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What Kind of Education Does China Need?

The Impact of Educational Attainment on Local Growth and Disparities

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Abstract

This paper analyses the impact of different levels of educational attainment on local growth and economic disparities in China. By applying decomposition analysis and quantile regression techniques to a set of sub-provincial level regional data, special emphasis is put on identifying and incorporating heterogeneities in the education-growth relationship across regions and income levels.

Previous analyses revealed significant differences in income disparities within provinces across China. So far, no explanation for the cross-provincial pattern of intra-provincial inequality has been offered in the literature.

This paper proposes that differences in human capital (proxied by educational variables) affect local growth performance. Can disparities on various levels of education, at least partly, account for the pattern of inter-provincial variation in intra-provincial disparities?

Keywords: China, education, disparities, decomposition, quantile regression

JEL classification: O15, J24, I21

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1 Introduction

One of the developments in the world economy that has gained much attention among academics as well as the general public is the impressive growth experience of China over the last quarter of a century. It has, however, also become common knowledge that this rise to economic power was accompanied by a steep increase in economic disparities in recent years.

Although a vast literature exists on this topic,[1] there are surprisingly several aspects that are only inadequately addressed. One of those is the large regional disparities at lower levels of aggregation, which can be shown to account for a large proportion of total inequality, and for the significant differences in the disparities between regions, visualized in Figure 1.[2]

However, researchers have not been able to explain the seemingly random variation of regional inequality within Chinese provinces.[3] Thus, the first objective of this paper is to shed light on the intra- (as opposed to inter-) provincial dynamics of regional disparities. To do so, the paper uses data at a low aggregated level, mainly for cities and counties, across all provinces.[4] Furthermore, analytical methods are applied that specifically account for distributional aspects of that data, as decomposition analysis or quantile regression.

A second albeit still unsatisfactorily analysed area of research on disparities in China concerns the diverging social conditions throughout China, as well as their developmental impact.[5] Although some social indicators appear in most studies on regional growth, an in-depth discussion of the available indicators, their distribution and especially their economic impact remains rare. Considering the regional structure of educational attainment in China, this paper hypothesizes that the distribution of education has a strong impact on economic disparities within and between China's provinces.

Therefore, the paper addresses two interrelated problems. In the first section, it provides a detailed overview of educational disparities between Chinese regions. Analysing data from population surveys in 1990 and 2000, the study focuses on disparities between cities, but also provides additional evidence for the more disaggregated county and district level.

Second, the results on educational inequality are applied to investigate the long-debated question of what impact educational variables, approximating human capital endowment, may have on regional growth. More specifically, educational attainment is decomposed into various educational levels to assess the effectiveness of different kinds of education in influencing local growth. To overcome estimation problems, special

1 See, for example, Bao *et al.* (2002); Kanbur and Zhang (2005) with further references.

2 See also Reuter (2004: 135-40).

3 See Khan *et al.* (1993: 66).

4 Such a disaggregated approach is also advised by Herrmann-Pillath, Kirchert and Pan (2002); and Peng (1999).

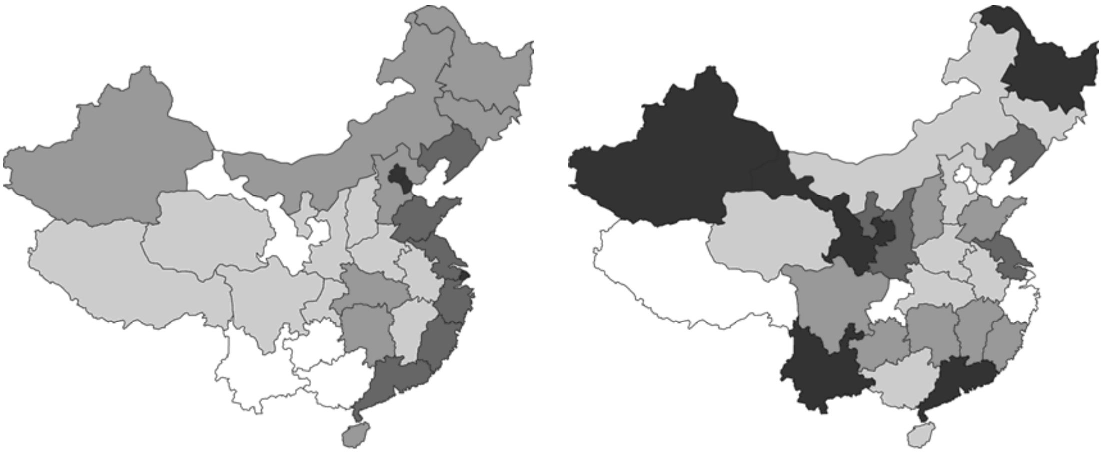
5 See Kanbur and Zhang (2003: 1).

emphasis is put on facilitating the more traditional, mean-focused OLS analysis by quantile regression methods that can better describe the entire distribution of the data, as well as account for outliers, nonlinearities and other data problems.

By addressing these two questions, the paper intends to present the interesting dynamics of educational disparities in China.

In addition to being of theoretical interest, the answers to these questions also have direct relevance for future policy design. Can disparities in education account, at least partly, for the observed large inter-provincial variation in intra-provincial disparities? And, can efforts to realize a more equal distribution of education help to reduce the substantial differences currently observed between regional incomes? The concluding section summarizes the results and discusses the policy implications derived from the analysis.

Figure 1
Regional disparities between and within Chinese provinces:
Per capita GDP and provincial Theil indices in 2001



Note: Provincial per capita GDP 2001

>20,000 yuan RMB
10,000–20,000 yuan RMB
6,000–10,000 yuan RMB
5,000–6,000 yuan RMB
< 5,000 yuan RMB

Note: Provincial Theil indices 2001; 2,317 counties/31 provinces

>0.45
0.40–0.45
0.35–0.40
0.30–0.35
< 0.30

Source: Compiled by the author, based on data from NBS (2002).

2 Educational disparities in China

2.1 Data description

In this section, the regional structure of educational inequality within and between Chinese provinces is examined. For that purpose, we analyse and decompose population census data at the highest educational level attained and average schooling years.

In the first step, we utilize data from the year 2000 population census for the prefectural as well as the county/district level, covering all provinces and province-level municipalities, to draw a detailed picture of China's educational landscape at that point of time.

The data are published by the National Bureau of Statistics of China based on the year 2000 population census, and include information on the educational attainment of the population (aged 6 years or older), for each county or city district. The educational levels are divided into 9 categories: (i) no formal education, (ii) literacy classes, (iii) primary education, (iv) lower secondary education, (v) higher secondary education, (vi) specialized secondary education, (vii) specialized college/university education, (viii) university education, and (ix) research.[6] Beside these, the average per capita years of education, and the illiteracy rate for the population aged 15 and older are reported. Data are available for 2,871 counties and districts in 344 prefectures in all 31 provinces or province-level municipalities. Additional descriptive statistics on the variables are given in section 3.2.

In the second stage, we limit the analysis to urban data, supplementing the previous data with figures from the year 1990 population census, published in the *Population Statistics Yearbook 2000* (NBS 2000) and from various issues of the *Urban Statistical Yearbooks* (NBS nd) This dataset covers a balanced sample of 454 cities in 26 provinces. The main objective here is to compare the development of educational disparities between the censuses in 1990 and 2000 for these 454 cities.

From this second dataset, however, Beijing, Tianjin, Shanghai and Tibet are excluded as no disaggregated data are available at the city-level in these locations. Data for Chongqing, which became a province-level municipality in 1996, have been incorporated with date on Sichuan. Although the excluded regions represent the extremes in income distribution, which could introduce a decomposition bias, their exclusion has no strong impact on the results of the analysis. The total number of 454 cities encompasses all municipalities that were available in 1990 and 2000, thus almost equalling the total overall number of cities in 1990 (467).[7]

2.2 Measurement issues

Inequality in this paper is measured and decomposed using the Theil index.[8] The index can be decomposed into between-group and within-group inequality. The Theil index T can easily be decomposed into within (T_W) and between (T_B) group components for different groups of income receivers, or, as in this case, regions. The common formula for this decomposition is:

$$T = T_B + T_W = \left[\sum_i \left(\frac{Y_i}{Y}\right) \ln\left(\frac{Y_i/Y}{n_i/N}\right)\right] + \left[\sum_i \left(\frac{Y_i}{Y}\right) T_i\right] \tag{1}$$

6 Specialized secondary schools include secondary technical schools and secondary teacher training schools. Specialized colleges, also called junior colleges, usually have three-year programmes (compared with the regular four-year university education), leading to a diploma (*wenping*).

7 Generally, the number of cities in China is increasing over time. While in 1984 there were data for only 295 cities in the *Urban Statistics Yearbook*, this by 2002 had increased to 660 cities, mainly due to the upgrading of county-seat towns into county-seat cities; see Song, Chu and Cao (2000: 250).

8 For a detailed description and discussion of this measure and possible alternatives, see Reuter (2004: 127-8; 130-2). All Theil index calculations in the present paper are performed using the software DAD 4.3; see Duclos, Araar and Fortin (2003).

with $Y_i = \sum_j Y_{ij}$ as the total income of the ith group, $n_i = \sum_j n_{ij}$ as the absolute frequency of population in ith group, and $T_i = \sum_j \left(\frac{Y_{ij}}{Y_i} \right) \ln \left(\frac{Y_{ij}/Y_i}{n_{ij}/n_i} \right)$ as the Theil index for the ith group.

As is evident from the formula, the Theil indices for each group i are weighted by the income share of their specific group. In sum, these group Theil indices form the within-group component of total inequality. The between-group inequality component, on the other and, equals a simple Theil index calculated with aggregated data at the group level.

In this paper, we go one step further by decomposing the within-group inequality for further disaggregated subgroups (e.g., prefectures as subgroups within provinces as groups):[9]

$$T = T_B + T_{WB} + T_{WW} \tag{2}$$

The between-subgroups component of the Theil index (indicated as T_{WB} as opposed to T_{WW} for the Theil index component for within subgroup disparities) is, technically, the difference between the Theil index calculated with subgroup aggregated data (e.g., prefecture-level data) and the Theil index calculated with group aggregated data (T_B; e.g., province-level data). A detailed description of the methodology and derivation of formulas can be found in Reuter (2004: 131ff.).

Applying this decomposition stepwise to the hierarchical levels of data, the absolute and relative contribution of each level can be accessed. In this study, we distinguish five levels of aggregation: (i) the national or central level, divided into (ii) three macro-regions or so called belts,[10] and consisting of (iii) 31 provinces and province level municipalities, each of these again being divided into (iv) prefectures,[11] which consist of (v) counties and city districts.

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9 A similar methodology has been used in Gustafsson and Li (2002) and Akita (2003).

10 These belts are commonly defined as:
Coastal: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan;
Central: Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and
Western: Sichuan, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

11 Prefectures are sometimes also referred to as ‘cities’. This term, however, is misleading because there are also prefectures without an prefecture-level city as its administrative centre, which are referred to as *diqu* or ‘regions’ in Chinese, as well as there are many county-level cities. The term ‘cities’ in this paper refers to municipalities at both the county level as well as prefectural level; for the latter, however, we include only the core or city part of the prefecture, excluding adjacent counties or county-level cities. For a discussion of this problem, see also Wei and Wu (2001: 8f., 25).

2.3 Distribution across educational levels

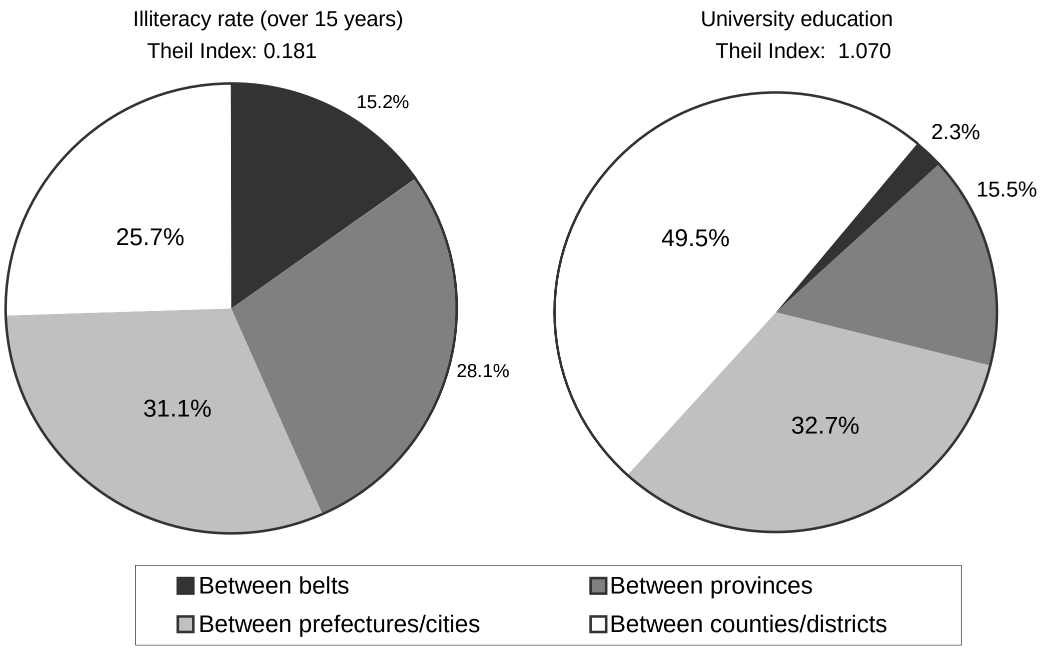
County and district level data

A first impression of the distribution of education is conveyed by Figure 2. The graphs shows the percentage shares of the aforementioned decomposed components of the Theil index of regional variation in illiteracy and the population share possessing a university education for different levels of aggregation, thus highlighting at which regional level disparities in education occur in China. Darker areas represent higher levels of aggregation. For example, while 15.2 per cent of regional disparities in illiteracy rates at the county level can already be explained by the location of a county in one of the so-called three belts (east, central, or west China), 25.7 per cent of all disparities are evident between counties located in the same prefecture. The absolute values of Theil indices are given above the graphs.

The results show that educational differences occur mainly within provinces, at the prefectural and county level, accounting for 57 and 82 per cent of total variation, respectively. Thus, Figure 2 proves that the approach of this paper to analyse the regional disparities at a low aggregated level is essential for identifying and understanding of their structure.

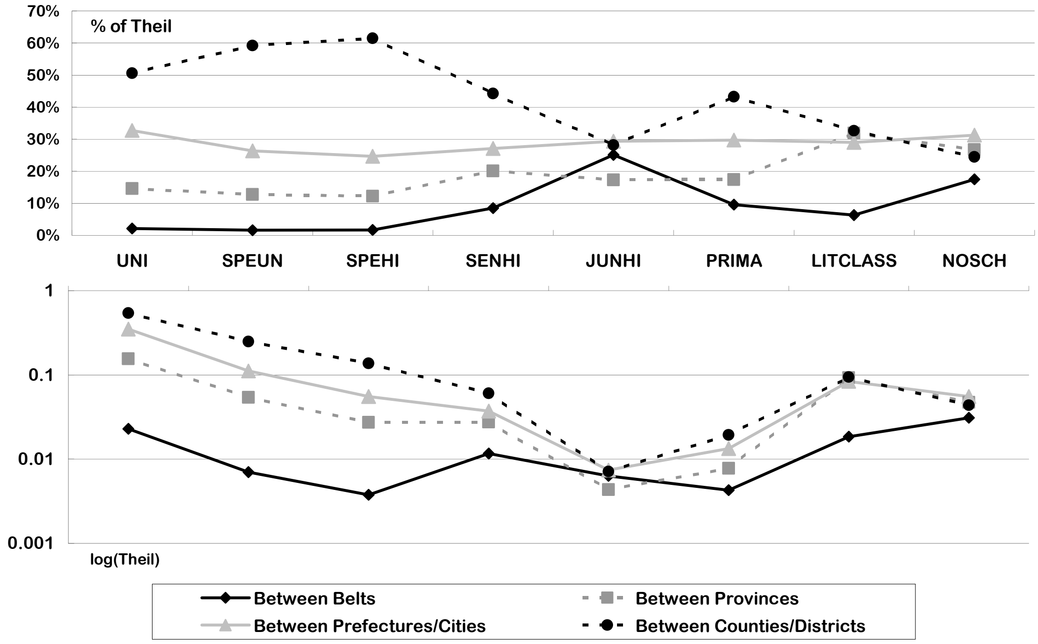
However, some important remarks need to be made. First of all, the structure of educational disparities differs significantly between the two measures used here. Variations in illiteracy rates, which tend to describe the lower part of the distribution of educational attainment, are not only significantly lower than differences in university education, but also have a very strong interregional component. Only 26 per cent of the variation is explained on the county level, while 28 per cent represents disparities that are evident between provinces, and 15 per cent even between macro-regions.

Figure 2
Decomposition analysis I of regional educational disparities, 2000



Note: Coverage = 2,871 counties and districts in 344 prefectures in all 31 provinces or province level municipalities.
Source: Compiled by the author, based on data from NBS (2003).

Figure 3
Educational disparities across educational levels, 2000



Note: Coverage = 2871 counties and districts in 344 prefectures in all 31 provinces or province level municipalities.

Source: Compiled by the author, based on data from NBS (2003).

University education, on the other hand, is better suited for describing the upper part in the distribution of education and income. Here, county-level disparities alone explain half of the total regional variation, while variation above the provincial level accounts for only less than 20 per cent. Thus, one might conclude that even though higher education is regionally much more unequally distributed than illiteracy, it is so relatively equally across all provinces and macro-regions.

The general message arising from this decomposition is clear: education is differently distributed, depending on the level of education one focuses on. Therefore, considering that the objective of this paper to analyse the relationship between education and regional development, the impact of education on development is likely to be different depending not only on the level of education, but also on the regional level. A simple linear relationship between the two is rather improbable.

But recognizing that the relationship cannot be linear, how can it be best described? Above, we have seen the regional distribution of education at two educational levels. On the one hand, there is the group with very low educational attainment represented by the illiterate people. These are concentrated in some provinces, but are relatively evenly dispersed over the prefectures and counties within these provinces. On the other hand, the upper part of the distribution of high educational attainment—and probably income as well—is highly concentrated within the provinces, but less so between the macro-regions. Could the rest of the distribution be a continuum between those two extremes?

To answer this question, and to get an overview of the distribution at different levels, Figure 3 summarizes the development of distribution over educational categories, ranked from the higher to lower levels of education. The upper part presents percentage data and the lower the absolute Theil index contributions in logged form.

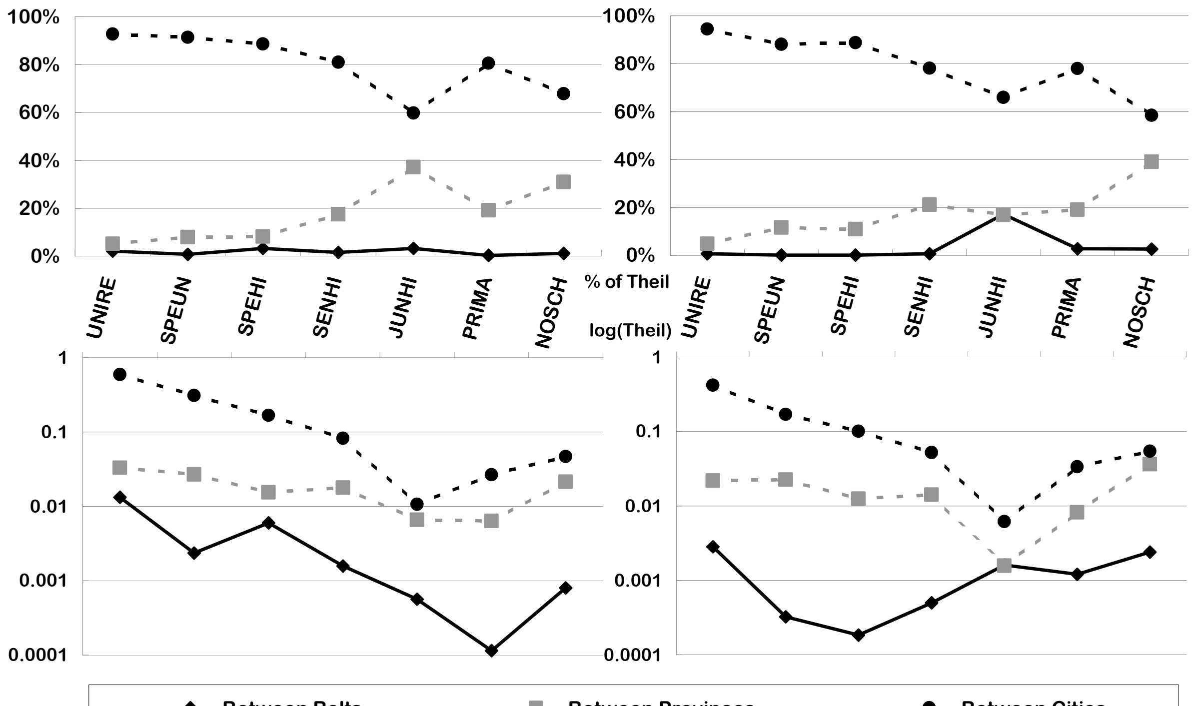
It becomes obvious that the structure of inequality varies between the different levels of education. The dispersion of primary education, like illiteracy representing the lower part of the educational distribution, is similar to that of higher secondary and university education, while lower secondary education, on the other hand, resembles more the distributional pattern of illiteracy rates.

Analysis of city data and time trends

Using city data for 454 prefecture- and county-level cities in 1990 and 2000, many of the main results of the previous section can be reproduced. Therefore, we want to focus here on describing the development of the distribution of education over time, which was not covered in the previous section.

Figure 4 compares the decomposition results for each educational category. The first noteworthy point is again the strong within-province component of disparities in education. The inter-provincial share in disparity increases for the share of population without formal education, but decreases for those with lower secondary education. Nevertheless, general trends are not apparent. Comparing the absolute size of educational disparities, one observes that variation in disparities decreases remarkably at all levels above lower secondary education, but increases with respect to non-schooling and primary education.

Figure 4
Educational disparities between 454 Cities in 26 provinces across educational levels, 1990 (left) versus 2000 (right)



Source: Compiled by the author, based on data from NBS (2000), NBS (2003), and NBS (nd).

2.4 Distribution across regions

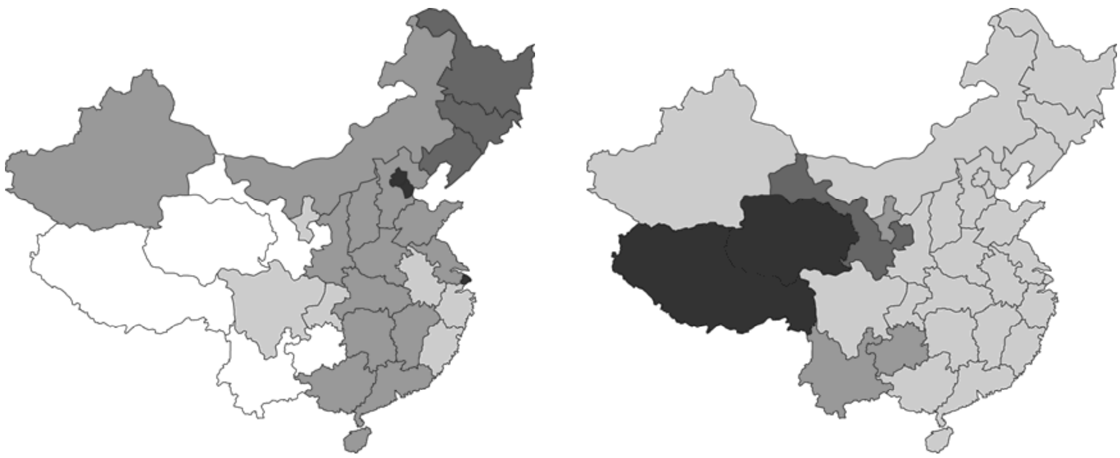
To explore the regional distribution of education in China, the maps in Figure 5 plot the average educational attainment for each province as represented by the years of education, and its variation within provinces (on the county/district level) described by the Theil index. The data are for the year 2000, and measured in standard deviations from the unweighted mean of the variable of interest.

The left map shows, not unexpectedly, that the average educational level in the eastern parts of the country is higher than in the western parts. Moreover, the educational level is especially high in the previously heavily industrialized north-east. On the other hand, it seems to be relatively low in the coastal provinces of Zhejiang and Fujian. Further disaggregation of educational categories (not reported here) reveals that this is mainly due to lower attainment rates in secondary education, especially higher secondary schooling.

Surprisingly, however, the right map suggests no noteworthy inter-provincial variation of educational disparities within provinces. Only three western provinces, all of them with a large minority share and rather difficult natural and geographic conditions, show relatively high disparities within their provincial borders. Therefore, could the impact of educational disparities on growth that this paper addresses be negligible?

One of the results from the previous analysis has been that the structure of educational disparity between localities varies widely between educational levels. Taking this into consideration, Figure 6 disaggregates overall educational attainment into its qualitative components.

Figure 5
Variation in average years of education per capita between and within provinces, 2000



Note: Average years of education per capita, province-level data.

Note: Provincial Theil indices of average years of education for 2,871 counties and districts in 344 prefectures in all 31 provinces or province level municipalities.

Legend for this and all the following maps:

Source: Compiled by the author, based on data from NBS (2003).

Figure 6
Educational disparities within provinces on different educational levels, 2000

No formal education

Primary education

Lower secondary education

Higher secondary education

Note: Coverage = 2,871 counties and districts in 344 prefectures in all 31 provinces or province level municipalities.
Source: Compiled by the author, based on data from NBS (2003).

As suspected, this changes the picture dramatically. Only lower secondary education resembles the pattern in Figure 5. Intra-provincial variation of all other categories is shown to differ strongly between provinces. Moreover, the pattern of differences varies for each educational level, explaining the relatively uniform distribution reported for average years of education.

Specifically, illiteracy is extremely dispersed within the provinces in the south-west, while large intra-provincial disparities in primary education exist in the north-east, in the south (especially in the province Guangdong), and in the north-western provinces. Intra-provincial distribution of secondary education is closer to the average education pattern, but even here some coastal provinces differ markedly from their neighbours.

The starkest contrasts between provinces, however, are revealed by the intra-provincial distribution of university education, as shown in the last map. Universities tend to be concentrated in the large metropolitan areas such as Beijing, Shanghai or Xian, and are seldom found outside the provincial capitals. University education thus represents not only the category of education with the highest share of total inequality explained at the intra-provincial level, but also with the most diverse regional structure of disparities on this level.

In this section, Theil index decomposition analysis is applied to show the structure of regional variation in education in China for different levels. It reveals that the overwhelming part of disparity is determined within provinces, but that the detailed structure differs strongly between levels of education as well as regions. Variation is especially large in the extremes of the educational spectrum, especially in higher education. Using city data, it can also be shown that educational disparities decrease over time for higher education, but that primary education has became less equally distributed.

Considering this diversity in the size, development and structure of regional educational disparity, it is necessary in the analysis both to consider different levels of education as well as different parts of the distribution of regional development. The quantile regression technique, the methodology proposed in the next section, is well suited for this job.

3 Education and growth

3.1 Background

The controversy over the impact of education on growth and income disparities has a long tradition in applied economic research. Although it is mainly undisputed in theory that human capital accumulation—in the form of education and subsequent technological progress—is one of the driving forces of economic growth, as well as a goal of economic development itself, empirical studies have often been unable to provide unambiguous evidence for that claim.

In the literature on economic growth, the importance of human capital as main the determinant of long-run productivity growth gained much attention with the emergence of the ‘endogenous growth theories’ in the 1980s.[12] In these theories, human capital, on the one hand, can be a direct input to the production function, representing productive skills of the workforce, which can be accumulated, e.g., by investment in schooling, training-on-the-job, or learning-by-doing. Such a link is proposed in the models of Lucas (1988),

12 Human capital, of course, has already been identified as such by the traditional growth theory. Early attempts to model the impact of human capital on growth are found in Nelson and Phelps (1966) and Uzawa (1965).

Mankiw, Romer and Weil (1992), or Uzawa (1965). In this case, changes in the stock of human capital lead to changes in the rate of growth.

On the other hand, human capital can be viewed as a determinant of the rate of technical progress, enhancing an economy's capacity to invent new technologies, or to exploit its catch-up potential by adopting and implementing existing ones. This kind of linkage is described, e.g., in Nelson and Phelps (1966), and Romer (1990). In this mechanism, the stock of human capital is important. Considering real world situations, both flows and stocks of human capital should be expected to have a positive impact on the rate of growth.

Empirical studies on the subject in general report a positive relationship between growth and human capital variables, but differ widely with respect to the size of the effects.[13] Partial explanations for these variations are thought to be differences in the education-growth relationship according to levels of development, as well as the aspects of schooling quality. Finally, data and estimation problems are often discussed as reasons for conflicting empirical evidence. One point here is that almost all studies focus entirely on formal education as the determinant of human capital, disregarding nonformal components of human capital as well as wider concepts of investment in human capital.

Moreover, some of the recent papers question the empirical relevance of any relationship between education and growth altogether. Benhabib and Spiegel (1994), Pritchett (1996), and Islam (1995), for example, provide evidence that such a relationship is empirically weak and even insignificant. Temple (1999) argues that some of this weak evidence may be due to heterogeneity in the data, especially outliers—a claim that is also addressed in this paper—while Topel (1999) focuses his explanation on the definition of variables in the regression. Data quality issues in these studies are addressed in Krueger and Lindahl (2001).

In summary, there is an overall tendency in applied research to verify a positive relationship between investment in education and growth performance, but the empirical results are far from undisputed.

Very much in line with the general literature, studies on China often find a significantly positive relationship between education and regional growth, or educational differences and income disparities, respectively.[14] Bramall (2000), using a long-run case study of four Chinese prefectures, shows the importance of inherited human capital in affecting prefectural growth rates. However, he also stresses that the conventional measures for the human capital stocks (he himself uses literacy rates) mis- and probably underestimates the true extent of differences in human capital endowments, because they take no account of the technical and other skills possessed by the workforce that are, for example, related to industrialization and historical path dependencies.[15] Wang and Yao (2003) argue that human capital accumulation in China has immense potential in contributing to productivity growth and welfare. In their results, however, they show that the contribution of human capital stock (measured in average schooling years) to GDP growth was

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13 A discussion of this evidence is provided in Sianesi and Van Reenen (2003).

14 See, for example, Fleisher and Chen (1997); Song, Chu and Cao (2000) and Yang (2004).

15 See Bramall (2000: 259ff.).

significantly higher in the pre-reform period (46.3 per cent during 1953-77) than in the reform period (11 per cent during 1978-99).[16] Other studies reporting positive effects of education on growth include, for example, Morduch and Sicular (2002: 102), Gustafsson and Wei (2001: 17), and Meng and Wu (1998: 76).

On the other hand, Gustafsson and Li's (1998) decomposition of income inequality on the household level for the 1988 Household Income Survey data reveals that only 13 per cent of income differences between households are explained by differences in educational attainment, compared with 87 per cent being due to disparities within educational groups, especially at the lower and middle educational level (primary and lower middle school).[17] Moreover, the coefficients for education in a regression model explaining the variation of equivalent household incomes are only very small in value, although highly significant when judged by their t-statistics.[18]

Finally, a number of other studies, as Wei et al. (2001: 161), Wu, Richardson and Travers (1996: 22), or Sandberg (2002: 15), even report insignificance of the effects of educational variables. Although there might partially be selection and measurement problems concerning the educational variables, these studies highlight the need for a more focused analysis of the education-growth relationship in China.

Considering the results of section 2 of this paper, such inconsistent or contradictory evidence is not really surprising. The local structure of educational attainment in China was shown to be not homogenous, neither across educational levels nor across regions. Therefore, a homogenous relationship between education and growth across the entire distribution of these variables is rather unlikely. Therefore, the working hypothesis in this paper is that educational attainment influences local growth, but this influence varies for different levels of education and economic development.

Such heterogeneity is, however, not a result of data defects or outliers as Temple (1999) argues, but a distinctive characteristic of the actual situation in China. Therefore, the exclusion of selected defective observation as influential outliers cannot be an appropriate strategy. Instead, inference has to attempt to specifically address the possibility of 'real' heterogeneity in the estimation process. One method available for this purpose, the quantile regression approach, which is used in this paper, is introduced in the following section.

3.2 Methodology

Estimation technique

Recent empirical studies aimed at linking various explanatory variables and growth mainly adopt two approaches. First, in cross-section growth regression, mostly on a cross-

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16 See Wang and Yao (2003: 48, 44).

17 See Gustafsson and Li (1998: 57). The decomposition results mentioned here are for the Theil index decomposition; decomposing the MLD-index produces shares of 12 and 88 per cent, respectively.

18 In their full model the effect of one additional year of schooling on equivalent income is slightly less than 2 per cent; see Gustafsson and Li (1998: 52). However, very different results are obtained for shadow wages for rural households; see Sicular and Zhao (2002, reported in Wang and Yao 2003: 48).

country level, a number of independently determined explanatory variables are linked to aggregate growth. The most prominent examples of this approach are Barro (1991, 2001), and Barro and Sala-i-Martin (1995). A second strand of research focuses on a growth-accounting approach, regressing the growth of production inputs (mainly physical capital, labour force, and human capital) on GDP growth. The latter method incorporates initial levels of human capital as proxies for technical capacity. This approach can be found in Benhabib and Spiegel (1994), or Pritchett (1996).

Both approaches rely usually on traditional OLS regression for their results, and have been criticized for a number of weaknesses.[19] Some of the discussed problems are parameter heterogeneity, the presence of extreme observations, model uncertainty and nonlinearities.

To address the above problems, several alternative options have been proposed, including GMM panel data techniques, robust regression analysis, extreme bounds analysis, the application of regression trees or the non-parametric density estimation of transition probability functions. In this paper, we apply a semi-parametric quantile regression technique introduced by Koenker and Bassett (1978) and operationalized by Koenker and D'Orey (1987).[20]

Quantile regression can be interpreted as a disaggregation of the traditional linear model. While the least square estimation assumes the relationship between two variables to be described by a single, representative coefficient with constant variance errors, quantile regression allows for a variation of that coefficient and its dispersion along the conditional distribution of the dependent variable. Thus, in the specific case of this paper, poorer cities (i.e., cities with an average per capita GDP that is located in a lower quantile of the sample distribution) can be statistically affected by an explanatory variable differently than cities with higher average per capita GDP.

Such a property is especially important if one is interested in the impact of the explanatory variable in different parts of the distribution. As Mello and Perrelli (2003: 646) point out, explanatory variables can statistically affect conditional distribution of the dependent variable in a number of ways. For instance, they can affect the dispersion, the skewness, stretch one tail, fatten the other, etc. In this case, we would like to estimate the entire conditional distribution, so that the use of quantile regression would be more appropriate then conditional mean estimation methods. On the other hand, if the explanatory variable affects only the location of the conditional distribution as in the classical homoskedastic linear regression model, then conditional mean estimation methods are preferable.

Although quantile regression shares the objective of uncovering relationships missed by traditional data analysis, its concept differs significantly from other robust regression methods. Robust estimation is designed to deal with mistakes due to inappropriate data. On the other hand, quantile regression as applied here is concerned with mistakes due to

19 See Temple (2000); Durlauf and Johnson (1995) and Sianesi and Van Reenen (2003).

20 All quantile regressions in this paper are estimated using the software package 'EasyReg International', by Herman J. Bierens, Pennsylvania State University, Version: 1 March 2004. Stata (StataCorp 2003) was used for cross-checking and additional inference.

summarizing disparate quantile effects into a single, potentially misleading, relationship.[21] When using quantile regression, questionable observations remain in the dataset. Instead, independent coefficients are estimated for the entire conditional distribution, using the entire dataset to derive each coefficient.

More specifically, the coefficients β_j in a quantile regression are estimated to minimize the sum of weighted absolute deviations for each quantile θ:[22]

$$\min_{b \in \Re} \left[\sum_{t \in \{t: y_t \geq b\}} \theta |y_t - x_t b| + \sum_{t \in \{t: y_t < b\}} (1-\theta) |y_t - x_t b| \right] \quad (3)$$

This minimization problem is solved via linear programming techniques. The coefficients of a quantile regression can be interpreted as the marginal change in the specific conditional quantile of the dependent variable due to marginal change in the corresponding explanatory variable.[23]

Since the technique in a quantile regression itself, as a point estimation method, belongs to the robust regression methods,[24] each observation will exert its influence strongly only in the specific part of the conditional contribution where it is located. The rest of the distribution is largely unaffected. Thus, one can obtain a result based on all information available in the dataset, without risking too much distortion due to defective data.

Quantile regression techniques have come into common use in labour economics and in the analysis of the quality of education.[25] Recently, it has also been proposed to apply this method to the subject of growth regressions.[26] The use of quantile regression techniques in this paper has primarily two motivations.

First of all, since the study is concerned with describing and analysing the distribution of education and growth within provinces, it is obviously necessary not only to operate with methods estimating central location measures like the sample mean (as it is done in the OLS case), but also to take the distribution of both variables into account. Quantile regression, describing the distribution of the dependent variable conditional to the explanatory variable, provides a tool to do so.

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21 See Bassett, Tam and Knight (2002: 17f).

22 Compare Koenker and Bassett (1978: 38).

23 See Buchinsky (1998: 98). As Buchinsky further points out, '[o]ne should be cautious with interpreting this result. It does not imply that a person who happens to be in the θth quantile of one conditional distribution will also find himself/herself at the same quantile had his/her x changed'.

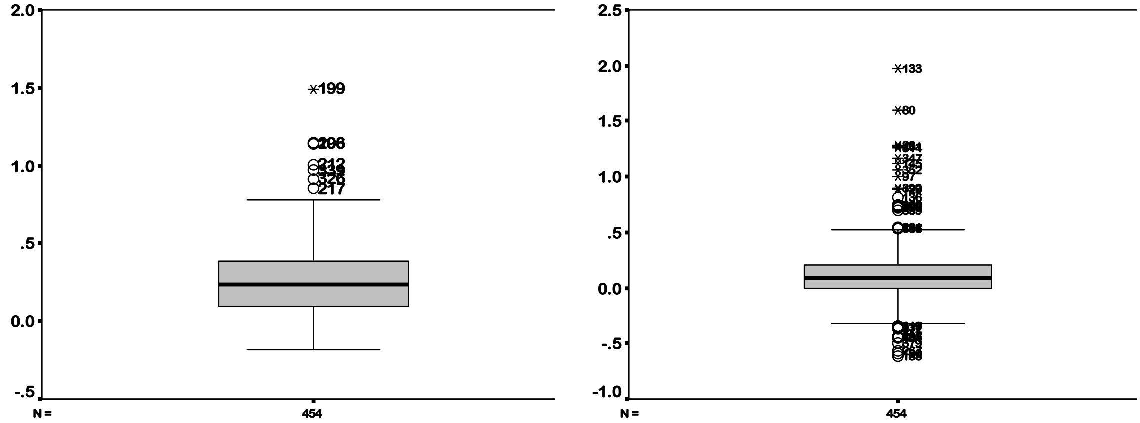
24 For example, the quantile regression for the 50 per cent quantile is also called the least absolute deviation (LAD) or median regression.

25 See, for example, Buchinsky (1994, 1995); Mwabu and Schultz (1996) and Eide and Showalter (1998, 1999).

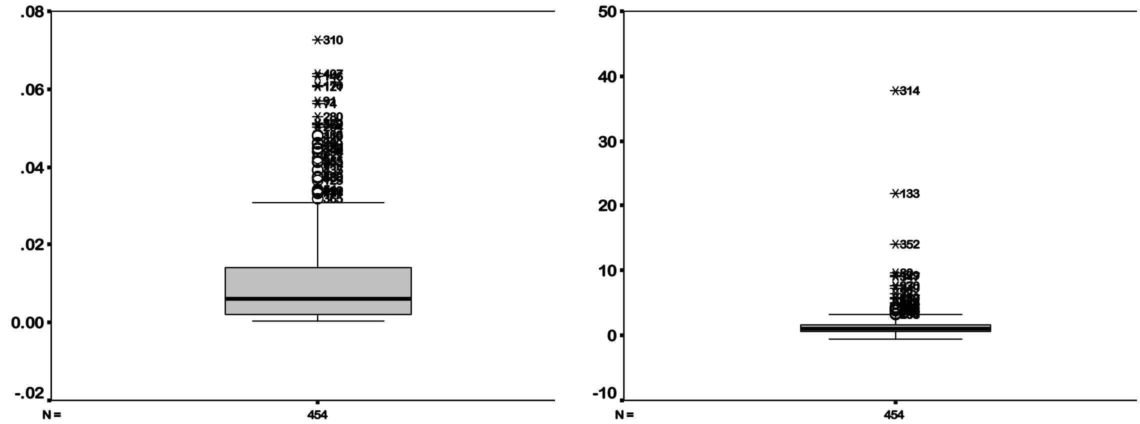
26 See Mello and Perrelli (2003); Cunningham (2003); Barreto and Hughes (2004).

Second, in a more technical sense, the use of conventional least square estimators can be problematic if some of the underlying assumptions of the classical model are violated. One of these assumptions is the Gaussian distribution of the regression errors. This assumption is known to be less restricting in large samples, because the errors encountered there can be viewed as the sum of a large number of small and independent elementary errors, and thus the central limit theorem is applicable.[27] However, this situation can not be viewed as given in cases where a few gross errors—even with only low probability—may be present in the data, causing serious deviation from the normality of errors assumption.[28]

Figure 7
Comparison of boxplot graphs for selected variables



Change in lower secondary education, 1990-2000 Change in higher secondary education, 1990-2000



Population share with university education, 1990 Change in university education, 1990-2000

Source: Compiled by the author, based on data from NBS (2000), NBS (2003), and NBS (nd).

27 See Haavelmo (1944).

28 See Koenker and Bassett (1978: 34).

One prominent example of such distorting errors is influential data points or *outliers*.[29] To overcome problems associated with the presence of possible outliers in the dataset, in practice, these observation are often eliminated from the dataset based on preliminary inspection of the data. However, such a procedure—based on the ad hoc assumption that the outliers are not elements of the distribution of interest but actually belong to a different dataset—may invalidate the inference procedure.[30] Moreover, it is more problematic to identify defiant observations in the context of linear models,[31] and if the multiple variable case is concerned.

To illustrate the last point, let us take a look at the boxplot graphs for some explanatory variables used in this paper, shown in Figure 7. They describe outliers and extreme outliers, marking them with empty circles or stars, respectively. The number of outliers for some variables is large, indicating the inappropriateness of simple OLS estimation. Furthermore, some important aspects can be noted.

For example, for changes in educational attainment, the observations 199, 212, 339, 326 and 217 can be identified as outliers in lower-secondary education changes, while the observations 133, 80, 314, 347, 145, 352, 97 and 399 are extreme outliers in changes in higher secondary education, and observations 314, 133, 352, 80, 129 and 347 represent extreme outliers in changes in university education.

In these examples, none of the observations are an outlier with regard to all variables. From this, it becomes obvious that different observations are outliers in different variables, which makes the task of identifying and addressing outliers manually rather impracticable. Here again, quantile regression might have some advantages, since it does not exclude the observation from analysis, but restricts its influence to its specific part of the conditional distribution.

Model specification

To identify the impact of educational variables representing human capital on regional growth, a basic growth-accounting framework regressing per capita GDP on previous per capita GDP, physical and human capital is applied.

Education as proxy for human capital is introduced in the form of a set of variables describing different levels of educational attainment, to account for the assumed heterogeneous dynamics of educational inequality.

The following test equation is estimated using both OLS and quantile regression technique:

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29 See Koenker and Bassett (1978: 35). Outliers are technically defined as observations with values smaller than the first quartile minus 1.5*IQR (interquartile ranges) or larger than the third quartile plus 1.5*IQR.

30 See Greene (2000: 263).

31 See Koenker and Bassett (1978: 37).

$$
\begin{aligned}
\log(\textit{Per capita GDP } 2000) = \; & \alpha_1 \log(\textit{Per capita GDP } 1990) + \\
& \alpha_2 \begin{pmatrix} \textit{Percentage Change in Log of} \\ \textit{Per capita Fixed Investment } 1990-2000 \end{pmatrix} + \\
& \alpha_3 \begin{pmatrix} \textit{Percentage Change in Log of} \\ \textit{Per capita Fixed Investment } 1990-2000 \end{pmatrix}^2 + \\
& \beta_{1L} (\textit{Population Share with Educational Attainment } L \; 1990) + \\
& \beta_{2L} \begin{pmatrix} \textit{Percentage Change in Population Share} \\ \textit{with Educational Attainment } L \; 1990-2000 \end{pmatrix} + \\
& \gamma_1 Dummy_1 + \gamma_2 Dummy_2 + \ldots + \gamma_{prov} Dummy_{prov} + \varepsilon
\end{aligned} \tag{4}
$$

In this test equation, per capita GDP in 2000 is explained by per capita GDP in 1990, changes and squared changes in per capita fixed capital investment to control for the effects of a changing investment rate,[32] and educational level and change variables. Per capita GDP and per capita investment both enter the test equation in log form.

Education, on the one hand, is measured by the population share holding a specific level of education, using the city data described in section 2.1 and used for decomposition analysis in section 2.3.

For statistical analysis, however, we reduce the number of variables by combining them in the following way. Higher secondary education and university education are introduced as one combined variable. This is mainly due to the fact that in virtually all county-level cities no institutions of higher education exist. Moreover, also specialized secondary and special college education are included in this higher education variable, since the individual value of these forms of education is rather small and its practical educational content may be considered not to differ significantly from that of regular educational institutions. Beside this, literacy school-level education, which is only reported for 2000, is included in primary education.

Another difficulty is the interrelation and correlation structure of the education data. For example, a lower share of population holding primary education might represent either a relatively higher share of population with secondary education or a high level of illiteracy. Thus, including all levels of education as explanatory variables into the regression will necessarily cause both collinearity and make the interpretation of estimation results ambiguous.

To avoid this ambiguity, we drop the population share of primary education from the regression, and define all educational levels above primary education (that are, lower secondary and higher education) as the cumulated share of the lowest educational level achieved. Thus, lower secondary education will enter the regression as the sum of the

32 Alternatively, we tried a number of differently defined changes in per capita capital stock as explanatory variable, derived from the cumulated investment flows between the two years and assuming linear as well as degressive depreciation and different depreciation rates. Since the main results with regard to education were not strongly affected by alternating investment or capital stock variables, these regressions are not reported here. The squared term of per capita investment changes is introduced to account for possible nonlinearities in the production function.

shares of the population holding lower secondary education and above, while the higher education variable only includes the corresponding population share with higher education. In this way, only an increase in educational attainment is captured by the variables for secondary and higher education.

As a result, the following educational levels are included in the test equation, measured as initial levels in 1990:

— population share with no formal education,

— population share with lower secondary education and above (called *lower secondary education*), and

— population share with higher secondary education higher education and above (called *higher education*).

Furthermore, we introduce variables describing the change in educational attainment between 1990 and 2000. This seems important because the educational composition of the urban Chinese workforce changed rapidly during the early 1990s. Specifically, the proportions of the labourforce having college or professional school education increased, while the proportions with only lower middle school and primary school education decreased.[33]

Corresponding to the level variables of education, three change variables are introduced: change in the population share with no formal education, change in the population share with lower secondary education and above, and change in the population share with higher secondary and higher education.

Finally, province-specific effects are included applying dummy variables. The coefficients γ_{prov} describe province-specific intercepts.

This basic formulation has similarities to the model of Benhabib and Spiegel (1994) and Temple (1999), but there are also some notable differences. First, instead of total values of output, capital and population, we are regressing per capita values of GDP and fixed capital. Second, we are not using these variables in differenced form, but retain the additional information available in the level data by comparing the year 2000 value with initial values in 1990.[34] Third, consequently, we include initial values as well as percentage change of all educational variables except average schooling years, for which data are available only in 2000. However, we refrain from taking logs on the educational variables, which seems to be not justified by the structure and nature of the data.[35] Finally, following the main argument of this paper that the distribution of

33 See Gustafsson and Li (2001: 130).

34 The level value of logged per capita fixed investment is, however, excluded to avoid multi-collinearity problems. The specification including initial and current values of the variables instead of explicit growth rates is partly motivated by the problems that unobserved ability bias may produce in the analysis of returns to education in a panel data setting; see Griliches (1977) and Arellano (2003: 10).

35 This formulation of comparing educational variables with the logarithm of per capita GDP approximates the common Mincerian human capital earning function; see Mincer (1974) and also Krueger and Lindahl (2001).

education may influence the distribution of growth within provinces, we additionally control for province-specific effects.

3.3 Estimation results

As a first step, results for the regression model as produced by OLS estimation are reported in Table 1. All educational variables except changes in the share of the population with lower secondary education appear to be insignificant. Thus, from a traditional point of view, the regression model using disaggregated educational data would have to be rejected.

However, this picture changes totally when quantile regression is applied. The following figure shows the impact of different educational variables for different parts of the conditional distribution.

The only result of the OLS-regression that is reconfirmed here is that changes in the population share with lower secondary education between 1990 and 2000 are significantly and positively related with the local growth performance, which is shown to be true across all quantiles of the conditional distribution in the top left graph (Figure 8).

For all other variables in Figure 8, the quantile regression reveals a significant impact on growth that has been neglected by the mean-focused regression. The important point

Table 1
OLS-regression results for model with different levels of education

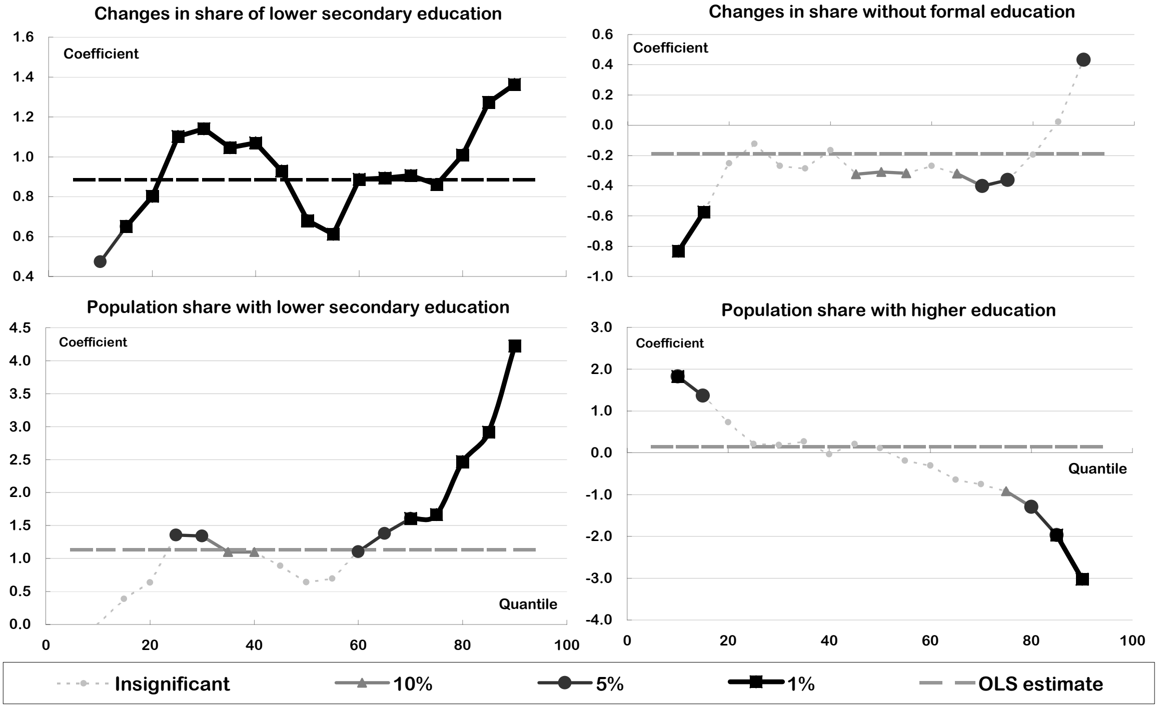
Dependent variable: Log of per capita GDP in 2000

Variable	Coefficient	Std error	t-Statistic	Prob.
Log of per capita GDP in 1990	0.985***	0.046	21.579	0.0000
Change in log of per capita fixed investment, 1990-2000	0.674***	0.155	4.340	0.0000
Squared change in log of per capita fixed investment, 1990-2000	-0.287***	0.081	-3.526	0.0005
Population share w/o formal education, 1990	*-0.061*	*0.548*	*-0.112*	*0.9109*
Change in population share w/o formal education, 1990-2000	*-0.188*	*0.234*	*-0.804*	*0.4218*
Population share with lower secondary education (and above), 1990	*1.132*	*0.740*	*1.529*	*0.1270*
Change in population share with lower secondary education (and above), 1990-2000	*0.885****	*0.243*	*3.644*	*0.0003*
Population share with higher education, 1990	*0.150*	*0.658*	*0.228*	*0.8197*
Change in population share with higher education, 1990-2000	*0.053*	*0.100*	*0.535*	*0.5929*
R-squared	0.742	S.E. of regression		0.358
Adjusted R-squared	0.722	Sum squared resid		53.876

Note: Method: Least squares; sample: 1-454; included observations: 454; *** Indicates significance at 1% level; white heteroskedasticity-consistent standard errors & covariance; *educational variables in italics.*

Source: Compiled by the author, based on data from NBS (2000), NBS (2003), and NBS (nd).

Figure 8
Quantile regression results for different levels of education



Note: Coefficients for the population share with no formal education and for changes in higher education are insignificant over the entire range of distribution.

Source: Compiled by the author, based on data from NBS (2000), NBS (2003), and NBS (nd).

here is that the impact of some educational variables appears to be significant only in certain parts of the distribution, while it does not matter for the rest of the localities. In extreme cases, the coefficients have even opposite signs in different parts of the distribution, rendering OLS-estimates ineffective.

The prime example for this situation can be found in the bottom right graph, which pictures the impact of differences in the population share with *higher education* on per capita GDP. In the lower parts of the distribution (10-15 per cent quantiles) a significant positive impact on local growth is identified. However, for richer cities (75-90 per cent quantiles of the distribution), the observed impact turns negative, again being highly significant.

This result is not unrealistic, though. Where higher education is in short supply, returns to it are high, and so are its growth impacts. Most institutions of higher education are concentrated in richer cities. Students coming from poorer regions take the chance of entering a university in richer cities by acquiring household registration and staying there. University graduates have traditionally been employed mostly in the large state-owned enterprises, where their skills were likely to be allocated sub-optimally. In summary, net economic benefits of higher education in rich cities might be reasonably expected to be small or even negative, as the quantile regression results show. Instead, cities that increased the share of the population with lower secondary education experienced comparatively higher growth rates.

Another change in the sign of coefficients can be observed for the variable describing changes in the population share *without formal education*. For poorer areas, an increase in illiteracy has clearly negative economic consequences, since basic education can be considered more relevant there. In middle-income regions, however, changes in the lowest part of education produce only smaller and less significant effects. Here, for overall economic growth, the literacy skills of the least educated less matter. Interestingly, the data even propose a positive relationship between illiteracy and growth in the highest quantiles of the conditional distribution. This reflects a growth-enhancing impact of low-qualified workers in richer cities, which play an important role in the fast economic growth in many newly-rich regions.

It becomes clear that the relationship between education and local growth is, by far, more complicated and specific to the conditions within each city to be described by plain mean values. The quantile regression approach applied in this section, however, is able to uncover some of these linkages. It is shown that specific categories of education have specific growth impacts conditional to the local development stage. Thus, educational attainment can foster growth in some cases, but it might not be able to do so in others. In extreme cases, improvements in educational attainment are shown to even harm local growth in some cities.

Finally, from a policy perspective, the clear positive impact of *lower level educational attainment* is rather worrying if one considers earlier findings in this paper about the development of educational disparities. As reported in Figure 4, educational disparities increase for the lower parts of the educational distribution, while decreasing for higher education. Since primary education significantly contributes to local growth, its increasingly unequal distribution will lead to a further widening of regional income gaps and overall income inequality.

4 Conclusion

This paper analyses regional educational disparities in China in the years 1990 and 2000, and examined the impact of various kinds of education on regional growth and income disparities. Special attention is directed to regional disparities within provinces, which have been found to account for the major share of total inequality.

The first section of the paper demonstrates that the structure and size of educational disparities differ strongly between educational levels and regions. It was shown that educational disparities in higher education decreased, but disparities in illiteracy and primary education increased during the 1990s.

The second part of the paper addresses the impact of educational variables on local growth. Based on the findings in the first section, this paper focuses on the quantile regression technique as a tool to analyse the education-growth relationship across the entire conditional distribution. To compare the effects of the different levels of education, education is introduced into the test regression not as a single measure, but is represented by a set of variables describing hierarchical levels of educational attainment.

The findings are shown to be, again, strongly influenced by the heterogeneous distribution of education. They reveal that educational attainment can have significant positive impact on local growth, and has had an impact in China, for example, in the case of lower secondary education. Under different circumstances, however, an increase in educational attainment is ineffective or even counterproductive. Especially the case of higher education provides an example for this heterogeneous relationship: while in the poorer areas a higher share of the population with higher education is significantly growth enhancing, the opposite is true for the richest quantiles of the cities. These results are driven by the very unequal distribution of higher education. Consequently, more equality in higher education has the potential to spur growth in both poorer and richer regions of the country.

Moreover, attention should be given to the significant positive relationship between lower level education and local growth that has been identified in this study. Because inequality in primary education is also shown to be strongly rising, this result predicts further upward pressure on regional income inequality.

Finally, from a technical point of view, the empirical analysis also makes clear that a weak relation between education and growth may not always be explained sufficiently by excluding a few influential observations, as Temple (1999) claims. Rather, distributional specifics have to be taken seriously to account for heterogeneity in the education growth relationship. Quantile regression, as applied in this paper, can be one appropriate way to do so. Further advances in statistical methods may even provide more powerful and sophisticated techniques to analyse conditional distributions in the future.

References

Akita, T. (2003). ‘Decomposing Regional Inequality in China and Indonesia Using Two-stage Nested Theil Decomposition Method’. *The Annals of Regional Science*, 37 (1): 55-77.

Arellano, M. (2003). *Panel Data Econometrics*. Oxford and New York: Oxford University Press.

Bao, S., G. H. Chang, J. D. Sachs, and W. T. Woo (2002). ‘Geographic Factors and China’s Regional Development under Market Reforms, 1978-1998’. *China Economic Review*, 13: 89-111.

Barro, R. J. (1991). ‘Economic Growth in a Cross-Section of Countries’. *The Quarterly Journal of Economics*, 106 (2): 407-43.

Barro, R. J. (2001). ‘Human Capital and Growth’. *American Economic Review*, 91 (2): 12-17.

Barro, R. J., and X. Sala-i-Martin (1995). *Economic Growth*. New York: Mc-Graw Hill.

Bassett, G. W. Jr., M.-Y. S. Tam, and K. Knight (2002). ‘Quantile Models and Estimators for Data Analysis’. *Metrika*, 55: 17-26.

Benhabib, J., and M. Spiegel (1994). ‘The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data’. *Journal of Monetary Economics*, 34 (2): 143-74.

Bramall, C. (2000). *Sources of Chinese Economic Growth, 1978-1996*. Oxford and New York: Oxford University Press.

Buchinsky, M. (1994). ‘Changes in the US Wage Structure 1963-1987: Application of Quantile Regression’. *Econometrica*, 62 (2): 405-58.

Buchinsky, M. (1995). ‘Quantile Regression, Box-Cox Transformation Model, and the US Wage Structure, 1963-1987’. *Journal of Econometrics*, 65: 109-54.

Buchinsky, M. (1998). ‘Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research’. *The Journal of Human Resources*, 33 (1): 88-126.

Cunningham, B. M. (2003). ‘The Distributional Heterogeneity of Growth Effects: Some Evidence’. *The Manchester School*, 71 (4): 417-47.

Duclos, J.-Y., A. Araar, and C. Fortin (2003). DAD: A Software for Distributive Analysis, Version 4.3. MIMAP Programme. International Development Research Centre, Government of Canada, and CIRPÉE, Université Laval.

Durlauf, S. N., and P. A. Johnson (1995). ‘Multiple Regimes and Cross-Country Growth Behaviour’. *Journal of Applied Econometrics*, 10 (4): 365-84.

Eide, E., and M. H. Showalter (1998). ‘The Effect of School Quality on Student Performance: A Quantile Regression Approach’. *Economics Letters*, 58 (3): 345-50.

Eide, E., and M. H. Showalter (1999). ‘Factors Affecting the Transmission of Earnings across Generations: A Quantile Regression Approach’. *The Journal of Human Resources*, 34 (2): 253-67.

Fleisher, B. M., and J. Chen (1997). ‘The Coast-Noncoast Income Gap, Productivity, and Regional Economic Policy in China’. *Journal of Comparative Economics*, 25 (2): 220-36.

Greene, W. H. (2000). *Econometric Analysis*, 4th edn. New York: Prentice Hall International.

Griffin, K., and R. Zhao (eds) (1993). *The Distribution of Income in China*. New York: St. Martin’s Press.

Griliches, Z. (1977). ‘Estimating the Returns to Schooling: Some Econometric Problems’. *Econometrica*, 45 (1): 1-22.

Gustafsson, B., and S. Li (1998). ‘Inequality in China at the End of the 1980s: Locational Aspects and Household Characteristics’. *Asian Economic Journal*, 12 (1): 35-63.

Gustafsson, B., and S. Li (2001). ‘The Anatomy of Rising Earnings Inequality in Urban China’. *Journal of Comparative Economics*, 29 (1): 118-35.

Gustafsson, B., and S. Li (2002). ‘Income Inequality within and across Counties in Rural China 1988 and 1995’. *Journal of Development Economics*, 69 (1): 179-204.

Gustafsson, B., and Z. Wei (2001). ‘Why Are Some People in Rural China Poor while Others Are Not?’. Paper presented at the international conference on the Chinese economy, Achieving Growth with Equity. Beijing.

Haavelmo, T (1944). ‘The Probability Approach in Econometrics’. *Econometrica*, 12 (Supplement, iii–vi): 1–115.

Herrmann-Pillath, C., D. Kirchert, and J. Pan (2002). ‘Disparities in Chinese Economic Development: Approaches on Different Levels of Aggregation’. *Economic Systems*, 26 (1): 31-54.

Islam, N. (1995). ‘Growth Empirics: A Panel Data Approach’. *The Quarterly Journal of Economics*, 110 (4): 1127-70.

Kanbur, R., and X. Zhang (2003). ‘Spatial Inequality in Education and Health Care in China’. Working Paper WP 2003-35. Ithaca: Department of Applied Economics and Management, Cornell University.

Kanbur, R., and X. Zhang (2005). ‘Fifty Years of Regional Inequality in China: A Journey through Central Planning, Reform and Openness’. *Review of Development Economics*, 9 (1): 87-106.

Koenker, R. W., and G. W. Bassett Jr. (1978). ‘Regression Quantiles’. *Econometrica*, 46: 33-50.

Koenker, R. W., and V. D’Orey (1987). ‘Algorithm AS 229: Computing Regression Quantiles’. *Applied Statistics*, 36: 383-93.

Krueger, A. B., and M. Lindahl (2001). ‘Education for Growth: Why and for Whom?’. *Journal of Economic Literature*, 39 (4): 1101-36.

Lucas, R. J. (1988). ‘On the Mechanics of Economic Development’. *Journal of Monetary Economics*, 22 (1): 3-42.

Mankiw, N. G., D. Romer, and D. N. Weil (1992). ‘A Contribution to the Empirics of Economic Growth’. *The Quarterly Journal of Economics*, 107 (2): 407-37.

Mello, M., and R. Perrelli (2003). ‘Growth Equations: A Quantile Regression Exploration’. *The Quarterly Review of Economics and Finance*, 43 (4): 643-67.

Meng, X., and H. X, Wu (1998). ‘Household Income Determination and Regional Income Differential in Rural China’. *Asian Economic Journal*, 12: 35-63.

Mincer, J. (1974). *Schooling, Earnings, and Experience*. New York: Columbia University Press.

Morduch, J., and T. Sicular (2002). ‘Rethinking Inequality Decomposition, with Evidence from Rural China’. *The Economic Journal*, 112 (476): 93–106.

Mwabu, G., and T. P. Schultz (1996). ‘Education Returns across Quantiles of the Wage Function: Alternative Explanations for Returns to Education by Race in South Africa’. *American Economic Review Papers and Proceedings*, 86 (2): 335-9.

National Bureau of Statistics (NBS) (2000). *China Population Statistics Yearbook 2000*. Beijing: China Statistics Press.

National Bureau of Statistics (NBS) (2002). *China Statistical Yearbook*. Beijing: China Statistics Press.

National Bureau of Statistics (NBS) (2003). ‘County Level Materials on the 2000 Population Census’ (on CD). Beijing: China Statistics Press.

National Bureau of Statistics (NBS) (various years). *Urban Statistical Yearbook* (USYB). Beijing: China Statistics Press.

Nelson, R. R., and E. S. Phelps (1966). ‘Investment in Humans, Technological Diffusion and Economic Growth’. *American Economic Review Papers and Proceedings*, 61: 69-75.

Peng, Y. (1999). ‘Agricultural and Nonagricultural Growth and Intercounty Inequality in China, 1985-1991’. *Modern China*, 25 (3): 235-63.

Pritchett, L. (1996). 'Where Has all the Education Gone?'. WB Policy Research Working Paper No. 1581. Washington, DC: World Bank.

Reuter, U. (2004). 'Intraregional Inequality in China: A Decomposition Analysis'. *Forum of International Development Studies*, 27: 123-44.

Romer, P. (1990). 'Endogenous Technological Change'. *Journal of Political Economy*, 98 (5): 71-102.

Sandberg, K. (2002). 'The Dynamics of Economic Growth 1985-2000 in Chinese Provinces'. IIASA Interim Report IR-02-080. Laxenburg: International Institute for Applied Systems Analysis.

Sianesi, B., and J. Van Reenen (2003). 'The Returns to Education: Macroeconomics'. *Journal of Economic Surveys*, 17 (2): 157-200.

Sicular, T., and Y. Zhao (2002). 'Employment, Earnings and Poverty in Rural China: A Microeconomic Analysis'. Paper presented at a conference on WTO Accession, 28-29 June. Beijing.

Song, S, G. S.-F. Chu, and R. Cao (2000): 'Intercity Regional Disparity in China'. *China Economic Review*, 11: 246-61.

StataCorp (2003). Stata Statistical Software: Release 8.0. Base Reference Manual, vol. 3. College Station, TX: Stata Corporation.

Temple, J. (1999). 'A Positive Effect of Human Capital on Growth'. *Economics Letters*, 65 (1): 131-4.

Temple, J. (2000). 'Growth Regressions and What the Textbooks Don't Tell You'. *Bulletin of Economic Research*, 52 (3): 181-205.

Topel, R. (1999). 'Labor Markets and Economic Growth.', in O. C. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*. Amsterdam: North-Holland.

Uzawa, H. (1965). 'Optimal Technical Change in an Aggregative Model of Economic Growth'. *International Economic Review*, 6: 18-31.

Wang, Y., and Y. Yao (2003). 'Sources of China's Economic Growth 1952-1999: Incorporating Human Capital Accumulation'. *China Economic Review*, 14: 32-52.

Wei, S.-J., and Y. Wu (2001). 'Globalization and Inequality: Evidence from within China'. NBER Working Paper No. 8611. Cambridge, MA: National Bureau of Economic Research.

Wei, Y., X. Liu. H. Song, and P. Romilly (2001). 'Endogenous Innovation Growth Theory and Regional Income Convergence in China'. *Journal of International Development*, 13 (2): 153-68.

Wößmann, L. (2003). 'Specifying Human Capital'. *Journal of Economic Surveys*, 17 (3): 239-70.

Wu, G., S. Richardson, and P. Travers (1996). 'Rural Poverty and its Causes in China'. Working Paper 96/2. Adelaide: School of Economics, Chinese Economies Research Centre, University of Adelaide.

Yang, D. T. (2004). 'Education and Allocative Efficiency: Household Income Growth during Rural Reforms in China'. *Journal of Development Economics*, 74: 137-62.