The limited role of education for income convergence: Norwegian regions[*]

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Abstract

Human capital is important for economic growth, but when and how? We study the role of tertiary education level and accumulation for regional income growth in Norway. If high education level stimulates economic growth, the education factor is expected to contribute to economic divergence. On the other hand, equalization of the education level may help income convergence by lifting the income level of the periphery lagging in both education and income. We use distribution analysis and the estimated change in distribution and first order Markov chains show overall income convergence and also convergence in education level. The hypothesis of equal income transition probabilities across subgroups of municipalities with different developments in the relative education level cannot be rejected. Rising educational attainment is as common in regions catching up as in regions falling behind, and whether a low income region increases the relative level of education or not does not affect the chances of catching up. High education level is associated with upward income transitions in high income regions. Overall we conclude that equalization of the education level has not been important for the observed income convergence.

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1. Introduction

Education is presumably an important aspect of most economic growth processes. But it is not obvious how education influences income convergence. If high education level stimulates economic growth, the education factor is expected to contribute to economic divergence. Equalization of the education level may help income convergence by lifting the income level of the periphery lagging in both education and income. We study regional income convergence in an advanced economy, Norway, during a period of equalization of education levels across the country. The overall education level is high, and primary and secondary education are compulsory, but the share of the grown up population with tertiary education has been varying significantly between regions. The growth process is studied by distribution analysis.

The importance of education for growth has primarily been investigated across countries. Benhabib and Spiegel (1994) started up a large empirical literature that has found some effect of the stock of human capital, but limited effect of accumulation of education in cross-country data. Krueger and Lindahl (2001) and Benhabib and Spiegel (2005) offer overviews of the early literature and clarify the roles of accumulation and level of education. The first emphasizes human capital as a characteristic of labor input in extended production functions. In this case accumulation of human capital expands production and income, as developed by Lucas (1988). In regional growth analysis rising educational attainment is related to rising income level when this channel is important. Rising education level may lift low income regions into income convergence. The second mechanism assumes that the stock of human capital is important for technological innovation and adoption and thereby productivity and income growth, as originally formulated by Nelson and Phelps (1966). Higher stock of human capital generates more income growth, a possible source of economic divergence. High income regions with high education level may take off and away from regions with lower education level. But the country level analyses have not indicated such important effects of education. The disappointing results of the early literature are summarized by Pritchett (2001) under the title 'where has all the education gone?'.

Two robust stylized facts stand out. At the macro level, more educated countries are more productive and have higher income levels, and this is also true for regions within a country. At the micro level, additional years of schooling are related to higher individual earnings.

Then there is a micro-macro paradox in that the individual earning gains are hard to find in aggregate data about educational attainment and income growth. And productivity growth rates have declined over recent decades along with increased education levels, which is hard to reconcile with strong productivity growth effects of human capital. Recent research has tried new approaches to understanding the empirical experiences. De la Fuente and Domenech (2006) find room for human capital in the augmented neoclassical growth model of factor stocks and technical progress using OECD data. Ciccone and Papaioannou (2009) show that human capital level and accumulation stimulate human-capital intensive industries. Hanushek and Kimko (2000) and Hanushek and Woessman (2007) turn the attention to education quality, some measure of cognitive skills created, and conclude that this is related to economic growth in cross-country data. Vandenbussche et al. (2006) analyze investments in higher education in the US states and find that tertiary education is growth enhancing in states that are close to the technological frontier. It follows that human capital is not a sufficient statistic to predict growth since both composition of the human capital and the distance to the frontier are important. Glaeser et al. (1995) show that initial level of schooling is an important determinant of economic growth in American cities. This positive effect of schooling contributes to divergence of income levels as cities with high education and income levels grow faster.

We use regional data with variation in tertiary education to throw light on the possible importance of education. The education level is measured by the share of the grown up population with tertiary education and is observed every year during the period 1980-2003. Compared to the international literature, we expect the quality of the tertiary education to vary less across regions and the distance to the technological frontier is presumably the same all over the country. We are able to establish a measure of the income level per capita in municipalities and regions based on the personal income from tax data. The income concept basically covers wage income.

Econometric analyses of education effects face serious methodological challenges of endogeneity, and in particular in regions with high mobility of people with higher education. Also income convergence econometrics has problems of averaging discussed by Quah (1993a, b). We therefore turn to distribution analysis and study the development of the entire cross-regional distribution of income per capita and education level. The analysis concentrates on patterns of income transitions and relations to the education level and accumulation in the regions. Compared to the existing literature this is an alternative method to analyze the role of education. The investigation of systematic patterns between tertiary education and income transitions offers information of the plausibility of causal effects.

Direct observation of the distribution across municipalities in 1980 confirms the expected relationship between education level and income level. Small municipalities in the periphery have low income and education level, while the large cities have high share of the grown up population with tertiary education and high income level. The scene is set for education level as a source of divergence. But distribution analysis shows convincing income convergence. The kernel density function of income levels is narrowing over time and first order Markov chains have ergodic distribution with single peak. We also analyze the distribution dynamics of the education level of the municipalities. Both the Kernel density estimates and the estimated Markov chains reflect convergence of education level over time. Equalization of the education level goes hand in hand with income convergence. Education may be the source of income convergence. Empirical analysis can clarify whether education contributes to divergence or convergence.

The data do not show systematic differences in income transitions with respect to change in the relative education level. The transitions in the income distribution are independent of whether regions are moving up or down in the distribution of relative education levels. Rising educational attainment is as common in regions catching up as in regions falling behind, and whether a low income region increases the relative education level or not does not affect the chances of catching up. The results of the analysis of accumulation of human capital are hardly consistent with education as a driving factor for convergence or divergence. And they are consistent with a large literature of cross-country analysis that show small growth effects of rising educational attainment.

Education and income levels are highly correlated across regions. Low income regions with high education level and high income regions with low education level are deviations from the normal pattern. And the relationships between income transitions and education levels are weak. Only a few observations are consistent with a role for education level and this effect work in favor of divergence. Overall we conclude that education has a limited role in the income convergence process among Norwegian regions.

The methodological approach is discussed in section 2. Section 3 shows the evidence for income convergence among Norwegian municipalities. Section 4 analyzes the convergence in education level. The relationship between income convergence and rising educational attainment is investigated in section 5. Section 6 studies income convergence and education level. Some robustness checks of the results are reported in section 7. Concluding remarks are offered in section 8.

2. Methodological issues

Our main motivation to use Markov chains is the importance of the two ends of the distribution of per capita incomes – relatively low income and relatively rich regions. Income convergence and divergence are heterogeneous processes with different growth paths from different starting points. In addition the challenges of the econometric methods are serious. We take benefit of the methodological innovations of Quah (1993a, 1993b, 2001) using Markov chains, more recently developed by Kremer et al. (2001). The basics of the method are presented by Shorrocks (1978). We estimate the transitional probabilities of the Markov chains by the maximum likelihood method to facilitate tests of homogeneity and dependence. Our discussion of the method is related to Bichenbach and Bode (2003).

The analysis is based on data for taxable income of each of 401 municipalities and calculated per capita based on the number of residents in the beginning of the year. The data cover all years during the period 1980-2003 and it follows that we have 9624 observations of per capita incomes. Personal income measured in the tax statistic basically reflects wage income, and capital income is hard to locate at this level of disaggregation. No municipal GDP measure is available.

The database covers per capita income Y_{kt} for municipality k in year t, 401 municipalities (k = 1,..,401) for the period 1980 to 2003 (t=1980,…,2003). In general terms we describe these as regions. In the analysis the income level is measured relative to the average income per capita across regions in each year, and we describe this relative per capita income by y_{kt}. The whole range of relative per capita income is divided into a finite number of N mutually exclusive states and in this analysis we follow the convention of working with quintiles (N=5). For each region k we get a sequence of variables describing the states of that region at time t. The sequences are considered as independent realizations of a single homogeneous Markov chain with finite state space N. The assumption of a finite first order Markov chain implies that the probability of being in a specific state at time t only depends on the state of the previous period (and not earlier periods). The transition probability, the probability of moving from state i to state j from period $t-1$ to period t is described by $p_{ij}(t)$. The probability is estimated based on observations of how regions move between states over time. The number of regions moving from state i to state j from period $t-1$ to t is measured by $n_{ij}(t)$. The total number of regions moving from state i from period $t-1$ to t is measured by $n_i(t-1) = \sum_j n_{ij}(t)$. The Markov chain can be reduced to a product of N mutually independent multinomial distributions for each row i and time period t of the transition matrix and the distribution function is:

$$f\left(n_{ij}(t)\right)=\prod_{i=1}^{N} f_i\left(n_{ij}(t)\right)=\prod_{i=1}^{N}\left[\frac{n_i(t-1)!}{\prod_{j=1}^{N} n_{ij}(t)!}\prod_{j=1}^{N} p_{ij}^{n_{ij}(t)}\right] \tag{1}$$

The transition probabilities can be estimated by maximizing the log likelihood of the T multinomials above with respect to p_{ij}:

$$f\left(n_{ij}(t)\right)=\prod_{t=1}^{T} f\left(n_{ij}(t)\right) \tag{2}$$

Given the constraint that the sum of p_{ij} over all j is 1, the maximum likelihood estimator is simply the relative frequency of transitions:

$$\hat{p}_{ij}=\frac{n_{ij}}{n_i}=\frac{\sum_{t=1}^{T} n_{ij}(t)}{\sum_{t=1}^{T} n_i(t-1)} \tag{3}$$

where n_{ij} and n_i are the sums of the observed frequencies over all transition periods.

With five income states the Markov transition matrix Ω is given as:

$$\Omega=\begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} & p_{15} \\ p_{21} & p_{22} & p_{23} & p_{24} & p_{25} \\ p_{31} & p_{32} & p_{33} & p_{34} & p_{35} \\ p_{41} & p_{42} & p_{43} & p_{44} & p_{45} \\ p_{51} & p_{52} & p_{53} & p_{54} & p_{55} \end{bmatrix} \tag{4}$$

Given the initial distribution of regional income per capita across income quintiles, $h(0) = [h_1(0), h_2(0), h_3(0), h_4(0), h_5(0)]$ where $\sum_i h_i(0) = 1$, the distribution after the first transition period can be calculated as $h(1) = h(0)\Omega$. And similar, the distribution after m transition periods follows as $h(m) = h(0)\Omega^m$. Given that the matrix is regular[1], the distribution converges to the limiting distribution $h^* = \lim_{m\to\infty} h(0)\Omega^m$, which is independent of the initial distribution. This is the ergodic long-run distribution of regional incomes and is estimated based on the Markov chain matrix under the assumption that the transition dynamics remain unchanged.

3. Income level convergence

Income convergence is analyzed using Kernel density functions as well as Markov chain transition matrices. The most intensive use of the data estimates Markov chains using annual transitions, and this replicates the transition probability matrices suggested by Quah (1993a, b) for studies of cross-country income dynamics. We have investigated annual transitions, but report only full-period transition and 4-year transitions in Table 1 below. The pattern is the same, and the argument for 4-year intervals is to avoid short term fluctuations and thereby have more stable transition paths. We apply the average income per capita over each 4-year period and thereby avoid single year outliers.

To examine how the distribution of municipal income per capita develops over time, we compare the estimated Kernel density functions for the 4-year periods 1980-83 and 2000-03, as shown in Figure 1.[2] The horizontal axis represents income per capita relative to the average level across municipalities, while the vertical axis gives the density of municipalities at different relative income levels. Both functions have a single-peak distribution with the majority of municipalities located close to the average level of income per capita. The estimated distributions show a clear pattern of convergence between the two periods. The distribution is more concentrated around the peak in 2000-03 compared to 1980-83.

[1] The Markov chain is regular if for some integer m, all entries of Ω^m are positive.
[2] The density estimates are calculated using a Gaussian kernel with bandwidth set according to Silverman's rule of thumb; $1.06\sigma B^{-0.2}$, where σ is the standard deviation of the data and B is the number of observations. This gives bandwidth equal to 0.046 and 0.04 for 1980-83 and 2000-03, respectively.

Figure 1 about here

To estimate Markov chain matrices we follow the convention of discretization based on quintiles in the first period and the quintiles have about 80 municipalities each: 1) less than 87.6% of the average income per capita, 2) between 87.6% and 94.2%, 3) between 94.2% and 100.5%, 4) between 100.5% and 110%, and 5) more than 110% of the average income per capita across municipalities.

Table 1 shows transition probability matrices with respect to the level of income per capita. The Markov matrices confirm the pattern of income convergence across municipalities indicated by the Kernel functions. The distribution of per capita incomes is tending towards a point mass, rather than towards a two-point distribution. A municipality that is in the lowest income quintile initially (income level relative to the average below 0.876) has a relatively high probability of catching up. Using the full period transition in panel a, the probability of transition to a higher income quintile during the 20 year period from 1980-83 to 2000-03 equals 60%. There is more than 40% probability that initially rich municipalities (relative income above 1.1) move down the income distribution. For income quintiles 2 and 4 (below and above the middle income quintile, respectively) the probability of moving to the lower or upper tail of the distribution is below 10%. In other words, the distribution dynamics show no tendencies of a bimodal twin peaked distribution, but rather a movement towards the middle income quintile.

Table 1 about here

The 4-year transition probability matrix for the period 1980-83 to 2000-03 is shown in panel b. The calculation is based on 2005 observations (compared to 401 observations for the full-period transitions), which gives more reliable results. As expected, the probability of remaining in the same income quintile is higher when the transition period is shorter (4-year transitions rather than 20-year transition). But the overall picture is still one of convergence. Municipalities in the two low income quintiles have about 25% probability of catching-up during a 4-year period, and the richest municipalities have 16.5% chance of moving down the distribution. The probability of moving from quintile 4 to the richest income quintile is only 6.5%. Similarly, the chance that municipalities in income quintile 2 move down the distribution is below 10%.

The pattern is confirmed by the implied ergodic distribution, which is given in the last row of the matrices. The ergodic distribution represents the long-run distribution of municipal incomes. The distribution tends to accumulate in the middle, combined with thinning of both the lower and the higher tail, consistent with income convergence. Low income municipalities tend to become relatively richer and rich municipalities tend to move towards relative middle income, i.e. living standards converge across municipalities. The ergodic distribution is independent of the length of transitions. Whether the expected long-run distribution of municipal incomes is based on the full period 20-year transition matrix or the 4-year transition matrix for the same period does not matter much. In both cases, municipal incomes seem to be normally distributed with thinning of the tails and the majority of municipalities gathering in the middle. In the long-run, income quintiles 3 and 4 (relative income between 94.2% and 110% of the average) account for about 60% of the municipalities.

The income convergence result is consistent with Rattsø and Stokke (2010). Their focus is on the role of labor migration, and they use the same data (somewhat extended) and offer more statistical tests. They also analyze economic regions with common labor markets based on an aggregation of municipalities, with the same convergence result. Income convergence has previously been shown for the Scandinavian countries in econometric analyses by Aronsson et al. (2001) for Sweden and Østbye and Westerlund (2007) for Sweden and Norway. Their analyses are based on data for counties (about 20 in each country) and consequently offer less information about income distribution and do not capture income differences between periphery and urban centers or between functional economic regions well.

4. Education level convergence

The education level across Norway is quite similar for primary and secondary education, since both are compulsory. The interesting variation in education level relates to tertiary education. We measure the level of education in each municipality as the share of the grown up population with tertiary education, including both short higher education (up to 4 years in duration) and long higher education (more than 4 years in duration).[3] The data cover all years

[3] Data source: Statistics Norway, Table 06983; Number of persons above 16 years according to the level of education, data available for 1970 and 1980-2003.

during the period 1980-2003 and it follows that we have 9624 observations of educational levels in different localities at different years.

We have not seen Markov chain analyses of the education level in the literature, but convergence in education levels has been observed across countries in OECD data. Wolff (2000) find convergence in schooling levels using dispersion measures and observe that it corresponds to convergence in labor productivity levels. Cuaresma (2006) estimate Kernel density functions for educational attainment, but different data sets provide contradictory conclusions. We are not concerned with alternative descriptions of the education level in the Norwegian data. The development of the distribution of the education level in the municipalities is first described by estimated Kernel density functions for the first 4-year period 1980-83 and the last 4-year period 2000-03, as shown in Figure 2. The horizontal axis represents the share of the grown up population with tertiary education relative to the average share across municipalities, while the vertical axis gives the density of municipalities at different relative education levels.[4] The distributions have a single-peak around the average educational level, but compared to the distribution of income per capita, the variations in educational levels are larger across municipalities. Over time, the distribution becomes narrower and the peak more pronounced, indicating convergence also with respect to the level of education.

Figure 2 about here

The Markov chains, now for educational level, are based on quintiles. Discretization with respect to the level of education gives the following five quintiles: 1) less than 70.5% of the average educational level, 2) between 70.5% and 84.95%, 3) between 84.95% and 99%, 4) between 99% and 121%, and 5) more than 121% of the average level of education. The wider range reflects larger differences across municipalities with respect to level of education compared to income level.

Table 2 shows Markov matrices with respect to the level of education, measured as the share of the grown up population with tertiary education. The transition matrices are consistent with the findings from the Kernel functions with convergence in educational levels across

[4] Consistent with Silverman's rule of thumb the bandwidth is set to 0.126 and 0.101 for 1980-83 and 2000-03, respectively.

municipalities. Municipalities located in the lowest education quintile initially (below 70.5% of the average level) have about 55% chance of moving up the distribution during the full 20-year period. Similarly, municipalities in education quintiles 2 and 4 have low probability (below 10%) of moving to the respective ends of the distribution. The main difference from the income distribution given in Table 1 is that municipalities in the highest education quintile have good chances of remaining in this group (85%). This implies that education quintile 5 (educational level at least 21% higher than the average) remains significant in the long-run distribution (with more than 20% of the municipalities). But the ergodic distribution has a single peak at education quintile 4 (between 99% and 121% of the average educational level), which accounts for about 30% of the municipalities in the long run.

Table 2 about here

To sum up, the density functions and the Markov matrices identify a clear pattern of convergence with respect to educational level among Norwegian municipalities during 1980-2003. The obvious hypothesis based on the simultaneous convergence in the levels of income and education, is that low income municipalities catch-up by increasing their educational level. We investigate the relationship between education and income transitions in the following sections.

5. Relationship between rising educational attainment and income transitions

Our starting point is the above analysis of income and education transitions in Tables 1 and 2. We first look at the relationship between the income transitions and the changes in the relative education levels in the municipalities. Is there a systematic pattern of rising educational attainment in municipalities moving upward in the income distribution? By considering the data underlying the matrices in panel a of Tables 1 and 2, we check the co-movement of a municipality's relative level of income and education. Among the 401 municipalities, 108 experience income catch-up during 1980/83-2000/03. Among these, about 30% simultaneously increased their level of education relative to the average. More than 7% actually moved down the education distribution while catching-up with respect to income. During the 20 year period, 96 out of 401 municipalities moved down the income distribution. Of these, 18% were also falling behind with respect to the relative educational level, but as much as 23% were actually catching-up in terms of education while falling behind in terms of income. This observation of the pattern of income transitions and rising educational attainment does not give much systematic role for education in the income convergence process.

The income transitions are analyzed for subgroups of the municipalities defined according to the movement in the distribution of education. The municipalities are ranked according to the change in their relative level of education during 1980/83-2000/03, and the sample is divided in three subgroups (top 25%, mid 50%, bottom 25%). We concentrate on the top 25% of the 401 municipalities with the largest increase in the relative level of education and the bottom 25% with the largest decrease in the relative level of education. Among the top 100 municipalities, the relative level of education on average increased by 0.14 (from 0.82 to 0.96). Hence, this education group reflects municipalities with below average level of education that is gradually catching-up. In the other end, the 100 municipalities with the largest decrease in relative education mainly have above average level of education, but are gradually moving towards the middle of the distribution (decreasing by 0.17 from 1.37 to 1.20). The estimated 4-year transition probability matrices for the three subsets of the municipalities are given in Table 3. The relationship between income level and change in the relative education level is reflected in the number of observations for the different income quintiles in the three education groups. The group with large decreases in the relative educational level is dominated by municipalities in the upper half of the income distribution, while movements up the education distribution are common across all income groups, except the richest.

If increased education level is important for upward income transitions, we expect the numbers above the diagonal in the top matrix of Table 3 to be large. But this group with highest increase in education level does not deviate much from all municipalities (shown in panel b Table 1). Low income municipalities with large increases in the relative educational level have probability of moving up the income ladder equal to 25% (24.1% + 0.9%) compared to 27 % for the low income group in the whole sample [given as the sum of cells (1, 2) and (1, 3) in panel b of Table 1]. Similar, municipalities moving up in the second income quintile have 20.1% (17.8% + 2.3%) chance of catching-up compared to 25.3% among all municipalities [given as the sum of cells (2, 3) and (2, 4) in panel b of Table 1]. The middle matrix of Table 3 shows that low income municipalities that remain relatively stable in the education distribution have about the same probability of catching-up (27.7% and 26.5% for income quintiles 1 and 2, respectively).

If reduced relative education level is important for downward income transitions we expect the numbers below the diagonal in the bottom matrix of Table 3 to be large. But they are not. The broad picture is that whether a low income municipality move up or down in the distribution of relative educational levels does not affect its chances of catching up with respect to income. Rising educational attainment is observed in regions both catching up and falling behind, and cannot explain the income convergence seen in the data. The transition probabilities in the upper end of the distribution are consistent with this view. Municipalities with increasing relative level of education that are in the third income quintile have 20.9% (20% + 0.9%) chances of catching-up. For municipalities with stable and decreasing relative educational levels the same probability equals 17.6% and 15.8%, respectively. Similar, the probability of catching-up from the fourth income quintile is independent of the development in the relative level of education.

Table 3 about here

To statistically test for the importance of changes in the relative educational level for the convergence process, we apply Pearson and Likelihood Ratio tests in similar ways as for tests of time stationarity, as described in Bichenbach and Bode (2003). In this way, we can investigate whether the transition probabilities are independent of the change in the relative education level. The test divides the entire sample of municipalities into *M* mutually exclusive and exhaustive subsamples and compares the transition matrices under each of the *M* subsamples to the entire sample. The following Pearson (*Q*) and Likelihood Ratio (*LR*) test statistics have an asymptotic χ^2 distribution with degrees of freedom equal to the number of independent pairwise comparisons:

$$Q = \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j\in A_i} n_{i|m} \frac{\left(\hat{p}_{ij|m} - \hat{p}_{ij}\right)^2}{\hat{p}_{ij}} \sim asy\chi^2\left(\sum_{i=1}^{N}(a_i - 1)(b_i - 1)\right) \tag{5}$$

$$LR = 2\sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j\in A_{i|m}} n_{ij|m} \ln\frac{\hat{p}_{ij|m}}{\hat{p}_{ij}} \sim asy\chi^2\left(\sum_{i=1}^{N}(a_i - 1)(b_i - 1)\right) \tag{6}$$

A_i is the set of nonzero transition probabilities in the *i*th row of the transition matrix estimated from the entire sample, while $A_{i|m}$ is the set of nonzero transition probabilities in the *i*th row of the matrix estimated from the *m*th subsample. *N* is the number of income states. The total number of transitions from state *i* in subsample *m* and the total number of transitions from state *i* to state *j* in subsample *m* are given by $n_{i|m}$ and $n_{ij|m}$, respectively. The degrees of freedom is given in the last parenthesis, where a_i is the number of elements in A_i and b_i is the number of subsamples with a positive number of observations in the *i*th row.

The sample of 401 municipalities is divided into three subsamples according to the change in relative education, as defined above. Comparing the matrix for each of these subsamples (given in Table 3) to the matrix for the entire sample (given in panel b of Table 1) simultaneously results in test statistics of Q = 39.76 and LR = 40. With 26 degrees of freedom, the 5% and 1% critical values equal 38.89 and 45.64, respectively. The null hypothesis of equal transition probabilities across different developments in relative education cannot be rejected at 4% significance level. To investigate this test further we show the contributions to the Pearson test statistic from each transition in the three subsamples in Table 4. About 65% of the 54 comparisons (18 probabilities, 3 subsamples) contribute with less than 0.5 to the test statistics. It is evident that the relatively high value of the test statistic is driven by a few large contributions.[5] Excluding transitions with five or less observations lowers the Pearson test statistics to 26.13 (and reduces the degrees of freedom to 20) and the null hypothesis of independent transition probabilities holds at 15% significance level.[6] The same result follows from the Likelihood Ratio test.

Table 4 about here

To sum up, the hypothesis that the transition probabilities are independent of the change in the relative educational level cannot be rejected. A closer look at the test statistic contributions show that in particular municipalities in the lower half of the distribution have similar transition probabilities and are not affected by the development in the relative level of

[5] There are in total five observations (out of 2005 observations) of transitions from income quintile 4 to quintile 2, giving a transition probability of 1% for the full sample. Four of these transitions occur in municipalities with large increases in the relative level of education. The estimated probability is therefore much higher for this subgroup, reflected in a test statistic contribution as high as 8.17.

[6] We exclude the observations related to the following transitions: 3-5, 4-2 and 5-3, which sums up to eight observations totally. Remaining observations equal 1997.

education over time. Large increases in the relative educational level cannot explain the income catch-up of low income municipalities. In fact, the probability of moving up the income distribution is somewhat lower for municipalities that are catching up with respect to education. Similarly, the probability of remaining in the top income quintile is highest among municipalities with large decreases in the relative level of education. These counterintuitive findings might indicate an importance of the level of education for the convergence process. The group of municipalities moving up the education distribution typically starts from below average level of education, while municipalities moving down the distribution start with above average level of education. We investigate the potential role of education level for income convergence in the next section.

6. Relationship between initial level of education and income transitions

The role of the education level as a stock is analyzed using the same method as above for the accumulation of educational attainment. The focus is now on whether the income transitions in Table 1 are related to the initial level of education. As earlier, we measure education level in each municipality as the share of the grown up population with tertiary education. Among the 401 municipalities the education level in the first 4-year period 1980-83 on average equaled 7.9% and with a standard deviation of 3.1%. Table 5 illustrates how this measure of education varies across different income transitions.[7] The calculation is based on the 4-year transition matrix given in panel b of Table 1, which means that each municipality has five income transitions, giving a total of 2005 observations.

If the initial level of education is important for the income convergence pattern found in the data, the share of the grown up population with tertiary education should be higher in municipalities moving up the distribution than in municipalities falling behind. The limited role of the education level is quite apparent in Table 5. The variation in the level of education seen in the data is primarily between income quintiles (vertical variation) rather than between movements up and down within a given quintile (horizontal variation). It should be noticed that low income regions with high education level and high income regions with low education level are deviations from the normal pattern. The initial level of education increases with the income level, but except for the richest income quintile the differences are not that

[7] Blank cells indicate either no transitions or less than 10 transitions in total in the respective income mobility group.

large. The average level of education varies from 5.6% in the lowest quintile to 8.2% in quintile 4, while high income municipalities have a tertiary share of 11.7%.

Table 5 about here

If education level is important for income transitions we expect high above diagonal numbers and low below diagonal numbers in Table 5. But the difference is not that clear. Among municipalities starting in the same income quintile at the beginning of a 4-year period, the education level is about the same whether they move up or down in the distribution (no horizontal variation). As seen in the first row of the matrix, municipalities remaining in the lowest income quintile on average had a tertiary share of 5.5%, which is below the full sample average of 7.9%. However, low income municipalities moving up the distribution have about the same level of education (6%). Similarly, for municipalities in the second income quintile the educational level is independent of whether they are catching up or falling behind (the share of the grown up population with tertiary education lies in the range 6.2-6.7%). Low initial level of education does not hinder catching up. Similar findings apply to the other income quintiles. For municipalities in quintile 4 at the beginning of a 4-year period, the education level is not much higher among those catching up than among those falling behind (9% vs. 7.7%). The only noticeable difference with respect to education level is between rich municipalities remaining rich and rich municipalities moving down the income distribution (12.2% vs. 9.1%).

The role of education level in the convergence process is analyzed by calculating income transition probability matrices for subgroups of the municipalities based on the initial level of education. The municipalities are ranked according to the tertiary education share of the grown up population in 1980-83, and the sample is divided in three groups; the 25% with the lowest level of education, the 25% with the highest level and the 50% around the middle. Among the municipalities with high level of education the share of the grown up population with tertiary education is on average equal to 12%, while the municipalities with medium and low educational level had an average tertiary share of 7.3% and 5.1%, respectively. This implies that the main difference when it comes to level of education is between the top group and the rest. This is consistent with the large upper tail of the Kernel distribution in Figure 2. The estimated Markov matrices of the three groups are shown in Table 6. Tables 3 and 6 are similar, but the municipalities in the three groups are different, now based on education level.

Each education group is divided into quintiles with respect to per capita income. The number of observations in each income quintile (shown in the last column) reveals the relationship between income level and education level. Of the 500 observations of low education level municipalities, 356 are in the two lowest income quintiles. At the other end, 388 of the 500 observations of high education level municipalities are in the two top income quintiles.

The first row of the bottom matrix of Table 6 shows that among the lowest income municipalities with low educational level, the probability of moving up the income ladder equals 22.6% (21% + 1.6%). For the sample as a whole we have shown that the probability of catching-up from the lowest income quintile equals 27%. Similar, municipalities with low level of education that are in income quintile 2 at the beginning of a 4-year transition have 20% (18.2% + 1.8%) chance of catching-up, compared to 25.3% among all municipalities (Table 1). The middle matrix of Table 6 shows that municipalities with medium level of education that are in the lowest income quintile have 35.2% chance of catching up. When it comes to low income municipalities with high level of education the number of observations is too low to give reliable results. For municipalities in the second income quintile the chances of catching up also are about the same independent of the level of education. Upward income transitions are likely and possible both when you have high and low education level, although somewhat higher when you are in the lowest income group with medium level of education. But as noted above, the difference in the education level between the low and the medium group is not large (5.1% vs. 7.3%).

The transition probabilities in the upper end of the distribution are somewhat more favorable for a positive role of education level. But the size of the effect is small. With high level of education the probability of remaining in the top income quintile increases from 83.5% (Table 1) to 88.6% (top matrix of Table 6). Similar, municipalities with high education level that are in income quintile 4 at the beginning of a 4-year transition have probability of catching-up equal to 9.3%, compared to 6.5% for the full sample (Table 1).

The limited role of education level for income catch-up is confirmed by the implied ergodic distributions of the three submatrices. If the level of education is important to generate growth, low income municipalities with low educational level should remain in the lowest income quintile, while high income municipalities with high educational level should take off and increase the income gap. The opposite is happening. Among municipalities with low education, 37.2% is initially in the lowest income quintile, but instead of being stuck in a poverty trap, they are able to catch-up. The estimated transition probabilities imply that in the long-run ergodic distribution, the lowest income quintile is significantly reduced, and contains less than 20% of the municipalities. Similarly, among municipalities with high education, the top income group is not taking off, but is decreasing from 47.4% of the municipalities initially to 29.2% in the long run.

Table 6 about here

The test for the importance of the educational level for the convergence process follows the design above using Pearson (Q) and Likelihood Ratio (LR). The sample of 401 municipalities is divided into three subsamples according to the initial level of education. Comparing the matrix for each of these subsamples to the matrix for the entire sample simultaneously results in test statistics of $Q = 63.21$ and $LR = 61.87$. With 26 degrees of freedom, the 5% and 1% critical values equal 38.89 and 45.64, respectively. The null hypothesis of equal transition probabilities across different levels of education is rejected. Statistically the income transitions are different between the three education level groups indicating that education level has some effect.

Table 7 about here

We look into the details of the test in Table 7 and show the contributions to the Pearson test statistic from each transition in the three subsamples. More than half of the 54 comparisons contribute with less than 1 to the test statistics. Some large error terms are the main source of the relatively large test statistic. Among low education level municipalities it is primarily the transition probabilities down the income distribution (from quintiles 2, 4 and 5) that deviate from the full sample probability. Similarly, among municipalities with medium educational level the contribution to the test statistic is driven by movements down the income distribution (from quintiles 2 and in particular 5, but also up from quintile 1). The matrix based on municipalities with high education level deviates from the full sample matrix mainly for the movement down from quintiles 4 and 5. We can reject equal transition probabilities for the three groups of municipalities according to education level, but it seems like the deviation is not that important for upward mobility.

Based on the analyses in sections 5 and 6, we conclude that changes in the relative level of education cannot explain income transitions, and that the relationship between education level and income transitions is weak. Large increases in the relative educational level cannot explain the income catch-up of low income municipalities. Also, high education levels in low income municipalities are not very helpful for upward income mobility.

7. Robustness checks, absolute change in education level and extended time periods

To further check the robustness of our results, we experiment with alternative classifications of municipalities according to the education dynamics. Instead of focusing on the movement in the distribution of education (the development in a municipality's level of education relative to the average) we consider the absolute change in the level of education, measured as the percentage point increase in the tertiary education share of the grown up population during 1980/83-2000/03. As a simple start, we consider how this measure of educational change varies across different income transitions. If educational change is important for the income convergence pattern found in the data, municipalities moving up the distribution should have larger increases in the education level than municipalities falling behind. Similar to the findings with respect to the level of education in section 6, the variation in educational change is primarily between income quintiles (vertical variation) rather than between movements up and down within a given quintile (horizontal variation). Among municipalities starting in the same income quintile at the beginning of a 4-year period, the change in the education level is about the same whether they move up or down in the distribution. Lack of increase in the education level does not hinder catching up, and large increases are as common in municipalities catching-up as in municipalities falling behind.

Following the analysis in the previous sections, we split the sample of 401 municipalities in three subgroups; the top 25% with the largest increase in the level of education, the mid 50% with medium increase, and the bottom 25% with the smallest increase in the education level. Among the 100 municipalities with largest increase in the level of education, the share of the grown up population with tertiary education on average increased by 10.4% points during 1980/83-2000/03 (from 11% to 21.4%), while the 100 municipalities with the smallest increase had an increase in the educational level of 5.2% points (from 6% to 11.2%). Given this classification of municipalities according to the extent of increase in the educational level, we perform the same analyses and tests as above, and our main results remain. Rising educational attainment cannot explain the income convergence found in the data.

Finally, extending the time period backwards to the 1970s does not change the results. Based on Kernel density functions and Markov chain matrices, Rattsø and Stokke (2010) document income convergence among Norwegian municipalities during 1972-2003. Since data on tertiary education in the grown up population is available for the single year of 1970, we classify municipalities based on the increase in the educational level during 1970-2003. Applying this to the estimated Markov matrix for 1972-2003, the main findings of this paper remains. Large increases in education are as common in municipalities catching-up as in municipalities falling behind, and transition probabilities are mainly independent of the extent of increase in the educational level.

8. Concluding remarks

We have investigated the role of education for economic growth. Our distribution analysis shows that Norwegian regions experience both income convergence and convergence in education level during 1980-2003. The existing literature on human capital and economic growth offers conflicting hypotheses about the importance of education for income convergence. The growth effect of the education level is expected to lead to income divergence, since high income regions with high education level will grow faster. On the other hand, the convergence of the education level is expected to lead to income convergence. The education level is increasing faster in low income regions, and this may generate income catching up. The overall conclusion of the analysis is that education has a limited role in explaining the income convergence among Norwegian regions. The separate effects of the stock and the accumulation of the education level are small. Increased education is not an important aspect of regions catching up, but high education level has some positive effect for already high income regions.

The Norwegian economy is characterized by large movements of population and economic activity from the periphery to urban centers. Interestingly, this structural change is combined with income convergence and convergence in education level. The rising education level is certainly a candidate explanation for the income convergence. But our analysis of the relationship between income transitions and education level and change indicates no important effect. The result may follow from low return to tertiary education in Norway. It is well known that the compressed wage structure implies low return to education. This may be of particular importance in the periphery, where the highly educated easily end up in public sector employment. It is of interest to analyze the role of the public sector for income convergence in future work.

It can be argued that our result follows from heterogeneity and variation in quality of tertiary education. Compared to international studies, the quality across tertiary education in Norway probably is small. But the quality differences existing may sort themselves geographically so that the high quality competence ends up in the urban centers. If this is true, we expect urban centers to have even higher growth. It is obvious that this mechanism cannot contribute to income convergence.

It is worth thinking about other factors that are important for regional income growth. Direct observation of the data tells you that catching up municipalities from relative low income may be associated with industrial successes like bases for oil extraction and oil services production, along the coast also rise in farming of salmon, and expansion of public and private services in regional centers. Many of the expanding sectors in an advanced service economy are not that tertiary education intensive. The population is maybe overeducated, certainly the private return to education is low as stated above.

Income growth following higher education level must result from both supply and demand effects at the market for human capital. The increased education level measured in this analysis shows that the supply side has delivered in quantity. The demand side of higher education must work to transform education to production and income. Stagnant demand for tertiary education in the private sector may explain limited growth effect. Most of the new candidates from higher education in Norway end up in the public sector. We cannot dismiss the possibility that much of the tertiary education absorbed in public administration does not contribute much to overall income growth.

References

Aronsson T., J. Lundberg and M. Wikstrøm (2001), Regional income growth and net migration in Sweden, 1970-1995. *Regional Studies* 35, 9, 823-830.

Benhabib J. and M. Spiegel (1994), Role of human capital in economic development: Evidence from aggregate cross-country data. *Journal of Monetary Economics* 34: 143-173

Benhabib J. and M. Spiegel (2005), Human capital and technology diffusion, in P, Aghion and S. Durlauf (eds.), *Handbook of Economic Growth*, Amsterdam: North Holland, 935-966.

Bickenbach, F. and E. Bode (2003), Evaluating the Markov property in studies of economic convergence. *International Regional Science Review* 26, 363-392.

Ciccone, A. and E. Papaioannou (2009), Human capital, the structure of production, and growth, *Review of Economics and Statistics* 91, 1, 66-82.

Cuaresma, J. (2006), Convergence of educational attainment levels in the OECD: More data, more problems? *Economics of Education Review* 25, 173-178.

de la Fuente, A. and R. Domenech (2006), Human capital in growth regressions: How much difference does data quality make? *Journal of the European Economic Association* 4, 1, 1-36.

Glaeser E. L., J. Scheinkman and A. Shleifer (1995), Economic growth in a cross section of cities. *Journal of Monetary Economics* 36, 117-143

Hanushek, E. and D. Kimko (2000), Schooling, labor force quality, and the growth of nations, *American Economic Review* 90, 5, 1184-1208.

Hanushek, E. and L. Woessmann (2007), The role of education quality in economic growth, World Bank Policy Research Working Paper 4122.

Kremer, M., A. Onatski and J. Stock (2001), Searching for prosperity, *Carnegie-Rochester Conference Series on Public Policy* 55, 275-303.

Krueger A. and M. Lindahl (2001), Education for growth: Why and for whom? *Journal of Economic Literature* 39, 4, 1101-1136

Lucas, R. (1988), On the mechanics of economic development, *Journal of Monetary Economics* 22, 3-42.

Nelson, R. and E. Phelps (1966), Investment in humans, technology diffusion and economic growth, *American Economic Review* 56, 2, 69-75.

Pritchett, L. (2001), Where has all the education gone? *World Bank Economic Review* 15, 3, 367-391

Quah, D. (1993a), Empirical cross-section dynamics in economic growth. *European Economic Review* 37, 426-434.

Quah, D. (1993b), Galton's fallacy and tests of the convergence hypothesis. *Scandinavian Journal of Economics* 95, 427-43.

Quah, D. (2001), Searching for prosperity: A comment, *Carnegie-Rochester Conference Series on Public Policy* 55, 305-319.

Rattsø, J. and H. Stokke (2010), Income convergence, migration and geography: Distribution analysis of regions in Norway, mimeo, Department of Economics, Norwegian University of Science and Technology.

Shorrocks, A. (1978), The measurement of mobility, *Econometrica* 46, 5, 1013-1024.

Vandenbussche, J., P. Aghion and C. Meghir (2006), Growth, distance to the frontier and composition of human capital, *Journal of Economic Growth* 11, 2, 87-127.

Wolff, E. (2000), Human capital investment and economic growth: exploring the cross country evidence, *Structural Change and Economic Dynamics* 11, 433-472.

Østbye, S. and O. Westerlund (2007), Is migration important for regional convergence? Comparative evidence for Norwegian and Swedish counties, 1980-2000, *Regional Studies* 41, 7, 901-915.

Figure 1: Kernel density estimates, relative income per capita, 401 municipalities, average values during 1980-1983 and 2000-2003.

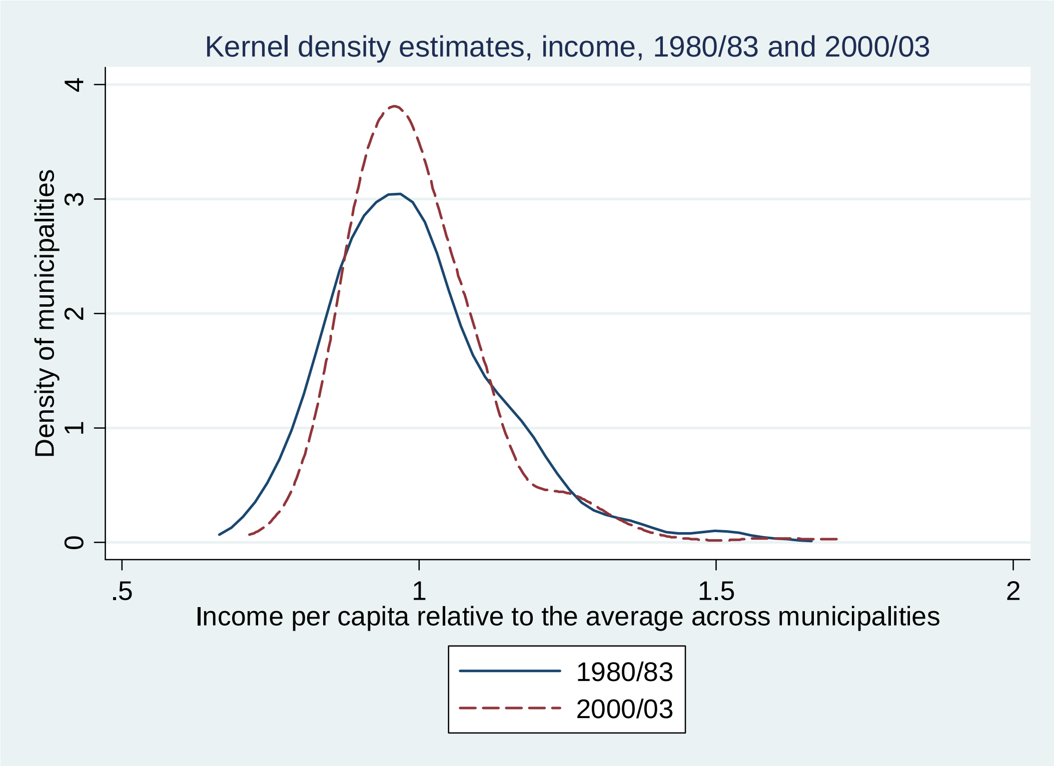

Figure 2: Kernel density estimates, relative level of education, 401 municipalities, average values during 1980-1983 and 2000-2003.

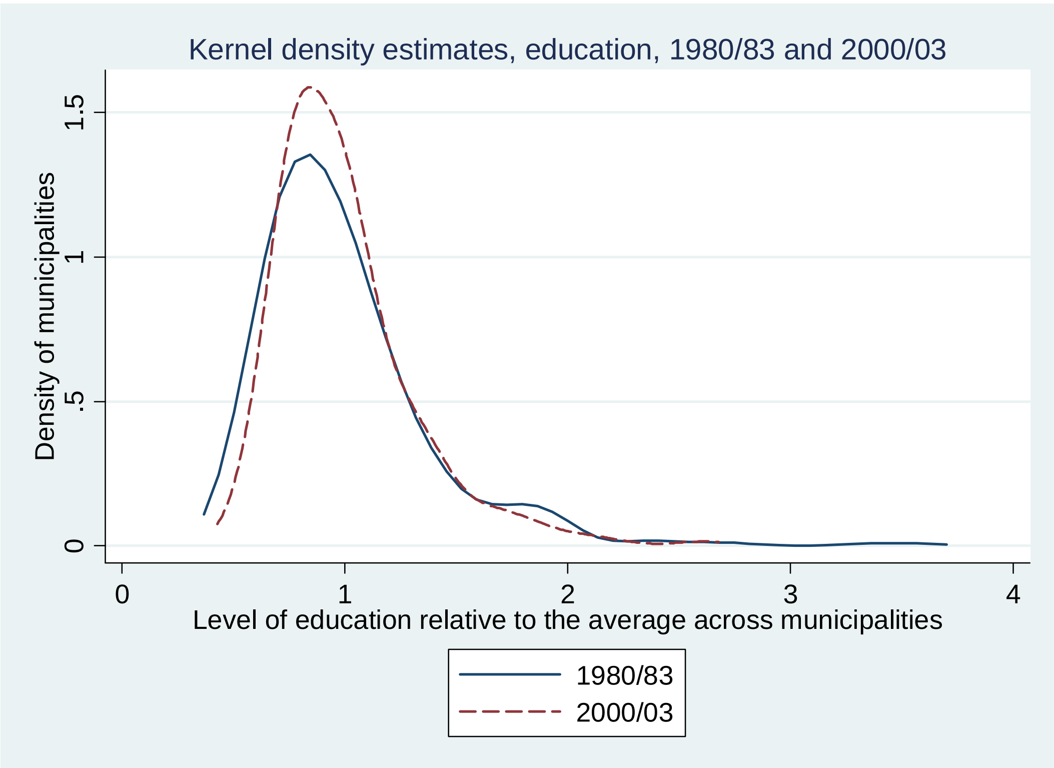

Table 1: Markov chain transition probability matrix, income per capita, 1980/83-2000/03.

Panel a: Full period 20-year transition (401 observations)

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Obs.
1	**40.0**	40.0	13.8	5.0	1.2	80
2	8.7	**48.8**	27.5	13.8	1.2	80
3	2.5	25.0	**47.5**	17.5	7.5	80
4	1.2	6.3	32.5	**52.5**	7.5	80
5			4.9	38.3	**56.8**	81
Initial distribution	20.0	20.0	20.0	20.0	20.0	
After 1 transition	10.5	23.9	25.2	25.4	15.0	
Ergodic distribution	5.3	23.2	32.0	28.2	11.3	

Panel b: 4-year transitions (2005 observations)

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Obs.
1	**73.0**	23.8	3.2			281
2	8.7	**66.0**	23.7	1.6		435
3		19.8	**62.2**	17.6	0.4	466
4		1.0	17.2	**75.3**	6.5	489
5			0.3	16.2	**83.5**	334
Initial distribution	14.0	21.7	23.2	24.4	16.7	
After 1 transition	12.1	22.5	24.3	25.5	15.6	
Ergodic distribution	7.2	22.3	28.2	29.7	12.6	

Table 2: Markov chain transition probability matrix, level of education, 1980/83-2000/03.

Panel a: Full period 20-year transition (401 observations)

Education quintiles	1 ≤ 0.705	2 ≤ 0.8495	3 ≤ 0.99	4 ≤ 1.21	5 > 1.21	Obs.
1	**44.4**	50.6	5.0			81
2	5.0	**67.5**	23.8	3.7		80
3	1.2	16.3	**48.7**	31.3	2.5	80
4			27.5	**63.8**	8.7	80
5			1.2	13.8	**85.0**	80
Initial distribution	20.0	20.0	20.0	20.0	20.0	
After 1 transition	10.2	26.9	21.2	22.5	19.2	
Ergodic distribution	2.0	16.0	25.8	32.8	23.4	

Panel b: 4-year transitions (2005 observations)

Education quintiles	1 ≤ 0.705	2 ≤ 0.8495	3 ≤ 0.99	4 ≤ 1.21	5 > 1.21	Obs.
1	**77.9**	22.1				335
2	7.5	**82.1**	10.4			452
3		9.3	**75.5**	14.9	0.3	376
4			11.1	**85.6**	3.3	450
5				4.9	**95.1**	392
Initial distribution	16.7	22.5	18.8	22.4	19.6	
After 1 transition	14.7	23.9	19.0	23.0	19.4	
Ergodic distribution	6.7	19.7	21.9	29.9	21.8	

Table 3: Markov chain transition probability matrix, income per capita, 4-year transitions, conditioning on the movement in the distribution of education during 1980/83-2000/03.

Panel a: Top 25% with large increase in the relative educational level (500 observations)

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Obs.
1	**75.0**	24.1	0.9			108
2	10.9	**69.0**	17.8	2.3		129
3		15.6	**63.5**	20.0	0.9	115
4		3.9	19.2	**69.2**	7.7	104
5				25.0	**75.0**	44
Initial distribution	21.6	25.8	23.0	20.8	8.8	
After 1 transition	19.0	27.4	23.4	21.8	8.4	
Ergodic distribution	11.1	25.6	27.0	27.0	9.3	

Panel b: Mid 50% with stable relative educational level (1005 observations)

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Obs.
1	**72.3**	23.3	4.4			159
2	7.6	**65.9**	24.9	1.6		249
3		20.8	**61.6**	17.2	0.4	250
4		0.4	17.5	**76.7**	5.4	240
5			0.9	23.4	**75.7**	107
Initial distribution	15.8	24.8	24.9	23.9	10.6	
After 1 transition	13.3	25.3	26.5	25.5	9.4	
Ergodic distribution	6.5	23.5	30.6	31.8	7.6	

Panel c: Bottom 25% with large decrease in the relative educational level (500 observations)

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Obs.
1	**64.3**	28.6	7.1			14
2	8.8	**59.6**	31.6			57
3		21.8	**62.4**	15.8		101
4			15.2	**77.2**	7.6	145
5				9.8	**90.2**	183
Initial distribution	2.8	11.4	20.2	29.0	36.6	
After 1 transition	2.8	12.0	20.8	29.2	35.2	
Ergodic distribution	4.4	17.8	27.3	28.5	22.0	

Table 4: Test of whether the change in the relative educational level affects transition probabilities, 401 municipalities 1980/83-2000/03, 4-year transitions. Contributions of single subsamples to the Pearson test statistics.

Change in relative educational level	Income quintiles	Number of obs.	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Sum
Top 25% large increase (500 obs)	1	108	0.06	0.00	1.74			1.80
	2	129	0.66	0.18	1.86	0.42		3.12
	3	115		0.97	0.03	0.38	0.52	1.90
	4	104		8.17	0.25	0.50	0.21	9.13
	5	44			0.13	2.12	0.38	2.63
	Sum							**18.58**
Mid 50% stable (1005 obs)	1	159	0.01	0.02	0.72			0.75
	2	249	0.35	0.00	0.16	0.00		0.51
	3	250		0.14	0.02	0.02	0.01	0.19
	4	240		0.85	0.01	0.06	0.46	1.38
	5	107			1.42	3.42	0.79	5.63
	Sum							**8.46**
Bottom 25% large decrease (500 obs)	1	14	0.14	0.13	0.68			0.95
	2	57	0.00	0.35	1.50	0.92		2.77
	3	101		0.21	0.00	0.18	0.43	0.82
	4	145		1.48	0.34	0.08	0.24	2.14
	5	183			0.55	4.53	0.96	6.04
	Sum							**12.72**
Pearson test statistic								**39.76**

Table 5: Average level of education in 1980/83 in different income transitions. Based on 4-year transitions illustrated in panel b of Table 1.

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Quintile average
1	5.5	6.0				5.6
2	6.2	6.6	6.7			6.6
3		7.0	7.6	7.3		7.4
4			7.7	8.3	9.0	8.2
5				9.1	12.2	11.7

Table 6: Markov chain transition probability matrix, income per capita, conditioning on the initial level of education, 4-year transitions 1980/83-2000/03.

Panel a: Top 25% with high level of education in 1980/83 (500 observations)

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Obs.
1	**57.1**	42.9				7
2	14.8	**59.3**	25.9			27
3		11.5	**73.1**	14.1	1.3	78
4			11.3	**79.5**	9.3	151
5				11.4	**88.6**	237
Initial distribution	1.4	5.4	15.6	30.2	47.4	
After 1 transition	1.6	5.6	16.2	31.6	45.0	
Ergodic distribution	3.7	10.6	23.9	32.6	29.2	

Panel b: Mid 50% with medium level of education in 1980/83 (1005 observations)

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Obs.
1	**64.8**	28.4	6.8			88
2	5.0	**66.0**	27.3	1.7		238
3		20.0	**61.6**	18.1	0.3	310
4		1.1	19.7	**74.4**	4.9	285
5			1.2	26.2	**72.6**	84
Initial distribution	8.8	23.7	30.8	28.4	8.4	
After 1 transition	6.9	24.6	31.7	29.2	7.6	
Ergodic distribution	3.4	24.0	34.3	32.1	6.2	

Panel c: Bottom 25% with low level of education in 1980/83 (500 observations)

Income quintiles	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Obs.
1	**77.4**	21.0	1.6			186
2	12.9	**67.1**	18.2	1.8		170
3		26.9	**53.9**	19.2		78
4		3.8	20.8	**67.9**	7.6	53
5				38.5	**61.5**	13
Initial distribution	37.2	34.0	15.6	10.6	2.6	
After 1 transition	33.2	35.2	17.4	11.8	2.4	
Ergodic distribution	19.1	33.4	23.0	20.5	4.0	

Table 7: Test of whether the initial level of education affects transition probabilities, 401 municipalities 1980/83-2000/03, 4-year transitions. Contributions of single subsamples to the Pearson test statistics.

Educational level in 1980	Income quintiles	Number of obs.	1 ≤ 0.876	2 ≤ 0.942	3 ≤ 1.005	4 ≤ 1.1	5 > 1.1	Sum
Bottom 25% low level (500 obs.)	1	186	0.51	0.64	1.47			2.62
	2	170	3.43	0.03	2.12	0.02		5.60
	3	78		2.04	0.88	0.12	0.34	3.38
	4	53		3.93	0.39	0.38	0.08	4.78
	5	13			0.04	3.99	0.75	4.78
	Sum							**21.16**
Mid 50% medium level (1005 obs.)	1	88	0.81	0.77	3.60			5.18
	2	238	3.73	0.00	1.32	0.01		5.06
	3	310		0.01	0.02	0.04	0.09	0.16
	4	285		0.00	1.01	0.03	1.16	2.20
	5	84			2.22	5.22	1.20	8.64
	Sum							**21.24**
Top 25% high level (500 obs.)	1	7	0.24	1.06	0.22			1.52
	2	27	1.14	0.18	0.06	0.43		1.81
	3	78		2.66	1.48	0.54	1.31	5.99
	4	151		1.54	3.08	0.36	1.72	6.70
	5	237			0.71	3.35	0.73	4.79
	Sum							**20.81**
Pearson test statistic								**63.21**