The Role of Schooling in Struggling with the Middle-Income Trap: Dynamic Panel Data Analysis

By Umit BULUT[a†] & Ahsen Seda BULUT[b]

Abstract. This paper aims at examining the relationship between average years of total schooling and GDP per capita for six middle-income countries over the period 1950-2010. To this end, the paper employs panel FMOLS and panel DOLS estimators and panel Granger causality test based on vector error correction model. According to the output from estimations, GDP per capita is positively related to average years of total schooling and there is a bidirectional causality between variables. In conclusion, the paper argues that average years of schooling of people should be increased to struggle with the middle-income trap.

Keywords. Middle-income trap, Human capital, Schooling, GDP per capita, Panel data analysis.

JEL. C23, I25, O15.

1. Introduction

According to the World Bank, for the current 2015 fiscal year, low-income economies are characterized as those with a gross national income (GNI) per capita, that is calculated using the Atlas method, of $1045 or less in 2013; middle-income economies are those with a GNI per capita between $1045-$12746$; high-income economies are those with a GNI per capita of $12746 or more. Besides, lower-middle-income and upper-middle-income economies are separated at a GNI per capita of $4125.As Tho (2013) remarks, low-income economies are those that are facing with poverty traps. The development economics literature has mainlypaid attention to the notion of the poverty trap to explain why some poor countries don't grow faster than rich countries and why poverty prevails from generation to generation in these countries (Kharasand Kohli, 2011; Zeng and Fang, 2014). Therefore, middle-income countries are neglected compared with low-income countries in the development economics literature. On the other hand, when growth performances of some middle-income countries are examined, it is seen there is a serious slowdown in growth rates of these economies, and thus these countries have been defined as middle-income countries for years. This case that middle-income countries have been experiencing is called 'middle-income trap' (Tho, 2013).

[a†]Ahi Evran University, Faculty of Economics and Administrative Sciences, Department of Economics, Kirsehir 40100, Turkey.
✉. ubulut@ahievran.edu.tr
[b]Çanakkale 18 Mart University, Faculty of Education, Department of Primary Mathematics Education, Canakkale 17100, Turkey.
✉. as_kilic@windowslive.com

The term middle-income trap was first used by Gill andKharas (2007) in a World Bank report titled 'An East Asian Renaissance: Ideas for Economic Growth'. In this report, Gill andKharas (2007) present that middle-income countries have grown more slowly than either rich or poor countries in recent years.In another World Bank report, Agenor et al. (2012) emphasize while many countries reach middle-income status, few have become high-income economies in the post-war era, and thus Agenor et al. (2012) remark that many countries have fallen into the middle income trap due to a sharp slowdown in productivity and growth. After these reports, debates on the middle income trap have been increased among economists and policy makers. These debates especially focus on the definition and causes of the middle-income trap, on how the middle-income trap will be investigated empirically, andon escaping the middle-income trap.

When the literature on the middle-income trap is examined, six middle-income countries become prominent. These countries are Brazil, Malaysia, Mexico, South Africa, Thailand, and Turkey. Recent studies on this topic argue that these countries are in the middle-income trap or can fall into the middle-income trap unless they improve human capital and technology to gain competitiveness (Eichengreen et al., 2013; Felipe et al., 2012; Yılmaz, 2014). On the other hand, South Korea is one of the best examples of a high-income country that did not fall into the middle-income trap. Many studies that investigate the reasons of this event emphasize the importance of the strong human capital (people's abilities, knowledge, and skills)together with research and development expenditures and thus technological improvement and innovation in South Korea (see, e.g., Agenor et al., 2012; Gill andKharas, 2007; Kharas andKohli, 2011). South Korea's growth success is compatible with endogenous growth theories. These theories, which were developed in 1980s and in 1990s, put emphasis on human capital and technological progress (Barro, 1991; Lucas, 1988; Romer, 1986; 1990). When it is considered human capital stimulates technological innovations (Karahasan and Lopez-Bazo, 2013; Mathur, 1999; Romer, 1990;Van ZylandBonga-Bonga, 2009), the importance of human capital is apparent to climb out of the middle-income trap for middle-income countries.

Education indicators are usually utilized as the proxy of the level of human capital. When one examines education indicators in the literature, he/she observes that both quantitative and qualitative indicators are utilized. Accordingly, school enrolment rates, literacy rates, and average years of schooling are usually used as the quantitative indicators. TIMSS assessments, which are produced by International Association for the Evaluation of Educational Achievement (IEA), and PISA assessments, which are propounded by Organisation for Economic Co-operation and Development (OECD), are made use of as the qualitative indicators. Qualitative education indicators are utilized measures of cognitive skills.

This paper uses average years of total schooling as the quantitative indicator of the level of human capital, and the purpose of this paper is to examine the relationship between average years of total schooling andGDP per capita using a panel data set of six middle-income countries mentioned above. In this way, the paper investigates whether an increase in schooling increases GDP per capita in these countries and thus examines whether this increasehelps to tackle the middle-income trap. The rest of the paper is organized as follows: Section 2 discusses related literature on education-growth nexus. Section 3 presents data, methodology, and estimation results. Section 4 concludes the paper with a summary of the findings and policy implications.

2. Related Literature

Seminal studies by Schultz (1961; 1962) use educational capital as the proxy of human capital. Educational capital is defined as total costs of elementary, high-school, and college, and university education of labor force in these studies. Schultz (1962) remarks that the estimated return to educational capital seems to account for about one-fifth of the economic growth of the period 1930-1957 in the US. In some studies, human capital is proxied by other education indicators, such as school enrolment rates and literacy rates in the later years (see e.g., Asteriou and Agiomirgianakis, 2001; Barro, 1991; Hicks, 1980;Romer, 1989; Wheeler, 1980).Additionally, many studies have utilized average years of schooling data as the proxy of the level of human capital. Among these studies, Barro (2001), Bloom et al. (2004), Borensztein et al. (1998), Edison et al. (2002)Hanushek andKimko (2000), and Rioja andValev (2004)yield that economic growth is positively related to average years of schooling.

There are some studies investigating the effects of both quantity and quality of schooling on economic growth and yielding different findings about these effects. For instance, recent studies by Hanushek and Woessman (2008; 2010) and Breton (2011)examine the effects of quantity and quality of schooling on economic growth. In these studies, PISA and TIMSS test scores are used as the indicator of the quality of schooling while years of schooling are used as the quantity of schooling. In Hanushek and Woessman's (2008; 2010) models, average growth rate in GDP per capita over the period 1960-2000 for fifty countries is a function of years of schooling in 1960 and average test scores over 1960-2000. In both studies, it isfound that the quality of schooling, rather than quantity of schooling, has a statistically significant positive effect on average growth rate in GDPand is emphasized that the quality of schooling determines a nation's rate of economic growth. Besides, Breton (2011) uses GDP per capita as the dependent variable for forty six countries for the year 2000. He yields thatthe quantity ofschooling attainment has greater statistical significance in comparison with thequality of schooling.

## 3. Model, Data, Methodology, and Estimation Results

3.1. Model and Data

Based on the discussions above, GDP per capita is described as a function of an education indicator (EI):

$$GDP_{it} = \beta_{0i} + \beta_{1i}EI_{it} + \varepsilon_{it} \qquad (1)$$

Here the question is which education indicator will be used in the paper. Psacharopoulos and Arriagada (1986) and Barro and Lee (1993) argue that school enrolment rates have an important shortcoming for human capital measures. Accordingly, current enrolment rates measure the flows of schooling, and the cumulation of these flows create future human capital stocks. Because of the fact that the educational process takes many years, the lag between flows and stocks is long. Besides, as Barro and Lee (1993) remark, literacy is only the first step in the path of human capital formation. Numeracy, logical and analytical reasoning, and several types of technical knowledge are important for labor productivity as other aspects of human capital.In addition to these, Breton (2011) criticizes the usage of international test scores as education indicators. Firstly, he denotes that international test scores have been available for a large number of countries since 1990. Secondly, there is a lag between when the tests are given and when the students may enter the work force, so a possible good degree in these tests in a

period only may affect future human capital. Therefore, even if the economic growth data and test scores data belong to the same point in time, average test scores may not be available as an indicator of the level of human capital. Because of plausible criticisms of Psacharopoulos and Arriagada (1986), Barro and Lee (1993), and Breton (2011) about the utilization of school enrolment rates, literacy rates, and international test scores as education indicators, average years of total schooling become prominent as a good education indicator. Figure 1 supports the usage of average years of total schooling as the education indicator in the paper.
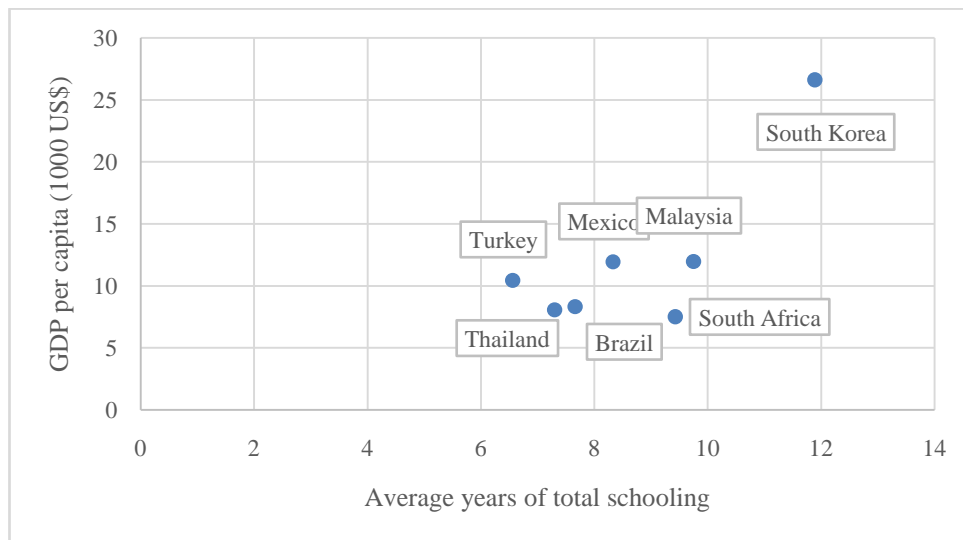
Graph 1. *GDP per capita and average years of total schooling in 2010*
Source: Barro and Lee (2013) and Heston et al. (2012).

Graph 1 depicts the relationship between GDP per capita and average years of total schooling in six middle-income countries that constitute the data set and in South Korea in 2010. It was mentioned in the introduction part of the paper that South Korea was a good example that had not fallen into the middle-income trap and that many studies emphasized the strong human capital of South Korea. As seen, GDP per capita and average years of total schooling in South Kore are highly greater than those of six middle-income countries. Therefore, one may claim that great average years of total schooling contribute to the growth success of the South Korean economy.

After these explanations above, equation (1) can be re-written as follows:

$$\ln GDP_{it} = \beta_{0i} + \beta_{1i} \ln SC_{it} + \varepsilon_{it} \qquad (2)$$

The variables in equation (2) are GDP per capita (converted through purchasing power parity and at 2005 constant prices) and average years of total schooling of people twenty five years and over. The data used in this paper cover six middle-income countries (Brazil, Mexico, Malaysia, South Africa, Thailand, and Turkey) and are multi-year using five-year intervals (1950-2010). While GDP data are extracted from Heston et al.(2012), schooling data are obtained from Barro and Lee (2013). Both variables are used in logarithmic forms, and thus their notations are lnGDP and lnSC, respectively.

Table 1. *Descriptive Statistics and Correlation Matrix for lnGDP and lnSC*

	lnGDP	lnSC
Descriptive Statistics		
Mean	8.420	1.329
Median	8.605	1.387
Maximum	9.389	2.277
Minimum	6.608	-0.010
Std. deviation	0.673	0.548
Observations	78	78
Correlation Matrix		
lnGDP		0.784
lnSC	0.784	

Descriptive statistics and correlation matrix are presented in Table-1. One notes that the all descriptive statistics of lnGDP are greater than those of lnSC. One may notice, as well, there is a high and positive correlation between two variables.

Descriptive statistics of course are to provide one with some initial and/or preliminary analysis. However, beyond table observations, one needs to employmore reliable statistical methodologies such as unit root, cointegration, and causality estimations to obtain unbiased and efficient output.

3.2. Panel Unit Root Tests

Specifying the order of integration of variables is the first step in panel data analyses to prevent possible spurious regression problems. In this respect, this paper employs panel unit root tests developed by Levin et al. (2002, henceforth LLC), Im et al. (2003, henceforth IPS), and Maddala and Wu (1999, ADF-Fisher).

The LLC panel unit root test entails estimating the following panel model:

$$\Delta y_{it} = \delta y_{it-1} + \sum_{L=1}^{pi} \theta_{iL} \Delta y_{it-L} + \alpha_{mi} d_{mt} + \varepsilon_{it}, \qquad m = 1, 2, 3. \qquad (3)$$

where Δ is the first difference operator, d_{mt} is the vector of deterministic variables, and α_m is the corresponding vector of coefficients for model $m = 1, 2, 3$. In this way, $d_{1t} = \emptyset$ (the empty set), $d_{2t} = \{1\}$, and $d_{3t} = \{1,t\}$. The null hypothesis of $\delta = 0$ for all i is tested against the alternative hypothesis of $\delta < 0$ for all i. The rejection of the null hypothesis indicates a panel stationary process. The parameter δ is homogenous across i for LLC test whereas Im et al.(2003) suggest a panel unit root test that allows δ to vary across all i. Therefore, the equation (3) is re-written as follows:

$$\Delta y_{it} = \delta_i y_{it-1} + \sum_{L=1}^{pi} \theta_{iL} \Delta y_{it-L} + \alpha_{mi} d_{mt} + \varepsilon_{it}, \qquad m = 1, 2, 3. \qquad (4)$$

While the null hypothesis is $\delta = 0$ for all i, the alternative hypothesis is $\delta < 0$ for at least one i. The rejection of the null hypothesis indicates a panel stationary process. Fisher-ADF Test, which is proposed by Maddala and Wu (1999), combines the p-values from unit root tests for each cross section i. The test is non-parametric and has a chi-square distribution with 2n degrees of freedom, where n is the number of countries in the panel as given in equation (5):

$$\lambda = -2 \sum_{i=1}^{n} \log_e(p_i) \sim \chi^2_{2n(d.f.)} \qquad (5)$$

wherep_i is the p-value from the ADF unit root test for unit i. The rejection of the null hypothesis of the test indicates a panel stationary process.

Table 2.*Panel Unit Root Tests Results*

Variable	LLC[a,b]	IPS[b]	ADF-Fisher[b]
lnGDP	-2.546[c]	0.571	9.563
	(0.005)	(0.716)	(0.654)
lnSC	-2.624[c]	1.884	6.762
	(0.004)	(0.970)	(0.872)
ΔlnGDP	-6.780[c]	-4.281[c]	38.790[c]
	(0.000)	(0.000)	(0.000)
ΔlnSC	-3.323[c]	-2.085[d]	22.350[d]
	(0.000)	(0.018)	(0.033)

Notes:
[a] Newey-West Bandwidth selection with Bartlett Kernel is used.
[b] The values in parentheses are prob-values.
[c] Illustrates 1% statistical significance.
[d] Illustrates 5% statistical significance.

Table-2 depicts panel unit root test results. Accordingly, the test statistics for the first differences reject the null hypotheses and indicate that the series are stationary in first differences. Hence one can state that the series are integrated of order one.

3.3. Panel Cointegration Test

Pedroni (1999; 2004) suggests seven test statistics that have the null hypothesis of no cointegration in order to examine thecointegration relationship among variables in a panel data model.While large positive values imply the rejection of the null hypothesis for the panel variance statistic, large negative values imply the null of no cointegration is rejected for other statistics (Pedroni, 1999). See Pedroni (1999) for further discussion of notation and proceduresof theimplementation.

Table3.*Panel Cointegration Test Results*

Test[a]	Test Statistic[b]
Panel v-Statistic	4.780[c]
	(0.000)
Panel rho-Statistic	0.238
	(0.594)
Panel PP-Statistic	-2.137[d]
	(0.016)
Panel ADF-Statistic	-3.551[c]
	(0.000)
Group rho-Statistic	1.652
	(0.950)
Group PP-Statistic	-1.434[e]
	(0.075)
Group ADF-Statistic	-3.357[c]
	(0.000)

Notes:
[a] Newey-West Bandwidth selection with Bartlett Kernel is used.
[b] The values in parentheses are prob-values.
[c] Illustrates 1% statistical significance.
[d] Illustrates 5% statistical significance.
[e] Illustrates 10% statistical significance.

The results for the panel cointegration tests are reported in Table-3. As seen, five of seven statistics suggest the rejection of the null hypothesis of no cointegration. Accordingly, it can be claimed that there is a cointegration relationship between variables and that lnGDP converges to its long-run equilibrium by correcting any possible deviation from this equilibrium in short run.

After determining the cointegration relationship, the next step is to estimate the cointegration (long-run) coefficient of lnSC by employing panel fully modified ordinary least squares (FMOLS) and panel dynamic ordinary least squares (DOLS) estimators developed by Pedroni(2000; 2001). The FMOLS estimator generates consistent estimations of the parameters in small samples and controls for the possible endogeneity of the regressors and serial correlation (Kiran et al., 2009). The panel FMOLS estimator can be constructed as follows (Pedroni, 2001):

$$\hat{\beta}^*_{GFM} = N^{-1} \sum_{i=1}^{N} \hat{\beta}^*_{FM,i} \tag{6}$$

where $\hat{\beta}^*_{FM,i}$ is the conventional FMOLS estimator applied to ith member of the panel. The associated t-statistic can be constructed as:

$$t_{\hat{\beta}^*_{GFM}} = N^{-1/2} \sum_{i=1}^{N} t_{\hat{\beta}^*_{FM,i}} \tag{7}$$

To obtain the panel DOLS estimator, the following model is estimated:

$$lnGDP_{it} = \alpha_i + \beta_i lnSC_{it} + \sum_{k=-K_i}^{K_i} \gamma_{ik} \Delta lnSC_{it-k} + \varepsilon_{it} \tag{8}$$

where $-K_i$ and K_i are leads and lags. The panel DOLS estimator can be built up as inequation(16):

$$\hat{\beta}^*_{GD} = N^{-1} \sum_{i=1}^{N} \hat{\beta}^*_{D,i} \tag{9}$$

where $\hat{\beta}^*_{D,i}$ is the conventional DOLS estimator, applied to the ith member of the panel. The associated t-ratio can be built up as in equation (17):

$$t_{\hat{\beta}^*_{GD}} = N^{-1/2} \sum_{i=1}^{N} t_{\hat{\beta}^*_{D,i}} \tag{10}$$

Table 4. *Panel Cointegration Coefficient (lnGDP is the dependent Variable)*

Variable	Panel FMOLS[a]	Panel DOLS[a]
lnSC	0.99[b]	0.98[b]
	[14.613]	[13.348]

Notes:
[a] The values in parentheses are t-statistics.
[b] Illustrates 1% statistical significance.

Table-4 denotes the output of panel FMOLS and panel DOLS estimations. As seen, the coefficient of average years of total schooling is positive according to the both estimators and two estimators also present nearly the same results in terms of the magnitude of the coefficient. In other words, average years of total schooling affect GDP per capita positively.

3.4. Panel Causality Test

As the cointegration analysis is not able to present the direction of the causality, causality analyses are commonly utilized to investigate causal relationships between variables. This paper employs panel Granger causality test based on vector error correction model (VECM) to investigate causal relationships.

Panel VECM is established by augmenting a vector auto regression (VAR) model in first differences with one-lagged error correction term. In order to investigate causal interactions between variables, a panel VECM can be constructed as follows (Apergisand Payne, 2009):

$$\Delta lnGDP_{it} = \alpha_{1i} + \sum_{k=1}^{q} \beta_{11ik}\Delta lnGDP_{it-k} + \sum_{k=1}^{q} \beta_{12ik}\Delta lnSC_{it-k} + \lambda_{1i}\hat{\varepsilon}_{it-1} + \upsilon_{1it} \quad (11)$$

$$\Delta lnSC_{it} = \alpha_{2i} + \sum_{k=1}^{q} \beta_{21ik}\Delta lnSC_{it-k} + \sum_{k=1}^{q} \beta_{22ik}\Delta lnGDP_{it-k} + \lambda_{2i}\hat{\varepsilon}_{it-1} + \upsilon_{2it} \quad (12)$$

where Δ is the first-difference operator, q is the optimal lag length, $\hat{\varepsilon}_{it}$ is the residuals obtained from the panel FMOLS estimation, and υ is the serially uncorrelated error term. This notation for causality lets one examine both short-run and long-run causal relationships. The short-run causality from average years of total schooling to GDP per capita is tested using a Wald test by executing $\beta_{12ik}= 0$. The long-run causality is examined according to the statistical significances of the coefficients of the error correction terms represented by λ. As Hill et al. (2011) and Enders (2015) remark[1], error correction coefficients, namely λ_{1i} and λ_{2i} show how much $\Delta lnGDP_{it}$ and $\Delta lnSC_{it}$ respond to the cointegration error $lnGDP_{it-1} - \beta_{0i} - \beta_{1i}lnSC_{it-1} = \varepsilon_{it-1}$. The idea that the error leads to a correction comes about because of the conditions put on λ_{1i} and λ_{2i} to ensure stability, namely $(-1 <\lambda_{1i}\leq 0)$ and $(0 \leq \lambda_{2i}< 1)$. To appreciate this idea, consider a positive error $\varepsilon_{it-1}> 0$ that occurred because $lnGDP_{it-1}> (\beta_{0i} + \beta_{1i}lnSC_{it-1})$. A negative error correction coefficient in the first equation (λ_{1i}) ensures that $\Delta lnGDP$ falls, while the positive error correction coefficient in the second equation (λ_{2i}) ensures that $\Delta lnSC$ rises, thereby correcting the error. Having the error correction coefficients less than 1 in absolute value ensures that the system is not explosive. Based on these explanations, the statistically significant and negative λ_{1i} indicates that average years of total schooling Granger cause GDP per capita while the statistically significant and positive λ_{2i} indicates that GDP per capita Granger causes average years of total schooling in the long run.

Table 5. *Panel Granger Causality Test Results*

Variable	Short-Run Causality[a]		Long-Run Causality[b]
	$\Delta lnGDP$	$\Delta lnSC$	ECT
$\Delta lnGDP$		4.046	-0.557[c]
		(0.256)	[-4.781]
$\Delta lnSC$	4.079		0.184[d]
	(0.253)		[1.889]

Notes:
[a] The values in parentheses are prob-values.
[b] The values in brackets are t-statistics.
[c] Illustrates 1% statistical significance.
[d] Illustrates 10% statistical significance.

Table 5 depicts the results of the panel causality test. Accordingly, there is a bidirectional Granger causality between average years of total schooling and GDP per capita in the long run while there is not a causal relationship between variables in the short run. The causal relationship from average years of total schooling to

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[1] While Hill et al. (2011) and Enders (2015) analyse error correction models in time series analyses, we extend their analysis for panel data models.

GDP per capita is consistent with panel FMOLS and panel DOLS results and indicates that an increase in average years of total schooling causes an increase in GDP per capita. Additionally, the causal relationship from GDP per capita to average years of total schooling indicates that demand for education of people increases as a result of increasing income levels. Therefore, there seems to be a feedback mechanism between these variables.

4. Conclusion

This paper examines the relationship between average years of total schooling and GDP per capita for 6 middle-income countries by utilizing multi-year data thatcover the period 1950-2010. After carrying out panel unit root tests and panel cointegration test, the paper employs panel FMOLS and panel DOLS estimators suggested by Pedroni (2000; 2001). Then, it follows panel Granger causality test based on vector error correction model. Panel FMOLS and panel DOLS estimators indicate that GDP per capita is positively related to average years of total schooling. Panel Granger causality test's resultssupport panel FMOLS and panel DOLS estimators and indicate a feedback mechanism between variables. Accordingly, there is a bidirectional causality between average years of total schooling and GDP per capita in the long run.

These findingsimply that the more years of schooling can lead to more GDP per capita in selected middle income countries. It can be argued that schooling affects economic growth positively since schoolingi) can increase productivity of employees, ii)can stimulate technological development, and iii) can facilitatethe adaptation to imported technologies.Both the findings obtained from the cointegration and causality analyses and the case of South Korea reveal the importance of schooling for economies to grow faster. Therefore, this paper argues that middle-income countries should implement policies in order to increase years of schooling of people.

This paper contributes to literature in several ways. First, the paper uses data that belong to middle-income countries, accentuates middle-income trap which is a relatively new concept in the literature of development economics and proposes that middle-income countries should increase average years of schooling of people while struggling with the middle-income trap based on empirical findings. Second, the paper adopts dynamic panel data methods such as panel DOLS and panel Granger causality test based on vector error correction model whereas the other studies, which are given in Section 2, perform cross-sectional analyses or panel OLS.In this way the paper tries to catch up with dynamic relationships between GDP per capita and schooling. Third, the paper examines causal relationships between schooling and GDP per capita unlike the other studies that only estimate the coefficient of schooling. Hence the paper presents causal relationships from average years of schooling to GDP per capita and from GDP per capita to average years of total schooling.

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