

## Education-growth nexus in middle-income countries: an empirical examination for schooling rates\*

Ümit Bulut<sup>1</sup> Ahsen Seda Kılıç Bulut<sup>2</sup>

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### **Abstract**

*The goal of this paper is to examine the education-growth nexus for 5 middle-income countries (Malaysia, Mexico, South Africa, Thailand, and Turkey) using schooling rate as the indicator of education over the period 1987-2015. The paper first performs cross-sectional dependence and heterogeneity tests and then employs the bootstrap panel Granger causality test developed by Konya (2006). According to the findings, while there is unidirectional causality from schooling rate to GDP in Thailand, there is unidirectional causality from GDP to schooling rate in South Africa. The findings of the paper indicate that schooling rate is not a good proxy for human capital. Theoretical and policy implications are discussed in the conclusion part.*

**Keywords:** middle-income trap, human capital, education, schooling rate, PISA test, panel data

### **1. Introduction**

The development economics literature has mainly focused on poverty trap and tried to explain the definition of poverty trap, why many countries cannot become middle-income economies, and why poverty remains from generation to generation in these countries (Kharas and Kohli 2011; Zeng and Fang 2014). For this reason, one can argue that middle-income countries are neglected in the development economics literature compared to low-income countries as the commonly supported view argues that low-income countries will have a growth pattern just after they become middle-income countries. On the other hand, when some economies' growth performances are researched, it is clear that there is a slowdown in growth rates of these economies and that these economies have been middle-income countries for a long time. This case is denominated as "middle-income trap" in the economics literature (Felipe et al. 2012; Tho 2013). The term middle-income trap was first used in a World Bank report titled "An East Asian Renaissance: Ideas for Economic Growth" by Gill and Kharas (2007). Gill and Kharas (2007) reveal that middle-income countries have a slower growth performance compared to high- and low-income countries in this report. In a similar way, Agenor et al. (2012) exhibit that many countries became middle-income countries but only a few of them became high-income countries while lots of them remained in middle-income level. After these works, policy makers and economists have begun to pay attention to middle-income trap. When one researches on middle-income trap, he/she will observe that

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<sup>1</sup> Assoc. Prof. Dr. Kırşehir Ahi Evran University, Kırşehir/TURKEY, [ubulut@ahievran.edu.tr](mailto:ubulut@ahievran.edu.tr)

<sup>2</sup> Asst. Prof. Dr. Kırşehir Ahi Evran University, Kırşehir/TURKEY, [ahsenseda@ahievran.edu.tr](mailto:ahsenseda@ahievran.edu.tr)

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the theoretical and empirical literature deals with 6 countries, namely Brazil, Malaysia, Mexico, South Africa, Thailand, and Turkey (Bulut and Bulut 2015).

Then, how can these countries avoid the middle-income trap? Recent theoretical and empirical works argue that these countries should improve human capital and technology to obtain competitive power with regard to endogenous growth theories (Felipe et al. 2012; Eichengreen et al. 2013). Endogenous growth theories underline human capital and technological improvement for economic growth (Romer 1986; 1990; Lucas 1988; Barro 1991). Acemoglu (2009) defines human capital as “the stock of skills, education, competencies and other productivity-enhancing characteristics embedded in labour”. Human capital is of crucial importance to avoid middle-income trap since technological innovations are encouraged by human capital (Romer 1990; Mathur 1999; Van Zyl and Bonga-Bonga 2009; Karahasan and Lopez-Bazo 2013). Education indicators are commonly used to represent the level of human capital.

When one considers education indicators in the literature, he/she observes that both quantitative and qualitative indicators are used. Accordingly, schooling rates, literacy rates, and average years of total schooling are used as quantitative indicators while Trends in International Mathematics and Science Study (TIMSS) assessments, which are suggested by International Association for the Evaluation of Educational Achievement, and Programme for International Student Assessment (PISA) scores, which are produced by Organization for Economic Co-operation and Development (OECD), are utilized as the qualitative indicators. Chen and Luoh (2010) and Yu et al. (2012) argue that PISA is better than TIMSS to measure labor-force quality since PISA tests (i) are not based on curriculum, and (ii) measure applications of knowledge of students against different situations and utilization of knowledge for different scenarios. Economists have begun to focus on PISA test scores especially in the last years. PISA test measures performances of 15-year-old students in mathematics, science, and reading. Countries in which PISA test is conducted are ranged with regard to test scores for all three fields by the OECD.

There are many theoretical papers focusing on the relationship between economic growth and human capital/education. For instance, Lucas (1988) argues that more educated workforce increases the productivity of capital while Romer (1990) remarks that the growth rate of an economy is essentially determined by human capital. Perotti (1993) argues that educated people not only increase their own productivity but also that of others with whom they work. Soubbotina and Sheram (2000) point out that human capital determines a country’s ability to produce and adopt technological innovations. Ranis et al. (2000) remark higher levels of human capital affect an economy by rising capabilities, creativity, and productivity of people and by contributing to technological capacity and technological change in industry. Using some papers revealing endogenous growth theories, Hanushek and Woessman (2010, 2012) clarify the mechanisms through which education affects economic growth positively. Accordingly, education can increase economic growth by i) increasing the human capital inherent in labour force that rises labour productivity, ii) increasing the innovative capacity of an economy, and iii) facilitating the diffusion and the transmission of knowledge for the implementation of new technologies.

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Table 1. Some seminal papers investigating the education-economic growth nexus

Paper	Education variable(s)	Method	Findings
Barro (1991)	Schooling rate	Ordinary least squares (OLS)-cross section	Positive effects
Mankiw et al. (1992)	Schooling rate	OLS-cross section	Positive effects
Islam (1995)	Years of schooling	OLS-panel data	Mixed findings
Nonneman and Vanhoudt (1996)	Schooling rate	OLS-cross section	Mixed findings
Easterly and Levine (1997)	Years of schooling	Seemingly unrelated regressions-cross section	Positive effects
Hanushek and Kimko (2000)	Years of schooling Test scores	OLS-cross section	Mixed findings for years of schooling Positive effects for test scores
Doppelhofer et al. (2000)	Schooling rate	Bayesian Averaging of Classical Estimates-cross section	Mixed findings
Barro (2001)	Years of schooling Test scores	Three-stage least squares (3SLS)-panel data	Mixed findings for average years of schooling, mathematics and reading scores Positive effects for science scores
Pritchett (2001)	Years of schooling Test scores	OLS-panel data	No effects
Cohen and Soto (2007)	Years of schooling	Fixed effects and generalized method of moments-panel data	Positive effects
Hanushek and Woessman (2008)	Years of schooling Test scores	OLS-cross section	Mixed results for years of schooling Positive effects for test scores
Durlauf et al. (2008)	Years of schooling	Bayesian model averaging-panel data	Mixed results
Chen and Luoh (2010)	Schooling rate Test scores	OLS-cross section	Mixed results
Henderson (2010)	Years of schooling	Non parametric local linear least squares-panel data	No effects
Afzal et al. (2011)	Schooling rate Adult literacy index	Cointegration and causality-Pakistan	Bidirectional causality
Yu et al. (2012)	Schooling rate Test scores	OLS-cross section	No effects
Glewwe et al. (2014)	Years of schooling Test scores	OLS-cross section	Positive effects
Delgado et al. (2014)	Years of schooling	OLS-cross section	Mixed results
Bulut and Bulut (2015)	Years of schooling	Cointegration and causality-panel data	Positive effects Bidirectional causality

There is a continuously expanding empirical literature on education-growth nexus as is depicted in Table 1. As is seen, some studies use schooling rates while some others use average years of schooling. Besides, some papers utilize international test scores as the education indicator. While schooling rates and average years of schooling are quantitative indicators, tests scores

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are the qualitative indicators as was stated above. Among these education indicators, only schooling rate lets researchers examine dynamic relationships between education and economic growth within a panel data framework. This paper therefore examines the education-growth nexus for Malaysia, Mexico, South Africa, Thailand, and Turkey over the period 1987-2015 using schooling rate as the education indicator. The paper first conducts cross-sectional dependence and heterogeneity tests, and second employs the bootstrap panel Granger causality test developed by Konya (2006). This causality test has some great advantages. First, researchers can use level values of variables without investigating time series properties of variables while employing this test. Second, this test is capable of presenting efficient output as it based on bootstrapping.

The rest of the paper is organized as follows: Section 2 presents empirical literature on the education-growth nexus. Section 3 gives data. Methodology and results are reported in Section 4. The final section concludes the paper with main findings and some implications.

## 2. Brief literature

There is an expanding empirical literature on education-growth nexus as was denoted in the previous part. While some of these papers use quantitative education indicators (Barro 1991; Mankiw et al. 1992; Islam 1995; Nonneman and Vanhoudt 1996; Easterly and Levine 1997; Doppelhofer et al. 2000; Cohen and Sato 2007; Durlauf et al. 2008; Henderson 2010; Delgado et al. 2014; Bulut and Bulut 2015), some others use both quantitative and qualitative education indicators (Hanushek and Kimko 2000; Barro 2001; Pritchett 2001; Hanushek and Woessman 2008; Chen and Luoh 2010; Yu et al. 2012; Glewwe et al. 2014). Table 1 summarizes these papers.

When one examines these papers, he/she will observe that only a few papers examine the education-growth nexus through dynamic approaches, such as cointegration and causality. He/she can also observe that empirical studies on the education-growth nexus do not exhibit clear-cut evidence. Therefore, there appears to be a research gap on the education-growth nexus in the empirical literature. This paper tries to fulfil this gap to some degree by employing advanced panel data techniques.

## 3. Data

This paper examines the relationship between education and GDP for 5 middle-income countries, namely Malaysia, Mexico, South Africa, Thailand, and Turkey. The reason why the data set excludes Brazil is that we cannot able to obtain schooling rate data for Brazil. The variables are schooling rate (gross primary enrolment ratio for both sexes %) and GDP (constant 2010 USD). The data are annual and cover the period from 1987 to 2015. Both variables are extracted from the World Bank Database (2018). SC and GDP refer to schooling rate and GDP, respectively.

## 4. Estimation methodology and findings

In a panel data model, the first stage is to test cross-sectional dependence and heterogeneity. While the former indicates that a shock in one cross section unit can affect other cross section units in the panel, the latter implies that researchers should focus on unit-specific findings instead of the findings for the whole panel. Then, if researchers detect the existence of cross-sectional dependence and heterogeneity, they should employ unit root, cointegration, and/or causality tests which are robust to cross-sectional dependence and heterogeneity. We therefore begin by testing for cross-sectional dependence and heterogeneity prior to performing the causality test.

#### 4.1. Cross-sectional dependence and heterogeneity tests

Breusch and Pagan (1980) produce the Lagrange multiplier (LM) test statistic to test for cross-sectional dependence. They first estimate the following panel data model:

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it} \text{ for } i=1, 2, \dots, N; t = 1, 2, \dots, T \quad (1)$$

where  $i$  is the cross section dimension,  $t$  is the time dimension,  $x_{it}$  is  $k \times 1$  vector of explanatory variables,  $\alpha_i$  stands for intercepts, and  $\beta_i$  denotes slope coefficients, respectively. Based on the panel data model in Equation (1), LM test is computed as follows:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \sim \chi_{N(N-1)/2}^2 \quad (2)$$

where  $\hat{\rho}_{ij}$  is the sample estimate of pairwise correlation of the residuals obtained from individual ordinary least squares (OLS) estimation of the Equation (1). Pesaran (2004) propounds two new tests to test cross-sectional dependence when  $N$  is large. This tests are calculated as

$$CD_{lm} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N (T \hat{\rho}_{ij}^2 - 1) \sim N(0,1) \quad (3)$$

$$CD = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}\right) \sim N(0,1) \quad (4)$$

Besides, Pesaran et al. (2008) produce the bias-adjusted LM test for large panels defined as the following:

$$LM_{adj} = \sqrt{\left(\frac{2}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} \sim N(0,1) \quad (5)$$

where  $k$  stands for the number of regressors,  $\mu_{Tij}$  and  $v_{Tij}^2$  denote the exact mean and variance of  $(T-k)\hat{\rho}_{ij}^2$ , respectively.

The null hypothesis of no cross-sectional dependence is tested against the alternative hypothesis for all cross-sectional dependence tests above.

Pesaran and Yamagata (2008) produce ( $\tilde{\Lambda}$ ) tests to test for slope homogeneity. The null hypothesis of slope homogeneity is tested against the alternative hypothesis of slope heterogeneity under these tests. They first compute the modified version of Swamy (1970) test calculated as

$$\tilde{S} = \sum_{i=1}^N (\hat{\beta}_i - \tilde{\beta}_{WFE})' \frac{X_i' M_\tau X_i}{\tilde{\sigma}_i^2} (\hat{\beta}_i - \tilde{\beta}_{WFE}) \quad (6)$$

where

$$\tilde{\sigma}_i^2 = \frac{(y_i - X_i \hat{\beta}_i)' M_\tau (y_i - X_i \hat{\beta}_i)}{(T-k-1)} \quad (7)$$

where  $M_\tau$  denotes an identity matrix of order  $T$  and  $\tilde{\beta}_{WFE}$  stands for the weighted fixed effect pooled estimator defined as follows:

$$\tilde{\beta}_{WFE} = \left( \sum_{i=1}^N \frac{X_i' M_\tau X_i}{\tilde{\sigma}_i^2} \right)^{-1} \sum_{i=1}^N \frac{X_i' M_\tau y_i}{\tilde{\sigma}_i^2} \quad (8)$$

The first test Pesaran and Yamagata (2008) propound is defined as the following:

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$$\tilde{\Delta} = \sqrt{N} \left( \frac{N^{-1} \tilde{S}_k}{\sqrt{2k}} \right) \quad (9)$$

Pesaran and Yamagata (2008) improve the small sample properties of the  $\tilde{\Delta}$  test by utilizing the following mean and variance bias adjusted version of this test:

$$\tilde{\Delta}_{adj} = \sqrt{N} \left( \frac{N^{-1} \tilde{S}_k - E(\tilde{z}_{iT})}{\sqrt{\text{Var}(\tilde{z}_{iT})}} \right) \quad (10)$$

where

$$E(\tilde{z}_{iT}) = k, \quad \text{Var}(\tilde{z}_{iT}) = \frac{2k(T-k-1)}{T+1}$$

Table 2. Cross-sectional dependence and heterogeneity tests

Test	Statistic	p-value
Cross-sectional dependence tests		
LM	115.41*	0.00
CD <sub>LM</sub>	23.57*	0.00
CD	8.82*	0.00
LM <sub>adj</sub>	55.40*	0.00
Heterogeneity tests		
$\tilde{\Delta}$	50.04*	0.00
$\tilde{\Delta}_{adj}$	13.89*	0.00

Note:

(1) \* denotes 1% statistical significance.

Table 2 reports the results of the cross-sectional dependence and heterogeneity tests. As is seen, the null hypothesis of no cross-sectional dependence is rejected at 1% significance level by all cross-sectional dependence tests. This finding means that a shock occurring in one middle-income country in the sample can be transmitted to other countries. Table 2 also shows that the null hypothesis of homogeneity can be rejected at 1% significance level by both tests, which support country-specific heterogeneity. Under these conditions, the paper employs the bootstrap panel Granger causality test that can present efficient output in the presence of cross-sectional dependence and heterogeneity.

#### 4.2. Konya (2006) bootstrap panel Granger causality test

After detecting the presence of cross-sectional dependence and heterogeneity, to investigate the causal relationships between schooling rate and GDP, the paper employs the bootstrap panel Granger causality test produced by Konya (2006). This method is based on seemingly unrelated regression (SUR) estimates for a set of equations and reports the Wald tests and country-specific bootstrap critical values for each country in the sample. Hence, researchers can use level values of variables irrespective of their order of integration while performing this test.

The equation system set up below is estimated for this test:

$$\begin{aligned} \text{GDP}_{1t} &= \alpha_{11} + \sum_{l=1}^{mly1} \beta_{11l} \text{GDP}_{1t-l} + \sum_{l=1}^{mly1} \gamma_{11l} \text{SC}_{1t-l} + \varepsilon_{11t} \\ &\vdots \\ \text{GDP}_{Nt} &= \alpha_{1N} + \sum_{l=1}^{mly1} \beta_{1Nl} \text{GDP}_{Nt-l} + \sum_{l=1}^{mly1} \gamma_{1Nl} \text{SC}_{Nt-l} + \varepsilon_{1Nt} \end{aligned} \quad (11)$$

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$$\begin{aligned}
 SC_{1t} &= \alpha_{21} + \sum_{l=1}^{mly_2} \beta_{21l} GDP_{1t-l} + \sum_{l=1}^{mlx_2} \gamma_{21l} SC_{1t-l} + \varepsilon_{21t} \\
 &\vdots \\
 SC_{Nt} &= \alpha_{2N} + \sum_{l=1}^{mly_2} \beta_{2Nl} GDP_{Nt-l} + \sum_{l=1}^{mlx_2} \gamma_{2Nl} SC_{Nt-l} + \varepsilon_{2Nt}
 \end{aligned} \tag{12}$$

where N is the number of countries in the panel ( $i = 1, 2, \dots, N$ ), t is the time period ( $t = 1, 2, \dots, T$ ), l is the lag length, mly and mlx respectively stand for maximum lags for y and x.

According to the SUR systems, in country i (i) there is unidirectional Granger causality running from SC to GDP if in Equation (11) not all  $\gamma_{1i}$ s are zero, but in Equation (12) all  $\beta_{2i}$ s are zero, (ii) there is unidirectional Granger causality running from GDP to SC if in Equation (11) all  $\gamma_{1i}$ s are zero but in Equation (12) not all  $\beta_{2i}$ s are zero, (iii) there is bidirectional Granger causality between GDP and SC if neither all  $\beta_{2i}$ s nor all  $\gamma_{1i}$ s are zero, and (iv) there is no Granger causality between GDP and SC if all  $\beta_{2i}$ s and  $\gamma_{1i}$ s are zero. To determine the direction of the causal relationships, Wald statistics are compared to country-specific critical values extracted from the bootstrap procedure.

Before the estimation, the number of lags must be specified. This is a crucial step since the results depend on the number of lags. While too many lags may lead to redundant variable problem, too few lags may result in omitted variable bias. As the lag structure is varied across countries and variables in the panel, this will significantly rise the computational burden. This paper therefore lets different maximum lags for GDP and SC, but does not let them be different across countries. The paper estimates the system using from 1 to 4 lags and then select the combinations which minimize Akaike Information Criterion and Schwarz Bayesian Criterion.<sup>1</sup>

Table 3. Panel Granger causality test

	H <sub>0</sub> : SR does not cause GDP				H <sub>0</sub> : GDP does not cause SR			
	Statistic	Critical values			Statistic	Critical values		
		1%	5%	10%		1%	5%	10%
Malaysia	0.90	11.59	6.41	4.42	2.63	13.32	6.92	4.65
Mexico	0.01	14.06	7.42	5.19	0.91	10.52	5.84	4.01
South Africa	0.01	12.15	6.56	4.42	5.06**	13.45	6.92	4.90
Thailand	8.46*	10.66	5.98	4.10	0.32	11.34	6.17	4.27
Turkey	0.42	11.34	6.00	4.03	0.01	11.32	6.31	4.45

Notes:

- (1) \* and \*\* indicate 1% and 5% statistical significances, respectively.
- (2) Critical values are calculated through 10,000 bootstrap replications.

The results of the bootstrap panel Granger causality test are depicted in Table 3. As is seen from the table, the null hypothesis of no causality running from schooling rate to GDP can be rejected at 5% significance level for only Thailand while the null hypothesis of no causality running from GDP to schooling rate can be rejected at 10% significance level for only South Africa. These findings exhibit weak evidence about the positive relationship between schooling rate and GDP. Therefore, schooling rate appears not to be a good proxy for human capital in middle-income countries in the sample.

<sup>1</sup> In order to save space, the results from the lag selection procedure are not presented in the paper but are available upon request.

## 5. Conclusion

This paper investigates the causal relationships between schooling rate and GDP for 5 middle-income countries (Malaysia, Mexico, South Africa, Thailand, and Turkey) using annual data from 1987 to 2015. After conducting cross-sectional dependence and heterogeneity tests and detecting the existence of cross-sectional dependence and heterogeneity, the paper employs the bootstrap panel Granger causality test of Konya (2006) which can present efficient output in the presence of cross-sectional dependence and heterogeneity. The findings of the causality test indicate that while there exists a unidirectional causal relationship from schooling rate to GDP in Thailand, there exists a unidirectional causal relationship from GDP to schooling rate in South Africa. Based on these empirical findings, the paper explores that human capital cannot be represented by schooling rate.

The theoretical literature on the usage of education indicators supports the empirical findings. For instance, Psacharopoulos and Arriagada (1986) and Barro and Lee (1993) denote that schooling rates measure the flows of schooling and that the accumulation of these flows create future human capital stock since the educational process takes many years and the lag between flows and stock is long. Apart from comments towards the use of schooling rate as the education indicator, some other papers criticize the usage of years of schooling and international test scores. For example, Hanushek and Woessman (2010) remark that years of schooling do not generate the same cognitive skills in every country and that families and peers contribute to education. Besides, Breton (2001) criticizes the usage of international test scores as the education indicator. He first remarks that international test scores have been available for a large number of countries since 1990 and second points out that there is a lag between when the tests are given and when the students may enter the work force. Thus he argues that a possible good degree in these tests in a period may affect future human capital. All these remarks above seem to be reasonable.

On the other hand, in the literature, recent studies argue that PISA test scores can measure quality of education and thus can be a good proxy for human capital as PISA test represents cognitive skills and knowledge level of students (see e.g., Hanushek and Woessman 2009; 2012, among others). PISA began in 2000, has went on at three-year intervals and has been implemented to more countries over time. When one examines the rankings of the countries in the sample with regard to PISA test, he/she can observe that these countries take place at the bottom of the list (OECD 2018). Therefore, this paper argues that middle-income countries should increase quality of education and their PISA scores to be able to avoid middle-income trap and to catch up with developed countries.

The reason why the paper does not employ PISA test scores as the education indicator is that there exists a lag between when the tests are applied to students and when the students can enter the work force as Breton (2001) denotes above. There are only 6 observations for each country about PISA test scores (2000, 2003, 2006, 2009, 2012, 2015). Hence, researchers are not able to obtain reliable output with such a small sample through dynamic estimation methods, such as cointegration and causality approaches. On the other hand, most of the papers that employ PISA test scores as the education indicator in Table 1 do not take the lagged effects of test scores on human capital and GDP into consideration. Put differently, they examine whether PISA scores in  $t$  period affect GDP in  $t$  period. The only paper considering the lagged effects of test scores on human capital and GDP belongs to Yu et al. (2012). They consider a 7-year lag and investigate whether PISA scores in 2000 affect GDP in 2007 by conducting a cross-sectional analysis. We



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argue that they cannot catch the dynamic interactions between PISA scores and GDP and that they cannot explore the effects of changes in PISA scores on GDP since they perform cross-sectional analysis. Therefore, the findings of all these papers appear to be unreliable. Hence, in this paper, to be able to conduct reliable empirical analyses using test scores, we argue that (i) the OECD should consider increasing frequency of implementation of PISA test, (ii) future empirical works should employ dynamic estimation methods, and (iii) they should consider the lagged effects of test scores on human capital and GDP.

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