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The Shape of the Income Distribution and Economic Growth: Evidence from Swedish Labor Market Regions

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ABSTRACT

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We analyze the association between inequality and growth across 72 labor market regions in Sweden 1990-2006. Highly accurate measures of growth and inequality (gini, Q3, p9075, p5010) are derived from population register data. The regional set-up also reduces problems with omitted variable bias and endogeneity found in cross country comparisons since the regions within a country share the same redistributive policies and institutions. The findings suggest that inequality between the 90th and 75th percentiles enhances regional growth. This result no longer holds when we take into account changes in commuting patterns. Although only suggestive, the finding is interesting in that it is consistent with the hypothesis that inequality enhances growth by stimulating commuting incentives.

JEL Classification: O4, D3, J6

Keywords: growth, income distribution, inequality, gini

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1. Introduction

A potential equity-efficiency trade-off poses a severe restriction on egalitarian policymaking, and it serves to explain why cross-country estimations of the inequality-growth relation have generated great interest among economists. To empirically establish and possibly quantify such links is of high policy relevance since it could improve our understanding of the costs and benefits of e.g. changes in the tax system and other redistributive policies. In the 1990s, following Kuznets (1955), several studies presented empirical evidence of negative inequality-growth associations (e.g. Bertola 1993, Alesina and Rodrik 1994, Persson and Tabellini 1994, Clarke 1995), suggesting that a high level of inequality may hamper growth by increasing the pressure for redistributive policies. These studies were followed by others which reported mixed results. In a much debated study, Forbes (2000) found a positive relation between inequality and growth when studying an unbalanced panel of "high quality" data from Deininger and Squire (1996) covering the period 1966 through 1995.[1] Barro (2000) divided his sample into poor and rich countries and found a negative inequality-growth relationship in the group of poor countries (see also Li and Zou 1998), but a positive one in rich countries, implying that reducing inequality is good for growth at an initial stage but that inequality enhances growth in developed countries. However, analyzing data from the Luxembourg Income Study (LIS) on 17 countries within the OECD, Brandolini and Rossi (1998) found a positive relation between initial inequality and growth for a selection of Anglo-Saxon countries but a negative relation for a selection of countries from continental Europe. Voitchovsky (2005) also used LIS-data and included 25 relatively wealthy countries for a period of 15 years (1980-1995),

[1] Atkinson and Brandolini (2009) compare the Deininger and Squire data with inequality trajectories indicated by national sources, finding that three countries out of four display different trends depending on data source. Also, Hanousek *et al.* (2008) points out that cross country comparisons are sensitive to whether the conversion of GDP expressed in local currency is converted to US dollars by using one single exchange rate. Using corrected values, they claim the results in Forbes (2000) are no longer significantly different from zero. Roodman (2009) reaches a similar result when empirically analyzing the assumptions regarding the set of instrumental variables.

but instead emphasized the importance of looking at different parts of the income distribution. Higher end inequality was indicated by the ratio of incomes between the 90^{th} and 75^{th} percentile, p9075, while the ratio of the 50^{th} and 10^{th} percentile, p5010, reflected lower end inequality. The hypotheses tested were that higher end inequality enhances growth whereas lower end inequality is harmful for growth. Empirical support was presented for both hypotheses.

The inequality-growth estimations are plagued by several inherent problems such as endogeneity, omitted unobservable variables and measurement errors, all of which are exacerbated by the fact that countries differ in their methodologies to collect data. In the last decade or so, a branch of the inequality-growth literature has focused on regional data to reduce bias due to omitted variables and steer clear of issues of incomparability across countries.[2] Partridge (1997, 2005) explored data on US states 1960-1990 and 1960-2000 respectively, based on US census bureau sources, reporting a positive impact on growth of overall inequality (gini) as well as of the share of income falling to the third quintile, Q3. There was also a positive inequality-growth link when the two measures were used simultaneously, i.e. when the parameter of the gini reflected the effects of inequality in the tails of the distribution. Frank (2009a, 2009b) partly supported the latter finding, showing a positive association between growth and income shares of top deciles when exploring data on gross income in US states 1940-1990, but Panizza (2002) did not find any evidence of a positive association between the gini or Q3 (or both) and growth across US states 1940-1980.[3] On a more detailed regional level, Fallah and Partridge (2007) used US census data to analyze US counties 1990-2000, reporting a positive inequality-growth link in metropolitan areas but a reverse (negative) link for rural areas. On European data, Perugini and Martino (2008) studied the association between inequality and growth across 63 regions in the UK, Italy, France and Germany for the period

[2] In their meta-analysis, Dominics, Florax and de Groot (2008, p678) conclude that “it is particularly promising if attention would shift towards samples of regions within one country”.
[3] These studies are based on Statistics of Income data from the IRS. Information on income classes is used to approximate the various measures of inequality, disregarding individuals below the tax threshold.

1995-2004, reporting a positive relation. A similar result was found in Rodríguez-Pose and Tselios (2008) who analyzed 94 regions from 13 countries of the European Union 1994-2001, via the European Community Household Panel.[4]

The present paper analyzes the association between inequality and growth across 72 Swedish labor market regions for a period of 17 years, that is, 1990 through 2006. The regional set up should reduce omitted variable bias as Swedish regions share very similar redistributive policies and institutions. Further, the data is based on population register data from Statistics Sweden, collected in a uniform manner across regions to reasonably ensure comparability and minimize measurement errors. This differs from earlier studies which are based on survey data on subsamples of the population. We also provide tentative estimates to explore the interplay between inequality, growth and changes in commuting patterns. This is done by using an alternative measure of per capita earnings based on "day populations", i.e. where earnings are attributed to the region where the working site is situated rather than to where the individual worker resides. To our knowledge, this has not previously been applied in the inequality-growth literature. Our empirical analysis considers four inequality measures; the gini, Q3, p9075 and p5010, thereby covering the vast majority of alternative specifications in the existing literature. Since previous studies have shown that results tend to partly depend on the methods used, we employ cross-sectional OLS, pooled (panel) OLS with and without regional fixed effects and system GMM models.

The theoretical motivations for a study of the inequality-growth relation across regions differ somewhat from a cross-country framework. For instance, redistributions may enhance growth by reducing corruption, crime, social unrest and by alleviating credit constraints to al-

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[4] Outside peer-reviewed publications, Nahum (2005) found a positive inequality growth link when studying 24 Swedish regions 1960-2000. However, the results are not straightforward to interpret since the period comprises a strong increase in the labour force participation among females, where the growing public sector was their major employer. With data based on individual tax records – not collapsed into households – it is therefore likely that the decreases in inequality are both overstated and correlated with public sector expansion across regions, which is unlikely to be orthogonal to growth.

low for investments in human and physical capital (Alesina and Rodrik 1994, Alesina and Perotti 1996, Aghion *et al.* 1999, Barro 2000, Persson and Tabellini 1994). In the Swedish context, political stability and security are relatively minor issues and education and health care are virtually free of charge and of similar quality across regions.

If inequality influences growth across Swedish labour market regions, more likely mechanisms include that it provides incentives for more effort, longer working hours, attracts high skilled rent seekers, stimulates risk-taking, entrepreneurship, innovation and/or technological advances (Bell and Freeman 2001, Galor and Tsiddon 1997, Hassler and Mora 2000, Siebert 1998). Inequality may also hamper growth by generating unequal opportunities through family background factors (e.g. Björklund and Jäntti 1997, Bratsberg *et al*. 2007). The association between the overall inequality (gini) and growth would then reflect the net effect of the opposing influences. Alternatively, following Voichovsky (2005), the inequality measures p5010 and p9075 may more appropriately capture the influence on growth if unequal opportunities are primarily related to lower end inequality, and the incentive effect to higher end inequality.

For our empirical implementation, the above discussion implies that an inequality-growth link across Swedish labour market regions may only stem from a subset of potential theoretical mechanisms, making it easier to interpret. However, initial inequality may reflect regional differences in the prevailing business structures, the bargaining power of unions, the degree of specialization, the presence of excess rents (emerging markets) and/or policy. To the extent that these “initial conditions” have a causal influence on future growth rates, they constitute sources of potential endogeneity. From this perspective, the analysis of Swedish labour market regions is promising since institutions and most redistributive policies are determined by the central government.[5] The differences in other initial conditions are also likely to be smaller than across countries, and empirically modeling the mechanisms determining economic

[5] Hence, there is little scope for migration of low productive individuals to regions with more egalitarian policies (Borjas *et al.* 1992).

growth is facilitated as these should be more similar across regions than across countries. Moreover, inequality in the area of residence may be the most significant in shaping individual's incentives, and any potential influence of inequality on growth should be exacerbated by that factor flows across regions in a country are subject to only a minimum of barriers such as language, information or legislative restrictions.

The contribution of the present study is to use data of exceptional quality to analyze if and how inequality influences growth across regions with very similar institutions. Sweden is in this respect an interesting object of study since it is a highly egalitarian country. Any credibly detected inequality-growth link is therefore likely to hold in many other developed countries, unless it appears specifically associated with the egalitarian institutions. Our most stable results indicate a positive link between p9075 and growth, but we also find that a key mechanism behind the results is changes in commuting patterns. It implies that inequality enhances regional growth through incentives rather by attracting skilled labour (migration) or investments.

The outline of the paper is as follows. In the next section, we discuss two important facts which possibly influence our results; the economic recession that hit Sweden in the early 1990s and the Adult Education Initiative 1997-2002. Section 3 contains an account of our data and descriptive statistics. Section 4 presents our empirical approaches, while results and robustness checks are presented in Section 5. A concluding discussion is found in Section 6.

2. The Swedish economy 1990-2006

During the period of study, two Swedish specific facts are important to acknowledge; the economic downturn 1990-1993 and the Adult Education Initiative (AEI) 1997-2002, which particularly in its first years attracted non-negligible proportions of employed into full-time studies. As will be further discussed in Section 5, we expected the inclusion of the period 1990-

1993 to have some impact on the estimated inequality-growth link, but we also found the results sensitive to the inclusion of the year 1998 or 1999. To us, the most likely explanation of the latter finding is the increase in the AEI during these years. In the following we discuss these two facts in more detail.

Figure 1 displays the number of individuals being unemployed 1990-2006. The period started with an unusually deep recession which, for our purposes, is difficult to overlook. Unlike most European countries, unemployment in Sweden remained low during the 1980s and was even at historically low levels between 1985 and 1990. It was followed by the worst recession recorded since the 1930s, as unemployment increased from 1.8 percent in 1990 to 8.2 percent in 1993, and the yearly GDP in Sweden decreased three years in succession from 1990/1991. The fluctuations were related to several factors. One important issue was an extensive deregulation of the credit markets in 1985 which allowed consumption to increase. Highly progressive tax rates, for many individuals around 80 percent on the margin, made credit costs low as interest rates were fully deductible. A comprehensive tax reform was implemented in 1990 and 1991, where central issues were to decrease marginal tax rates and reduce deductions of credit costs. This led to increased credit costs, prices on real estate plummeting and by 1992, households had increased their savings by 12 percentage points compared with 1988. The sudden decrease in consumption was accompanied by large cut-backs in the public sector, which added to the short term decline. In addition, wage increases which exceeded those of competing countries contributed to high inflation rates, rising in the late 1980s from 4 percent to 10 percent, and to low real interest rates. Since the policy of the central bank was to maintain a fixed exchange rate of the Swedish currency, exports decreased by 10 percent already 1989-1990. The fixed exchange rate continued to weaken the competitiveness of the Swedish export industry until it was abandoned in October 1992.

A potential further complication with the period concerns the AEI, which foremost affected growth temporarily in the years 1998-1999. To understand the background, one must appreciate that adult education at municipal education centers, Komvux, is a widely accepted and popular way of re-enrolment in compulsory and/or upper secondary level schooling. The numbers registered yearly has been relatively stable around 100,000 since the 1970s but its effects on regional earnings levels (and inequality) need not be very large as many individuals registered in only one course. As can be seen in Figure 1, enrolment in adult education at Komvux did not increase following the economic recession starting in 1991 since it traditionally was *not* used as an active labor market program. From 1993, the government started to fund municipalities (but not the participating individuals) to provide seats at Komvux for unemployed individuals. In autumn 1997, the AEI was launched. The central government then made the offer for interested individuals aged 25-55 to enroll in a year of full time studies at Komvux. Their financial support would be very generous in the form of a special grant for education and training, UBS, equal to the individual's level of unemployment insurance benefits.[6] The numbers enrolled at Komvux almost doubled. For our purposes, those who registered at Komvux and received the UBS may in particular have affected regional per capita earnings growth, as they included individuals withdrawing from productive work to instead attend a year of full time studies at Komvux. The numbers with UBS in 1998 and 1999 represented roughly 3 percent of the Swedish the population aged 20-64, but with one fourth of the labour market regions seeing between 5 and 8 percent of the population aged 25-55 enrolled in the AEI. After the initial years, the numbers receiving UBS fast decreased, dropping from 125,000 in 1998 to 35,000 in 2002. Although Komvux continued to attract rather high numbers, the latent demand for Komvux among employed had largely been saturated, and it plau-

[6] The AEI is described in more detail in Stenberg and Westerlund (2008).

sibly had less of an effect on growth as Komvux was increasingly directed towards individuals with a weak attachment to the labor market.

3. Data

This study is based on register data of the Swedish population (LISA) administered by Statistics Sweden and includes records of individuals' tax reports and of transfers from responsible national agencies. It has been used by The National Agency for Growth Analysis (ITPS) to construct measures of regional per capita labor earnings, as the sum of labor earnings in a region (including the self-employed), divided by the population and corrected for inflation (assumed identical for all regions). Our measures of inequality in disposable income are generated from a subset of the regional populations each year, aged 20-64. To describe the shape of the income distribution, we use the gini coefficient and Q3, with the latter reflecting the median voter and/or the relative affluence of the middle class. In line with Voitchovsky (2005), we also employ the ratio of disposable income p9075, for upper end inequality and the ratio p5010 for lower end inequality. These variables, as well as the others (presented below) should be virtually free from measurement errors due to recall errors, rounding errors and/or top-coding. The regions we study have been constructed by Statistics Sweden by collapsing 289 municipalities into 72 regional labor markets, based on commuting patterns of the labor force.

An advantage with our data is the relatively large number of regions and their high degree of homogeneity in terms of democratic functions, public transfer systems, educational systems, labor market institutions and access to medical care. Municipal parliaments decide on the level of proportional taxation, which varies from around .29 to .34. The progressive part of the tax system is set by the government which is also responsible for redistributive transfers such as parental leave, unemployment insurance benefits and sick-leave and sets a norm for municipalities' social welfare payments. The government also redistributes resources from rich to relatively poor municipalities ("Robin Hood" taxation) to guarantee a high level of public service. These factors taken together should reduce omitted variable bias in regressions on regional growth. Potential flaws still exist, and include that the measures of disposable income and labour earnings do not take into account regional differences in the size of the informal sector, indirect taxations or non-cash benefits, even though these are likely to be relatively similar following the above mentioned homogeneity across regions.

An obvious disadvantage of using the per capita earnings as an indicator of regional growth is that it does not include surplus values of firms and other organizations. However, this is also an advantage for the reliability of the measure as there is no need for us to make indirect decompositions of surplus values to regional levels. A remaining problem is that some individuals work outside their region of residence (e.g. commuters). To address this concern, we present estimations with data on per capita earnings calculated from "day populations", provided by the National Agency for Growth Analysis (1990-2005). Earnings are then attributed to the region where the main employer of an individual is located (see Section 5.5).

Our measures of within-region inequality are based on disposable income which includes the sum of a large number of different incomes such as registered labor earnings, cash property income, social retirement pensions, child allowances, benefits associated with parental leave, unemployment, sick-leave etc. The disposable income is expressed net of taxes and is constructed as the individual's component of total family income, where the share of income attributed to an individual follows the formula used by Statistics Sweden.[7]

Women are included when our measures of inequality and growth are generated. There is no upward trend in female labor force participation during the period of study, which otherwise would tend to compress earnings. In 1990, participation rates were 84 percent and 78

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[7] For instance, a child aged 0-3 is given the weight .42 and aged 4-10 is .52 whereas an adult member is 1.00.

percent for men and women respectively, which was 8 percentage points lower for both genders in 2006 (in 1990, the economic boom was at its peak). Importantly, during child rearing, 12 months of parental leave benefits limit the fall in disposable income. They are equal to 80 percent of the previous earnings level or a minimum transfer of about € 600 a month net of taxes. Most of the parental leave is used before the child is two years old (Ekberg *et al.* 2005).

In Table 1, descriptive statistics of the 72 regions as recorded 1990-2006 are presented. Annual regional growth is on average 1.5 percent (standard deviation 3.8), but note that if one excludes observations prior to 1994, the average is 3.0 percent (2.2). The corresponding figures of the day population (defined above) are roughly similar. The spatial lag is constructed to take into account the influence on growth stemming from surrounding regions.[8] The average gini coefficient is .24 (with a standard deviation of .03) which is considerably smaller than the .37 (.03) for US states (Partridge 2005) or the .38 (.04) for US counties in Fallah and Partridge (2007), but closer to the .29 (.05) recorded in Perugini and Martino (2008) across 63 regions in Germany, France, Italy and the UK and to .28 (.05) reported in Voitchovsky (2005) for 21 countries.[9]

Population size across Swedish labor market regions is, of course, small compared with cross-country data. This could potentially make our variables more sensitive to measurement errors and exacerbate downward measurement error bias in our parameters of interest. The average population size of the included regions is 123,051 inhabitants (standard deviation 287,469, median 38,221), which is slightly higher than the 81,516 in Fallah and Partridge (2007) for US counties (standard deviation 268,219, median not reported). Neither Perugini and Martino (2008) nor Rodríguez-Pose and Tselios (2008) report the population size in their

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[8] The spatial lag is a weighted average of income levels of the regions with a border to region *i*. The sum of the weights is normalized to one and is proportional to the population levels and inversely proportional to the square of the distance between the main cities of region *i* and the neighboring region.

[9] The average ratios of p9075 and p5010 in Table 1, 1.21 and 1.84, are also slightly smaller compared with Voitchovsky's study, 1.33 and 2.00, and the mean of the Q3 ratio is .194 which is slightly higher than .175 in Partridge (2005).

studies of European regions. The average hides a large variation since the Stockholm commuting area includes about one fourth of the Swedish labor force, and the three largest regions comprise about 45 percent of the labor force.

Table A.1 in the Appendix shows descriptive statistics where the regions have been separated into seven region types, as defined by the National Agency for Growth Analysis. These statistics reveal that the level of log earnings per capita is clearly higher in regions with larger populations. This is not surprising since one might assume that large agglomerations are associated with a higher level of efficiency in matching and/or with greater innovative power. However, the average annual growth is relatively equal across different region types. For example, the average growth rate of the region category "service producing small regions" (column to the far right) is only slightly below the rate recorded for the three big cities, despite the fact that this group of regions has the second lowest proportion of college graduates and the lowest shares in active working age. These regions also have by far the highest share of employment in farming and mining, 8.1 percent, whereas the overall average in the other regions is 3.5 percent. This is a potential indication of the importance of the business structure for differences in growth rates, since regions are relatively similar in terms of policy and institutions.[10]

Figures 2 and 3 display the distribution of yearly growth rates and gini coefficients for the period 1990-2006.[11] As expected, the variation at a particular time *t* is large relative to how the distributions change over time. Thus, in line with earlier studies, most of the variation is cross-sectional rather than temporal (e.g. Deininger and Squire 1996, Voitchovsky 2005, Partridge 2005). In our data, the increase in the average level of per capita earnings is about 30 percent over the period 1990-2006. This is almost a third less than the Swedish GDP per capita growth

[10] By construction, the business sectors' shares of total employment sum to one in each region.
[11] For expositional reasons, we exclude two growth outliers recorded in 2006, one negative and one positive, shown as max and min values in Table 1. The second largest numbers are -12.1 and 9.4, both found in Figure 2.

during the period, which was 43 percent. This reflects the fact that we treat each region as an entity, thereby attaching the weight 1/72 to each region including a growth region like the Stockholm-Uppsala area which comprises about one fourth of the labor force.

The spread in the gini coefficients is markedly larger in 2006 as compared with the start of the period. The median gini coefficient increased from .21 in 1990 to .28 in 2006. This increase in inequality has been much debated in Sweden. A number of candidate explanations have been suggested, including technological change, increased individual wage setting and a lower overall employment (e.g. Nordström Skans *et al.* 2006, Björklund and Freeman 2008).

To facilitate the understanding of our regression results in Section 5, it is informative to explore how the inequality variables are interrelated with our other independent variables. Tables A.2 and A.3 present results from regressions where inequality, per capita earnings levels and per capita earnings growth are dependent variables. However, at this stage we do not explore the inequality-growth link. Table A.2 presents cross-sectional regression estimates on the four (standardized) inequality measures in 2006, using 1990 as the year of observations for the explanatory variables. The results are by and large stable to the use of other initial years and/or end years. The proportion of college graduates is positively related to higher inequality. This is consistent with the notion that an increased level of skills tends to generate inequality by influencing the degree of specialization. The negative influence on Q3 may reflect that the higher inequality partly comes at the expense of the middle class. The demographic variables do not show any clear patterns except that the fraction aged 30-54 is negatively associated with higher end inequality as measured by p9075, possibly compressing higher end earnings due to increased competition. The share of employment in the public sector tends to reduce the gini, p9075 and p5010, but to increase the Q3 ratio, presumably reflecting the compressed earnings structure in the public sector.

In Table A.3, columns (1) and (2), the data manages to explain relatively well the level of earnings per capita, with R^2 above .72. The explanatory power falls dramatically in columns (3) and (4) where growth now is the dependent variable, to R^2 levels below .15. The only variable to consistently display statistical power is the proportion of college graduates. The fraction aged 30-54 is associated with a higher per capita earnings levels but not with growth rates. The parameter associated with the lag of the per capita earnings is negative, indicating convergence in levels and its inclusion also tends to destabilize the parameters of the demographic variables.[12]

In columns (5) to (8), we report results from panel estimates 1990-2006, using observations every fourth year (T=5). In column (6), the proportion of college graduates is the only explanatory variable, and highly significant. However, as soon as we include the time specific effects in column (7), there is no statistically significant link between college and regional growth, possibly indicating that the panel structure consisting of four year intervals is a time frame which is too short for college to have an effect on growth. The regional framework of our data also means that, unlike the case of cross-country evidence, college achievement is less likely to capture other institutional factors correlated with educational attainment.

4. Empirical considerations

Empirical estimations of an inequality-growth link are typically plagued by endogeneity, omitted variable bias and measurement error bias. There is little doubt that both growth and inequality are endogenous variables which are partly determined by the same factors (e.g. Lundberg and Squire 2003, Benarjee and Duflo 2003). Many of these are difficult to appropriately measure and an inequality-growth regression coefficient therefore reflects an unknown mix-

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[12] The regressions presented in columns (4) and (8) of Table A.3 are similar to the growth regressions analyzed in Section 5, except that the inequality measures are omitted from the equation.

ture of factors such as e.g. the level of corruption, the quality of democratic functions, credit markets, health care systems and educational systems. Thus, the omitted variable bias is closely related to the endogeneity issue but in the case of Swedish regions, the factors mentioned are to a large extent evened out and the considerable room for interpretation is narrowed down, improving our possibilities of correctly interpreting the results. Measurement errors can never be completely neglected but, as discussed in the previous section, they are likely to be relatively small in our data.

In the empirical analysis, we estimate growth models where we consider a region *i* at time *t*, which has per capita earnings level y_{it} and a growth per time period

$$\Delta y_{it} = \alpha y_{it-1} + \beta X_{it-1} + \lambda G_{it-1} + \gamma_i + \theta_t + \varepsilon_{it} \qquad [1]$$

where $\Delta y_{it} \left(= y_{it} - y_{it-1}\right)$ and the vector X_{it-1} include controls for business structures, demographic variables, educational attainment and a spatial lag which takes into account the influence of neighboring regions on growth in region *i*. Further, G_{it-1} is a measure of inequality in region *i* at time *t-1* whereas θ_t and γ_i are time- and regional fixed effects respectively. Our four measures of inequality; gini, Q3, p9075 and p5010, will be used in separate regressions. In addition, gini will be combined with the Q3 ratio to check the influence of the tails of the distribution and p9075 will be combined with gini primarily as a robustness check, the gini then reflecting inequality outside the p9075 space.

Our first approach is to use cross sectional estimations, which only include one observation per region. The terms θ_t and γ_i then naturally drop out, but one may argue that as our variables of interest are relatively persistent over time, the exclusion of γ_i comes at a relatively low cost. In our data, the variation within regions represents about .09 percent of the variation in the gini coefficient and p9075 while about .20 of the variation in Q3 and p5010.

Our second approach is to exploit the panel structure of the data to estimate pooled OLS regressions, where time specific fixed effects θ_t take into account trends common to all regions. With more cross-sections exploited, the number of observations increase and potentially also the precision of the estimates. However, a pooled OLS regression will typically overestimate the parameter α in equation [1] since y_{it-1} will be correlated with the regional specific effects γ_i (which are then part of the error term). The coefficients β and λ are then also likely to be biased due to the correlation between the lagged dependent variable and the other explanatory variables. However, this bias is not necessarily a major concern.[13]

When exploring the panel structure of the data, one is also forced to choose the length of time between *t* and *t-1* in regressions [1]. A neo-classical growth model framework stipulates a steady-state level of growth. A change in the economic environment will change the growth rate until a new steady state level of per capita earnings growth is reached. Thus, the growth rate is affected only during the convergence process which is of an unknown time length. Hypothetically, a few years could be sufficient for individuals to react by altering their behavior, and five years is an often used interval. Classical growth models, however, tend to emphasize long-term effects due to fixed capital investments and relocation costs of capital and labour. Our approach will be a pragmatic one where we consider different time lengths to check the stability of the results. Given the data at hand, the longest time frame possible is to measure growth 1990-2006 and use 1990 as *t-1*. While longer or shorter time spans may also be feasible, data obviously sets a limit for us to explore longer intervals.

A natural extension of the pooled estimates is to include the regional fixed effects term γ_i to control for time invariant omitted variables. A drawback is then that the parameter of the lagged dependent variable α instead will be downward biased and, as in the pooled OLS

[13] Judson and Owen (1999) show in one of their examples (for T=5) that this bias is less than three percent, while the bias in the lagged dependent variable is fifty percent.

model (but now in the reverse direction), bias will spill over on the other parameter estimates. Another property of the regional fixed effects model is that the parameters β and λ are identified by the variation within regions (which cannot be explained by overall time-trends). Since cross-sectional variation is typically much larger, the limited variation left to explore may be too small to be informative as precision deteriorates. Put differently, fixed effects models risk to disregard effects on growth stemming from persistent differences in inequality, i.e. the very variation which we are interested in is captured by the fixed effects. In addition, the probability of finding insignificant coefficient results is strengthened by that region specific fixed effects increases downward measurement error bias. This has been emphasized by several authors, but as pointed out by Durlauf *et al.* (2005), it does not necessarily imply that the factors do not matter but rather that one cannot identify any significant effects with the available data.

Our fourth strategy is to explicitly address the endogeneity of the right hand side variables by employing system GMM models (Arellano and Bover 1995, Blundell and Bond 1998). This approach takes regional fixed effects into account, but retains the cross-sectional information in the data. This is accomplished by constructing a system of equations which consists of both a levels equation [1] and a transformed equation expressed in first differences

$$\Delta y_{it} = \alpha \Delta y_{it-1} + \beta \Delta X_{it-1} + \lambda \Delta G_{it-1} + \Delta \varepsilon_{it} \qquad [2]$$

In order to tackle endogeneity, the explanatory variables in the transformed difference equation [2] are instrumented with appropriately lagged values of y_{it} and X_{it} whereas the explanatory variables in the levels equation [1] are instrumented with lags of Δy_{it-1} and ΔX_{it-1}. In the empirical section, the Hansen *J*-statistic is reported to test the null hypothesis that the instruments are jointly valid. However, a general problem is that when the number of instruments becomes large, a high predictive power in the first stage regression may create an "overfit" of the endogenous variable, such that one is stuck with the original endogeneity bias. Another problem is specific to the GMM technique and related to the optimal weighting matrix used to identify the moments between the instruments and the error terms.[14] Roodman (2009) demonstrates how these two issues, when the instrument count is high, may generate Hansen *J*-statistics which despite invalid instruments tend to not reject the null of joint validity. He argues that these risks are largely underestimated and that they potentially generate false-positive results. As a demonstration of this, the results in Forbes (2000) are shown not to hold when some simple test procedures of the validity of the GMM model are performed. In the empirical analysis, we follow Roodman (2009) and check the coherence of the Hansen test statistics by varying the set-up of the instrumental variables. The exact procedure is explained in Section 5.4.

5. Results

The results presented in this section are first based on cross-sectional data where average annual growth across 72 regions is measured over time-spans between eight and 16 years. This is followed in Section 5.2 by pooled OLS panel data regressions where we explore observations at several points in time. In Section 5.3, the model is augmented with regional fixed effects while Section 5.4 presents system GMM estimates. In Section 5.5, we check the sensitivity of our results with respect to the earnings of commuters, by attributing earnings to the regions where the work is located. Throughout, we run stability checks by changing the base year and/or the final year of regional income growth as well as the length of panel intervals. The system GMM estimates also include statistical tests of the model specifications.

[14] The weighting matrix also has consequences for the estimated standard errors, which is why it is necessary to apply Windmeijer (2005) correction to the covariance matrix.

5.1 Cross sectional estimates of inequality on growth

The analysis of a single cross section allows for a regression on long term growth rates. A natural starting point is therefore to use the longest possible inequality-growth link between the first and last years available, 1990 and 2006. The stability of the results is then checked by changing the final year of observation to 2005, 2004, 2003 etc back to 1998, and by repeating the procedure using 1994 as the base year. The latter is motivated by that the exceptional economic slump in the early 1990s may affect the statistical associations between growth rates and explanatory variables.

Table 2 shows coefficient estimates of the inequality-growth relation as measured between 1990 and 2006, columns (1) through (6), and between 1994 and 2006, columns (7) through (12). In the first six columns of Table 2, most explanatory variables have low statistical power. One exception is the proportion of college graduates whereas the only measure of inequality which appears related to growth is the p9075 measure (p-value of .119). However, the inequality-growth relation is stronger when growth is measured 1994-2006, and as one explores cross-sections with shorter time spans, the weak explanatory power for the 1990-2006 regression is somewhat of an exception. Table A.4 in the Appendix presents results from using shorter cross-sections with both 1990 and 1994 as base years.[15] Studying one measure of inequality at a time, the picture emerging is relatively stable for Q3 (negative) and p9075 (positive), whether we use 1990 or 1994 as the base year and as we shorten the time frame of the growth period to 2001, p-values are throughout below .12. When Q3 or p9075 is combined with the gini, the parameter estimates are less precise, but their absolute magnitudes are only slightly reduced. In regressions where 2000 is the final year, the coefficients of the inequality measures display higher p-values (about .20) and when using 1998, the year when the Adult

[15] To save space, we then only display the estimated parameters linked with our inequality measures. Complete results are available on request.

Education Initiative was at its largest (see Section 2), they are close to zero and associated with p-values above .60. The weaker results are plausibly related to the AEI, or long standing effects of the economic slump 1990-1993, rather than a shorter time frame. Results from a regression based on 1994 and 2002 (same time length) renders p-values below .030 for all inequality measures, including the gini and p5010.

If the analysis is restricted to 1994 as the base year, and employing years beyond the AEI to measure average annual growth, the results indicate relatively persistent statistically significant inequality-growth relations for the gini (positive), Q3 (negative) and p9075 (positive), see columns (9) through (12) in Table A.4.[16] This impression is slightly altered when 1990 is the base year, with p9075 appearing as the least sensitive of these relationships, followed by Q3 while the estimates of the gini are relatively imprecise. Another reservation against the results based on 1994 as the base year is that the proportion of college graduates has very little explanatory power since the inequality measures, one by one, absorb the positive effect of college graduates on growth.[17] Without an inequality measure in the 1994 and 2002 regression, the estimate of the college variable is .11, p-value .002, suggesting that education is a potential confounding factor when we analyze the growth inequality relationship.

The magnitude of the estimates should not be interpreted uncritically as it is reasonable to believe that they only partially reflect causality. However, if one accepts our estimates as upper bounds, it is interesting to quantify the p9075-growth relation even though it is not altogether stable. Using the estimates obtained 1994-2004 indicates that a standard deviation increase in p9075 increases the yearly growth rate by .131*.207 = 2.5 per cent, and a corresponding calculus based on 1994-2002 generates .144*.371 = 5.3 per cent. The estimates are

[16] The parameter of the gini, when combined with Q3, captures the effects of the tails of the distribution. It would potentially reveal the importance of wealth available for investments. Given that our data only encompass a single country, investments may be more likely to be financed by individuals residing outside a region. In addition, the tails of the disposable income distribution are not necessarily good measures of wealth.

[17] Using 1990 as the base year, the proportion of college degrees is in general highly significant.

very similar if 1990 is the base year and the gini estimates imply effects in a similar range. Of course, these numbers should not be read literally but the relatively large numbers signal the potential importance of improving our knowledge regarding costs and benefits associated with policies influencing the shape of the income distribution.

The negative association between the Q3 ratio and economic growth is in stark contrast to Partridge (1997, 2005) who reported a positive Q3-growth relation across US states using a similar regression framework, consistent with the hypothesis that a high Q3 ratio would enhance growth by making increases in tax distortions less likely. The welfare of the middle class is often seen as a proxy of the overall state of a region, which in patterns across countries appears to be favorable to economic growth (e.g. Alesina and Perotti 1996). In the context of Swedish labor market regions, a higher share of Q3 may generate increased public spending since the confidence in public authorities is relatively high, possibly related to common norms e.g. "in favor of work" (Lindbeck 1995). This interpretation finds some support in regressions on the relative size of the public sector in 2006, which indicate a significant and positive relation with Q3 in 1994, but the result is not significant when the difference (1994-2006) in the relative public sector size is used as the dependent variable. Regarding growth, it may be that the larger public investments only deteriorate short-run growth, but generate higher growth in the long-run (Partridge 2005). Alternatively, public investments finance common goods which enhance utility to compensate for lower economic growth.

5.2 Panel data results

As the cross sectional evidence above covers relatively long time frames, one might argue that a lot of useful information is wasted with such a set up. Table 3 displays results from panel data observations for the period 1994-2006 using every third year (columns 1-6) or every fourth year (columns 7-12). The explanatory power of the time specific effects (coefficients not displayed) is relatively strong, whereas the coefficient of the lagged level of income is consistently negative, indicating convergence in income levels.[18] There are significant coefficients linked with the Q3 ratio (negative) and the p9075 (positive), whereas the gini and the p5010 ratio again display weaker associations with growth. In terms of coefficient signs, the results for Q3 and p9075 are relatively stable to alternative settings of the panel data, but the precision is not. Table A.5 in the Appendix display results from 22 regressions where we use alternative panel set-ups, i.e. different time periods where the interval lengths are varied from three years to six years. The Q3 measure, when being included on its own in the growth regression, has a negative coefficient in 19 cases, with a p-value below .10 in seven instances. When also the gini is included together with the Q3 ratio, the number of negative coefficients is 20, with three of these statistically significant. As for the p9075, whether included on its own or together with the gini, it has a positive sign in all cases, being statistically significant in exactly half of the 44 regressions.

One should perhaps not be surprised that the Q3- and p9075-growth relations are weaker compared with the results obtained with the cross-sectional models, as most panels include observations from the economic downturn and/or years of the AEI 1997-2000. If one avoids panel set-ups where years prior to 1994 are included, the parameters of the p9075 are significant in 15 out of 20 instances, the Q3 eight times out of 20. Thus, despite the instability in terms of precision, the results of foremost p9075 are not easily refuted.

[18] Neoclassical convergence suggests diminishing returns and that a high initial level of per capita earnings would decrease growth. If regions are close to their steady state levels of income, the growth paths are primarily affected by transitory cyclical and structural shocks, and the lagged income variable need not be included. This generates a tendency for larger absolute values of the parameters associated with inequality.

5.3 Controlling for regional fixed effects

As mentioned previously, one problem with the cross-sectional estimates, single or pooled, is omitted variable bias. It means that the Q3/p9075-growth relations indicated by the panel results above may be driven by time invariant unobserved heterogeneity between regions. Table 4 displays results from regressions where region fixed effects have been added. The inequality coefficients should now be interpreted as how a change in inequality is related to a change in growth (i.e. the second difference of per capita log earnings). Hence, the magnitude of the coefficients is not comparable to the ones discussed in the previous sections.[19] As expected, with parameters only reflecting the limited variation within regions, we find very weak inequality-growth associations. Only when Q3 is being combined with the gini is the estimate statistically significant.

In Table A.6 in the Appendix, estimates from 13 different panels are presented. We do not consider five and six year intervals since only the temporal variation is used for identification of the parameters.[20] Out of the 13 different specifications being used, the Q3-estimate has a negative sign in 25 out of the 26 regressions, as counted when also the gini is included, but the coefficients are only statistically significant in a few cases. A similar but reverse picture emerges for the p9075 coefficient which is positive in 25 out of the 26 estimates but with very low precision, only significant in three instances. Even though the sign of the estimates is relatively stable, the inequality-growth relationship is statistically very weak.

A common way to retain some cross-sectional variation is to use fixed effects for types of regions (e.g. Persson and Tabellini 1994, Barro 2000, Panizza 2002, Partridge 1997, 2005). In Table 5 and Table A.7, we present results from regressions where dummy variables control for

[19] Barro (2000) argues that it is more relevant to study how differences in inequality affect growth rates (pooled OLS) rather than how changes in the inequality affect changes in growth rates (fixed effects).
[20] In this case the number of periods of observations might be too small to reach sensible identification.

the region types presented in Table A.1 (discussed in Section 3). The parameter estimates are now very close to the ones obtained with our pooled OLS approach in Section 5.2 above (Table 3 and Table A.5). Hence, the variation across regions within region families is sufficient to generate these results.

5.4 System GMM

As discussed in Section 4, two attractive features of the system GMM model is that it includes regional specific controls, but still exploits variation across regions, and that it explicitly addresses endogeneity by using available lags as instrumental variables. However, the set-up relies on strong assumptions, not least regarding the validity of the instruments. We therefore avoid the potentially misleading convention in the literature, to rely on a test statistic from a single model specification (Forbes 2000, Panizza 2002, Benarjee and Duflo 2003, Voitchovsky 2005), and extend the test procedure of their joint validity (explained below). As our point of departure, we use a panel with three year intervals 1994-2006. It leaves us with T=5 and enables us to make straightforward tests of the model by varying the set-up of the instrumental variables. The number of explanatory variables is restricted to a minimum as they quickly increase the number of instruments and weaken the Hansen test of joint validity. Consequently, we only include the proportion with a college degree together with time specific effects and the respective inequality measures. Below, we also present estimates based on four year intervals (T=4) in the same period 1994-2006. In our pooled regressions, both these panels resulted in strong statistical associations between the Q3/p9075 and growth (Table 3). This is useful from the perspective that employing GMM puts high demands on variation in the data.

As there is an arbitrary element to how one specifies the set of instruments, we follow Roodman (2009) to explore four versions. The first approach is to use all available lags as instruments.[21] We then reduce the number by either only using the first available lag and/or by "collapsing" the instrument set, i.e. restricting subsets of the instrumental variables to have the same coefficient, thereby squeezing the matrix horizontally. The estimates presented in Table 6 are thus as follows; columns (1), all available lags are used as instrumental variables; columns (2), the count of instruments is reduced through the use of a collapsed matrix; columns (3), only the first available lag is used; columns (4), the two strategies are combined.

In Table 6, the parameter of the Q3 measure is unstable, but significantly negative when we use four year intervals combining both strategies to reduce the number of instruments (4). However, we also find a significantly positive Q3-growth relationship, which could question the previous findings. The p9075 parameter estimates are more stable in that they are always positive, consistent with earlier estimates, irrespective of how the GMM function is specified. Regarding precision, when based on three year intervals, the p-values are relatively low at .170 in (1) and .089 in (2). If one includes the gini among the explanatory variables, the p-values of p9075 remain around .15 in columns (1) and (4).[22]

However, importantly, by looking more closely at Table 6, it becomes apparent that the test for joint validity of the instrumental variables is not completely reliable. First, joint validity cannot be rejected by the Hansen *J*-statistic in column (1) (p-value .110).[23] Then, the Hansen test consistently rejects joint validity in columns (2) through (4), despite the fact that the instrument count is reduced compared with column (1). This is quite counter intuitive (but in

[21] All available lags means the first through to the last observable lag in the case of the transformed equation, but only the first lags of Δy_{it} and ΔX_{it} for the level equation. The reason is related to the fact that for Δy_{it} and ΔX_{it} to be valid instruments, they must be uncorrelated with the region specific fixed effects (since these are in the error terms), and further lags would in such a case be redundant. Another requirement is that to use y_{it} and X_{it} as instruments in the transformed equation [2], ε_{it} must not display serial correlation. An explicit test for serial correlation is provided by the Arellano-Bond test for autocorrelation in the residuals of the transformed equation. A negative AR(1) is expected since neighbouring differenced residuals share one term, but a check for AR(2) in differences, displayed in Table 6, is a test for AR(1) in levels.

[22] With corresponding models, Voitchovsky (2005) used .15 as threshold "significance level".

[23] The number of instruments is 31, which in comparison is not excessive (e.g. Voitchovsky 2005, Forbes 2000). One factor which is not satisfactory here is that the coefficient value of the lagged dependent variable (.981) does not lie between the estimates obtained with pooled OLS (upward biased estimate; .962) and a regression with regional fixed effect (downward biased estimate; .401).

line with the remarks of Roodman, 2009) and indicates that the Hansen test, or any other test of the structural specification, can easily be misleading when one uses a large number of instrumental variables.

Estimates based on four year intervals are slightly larger in magnitude, but there is no statistically significant link between p9075 and growth, and the Hansen tests reject joint validity of the instrumental variables. We estimated several alternative models where 1990 was included and/or where the explanatory variable college was left aside, and the nature of the results were throughout insignificantly different from zero (not displayed).

To summarize this subsection, the GMM estimates imply that the relation reported earlier between regional growth and Q3/p9075 reflects some endogenous mechanisms.

5.5 Commuters – day populations and night populations

The estimates above are silent about the mechanisms driving the p9075-growth-link. It may partly work through some confounding variable(s) which influences both initial p9075 and future growth. One candidate is amenities which may be a driving force behind migration patterns, potentially independently of income distributions. Another one is related to spillover effects between regions, e.g that growth is affected by the technological progress in neighboring regions, by an inflow of commuting labor or, conversely, by emerging firms in neighboring regions, which provide job-offers. Commuting is arguably one of the largest manifestations of spillover effects. [24] Thus, one way to assess their importance for the inequality-growth link is

[24] The inclusion of the spatial lag, which captures characteristics of surrounding regions, tends to reduce the statistical power of p9075 (although it is itself non-significant throughout), indicating a relation between p9075 and the surrounding regions.

to directly ascribe the earnings of commuters to the regions where the working site is situated, referred to as "day populations".[25]

To obtain the average per capita earnings of the day population, the sum of in-commuters' earnings is added whereas the sum of out-commuters' earnings are excluded. This measure of the per capita earnings growth is provided by the National Agency for Growth Analysis (until 2005). To see how the two measures could be expected to differ, one may assume a region has an initial level of in- and out-commuting which generates a given level of per capita earnings of the night populations and the day populations, respectively. Assume there are emerging markets in neighboring regions which increase the number of out-commuters. The per capita earnings growth used thus far is then related to the potential increase in earnings of the commuter, as well as the dynamic effects on the local labor market. If out-commuters tend to be replaced by unemployed individuals from the region, the growth may be substantial. In contrast, out-commuting makes the sum of earnings of the day population fall instantly, having a strong *negative* effect on growth.[26] The fall in growth is halted to the extent that unemployed individuals fill the vacancies generated by commuters. To simplify, if inequality attracts commuters (and/or investors); one would expect a positive inequality-growth link to be strengthened when analyzing day-populations. On the other hand, if inequality tends to provide incentives to commute, a positive inequality-growth link should be weakened.

Table 7 presents estimates of per capita earnings growth based on day populations. The regressions are cross sectional and are comparable to the results in Table 2, with average annual growth measured between 1990 and 2005, columns (1) to (6), and between 1994 and 2005 in columns (7) to (12). The estimated coefficients of inequality are generally insignificantly different from zero. Moreover, going through the rather large set of alternative cross-

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[25] The per capita earnings used in the preceding sections are based on the sum of earnings pertaining to "night populations", i.e. earnings are ascribed to the region where an individual lives.

[26] Hypothetically, if all positions of new out-commuters are taken by unemployed individuals from the local labor market, there could be no losses in per capita earnings of the day population.

sections and panel set-ups discussed in previous sections, the coefficients of the p9075 measure are only rarely associated with p-values below .10.[27] The results indicate that commuters may constitute an important mechanism behind the p9075-growth link reported above. A stylized interpretation is that inequality is more discernable to individuals in the region where they reside. Inequality in the home region may then provide increased incentives to seek better paid jobs, thereby generating a higher probability of out-commuting which enhances per capita earnings growth of night populations (used in our earlier regressions) but not of day populations. The estimates of the other coefficients are by and large similar to those of Table 2 (discussed in Section 5.1), except that the share of employment in the public sector is negatively associated with growth. This negative association indicates that the public sector is not associated with in-commuting, or reversely, that the share of private sector employment *is* linked to increased in-commuting.

The results above possibly reflect that inequality drives growth through enhanced incentives for residents rather than by attracting skilled labour or investments. However, we do not wish to jump to conclusions and only view the above results as suggestive. Also, we certainly do not exclude that the inequality growth mechanisms may be different between economic environments.

Intuitively, one would expect out-commuting to be more common in small regions. Since the results imply that out-commuting drive the results found in the preceding sections (based on night-populations), small regions may drive the positive results between p9075 and growth which we found earlier. We use the median population in 1990 as a threshold to divide our regions into samples of small and large regions. Estimation results (not displayed) indicate coefficient signs which support the hypotheses, but the issue is difficult to properly investigate

[27] The parameter of p9075 is never significant at a 10 percent level when we use cross sections with 1990 as the base year (once when 1994 (-2002) is the base year), nor is it significant in pooled panel regressions with four or five year intervals, only once with six year intervals (1990-2002) and twice with three year intervals (1993-2005 and 1996-2005). The gini and Q3 perform even worse in terms of explanatory power.

since we lose precision when each regression is based on 36 regions. Consequently, there is no support for the inverse hypotheses either, implied by the results in Fallah and Partridge (2007) on US counties. They found a positive link between inequality (gini) and growth in metropolitan areas but a negative link in rural areas.

6. Concluding discussion

The results presented in this paper concern the context of a country with a highly developed welfare state and imply that inequality between the 90th and the 75th percentiles enhanced per capita earnings growth in the Swedish labor market during the period 1990 through 2006. It is interesting that the finding partly corroborates Voitchovsky (2005), which was based on cross country data from the Luxembourg Income Study. The recurring pattern of a positive p9075-growth relation might be a promising path for future studies as longer time-series and data from other regions with other characteristics gradually become available. It would also be interesting if the magnitude of the effects could be assessed, potentially indicating at least crudely quantifiable costs and benefits of policies which affect the shape of the income distribution.

We find virtually no support for an association between lower end inequality (p5010) and growth, but weak evidence that the proportion of incomes falling to the third quintile (Q3) is negatively related to regional growth. This is in contrast with Partridge (1997, 2005) who reported the Q3 ratio was positively related to growth across US states 1960-2000. The negative relation between Q3 and growth found here indicates either that the Q3 is not a good proxy of the median voter behavior in Swedish regions or the behavior of the median voter is different from the US context. For instance, the Q3 ratio may be associated with opposing preferences regarding public spending, which in turn may imply different short-run effects on growth.

Concerning overall inequality (gini coefficient), the results are very weak even though cross sectional estimates limited to years avoiding the economic downturn at the start of the

1990s, and the years of the Adult Education Initiative 1997-2000, actually render stable positive estimates. Future studies may thus be more successful in stabilizing the results as it is possible that temporary fluctuations are at the root of our otherwise diverging findings. The results are only weakly supportive of earlier evidence based on US states (Partridge 1997, 2005) or European regional data (Perugini and Martino 2008, Rodríguez-Pose and Tselios 2008) which has indicated a positive relation between overall income inequality and growth. Our findings are more similar to the unstable results on US states 1940-1990 in Panizza (2002), and on US counties in Fallah and Partridge (2007), even though they reported significant relations between the gini and growth in metropolitan areas (positive) and rural areas (negative) when studied separately.

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Figures:

Figure 1. Numbers unemployed, in adult education at Komvux 1990-2006 and recipients 1997-2002 of UBS, the special grant for education and training.

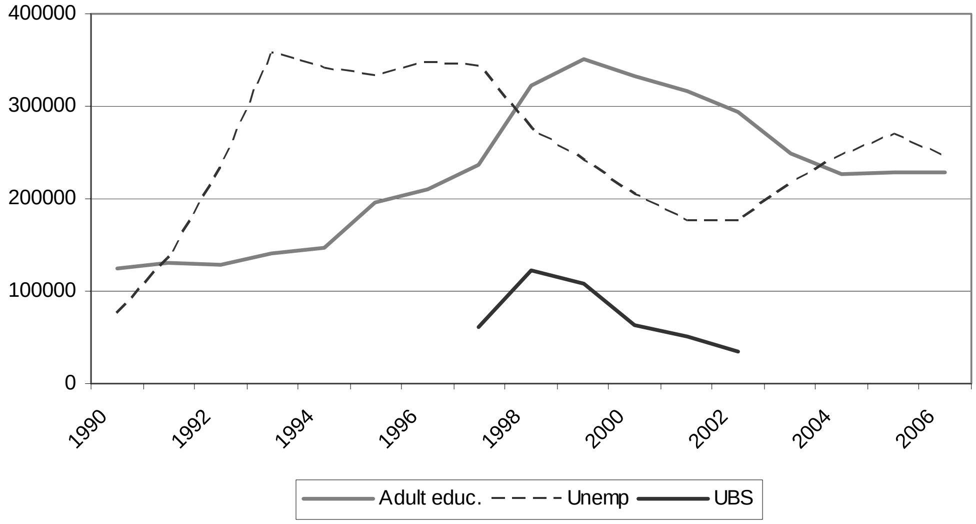


Figure 2. Distributions of income growth across regions 1990-2006.

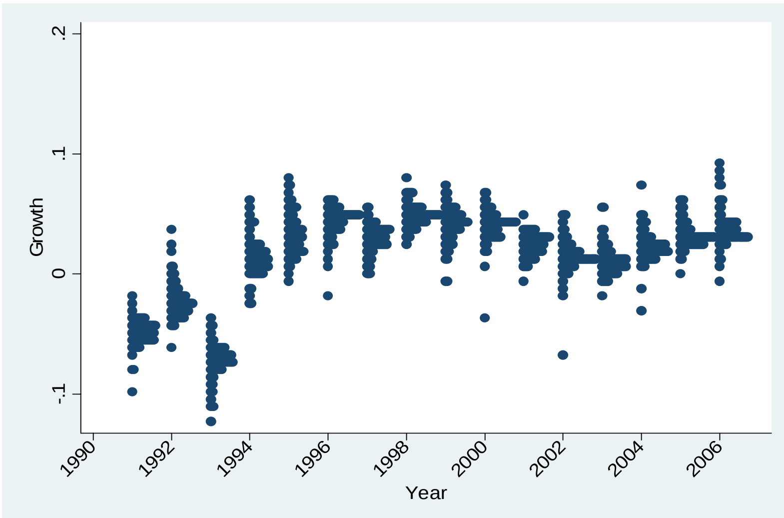
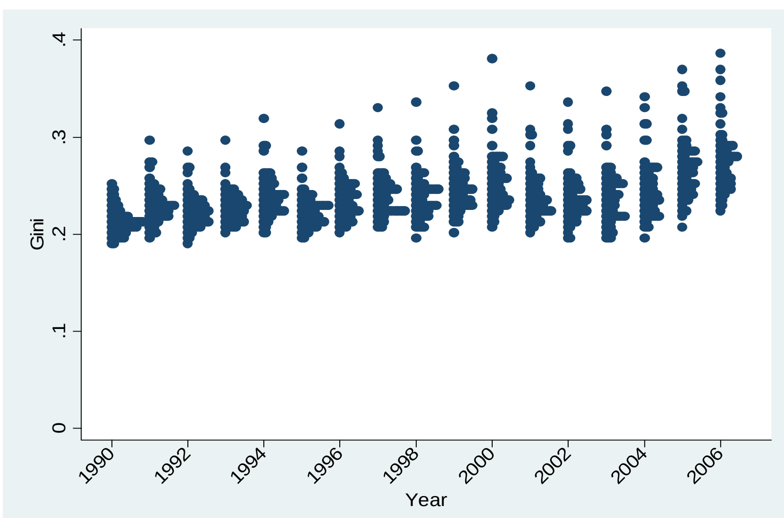


Figure 3. Distributions of gini coefficients across regions 1990-2006.



Tables:

Table 1: Descriptive statistics of 72 regions 1990-2006.

N = 1,224

	Mean	Std. Dev.	Min	Max
Annual earnings growth per capita	1.54	3.79	-23.92	27.73
Earnings level per capita	11.307	.178	10.839	11.838
Earnings growth (day population) [a)]	1.57	3.93	- 13.40	18.20
Earnings level (day population) [a)]	11.249	.184	10.682	11.865
Spatial lag	83.9	10.7	61.8	116.0
Gini coefficient	.240	.0276	.1899	.3859
Third quintile	19.37	.497	16.37	20.91
P9075	1.208	.027	1.147	1.370
P5010	1.823	.120	1.520	2.463
Percent college grad.	9.00	3.92	3.45	27.84
Population (see also below)	123,051	287,469	2,867	2,260,071
Percent aged 20-29	11.01	1.95	6.03	17.65
Percent aged 30-54	32.56	1.56	27.13	37.36
Farming & mining	5.04	3.58	.65	30.35
Construction	6.80	1.73	3.71	17.80
Manufacturing	21.82	8.84	3.07	55.66
Finance & insurance	8.25	2.79	3.51	23.63
Public sector	33.58	6.27	7.40	48.09
Other sectors	24.51	3.83	16.64	38.39

[a)] Refers to the case where earnings are attributed to the region where work is situated, 1990-2005 only.

Percentiles of population size	
1st	3,224
5th	3,859
10th	6,679
25th	11,842
50th	38,221
75th	137,366
90th	201,352
95th	408,233
99th	2,028,513

Table 2. Cross sectional regressions on average annual growth 1990-2006 and 1994-2006, initial values in 1990 and 1994 as explanatory variables, robust standard errors in parentheses.

Dependent variable:	Average annual growth 1990-2006						Average annual growth 1994-2006					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gini (standardized)	.216		.210		.100		.390**		.287		.309*	
	(.244)		(.243)		(.266)		(.166)		(.182)		(.184)	
Q3 (standardized)		- .147	- .142					- .364***	- .298**			
		(.166)	(.167)					(.125)	(.135)			
P9075 (standardized)				.249	.226					.258**	.174	
				(.158)	(.177)					(.122)	(.136)	
P5010 (standardized)						.039						.103
						(.113)						(.156)
Ln(Income)	- .437	- 1.339*	- .655	- .412	- .153	- .897	- .787	- 3.080***	- 1.762	- 1.733**	- .668	- 1.981*
	(.863)	(.742)	(.877)	(.797)	(.833)	(.864)	(.978)	(.645)	(1.059)	(.862)	(.933)	(.994)
Spatial lag	.414	.412	.270	.176	.140	.571	.323	.256	- .047	.392	.105	.844
	(.559)	(.534)	(.575)	(.606)	(.609)	(.523)	(.876)	(.728)	(.784)	(.791)	(.852)	(.890)
College graduates	.066	.086**	.061	.059	.050	.084**	- .020	.022	- .036	.004	- .047	.046
	(.040)	(.034)	(.040)	(.038)	(.040)	(.038)	(.061)	(.045)	(.061)	(.055)	(.063)	(.051)
Fraction aged 20-29	- 1.930	- .066		- 2.044		- .467	- 4.640	- .102		- 2.570		- 2.209
	(6.492)	(6.603)	(6.492)	(6.425)	(6.492)	(6.590)	(8.428)	(7.707)	(8.428)	(7.839)	(8.428)	(8.081)
Fraction aged 30-54	1.093	2.489		2.757		1.383	2.409	9.733		6.706		4.470
	(6.656)	(6.766)	(6.492)	(6.579)	(6.492)	(6.679)	(6.811)	(7.939)	(6.811)	(7.302)	(6.811)	(7.146)
<u>Employment proportions</u>												
Farming & mining	2.646	2.431		3.241		1.820	1.183	2.196		2.977		- .379
	(3.043)	(2.804)	(3.043)	(2.919)	(3.043)	(2.572)	(3.377)	(3.330)	(3.377)	(3.777)	(3.377)	(3.164)
Construction	.535	- .170		1.325		- .742	6.917	4.719		5.187		5.036
	(5.309)	(5.463)	(5.309)	(6.053)	(5.309)	(5.070)	(5.607)	(4.920)	(5.607)	(5.181)	(5.607)	(5.346)
Manufacturing	- .034	- .233		.076		- .486	.780	1.274		1.284		.279
	(2.309)	(2.095)	(2.309)	(2.194)	(2.309)	(2.094)	(2.400)	(2.328)	(2.400)	(2.447)	(2.400)	(2.430)
Finance & insurance	- 3.487	- 3.978		- 5.074		- 3.727	1.251	1.000		.731		1.571
	(4.844)	(4.675)	(4.844)	(4.314)	(4.844)	(4.960)	(3.812)	(3.591)	(3.812)	(3.553)	(3.812)	(3.820)
Public sector	- 2.285	- 3.574		- 2.525		- 3.269	.869	- 1.351		- .347		- 1.744
	(3.185)	(2.306)	(3.185)	(2.739)	(3.185)	(2.839)	(2.944)	(2.197)	(2.944)	(2.794)	(2.944)	(3.008)
Constant	2.175	12.038		4.164		5.635	7.350	31.119***		15.551		14.461
	(10.03)	(9.745)	(10.03)	(9.981)	(10.03)	(11.25)	(12.68)	(9.763)	(12.68)	(11.12)	(12.68)	(12.66)
R^2	.150	.148	.158	.170	.172	.142	.184	.201	.228	.171	.200	.137
Prob > *F*	.040	.044	.030	.007	.007	.051	.008	.001	.000	.008	.005	.073
No. of regions	72	72	72	72	72	72	72	72	72	72	72	72
No. of obs.	72	72	72	72	72	72	72	72	72	72	72	72

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table 3. Pooled OLS panel regressions on average annual growth 1994-2006, as measured in three- and four-year intervals, robust standard errors in parentheses.

Dependent variable:	Average annual growth 1994-2006 (every third year)						Average annual growth 1994-2006 (every fourth year)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gini (standardized)	.309**		.212		.145		.196		.092		.029	
	(.147)		(.212)		(.169)		(.152)		(.148)		(.149)	
Q3 (standardized)		- .225**	- .127					- .353***	- .332**			
		(.113)	(.150)					(.130)	(.132)			
P9075 (standardized)				.379***	.313**					.323**	.313**	
				(.135)	(.156)					(.146)	(.153)	
P5010 (standardized)						.197						.105
						(.113)						(.113)
Ln(Income)	- 1.002	- 2.680***	- 1.687	- 1.263	- .907	- .839	- 1.804	- 3.744***	- 3.286***	- 1.766	- 1.864*	- 1.987
	(.334)	(.007)	(.170)	(.213)	(.372)	(.488)	(.117)	(.000)	(.004)	(.115)	(.092)	(.115)
Spatial lag	.203	.405	.160	- .017	- .165	.457	- .288	- .576	- .683	- .589	- .562	- .133
	(.821)	(.620)	(.856)	(.985)	(.851)	(.621)	(.765)	(.523)	(.467)	(.534)	(.539)	(.889)
College graduates	- .048	- .004	- .040	- .063	- .080	- .030	- .007	.008	- .010	- .029	- .024	.008
	(.381)	(.933)	(.479)	(.221)	(.137)	(.583)	(.896)	(.861)	(.862)	(.617)	(.646)	(.880)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.452	.450	.453	.458	.460	.447	.264	.278	.278	.277	.277	.262
Prob > *F*	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
No. of obs.	288	288	288	288	288	288	216	216	216	216	216	216
No. of regions	72	72	72	72	72	72	72	72	72	72	72	72

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table 4. Regional fixed effects panel regressions (OLS) on average annual growth 1994-2006, as measured in three- and four-year intervals, robust standard errors in parentheses.

Dependent variable:	Average annual growth 1994-2006 (every third year)						Average annual growth 1994-2006 (every fourth year)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gini (standardized)	- .007		- .019**		- .008		- .009		- .010		- .014	
	(.007)		(.009)		(.007)		(.013)		(.013)		(.013)	
Q3 (standardized)		- .004	- .014**					.000	- .002			
		(.005)	(.007)					(.011)	(.012)			
P9075 (standardized)				.001	.004					.009	.014	
				(.007)	(.008)					(.014)	(.014)	
P5010 (standardized)						.002						.006
						(.006)						(.008)
Ln(Income)	.499***	.481***	.423***	.504***	.511***	.508***	.090	.126	.081	.161	.129	.157
	(.117)	(.120)	(.122)	(.120)	(.120)	(.118)	(.188)	(.185)	(.194)	(.190)	(.193)	(.188)
Spatial lag	- .217	- .227	- .247	- .219	- .227	- .207	- .250	- .246	- .251	- .262	- .276	- .235
	(.152)	(.152)	(.151)	(.153)	(.154)	(.154)	(.225)	(.225)	(.226)	(.226)	(.226)	(.225)
College graduates	- .004	- .004	- .002	- .004	- .004	- .004	- .002	- .003	- .002	- .002	- .001	- .003
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.507	.523	.433	.534	.517	.538	.396	.420	.401	.443	.418	.427
No. of obs.	216	216	216	216	216	216	216	216	216	216	216	216
No. of regions	72	72	72	72	72	72	72	72	72	72	72	72

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table 5. Region type/family fixed effects panel regressions (OLS) on average annual growth 1994-2006, as measured in three- and four-year intervals, robust standard errors in parentheses.

Dependent variable:	Average annual growth 1994-2006 (every third year)						Average annual growth 1994-2006 (every fourth year)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gini (standardized)	.335**		.262		.196		.227		.137		.057	
	(.155)		(.208)		(.184)		(.175)		(.166)		(.160)	
Q3 (standardized)		- .216*	- .097					- .385**	- .358**			
		(.114)	(.155)					(.162)	(.157)			
P9075 (standardized)				.394**	.306					.396**	.377**	
				(.162)	(.191)					(.175)	(.174)	
P5010 (standardized)						.222						.126
						(.123)						(.116)
Ln(Income)	- 1.500	- 3.162	- 2.005	- 1.742	- 1.307	- 1.252	- 2.043	- 4.098***	- 3.468	- 2.081	- 1.891	- 2.223
	(1.135)	(1.125)	(1.240)	(1.216)	(1.146)	(1.276)	(1.368)	(1.140)	(1.220)	(1.297)	(1.350)	(1.407)
Spatial lag	.117	.347	.048	- .144	- .354	.540	- .789	- 1.156	- 1.310	- 1.237	- 1.285	- .557
	(1.232)	(1.126)	(1.195)	(1.144)	(1.176)	(1.232)	(1.311)	(1.224)	(1.252)	(1.243)	(1.270)	(1.307)
College graduates	- .085	- .033	- .075	- .074	- .098	- .084	- .016	.020	- .004	- .013	- .022	- .008
	(.060)	(.054)	(.063)	(.058)	(.060)	(.062)	(.061)	(.055)	(.061)	(.058)	(.062)	(.059)
Region type dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.471	.468	.472	.475	.478	.467	.279	.292	.294	.295	.295	.277
No. of obs.	288	288	288	288	288	288	216	216	216	216	216	216
No. of regions	72	72	72	72	72	72	72	72	72	72	72	72

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table 6. System GMM estimations.

Dependent variable: **Annual growth 1994-2006 (3 yr intervals)**

Variable	(1)	(1)	(1)	(2)	(2)	(2)	(3)	(3)	(3)	(4)	(4)	(4)
Gini (standardized)	.005		- .000	.021		- .005	.009		.003	.021		- .006
	(.007)		(.005)	(.022)		(.016)	(.009)		(.009)	(.036)		(.012)
Q3 (standardized)	-.001			.006			.002			.012		
	(.006)			(.015)			(.007)			(.030)		
P9075 (standardized)		.008	.008		.016*	.017		.007	.004		.011	.014
		(.006)	(.006)		(.009)	(.014)		(.009)	(.010)		(.008)	(.010)
Ln(Income)	.953***	.981***	.981***	.948***	1.108***	.987***	1.028***	1.030***	1.012***	1.003***	.999***	.926***
	(.037)	(.035)	(.031)	(.098)	(.081)	(.091)	(.061)	(.041)	(.038)	(.130)	(.122)	(.091)
College graduates	- .000	- .001	- .001	- .002	- .005	- .003	- .003	- .003	- .002	- .003	- .004	- .001
	(.001)	(.002)	(.002)	(.004)	(.003)	(.004)	(.002)	(.002)	(.002)	(.005)	(.004)	(.003)
AR(2)	.160	.192	.201	.104	.136	.178	.123	.143	.142	.117	.139	.218
Hansen test	.045	.110	.066	.002	.031	.003	.010	.025	.025	.000	.004	.000
No. of instruments	40	31	40	20	16	20	28	22	28	12	10	12
No. of regions	72	72	72	72	72	72	72	72	72	72	72	72
No. of obs.	288	288	288	288	288	288	288	288	288	288	288	288

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

System GMM has been performed by using Stata10 and xtabond2 (Roodman, 2006).

Columns (1): all available lags are used as IV. Columns (2): IV count is reduced through the use of a collapsed matrix. Columns (3): only the first available lag is used as IV. Columns (4): the strategies of (2) and (3) are combined. In all estimates, Windmeijer (2005) correction to the covariance matrix is applied. See footnote 11 for further explanations.

Table 6 cont'd. System GMM estimations.

Dependent variable: **Annual growth 1994-2006 (4 yr intervals)**

Variable	(1)	(1)	(1)	(2)	(2)	(2)	(3)	(3)	(3)	(4)	(4)	(4)
Gini (standardized)	.008		- .000	.010		.002	.015		.012	- .002		- .007
	(.009)		(.007)	(.010)		(.011)	(.011)		(.014)	(.009)		(.012)
Q3 (standardized)	- .003			.036*			- .011			- .034***		
	(.011)			(.019)			(.015)			(.013)		
P9075 (standardized)		.015	.011		.019	.020		.013	.008		.010	.010
		(.016)	(.013)		(.018)	(.016)		(.020)	(.017)		(.016)	(.545)
Ln(Income)	.942***	.991***	.958***	.812***	.998***	.977***	.975***	1.058***	.999***	.781***	.966***	.942***
	(.083)	(.060)	(.057)	(.162)	(.114)	(.110)	(.111)	(.071)	(.061)	(.126)	(.098)	(.106)
College graduates	- .000	- .003	- .001	- .003	- .004	- .003	- .004	- .005	- .004	- .000	- .002	- .000
	(.003)	(.005)	(.004)	(.005)	(.005)	(.006)	(.004)	(.005)	(.004)	(.004)	(.004)	(.005)
AR(2)	-	-	-	-	-	-	-	-	-	-	-	-
Hansen test	.004	.002	.002	.000	.000	.000	.001	.001	.001	.003	.001	.000
No. of instruments	23	18	23	15	12	15	19	15	19	11	9	11
No. of regions	72	72	72	72	72	72	72	72	72	72	72	72
No. of obs.	216	216	216	216	216	216	216	216	216	216	216	216

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

System GMM has been performed by using Stata10 and xtabond2 (Roodman, 2006).

Columns (1): all available lags are used as IV. Columns (2): IV count is reduced through the use of a collapsed matrix. Columns (3): only the first available lag is used as IV. Columns (4): the strategies of (2) and (3) are combined. In all estimates, Windmeijer (2005) correction to the covariance matrix is applied. See footnote 11 for further explanations.

Table 7. Day populations; cross sectional regressions on average annual growth 1990-2005 and 1994-2005, initial values in 1990 and 1994 as explanatory variables, robust standard errors in parentheses.

Dependent variable:	Average annual growth 1990-2005						Average annual growth 1994-2005					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gini (standardized)	- .124		- .124		- .127		.323*		.267		.272	
	(.225)		(.221)		(.258)		(.179)		(.202)		(.247)	
Q3 (standardized)		- .162	- .162					- .228	- .164			
		(.170)	(.170)					(.162)	(.175)			
P9075 (standardized)				- .035	.005					.188	.095	
				(.142)	(.170)					(.141)	(.190)	
P5010 (standardized)						- .050						.173
						(.113)						(.176)
Ln(Income)	- 1.805**	- 1.755***	- 2.001**	- 1.625**	- 1.802**	- 1.755**	- 1.280	- 2.721***	- 1.754	- 2.025**	- 1.301	- 1.736*
	(.736)	(.660)	(.758)	(.730)	(.760)	(.751)	(.886)	(.839)	(1.160)	(.814)	(.876)	(.976)
Spatial lag	.187	- .090	- .038	.184	.181	.095	.184	- .011	- .133	.183	.072	.527
	(.891)	(.911)	(.923)	(.902)	(.908)	(.872)	(1.300)	(1.216)	(1.232)	(1.278)	(1.314)	(1.387)
College graduates	.182***	.158***	.173***	.171***	.181***	.177***	.053	.087	.039	.078	.041	.086
	(.060)	(.050)	(.061)	(.055)	(.062)	(.056)	(.081)	(.064)	(.081)	(.071)	(.077)	(.073)
Fraction aged 20-29	9.770	8.963	10.398	8.720	9.749	9.007	8.078	12.867	9.856	10.725	8.363	10.084
	(7.437)	(7.447)	(7.479)	(7.682)	(7.548)	(7.599)	(6.924)	(7.927)	(7.431)	(7.123)	(6.938)	(7.699)
Fraction aged 30-54	- 7.799	- 6.517	- 6.959	- 7.719	- 7.756	- 7.559	- 14.655*	- 8.313*	- 11.695	- 10.480	- 13.560*	- 13.721*
	(7.400)	(7.267)	(7.392)	(7.503)	(7.520)	(7.374)	(7.705)	(8.765)	(9.000)	(7.257)	(7.726)	(7.428)
Employment proportions												
Farming & mining	4.448	5.844*	5.269	4.792	4.468	4.956	4.512	4.316	5.418	5.460	5.648	2.752
	(2.928)	(3.039)	(3.130)	(2.967)	(3.006)	(2.796)	(3.733)	(3.582)	(3.708)	(4.043)	(4.363)	(3.788)
Construction	7.937	9.888	8.874	8.579	7.968	8.568	21.472**	16.783**	20.511**	18.465**	21.476**	19.707**
	(6.543)	(6.629)	(6.725)	(6.722)	(6.759)	(6.401)	(8.872)	(8.139)	(8.617)	(8.433)	(8.701)	(9.150)
Manufacturing	- .421	.408	.059	- .173	.415	- .201	2.476	2.357	2.890	2.640	2.723	2.035
	(2.062)	(2.156)	(2.186)	(2.078)	(2.103)	(2.027)	(2.624)	(2.430)	(2.564)	(2.636)	(2.803)	(2.682)
Finance & insurance	- 6.838	- 6.363	- 6.753	- 6.298	- 6.871	- 6.853	.328	- .861	.033	- .540	.244	.763
	(5.006)	(4.845)	(4.998)	(4.930)	(4.845)	(4.995)	(4.133)	(4.200)	(4.163)	(4.085)	(4.129)	(4.172)
Public sector	- 8.579***	- 7.491***	- 8.300***	- 7.930***	- 8.575***	- 8.318***	- 3.700	- 5.798**	- 3.428	- 5.038*	- 3.253	- 4.929*
	(2.645)	(2.336)	(2.750)	(2.348)	(2.679)	(2.525)	(2.774)	(2.196)	(2.860)	(2.924)	(2.908)	(2.773)
Constant	22.126*	23.901*	26.330**	20.005*	22.143*	22.503**	18.078	34.449**	25.666	25.042**	18.953	19.181
	(11.60)	(12.03)	(12.45)	(11.58)	(11.64)	(12.37)	(16.59)	(15.01)	(17.99)	(14.72)	(16.62)	(16.27)
R^2	.497	.501	.503	.495	.497	.496	.382	.372	.393	.366	.385	.364
Prob > *F*	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
No. of regions	72	72	72	72	72	72	72	72	72	72	72	72
No. of obs.	72	72	72	72	72	72	72	72	72	72	72	72

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

APPENDIX:

Table A.1: Descriptive statistics of seven regional types as defined by the Swedish National Agency for Growth Analysis. 1990-2006.

	Big cities	Regional univeristy centers	Regional centers	Local centers, manufacturing	Local centers, services	Small regions, manufacturing	Small regions, services
Number of regions	3	8	12	6	5	14	24
Number of obs.	51	136	204	102	85	238	408
Annual growth per capita	1.61	1.39	1.57	1.71	1.43	1.48	1.57
	(3.64)	(3.23)	(3.44)	(3.53)	(3.42)	(4.70)	(3.70)
Log earnings level per capita	11.516	11.416	11.387	11.396	11.333	11.261	11.203
	(.169)	(.122)	(.131)	(.139)	(.139)	(.152)	(.171)
Growth – day population[a)]	1.50	1.24	1.39	1.88	1.23	1.56	1.77
	(3.87)	(3.26)	(3.52)	(3.56)	(3.53)	(4.71)	(4.01)
Log earnings – day population[a)]	11.518	11.384	11.348	11.358	11.235	11.194	11.128
	(.184)	(.115)	(.125)	(.153)	(.113)	(.171)	(.199)
Spatial lag	86.6	82.0	90.5	85.2	89.3	83.2	79.8
	(10.1)	(9.6)	(11.8)	(9.8)	(11.4)	(10.2)	(8.6)
Gini coefficient	.304	.247	.251	.235	.238	.231	.231
	(.035)	(.021)	(.018)	(.016)	(.020)	(.022)	(.026)
Third quintile	18.39	19.09	19.13	19.25	19.23	19.64	19.60
	(.66)	(.30)	(.35)	(.40)	(.34)	(.47)	(.36)
P9075	1.283	1.220	1.220	1.202	1.212	1.191	1.198
	(.035)	(.018)	(.018)	(.013)	(.018)	(.017)	(.019)
P5010	2.051	1.813	1.851	1.771	1.809	1.804	1.812
	(.129)	(.083)	(.068)	(.073)	(.108)	(.099)	(.140)
College graduates (%)	17.14	12.70	10.49	8.10	9.31	6.66	7.53
	(4.94)	(4.23)	(3.16)	(2.54)	(2.77)	(2.27)	(2.53)
Population	1,340,812	194,120	164,244	57,836	66,651	21,627	13,762
	(548,077)	(89,730)	(28,718)	(13,956)	(12,391)	(12,819)	(8,924)
Aged 20-29 (%)	13.87	13.28	12.16	10.91	10.86	10.17	9.85
	(.91)	(1.68)	(1.02)	(1.46)	(1.22)	(1.47)	(1.60)
Aged 30-54 (%)	35.22	33.46	33.12	32.96	33.37	31.82	31.82
	(1.17)	(.78)	(.78)	(.70)	(.92)	(1.19)	(1.78)
Employment (%) [b)]							
Farming & mining	1.42	2.87	2.97	3.21	4.70	4.52	8.10
	(.75)	(1.02)	(1.15)	(1.71)	(2.02)	(1.50)	(4.34)
Construction	5.86	6.40	6.32	6.57	6.79	6.31	7.63
	(1.06)	(1.25)	(1.28)	(1.61)	(1.47)	(1.62)	(1.93)
Manufacturing	16.07	17.94	23.95	32.83	20.25	31.78	14.52
	(3.67)	(4.46)	(3.42)	(7.09)	(4.31)	(5.45)	(5.81)
Finance & insurance	15.00	10.23	9.17	7.30	8.75	6.24	7.60
	(3.78)	(1.79)	(1.65)	(2.01)	(1.85)	(1.30)	(2.44)
Public sector	30.37	36.47	33.13	28.67	34.72	30.75	35.88
	(4.10)	(5.47)	(4.77)	(5.39)	(5.09)	(5.37)	(6.71)
Other sectors	31.28	26.08	24.46	21.43	24.80	20.40	26.28
	(1.74)	(1.62)	(2.43)	(2.23)	(2.20)	(2.11)	(3.62)

[a)] Refers to the case where earnings are attributed to the region where work is situated.
[b)] The sum of the employment shares sum to one in each region.

Table A.2. Regressions on inequality measures (standardized values).

Observations in 1990 and 2006.

Dependent variable:	Gini (1)	Gini (2)	Q3 (3)	Q3 (4)	P9075 (5)	P9075 (6)	P5010 (7)	P5010 (8)
Ln(Income)		- .247***		- 2.251		- 1.342		- 10.126***
		(.050)		(1.977)		(.949)		(2.005)
Spatial lag	.047	.064*	- 4.102***	- 3.947***	2.455**	2.547**	- .616	.077
	(.037)	(.037)	(1.295)	(1.207)	(.982)	(.979)	(1.748)	(1.388)
College graduates	.009**	.011***	- .323***	- .301***	.399***	.412***	.195	.294***
	(.004)	(.003)	(.111)	(.104)	(.106)	(.110)	(.137)	(.101)
Fraction aged 20-29	.689	1.127***	- 2.838	1.154	- 9.773	- 7.393	13.075	31.031**
	(.399)	(.352)	(13.43)	(14.85)	(11.35)	(11.72)	(16.81)	(14.74)
Fraction aged 30-54	- 1.061***	- .144	22.127**	30.489***	- 23.603***	- 18.618**	- 11.908	25.705**
	(.361)	(.305)	(9.907)	(9.353)	(7.038)	(7.520)	(12.81)	(12.56)
Employment proportions								
Farming & mining	- .196	- .139	- 1.406	- .892	- 8.112*	- 7.805*	- 6.297	- 3.985
	(.164)	(.146)	(4.688)	(4.431)	(4.467)	(4.536)	(6.167)	(5.181)
Construction	.098	- .032	6.575	5.391	- 1.470	- 2.175	9.490	4.163
	(.395)	(.333)	(10.876)	(10.738)	(8.993)	(8.912)	(15.31)	(12.68)
Manufacturing	- .125	- .045	1.334	2.068	- 6.951**	- 6.513**	- 3.154	.150
	(.109)	(.102)	(2.971)	(2.925)	(2.859)	(2.909)	(3.956)	(3.741)
Finance & insurance	- .099	.160	- 6.004	- 3.642	- 2.292	- .884	- 5.824	4.801
	(.298)	(.264)	(8.132)	(8.707)	(7.326)	(7.158)	(10.91)	(10.28)
Public sector	- .400***	- .413***	8.841***	8.721***	- 15.374***	- 15.445***	- 9.884**	- 10.425**
	(.144)	(.127)	(3.015)	(3.143)	(3.194)	(3.168)	(4.856)	(4.579)
Constant	.115	2.313***	37.93***	57.99**	13.506	- 1.548	12.475	102.70***
	(.419)	(.000)	(14.17)	(24.90)	(10.38)	(14.66)	(19.71)	(29.36)
R^2	.527	.687	.555	.567	.752	.757	.274	.549
No. of obs.	72	72	72	72	72	72	72	72

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table A.3. Regressions on regional level of income and growth.

	Observations in 1990 and 2006.				**Panel data 1990-2006, every 4 years.**			
Dependent variable:	Ln(Income) (1)	Ln(Income) (2)	Growth (3)	Growth (4)	Ln(Income) (5)	Growth (6)	Growth (7)	Growth (8)
Gini		- .107**			- .031**			
		(.045)			(.013)			
Ln(Income)				- 1.136				- 2.148**
				(.731)				(.941)
Spatial lag	.147	.198	.489	.566	- .002			- .082
	(.121)	(.121)	(.534)	(.513)	(.071)			(.778)
College graduates	.023*	.033**	.081***	.092***	.033***	.170***	- .004	.037
	(.012)	(.013)	(.030)	(.034)	(.004)	(.000)	(.821)	(.046)
Fraction aged 20-29	1.417	1.654	- 2.227	- .213	- 3.389***			2.473
	(1.224)	(1.161)	(6.393)	(6.575)	(.419)			(7.747)
Fraction aged 30-54	3.298***	2.270*	- 2.604	1.615	5.236***			4.051
	(1.211)	(1.326)	(6.225)	(6.778)	(.511)			(7.442)
Employment proportions								
Farming & mining	.472	- .035	1.524	1.783	- .362			.433
	(.538)	(.494)	(2.427)	(2.486)	(.340)			(3.629)
Construction	- .587	- 1.156	- .382	- .979	- 3.169***			1.278
	(.974)	(.913)	(5.153)	(4.975)	(.621)			(6.402)
Manufacturing	.173	- .214	- .957	- .587	.124			- .428
	(.329)	(.367)	(1.889)	(1.932)	(.203)			(1.876)
Finance & insurance	.217	- .404	- 5.199	- 4.007	.426			1.215
	(.857)	(.981)	(4.792)	(4.812)	(.513)			(4.294)
Public sector	- .641	- 1.339**	- 3.670*	- 3.731*	- .612*			- 3.533
	(.391)	(.529)	(2.232)	(2.187)	(.314)			(2.231)
Constant	8.636***	8.639***	- 1.715*	8.407	10.135***	.153	- 3.231***	21.062*
	(1.336)	(1.259)	(5.655)	(9.168)	(.852)	(.741)	(.000)	(12.06)
Time fixed effects	No	No	No	No	No	No	Yes	Yes
R^2	.723	.760	.115	.140	.777	.036	.723	.901
No. of obs.	72	72	72	72	288	288	288	288

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table A.4. Cross sectional regressions on average annual growth, initial values in 1990 and 1994 as respective explanatory variables, robust standard errors in parentheses

Year interval	**1990-2005**	**1990-2004**	**1990-2003**	**1990-2002**	**1990-2001**	**1990-2000**	**1990-1999**	**1990-1998**	**1994-2005**	**1994-2004**	**1994-2003**	**1994-2002**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gini (standardized)	.282	.249*	.179	.200	.267	.338	.196	.064	.299*	.251*	.260**	.314**
	(.178)	(.147)	(.146)	(.170)	(.176)	(.228)	(.200)	(.212)	(.151)	(.141)	(.123)	(.122)
Q3 (standardized)	- .211	- .187*	- .273**	- .242*	- .257*	- .330	- .157	.002	- .278**	- .209*	- .294**	- .279**
	(.130)	(.101)	(.134)	(.128)	(.152)	(.238)	(.197)	(.166)	(.124)	(.113)	(.140)	(.124)
Gini (standardized)	.272	.241*	.169	.188	.256	.327	.191	.064	.216	.191	.184	.233
	(.175)	(.143)	(.138)	(.161)	(.169)	(.223)	(.199)	(.212)	(.168)	(.155)	(.134)	(.140)
Q3 (standardized)	- .204	- .181*	- .267**	- .237*	- .250*	- .319	- .151	.004	- .231*	- .167	- .247	- .227*
	(.130)	(.101)	(.133)	(.126)	(.149)	(.231)	(.194)	(.165)	(.135)	(.123)	(.150)	(.135)
P9075 (standardized)	.190	.229**	.255**	.347**	.288*	.236	.136	.004	.221*	.207	.265**	.371**
	(.117)	(.113)	(.113)	(.147)	(.157)	(.193)	(.185)	(.159)	(.121)	(.131)	(.124)	(.144)
Gini (standardized)	.209	.173	.085	.069	.174	.270	.164	.070	.227	.193	.178	.197
	(.186)	(.153)	(.143)	(.156)	(.170)	(.228)	(.206)	(.210)	(.193)	(.184)	(.168)	(.156)
P9075 (standardized)	.143	.183	.231**	.327**	.238	.162	.086	- .015	.158	.146	.207	.305*
	(.123)	(.120)	(.115)	(.148)	(.152)	(.187)	(.185)	(.152)	(.149)	(.165)	(.155)	(.168)
P5010 (standardized)	.103	.126	.100	.100	.102	.084	.090	.040	.175	.205*	.185*	.241**
	(.081)	(.082)	(.076)	(.087)	(.081)	(.078)	(.073)	(.085)	(.118)	(.120)	(.097)	(.102)

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table A.5. Pooled OLS panel regressions on average annual growth, interval lengths of between three and six years with varying evaluation periods, robust standard errors in parentheses.

	Every third year						**Every fourth year**						
Year interval	**1991-2006** (1)	**1990-2005** (2)	**1995-2004** (3)	**1993-2005** (4)	**1992-2004** (5)	**1996-2005** (6)	**1990-2006** (7)	**1991-2003** (8)	**1994-2002** (9)	**1990-2002** (10)	**1992-2004** (11)	**1993-2005** (12)	**1998-2006** (13)
Gini (standardized)	.208	.114	.087	.171	-.080	.216*	.114	-.064	.125	.094	-.163	.090	.132
	(.134)	(.116)	(.177)	(.114)	(.152)	(.129)	(.144)	(.111)	(.148)	(.131)	(.163)	(.156)	(.219)
Q3 (standardized)	-.181*	-.164	-.095	-.187*	-.037	-.291***	-.288**	-.016	-.209*	-.205**	.009	-.098	-.458***
	(.104)	(.102)	(.133)	(.108)	(.127)	(.094)	(.117)	(.114)	(.115)	(.101)	(.141)	(.149)	(.165)
Gini (standardized)	.111	.058	.053	.108	-.104	.090	.024	-.093	.026	.001	-.210	.058	-.008
	(.172)	(.123)	(.177)	(.119)	(.150)	(.133)	(.144)	(.138)	(.180)	(.151)	(.180)	(.154)	(.207)
Q3 (standardized)	-.132	-.149	-.082	-.159	-.061	-.267***	-.282**	-.050	-.201	-.204	-.069	-.084	-.460***
	(.133)	(.109)	(.136)	(.116)	(.126)	(.099)	(.120)	(.135)	(.146)	(.121)	(.144)	(.153)	(.160)
P9075 (standardized)	.294**	.151	.270**	.190*	.139	.286***	.250**	.059	.296**	.220**	.108**	.110	.267
	(.120)	(.099)	(.133)	(.107)	(.117)	(.108)	(.123)	(.102)	(.124)	(.101)	(.124)	(.141)	(.195)
Gini (standardized)	.070	.026	-.050	.066	-.171	.048	-.036	-.127	.006	-.011	-.265	.038	-.016
	(.151)	(.145)	(.184)	(.141)	(.141)	(.150)	(.150)	(.142)	(.169)	(.153)	(.188)	(.171)	(.205)
P9075 (standardized)	.263*	.141	.287**	.165	.194	.268**	.263**	.111	.294*	.225*	.194	.098	.273
	(.136)	(.123)	(.145)	(.131)	(.131)	(.127)	(.131)	(.125)	(.151)	(.123)	(.142)	(.156)	(.195)
P5010 (standardized)	.143	.002	.136	.027	.062	.061	.037	.106	.149	.063	.042	-.007	.002
	(.102)	(.085)	(.117)	(.092)	(.097)	(.097)	(.095)	(.089)	(.131)	(.104)	(.100)	(.094)	(.156)

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table A.5 cont'd. Pooled OLS panel regressions on average annual growth, interval lengths of between three and six years with varying evaluation periods, robust standard errors in parentheses.

	Every fifth year					**Every sixth year**				
Year interval	**1990-2005**	**1991-2006**	**1996-2006**	**1994-2004**	**1995-2005**	**1990-2002**	**1991-2003**	**1994-2006**	**1992-2004**	**1993-2005**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gini (standardized)	- .209	.040	.123	.106	- .216	.177	- .020	.119	- .084	.177
	(.150)	(.152)	(.196)	(.121)	(.162)	(.140)	(.140)	(.154)	(.149)	(.146)
Q3 (standardized)	.073	- .149	- .216	- .153	.093	- .152	- .088	- .203	.001	- .092
	(.125)	(.134)	(.166)	(.109)	(.132)	(.111)	(.108)	(.124)	(.129)	(.124)
Gini (standardized)	- .207	- .020	.055	.012	- .200	.131	- .080	- .046	- .101	.156
	(.181)	(.149)	(.180)	(.136)	(.199)	(.151)	(.175)	(.188)	(.160)	(.171)
Q3 (standardized)	.002	- .154	- .204	- .149	.020	- .117	- .120	- .222	- .033	- .032
	(.141)	(.134)	(.158)	(.121)	(.151)	(.120)	(.142)	(.147)	(.137)	(.148)
P9075 (standardized)	.138	.180	.283*	.152	.192	.269***	.134	.352**	.129	.104
	(.139)	(.133)	(.171)	(.126)	(.152)	(.093)	(.134)	(.150)	(.095)	(.119)
Gini (standardized)	- .356**	- .062	- .027	.036	- .392*	.045	- .099	- .105	- .189	.151
	(.209)	(.150)	(.176)	(.142)	(.199)	(.170)	(.164)	(.190)	(.183)	(.183)
P9075 (standardized)	.254*	.197	.290*	.136	.317**	.253**	.169	.393**	.204	.037
	(.139)	(.135)	(.162)	(.143)	(.157)	(.121)	(.116)	(.170)	(.131)	(.149)
P5010 (standardized)	.097	.029	.048	.096	.169	.089	.001	.105	.030	.064
	(.096)	(.084)	(.098)	(.108)	(.125)	(.089)	(.087)	(.134)	(.091)	(.092)

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table A.6. Regional fixed effects panel regressions on average annual growth, interval lengths of between three and six years with varying evaluation periods, robust standard errors in parentheses.

	Every third year						**Every fourth year**						
Year interval	**1991-2006**	**1990-2005**	**1993-2005**	**1992-2004**	**1995-2004**	**1996-2005**	**1990-2006**	**1990-2002**	**1991-2003**	**1992-2004**	**1993-2005**	**1994-2002**	**1998-2006**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Gini (standardized)	- .002	.002	.004	.002	.003	.003	.003	.006	- .002	.002	- .003	- .021**	.020
	(.006)	(.005)	(.005)	(.006)	(.006)	(.006)	(.010)	(.008)	(.006)	(.007)	(.008)	(.010)	(.021)
Q3 (standardized)	- .005	- .006	- .007	- .008**	- .010**	- .005	- .008	- .008	- .001	- .007	- .008	.003	- .010
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.008)	(.005)	(.005)	(.005)	(.006)	(.006)	(.019)
Gini (standardized)	- .012	- .002	- .000	- .005	- .006	- .001	- .002	- .003	- .002	- .013	- .010	- .034**	.018
	(.008)	(.006)	(.006)	(.006)	(.006)	(.007)	(.011)	(.011)	(.008)	(.010)	(.009)	(.013)	(.023)
Q3 (standardized)	- .011*	- .006	- .007	- .010**	- .012**	- .005	- .009	- .009	- .000	- .013**	- .011	- .012	- .004
	(.006)	(.005)	(.005)	(.004)	(.005)	(.005)	(.009)	(.007)	(.006)	(.006)	(.007)	(.008)	(.021)
P9075 (standardized)	.002	.004	.011**	.005	.001	.007	.010	.007	.005	.007	.012	.000	.016
	(.006)	(.004)	(.005)	(.005)	(.007)	(.006)	(.008)	(.006)	(.006)	(.007)	(.008)	(.011)	(.023)
Gini (standardized)	- .004	- .000	- .000	.000	.003	.000	- .004	.003	- .004	- .000	- .007	- .023**	.016
	(.006)	(.006)	(.005)	(.006)	(.007)	(.007)	(.011)	(.009)	(.006)	(.008)	(.008)	(.010)	(.024)
P9075 (standardized)	.004	.004	.011**	.005	- .000	.006	.011	.006	.006	.007	.014*	.007	.008
	(.007)	(.005)	(.005)	(.006)	(.008)	(.007)	(.010)	(.008)	(.006)	(.007)	(.008)	(.011)	(.026)
P5010 (standardized)	.005	- .001	- .000	- .002	- .010*	.001	.005	- .003	.005	- .003	- .007	.005	.019
	(.005)	(.004)	(.004)	(.005)	(.005)	(.005)	(.006)	(.006)	(.006)	(.006)	(.007)	(.008)	(.016)

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table A.7. Region type fixed effects panel regressions on average annual growth, interval lengths of between three and six years with varying evaluation periods, robust standard errors in parentheses.

	Every third year						**Every fourth year**						
Year interval	**1991-2006** (1)	**1990-2005** (2)	**1993-2005** (3)	**1992-2004** (4)	**1995-2004** (5)	**1996-2005** (6)	**1990-2006** (7)	**1990-2002** (8)	**1991-2003** (9)	**1992-2004** (10)	**1993-2005** (11)	**1994-2002** (12)	**1998-2006** (13)
Gini (standardized)	.229	.139	.209	- .055	.089	.205	.139	.130	- .014	- .157	.120	.169	.156
	(.141)	(.124)	(.123)	(.161)	(.187)	(.142)	(.159)	(.130)	(.120)	(.177)	(.164)	(.150)	(.268)
Q3 (standardized)	- .171	- .166	- .200*	- .026	- .091	- .327***	- .285**	- .218**	- .040	- .021	- .083	- .254**	- .518**
	(.105)	(.110)	(.117)	(.135)	(.145)	(.104)	(.140)	(.104)	(.116)	(.143)	(.157)	(.119)	(.230)
Gini (standardized)	.153	.087	.151	- .069	.062	.079	.061	.039	- .047	- .192	.010	.061	.044
	(.186)	(.130)	(.127)	(.157)	(.181)	(.146)	(.155)	(.148)	(.145)	(.192)	(.158)	(.177)	(.250)
Q3 (standardized)	- .103	- .144	- .163	- .041	- .078	- .308***	- .272**	- .206*	- .058	- .051	- .061	- .236	- .509**
	(.141)	(.116)	(.124)	(.131)	(.143)	(.109)	(.138)	(.122)	(.136)	(.144)	(.157)	(.146)	(.214)
P9075 (standardized)	.309**	.165	.231**	.164	.279*	.309**	.285**	.262***	.093	.127	.123	.376***	.331
	(.138)	(.107)	(.117)	(.131)	(.153)	(.122)	(.140)	(.099)	(.108)	(.138)	(.157)	(.123)	(.245)
Gini (standardized)	.109	.055	.101	- .136	- .025	.045	- .013	.014	- .080	- .249	.075	.037	.008
	(.162)	(.149)	(.145)	(.161)	(.189)	(.161)	(.156)	(.147)	(.146)	(.196)	(.171)	(.163)	(.235)
P9075 (standardized)	.261	.145	.195	.204	.286	.293**	.290**	.256**	.125	.202	.102	.362**	.328
	(.160)	(.128)	(.137)	(.134)	(.156)	(.138)	(.143)	(.116)	(.127)	(.148)	(.166)	(.142)	(.230)
P5010 (standardized)	.164	.013	.045	.080	.143	.052	.055	.066	.110	.044	.016	.145	.045
	(.104)	(.087)	(.094)	(.096)	(.109)	(.101)	(.097)	(.103)	(.088)	(.103)	(.091)	(.129)	(.175)

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.

Table A.7 cont'd. Region type fixed effects panel regressions on average annual growth, interval lengths of between three and six years with varying evaluation periods, robust standard errors in parentheses.

	Every fifth year					**Every sixth year**				
Year interval	**1990-2005** (1)	**1991-2006** (2)	**1995-2005** (3)	**1996-2006** (4)	**1994-2004** (5)	**1990-2002** (7)	**1991-2003** (8)	**1992-2004** (9)	**1993-2005** (10)	**1994-2006** (11)
Gini (standardized)	- .221	.047	- .294	.108	.173	.188	.010	- .054	.237	.109
	(.155)	(.164)	(.175)	(.226)	(.131)	(.148)	(.137)	(.158)	(.160)	(.172)
Q3 (standardized)	- .082	- .143	.103*	- .222	- .208	- .161	- .097	- .004	- .123	- .217
	(.125)	(.141)	(.135)	(.185)	(.105)	(.119)	(.108)	(.142)	(.129)	(.124)
Gini (standardized)	- .216	-.004	- .297	.058	.053	.144	- .051	- .063	.208	- .069
	(.188)	(.158)	(.210)	(.213)	(.143)	(.158)	(.173)	(.164)	(.179)	(.206)
Q3 (standardized)	- .007	- .143	- .004	- .213	- .189*	- .125	- .118	- .018	- .044	- .244
	(.142)	(.138)	(.147)	(.174)	(.113)	(.127)	(.142)	(.145)	(.150)	(.142)
P9075 (standardized)	.121	.203	.144	.294	.215	.305***	.193*	.193*	.151	.409**
	(.147)	(.157)	(.183)	(.212)	(.133)	(.096)	(.098)	(.099)	(.130)	(.184)
Gini (standardized)	- .351*	- .043	- .424**	- .010	.086	.049	- .088	- .175	.192	- .113
	(.186)	(.158)	(.212)	(.201)	(.145)	(.172)	(.155)	(.183)	(.186)	(.196)
P9075 (standardized)	.235	.214	.274	.296	.179	.288**	.224**	.260**	.066	.454**
	(.150)	(.155)	(.179)	(.198)	(.143)	(.121)	(.113)	(.127)	(.152)	(.195)
P5010 (standardized)	.086	.033	.132	.043	.071	.088	.018	.054	.096	.086
	(.099)	(.084)	(.125)	(.097)	(.103)	(.097)	(.086)	(.090)	(.092)	(.145)

Notes: ***significant at the 1 % level. **at the 5 % level. *at the 10 % level.