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ACCUMULATION OF EDUCATION AND REGIONAL INCOME GROWTH: LIMITED HUMAN CAPITAL EFFECTS IN NORWAY

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Accumulation of education and regional income growth: Limited human capital effects in Norway*

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Abstract

Accumulation of education and geographic concentration of educated people in cities are expected to generate urban income growth. New economic geography predicts income divergence across regions. We investigate the dynamic process of accumulating tertiary education and regional income growth in Norway during the past four decades. The expansion of smart cities goes along with catching up of education level in the periphery and overall the education levels converge. Income levels also are shown to converge in distribution analysis using Kernel functions and first order Markov chains. However, the movements in the income distribution are unrelated to the accumulation of education. The hypothesis of equal income transition probabilities across subgroups of regions with different increases in education cannot be rejected. We conclude that accumulation of education has not been important for the pattern of income growth. Catching up from low income is not driven by education and income growth has not taken off in cities with increasing education level.

JEL codes: C14, I21, O15, R11, R12

Key words: Human capital, knowledge, urban growth, income convergence, education convergence, Markov chain, Kernel density function

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1. Introduction

Highly educated people concentrate in urban areas and generate ‘skilled cities’ or ‘smart cities’ (see Glaeser and Saiz, 2004 and Winters, 2011). The urban evolution is biased towards skill. Glaeser and Saiz find that areas with large initial concentrations of college-educated adults have experienced above-average population growth. And many of the growing cities have increasing share of highly educated inhabitants. Highly educated people move to cities to enjoy well-paid jobs and urban amenities, but even more young people move to cities to educate and stay. Winters conclude that smart cities are growing primarily by gaining young people pursuing education. The institutions of higher learning are located in cities. This broad pattern can be observed in most industrialized countries.

Smart cities are expected to have higher income. The highly educated have human capital that adds to production factor inputs. Also human capital is assumed to raise the innovative capacity and the capacity to imitate and absorb technology innovation elsewhere, and with spillover effects. The positive association between education and income levels is well established across countries and is also observed across regions within countries. Using individual data for France, Combes et al. (2008) find that the related skill sorting explains 40-50% of wage disparities between regions. The number is consistent with the finding of Glaeser and Gottlieb (2008) that differences in human capital account for about 50% of the variance in metropolitan-area wage levels in the US. The hard question concerns the relationship between increasing education level and economic growth.

The understanding of human capital and knowledge spillovers in the regional context is summarized by Henderson (2007). This literature views smart cities as engines of growth. Early empirical evidence is provided by Jaffe et al. (1993) and Rauch (1993). Black and Henderson (1999) model urban growth with human capital externalities including both agglomeration economies and localized knowledge spillovers. Recent empirical evidence confirms the relationship between cities, skills and income growth. Glaeser and Resseger (2010) find that agglomeration effects are stronger in cities with high skill. This literature predicts that increased education level in urban areas is related to increased income growth. Our dataset of regions in Norway contradicts this expectation.

We address the dynamic process of accumulating education and income generation across 396 Norwegian municipalities during the past four decades.[1] The overall education level is high, and primary and secondary education are compulsory, but tertiary education has been varying significantly between regions. The education level is measured by the share of the grown up population with tertiary education and is observed in 1970, as well as every year during the period 1980-2008. The quality of the tertiary education realistically is similar across regions. This is an important advantage compared to cross-country studies, education is a more homogenous commodity within a country. We are able to establish a measure of regional income per capita for the period 1972-2008 based on personal income from tax data. The income concept basically covers wage income.

Econometric analyses of long-term education effects face serious methodological challenges of endogeneity, 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 accumulation of education levels 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 regions in the early 1970s confirms the expected relationship between education level and income level. Small regions 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. But the correlation between education level and income level is decreasing over time (raw correlation coefficient 0.74 falling to 0.56, across 396 regions). This is our first indication that change in education level has not been of much importance for the income level.

While we observe that highly educated concentrate in cities, the overall distribution dynamics is convergence of the education level across regions during this period. Kernel density estimates of education levels and estimated Markov chains show convergence of education

[1] In general terms we refer to municipalities as regions.

levels over time. The share of the population with tertiary education has increased more in the periphery. The emergence of smart cities has been dominated by catching up from behind. The distribution analysis also 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. The increased education level of the cities has not contributed to strong growth effects and consequent income divergence.

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. We also investigate the role of the education stock, but find only a weak relationship between education level and income growth. Given the evidence of income convergence this is not surprising. Overall we conclude that growth effects of human capital and knowledge spillovers are limited in Norway. The result is consistent with the analysis of lacking agglomeration effects by Rattsø and Stokke (2011).

The relationship between accumulation of educational level and income generation is discussed in section 2. The methodological approach is addressed in section 3. Section 4 analyzes the accumulation of the education level across regions. Section 5 shows the evidence for regional income convergence in Norway. The relationship between income convergence and rising educational attainment is investigated in section 6. Section 7 studies income growth and education level. Concluding remarks are offered in section 8.

2. Accumulation of education and income growth

The microeconomic evidence that education raises earnings is convincing. At the individual level investment in education offers a good payoff in most countries (see overview by Krueger and Lindahl, 2001). But the relationship between increased education and income has been harder to detect at the aggregate level. 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), Benhabib and Spiegel (2005) and Hanushek and Woessman (2007) 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. The second mechanism assumes that the stock of human capital is important for technological innovation and adoption and thereby productivity and income growth, a mechanism originally formulated by Nelson and Phelps (1966). Higher stock of human capital generates more income growth, a possible source of economic divergence.

The main stylized fact that stands out at the macro level is that more educated countries are more productive and have higher income levels. Here we concentrate on the dynamics of the process, the role of increased education. The micro-macro paradox is most starkly formulated by Pritchett (2001): Where has all the education gone? He finds no association between increases in human capital attributable to rising educational attainment and income growth across countries. His result is consistent with casual observation, 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 to re-establish a positive association between accumulation of education and income growth across countries. 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) find support for a positive effect of change in education on economic growth using cross-country industry-level panel data and they conclude that human capital level and accumulation stimulate human-capital intensive industries. Vandenbusche et al. (2006) separate between basic and higher education and show that basic education is important for imitation, while higher education is important for innovation. 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.

As discussed in the introduction, increased education level is expected to have a stronger effect at the regional level within countries. Highly educated people concentrate to cities and combined with agglomeration effects the increased education level of cities is expected to generate income growth. In particular, institutions of higher education are located in cities and attract young people from the periphery to educate and stay. The literature on city growth shows the importance of the education factor. Glaeser et al. (1995) show that initial level of schooling is an important determinant of economic growth in American cities. This study feeds into the more recent literature on regional growth and agglomeration, see overview by Puga (2011). The positive effect of schooling contributes to divergence of income levels as cities with high education and income levels grow faster. High income regions with high education level are expected to take off and away from regions with lower education level. We challenge these results below.

The empirical literature has been looking for a positive association between accumulation and level of education and income growth (both across countries and across regions). The methodological challenge is to sort out the causal effect of education compared to other mechanisms at work. The income growth in urban regions may result from local resources as the source of high productivity growth. Highly educated people move to cities because they are more productive and offer higher wages, the cities are not necessarily more productive because they have more educated people. And cities may offer amenities and services that motivate skilled and productive people to move to cities. Cities have productive people, they don't necessarily make them productive.

The econometric studies discussed above address these endogeneity and sorting issues. The migration decisions of highly educated imply the endogeneity of smart cities. The concentration of skills is determined simultaneously with productivity and income. The causal effect of education consequently is hard to identify. The literature offers various instruments to predict education level from historical observations. We are interested in the long run growth process and the dynamics of the accumulation of education. The desired dataset would reflect a natural experiment with large shifts in education levels over time independent of local income generation. But finding instruments to represent some exogenous part of the long run shift in the education pattern is difficult. We want to take benefit of a long time series of education and income growth and it follows that we cannot convincingly separate between the consequences of education for income growth, the importance of income growth for migration of highly educated, and other sources of increasing productivity and income. Our ambition is more modest, we will investigate whether our time series observations are consistent with strong income effects of increased education. The analysis addresses the relationships between changes and levels of education and changes of income levels.

Given the literature on smart cities we expect to observe high income growth in regions with large increase in the education level. The income growth in regions with increased education is expected to give overall income divergence. The interpretation of the empirical results below must take into account other factors at work. The endogeneity of the smart city implies that income growth may motivate the education growth. And the expansion of highly educated has a labor supply effect that works in the direction of lower wages. We conclude that observation of a positive association between increased education and income growth is a necessary, but not sufficient, condition to have a positive growth effect of increased education. It is necessary assuming that the education productivity effect is strong enough to dominate the labor supply effect of more education. But it is not sufficient, since other factors beside education may explain the income growth following increased education. Anyway, the lack of a relationship between increased education and income growth among regions indicates that the income effects of increased education are limited.

3. Methodological issues

There is a large literature applying Markov chain transition probability matrices to study income convergence across regions and countries. Quah (1993a, 1993b, 2001) developed this methodology, more recently applied and extended by Kremer et al. (2001). The basics of the method are presented by Shorrocks (1978). While econometric methods face serious challenges related to averaging, distribution analysis captures heterogeneous processes with different growth paths from different starting points. In particular, we can study the two ends of the distribution of per capita incomes – relative low income and relative high income regions.

In addition to the standard application to income convergence, we also apply distribution analysis to study education convergence across regions in Norway. 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) finds convergence in schooling levels using dispersion measures and observe that it corresponds to convergence in labor productivity levels. Cuaresma (2006) estimates 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.

We estimate the transition probabilities of the Markov chains by the maximum likelihood method to facilitate tests of homogeneity and dependence, as well as tests of how education levels and changes are related to income transitions. The discussion of the method below relates to the distribution of educational levels, but is applied to both education and income data.

The whole range of education levels is divided into a finite number of N mutually exclusive education groups and in this analysis we follow the convention of working with five groups (N=5). For each region we get a sequence of variables describing the education group of that region at time t. The sequences are considered as independent realizations of a single homogeneous Markov chain with finite group space N. The assumption of a finite first order Markov chain implies that the probability of being in a specific education group at time t only depends on the group of the previous period (and not earlier periods). The transition probability, the probability of moving from group i to group 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 education groups over time. The number of regions moving from group i to group j from period $t-1$ to t is measured by $n_{ij}(t)$. The total number of regions moving from group 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 five mutually independent multinomial distributions (one for each row i of the transition matrix). For each time period t, the distribution function is:

$$f\left(n_{ij}(t)\right) = \prod_{i=1}^{5} f_i\left(n_{ij}(t)\right) = \prod_{i=1}^{5}\left[\frac{n_i(t-1)!}{\prod_{j=1}^{5} n_{ij}(t)!}\prod_{j=1}^{5} p_{ij}^{n_{ij}(t)}\right] \tag{1}$$

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

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

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.

Given the initial distribution of regional education levels across education groups, $h(0) = \left[h_1(0), h_2(0), h_3(0), h_4(0), h_5(0)\right]$ where $\sum_i h_i(0) = 1$, the distribution after the first transition period can be calculated as $h(1) = h(0)\Omega$, where Ω is the estimated 5x5 Markov transition matrix. And similar, the distribution after k transition periods follows as $h(k) = h(0)\Omega^k$. Given that the matrix is regular[2], the distribution converges to the limiting distribution $h^* = \lim_{k\to\infty} h(0)\Omega^k$, which is independent of the initial distribution. This is the ergodic long-run distribution of regional educational levels and is estimated based on the Markov chain matrix under the assumption that the transition dynamics remain unchanged.

To statistically test for the relationship between income growth and education (both level and change), we apply Pearson and Likelihood Ratio tests in similar ways as for tests of time stationarity, as described in Bichenbach and Bode (2003). The test investigates whether the income transition probabilities are independent of the level of education and the increase in the education level. The test divides the entire sample of regions into M mutually exclusive and exhaustive subsamples according to the degree of education change/level 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:

$$Q = \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j\in A_i} n_{i|m} \frac{\left(\hat{p}_{ij|m} - \hat{p}_{ij}\right)^2}{\hat{p}_{ij}} \sim asy\chi^2\left(\sum_{i=1}^{N}(a_i - 1)(b_i - 1)\right) \tag{4}$$

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

[2] The Markov chain is regular if for some integer k, all entries of Ω^k are positive.

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 groups. The total number of transitions from group i in subsample m and the total number of transitions from group i to group 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.

4. Education level convergence

The education level has increased significantly in Norway during the period studied, and we expect the emergence of smart cities where the highly educated concentrate. The education level across regions is quite similar for primary and secondary education, since both are compulsory. The interesting variation relates to tertiary education. We measure the level of education in each region (municipality) as the share of the grown up population with tertiary education, including both short higher education (college level, up to 4 years in duration) and long higher education (university level, more than 4 years in duration).[3] The data cover the single year 1970 and all years during the period 1980-2008. In the analysis the education level is measured relative to the average level of education across regions in each year.

The development of the distribution of the education level in the regions is first described by estimated Kernel density functions for the first year 1970 and the last year 2008, as shown in Figure 1. The horizontal axis represents the share of the grown up population with tertiary education relative to the average share across regions, while the vertical axis gives the density of regions at different relative education levels.[4] Both distributions have a single-peak around the average educational level, but over time, the distribution becomes narrower and the peak more pronounced, indicating convergence with respect to the level of education.

Figure 1 about here

[3] Data source: Statistics Norway, Table 06983; Number of persons above 16 years according to the level of education.
[4] 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 0.1635 and 0.0915 for 1970 and 2008, respectively.

Furthermore, we investigate the education dynamics through a Markov chain transition matrix for the period 1970-2008. We focus on decade transitions, and apply the relative education levels in 1970, 1980, 1990, 2000, and 2008. Four transitions and 396 regions imply that transition probabilities are estimated based on 1584 observations. We follow the convention of discretization based on a uniform initial distribution of relative educational levels across education groups, which gives the following five groups: 1) less than 72% of the average educational level, 2) between 72% and 84%, 3) between 84% and 99%, 4) between 99% and 121%, and 5) more than 121% of the average level of education. The Markov matrix with respect to the level of education is given in Table 1. All the diagonal and immediately off-diagonal transition probabilities are significant, while the estimates of the probability of moving two or more education groups during a decade are typically insignificant, or at least less significant.

The transition matrix is consistent with the findings from the Kernel functions with convergence in educational levels across regions. Regions located in the lowest education group (below 72% of the average level) have about 33% chance of moving up the distribution during a 10-year period. Regions in education groups 2 and 4 are more likely to move towards the middle of the distribution than towards the respective ends. The probability of moving upwards from education group 2 is more than 30%, compared to 13% chance of moving downwards. Regions in the highest group (educational level at least 21% higher than the average) have good chances of remaining in this group (86%). This implies that group 5 remains significant in the long-run distribution with about 20% of the regions (given in the last row of the matrix). This is the small trace we have of smart cities, to be discussed below. But the ergodic distribution has a single peak at education group 4 (between 99% and 121% of the average educational level), which accounts for more than 30% of the regions in the long run. The distribution of educational levels goes from a uniform distribution initially towards a normal distribution and shows no tendencies of a bimodal twin peaked distribution.

Table 1 about here

To sum up, the density functions and the Markov matrix both identify a clear pattern of convergence with respect to educational level among Norwegian regions during 1970-2008.

The share of the population with tertiary education has increased more in the periphery, and the emergence of smart cities has been dominated by catching up from behind.

5. Income level convergence

To sort out the relationship between accumulation of education and income growth, we need to address the income generation process. Income convergence is analyzed in the same manner as education convergence by using Kernel density functions as well as Markov chain transition matrices. The analysis is based on data for taxable income of each of 396 regions (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 1972-2008 and it follows that we have 14652 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. In the analysis the income level is measured relative to the average income per capita across regions in each year.

To examine how the distribution of regional income per capita develops over time, we compare the estimated Kernel density functions for the first year 1972 and the last year 2008, as shown in Figure 2.[5] The horizontal axis represents income per capita relative to the average level across regions, while the vertical axis gives the density of regions at different relative income levels. Both functions have a single-peak distribution with the majority of regions located close to the average level of income per capita. The estimated distributions show a clear pattern of convergence over time. The distribution is narrower and more concentrated around the peak in 2008 compared to 1972. Compared to the distribution of education levels, the variations in income per capita are smaller across regions.

Figure 2 about here

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 both annual and 4-year transitions, but focus on longer transitions in the analysis below. The pattern is the same, and the argument

[5] Consistent with Silverman's rule of thumb the bandwidth is set to 0.0606 and 0.0376 for 1972 and 2008, respectively.

for long intervals is to avoid short term fluctuations and thereby have more stable transition paths. Since the database covers the period 1972-2008, we focus on the years 1972, 1980, 1990, 2000, and 2008. This gives two 8-year transitions and two 10-year transitions and a total of 1584 observations to estimate transition probabilities. We follow the convention of discretization based on a uniform initial distribution of relative incomes across income groups, which gives the following five income groups: 1) less than 89% of the average, 2) between 89% and 95%, 3) between 95% and 101%, 4) between 101% and 109%, and 5) more than 109% of the average across regions. The transition probability matrix is shown in Table 2. As seen from the binomial standard errors given in parentheses, most of the estimated transition probabilities are significant. The exception is the probabilities of moving three or more income groups during a decade, which are typically insignificant or at least less significant.

Table 2 about here

The Markov matrix shows income convergence across regions. The distribution of per capita incomes is tending towards a point mass, rather than towards a two-point distribution. Regions in the lowest income group (income level relative to the average below 0.89) have 41.5% probability of catching-up during a transition period, and the high income regions have 32% chance of moving down the distribution. Regions in income groups 2 and 4 have much higher probability of moving towards the middle of the distribution than towards the end. The probability of moving from group 4 to the high income group is 11.7%, compared to about 35% chance of moving down the distribution. In other words, the distribution dynamics show no tendencies of a bimodal twin peaked distribution. This pattern is confirmed by the implied ergodic (long-run) distribution given in the last row of the matrix. Regional incomes go from a uniform distribution initially to a normal distribution in the long-run. The lowest and the highest income groups are reduced from 20% initially to about 13%, while the middle-income group accounts for 27% of the regions in the long-run. 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 regions become richer and high income regions become poorer (relatively speaking), i.e. living standards converge across regions.

The income convergence result is consistent with Rattsø and Stokke (2011), and is discussed in more detail there. Their focus is on the role of labor migration and agglomeration effects, and they use the same data 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.

6. Relationship between rising educational attainment and income transitions

The data analyzed above show large regional heterogeneity with respect to education and income. Since smart cities do not dominate education convergence and income divergence is not observed, the big picture is not consistent with strong human capital effects as a result of geographic concentration of highly educated. The obvious hypothesis based on the simultaneous convergence in the levels of income and education documented above, is that low income regions catch-up by increasing their educational level. In this section we investigate the relationship between the income transitions and the changes in the relative education levels in the regions. Is there a systematic pattern of rising educational attainment in regions moving upward in the income distribution?

As a simple start, we check the co-movement of a region's relative level of income and education during the last four decades. We rank the 396 regions both according to the change in their relative level of education and their degree of income catch-up, and divide both samples into three equal subsamples (top 33%, mid 33%, bottom 33%). We concentrate on the top 33% with the largest increase in the relative level of education and the bottom 33% with the largest decrease in the relative level of education. Among the top 132 regions, the relative level of education on average increased by 0.24 (from 0.73 to 0.97). Hence, this subsample reflects regions with below average level of education that is gradually moving up in the education distribution. Among these 132 regions, about half (71 regions) also belong to the top 33% in the income ranking and experience large increases in the relative income level. But as much as 23 out of the 132 regions are in the bottom 33% of the income ranking and are moving down the income distribution as the relative educational level increases. In the other end, the 132 regions with the largest decrease in relative education mainly have above average level of education, but are gradually moving towards the middle of the education distribution (decreasing by 0.28 from 1.41 to 1.13). Of these, 57% were also falling behind with respect to the relative income level, but 13% were actually catching-up in terms of income while falling behind in terms of education. These observations of the pattern of the changes in relative income and education do not give much systematic role for education in the income convergence process.

Furthermore, we investigate the role of education for income growth by calculating income transition probability matrices conditioned on the movement in the distribution of education. We estimate Markov matrices for the three subsamples of the regions defined according to the change in the relative educational level over time, as explained above. The matrices 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 groups in the three education subsamples. The subsample with large decreases in the relative educational level is dominated by regions in the upper half of the income distribution, while movements up the education distribution are more common in the bottom half of the income distribution.

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 the transition probabilities for this subsample of regions do not deviate much from the full sample (given in Table 2). Low income regions with large increases in the relative educational level have 40.4% chance of moving up the income ladder compared to 41.5% for the low income group as a whole. Similar, regions in the second income group have about 38% chance of catching-up both in the full sample and in the subsample with increasing relative educational level. The middle matrix of Table 3 shows that low income regions that remain relatively stable in the education distribution have about the same probabilities of catching-up (40.5% and 38.1% for income groups 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 region 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. Regions with increasing relative level of education that are in the third income group have 20.9% chance of catching-up. For regions with stable and decreasing relative educational levels the same probability equals 26.6% and 21.1%, respectively. Similar, the probability of catching-up from the fourth income group is largely independent of the development in the relative level of tertiary education. Income growth has not taken off in high income regions with rising relative education level.

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, as explained in section 3. In this way, we can investigate whether the transition probabilities are independent of the change in the relative education level. Comparing the matrices in Table 3 to the matrix for the entire sample of 396 regions (given in Table 2) simultaneously results in test statistic equal to about 35 for both tests.[6] With 30 degrees of freedom, the 5% critical value equals 43.8. This implies that the null hypothesis of equal transition probabilities across different developments in relative education cannot be rejected. It even holds at 20% significance level, and has a p-value of 0.23. The contributions to the Pearson test statistic from each transition in the three subsamples are given in Table 4. To sum up, rising educational attainment cannot explain the income catch-up of low income regions, and income growth has not taken off in high income regions with increasing education level.

Table 4 about here

To check the robustness of our results, we experiment with alternative classifications of regions according to the education dynamics. Instead of focusing on the movement in the distribution of education (the development in a region's level of education relative to the average) we consider the change in the absolute level of education, measured as the percentage point increase in the tertiary education share of the grown up population during 1970-2008. Given this classification of regions, we perform the same analyses and tests as

[6] When comparing the matrices, we exclude transitions with five or less observations in the full sample matrix. This corresponds to the insignificant transition probabilities in Table 2.

above, and our main results remain. Rising educational attainment cannot explain the income convergence found in the data.

As seen from Table 3, the probability of remaining in or moving to the lowest income group is in fact highest for regions that are catching up with respect to education. Similarly, the probability of remaining in the top income group is highest among regions with large decreases in the relative level of education. These counterintuitive findings might indicate an importance for the level of education in income growth. The group of regions moving up the education distribution typically starts from below average level of education, while regions moving down the distribution start with above average level of education. We investigate the potential role of education level for income growth in the next section. But given the convincing evidence of income convergence among Norwegian regions (section 5) together with high correlation between income and education, we do not expect a strong positive effect of the education level on income growth.

7. Relationship between average level of education and income transitions

The role of the education level for income growth is analyzed using the same method as above for the accumulation of educational attainment. We estimate income transition probability matrices conditioned on the average level of education during the past four decades. The regions are ranked according to the tertiary education share of the grown up population, and the sample is divided into three equal subsamples (top 33%, mid 33%, bottom 33%). Among the regions with high level of education the average tertiary share equals 15%, while the regions with medium and low educational level has an average tertiary share of about 10% and 8%, 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 distributions in Figure 1. The estimated Markov matrices are shown in Table 5. Tables 3 and 5 are similar, but the regions in the three subsamples are different, now based on the education level. The relationship between income level and education level is reflected in the number of observations for the different income groups in the three education subsamples. Of the 528 observations of high education level regions, 344 are in the two top income groups. At the other end, 361 of the 528 observations of low education level regions are in the two lowest income groups.

By comparing the estimated transition probabilities we observe a positive role of education level for income growth, in particular in the two ends of the distribution. But the size of the effect is small, and not sufficient to generate income divergence, as one would expect. The first row of the bottom matrix of Table 5 shows that among the lowest income regions with low educational level, the probability of moving up the income ladder equals about 35%. For the sample as a whole we have shown that the probability of catching-up from the lowest income group equals 41.5% (Table 2). Similar, regions with low level of education that are in income group 2 have 31% chance of catching-up, compared to 38% among all regions. According to the middle matrix of Table 5, regions with medium level of education have somewhat higher probabilities of catching up from the lowest income groups. When it comes to low income regions with high level of education the number of observations is too low to give reliable results. In the other end of the distribution, high level of education increases the probability of remaining in the top income group from 68% for the full sample (Table 2) to 77% (top matrix of Table 5). Similar, regions with high education level have about 15% chance of catching-up from income group 4, compared to 12% for the full sample. This is again only a small trace of smart cities, to be pursued below.

The limited role of education level for income growth is confirmed by the implied ergodic distributions of the three sub-matrices. If the level of education is important to generate growth, low income regions with low educational level should remain in the lowest income group, while high income regions with high educational level should take off and increase the income gap. The opposite is happening. Among regions with low education, more than 40% is initially in the lowest income group, 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 group is significantly reduced, and contains about a quarter of the regions. Similarly, among regions with high education, the top income group is not taking off, but is cut in half from 42% of the regions initially to 21% in the long run.

Table 5 about here

The test for the importance of the education level for the income growth follows the design above using Pearson and Likelihood Ratio tests. Comparing the transition probabilities in the three sub-matrices in Table 5 to the full sample matrix simultaneously results in test statistics of about 80 for both tests. With 30 degrees of freedom, the 5% critical value equals 43.8, and the null hypothesis of equal transition probabilities across different levels of education is rejected. Statistically the income transitions are different between the three education subsamples indicating that education level has some effect.

Table 6 about here

We look into the details of the test in Table 6 and show the contributions to the Pearson test statistic from each transition in the three subsamples. More than half of the 60 comparisons contribute with less than 1 to the test statistics. Some large error terms are the main source of the relatively large test statistic. The matrix based on regions with low education level deviates the most from the full sample matrix. But the high contribution is driven by large error terms in the top income group, where transition probabilities are estimated from only 24 observations. Also, the probability estimate from income group 3 to the lowest income group (with an error term close to 5) has very low level of significance. Among regions with medium level of education, transition probabilities in the two ends of the distribution deviate from the full sample estimates, but again these are based on rather few observations. The same applies to the transition probabilities in the two lowest income groups for the high education sample. Overall, a large share of the error terms comes from the two ends of the distribution, and in particular the top end. This might reflect the highly unequal number of observations in the three subsamples for these income groups.

Based on the analyses in sections 6 and 7, 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 positive, but weak. Large increases in the relative educational level cannot explain the income catch-up of low income regions, and high income regions with high level of education do not take off and generate income divergence.

The top 20 smart cities in Norway are presented in Table 7. The 20 regions all have tertiary education share above 26% in 2008, with Oslo and neighbors Asker and Bærum at the top with about 40%. While the education level has increased significantly, the relative education has been reduced among most of the top 20. Asker and Bærum at the top had education levels 4-5 times higher than average in 1970, but only somewhat more than 2 times higher in 2008. This is consistent with education level convergence. And the top 20 smart cities have not had income growth take off. Rather, most of them have reduced relative income in 2008 compared to 1972, and some are even below average income in 2008. The numbers are consistent with income convergence. Interestingly, the small region Leikanger with about 2.000 inhabitants has entered the list of top 20 in terms of education level. In this community about 2/3 of the employed work in the public sector and the many nurses and teachers and other public servants have college education. The periphery has raised the education level along with an increasingly dominant public sector.

Table 7 about here

8. Concluding remarks

We have investigated the role of increased education level for regional income growth. The background literature on smart cities reports that highly educated people concentrate in cities and that the associated increase in human capital contributes to income growth. Our dataset for Norwegian regions confirms the accumulation of education biased to urban areas, but also periphery regions are catching up in education level. Overall the education level converges. Regions with increasing education level are expected to have higher income growth. The Norwegian data offer some contrarian observations worth contemplating. The regional income level also is converging, but the movements in the income distribution are unrelated to the accumulation of education. The overall conclusion of the analysis is that education has a limited role in explaining the income growth among Norwegian regions.

Econometric studies in this area face serious challenges of endogeneity and sorting and it is difficult to find good instruments to predict the dynamics of education over the long period studied here. We offer an alternative methodology, distribution analysis, to investigate whether the pattern of the income data are consistent with causal effects of the pattern of education data. We accept that we cannot convincingly separate between the consequences of education for income growth, the importance of income growth for migration of highly educated, and other sources of increasing productivity and income. Given the lack of relationship between education transitions and income transitions and the lack of income growth in regions with high and increasing education level, the data are hardly consistent with strong income effects of increased education.

The Norwegian economy is characterized by large movements of population and economic activity from the periphery to urban centers. Interestingly, this urbanization and structural change is combined with income convergence and convergence in education level. The emergence of smart cities with high education level and income growth is not dominating the pattern of income growth.

It can be argued that our result follows from heterogeneity and variation in quality of tertiary education. But compared to international studies, the quality differences across tertiary education in Norway probably is small. And 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. The expanding service sectors in the advanced urban economy seem not to be that tertiary education intensive, as they also invite inflow of unskilled labor. And they don't contribute much to income level growth in our data.

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. In particular the relative size of the public sector is expanding in the periphery with many college educated nurses and teachers in local services. They help keep up the income level in the many small regions, but the expanded public administration does not contribute much to overall income growth. The return to tertiary education is low, in particular in the public sector. It is well known that the compressed wage structure implies low return to education. The population is possibly overeducated.

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Figure 1: Kernel density estimates, relative level of education, 396 regions (municipalities), 1970 and 2008.

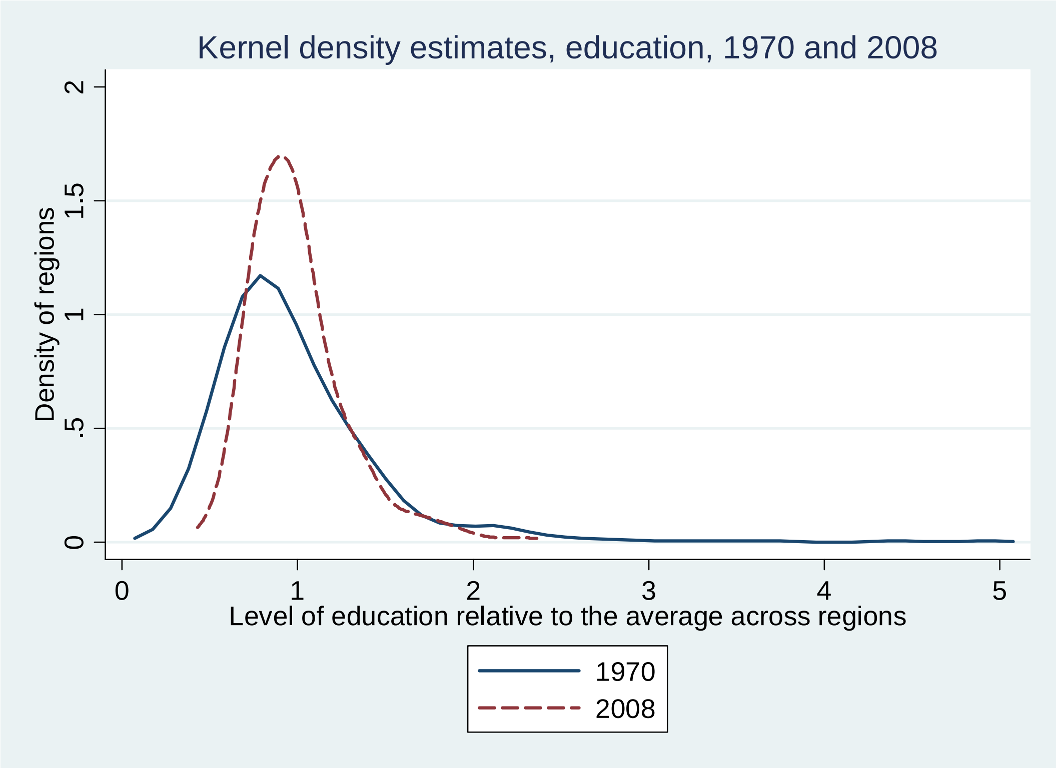

Figure 2: Kernel density estimates, relative income per capita, 396 regions (municipalities), 1972 and 2008.

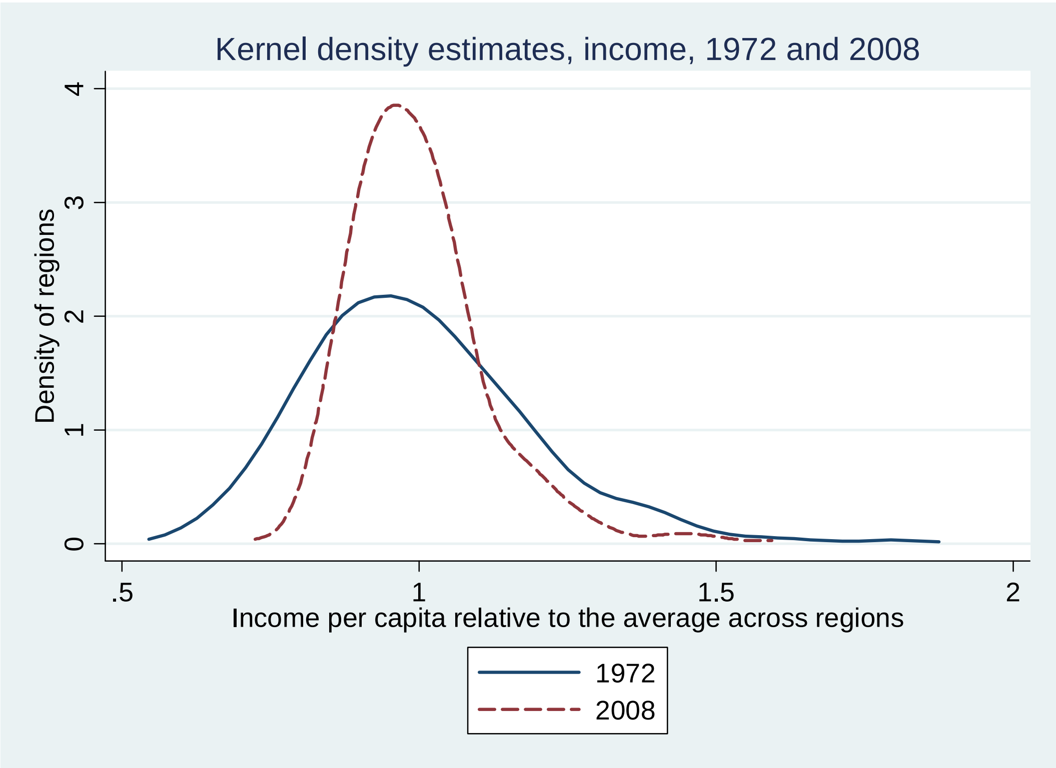

Table 1: Markov chain transition probability matrix, level of education, decade transitions, 1970-2008, 1584 observations (binomial standard errors in parentheses).

Education groups	1 ≤ 0.72	2 ≤ 0.84	3 ≤ 0.99	4 ≤ 1.21	5 > 1.21	Obs.
1	**67.2**	29.3	2.8	0.3	0.3	317
	(2.6)	(2.6)	(0.9)	(0.3)	(0.3)	
2	12.9	**55.5**	29.0	2.5		317
	(1.9)	**(2.8)**	(2.5)	(0.9)		
3	0.6	15.1	**61.8**	21.8	0.6	317
	(0.4)	(2.0)	**(2.7)**	(2.3)	(0.4)	
4	0.3	1.0	18.3	**72.2**	8.2	317
	(0.3)	(0.6)	(2.2)	**(2.5)**	(1.5)	
5			0.3	13.3	**86.4**	316
			(0.3)	(1.9)	**(1.9)**	
Initial distribution	20.0	20.0	20.0	20.0	20.0	
Ergodic distribution	6.3	13.9	26.7	32.2	20.8	

Table 2: Markov chain transition probability matrix, income per capita, decade transitions, 1972-2008, 1584 observations (binomial standard errors in parentheses).

Income groups	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Obs.
1	**58.5**	32.3	5.7	2.2	1.3	316
	(2.8)	(2.6)	(1.3)	(0.8)	(0.6)	
2	17.0	**45.1**	28.7	7.9	1.3	317
	(2.1)	**(2.8)**	(2.5)	(1.5)	(0.6)	
3	3.1	29.7	**44.2**	19.6	3.5	317
	(1.0)	(2.6)	**(2.8)**	(2.2)	(1.0)	
4	0.6	4.7	29.3	**53.6**	11.7	317
	(0.4)	(1.2)	(2.6)	**(2.8)**	(1.8)	
5	0.3	1.6	2.5	27.4	**68.1**	317
	(0.3)	(0.7)	(0.9)	(2.5)	**(2.6)**	
Initial distribution	20.0	20.0	20.0	20.0	20.0	
Ergodic distribution	12.4	24.2	26.7	23.7	13.0	

Table 3: Markov chain transition probability matrix, income per capita, decade transitions, conditioning on the change in the relative educational level during 1970-2008 (binomial standard errors in parentheses).

Panel a: Top 33% with large increase in the relative educational level (528 observations)

Income groups	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Obs.
1	**59.6**	31.3	4.8	2.4	1.8	166
	(3.8)	(3.6)	(1.7)	(1.2)	(1.0)	
2	20.0	**41.6**	24.8	10.4	3.2	125
	(3.6)	**(4.4)**	(3.9)	(2.7)	(1.6)	
3	4.8	28.6	**45.7**	17.1	3.8	105
	(2.1)	(4.4)	**(4.9)**	(3.7)	(1.9)	
4	1.4	8.2	28.8	**48.0**	13.7	73
	(1.4)	(3.2)	(5.3)	**(5.8)**	(4.0)	
5		5.1	3.4	28.8	**62.7**	59
		(2.9)	(2.4)	(5.9)	**(6.3)**	
Initial distribution	31.4	23.7	19.9	13.8	11.2	
Ergodic distribution	15.9	24.8	24.8	21.2	13.2	

Panel b: Mid 33% with stable relative educational level (528 observations)

Income groups	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Obs.
1	**59.5**	32.5	5.6	1.6	0.8	126
	(4.4)	(4.2)	(2.0)	(1.1)	(0.8)	
2	18.2	**43.8**	33.1	5.0		121
	(3.5)	**(4.5)**	(4.3)	(2.0)		
3	3.4	26.5	**43.6**	21.4	5.1	117
	(1.7)	(4.1)	**(4.6)**	(3.8)	(2.0)	
4	1.0	4.8	29.5	**56.2**	8.6	105
	(1.0)	(2.1)	(4.5)	**(4.8)**	(2.7)	
5	1.7	3.4	6.8	35.6	**52.5**	59
	(1.7)	(2.4)	(3.3)	(6.2)	**(6.5)**	
Initial distribution	23.9	22.9	22.2	19.9	11.2	
Ergodic distribution	14.4	24.7	29.3	23.9	7.7	

Panel c: Bottom 33% with large decrease in the relative educational level (528 observations)

Income groups	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Obs.
1	**45.8**	37.5	12.5	4.2		24
	(10.2)	(9.9)	(6.8)	(4.1)		
2	9.9	**53.5**	28.2	8.5		71
	(3.5)	**(5.9)**	(5.3)	(3.3)		
3	1.1	34.7	**43.2**	20.0	1.1	95
	(1.1)	(4.9)	**(5.1)**	(4.1)	(1.1)	
4		2.9	29.5	**54.7**	13.0	139
		(1.4)	(3.9)	**(4.2)**	(2.9)	
5			1.0	24.6	**74.4**	199
			(0.7)	(3.1)	**(3.1)**	
Initial distribution	4.5	13.4	18.0	26.3	37.7	
Ergodic distribution	5.4	26.9	28.0	25.5	14.1	

Table 4: Test of whether the change in the relative educational level affects transition probabilities, 1972-2008, decade transitions. Contributions of single subsamples to the Pearson test statistics.

Change in relative educational level	Income groups	Number of obs.	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Sum
Top 33% large increase (528 obs)	1	166	0.03	0.04	0.23	0.03		0.33
	2	125	0.65	0.34	0.67	1.00		2.66
	3	105	0.86	0.04	0.06	0.31	0.03	1.30
	4	73		1.88	0.01	0.44	0.26	2.59
	5	59			0.18	0.04	0.26	0.48
	Sum							**7.36**
Mid 33% stable (528 obs)	1	126	0.02	0.00	0.00	0.22		0.24
	2	121	0.09	0.05	0.80	1.32		2.26
	3	117	0.03	0.39	0.01	0.20	0.93	1.56
	4	105		0.00	0.00	0.13	0.86	0.99
	5	59			4.25	1.43	2.11	7.79
	Sum							**12.84**
Bottom 33% large decrease (528 obs)	1	24	0.66	0.20	1.95	0.41		3.22
	2	71	2.14	1.11	0.01	0.03		3.29
	3	95	1.33	0.83	0.02	0.01	1.60	3.79
	4	139		1.01	0.00	0.03	0.19	1.23
	5	199			1.80	0.58	1.13	3.51
	Sum							**15.04**
Pearson test statistic								**35.24**
Critical value at 5% significance level (30 degrees of freedom)								**43.77**

Table 5: Markov chain transition probability matrix, income per capita, 10-year transitions, conditioning on the average level of education (binomial standard errors in parentheses).

Panel a: Top 33% with high level of education (528 observations)

Income groups	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Obs.
1	**50.0**	32.1	10.7	3.6	3.6	28
	(9.4)	(8.8)	(5.8)	(3.5)	(3.5)	
2	8.6	**44.8**	41.4	5.2		58
	(3.7)	**(6.5)**	(6.5)	(2.9)		
3	2.0	26.5	**46.9**	22.5	2.0	98
	(1.4)	(4.5)	**(5.0)**	(4.2)	(1.4)	
4		1.6	26.8	**56.9**	14.6	123
		(1.1)	(4.0)	**(4.5)**	(3.2)	
5		0.5	1.8	20.4	**77.4**	221
		(0.5)	(0.9)	(2.7)	**(2.8)**	
Initial distribution	5.3	11.0	18.6	23.3	41.9	
Ergodic distribution	4.2	17.5	29.3	27.7	21.3	

Panel b: Mid 33% with medium level of education (528 observations)

Income groups	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Obs.
1	**40.6**	47.8	10.1	1.5		69
	(5.9)	(6.0)	(3.6)	(1.5)		
2	14.5	**43.6**	30.8	10.3	0.9	117
	(3.3)	**(4.6)**	(4.3)	(2.8)	(0.9)	
3	1.4	27.9	**47.1**	20.7	2.9	140
	(1.0)	(3.8)	**(4.2)**	(3.4)	(1.4)	
4	0.8	5.4	30.0	**54.6**	9.2	130
	(0.8)	(2.0)	(4.0)	**(4.4)**	(2.5)	
5		1.4	2.8	43.1	**52.8**	72
		(1.4)	(1.9)	(5.8)	**(5.9)**	
Initial distribution	13.1	22.2	26.5	24.6	13.6	
Ergodic distribution	7.2	24.8	32.1	28.0	7.9	

Panel c: Bottom 33% with low level of education (528 observations)

Income groups	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Obs.
1	**65.3**	27.4	3.7	2.3	1.4	219
	(3.2)	(3.0)	(1.3)	(1.0)	(0.8)	
2	22.5	**46.5**	21.8	7.0	2.1	142
	(3.5)	**(4.2)**	(3.5)	(2.1)	(1.2)	
3	7.6	36.7	**35.4**	13.9	6.3	79
	(3.0)	(5.4)	**(5.4)**	(3.9)	(2.7)	
4	1.6	9.4	32.8	**45.3**	10.9	64
	(1.6)	(3.6)	(5.9)	**(6.2)**	(3.9)	
5	4.2	12.5	8.3	45.8	**29.2**	24
	(4.1)	(6.8)	(5.6)	(10.2)	**(9.3)**	
Initial distribution	41.5	26.9	15.0	12.1	4.5	
Ergodic distribution	26.6	31.8	20.7	15.2	5.7	

Table 6: Test of whether the average level of education affects transition probabilities, 1972-2008, 10-year transitions. Contributions of single subsamples to the Pearson test statistics.

Average education level	Income groups	Number of obs.	1 ≤ 0.89	2 ≤ 0.95	3 ≤ 1.01	4 ≤ 1.09	5 > 1.09	Sum
Top 33% high level (528 obs.)	1	28	0.34	0.00	1.19	0.22		1.75
	2	58	2.41	0.00	3.24	0.54		6.19
	3	98	0.38	0.32	0.17	0.42	0.58	1.87
	4	123		2.50	0.26	0.25	0.92	3.93
	5	221			0.44	4.02	2.76	7.22
	Sum							**20.96**
Mid 33% medium level (528 obs.)	1	69	3.80	5.17	2.39	0.18		11.54
	2	117	0.43	0.06	0.17	0.83		1.49
	3	140	1.31	0.15	0.28	0.09	0.15	1.98
	4	130		0.12	0.02	0.02	0.66	0.82
	5	72			0.02	6.31	2.46	8.79
	Sum							**24.62**
Bottom 33% low level (528 obs.)	1	219	1.69	1.59	1.59	0.00		4.87
	2	142	2.48	0.06	2.29	0.13		4.96
	3	79	4.94	1.33	1.36	1.28	1.86	10.77
	4	64		2.88	0.26	0.81	0.03	3.98
	5	24			2.68	2.46	4.46	9.60
	Sum							**34.18**
Pearson test statistic								**79.76**
Critical value at 5% significance level (30 degrees of freedom)								**43.77**

Table 7: Top 20 smart cities in Norway

Region	Education 2008 (%)	Education 1970 (%)	Relative education 2008	Relative education 1970	Relative income 2008	Relative income 1972	Population 2008
Bærum	43.0	22.5	2.36	4.91	1.59	1.79	108 144
Asker	41.0	20.1	2.25	4.40	1.50	1.65	52 922
Oslo	38.7	12.3	2.12	2.68	1.43	1.82	560 484
Nesodden	36.1	13.0	1.98	2.85	1.16	1.43	16 868
Oppegård	35.2	14.9	1.93	3.27	1.41	1.59	24 201
Leikanger	35.2	7.1	1.93	1.54	1.08	1.05	2 179
Trondheim	34.0	10.2	1.87	2.24	1.11	1.37	165 191
Ås	33.4	16.9	1.83	3.70	1.12	1.41	15 324
Tromsø	32.5	7.3	1.78	1.59	1.05	1.23	65 336
Bergen	32.4	9.8	1.78	2.15	1.19	1.37	247 746
Stavanger	32.4	8.4	1.78	1.84	1.49	1.34	119 586
Lillehammer	32.1	8.9	1.76	1.94	1.07	1.26	25 776
Volda	30.9	8.9	1.69	1.94	0.98	1.01	8 406
Førde	30.9	7.2	1.69	1.58	1.05	1.10	11 650
Kongsberg	30.1	9.4	1.65	2.05	1.24	1.33	23 997
Molde	29.9	9.9	1.64	2.17	1.14	1.27	24 294
Frogn	29.9	10.2	1.64	2.22	1.34	1.41	14 245
Sogndal	29.9	6.4	1.64	1.39	0.99	0.98	6 899
Nøtterøy	29.4	7.8	1.61	1.71	1.12	1.37	20 410
Kristiansand	28.6	9.6	1.57	2.10	1.11	1.33	78 919
Average across all regions	18.2	4.6					10 634