data analysis. In section 3 we present the empirical analysis. Concluding remarks are in section 4.

2. Data and Exploratory Data Analysis

We use regional income data on the twenty-four Swedish Counties for the period 1911-1993. The sample period is split up into eight roughly 10-year periods. Thus, we use a panel data set. We end the sample period in 1993 partly to obtain sub periods of roughly equal size and partly because of a reform in 1997-1998 that reduced the number of counties from 24 to 21 counties. The income concept is real per capita income net of taxable government transfers. There are no official regional price indices for Sweden. However, we make use of cost-of-living adjusted incomes based on Persson (1997). Persson (1997) shows that the main reason to the county differences in price levels is due to county differences in the cost-of-housing. As a result, the cost-of-living adjustment is mainly based on the cost of housing.

We first analyse geographical or spatial dependence between the counties' per capita income growth rates; that is, we analyse whether a county's growth rate of per capita income is correlated with the growth rates of its neighbouring counties[2]. To be more precise, we study the spatial dependence between the growth rate of per capita income (g) and the average growth rate of neighbouring counties - the so-called spatial lag (Wg). W is a square, block diagonal matrix, with the number of rows and columns in each block equal to the number geographical units. The element w_{ij} reflects the assumed spatial dependence between locations i and j. Thus, the values of the matrix are assumed a priori. We let W to be a first order contiguity matrix, which means that $w_{ij} = 1$ if county i and j share a common border and $w_{ij} = 0$ otherwise.[3] Spatial dependence is measured by the Moran I statistic[4] and found to be statistically significant (p-value = 0.005[5]) with a value of 0.24. Thus, counties with high (low) growth rates tend to be located near counties with high (low) growth rates, more than would be expected due to randomness.

Figure 1 and 2 provide a more detailed picture on spatial dependence. *Figure* 1 plots the average annual growth rate of per capita income, (growth) and the growth rate of neighbouring counties, (W·growth). In *Figure 1* and *2* the observations are ordered so that within each time period there are twenty-four observations. Each observation represents one county. One conclusion we draw from *Figure 1* is that it appears to be a greater variation in the growth rate over time than over counties. This result indicates that that Sweden is a rather well-integrated economy, which should come as no surprise. The sample variance of the growth rate of per capita income between and within time periods is 0.00035 and 5.1E-05 respectively. This may be taken as an indication of an integrated economy.

Figure 2 plots the local Moran statistics. It indicates for each location whether it is spatially autocorrelated with its neighbours. Thus, for each observation this statistic gives an indication of the extent of significant spatial clustering of similar values around that observation[6]. We calculate one local Moran statistic for each county and time period. *Figure 2* plots both the local Moran statistics and their corresponding z-values. The z-value follows a standard normal

[2] Spatial dependence is sometimes called spatial autocorrelation.
[3] The only island in the sample, Gotland, is treated as an isolated observation in the weight matrix W.
[4] Cliff and Ord, (1972, 1973, 1981).
[5] All spatial tests and regressions were obtained using *SpaceStat*, Anselin (1995). The p-value is based on 2000 permutations. Moreover, if we use unadjusted incomes we also find a positive and significant spatial interdependence for the growth rate of per capita income.
[6] The average of the local Moran statistics will equal the global Moran I statistic, up to a factor of proportionality.

distribution. In order to obtain roughly the same amplitude between the local Moran statistic and its z-value, the local Moran statistic is multiplied by a factor of five. Several observations can be made from *Figure* 2. First, the spatial autocorrelation tends to be non-negative. Second, the degree of spatial autocorrelation varies across time periods. For example, the periods 1911-1921, 1940-1950 and 1980-1993 are characterized by relatively high positive spatial dependency. Third, there is a greater variation in spatial dependence over time than over counties (within a given time period): The sample variance in the local Moran statistic, between and within time periods is 0.35 and 0.06, respectively. Fourth, there appears to be no time trend (upward or downward) in the degree of spatial dependence. Moreover, from *Figure 1* and *2* we see that for most time periods, except for the 1980s, high growth is associated with a high degree of positive spatial dependence. (The sample correlation between the growth rate of per capita income and the local Moran statistics is 0.71 (p-value=0.00) for the period 1911-1980. However, for the whole sample period the corresponding sample correlation is practically zero, 0.01). The 1980s is an exception in the sense that despite a low average growth rate of per capita income, there is a statistically significant strong positive spatial dependence.

Fig 1. Per capita income growth and its spatial lag.

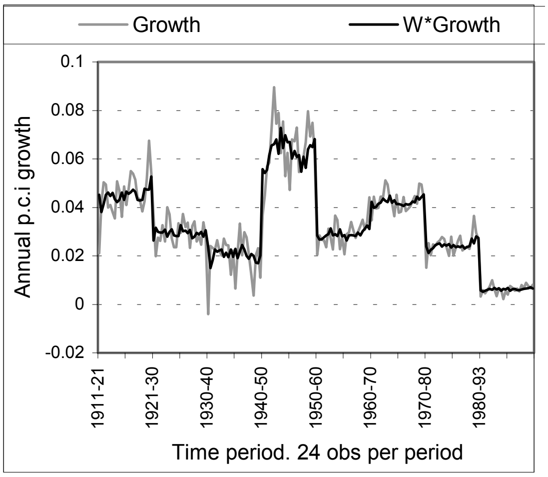
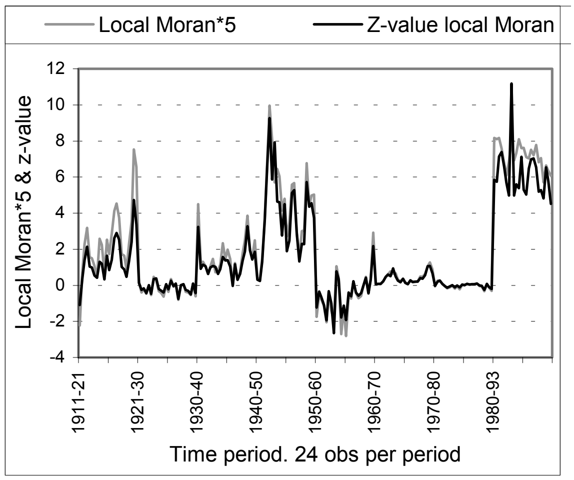


Fig 2. The local Moran statistic.



An alternative way to view the data is to study maps. *Figure A1* shows the counties' per capita incomes for 1911, 1960, and 1993. Even though we do not present any statistical test there appear to be spatial clustering with respect to per capita income. As there is strong empirical evidence of unconditional income convergence (as shown previously by Persson, 1997), *Figure A1* indirectly also indicate spatial clustering with respect to growth rates. *Figure A1* also shows that the income ranking when the cost of living adjustment is invoked. For example, comparing cost of living adjusted income with unadjusted income in 1993, we can see that the ranking, with respect to per capita income, changes for the upper north of Sweden. When differences in cost of living are accounted for the sparsely populated upper north belong to the class of counties with the highest per capita income.

3. Empirical Results

3.1. Unconditional convergence analysis

In this section we contrast the results from the standard unconditional convergence regression, which do not allow for spatial dependence, to the results from unconditional convergence regressions, which do allow for such dependence. To test for unconditional convergence across counties the following equation is estimated:

$$(1/T)\ln(y_{i,t+T} / y_{i,t}) = \alpha_t + \beta_t \ln(y_{i,t}) + \varepsilon_{i,t} \quad (1)$$

where t = 1911, 1921, 1930, 1940, 1950, 1960, 1970, and 1980. T is the length of the sample period, y_{it} is county i's income per capita at time t, $\varepsilon_{i,t}$ is the error term, α_t is the time-varying intercept, and β is the convergence parameter.

The results from unconditional convergence regressions that do not account for spatial dependence are reported in columns 1 and 4 of *Table 1*. Column 1 report the results based on incomes that are adjusted for regional differences in cost of living, and column 4 reports results based on income that are not adjusted for such differences. The results displayed in column 1 indicate that convergence occurs in most 10-year periods. Only in the 1920s and 1980s, there is a lack of convergence. We may note that the 1920s was a period with falling relative prices of agricultural products that hurt the relatively poor agricultural counties most. Column 4 gives the same qualitative results.

Introducing spatial effects

We allow for spatial interdependency in the unconditional convergence regressions both by including neighbours' growth rates as an explanatory variable and by a spatially interdependent error term (common shocks). These models, the spatial lag model and the spatial error model, are[7]:

$$(1/T)\ln(y_{i,t+T} / y_{i,t}) = \alpha_t + \beta_t \ln(y_{i,t}) + \rho\ W_i^r (1/T)\ln(y_{i,t-Y} / y_{i,t}) + \upsilon_{i,t} \quad (2.1)$$

$$(1/T)\ln(y_{i,t+T} / y_{i,t}) = \alpha_t + \beta_t \ln(y_{i,t}) + \varepsilon_{i,t}\ ;\ \varepsilon_{i,t} = \lambda\ W_i^r \varepsilon_{i,t} + \upsilon_{i,t} \quad (2.2)$$

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[7] Anselin (1988) describes the relationship between these two models as well as provides a survey of spatial models in general.

where W^r is a row standardised first order contiguity matrix. Row standardising means that each row sums to one, which implies that the coefficient of spatial dependence, ρ, is bounded from above by one. λ measures error dependency, $\varepsilon_{i,t}$ is the spatially autocorrelated error term, and v_{it} is white noise.

To estimate the spatial lag model, we use a 2SLS-estimator that allows for time wise heteroscedasticity[8] and to estimate the spatial error model, we use a GMM-estimator that also allows for time wise heteroscedasticity[9].

The results reported in *Table 1* indicate the presence of significant spatial dependency, regardless of model (spatial lag or error)[10]. The interpretation of an estimated spatial lag parameter of 0.0997 (t-value=3.19) is as follows: if the average growth rate of per capita income in neighbouring locations increases by one percentage point we expect the per capita income to grow by 0.0997 percentage points. For the spatial error model, the interpretation is: for a given average (growth) shock to neighbours of one unit, the county is expected to be hit by a shock of λ units. The estimated λs are found to be in the neighbourhood of 0.24 (0.34) when using PPP-adjusted (unadjusted) income. Moreover, when comparing these models by LM-tests (reported on the last row), we see that the coefficient measuring spatial error dependency is statistically significant at a higher level than the spatial lag coefficient.

A common result from all regressions (conditional and unconditional) is that when basing the regressions on *unadjusted income,* the parameter measuring spatial dependence is larger (and more significant). Therefore, adjusting income for regional cost of housing may pick up some spatial effects. Considering that income per capita is spatially clustered and that cost-of-living is correlated with per capita income level, this result is logical. It is further supported by a Moran's I-statistic on the cost of housing index, which indicates positive spatial autocorrelation (p=0.000).

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[8] IV-based (robust) spatial estimators use spatial lagged transformations of independent variables as instruments.

[9] Kelejian and Prucha, (1999).

[10] In addition to the contiguity matrix, we also tried alternative weight matrices where $w_{ij} = d_{ij}^{-k}$, $k>0$, and d_{ij} is an estimate of the travel time by car (1996) from location i to j. Setting $k = 2$ gave results similar to those produced by the contiguity matrix. Finally, we tried with GDP weighting such that w_{ij} is increasing in GDP_j and decreasing in d_{ij}. The logic behind this weighting is that, for a given distance between location i and j, county i should be more affected of county j the bigger GDP is in j. This specification did not improve the performance.

Table 1:
Dependent variable: average annual growth rate of income per capita.

	PPP-adjusted income			Unadjusted income		
Model Estimator	**OLS**	**Spatial lag[A] 2SLS-G[B]**	**Spatial error GMM-G**	**OLS**	**Spatial lag[A] 2SLS-G**	**Spatial error GMM-G**
Variable	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)
y(1911)	-0.019 (-6.66)	-0.019 (-5.53)	-0.019 (-5.02)	-0.017 (-6.31)	-0.016 (-5.13)	-0.017 (-4.65)
y(1921)	-0.004 (-1.20)	-0.004 (-1.14)	-0.004 (-0.94)	-0.004 (-1.13)	-0.004 (-1.09)	-0.003 (-0.83)
y(1930)	-0.020 (-5.94)	-0.021 (-4.43)	-0.023 (-5.07)	-0.022 (-6.67)	-0.020 (-4.78)	-0.025 (-5.59)
y(1940)	-0.048 (-11.49)	-0.047 (-9.38)	-0.047 (-9.31)	-0.045 (-11.45)	-0.043 (-9.72)	-0.045 (-9.40)
y(1950)	-0.027 (-3.72)	-0.027 (-4.51)	-0.025 (-3.70)	-0.018 (-2.66)	-0.024 (-4.62)	-0.017 (-3.24)
y(1960)	-0.038 (-4.18)	-0.040 (-10.76)	-0.037 (-11.26)	-0.023 (-2.92)	-0.032 (-8.56)	-0.024 (-6.79)
y(1970)	-0.056 (-3.93)	-0.057 (-13.17)	-0.054 (-11.28)	-0.045 (-4.40)	-0.036 (-9.34)	-0.042 (-12.37)
y(1980)	-0.013 (-0.44)	-0.014 (-1.32)	-0.010 (-1.00)	0.001 (0.07)	-0.015 (-2.83)	0.001 (0.28)
W^r*e			0.2350			0.340
W^r*g		0.0997 (3.19)			0.1086 (2.98)	
R^2. (Sq. Corr)	0.940	0.942 (0.946)	0.943 (0.939)	0.933	0.942 (0.940)	0.936 (0.932)
p-value. LM-test spat error (lag) dependence[C]	0.002 (0.077)			0.000 (0.036)		

Notes to *Table 1*: Weight matrix W^r = Row standardised first order contiguity matrix.
192 observations in each model. Time effect (not reported) in all models.
g = mean annual growth in per capita income.

[A] Instruments: Spatially lagged; income per capita, GDP, population shares of young and old people, agglomeration, the population growth rate, and the net migration rate.

[B] "G" indicates that the estimator allows for heteroscedasticity over time.

[C] No t-value is available for the error parameter in the GMM-estimations. As a result, we report a separate test of spatial dependence in the last row the table.

3.2. Conditional convergence analysis

We now proceed to estimate conditional convergence regressions that among other things, allows us to investigate some specific sources of spillovers. The theoretical framework is based on the neoclassical growth model. More specifically, following the main idea behind Persson (1999), in which the population age structure is an additional determinant to the steady state equilibrium in the Mankiw, Romer, and Weil (1992) model, yields the following conditional convergence regression equation:

$$(1/\mathrm{T})\ln(\mathrm{y}_{\mathrm{i,t+T}}/\mathrm{y}_{\mathrm{i,t}}) = \alpha_t + \beta_t \cdot \ln(y_{i,t}) + c_1 \cdot n_{0-14,i,t} + c_2 \cdot n_{65+,i,t} + \theta \cdot X_{i,t} + \varepsilon_{i,t} \qquad (3)$$

where n_{0-14} is the young dependency ratio; that is, the number of people below the age of 15 divided by the number of people aged 15-64 years. n_{65+} is the old dependency ratio: the number of people over 65 years divided by the number of people aged 15-64 years. $X_{i,t}$ is a matrix of additional explanatory variables, and θ is its coefficient vector. The regression coefficients of the age structure variables and of the other explanatory variables are time-invariant.

We expect that increasing dependency ratios to have a negative effect on the growth rate of income per capita over the next ten years as higher dependency ratios imply a smaller part of the population in production.[11]

To investigate channels for growth spillovers we include neighbouring counties' market size and income per capita. Further, the population density is included as a measure of the level of agglomeration, which from the new economic geography literature is likely to have a positive effect on the economic growth rate.[12]

3.2.1. Results

The Population Age Structure and Agglomeration

Table 2 shows that when using accost-of-living adjusted income data the age structure variables do not have statistically significant effects on the economic growth rate. In contrast, when using unadjusted income data the estimated coefficients on the dependency ratios turns out to be negative and statistically significant indicating that the age structure is correlated with the cost-of-housing index. To estimate the strength of the connection between demography and the cost-of-living we perform a regression with the old dependency ratio (young dependency ratio) as the dependent variable and the cost of living index and

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[11] It is also possible that a large share of dependents reduce the time spent in production of the people of the working-age (15-64 years) as they may divert time away from market production to household production (see Barro and Sala-i-Martin, 1995, p. 438).

[12] See e.g. Fujita *et al,* (1999)

period dummies as the independent variables. The regression yields an estimated coefficient on the cost-of-living index of –0.84 (-0.22) with a t-value of –12.0 (-1.24) for the share of old (young) people. Thus, the old dependency ratio is, in a statistically significant way, related to the cost-of-living. Old people tend to live in regions with low cost of housing. Thus, using non-adjusted incomes together with age structure variables appears to pick up differences in cost-of-living.

Using PPP-adjusted income, the estimated growth impact of agglomeration on growth is negative but only (marginally) statistically significant in one of three regressions. When using unadjusted incomes, the estimated growth effect of population density turns out negative and statistically significant. Thus, population density appears to have a positive growth effect but when controlling for regional differences in cost of living this positive estimated growth impact disappears. The correlation between cost of living and population density is, not surprisingly, positive; that is, a high population density is associated with a high cost of living. Regressing population density on the cost of housing index (together with time dummies) yields an estimated coefficient on the cost of housing index of 0.0002(t-value=4.88).

Population growth and migration

In the regressions in *Table 2* we decomposes population growth into: the average annual population growth rate (net of migration flows) and the net in-migration rate. These variables are measured over each time period; that is, contemporaneously with the growth rate of income per capita. To account for potential endogeniety problems, IV estimation is used in regressions that include these variables (see notes to *Table 2*). [13]

The estimated coefficient on the population growth rate net of migration is statistically insignificant when using PPP-adjusted incomes, which is not unusual in the literature. The surveys of Fagerberg (1994) and of Durlauf and Quah (1999) report inconclusive country evidence regarding the impact of population growth on the rate of economic growth. We also note that the estimated coefficient turn positive and statistically significant when non-adjusted incomes are used. In view of the previous result that the age structure is correlated with the cost of housing, it is not surprising that we also find that the natural population growth rate is correlated with the cost of housing.

The estimated impact of the net in-migration rate on the growth rate of income per capita is negative and statistically significant regardless of whether incomes are adjusted for regional differences in cost of living or not. This empirical result thus indicates that net in-migration lowers the growth rate of income per capita. In other words and loosely speaking, rich counties, which tend to be net receivers of migrants, are on average hurt in terms of income per capita income

[13] The R^2 -values for the first-stage regressions are 0.59 and 0.45, respectively.

Table 2: Dependent variable: Average annual growth rate of income per capita.

Income concept	PPP-adjusted income			Unadjusted income		
Model **Estimator**	**Mod c1** **GMM-G**	**Mod c2** **GMM-G**	**Mod c3** **GMM-G**	**Mod c1** **GMM-G**	**Mod c2** **GMM-G**	**Mod c3** **GMM-G**
Variable	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)	Coeff (t-value)
y(1911)	-0.020 (-4.77)	-0.017 (-4.26)	-0.017 (-4.37)	-0.218 (-5.35)	-0.019 (-4.97)	-0.020 (-5.08)
y(1921)	-0.005 (-1.11)	-3.0E-4 (0.06)	-9.9E-05 (-0.02)	-0.009 (-2.33)	-0.004 (-0.98)	-0.004 (-1.03)
y(1930)	-0.024 (-5.00)	-0.019 (-3.83)	-0.020 (-3.87)	-0.032 (-6.76)	-0.027 (-5.34)	-0.027 (-5.36)
y(1940)	-0.048 (-9.15)	-0.038 (-5.92)	-0.038 (-5.96)	-0.052 (-10.79)	-0.043 (-7.28)	-0.043 (-7.27)
y(1950)	-0.025 (-3.47)	-0.011 (-1.32)	-0.011 (-1.37)	-0.027 (-4.62)	-0.015 (-2.04)	-0.015 (-2.06)
y(1960)	-0.036 (-8.62)	-0.020 (-2.60)	-0.020 (-2.64)	-0.035 (-8.11)	-0.022 (-3.16)	-0.022 (-3.15)
y(1970)	-0.050 (-8.23)	-0.072 (-8.03)	-0.071 (-7.96)	-0.059 (-10.75)	-0.067 (-10.01)	-0.067 (-10.03)
y(1980)	-0.003 (-0.24)	-0.023 (-2.01)	-0.022 (-1.87)	-0.026 (-2.78)	-0.026 (-3.040)	-0.025 (-2.97)
W^r*e	0.212	0.233	0.2511	0.3443	0.3241	0.3214
W^r*y		8.5E-04 (3.00)			8.0E-04 (2.94)	
W^r*ln GDP			1.6E-04 (2.78)			1.6E-04 (2.76)
Share age < 15 years	-0.0102 (-1.23)	-0.0119 (1.37)	-0.0128 (-1.48)	-0.0227 (-2.55)	-0.0194 (-2.21)	-0.0202 (-2.30)
Share age > 65 years	-0.0033 (-0.40)	-0.0055 (-0.68)	-0.0055 (-0.68)	-0.0272 (-2.73)	-0.0259 (-2.92)	-0.0259 (-2.89)
Population density	-1.1E-05 (-1.97)	-4.3E-07 (-0.07)	-9.6E-07 (-0.16)	1.8E-05 (2.36)	2.6E-05 (3.39)	2.5E-05 (3.35)
Net in-migration rate		-0.6402 (-2.86)	-0.6264 (-2.80)		-0.4989 (-2.18)	-0.4968 (-2.17)
Population growth rate (net migration)		0.0387 (0.89)	0.0390 (0.89)		0.1218 (2.96)	0.1218 (2.95)
R^2 (Sq.corr)	0.942 (0.940)	0.945 (0.940)	0.946 (0.940)	0.941 (0.935)	0.940 (0.937)	0.942 (0.938)
p-val. LM-test. Spatial, error (lag) dependence	0.002 (0.049)	0.048 (0.291)	0.057 (0.438)	0.002 (0.037)	0.006 (0.892)	0.008 (0.345)

Notes: Time effects (not reported) in all regressions. Estimation method: GMM that allows for heteroscedasticity over time. The instruments for the average annual population growth rate (net of migration) and the net in-migration rate are period dummies, the log of initial real income per capita, the age group variables (dated at time t), and the lagged value of respective variable.

whereas poor counties, from which migrants tend to move, benefit on average from migration.[14] A negative effect from net in-migration on the economic growth rate is consistent both with the neoclassical model given the assumption that migrant do not have substantially higher level of human capital than the average (see Barro and SalaiMartin, 1995, Ch.9), and with some previous cross-regional evidence (see BS, 1995, Ch. 11). The estimated coefficients suggest that a 0.1 percentage point increase of net migration as a share of total population reduces growth in "receiving" regions by roughly 0.06 (0.05) percentage points, using PPP adjusted (unadjusted) income.

Substantial spatial spillovers

To analyse possible channels of growth spillovers, the *Table 2* regressions include income per capita in contiguous counties (Wy), and regional GDP in surrounding counties to the analysis (*W*ln GDP*) as explanatory variables. High income per capita in contiguous counties may promote growth through demand effects from rich counties,[15] or through human capital spillovers. A high income per capita may indicate a high level of human capital, and the idea is that a high level of human capital facilitates the absorption of new technologies. (Cohen, 1989). With this dataset we cannot discriminate among these hypothesis.

Columns c2 of *Table 2* report estimated coefficients on income per capita in contiguous counties (Wy) that are positive and statistically significant. Thus, the result indicates a positive growth effect through income levels in surrounding counties. On the basis of the estimates, we expect a weighted increase in income of 10 percent in contiguous counties to increase the growth rate by 0.008 percentage units. This result is smaller but qualitatively the same as the cross-country result of Moreno and Trehan (1997). In contrast, Rey and Montourin (1999) do not find evidence of this effect for the US states.

Location close to a large market, measured by regional GDP, may be beneficial for growth if trade and expenditures have a tendency to decrease with respect to distance. The models c3 of *Table 2* indicate that a positive and statistically significant impact on growth of GDP in surrounding counties (*W*ln GDP*). Thus, there is empirical evidence of significant growth spillovers through neighbouring counties' GDP. Quantitatively, the estimates indicate that a weighted average increase of 10 percent in GDP in surrounding counties increases the growth rate of income per capita income by roughly 0.0016 percentage points.[16] It is however, difficult to empirically distinguish between

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[14] When regressing the net migration rate on period dummies and initial income per capita, the estimated coefficient on initial income per capita is 0.011 (t-value = 8.90).

[15] Demand effects may have a bias towards firms located relatively close. In a global sense, this is highlighted by the commonly estimated gravity equations; see Frankel and Romer (1999) for a recent study.

[16] Moreno and Trehan (1997) also find a positive growth effect through GDP in contiguous countries. In their study, the GDP spillover was more robust than spillovers through the level

spillovers through income or market size.[17] When spatially weighted income per capita and spatially weighted market size are included jointly in the regressions, the estimated coefficient of neither of these variables are individually statistically significant. (The correlation between these two variables is around 0.8.) Estimated coefficients of other variables, however, are not substantially affected.

When allowing for specific channels of spillovers, the spatial lag specification ceases to produce a significant coefficient for the spatially lagged growth rate (see last row of Table 2). That is, to the included spillover variables pick up the otherwise unspecified growth spillovers. In contrast, the estimated coefficient of the spatial error term is basically unaffected compared to the results from the estimated spatial unconditional regression models presented in *Table 1*: a growth shock in contiguous counties of a weighted average size of one unit implies an expected shock of roughly 0.22 (0.34) units, using PPP-adjusted (unadjusted) income.

Robustness of results

In order to capture substantial spillovers, we performed the same analysis with the contiguity matrix which is not row standardised. This did not alter the results. Nor do the spillover results depend critically on the inclusion/ exclusion of other variables. Introduction of the net migration rate and population growth (net of migration) does not substantially affect the partial effect of demography (or other) variables on growth in per capita income.

One striking feature is that even though we add additional ways for spatial spillovers, or other control variables, the parameter value and significance of the spatial error term parameter measuring common shocks is basically unchanged. This gives us an indication of how difficult it is to find variables that capture all kinds of spillovers. At last, focusing on the speed of convergence, this is very stable when introducing additional variables, suggesting that β-convergence does not depend critically on the mechanisms analysed here.

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of income per capita. They do not, however, present an in-depth deeper analysis of collinearity.

[17] A possible way around this econometric ‘problem’ is to construct an interaction variable (y_{it}*GDP_{it}), but this does not deepen our understanding of spillovers.

4. Conclusions

This paper analyses determinants to economic growth with a particular focus on the spatial dimension for Swedish counties for the period 1911-1993. One overall result is that there is robust empirical evidence of common growth-shocks across counties, measured as a spatial interdependency in the error term. This result is robust in the sense that it remains regardless of what explanatory variables are included in the regressions and regardless of whether incomes are adjusted for regional differences in cost-of-living.

To investigate possible sources of growth spillovers, we include income per capita in contiguous counties and GDP in contiguous counties as explanatory variables. The estimated coefficients on these variables are positive and statistically significant. (Due to collinearity between these variables, we are, however, not able to distinguish between the income and market size effects.)

A particular feature of this regional study is that this paper uses regional incomes that are adjusted for regional differences in cost-of-living (see Persson, 1997). In view of the fact that regional growth studies typically do not adjust regional incomes for regional price differences, this paper reports regression results based on both non-adjusted and cost-of-living adjusted incomes. We find that:

(i) When using cost-of-living adjusted incomes the estimated spatial interdependency is lower relative to the estimated spatial interdependency when using unadjusted incomes. As there is significant spatial autocorrelation in the cost of housing, the PPP adjustment of income appear to pick up some of the reported spatial growth interdependence.

(ii) The level of agglomeration measured as the population density, and the age structure represented by the young and old dependency ratios are only estimated to impact the growth rate of income per capita when incomes are not adjusted for regional differences in cost of living. When correctly adjusting for such cross-county differences, the estimated growth effects of these variables disappear. Finally, another empirical finding is that the estimated growth effect of net in-migration is negative and statistically significant regardless of whether incomes are adjusted for regional differences in cost-of-living or not.

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Appendix

Table A1. Correlation matrix.

Corr (p-value)	Cost-index	Growth	Growth*	Y	Y*	ShareYoung	ShareOld	Dens (Aggl)	migr*	migr	Popg*	Popg	Wg	Wg*
Index	1.00													
Growth	-0.13 (0.06)	1.00												
Growth*	-0.15 (0.04)	0.99 (0.00)	1.00											
Y	0.21 (0.00)	-0.49 (0.00)	-0.49 (0.00)	1.00										
Y*	0.25 (0.00)	-0.50 (0.00)	-0.50 (0.00)	1.00 (0.00)	1.00									
Share young	-0.13 (0.08)	0.18 (0.01)	0.18 (0.02)	-0.79 (0.00)	-0.79 (0.00)	1.00								
Share old	-0.29 (0.00)	-0.46 (0.00)	-0.46 (0.00)	0.65 (0.00)	0.63 (0.00)	-0.43 (0.00)	1.00							
Pop-density	0.35 (0.00)	-0.23 (0.00)	-0.21 (0.00)	0.27 (0.00)	0.30 (0.00)	-0.31 (0.00)	-0.04 (0.59)	1.00						
Migr*	0.37 (0.00)	-0.31 (0.00)	-0.29 (0.00)	0.56 (0.00)	0.58 (0.00)	-0.64 (0.00)	0.22 (0.00)	0.55 (0.00)	1.00					
Migr	0.36 (0.00)	-0.30 (0.00)	-0.28 (0.00)	0.56 (0.00)	0.58 (0.00)	-0.64 (0.00)	0.22 (0.00)	0.53 (0.00)	0.99 (0.00)	1.00				
Popgr*	-0.18 (0.01)	0.19 (0.01)	0.21 (0.00)	0.01 (0.85)	0.00 (0.96)	-0.15 (0.04)	0.05 (0.48)	-0.22 (0.00)	-0.09 (0.23)	-0.08 (0.28)	1.00			
Popgr	-0.18 (0.01)	0.21 (0.00)	0.22 (0.00)	0.00 (0.97)	-0.01 (0.86)	-0.14 (0.06)	0.04 (0.58)	-0.26 (0.00)	-0.10 (0.18)	-0.09 (0.23)	1.00 (0.00)	1.00		
$W^r g$	0.07 (0.36)	0.83 (0.00)	0.82 (0.00)	-0.42 (0.00)	-0.41 (0.00)	0.13 (0.00)	-0.56 (0.00)	-0.06 (0.37)	-0.12 (0.09)	-0.12 (0.10)	0.01 (0.89)	0.02 (0.74)	1.00	
$W^r g$*	0.06 (0.38)	0.83 (0.00)	0.83 (0.009	-0.42 (0.00)	-0.41 (0.00)	0.13 (0.069	-0.55 (0.00)	-0.05 (0.45)	-0.12 (0.11)	-0.11 (0.12)	0.02 (0.81)	0.03 (0.67)	1.00 (0.00)	1.00
$W^r y$	0.18 (0.01)	-0.40 (0.00)	-0.41 (0.00)	0.86 (0.00)	0.86 (0.00)	-0.68 (0.00)	0.56 (0.00)	0.19 (0.01)	0.44 (0.00)	0.43 (0.00)	-0.07 (0.36)	-0.08 (0.27)	-0.23 (0.00)	-0.23 (0.00)
$W^r y$*	0.18 (0.01)	-0.40 (0.00)	-0.41 (0.00)	0.85 (0.00)	0.86 (0.00)	-0.68 (0.00)	0.56 (0.00)	0.19 (0.00)	0.44 (0.00)	0.43 (0.00)	-0.07 (0.36)	-0.08 (0.27)	-0.23 (0.00)	-0.23 (0.00)
$W^r gdp$	0.10 (0.15)	-0.47 (0.00)	-0.48 (0.00)	0.78 (0.00)	0.78 (0.00)	-0.53 (0.00)	0.68 (0.00)	0.13 (0.08)	0.39 (0.00)	0.39 (0.00)	0.07 (0.32)	0.06 (0.43)	-0.41 (0.00)	-0.41 (0.00)
$W^r gdp$*	0.11 (0.00)	-0.46 (0.00)	-0.46 (0.00)	0.76 (0.00)	0.76 (0.00)	-0.51 (0.00)	0.66 (0.00)	0.12 (0.09)	0.38 (0.00)	0.38 (0.00)	0.09 (0.21)	0.08 (0.29)	-0.41 (0.00)	-0.41 (0.00)

Table A1. Continued.

Corr (p-value)	Wy	Wy*	Wgdp	Wgdp*
Wy	1.00			
Wy*	1.00 (0.00)	1.00		
Wgdp	0.82 (0.00)	0.82 (0.00)	1.00	
Wgdp*	0.80 (0.00)	0.80 (0.00)	1.00 (0.00)	1.00

* Based on PPP-adjusted income.

Fig A1. The log of real per capita income.