

**EDUCATION, HUMAN CAPITAL INEQUALITY AND ECONOMIC GROWTH:
EVIDENCE FROM TURKEY**
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Abstract

Recent studies consider the unequal dispersion of human capital as a possible explanation for regional and cross-country variations in output growth. An unequal dispersion of human capital is expected to affect growth negatively through its negative effect on human capital accumulation and on the efficient allocation of resources. The paper focuses on the relationship between human capital inequalities and economic growth for the provinces of Turkey in the period 1975-2000. Education inequality turns out to be an important factor explaining variations in output growth and there is evidence that this effect occurs mainly through the inefficiency channel.

Keywords: human capital inequality; economic growth; panel data, Turkey.

JEL classification: O47, I20, O15

1. Introduction

A growing literature examines the effects of inequality on economic growth. Many studies related to this literature have focused on the effects of income and land inequality as alternative ways of measuring the effects of wealth inequality. More recent articles have also considered the unequal dispersion of human capital as a possible explanation for regional and cross-country variations in output growth (López, Thomas and Wang, 1998; Thomas, Wang and Fan, 2000; Castelló and Doménech, 2002; Castelló-Climont, 2004). An unequal dispersion of human capital is expected to have a negative effect on economic growth through two channels. First, education inequality leads to an inefficient allocation of resources. Secondly, education inequality has a negative impact on the rate of human capital accumulation.

Education is an important factor in determining whether resources are used efficiently in the production of goods and services. When average schooling levels are low this means that the adoption of new / frontier production techniques may not generate the expected increases in output. The efficient use of new technologies necessitates the employment of a better educated workforce that is able to work with these technologies (Stevens and Weale, 2003). In addition to the *level* of education, the widespread adoption and efficient use of new production techniques also requires a fairly even spread or distribution of human capital across an economy. Hence, education inequality is expected to play an important role in determining economic growth through its effect on economic efficiency.

Another channel through which education inequality is expected to affect growth is through its impact of the accumulation of human capital. In several studies (see, for example, De la Croix and Doepke, 2003), higher inequality leads to a lower rate of

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human capital accumulation. Lower overall human capital levels, in turn, lead to lower growth rates.

Castelló and Doménech (2002) have found that the negative effect of initial human capital or education inequality on economic growth is more robust than the effect of income distribution. In fact, human capital or education inequality is closely related to income inequality in that households with higher incomes tend to invest more in schooling and greater investment in schooling leads to higher returns in the labour market in terms of income. There appears to be a close correlation between education and income inequality measures so that education inequality measures can be used as complementary measures related to income inequality in growth regressions.

This paper provides a human capital inequality dataset for the provinces of Turkey where human capital is measured by the average years of schooling of the labour force. Education inequality turns out to be an important factor explaining the variation in output growth across Turkey's provinces. There is evidence that education inequality affects growth negatively mainly through the inefficiency channel rather than through its impact on capital accumulation. The study also updates and extends previous studies (e.g., Güngör, 1997) looking at the effect of education on economic growth in Turkey. Details of the education Gini coefficient as a measure of human capital inequality is given in Section 2 while Section 3 gives an overview of trends in the educational attainment of the labour force and education inequality. Section 4 provides an investigation of the effect of education inequality on economic growth in Turkey. Section 5 presents the conclusions and suggestions for improvements of the empirical model.

2. Measuring Human Capital Inequality: The Education Gini Coefficient

The mean or average years of schooling of the labor force (MYS) is the measure of human capital used in this study, and education inequality is measured by education Gini coefficients that are derived from the mean years of schooling measure (Thomas, Wang and Fan, 2000).

j = level of schooling	YR_j
1. no formal education	0
2. some formal education	2
3. primary school	5
4. junior high school	8
5. high school	11
6. higher education	15

The average years of schooling of the labor force for the provinces is calculated using information on schooling attainment provided in the censuses (see Tansel and Güngör, 1997 for MYS figures for Turkey, 1970-1990). The census data give us information only on the highest degree earned by individuals. It does not have information on the additional number of years of schooling of dropouts who have not obtained their degrees. The mean years of schooling, which is based on this information, is therefore an incomplete measure of the actual years of schooling a person has received.

Persons classified as illiterate without a degree are assigned a schooling level of zero. Those who are literate but do not possess a degree are assumed to have the equivalent of two years of schooling. These and the rest of the categories are given in the table below.

The mean years of schooling is calculated by summing over the shares of the labour force with different levels of schooling as follows: $MYS = \sum_{j=1}^6 p_j YR_j$ where p_j is the share of labour force with education level j ; and YR_j is the number of years of schooling associated with the j 'th education category.

The education Gini coefficient, which measures the dispersion of educational attainment, is given by the following formula

$$GINI_{ED} = \left(\frac{1}{MYS} \right) \sum_{i=2}^n \sum_{j=1}^{i-1} p_i |y_i - y_j| p_j$$

where $GINI_{ED}$ is the Gini education coefficient based on the average years of schooling; MYS is the average years of schooling; p_i is the share of the provincial population with schooling level i ; y_i is the number of years of schooling for education category i ; and n is the number of categories of schooling (Thomas, Wang and Fan, 2000). There are other measures of education inequality, such as the standard deviation of the education variable, which may be used. For the purpose of this study, the education Gini coefficient based on the average years of schooling of the labour force is the main measure considered. Trends in the mean years of schooling and the education Gini coefficient are taken up in the next section.

3. Trends in Educational Attainment and Education Inequality of Turkey's Labour Force

This section evaluates the trends in average years of schooling and education inequality for Turkey's labour force for the 1980-2000 period. While improvements are recorded in both the mean years of schooling and education inequality, much of this progress appears to have occurred in the 1980-1990 period.

The average years of schooling for the Turkish labour force was 4.2 years in 1980. It increased by slightly more than a year to 5.3 years in 1990. Improvements in average educational attainment levels continued in the following decade, reaching 6.5 years in 2000. Education inequality as measured by the distribution of educational attainment across the labour force also improved as witnessed by the decline in the education Gini coefficient over time¹. However, this decline was more substantial for the 1980-1990 period: the Gini coefficient fell from 0.46 in 1980 to 0.36 in 1990. Although there was a decline in the Gini coefficient in the subsequent decade, it was not as marked. Education inequality marginally improved and the fall in the Gini coefficient was less substantial. It fell to only 0.34.

Figure 1 presents the Lorenz curve for Turkey for the years 1980 and 2000. The 45-degree line represents the situation where the distribution of education is perfectly equitable. The figure indicates that education inequality in Turkey decreased over the 20-year span between 1980 and 2000. The proportion of the population with no schooling

declined from a little less than a third of the population in 1980 to a little over 10 percent in 2000.

Figure 2 shows the improvements in educational attainment levels at the regional level. The Marmara region, which has the highest level of GDP among Turkey’s regions, also has the highest level of educational attainment. The Southeast Anatolia region is Turkey’s poorest region in terms of GDP and also the lowest level of educational attainment. Regional trends in education inequality are presented in Figure 3. Since low education Gini coefficients represent a low level of inequality, we witness improvements in education inequality over time for all regions. However, much of this improvement appears to have occurred during the first decade of the period under study. As these figures indicate, educational attainment and education inequality are negatively related.

Figure 1: Education Lorenz Curve for Turkey’s Labour Force, 1980 and 2000

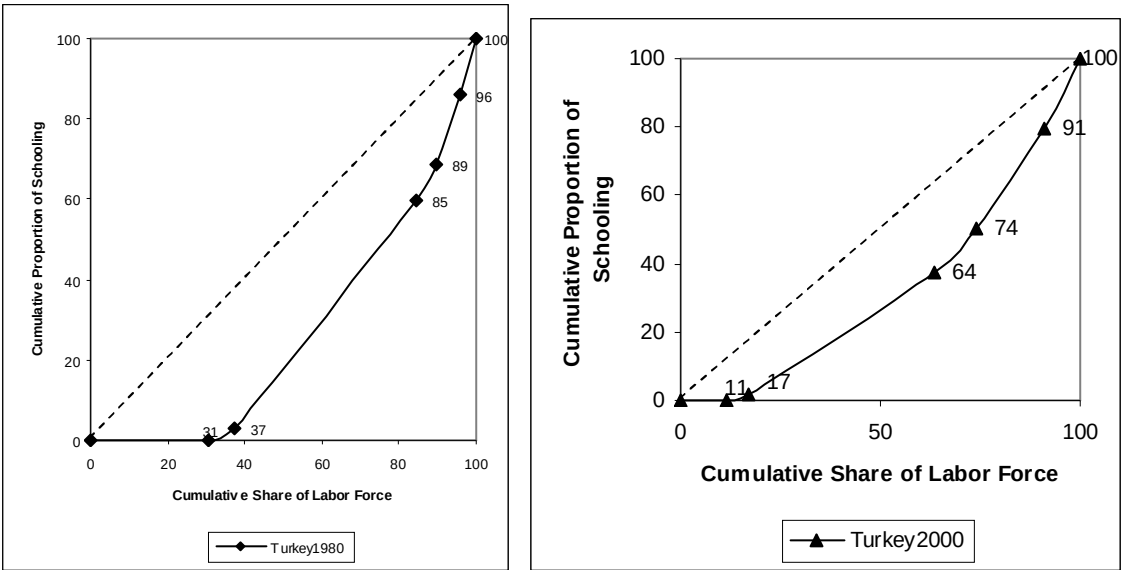
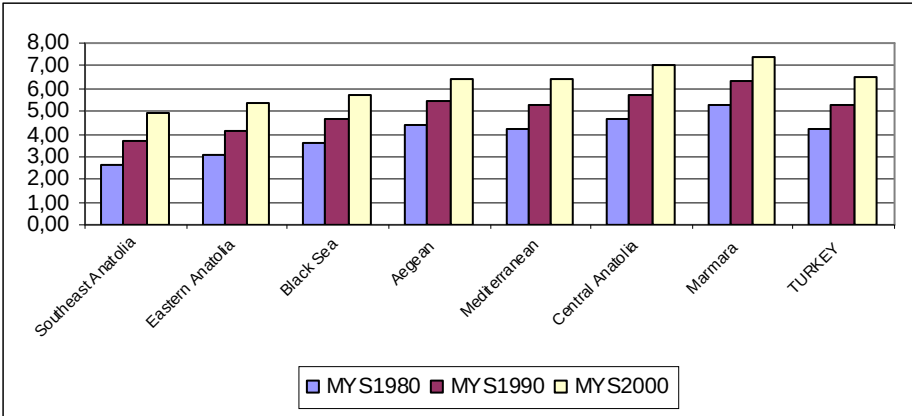


Figure 2:Regional Trends in Education Attainment of the Labour Force



There is, in fact, a negative correlation between the average years of schooling and education inequality for each of the years considered in the study. The greater the average schooling attainment level, the lower the level education inequality. Figure 4 illustrates this negative relationship with provincial data for the year 2000. Provinces with higher average educational attainment levels also have a less unequal distribution of education. This is similar to the finding in Castelló and Doménech (2002), who show a negative relationship between average education levels and human capital inequality for a wide group of countries using the Barro-Lee dataset (Barro and Lee, 2001).

Figure 3: Regional Trends in Education Inequality of Turkey’s Labour Force

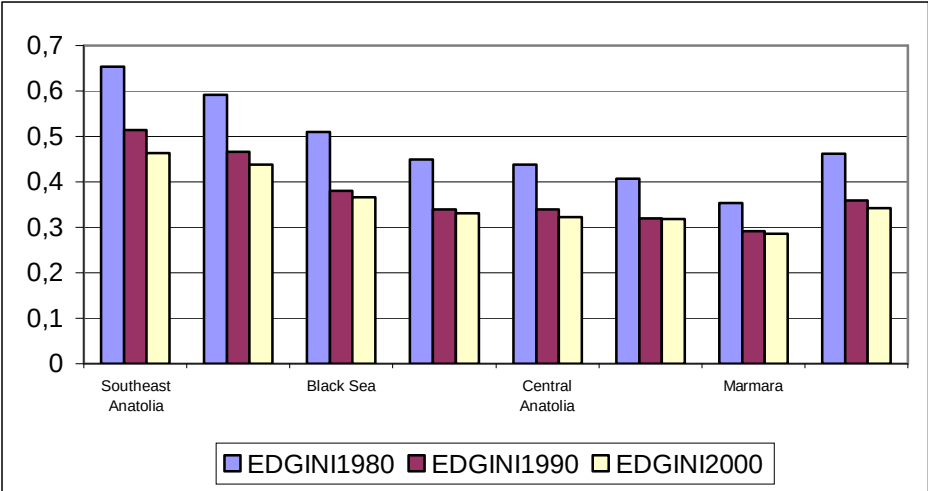
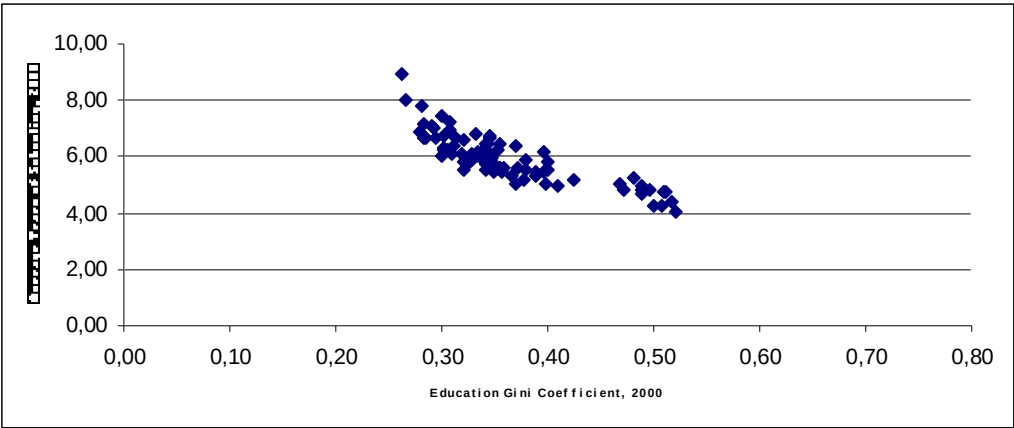


Figure 4. Relationship between MYS and Education Gini

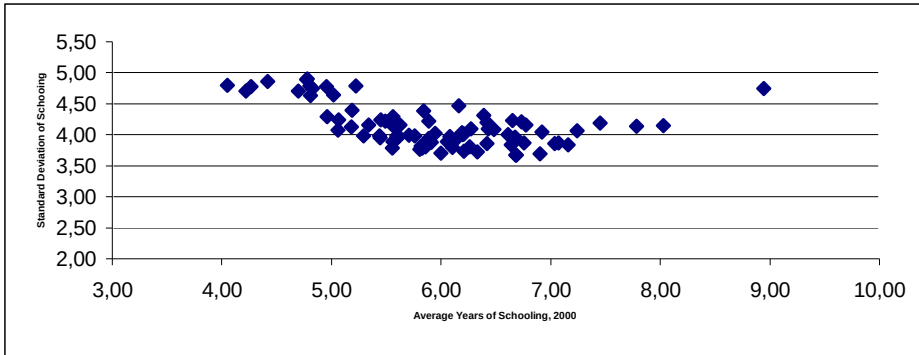


An inverted U-shape for the relationship between the standard deviation of schooling and the average years of schooling are reported in cross country studies (Ram, 1990; Thomas, Wang and Fan, 2000). This inverse U-shape relationship is said to provide evidence of an education Kuznets curve: as the average years of education increases, education variance first rises then falls. Our data for the provinces of Turkey give the

opposite result. We find a U-shaped relationship between average educational attainment and the standard deviation of schooling. Figure 5 illustrates this result for the year 2000². This may be related to the significant amount of internal migration that takes place from the poorer provinces with low levels of human capital to the richer provinces with higher levels of human capital³.

In the next section we present an empirical model to test whether education inequality has significant explanatory power in the growth performance of the provinces for the 1980-2000 period.

Figure 5. Relationship between MYS and Standard Deviation of Schooling



4. The Effect of Education Inequality on Economic Growth in Turkey

Model: In this study, our setup is an exogenous growth model extended to include human capital based on Mankiw, Romer and Weil (1992), which is developed into a panel data model by Islam (1995). In their study, Mankiw, Romer and Weil (1992) use a human capital augmented Cobb-Douglas production function.

$$Y(t) = K(t)^\alpha H(t)^\beta (A(t)L(t))^{1-\alpha-\beta}$$

where Y is the level of output, K is the stock of physical capital, H is the stock of human capital and L is the labour force. Output growth is governed by physical and human capital accumulation and the rate of growth of the labour force. Technology is given exogenously by $A(t)$.

The purpose of this paper is not to test the correctness of this production model but to provide an initial analysis of the effect of education inequality on the per labour force growth for the provinces of Turkey. Therefore, we make use of the general discrete form of the growth equation in panel form below.

$$(\ln y_{it} - \ln y_{it-\tau}) / \tau = \beta \ln y_{it-\tau} + X_{it-\tau} \delta + v_i + \xi_t + \varepsilon_{it}$$

where y is per capita output level, X is a matrix of explanatory variables including the share of physical and human capital invested from income, the growth rate of the population (or labour force) and a set of steady state factors representing initial conditions, such as the stock of human capital and education inequality; i represents the number of provinces⁴, t is the number of periods corresponding to available census years, and τ represents the end-year in each sub-period. v_i represents province-specific effects, ξ_t

represents factors that change over time but remain constant for each of the provinces and ε_{it} is the error term that varies over time and across provinces.

Data

The output data are obtained from Özötün (1988) for the years 1975, 1980 and 1985, and the publications of the State Institute of Statistics (SIS) for the years 1990 and 2000. The initial per capita output level (*pcgpp*) is calculated by dividing the initial level of output by the labour force. The provincial labour force data are also taken from the censuses published by the SIS, where the labour force is defined as the economically active population twelve years of age and older. The population growth rate, *n*, is calculated as the average annual growth rate of the labour force. Physical capital accumulation is proxied by industrial electricity consumption. It is calculated as the average over the periods concerned (*avind*). The mean years of schooling (*mys*) and education inequality measures (*edgini* and *sds*) are as defined in Section 2.

Empirical Analysis

The estimation results of the economic growth model with education inequality effects are presented in Tables 1-4. The random and fixed effects panel estimation results are reported in each table. The appropriate estimation model depends on whether the province-specific effects (v_i) can be treated as fixed or random. The Hausman test is a test of whether there is correlation between these province-specific effects and the regressors in the model. The null hypothesis is that there are no systematic differences in the coefficients estimated under the fixed and random effects models, which is the case when the province-specific effect are random. The Hausman test rejects the null hypothesis of random effects in every single regression. We, therefore, concentrate on the fixed effects results in assessing the effects of education inequality on economic growth.

Table 1 presents the estimation results of the model with education Gini coefficients as the measure of education inequality. The first two columns do not include education inequality measures. The first column gives the basic non-human capital augmented model described in Mankiw *et al.* (1992) where only initial per capita income, the log of physical capital accumulation and the log of labour force growth² are included. All coefficients are statistically significant at the 1 percent level with only capital accumulation ($\ln(avind)$) having a positive impact on economic growth. When the human capital variable measured by the initial level of average schooling of the labour force is added, capital accumulation becomes statistically insignificant. This suggests that the two variables are related and there is a multicollinearity problem. There is, in fact, a close positive association between the average years of schooling of the labour force and industrial electricity consumption which is used as a proxy for physical capital accumulation (see Figure A.5 in the appendix).

It was shown in Section 3 that education inequality and human capital endowment are negatively related, which means that low levels of human capital (educational attainment levels) are associated with high levels of education inequality. Including the measures of education inequality in the empirical model is therefore expected the lower the effect of the average years of schooling on growth.

² The labour force growth rate is augmented by the rate of technological change and the depreciation rate. Following the convention of other studies, we arbitrarily set the technology growth and the rate of depreciation to total 0.05.

The next set of columns in Table 1 (columns 3-7) show the effects of education inequality on economic growth when education inequality is measured by the education Gini coefficient. These regressions show that there is a negative relationship between education inequality and economic growth as suggested in the literature. It is statistically significant at the 1 percent significance level throughout. We see, however, that the inclusion of the education Gini reverses the sign of the average years of schooling variable and makes it insignificant. This stems from the negative relationship between the means years of schooling and the education Gini that was shown in Section 3.

The plot of per labour force growth against the education Gini coefficient suggests a nonlinear, possibly U-shaped relationship between these two variables. The possibility of a nonlinear relationship between output growth and education inequality is explored by including quadratic, cubic and quartic education inequality terms into the equation. In columns 4 and 5, a negative coefficient for the level and positive coefficient for the second power of the education Gini seems to confirm the U-shaped relationship. However, all of the education Gini terms including those raised to third and fourth powers are statistically significant at the 5 percent significance level, which suggests an even more complex non-linear nature relationship (an oscillating U-shape). The average years of schooling coefficients remain insignificant.

In Table 2, we use the standard deviation of schooling as an alternative measure of education inequality. The average years of schooling and the standard deviation of schooling are related nonlinearly to each other (as shown in Section 2 and Figure A.2 in the appendix). Including the standard deviation of schooling (*sds*) and its various powers in the regression equations does not affect the coefficient of the average years of schooling (*mys*). The effect of average years of schooling appears to be quite robust to the specification of education inequality as measured by the standard deviation of schooling. An additional year of schooling increases per labour force growth by about 6 percent.

Physical capital accumulation appears to be driven mainly by the average level of educational attainment. The negative effect of the education Gini on capital accumulation is significant only in the absence of the mean years of schooling variable, indicating that it is picking up the effect of this variable.

The *sds* measure of education inequality, however, shows more variability to different specification compared to the *mys* measure. In column 1, the negative effect of *sds* on economic growth is statistically significant at the 1 percent level. This again seems to verify the existence of a negative relationship between education inequality and economic growth. Once more, the complex, non-linear nature of this relationship is borne out by the statistically significant powers of *sds* in columns 4 and 5. Importantly, physical capital accumulation and population growth are statistically significant in all of the regressions that include *sds* and are robust to the various specifications of the *sds* inequality measures.

Time dummies (D1975, D1980, D1985) are added to the models in Tables 1 and 2 to see whether the results for education inequality are robust to the time specification. These additional results are presented in Table 3 and Table 4. Including time dummies makes all of the education Gini terms statistically insignificant as shown in Table 3. The models that include the standard deviation of schooling, on the other hand, are somewhat less affected, especially when higher powers are included (columns 4 and 5).

Table 1. Effect of education Gini (*edgini*) on physical capital accumulation (*lnavind*)

<i>lnavind</i>	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
<i>lnpcgpp</i>	0.0528	0.736	0.5049	0.001	0.2029	0.191	0.5835	0.000
<i>Lnn</i>	-0.1144	0.415	-0.1208	0.426	-0.0619	0.647	-0.1013	0.494
<i>Mys</i>	0.7229	0.000			0.7794	0.000		
<i>edgini</i>	-0.4226	0.731	-6.87	0.000	54.44	0.345	12.96	0.836
<i>edgini2</i>					-176.24	0.323	-93.74	0.631
<i>edgini3</i>					259.43	0.280	176.83	0.500
<i>edgini4</i>					-142.95	0.225	-113.53	0.378
<i>constant</i>	7.62	0.000	6.936	0.003	-1.31	0.864	4.47	0.591

Table 2. Effect of standard deviation of schooling (*sds*) on physical capital accumulation (*lnavind*)

<i>lnavind</i>	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
<i>lnpcgpp</i>	0.0783	0.598	0.8420	0.000	0.1415	0.337	0.8845	0.000
<i>Lnn</i>	-0.1329	0.322	-0.4094	0.009	-0.1093	0.406	-0.4008	0.009
<i>Mys</i>	0.6049	0.000			0.6161	0.000		
<i>Sds</i>	0.6237	0.000	1.50	0.000	244.9073	0.021	280.93	0.027
<i>Sds2</i>					-103.25	0.018	-116.08	0.026
<i>Sds3</i>					19.15	0.015	21.19	0.025
<i>Sds4</i>					-1.31	0.013	-1.43	0.024
<i>constant</i>	5.29	0.011	-7.01	0.000	-209.59	0.029	-257.09	0.025

Theory predicts that education inequality will have a negative effect on growth through two separate channels; one through the inefficient allocation of resources, the other through its effect on the rate of human capital accumulation. Which channel is more important? This paper considered the stock of human capital as measured by average educational attainment levels as a steady state factor (initial condition) affecting average growth rates. The rate of human capital accumulation was not included (although enrollment rates can serve as a measure). However, to the degree that physical capital accumulation (as proxied by industrial electricity consumption complements human capital accumulation, we can examine instead the effect of education inefficiency on the rate of physical capital accumulation. To do this, we ran a fixed effects regression with physical capital accumulation as the dependent variable on the various factors (*mys*, *edgini* or *sds*, *ln(pcgpp)*, *ln(n+0.05)*) to see which of the factors are significant in determining the rate of capital accumulation. The results are given in the tables below.

Table 1a: Fixed effects estimation results for model with education Gini coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ln(pcqpp)</i>	-0.142** (0.012)	-0.186** (0.012)	-0.174** (0.012)	-0.179** (0.012)	-0.179** (0.011)	-0.179** (0.012)	-0.185** (0.012)
<i>ln(avind)</i>	0.036** (0.005)	0.006 (0.006)	0.005 (0.005)	0.009 (0.005)	0.009+ (0.005)	0.007 (0.005)	0.008 (0.005)
<i>ln(n+0.05)</i>	-0.036** (0.012)	-0.023* (0.011)	-0.016 (0.010)	-0.018+ (0.010)	-0.018+ (0.010)	-0.020+ (0.010)	-0.023* (0.010)
<i>Mys</i>		0.047** (0.006)	0.007 (0.010)	-0.000 (0.010)		-0.004 (0.010)	-0.006 (0.010)
<i>Edgini</i>			-0.460** (0.090)	-0.911** (0.218)	-0.907** (0.173)	-2.755** (0.884)	-12.368** (4.336)
<i>edgini2</i>				0.409* (0.180)	0.407* (0.170)	4.079* (1.715)	34.237* (13.431)
<i>edgini3</i>						-2.388* (1.110)	-43.206* (18.066)
<i>edgini4</i>							20.076* (8.869)
<i>constant</i>	1.547** (0.147)	2.360** (0.166)	2.579** (0.162)	2.752** (0.178)	2.752** (0.177)	3.088** (0.235)	4.276** (0.574)
Observations	268	268	268	268	268	268	268
Provinces	67	67	67	67	67	67	67
Rsq within	0.43	0.56	0.61	0.62	0.62	0.63	0.64

Table 1b: Random effects estimation results for model with education Gini coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ln(pcqpp)</i>	-0.040** (0.008)	-0.069** (0.009)	-0.068** (0.009)	-0.072** (0.009)	-0.073** (0.009)	-0.072** (0.009)	-0.071** (0.009)
<i>ln(avind)</i>	0.013** (0.002)	0.011** (0.002)	0.010** (0.002)	0.011** (0.002)	0.011** (0.002)	0.011** (0.002)	0.011** (0.002)
<i>ln(n+0.05)</i>	-0.020* (0.009)	-0.003 (0.010)	0.000 (0.009)	-0.003 (0.009)	-0.002 (0.009)	-0.003 (0.009)	-0.002 (0.009)
<i>Mys</i>		0.020** (0.004)	-0.000 (0.006)	-0.004 (0.006)		-0.004 (0.007)	-0.004 (0.007)
<i>Edgini</i>			-0.214** (0.051)	-0.560** (0.194)	-0.508** (0.170)	-1.123 (0.928)	2.104 (4.656)
<i>edgini2</i>				0.319+ (0.173)	0.291+ (0.165)	1.462 (1.849)	-8.722 (14.514)
<i>edgini3</i>						-0.749 (1.207)	13.066 (19.566)
<i>edgini4</i>							-6.804 (9.618)
<i>constant</i>	0.401** (0.095)	0.792** (0.116)	0.975** (0.120)	1.115** (0.142)	1.107** (0.141)	1.204** (0.202)	0.824 (0.574)
Observations	268	268	268	268	268	268	268
Provinces	67	67	67	67	67	67	67
Rsq within	0.39	0.44	0.55	0.55	0.55	0.56	0.54
Rsq overall	0.12	0.21	0.26	0.27	0.27	0.27	0.27
Hausman test	119.41	248.21	334.19	364.20	313.32	408.62	370.57
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses; Dependent variable: Average annual growth rate
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 2a: Fixed effects estimation results for model with standard deviation of schooling

	(1)	(2)	(3)	(4)	(5)
<i>ln(pcgpp)</i>	-0.191**	-0.191**	-0.143**	-0.194**	-0.194**
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
<i>ln(avind)</i>	0.014**	0.014**	0.043**	0.015**	0.012*
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
<i>ln(n+0.05)</i>	-0.021*	-0.021*	-0.037**	-0.023*	-0.023*
	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)
<i>Mys</i>	0.060**	0.059**		0.058**	0.059**
	(0.006)	(0.006)		(0.006)	(0.006)
<i>Sds</i>	-0.075**	-0.052	0.154	2.285*	27.906**
	(0.013)	(0.117)	(0.140)	(1.029)	(7.908)
<i>sds2</i>		-0.003	-0.026	-0.656*	-11.219**
		(0.016)	(0.020)	(0.286)	(3.246)
<i>sds3</i>				0.060*	1.980**
				(0.026)	(0.588)
<i>sds4</i>					-0.130**
					(0.040)
<i>constant</i>	2.554**	2.518**	1.266**	-0.218	-23.309**
	(0.157)	(0.243)	(0.252)	(1.221)	(7.169)
Observations	268	268	268	268	268
Provinces	67	67	67	67	67
Rsqr within	0.63	0.63	0.45	0.64	0.66

Table 2b: Random effects estimation results for model with standard deviation of schooling

	(1)	(2)	(3)	(4)	(5)
<i>ln(pcgpp)</i>	-0.073**	-0.073**	-0.041**	-0.073**	-0.075**
	(0.009)	(0.009)	(0.007)	(0.009)	(0.009)
<i>ln(avind)</i>	0.011**	0.011**	0.013**	0.011**	0.011**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
<i>ln(n+0.05)</i>	-0.003	-0.006	-0.024*	-0.006	-0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
<i>Mys</i>	0.023**	0.023**		0.023**	0.025**
	(0.004)	(0.004)		(0.004)	(0.004)
<i>Sds</i>	-0.025**	-0.271**	-0.257*	-0.422	27.293**
	(0.007)	(0.099)	(0.106)	(1.025)	(9.243)
<i>sds2</i>		0.034*	0.033*	0.075	-11.297**
		(0.014)	(0.015)	(0.280)	(3.780)
<i>sds3</i>				-0.004	2.053**
				(0.025)	(0.682)
<i>sds4</i>					-0.138**
					(0.046)
<i>constant</i>	0.931** (0.12)	1.363** (0.21)	0.886** (0.21)	1.545 (1.25)	-23.549** (8.41)
Observations	268	268	268	268	268
Provinces	67	67	67	67	67
Rsqr within	0.58	0.56	0.33	0.55	0.55
Rsqr overall	0.25	0.27	0.16	0.27	0.29
Hausman test	481.1	125.58	119.08	802.25	fail
p-value	0.0000	0.0000	0.0000	0.0000	

Standard errors in parentheses; Dependent variable: Average annual growth rate

+ significant at 10%; * significant at 5%; ** significant at 1%

fail = data fails to meet the asymptotic assumptions of the Hausman test (negative statistic)

Table 3a: Fixed effects estimation results for model with education Gini coefficients and time dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ln(pcgpp)</i>	-0.159**	-0.164**	-0.163**	-0.162**	-0.158**	-0.162**	-0.165**
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
<i>ln(avind)</i>	0.008+	0.009+	0.009+	0.008	0.008	0.008	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
<i>ln(n+0.05)</i>	-0.025*	-0.024*	-0.024*	-0.024*	-0.024*	-0.024*	-0.026*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
<i>Mys</i>		0.029+	0.027	0.028		0.028	0.026
		(0.017)	(0.020)	(0.021)		(0.021)	(0.021)
<i>Edgini</i>			-0.024	0.052	-0.077	-0.077	-4.958
			(0.113)	(0.269)	(0.252)	(1.016)	(4.563)
<i>edgini2</i>				-0.059	-0.020	0.181	15.150
				(0.189)	(0.187)	(1.836)	(13.765)
<i>edgini3</i>						-0.152	-20.168
						(1.162)	(18.278)
<i>edgini4</i>							9.754 (8.89)
<i>constant</i>	2.157**	2.083**	2.097**	2.067**	2.187**	2.092**	2.714**
		(0.196)	(0.208)	(0.230)	(0.213)	(0.298)	(0.640)
<i>Time Dummies</i>	yes	yes	yes	yes	yes	yes	yes
Observations	268	268	268	268	268	268	268
Provinces	67	67	67	67	67	67	67
Rsquared within	0.67	0.68	0.68	0.68	0.68	0.68	0.68

Table 3b: Random effects estimation results for model with education Gini coefficients and time dummies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ln(pcgpp)</i>	-0.027**	-0.050**	-0.048**	-0.049**	-0.047**	-0.049**	-0.049**
	(0.007)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)
<i>ln(avind)</i>	0.009**	0.009**	0.009**	0.009**	0.009**	0.009**	0.009**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
<i>ln(n+0.05)</i>	-0.028**	-0.020*	-0.018*	-0.018*	-0.019*	-0.018*	-0.018+
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
<i>Mys</i>		0.016**	0.006	0.005		0.005	0.005
		(0.004)	(0.007)	(0.007)		(0.007)	(0.007)
<i>Edgini</i>			-0.100*	-0.179	-0.233	-0.268	2.723
			(0.049)	(0.181)	(0.164)	(0.841)	(4.156)
<i>edgini2</i>				0.072	0.096	0.253	-9.181
				(0.159)	(0.155)	(1.662)	(12.940)
<i>edgini3</i>						-0.118	12.676
						(1.079)	(17.439)
<i>edgini4</i>							-6.300 (8.57)
<i>constant</i>	0.212*	0.488**	0.570**	0.604**	0.610**	0.618**	0.268
	(0.091)	(0.111)	(0.118)	(0.139)	(0.139)	(0.191)	(0.513)
<i>Time Dummies</i>	yes	yes	yes	yes	yes	yes	yes
Observations	268	268	268	268	268	268	268
Provinces	67	67	67	67	67	67	67
Rsquared within	0.48	0.54	0.54	0.54	0.53	0.54	0.54
Rsquared overall	0.39	0.43	0.44	0.44	0.44	0.44	0.44
Hausman test	181.24	168.56	165.30	168.88	154.39	165.55	165.28
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses; Dependent variable: Average annual growth rate
 + significant at 10%; * significant at 5%; ** significant at 1%

Table 4a: Model with Standard Deviation of Schooling and Time Dummies: Fixed Effects

	(1)	(2)	(3)	(4)	(5)
<i>ln(pcgpp)</i>	-0.163**	-0.168**	-0.163**	-0.173**	-0.174**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
<i>ln(avind)</i>	0.008	0.009+	0.009+	0.010+	0.009+
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
<i>ln(n+0.05)</i>	-0.024*	-0.022*	-0.022*	-0.022*	-0.023*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
<i>Mys</i>	0.029+	0.029		0.026	0.030+
	(0.017)	(0.017)		(0.017)	(0.017)
<i>Sds</i>	0.005	0.188	0.192	2.586**	16.550*
	(0.022)	(0.135)	(0.135)	(0.983)	(7.849)
<i>sds2</i>		-0.024	-0.024	-0.690*	-6.462*
		(0.018)	(0.018)	(0.271)	(3.230)
<i>sds3</i>				0.061*	1.111+
				(0.025)	(0.586)
<i>sds4</i>					-0.071+ (0.04)
<i>constant</i>	2.064**	1.784**	1.844**	-0.997	-13.533+
	(0.210)	(0.292)	(0.291)	(1.165)	(7.086)
<i>Time Dummies</i>	yes	yes	yes	yes	yes
Observations	268	268	268	268	268
Provinces	67	67	67	67	67
Rsq within	0.68	0.68	0.68	0.69	0.70

Table 4b: Model with Standard Deviation of Schooling and Time Dummies: Random Effects

	(1)	(2)	(3)	(4)	(5)
<i>ln(pcgpp)</i>	-0.050**	-0.047**	-0.029**	-0.047**	-0.049**
	(0.009)	(0.009)	(0.007)	(0.009)	(0.009)
<i>ln(avind)</i>	0.009**	0.009**	0.009**	0.009**	0.009**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
<i>ln(n+0.05)</i>	-0.019*	-0.021*	-0.027**	-0.021*	-0.022*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
<i>Mys</i>	0.016**	0.013**		0.014**	0.015**
	(0.004)	(0.004)		(0.004)	(0.004)
<i>Sds</i>	-0.009	-0.239*	-0.331**	-0.795	10.518
	(0.007)	(0.105)	(0.102)	(0.901)	(8.612)
<i>sds2</i>		0.031*	0.043**	0.184	-4.460
		(0.014)	(0.014)	(0.246)	(3.524)
<i>sds3</i>				-0.014	0.826
				(0.022)	(0.636)
<i>sds4</i>					-0.056 (0.04)
<i>constant</i>	0.529**	0.920**	0.880**	1.586	-8.646
	(0.116)	(0.212)	(0.215)	(1.094)	(7.823)
<i>Time Dummies</i>	yes	yes	yes	yes	yes
Observations	268	268	268	268	268
Provinces	67	67	67	67	67
Rsq within	0.54	0.53	0.48	0.53	0.54
Rsq overall	0.43	0.44	0.42	0.45	0.45
Hausman test	173.79	170.35	174.26	176.12	154.09
p-value	0.0000	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses; Dependent variable: Average annual growth rate

+ significant at 10%; * significant at 5%; ** significant at 1%

In the nonlinear model, the education Gini coefficients have no effect on physical capital accumulation; they are insignificant both in the presence and absence of the *mys* variable. On the other hand, when education inequality is measured by the standard deviation of schooling there is a positive association with physical capital accumulation, which is contrary to expectations.

5. Conclusions

This paper has examined the effect of education inequality on the per labour force growth (labour productivity) performance of Turkey's provinces over the 1975-2000 period. The study presented education inequality measures for Turkey calculated for the first time at the provincial level. Education inequality is measured by education Gini coefficients that are derived from the mean years of schooling measure (Thomas, Wang and Fan, 2000). The study used educational attainment levels of the labour force to calculate the effect of education and education inequality on growth. The standard deviation of the average years of schooling was also looked at as an alternative measure of education inequality. Not surprisingly, provinces with higher levels educational attainment tend to be associated with lower levels of education inequality and vice versa.

An important finding that complements the findings of previous research is that the distribution of education matters for output growth. There appears to be a non-linear relationship between growth and education inequality. An improvement in the distribution of education (a fall in education inequality) is associated with a decline in output growth when education inequality levels are relatively low. At relatively high levels of inequality, however, output growth is positively associated with education inequality. This U-shaped relationship, which is also evident in the figures, is incorporated into the empirical model through the inclusion of a quadratic term for the education inequality measures.

The results provide confirmation of a nonlinear relationship between economic growth and education inequality. Economic growth is negatively related to education inequality at low levels of the education Gini coefficient, indicating that a more even distribution of education attainment leads to higher growth rates for provinces with more even education distributions. For provinces with relatively high levels of education inequality, on the other hand, a positive association exists between growth and education inequality. This could suggest some threshold level of education inequality beyond which improvements in the distribution of education will lead to higher growth rates³.

Theory predicts that education inequality has a negative effect on growth through two separate channels; one through the inefficient allocation of resources, the other through its effect on the rate of human capital accumulation. There is evidence that education inequality affects growth negatively mainly through the inefficiency channel rather than through its impact on capital accumulation.

The results of this study may be extended in various directions. The existence of multicollinearity among several of the regressors, such as the positive association

³ Güngör (1997) confirmed the existence of a threshold effect of the level of average educational attainment on industrial economic growth for Turkey's provinces for the 1980-1990 period.

between the initial average years of schooling and (log) average industrial electricity consumption, indicate that physical and human capital accumulation may have complementary effects on output growth. This suggests that a more flexible functional form such as a translog function may be fitted to the data to capture complementarities in production.

In addition, this study has taken the human-capital augmented Solow growth model as modeled by Mankiw, Romer and Weil (1992) and Islam (1995) as its starting point, where the accumulation human capital and labour force growth occurs exogenously. Further studies could scrutinise the causal relationship between growth and education as well as growth and education inequality more closely.

While further analysis is needed to understand the relationship between education inequality and economic growth, these preliminary results lead to several important policy implications. Policies to foster economic growth through education should also aim to improve the distribution of education. While increasing the educational attainment level of the labour force is necessary for output growth, the effect of education inequality on labour productivity should not be ignored. The non-linear relationship between education inequality and growth also suggests that a more equal distribution of education becomes especially important for provinces with relatively high levels of human capital and growth rates. On the other hand, building up a human capital base appears to be more important for provinces that begin with lower levels of human capital.

References

- Barro, R. J. and Lee, J. W. (2000) International data on educational attainment: updates and implications. CID Working Paper No. 42, Center for International Development, Harvard University.
- Castelló, A. and Doménech, R. (2002) Human capital inequality and economic growth: some new evidence. *The Economic Journal*, 112, pp. C187-C200.
- Castelló-Climent, A. (2004) A reassessment of the relationship between inequality and growth: what human capital inequality data say? Instituto Valenciano de Investigaciones Economicas Working Paper Series, WP-EC 2004-15, Valencia, Spain.
- Checchi, D. and Garcia-Penalosa, C. (2004) Risk and the distribution of human capital. *Economics Letters*, 82, pp. 53-61.
- Felipe, J. (1997) Total factor productivity growth in East Asia: a critical survey. EDRC Report Series No. 65, Economics and Development Resource Center, Asian Development Bank.
- Güngör, N. D. (1997) Education and economic growth in Turkey, 1980-1990: a panel study. *METU Studies in Development*, 24(2), pp. 185-214.
- Islam, N. (1995) Growth empirics: a panel data approach. *Quarterly Journal of Economics*, 110(4), pp. 1127-70.
- Lim, A. S. K. and Tang, K. K. (2006) Education inequality, human capital inequality and the Kuznets curve. CAMA Working Paper 8/2006, Center for Applied Macroeconomic Analysis, The Australian National University.

- Lopez, R., Thomas, V. and Wang, Y. (1998) Addressing the education puzzle: the distribution of education and economic reforms. World Bank Working Paper Series No. 2031, World Bank, Washington, DC.
- Mankiw, N. G., Romer, D. and Weil, D. N. (1992) A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, 107(2), pp. 407-37.
- Stevens, P. and M. Weale (2003) "Education and Economic Growth," to be published in G. and J. Johnes (eds.) *International Handbook on the Economics of Education*, Edward Elgar.
- Tansel, A. and Güngör, N. D. (1997) The educational attainment of Turkey's labor force: a comparison across provinces and over time. *METU Studies in Development*, 24(4), pp. 531-547.
- Tansel, A. and Güngör, A. D. (2000) Provincial inequalities in school enrollments in Turkey. Economic Research Forum Working Paper No. 2003, Cairo, Egypt.
- Thomas, V., Wang, Y. and Fan, X. (2000) Measuring education inequality: Gini coefficients of education. World Bank Working Paper No. 2525, Washington, DC: The World Bank.

ENDNOTES

¹ Low values for the education Gini coefficient indicates a more even distribution of education across the labour force while the converse is true for high levels of the education Gini coefficient. A value of zero indicates a

² Figures for other years are presented in the appendix. These figures show that the relationship between average years of schooling and the measures of education inequality are robust over time.

³ There is quite a bit of variation in the pattern of standard deviation over time for different countries. The standard deviation curve is also U-shaped for Thailand, while for other countries, it is either continually decreasing, continually rising or inverse U-shaped (Thomas, Wang and Fan, 2000).

⁴ The number of provinces across census years differs due to changes in provincial borders that led to the creation of new provinces. To deal with this problem, new provinces in 1990 and 2000 are added back to the original provinces from which they were created.

Appendix A

Figure A.1. Average years of schooling and the education Gini coefficient: patterns by year and provinces

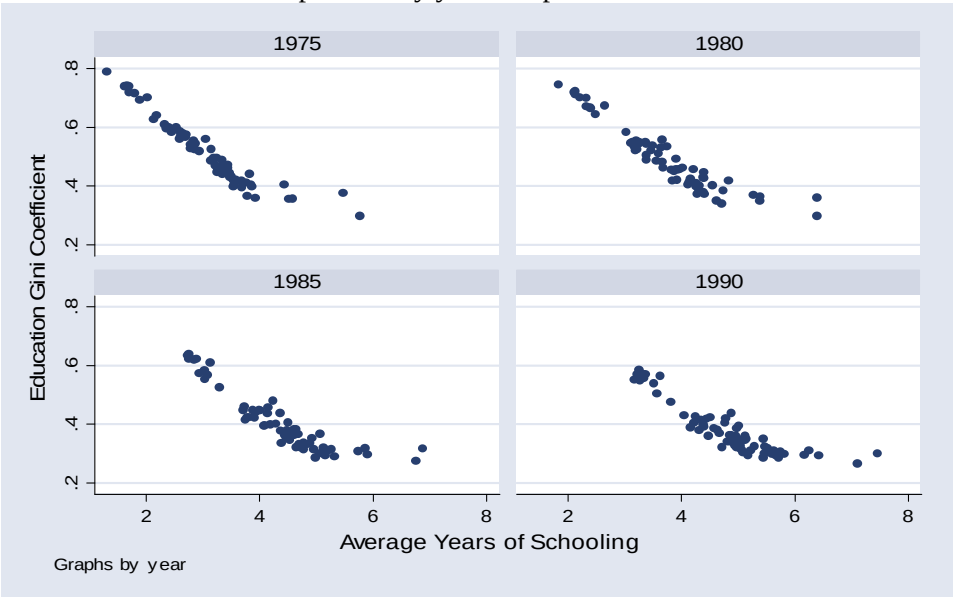


Figure A.2. Average years of schooling and standard deviation of schooling: patterns by year and provinces

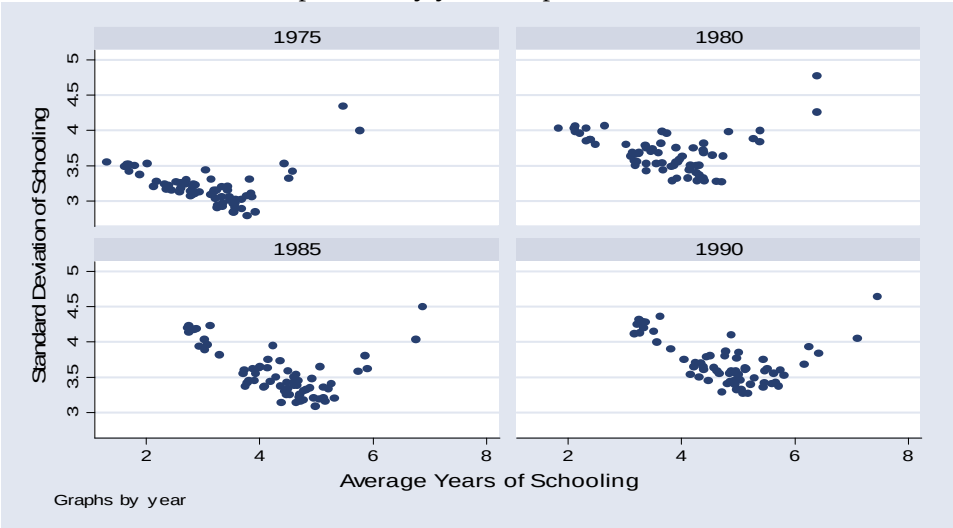


Figure A.3

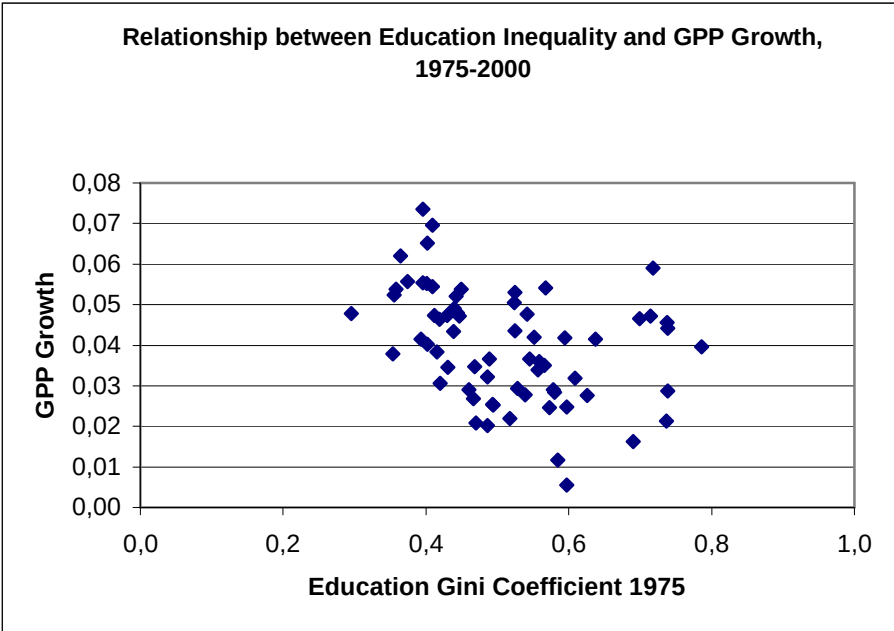


Figure A.4

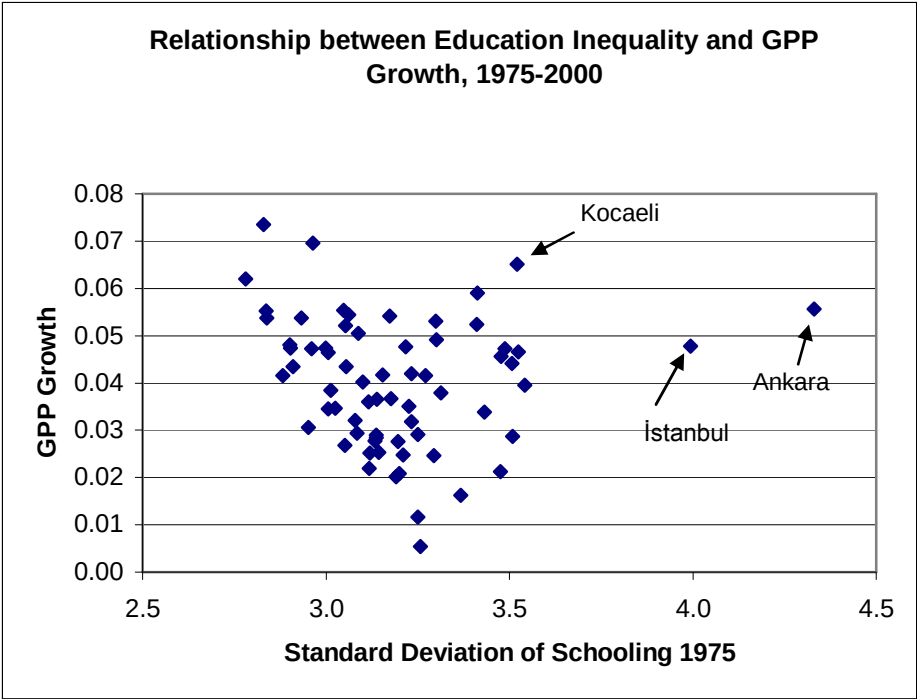


Figure A.5. Relationship between average years of schooling and physical capital accumulation (log of average industrial electricity consumption), pooled data

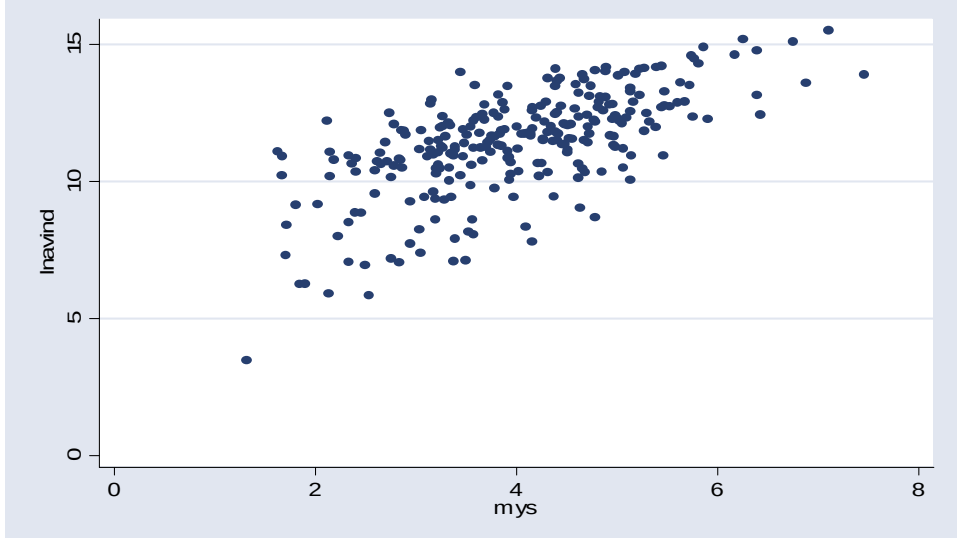


Figure A.6. Relationship between education Gini coefficient and physical capital accumulation (log of average industrial electricity consumption), pooled data

