STEM Education and Economic Performance in the American States

Ray, Rita

Gustavus Adolphus College

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Rita Ray[1,2]

This paper examines the effect of STEM graduates on the level and growth of real GDP per capita for the 50 US states and the District of Columbia between 1990 and 2011. This paper also examines the effect of STEM graduates on approved utility patents per one million people. The findings show that the share of STEM graduates has a statistically significant positive effect on the level and growth of real GDP per capita. The results are robust irrespective of estimation methods. The paper finds that an increase in the share of STEM graduates increases the number of approved utility patents per one million people but that the statistical significance of the results depends on the estimation methods.

JEL Classification: C33, C51, I24, O40, O51, R19

1. Introduction

This paper examines the effect of the share of STEM (Science, Technology, Engineering and Mathematics) graduates on economic performance and scientific innovation. The share of STEM graduates is measured by the ratio of the number of bachelor's, master's and Ph.D. graduates in STEM fields to the total number of bachelor's, master's and Ph.D. graduates in a state for a given year.[3] Economic performance is measured by the level and growth of the state's real GDP per capita. Using data for the 50 states and the District of Columbia between 1990 and 2011, this paper investigates whether an increase in the share of STEM graduates in tertiary education increases a state's economic performance. This paper also investigates the connection between the share of STEM graduates in tertiary education and a state's scientific innovation.

The relationship between education and economic growth is a long-standing topic in economics. Education is the most crucial element in innovation, which, in turn, increases productivity and growth. STEM education is one of the most important factors for scientific innovation and technological adaptation. However, no work has been done that examines the connection between the share of STEM graduates in a state with the state's scientific innovation and economic performance.

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[1] Assistant Professor of Economics, Gustavus Adolphus College, St Peter, MN. Email: rayecon@gmail.com
[2] The author is very grateful to two anonymous referees for their insightful comments.
[3]

$$Share\ of\ STEM\ Graduates_{AL,1990} = \frac{Total\ No\ of\ STEM\ Graduates\ with\ Bachleors, Masters\ and\ Ph.D._{AL,1990}}{Total\ No\ of\ Graduates\ with\ Bachleors, Masters\ and\ Ph.D._{AL,1990}}$$

Improving the quality of STEM education and attracting future generations of STEM students has become one of the major educational policies in the United States in recent years. In 2009, President Barack Obama's 'Educate to Innovate' campaign asked for collaboration between the federal government and businesses, non-profit organizations, engineers, scientists and policy makers. This campaign also prioritized the development of 100,000 new and effective STEM teachers over the next decade, an increase in federal investment in STEM education and widened participation to attract a diverse talent pool to STEM education.

The paper is organized as follows: Section 2 reviews the literature. Section 3 provides the stylized facts on regional shares of STEM graduates, the relationship between STEM graduates and real GDP per capita and the connection between STEM graduates and approved utility patents. Section 4 describes the econometric models. Section 5 explains the results, and Section 6 concludes.

2. Literature Review

The association between education and economic welfare can be traced back to Adam Smith's *Wealth of Nations* (1776). The research on the importance of education for technological change and growth started in the 1960s and was fully developed as endogenous growth theory in the 1980s. Arrow (1962) explained how the optimal allocation of resources for invention depends on the technological features of invention techniques and types of market for knowledge. Romer (1986) included knowledge as an input in production in long-run growth theory and explained how knowledge generates endogenous technological changes. Lucas (1988) developed two models that describe the connection between human-capital accumulation and neoclassical growth; he measured human-capital accumulation both by schooling and by learning by doing. Romer (1990) concluded that the growth rate depends on the stock of human capital. Grossman and Helpman (1991) explained how the strength of intertemporal knowledge spillover could foster growth.

Empirical research concentrating on education, innovation and economic growth started in the 1990s and is divided into two main groups. One group investigates the effect of R&D expenditures on total factor productivity, and the other investigates the effect of the quantity and/or quality of education on economic growth. Aghion and Howitt (1992) developed a model in which competition among research firms creates innovation that leads to growth. Jones (1995) found no positive connection between the number of scientists and engineers engaged in R&D research and total productivity growth. Sylwester (2001) found no strong association between R&D expenditures and economic growth for 20 OECD countries.

The results on the connection between education and economic growth are mixed. Barro (1991) examined the effect of the initial school enrollment rate on real GDP per capita growth rate for 98 countries between 1960 and 1985. He found that initial level of school enrollment has a positive effect on economic growth. Bils & Klenow (2000) found that the effect of education on growth is frail and explains only one third of the relationship. Barro (2001) included average years of schooling, as well as science, mathematics and language scores, as proxies for human capital and investigated the effect of the individual variables on economic growth for 100 countries between 1965 and 1995. He found that science scores and the average years of schooling had a significant positive effect on growth. Andres and Looker (2001) examined the effect of residential areas (rural or urban) on educational expectations and attainments in British Columbia and Nova Scotia and found that students living in rural areas had lower expectations and attainments. They also found that rural youth from British Columbia were more likely to pursue tertiary education compared to the rural youth in Nova Scotia. Blöndal et al. (2002) found that compulsory schooling brought high private and social rates of return to education for OECD countries. Trostel et al. (2002) found no proof of increasing rates of return of education in 28 countries between 1985 and 1995. Bronzini and Piselli (2009) examined the long-run connection among total factor productivity, R&D, human capital and public infrastructure between 1980 and 2001 in Italian regions. They documented that R&D, human capital and public infrastructure have a positive effect on productivity, with human capital having the most significant effect.

The relationship between education and economic performance in the US has been studied extensively. De Young (1985) found that differences in economic and demographic variables have some effect on regional differences in educational quality among Appalachian and non-Appalachian school districts in Kentucky. He also found that the source of counties' income affects the educational status significantly. Income originating from manufacturing has a significant positive effect, and external control on mineral income has a significant negative effect on educational status. Domazlicky et al. (1996) examined the cost of high school non-completion for 24 counties in Southeast Missouri. They found that a one-percentage- point rise in the high school non-completion rate reduced a county's per-capita income by $52 in 1980. Thompson (1998) estimated the economic cost of high school non-completion in the US using 1990 census data. He found that the cost is higher for states with lower per-capita expenditures on education. Sloboda (1999) also examined the effect of the high school non-completion rate on the per capita income of 102 counties in Southern Illinois. He found that a one-percentage-point increase in the high school non-completion rate decreased per-capita income by $336 in 1990. Fullerton Jr. (2001) found a very similar result for Texas: the loss of income resulting from high school dropouts was $3.6 billion for the border counties in Texas. Using panel data for 44 counties in Central Indiana from 1990 to 1999. Dodge (2003) found a positive effect of education performance on per capita income. Examining 267 metropolitan areas in the US between 1980 and 1997, Gottlieb and Fogarty (2003) found that college education has a significant positive effect on the growth of income and employment. Almada et al. (2006) investigated the effect of dropout rates on per capita personal income in Texas counties that share the border with Mexico. They found that a decrease in dropout rates could increase income in the border counties. Aghion et al. (2009) examined whether increased investment in education enhanced growth. They found that exogenous shocks of four-year colleges had a positive impact on growth, while exogenous shocks of two-year colleges had no significant effect on growth. Exogenous shocks on research universities affected growth positively only for the states near the technological frontier. Fullerton Jr. et al. (2013) estimated the public infrastructure stocks for El Paso, Texas between 1976 and 2009 and their effect on short-run and long-run growth. They found that infrastructure stocks might have a negative effect on short-run growth but had positive effect on long-run growth. Fullerton Jr. et al. (2014) investigated the effect of educational attainment, private capital stocks and public capital stocks on income for 114 counties in Missouri. They found that both educational attainment and private capital stocks had a significant positive effect on income. However, the effect of public capital stocks was not clear.

While many economists take primary and secondary education as a proxy of human capital, others argue that science[4] and engineering education are vital for innovation and economic growth. Murphy et al. (1991) argued that the occupational choice of talented people in a country depends on the returns to ability. When talented people engage in innovation, they foster growth, but when they engage in rent seeking, they hinder growth. Murphy et al. considered the share of enrollment in engineering majors as a proxy for innovation for 91 countries between 1970 and 1985. They found that an increase in the share of enrollment in engineering majors enhanced growth. Giovanni et al. (2013) examined the effect of wage growth among STEM workers in the labor market, comparing college- and non-college-educated workers for 219 US cities between 1990 and 2010. They found that an increase in the share of H1 B Visa holders in STEM jobs increased the wage rate for both STEM and non-STEM college-educated workers. They also found that STEM workers increased total factor productivity in these US cities.

[4] Mathematics is included in science.

3. Stylized Facts

This section provides an overview of the share of STEM graduates in the United States as a whole and in four particular regions between 1990 and 2011. It also discusses the relationship of the share of STEM graduates with real GDP per capita and approved utility patents.

Figure 1 depicts the share of STEM graduates[5] in the United States as a whole and in four particular regions for the period 1990 and 2011. During this period, the share of STEM graduates decreased from 30.1% to 29.3% in the United States. The share of STEM graduates increased in the Northeast (from 31.9% to 32.2%), the South (from 27.6% to 27.9%) and the West (from 31.3% to 31.7%). However, it decreased by one percentage point (from 27.7% to 26.7%) in the Midwest.

Figure 2 represents the growth in the share of STEM graduates in the United States between 1991 and 2011. The growth rate is lowest in 1990 (-1.68%) and highest in 2010 (1.72%). The growth rate becomes negative in 2008. A high percentage of STEM graduates are international students,[6] and the global financial crisis in 2008 may have reduced the graduation rate of foreign students due to the bad job market.

Figure 3 shows the connection between the share of STEM graduates and log of real GDP per capita for the period 1990 to 2011. Each scatter point in Figure 3 represents the combination of 22 years' average of the share of STEM graduates and log of real GDP per capita for a given state. The positive slope (0.031) of the fitted line represents the positive correlation.

Figure 4 portrays the relationship between the average share of STEM graduates and the average of approved utility patents per one million people for the period 1990 and 2011. Each point in Figure 4 represents a given state. The positive slope (11.062) of the fitted line shows a positive relationship between STEM graduates and innovation.

4. Econometric Models and Specifications

This section describes the models to estimate the effect of the share of STEM graduates on the level and growth of real GDP per capita for the 50 US states and the District of Columbia for the period 1990 to 2011.

[5] The share of STEM graduates is the same as the share of STEM graduates in tertiary education.
[6] Shares of international STEM graduates in the bachelor's, master's and doctorates are 3.75%, 26.03% and 36.85%, respectively, in 2011.

Econometric models in Sections 4.1 and 4.2 estimate the effect of the share of STEM graduates on the level of real GDP per capita using STEM graduates as exogenous and endogenous, respectively. Section 4.3 describes the econometric model to estimate the effect of STEM graduates on the growth rate of real GDP per capita. Section 4.4 illustrates a model to estimate the effect of STEM graduates on innovation.

4.1 STEM Graduates and the Level of Real GDP Per Capita (Exogenous Case)

To examine the effect of the share of STEM graduates on the level of real GDP per capita, I use the following model:

$$log(y_{it}) = \alpha + \beta STEMGRAD_{it} + \gamma PHYKPC_{it} + \delta PWORKFORCE_{it} + \theta SDUMMIES + \varepsilon_{it} \quad (1).$$

y_{it} represents the real GDP per capita for state *i* at year *t*. $STEMGRAD_{it}$ is the share of STEM graduates for state *i* at year *t*. $PHYKPC_{it}$ is the log of real gross private physical capital per capita, and $PWORKFORCE_{it}$ is the share of the potential workforce (share of people between ages 25 and 64) for state *i* at year *t*. To control for the state fixed effect, I use dummy variables for states ($SDUMMIES$).

Data on private physical capital stock are not available for the US states. I compute the state real physical capital stock using the method suggested by Garofalo and Yamarik (2002). The procedure is explained below.

$$k_{ij}(t) = \left[\frac{y_{ij}(t)}{Y_j(t)}\right] K_j(t)$$

$$k_i(t) = \sum_{j=1}^{9} k_{ij}(t), t = 1990, 1991, \ldots \ldots \ldots \ldots \ldots, 1996$$

and

$$k_i(t) = \sum_{j=1}^{14} k_{ij}(t), t = 1997, 1998, \ldots \ldots \ldots \ldots \ldots, 2011$$

where, $y_{ij}(t)$ and $k_{ij}(t)$ are real GDP and the real gross physical capital stock, respectively for state *i* and industry *j* for period t. $Y_j(t)$ and $K_j(t)$ are the US real GDP and the US real gross physical capital stock, respectively, for industry j for period t. The industrial classification system is different prior to and after 1997. Before 1997, the Bureau of Economic Analysis (BEA) used the SIC industrial classification system, and after 1997, BEA used the NAICS industrial classification system. Therefore, the number of industries is different prior to and after 1997. I use the GDP of nine industries[7] between 1990 and 1996 and the GDP of 14 industries[8] between 1997 and 2011. Data on nominal net capital stock and depreciation between 1990 and 2011 are available from BEA for 19 industries. I adjust the net capital stock and depreciation by industries to be consistent with the industrial classification of GDP. For example, the net capital stock and depreciation of educational services, health care and social assistance come into two separate categories for net capital stock and depreciation. I add the two categories to make it comparable with GDP between 1997 and 2011.

The level of real GDP per capita, explanatory variables and residuals can be non-stationary. In that case, the estimation of equation (1) will provide spurious results. I use the Levin-Lin-Chu unit root test for the log of real GDP per capita, explanatory variables and residuals. Table 2 presents the result. All variables are stationary. To estimate the parameters, I use pooled OLS, OLS with AR(1) disturbance and GLS with AR(1) disturbance and robust standard errors for the panel data for equation (1).

4.2 STEM Graduates and the Level of Real GDP Per Capita (Endogenous Case)

The share of STEM graduates can be endogenous for two reasons. First, the existence of omitted variables affect both the level of real GDP per capita and the share of STEM graduates. Second, there is reverse causality between the level of real GDP per capita and the share of STEM graduates. Income level may influence the share of STEM graduates. If the share of STEM graduates is endogenous, the coefficients of equation (1) would be biased and inconsistent. I use a two-stage least squares instrumental variable (IV) method for pooled data to handle the possible endogeneity problem. I begin by introducing the following reduced-form models for the share of STEM graduates.

$$STEMGRAD_{it} = \bar{\alpha} + \bar{\beta}AvgPubExp_{it-1} + \bar{\gamma}AvgPriExp_{it-1} + \bar{\delta}PHYKPC_{it} + \bar{\theta}PWORKFORCE_{it} + \bar{\vartheta}SDUMMIES + \bar{\varepsilon}_{it} \quad (2).$$

[7] 1. Agriculture, forestry, and fishing; 2. Mining; 3. Construction; 4. Manufacturing; 5. Transportation and public utilities; 6. Wholesale trade; 7. Retail trade; 8. Finance, insurance, and real estate; 9. Services

[8] (1. Agriculture, forestry, fishing, and hunting; 2. Mining; 3. Utilities; 4. Construction; 5. Manufacturing; 6. Wholesale trade; 7. Retail trade; 8. Transportation and warehousing; 9. Information; 10. Finance, insurance, real estate, rental, and leasing; 11. Professional and business services; 12. Educational services, health care, and social assistance; 13. Arts, entertainment, recreation, accommodation, and food services; 14. Other services, except government)

$AvgPubEx_{it-1}$ and $AvgPriEx_{it-1}$ represent the log of four-year average of lagged real public and private expenditures per pupil,[9] respectively. I also use GMM to handle the endogeneity problem of equation (1).

4.3 STEM Graduates and the Growth of Real GDP Per Capita

To examine the effect of the share of STEM graduates on the growth of real GDP per capita, I use the following model:

$$g_{it} = \bar{\bar{\alpha}} + \bar{\bar{\beta}}\log(y_{it-1}) + \bar{\bar{\gamma}}STEMEGRAD_{it} + \bar{\bar{\delta}}PHYKPC_{it} + \bar{\bar{\theta}}PWORKFORCE_{it} + \bar{\bar{\varepsilon}}_{it} \quad (3)$$
$$\bar{\bar{\varepsilon}}_{it} = \bar{\bar{\varphi}}_i + \bar{\bar{\omega}}_{it} \,.$$

g_{it} represents the growth of real GDP per capita for state i at year t. $\bar{\bar{\varphi}}_i$ and $\bar{\bar{\omega}}_{it}$ are both i.i.d. random variables and $E(\bar{\bar{\varphi}}_i) = E(\bar{\bar{\omega}}_{it}) = 0$.

The one-period lagged income variable is presented to capture the initial conditions: the possibility that states may not be on their balanced growth paths and that some states may be further away than others. The presence of lagged income may make the explanatory variables endogenous and OLS estimates biased.

To estimate equation (3), I use the system GMM. System GMM is a combination of the difference GMM estimator for dynamic panel data model proposed by Arellano and Bond (1991) and the improved version proposed by Arellano and Bover (1995) and developed by Blundell and Bond (1998). Roodman (2009) offers an introduction of system GMM to linear GMM. The GMM first difference estimator takes the explanatory variables as endogenous and generates moment conditions by taking the lagged levels as instruments of the first difference. Arellano and Bond's (1991) first difference GMM estimators are often criticized because the lagged levels are often poor instruments for the first difference. Additionally, first difference GMM estimators have poor finite sample properties. However, inclusion of the original equation in levels will develop additional instruments and increase efficiency and improve finite sample properties. For both GMM and GMMIV, I use the GMM-style instruments proposed by Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991) for these explanatory variables. I use two additional explanatory variables: four-year average of lagged real public and private expenditures per pupil for

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[9] $AvgPubExp_{MN,1990} = \log\left(\left(\sum_{t=1986}^{1989} Real\ Public\ \ Expenditure\ Per\ Pupil_{MN,t}\right)/4\right)$

GMMIV. I consider these two new explanatory variables exogenous and use IV style instruments for these variables.

4.4 STEM Graduates and Innovation

Theories of economic growth claim that an increase in education encourages innovation. To examine this claim, I use the following model:

$$UTILITYPATENT_{it} = \tilde{\alpha} + \tilde{\beta}STEMGRAD_{it} + \hat{\theta}PWORKFORCE_{it} + \tilde{\gamma}R\&D_{it} + \tilde{\varepsilon}_{it} \quad (4)$$

$UTILITYPATENT_{it}$ represents the number of approved utility patents per one million people for state *i* at period *t*. I use utility patent as a proxy for innovation because the United States Patent and Trademark Office defines this type of patent as 'patent for invention.' $R\&D_{it}$ shows the share of R&D expenditures in GDP for state *i* at period *t*. To estimate the parameters of equation (4), I use pooled OLS, OLS with AR(1) disturbance and GLS with AR(1) disturbance and robust standard errors for panel data.

The share of STEM graduates can be endogenous due to the presence of omitted variables. I use GMM of equation (4) to deal with the endogeneity. I also use pooled IV estimation using equation (5) as the first-stage equation. Equation (5) is given below:

$$STEMGRAD_{it} = \bar{\alpha} + \bar{\beta}AvgPubExp_{it-1} + \bar{\gamma}AvgPriExp_{it-1} + \bar{\delta}PWORKFORCE_{it} + \bar{\theta}R\&D_{it} + \bar{\vartheta}SDUMMIES + \bar{\varepsilon}_{it} \quad (5).$$

5. Results

Table 3 represents the results of equation (1) using the pooled OLS Method, OLS with AR(1) disturbance and GLS with AR(1) disturbance and robust standard errors for panel data. The share of STEM graduates has a statistically significant positive effect on the level of real GDP per capita, and the results are similar regardless of the econometric techniques. For example, a one-percentage-point increase in the share of STEM graduates will increase the level of real GDP per capita by 0.48 percent for pooled OLS. Pooled OLS does not account for the autocorrelation of the residuals. However, first-degree autocorrelation is present in the residuals of equation (1). I estimate equation (1) by using OLS with AR(1) disturbance and GLS with AR(1) disturbance and robust standard errors for panel data. The share of STEM graduates has a statistically significant positive effect on the level of real GDP per capita for both econometric techniques.

However, the effect is lower (0.17 for OLS with AR(1) disturbance and 0.24 for GLS) compared to the pooled OLS (0.48). The level of per-capita physical capital also has a significant positive effect on the level of real GDP per capita. A one-percentage-point increase in per capita physical capital will increase real GDP per capita by between 0.66 and 0.74 percent, depending on the estimation technique. The share of the potential workforce also has a statistically significant positive effect, and the results vary between 0.52 and 1.44 percent. Dodge (2003) found very similar results for 44 counties in Central Indiana. He found that an increase in test scores has a significant positive effect on per capita income.

Table 4 presents the results obtained from pooled IV for equation (1) using equation (2) as the first-stage equation. Table 4 also reports the results from the GMM estimation. Results from pooled IV show that the share of STEM graduates has a significant positive effect on the level of real GDP per capita. However, the values of the parameters for STEM graduates are higher for the pooled IV (2.67) compared to the pooled OLS (0.48). The GMM estimate also shows a positive effect (0.65) of STEM graduates on the level of real GDP per capita. The level of per capita physical capital and the share of the potential workforce both affect real GDP per capita positively, and the results hold for both estimation techniques. Table 5 shows the results from first-stage equation. The four-year average of lagged private and public expenditures per pupil has a significant positive effect on the share of STEM graduates. A one-percentage-point increase in lagged average private expenditures per pupil will increase the share of STEM graduates by 0.02 percent. The result is same (0.02) for lagged average public expenditures per pupil.

The results from the GMM and GMMIV estimates of equation (3) are presented in Table 6. Initial income is negative (-0.03) and statistically significant for both GMM and GMMIV. The results confirm beta convergence. A one-percentage-point increase in the share of STEM graduates increases the growth of real GDP per capita by 0.11 percent for both GMM and GMMIV. The share of per capita physical capital has a significant positive (0.02) effect only for GMM. The share of the potential workforce has no significant effect either in GMM or GMMIV. This result is very similar to Gottlieb and Fogarty's (2003). They found that a one-percentage-point increase in the share of college graduates will increase growth by 0.04 percent.

To investigate the effect of STEM graduates on innovation, I estimate equation (4) using pooled OLS, OLS with an AR(1) disturbance and GLS with AR(1) disturbance and robust standard errors. The results are presented in Table 7. The share of STEM graduates has a statistically significant positive effect on the number of approved utility patents per one million people only for pooled OLS. A one-percentage-point increase in the share of STEM graduates increases the number of approved utility patents per one million people by 755.15. The share of the potential workforce has a significant positive effect on the number of approved utility patents. A one-percentage-point increase in the share of the potential workforce increases the number of approved utility patents between 286.20 and 378.56. The share of R&D expenditures has a significant positive effect (1616.89) only for polled OLS.

Table 8 reports the results of the pooled IV and GMM estimations of equation (4). Equation (5) is considered the first-stage equation for pooled IV. The share of STEM graduates has no significant effect on the number of approved utility patents for either estimation technique. The share of the potential workforce and the share of R&D expenditures both have a significant positive (2410.06 and 1568.97, respectively) effect only for pooled IV. The results from the first-stage equation for pooled IV are presented in Table 9. Lagged average private and public expenditures per pupil have a significant positive (0.02 and 0.01, respectively) effect on the share of STEM graduates.

6. Conclusion

This paper investigates how the share of STEM graduates affects the economic performance in American States. The results demonstrate that share of STEM graduates is a crucial factor for economic performance. The results provide strong evidence in favor of educational policies concentrating on improving STEM education in the US and could be used to argue for future STEM education policies and allocation of educational funds.

The US is one of the most dominant countries in scientific innovation, and, to maintain its dominance, the US needs to increase the number of STEM undergraduates by 34%[10] annually. However, the share of STEM graduates in the US decreased by 0.13% between 1990 and 2011. Twenty-five states experienced negative growth in the share of STEM graduates in this period. The Midwest is the most affected region, with eight states in that region having negative growth. In the Northeast, West and South, respectively, six, six and five states experienced negative growth. The President's council of advisors on science and technology policy provides reports and recommendations to improve K-12 and post-secondary STEM education. However, weak implementation, lack of STEM teachers and standard syllabi make the progress slow. This

[10] Report To The President, 'Engage To Excel: Producing One Million Additional College Graduates With Degrees In Science, Technology, Engineering, and Mathematics,' Executive Office of the President, President's Council of Advisors on Science and Technology, February 2012.

paper advocates future research on the implementation of recommendations for STEM education and its effect on the quality of STEM education in the US.

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Data Appendix

Data on the share of STEM graduates and the share of R&D expenditure in GDP are collected from the National Science Foundation. Data on nominal GDP, nominal net physical capital stock and nominal depreciation are obtained from the Bureau of Economic Analysis. Population and CPI data are collected from the Census Bureau and the Bureau of Labor Statistics respectively. The United States Patent and Trademark Office provides the data on approved utility patents.

Figure 1: Share of STEM Graduates (%)

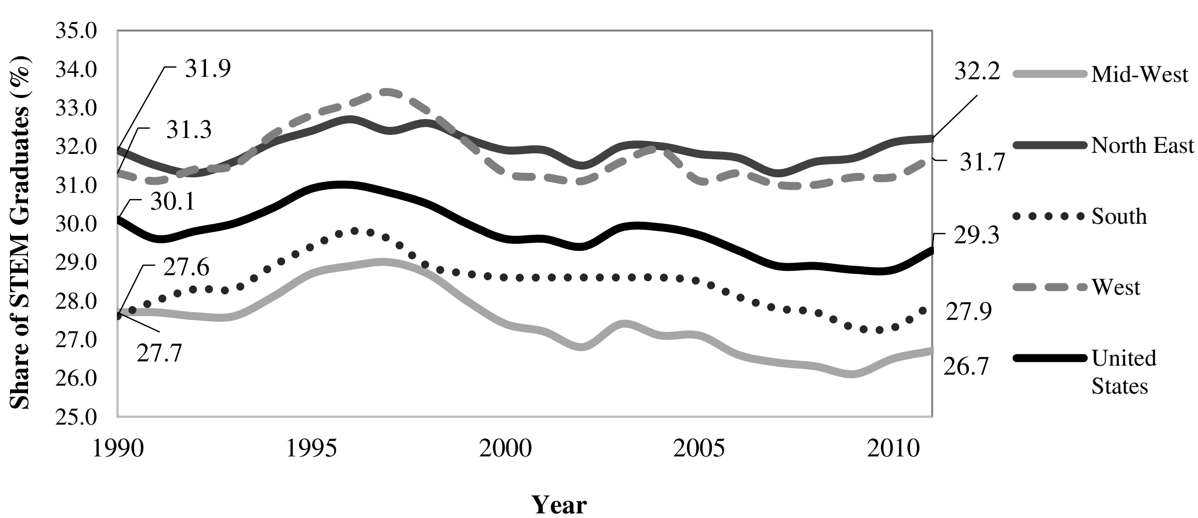


Figure 2: Growth of Share of STEM Graduates between 1991 and 2011 in the US

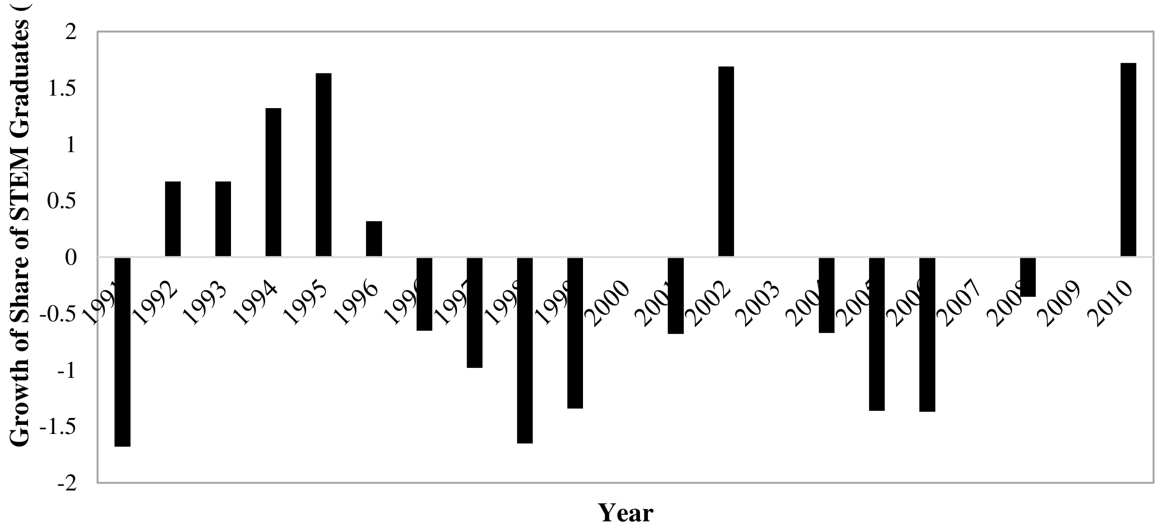
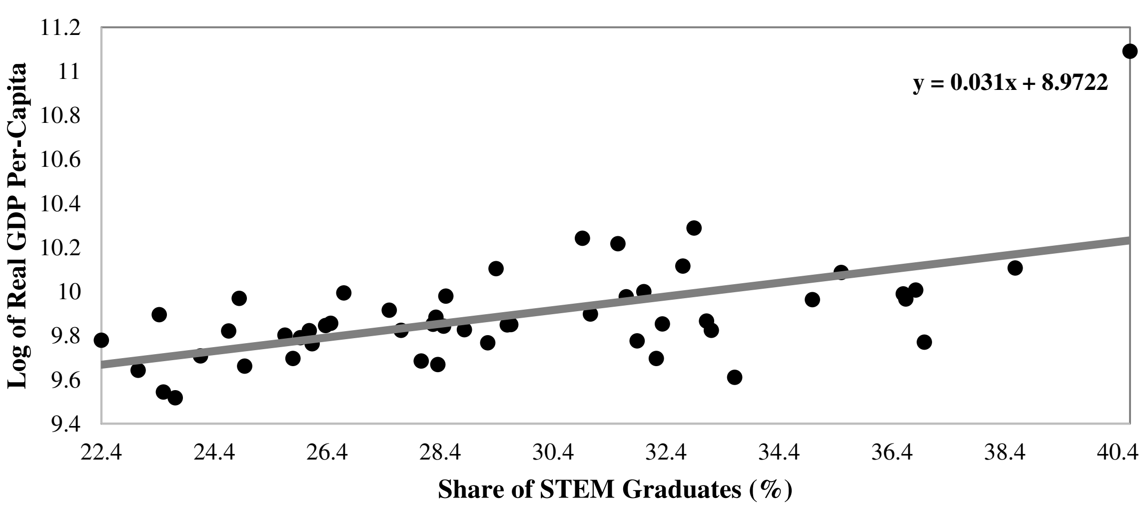


Figure 3: Share of STEM Graduates and Real GDP Per-Capita



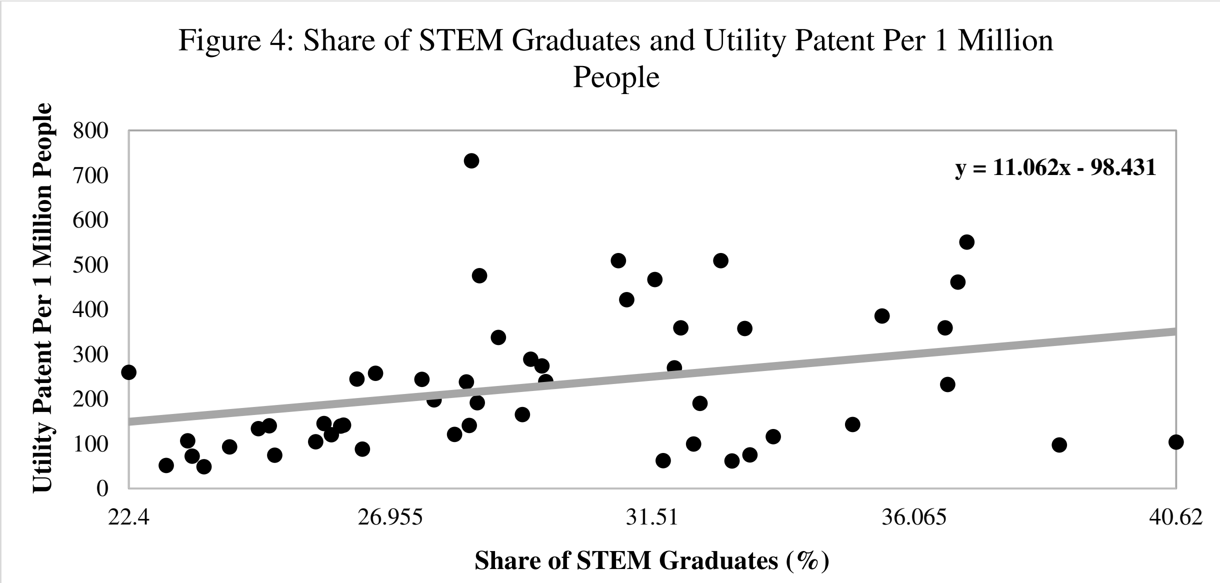


Table 1: Descriptive Statistics				
Variable	Mean	Standard Deviation	Min	Max
Real GDP Per-capita ($)	20485.10	7748.85	11498.48	81304.57
Share of STEM Graduates (%)	29.64	4.64	16.70	45.10
Capital Per-Capita ($)	24797.77	9510.37	14436.83	86995.24
Share of Workforce (%)	51.81	2.24	42.35	57.92
Public Expenditure Per Pupil ($)	8138.22	1821.32	3696.47	15072.49
Private Expenditure Per Pupil ($)	11658.50	6079.37	1185.76	37647.73
Utility Patent Per 1 Million People	229.45	178.27	26.46	1363.80
Share of R&D Performed in GDP (%)	2.11	1.54	0.09	9.73

Table 2: Levin-Lin-Chu unit-root test for Stationarity		
Ho: Panels contain unit roots Ha: Panels are stationary		
	Adjusted t	p-value
Real GDP Per-Capita	-8.429	0.000

Share of STEM Graduates	-2.622	0.004
Capital Per-Capita	-2.489	0.006
Share of Workforce	-3.010	0.001
Share of R&D Expenditure	-4.752	0.000
Utility Patent per 1 Million People	-1.689	0.046
Private Expenditure per Pupil	-4.006	0.000
Public Expenditure per Pupil	-11.362	0.000
Residual - Dependent variable: real GDP Per-Capita, Method: Pooled OLS with Robust Standard Error	-2.528	0.006
Residual - Dependent variable: real GDP Per-Capita, Method: OLS with AR(1) Disturbance	-2.621	0.004
Residual - Dependent variable: real GDP Per-Capita, Method: GLS with AR(1) Disturbance and Robust Standard Error	-2.592	0.005
Residual - Dependent variable: real GDP Per-Capita, Method: Pooled IV with Robust Standard Error	-3.442	0.000
Residual - Dependent variable: real GDP Per-Capita, Method: GMM	-3.069	0.001
Residual - Dependent variable: Utility Patent per 1 million People, Method: Pooled OLS with Robust Standard Error	-4.727	0.000
Residual - Dependent variable: Utility Patent per 1 million People, Method: OLS with AR(1) Disturbance	-4.989	0.000
Residual - Dependent variable: Utility Patent per 1 million People, Method: OLS with AR(1) Disturbance and Robust Standard Error	-1.386	0.083
Residual - Dependent variable: Utility Patent per 1 million People, Method: Pooled IV with Robust Standard Error	-3.442	0.000

Residual - Dependent variable: Utility Patent per 1 million People, Method: GMM	-4.299	0.000

Table 3: Level of Real GDP Per-Capita and Share of STEM Graduates (Exogenous Case)			
Dependent Variable: Log of Real GDP Per-Capita			
STEM Graduates	0.478**	0.175**	0.243***
	(0.101)	(0.074)	(0.073)
Capital Per-Capita	0.745***	0.658***	0.716***
	(0.017)	(0.017)	(0.015)
Share of Potential Workforce	1.437***	0.522***	0.819***
	(0.179)	(0.126)	(0.122)
R2	0.972	0.966	-
No. of Observation	1122	1122	1122
State Dummies	Yes	Yes	Yes
Estimate Auto-Correlation Coefficient	_	0.896	0.771
Method	Pooled OLS with Robust Standard Error	OLS with AR(1) Disturbance	GLS with AR(1) Disturbance and Robust Standard Error
Standard errors are in parenthesis. *** and ** represent significance at 1% and 5% level.			

Table 4: Level of Real GDP Per-Capita and Share of STEM Graduates (Endogenous Case)

Dependent Variable: Log of Real GDP Per-Capita

STEM Graduates	2.667***	0.654***
	(0.508)	(0.192)
Capital Per-Capita	0.780***	0.566***
	(0.022)	(0.108)
Share of Potential Workforce	1.831***	5.052***
	(0.228)	(0.827)
R^2	0.959	-
No. of Observation	1122	1122
Method	Pooled IV with Robust Standard Error	Pooled GMM

Standard errors are in parenthesis. *** represents significance at 1% level.

Table 5: First Stage Equation

Dependent Variable: Share of STEM Graduates

Average Private Expenditure per Pupil	0.023***
	(0.003)
Average Public Expenditure per Pupil	0.025***
	(0.004)
R^2	0.914
No. of Observation	1122

Heteroskedastic robust standard errors are in parenthesis. *** represents significance at 1% level.

Table 6: Real GDP Per-Capita Growth and Share of STEM Graduates

Dependent Variable: Real GDP Per-Capita Growth		
Initial Income	-0.031*	-0.030*
	(0.016)	(0.016)
STEM Graduates	0.112*	0.106***
	(0.063)	(0.036)
Capital Per-Capita	0.020*	0.018
	(0.011)	(0.012)
Share of Potential Workforce	-0.117	-0.105
	(0.099)	(0.093)
AR(1) in First Differences	-4.04	-4.14
No. of Observation	1071	1071
Method	GMM	GMMIV

Heteroskedastic robust standard errors are in parenthesis. *** and * represent significance at 1% and 10% level respectively.

Table 7: Approved Utility Patent and Share of STEM Graduates (Exogenous Case)

Dependent Variable: Approved Utility Patent per 1 Million People			
Share of STEM Graduates	755.153***	137.317	-87.958
	(195.520)	(198.887)	(68.346)
Share of Potential Workforce	2342.741***	387.569*	286.199***
	(245.828)	(361.257)	(95.835)
Share of R&D Expenditure	1616.887***	190.553	203.807
	(704.959)	(320.769)	(202.655)
R^2	0.789	0.753	-
No. of Observation	1122	1122	1122

State Dummies	Yes	Yes	No
Estimated Auto-Correlation Coefficient	-	0.900	0.735
Method	Pooled OLS with Robust Standard Error	OLS with an AR(1) Disturbance	GLS with AR(1) Disturbance and Robust Standard Error

Heteroskedastic robust standard errors are in parenthesis. *** and * represent significance at 1% and 10% level respectively.

Table 8: Approved Utility Patent and Share of STEM Graduates (Endogenous Case)

Dependent Variable: Approved Utility Patent per 1 Million People		
Share of STEM Graduates	968.236	23.551
	(630.948)	(128.845)
Share of Potential Workforce	2410.063***	50.425
	(308.575)	(239.949)
Share of R&D Expenditure	1568.968**	238.354
	(718.606)	(1379.143)
R^2	0.788	-
No. of Observation	1122	1122
Method	Pooled IV with Robust Standard Error	GMM

Standard errors are in parenthesis. *** represents significance at 1% level.

Table 9: First Stage Equation	
Dependent Variable: Share of STEM Graduates	
Average Private Expenditure per Pupil	0.022***
	(0.005)
Average Public Expenditure per Pupil	0.011***
	(0.004)
R^2	0.915
No. of Observation	1122
Heteroskedastic robust standard errors are in parenthesis. *** represents significance at 1% level.	