The Effects of STEM Education on Economic Growth

by

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ABSTRACT

CROAK, MALLORY A. The Effects of STEM Education on Economic Growth

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This thesis aims to build on existing studies of human capital and returns to education with a focus on innovation-fueling, STEM-based education, to answer: *How does STEM education affect macroeconomic growth across different countries?* A review of literature reveals that many studies account for human capital in growth equations, measured as average years of education. However, educational attainment as a measure of human capital leaves out the additional impact of research, technological know-how and innovation on growth. This thesis seeks to bridge some of the overlap between education and innovation as it affects productivity by focusing on education in STEM—fields that produce workers able to meet the growing science- and technology-based innovation that lies at the core of modern economic growth. The empirical framework for this study is derived from the traditional neoclassical growth model and is augmented to include an enhanced form of human capital: STEM educational attainment. The factor constraining data availability is reports of STEM first university degrees from the *National Science Foundation* (2014). One data set covers 87 countries for 2010 or most recent period. A second set covers 15 countries over the 2000-2010 period. Drawing on both cross-sectional and panel data sets, as well as on data for existing physical capital, human capital and level of development, estimates are obtained using regression analysis. The results of this study indicate significant, positive effects of STEM education on productivity across

specifications and call for policy that focuses on improving and promoting STEM programs at the post-secondary level.

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Chapter One

Introduction

I. Background Information

Studies of growth are among the most prominent publications in economic research. Essentially, they offer insight into what drives the health and vitality of economies over time. Understanding such underlying components has tremendously important policy implications, which can influence, among other things, employment, investment, individuals' standards of living and nations' relative positions in the world economy.

Historically, when assessing economic growth, studies have focused on two traditional inputs, which are labor and physical capital; however, when output was perceived as growing faster than the contributions of these two inputs, economists agreed that some residual factor was at play. This factor is often assumed to be the quality of labor or technological know-how, referred to as human capital. Overwhelmingly, studies have used educational attainment as a measure of this.

There is little dispute over the importance of human capital to productivity. The *National Science Foundation* (2014) states that, increasingly, governments around the world have come to regard movement toward a knowledge-based economy as key to economic progress. Realizing that this requires a well-trained workforce, they have invested in upgrading and expanding their higher education systems and broadening participation in them. A reasonable indicator of the importance of higher education is the percentage of a nation's resources devoted to it, measured by the ratio of expenditures on tertiary education to gross domestic product. Between 2005 and 2009, this ratio rose in nearly all OECD countries (*National Science Foundation* 2014).

While it is generally concluded that investment in human capital is beneficial for growth, the types of human capital investment that yield the greatest returns requires further investigation. A review of literature in the following chapter discusses the shortcomings of using general educational attainment as a measure of human capital. Primarily, it fails to consider both dimensions of the Solow residual, which is not only quality of labor, but also technological know-how. Emerging research suggests that education specifically related to science, technology, engineering and mathematics (STEM) disciplines is a better measure of human capital because it considers the importance of education that stimulates innovation and produces workers able to drive and respond to technological advancement, which lies at the center of economic prosperity.

Given the perceived importance of such innovation and technology-driven change in economies today, it is not surprising that STEM is a leading preoccupation of policy makers across nations. Now, the key becomes evaluating the ways in which countries promote STEM, and their effectiveness. This study seeks to investigate the benefits of STEM educational attainment, particularly at the post-secondary level. It takes as its inspiration reports like that by Marginson et al. (2013), which assert that science, universal learning, and economic prosperity all form a single interdependent system, which perhaps finds its bridge in STEM education.

II. Statement of Core Research Question

In an effort to build on existing studies of human capital and returns to education with a focus on innovation-fueling, STEM-based education, this thesis asks the following question: *How does STEM education as a form of human capital affect macroeconomic growth across different countries?* This study will focus on the 2000-2010 period and 15 Western/Asian countries in its panel estimation, and 87 regions/countries for 2010 or most recent year in its cross-sectional estimation. The selected time periods and countries are constrained by data availability for STEM first university degrees reported by the *National Science Foundation: Science and Engineering Indicators* (2014). My working hypothesis is that STEM educational attainment has a positive and significant effect on productivity across different countries, when measurements of existing physical capital stock, human capital and development level are included in estimations.

III. Significance of Thesis

This thesis—in addition to considering the importance of understanding what contributes to economic growth by examining the role of STEM education, with its potential to promote innovation—is significant for three key reasons. First, it takes a macroeconomic approach. Second, it uses data on undergraduate education. And third, it employs a panel data estimation.

While microeconomic studies establish nearly universally that there are tangible returns to individual investment in education—in the form of lower unemployment levels and higher earnings—these studies fail to account for the full extent of education's benefits, which spillover to the broader society and economy. This study employs macroeconomic regressions because, importantly, it is this kind of social return at the macro level that provides the relevant economic justification for the public support of education. Essentially, the aim of macroeconomic regressions is to investigate the role of the various inputs in contributing to GDP growth—in this case, STEM education among other control factors—in order to illuminate sources of difference in growth rates across countries and help identify policy measures most likely to promote growth. Indeed, governments and other agencies are increasingly funding studies of returns to education along with other research to guide macro-policy decisions about the organization and financing of education reforms. This study will go a step further to establish why such policy considerations should focus on STEM education.

Another distinguishing feature of this study is its concern with undergraduate STEM education, which many researchers regard as a highly important focal period, but one that is rarely central to policy. According to Krueger and Lindahl (2001), the empirical macro growth literature yields a principally different finding from the micro literature, which is that secondary and post-secondary education matter more for overall growth than primary education. Despite this, most studies looking at the effects of education on growth propose policy suggestions related to quality of teaching at the primary school level, but offer no tertiary suggestions. This is a serious area of limitation in growth studies, especially given the growing interest in STEM undergraduate programs. For one, the *National Science Foundation: Science and Engineering Indicators* (2014) reports that the baccalaureate is the most prevalent STEM degree in the U.S., accounting for roughly one-third of all bachelor's degrees over the last decade and for nearly 70% of all STEM degrees awarded in the U.S. Since 2000, the total number of bachelor's degrees and the number of STEM bachelor's degrees in the U.S. rose for all racial and ethnic groups from about 400,000 to more than 550,000 by 2011. Similar trends are taking place worldwide. In order to shed some light on a gap in the existing literature, this study will focus on STEM education at the undergraduate, post-secondary level.

Lastly, this thesis is significant because it employs a panel estimation. Cohen and Soto (2007) state that there are many cross-country growth regressions that exist, but that are limited because they do not exploit the time dimension. The few papers at the time of their report's publication that did progress towards panel data regressions—and which also accounted for physical capital, as this study does—failed to find significance for the effects of schooling on growth. This thesis will utilize panel data, harnessing cross-country as well as time-variant effects, to yield significant, robust results regarding the impact of STEM schooling on productivity over time, considering existing physical capital stock, human capital, and level of development.

IV. STRUCTURE OF THESIS

This thesis is divided into five chapters. Chapters One and Five are the introduction and conclusion, respectively. Chapters Two, Three and Four present the foundation for and specifications of macroeconomic regression analysis, which utilizes empirical data. Chapter Two offers a review of the relevant literature pertaining to existing macroeconomic growth studies and discusses the importance of STEM education, as well as why it is vital to consider level of development. Chapter Three presents the analytical framework of this study and develops specifications of a growth model that build on existing Solow neoclassical forms to include a STEM education variable. Chapter Four reports the regression results of both the panel and cross-sectional estimations. This is followed by an interpretation of the results and a discussion of their implications. The limitations of this study as well as some areas of future research are also considered.

CHAPTER TWO

REVIEW OF LITERATURE

I. INTRODUCTION

In this chapter, various sources of economic literature are reviewed and organized thematically by the ways in which they (i) support the relevance of using STEM Education as a measure of human capital, (ii) advocate for an aggregate or macroeconomic approach to assessing returns to education, in particular STEM education, and (iii) demonstrate why a consideration of countries' economic development levels is important when regressing productivity on education. While providing pertinent support for my thesis, to my knowledge, none of these works bridge the impacts of worker education and innovation to specifically answer the question that I aim to address. By drawing on elements of the literature discussed in the following sections, this thesis will build on existing studies of human capital and returns to education, with a focus on innovation-fueling, STEM-based education.

II. WHY STEM EDUCATION?

Prevailingly, studies on economic growth that consider the relevance of human capital use educational attainment as a measure (OECD 1998). For instance, Sianesi and Reenen (2002) review various studies that focus on the macroeconomic returns to education, regressing GDP per capita on average years of education. Similarly, Psacharopoulos and Patrinos (2004) estimate the average private and social rates of return to an additional year of schooling in various economies around the world. Mamuneas et al. (2006) estimate the effects of traditional inputs (capital and labor) as well as human capital (measured as mean years of schooling) using a semiparametric smooth coefficient model, which allows the effect of human capital on economic growth to be nonlinear. Furthermore, Cohen and Soto (2007) utilize data on educational attainment by age group and ultimately yield significant coefficients for schooling in their cross-country growth regressions.

However, a shortcoming of most reports like these is that the returns to specific types of education are not considered. Sianesi and Reenen (2002) emphasize an area for further research as a consideration of the type, quality and efficiency of education, which is shown to matter for productivity. Marginson et al. (2013) state that general educational attainment falls short as a proxy for human capital because it measures only quantity, not quality. Similarly, Islam, Ang and Madsen (2014) conclude that educational attainment is largely ineffective in predicting per capita gross domestic product (GDP) growth rates, suggesting that educational attainment may not adequately measure human capital if the quality dimension of education is omitted in the regressions. These assertions are evidenced, for instance, in one study that finds the relative importance of engineering in education (captured by the ratio of college enrollments in engineering to total college enrollments) to have a positive impact on growth, while finding the relative importance of legal studies to have a negative one (Sianesi and Reenen 2002).

Going hand in hand with this, many studies have been criticized for focusing only on educational attainment, leaving out the additional impact of research, technological know-how and innovation on growth (OECD 1998). A relevant conclusion by Sianesi and Reenen (2002) is that education yields *indirect* benefits to growth in addition to direct ones, primarily through stimulating technological development and adoption. Evidently, it is difficult to disentangle the impact of population (or workforce) education and an economy's technological capacity, which "average years of education" as the sole measurement of human capital neglects to account for. This thesis takes into consideration the effects of educational attainment, but with particular regard to STEM education in an effort to encompass the complexities of growth's "residual" factor, which relates to both labor quality and technology/innovation. This is supported by Marginson et al. (2013) who state that international evidence reveals educational quality, as measured by cognitive skills primarily in science and mathematics, is both a more accurate predictor of and a more significant influence on economic outcomes than general quantity of education.

In their comparison of STEM education in various countries, Marginson et al. (2013) conclude that there is widespread interest in building high-end STEM skills, linked to research & development as well as industry innovation. This is because it is assumed in most national jurisdictions that the quantity and quality of STEM competences affects economic performance. For this reason, a key focus should be improving the overall quality of the human capital supply as well as growing the high-skill group capable in research, innovation and effective response to technological change. Referencing various Asian economies that are at the top proficiency levels in science and math (based on the OECD's Programme for International Student Assessment) and that have simultaneously experienced exceptional economic performance over the last two decades, the report argues that a direct relationship exists between countries with leading economies and those with the strongest performing education and research-based science systems.

Indeed, economic modeling has consistently identified a relationship between direct measures of cognitive skills in math and science and long-term economic development. UNESCO refers to the role of science and technology capacity as being critical drivers for achieving sustainable development and gaining access to the knowledge economy and society. On the whole, governments agree that there is strategic importance to innovation and knowledge in STEM for the improvement of society and maintenance of economic growth over time. This may explain why, internationally, there has been an increase in both STEM enrollment and degrees. The *National Science Foundation* (2014) reports that, in 2010, more than 5.5 million S&E degrees were awarded worldwide, with nearly half in Asia (24% in China, 17% in the EU and 10% in the U.S.). For most countries (other than France, Japan and Spain) the number of bachelor's degrees awarded in S&E increased between 23% and 56% from 2000 to 2010.

Similarly, Atkinson and Mayo (2010) examine the significance of STEM education for productivity. Ultimately, the purpose of driving STEM education is not principally to create economic opportunity for individuals. Rather, it is to provide the “fuel” necessary for powering a technology-driven economy. Looking particularly at American STEM education, the paper cites a U.S. Department of Commerce finding that technological innovation has been responsible for as much as 75 percent of the growth in the American economy since World War II. Furthermore, Atkinson and Mayo (2010) state, some studies have estimated that innovation drives up to 90 percent of per-capita income growth. This is because innovation enables the productivity improvements that lie at the core of economic growth. Importantly, such science- and technology-based innovation is impossible without a workforce educated in science, technology, engineering and math.

Atkinson and Mayo (2010) caution that without the right number and quality of STEM-educated citizens, the innovation economy will falter, and with it, economic opportunity for all. The report cites as a warning the situation in the U.K. between 1960 and 1990, a time in which liberal arts education was stressed and the competitive position of industries was ignored. Due to this, the U.K. saw its technology industry decline significantly, with the total increase in U.K. manufacturing output only 1.3 percent, compared to 69 percent in Japan, 55 percent in the United States, and 32 percent in Germany. Atkinson and Mayo (2010) suggest following in the footsteps of China, whose officials recognize that STEM is more important than other subjects because the overall societal contribution from a STEM graduate exceeds that of a social sciences or humanities major. Without STEM graduates, a country does not innovate or, consequently, create jobs based on innovation.

In the end, it is important to recognize that innovation has huge advantages for the macro-economy. While Atkinson and Mayo (2010) and Marginson et al. (2013) mainly focus on national STEM education (in the U.S. and Australia, respectively)—and this thesis will broaden its analysis to the international level—both reports relevantly agree that, on average, companies don't accrue nearly all of the benefits from their research and innovation, most of it spills over to society. Likewise, STEM workers don't accrue the full benefits from their work, most spill over. Psacharopoulos and Patrinos (2004) discuss how various studies attempt to capture these externalities (spillover benefits) in the form of individuals' human capital enhancing the productivity of other factors of production. One study, for instance, that takes into account differences in technology, finds that social returns are comparable to private ones (whereas the private rate of return undoubtedly exceeded the social rate of return in literature that did not consider technology). STEM education, with its production of technology-specific knowledge, is therefore vital when considering overall economic growth, as driven largely by innovation.

III. A MACROECONOMIC FOCUS

OECD (1998) states that human capital investment bestows benefits on individuals, firms and societies. Economic benefits can accrue in the form of additional earnings or broader improvements in productivity and economic growth. Given this, there are two approaches for assessing the returns to human capital (taken as education). The individual benefits of investing in human capital are relatively straightforward: educational attainment is positively correlated with labor market performance, usually in the form of lower unemployment levels and higher earnings (OECD 1998). Due to the abundance of micro data, it is relatively easy to estimate the internal return rate using an earnings equation, taking into account the discount rate (which reconciles benefits received in the future, in the form of higher income, and costs incurred today, in the form of foregone earnings and additional schooling costs). In a study by Harmon, Oosterbeek and Walker (2002), wages are regressed on education using multivariate (OLS) analysis to derive meaningful estimates of the effect of one variable (in this case, education) on wages and 1995 International Social Survey Programme (ISSP) data. The results show wide cross-country variation on the returns to schooling in 25 countries; however, using UK micro data, the average return to a year of schooling in the UK is about 10% for women and 8% for men when employing a specification controlling for years of schooling and experience (current age minus the age left education). Overall, the conclusion is that there is an unambiguously positive effect on the earnings of an individual from participation in education.

Despite the relative lack of abundance in macro data, for the purposes of this thesis, the return to investment in human capital will be measured in relation to aggregate benefits, in particular productivity. Mamuneas et al. (2006) point out that numerous studies have estimated the return to human capital (education) on the basis of micro survey data, but do not provide estimates of the return to human capital based on aggregate (macro) data across various countries. Similarly, Psacharopoulos and Patrinos (2004) state that, whereas at the micro level it is established beyond a reasonable doubt that there are tangible and measurable returns to investment in education, such evidence is not as consistent and apparent in macro literature.

A macroeconomic understanding of returns to education is vital because individual level analyses like that by Harmon, Oosterbeek and Walker (2002), which only estimate the private returns to education, may underestimate the full returns to society. Sianesi and Reenen (2002) conclude that the benefits of individually acquired education may not be restricted to the individual but might very well spill over to other individuals in the same economy. Psacharopoulos and Patrinos (2004) add that if studies could account for the externalities (spillover benefits) of education, the social rates of return are likely higher than private ones. Note: economy-wide educational spillovers are by definition not taken into account in individual decisions on educational investments. Overall, there is compelling evidence that human capital increases productivity in the long run: on average, a one-year increase in average education raises the level of GDP per capita by 3-6%, according to Solow neo-classical specifications and by over 1% using estimates from new-growth theories (Sianesi and Reenen 2002).

Ultimately, regressions looking at the macroeconomic impact of human capital are positioned to capture the wider effects of such investments on national economic growth (Sianesi and Reenen 2002). So, while quantifying benefits to society may be more difficult, it is highly relevant given that the cost of investment in human capital is often borne with public money and the benefits are enjoyed by public institutions and the economy as a whole (OECD 1998).

Furthermore, it is vital to investigate what specific types of human capital investment yield the greatest returns, seeing as such benefits likely go far beyond additional earnings for individuals, yielding larger social and economic gain and therefore warranting policy consideration (OECD 1998).

Additionally, it is the social returns at the macro level that would provide the relevant economic justification for the public support of education. In their publication, Psacharopoulos and Patrinos (2004) state that, with the increase in academic literature on the returns to schooling, governments and other agencies are increasingly funding studies of returns to education along with other research to guide macro-policy decisions about the organization and financing of education reforms, as was the case in the UK and Australia over the prior decade. Looking specifically at STEM education and innovation, the societal return on investment from publicly funded research and development (R&D) are estimated to range from 20 percent to 67 percent, making studies of innovation-stimulating education of particular interest to policymakers (Atkinson and Mayo 2010). Marginson et al. (2013) confirm that, in recent years, many governments have policy agendas around lifting STEM performance (quantity and quality) to meet the challenges of international competitiveness and, in turn, productivity.

While macro regressions on education are evidently important, a limitation to them must be acknowledged. That is, the issue of reverse causality (i.e., the association between education and productivity growth may reflect the demand for education, as well as its supply effects). An example of this would be more developed countries often having high-tech production sectors that require a more educated workforce, stimulating an increase in the supply of technologically-skilled workers to match already-advanced levels of productivity (Sianesi and Reenen 2002).

IV. Level of Development Matters

Another important finding in the literature is that the existing level of economic development matters for assessing the impact of education on growth. When measuring the effect of human capital on productivity, Mamuneas et al. (2006) estimate the elasticity of output with respect to human capital, considering the possibility that the effect of human capital growth on economic growth differs across countries. Indeed, the results of the study indicate that returns to human capital vary significantly across countries based on existing levels of human capital: economies with relatively low levels of human capital have decreasing returns to scale for human capital, whereas middle-level human capital economies have increasing returns and highest human capital economies have constant or mildly increasing returns to human capital.

Similarly, Sianesi and Reenen (2002) corroborate studies that find the impact of increases in average education on productivity varies greatly based on the level of a country's development. In most cases, developing and developed countries are integrated into a single framework; however, some studies using sub-samples have found that the impacts of human capital vary considerably, both in statistical significance and in magnitude, according to the level of development of the countries considered. In one study, splitting the sample (of heterogeneous countries observed) according to the level of development clearly shows that various regressors have a different impact for the homogenous sub-samples (e.g. only OECD countries). For this reason, Sianesi and Reenen (2002) conclude that it is very hazardous to lump estimates on more restricted samples with those representing an average over more diverse countries.

Furthermore, in reference to a possible reverse causality bias, the Sianesi and Reenen (2002) report states that it is important to control for level of development when regressing growth on education because in countries at higher income levels that have already gone through the stages of development, a larger incidence of the service and high-tech production sectors will require a better-educated workforce. Due to recommendations from the relevant literature, this thesis will control for levels of economic development when regressing productivity on human capital (in particular, STEM education).

V. CONCLUSION

A review of the relevant literature has now been conducted. In the following chapter, I will expand on the dynamics of macroeconomic growth by presenting the analytical framework of this study. This begins with a discussion of both the neoclassical approach and new growth theories for estimating productivity. Ultimately, I introduce the methodology most apt for the purposes of this study's estimation of the effects of STEM education on growth, which takes an augmented Solow neoclassical approach.

CHAPTER THREE

THE ANALYTICAL FRAMEWORK

I. INTRODUCTION

This chapter presents the Analytical Framework and model that will be used to estimate the effects of STEM education on economic growth. In the first section, the two predominant growth models—Solow neoclassical and new growth theories—are compared. Ultimately, the model derived by Cohen and Soto (2007), which includes an augmented form of labor, is used as the foundation for this study's model. In the second section, I present variations of this model and the econometric functional forms that will be used to regress growth on STEM education, controlling for some relevant factors. I introduce each variable and discuss the reason for its inclusion.

II. NEOCLASSICAL APPROACH VERSUS NEW GROWTH THEORIES

Sianesi and Reenen (2002) distinguish in their report between two approaches used in the empirical literature to assess the effects of education on productivity: the Solow neo-classical approach, which looks at whether the stock of education affects the long-run *level* of the economy, and the new growth theories, which look at the long-run *growth rate* of the economy. The latter emphasize the endogenous determination of growth rates, which are determined within the model (i.e. by human capital, knowledge, and innovation, which can be affected by government policies), instead of being driven by exogenous technological progress. These new growth theories would argue that an increase in human capital is associated with a permanent increase in the growth rate, making the social benefits of education much greater in this case.

Sianesi and Reenen (2002) conclude that the implied effects of the stock of human capital on growth seem implausibly large in the new growth approach and are overstated due to methodological problems such as correlation with omitted variables. The neoclassical approach, on the other hand, generates effects that are more reasonable and consistent with the micro-economic evidence.

However, more recent developments in new growth theory have been made since the review by Sianesi and Reenen (2002), challenging their conclusion as outdated. In a more current study, Ang and Madsen (2011) state that the Schumpeterian growth model is the second-generation endogenous growth model that best explains growth in the United States and mature OECD countries. In their analysis, they set out to discover if this were also true for economies, like many of those in Asia, that have undergone marked growth spurts in recent years. The results show evidence of scale effects in ideas production, suggesting the presence of strong inter-temporal knowledge transfer. Additionally, consistently significant coefficients of R&D intensity suggest that R&D intensity has permanent growth effects. Essentially, the findings offer very strong evidence that growth is driven by research intensity, as predicted by Schumpeterian growth theory. Relevant to this study, Ang and Madsen (2011) conclude that a country which seeks to be competitive in the global economy requires a highly skilled labor force as well as significant R&D investment.

In another study, Islam, Ang and Madsen (2014) assert that endogenous growth models which look at the effects of human capital on productivity produce inconsistent macro-level empirical evidence. This is because they measure either the quantity or quality of education—by their definition, educational attainment measures the number of years of schooling among the adult population, whereas educational quality captures how much they have actually learned in school. Islam, Ang and Madsen (2014) argue in favor of using quality-adjusted educational attainment as the measure of human capital in growth regressions. Their regression results give support to the Solow growth model when it is extended to allow for quality-adjusted human capital as well as its interaction with DTF (i.e., Distance to Frontier, a measure of initial development level based on income data for the year 1970, which marks the start of their sample period).

Following this line of thinking, an augmented Solow neoclassical model, like that used by Cohen and Soto (2007) to regress growth on human capital, can be built upon to include not only a measure of enhanced labor, augmented by educational attainment (i.e. human capital), but furthermore a specific type of this human capital, which attempts to take into account the type/quality of education as well as dynamics of technology and initial level of development (i.e. innovation-fueling, STEM education across different countries).

The basic aggregate production function underlying the neoclassical growth model is as follows:

$$\mathbf{Y_{it} = A_{it}\, K_{it}^{\alpha}\, L_{it}^{1-\alpha}}$$

Y represents output or real income (GDP). A is Total Factor Productivity (TFP) or the portion of output not explained by the contributions of inputs used in production; this is also known as the Solow residual. Additionally, K is a measure of physical capital and L represents the total labor force.

Cohen and Soto (2007) derive the following expanded Solow model:

$$\mathbf{Y_{it} = A_{it}\, K_{it}^{\alpha}\, H_{it}^{1-\alpha}}$$

In this model, an augmented form of labor is considered, which is human capital enhanced by education (and measured as educational attainment).

Given that $\mathbf{H_{it}} = \mathbf{h_{it}}\ \mathbf{L_{it}}$, dividing by total labor force obtains the per-worker equation:

$$\mathbf{y_{it} = A_{it}\, k_{it}^{\alpha}\, h_{it}^{1-\alpha}}$$

In their study, Cohen and Soto (2007) conclude that standard cross-country growth regressions yield significant coefficients for schooling. Estimates using panel data are also significant even when the regressions account for the accumulation of physical capital. However, as mentioned above, taking into consideration the new developments in growth theory and particularly the importance of innovation, an augmented neo-classical specification, which builds on the model by Cohen and Soto (2007) to include STEM education is best to use when capturing the effects of human capital on growth.

Much as Cohen and Soto (2007) augment labor with human capital to obtain $\mathbf{H = hL}$, this study will further augment labor with not only general human capital, but with STEM education, in particular, to arrive at $\mathbf{H = h^a s^b L}$ (where a, b ≥ 0). Substituting this enhancement into their standard $\mathbf{Y = A\ K^{\alpha}\ (H)^{1-\alpha}}$ gives us:

$$\mathbf{Y = A\ K^{\alpha}\ (h^a s^b L)^{1-\alpha}}$$

Or the per-worker version:

$$\mathbf{y = A\ k^{\alpha}\ h^{a(1-\alpha)}\ s^{b(1-\alpha)}}$$

This can be specified as follows:

$$\mathbf{\log(\mathit{y}) = \log(\mathit{A}_{it}) + \alpha \log(\mathit{k}_{it}) + a(1-\alpha) \log(\mathit{h}_{it}) + b(1-\alpha) \log(\mathit{s}_{it}) + \varepsilon}$$

III. THE MODEL

This study uses four variations on a basic growth model to estimate the effects of STEM education on economic growth. The following specification of the Cohen and Soto (2007) model is used as a base:

$$\mathbf{\log(\mathit{y}_{it}) = \log(\mathit{A}_{it}) + \beta_0 + \beta_1 \log(\mathit{k}_{it}) + \beta_2 \log(\mathit{h}_{it}) + \varepsilon}$$

Below, Equation (1) shows a general model of per-worker GDP growth, which considers physical capital and human capital, extended to include measurements of development level and STEM education, as well. Logs are taken of all terms except initial GDP, which, unlike other variables in the estimation, measures a level at a single point in time and not a change (or growth) over the observed period. In an effort to capture a potentially more complex dynamic that some of the literature gestures towards, Equation (2) is developed. It builds on the first equation by specifying an interaction term between human capital and STEM education, representing an adjusted model that accounts for the effects of STEM educational attainment on per-worker growth, the magnitude of which depends on countries' existing human capital.

Equations (3) and (4) modify the first two by adding a quadratic term in the form of $[\log(s)]^2$. This considers the possibility of a non-linear relationship between STEM educational attainment and the dependent variable, annualized growth—i.e., that the effect of STEM educational attainment on growth changes as you get more it. A negative coefficient on $[\log(s)]^2$ would indicate that the slope of the curve (showing the relationship between $\log(s)$ and $\log(y)$) becomes less positive as the amount of STEM education increases. This is to say, the effect of STEM education on growth diminishes with more STEM education. Conversely, a positive coefficient on $[\log(s)]^2$ would indicate that the effect of STEM education on growth increases with more STEM education. Note: it is the STEM educational attainment variable (s) that is squared, not the Beta coefficient on it, which means (3) and (4) still qualify as linear models.

$$\textbf{(1)}\ \log(y_{it}) = \log(A_{it}) + \beta_0 + \beta_1 \log(k_{it}) + \beta_2 \log(s_{it}) + \beta_3 \log(h_{it}) + \beta_4 (y_{i,t-1}) + \varepsilon$$

$$\textbf{(2)}\ \log(y_{it}) = \log(A_{it}) + \beta_0 + \beta_1 \log(k_{it}) + \beta_2 \log(s_{it}) + \beta_3 \log(h_{it})*\log(s_{it}) + \beta_4 (y_{i,t-1}) + \varepsilon$$

$$\textbf{(3)}\ \log(y_{it}) = \log(A_{it}) + \beta_0 + \beta_1 \log(k_{it}) + \beta_2 \log(s_{it}) + \beta_3 [\log(s_{it})]^2 + \beta_4 \log(h_{it}) + \beta_5 (y_{i,t-1}) + \varepsilon$$

$$\textbf{(4)}\ \log(y_{it}) = \log(A_{it}) + \beta_0 + \beta_1 \log(k_{it}) + \beta_2 \log(s_{it}) + \beta_3 [\log(s_{it})]^2 + \beta_4 \log(h_{it})*\log(s_{it}) + \beta_5 (y_{i,t-1}) + \varepsilon$$

In the above specifications, y is the dependent variable or GDP per labor force, A is Total Factor Productivity, k is physical capital per labor force, h is a general measure of human capital per person, s is enhanced human capital measured as STEM degrees per worker, and $y_{i,t-1}$ is the control variable for level of economic development. It is important to reaffirm that, whereas growth is measured as the percentage change in GDP per worker, economic development is measured as the level of GDP per worker as of the year t-1 (the level of GDP before the year, t, for which all other data are collected for a given country). Furthermore, applying logarithms to the relevant variables creates a log-linear model, enabling an analysis of the relationship between growth and STEM educational attainment over time. Essentially, after estimating the above-specified equations, $\frac{\partial \log(y_t)}{\partial t}$ can be calculated, allowing a determination of the contributions of k, h and s to real GDP per worker growth.

IV. CONCLUSION

An analytical framework that considers the context of economic growth and enhanced human capital has now been developed. In the following chapter, I will introduce the sources from which data on each variable are collected. The data set includes real GDP, physical capital stock, an index of human capital and STEM educational attainment. Cross-sectional as well as panel data, which covers different economies over various years, is utilized. The data are examined and the regression results are analyzed in a discussion of how STEM education affects growth.

CHAPTER FOUR

DATA AND RESULTS

I. INTRODUCTION

In this chapter, I present the data and empirical results for this study. The first section introduces the data utilized and explains the importance of employing a panel—as opposed to a purely cross-sectional or time series—analysis. The second section reports and analyzes the regression results for the panel and cross-sectional data sets, respectively. A re-estimation of the cross-sectional regressions, which excludes outlying countries, follows. In the last section, I discuss the implications of the results and gesture towards relevant policy considerations.

II. SOURCES OF DATA

In their report, Sianesi and Reenen (2002) discuss various macroeconomic studies of the returns to education. They state that the measure of productivity is most often aggregate real GDP per capita (or per worker or per working-age person). Furthermore, regressors typically include proxies of human capital, initial level of GDP and physical investment ratios. As mentioned in the preceding chapters of this thesis, the pervasive measure of human capital is educational attainment (mean years of schooling) as in the studies by Psacharopoulos and Patrinos (2004), Mamuneas et al. (2006) and by most of those reviewed in the Sianesi and Reenen (2002) report.

Including many of these variables, the following data are collected from Summers and Heston (Penn World Tables). Growth data are Expenditure-side real GDP at chained purchasing power parity (PPPs) for the 2000-2010 period. To obtain per-worker GDP, Labor Force data are collected as Number of Persons Engaged. Physical Capital data are Capital Stock at Current PPPs for 2000-2010. Note: this requires a measure of prices to deflate the data and adjust for inflation. In order to do this, an index of the Price Level of the Capital Stock is collected for each year. Initial Development Level data are Expenditure-side real GDP at chained PPPs for the year preceding the relevant period of study: that is, 1999 for a panel data estimation, which looks at the 11 year inclusive period, and 2009 for a cross-sectional estimation, which focuses on the year 2010. Additionally, data on general educational attainment are obtained for 2000-2010 using the Index of Human Capital per Person, which is based on years of schooling reported in the 2012 Barro and Lee Educational Attainment Dataset and on returns to education from Psacharopoulos (1994).

For data on enhanced or augmented human capital, this study focuses on a report of STEM educational attainment. The *National Science Foundation: Science and Engineering Indicators* publication (2014) provides comprehensive data on the number and proportion of first university STEM degrees. One data set includes number of first university degrees in “All Fields” as well as “All S&E Fields” and other STEM subfields, by selected region for 87 countries, during 2010 or the most recent year. **Table 4.1** below denotes the countries for which 2010 STEM degree data were not used and the most recent year available for which data were collected instead. Note: all other data for a given country corresponds to the year for which STEM degree data are collected (as mentioned, this means initial level of GDP is collected from whichever the preceding year is).

Country	**Year**
Bangladesh	2003
Cambodia	2009
Georgia	2007
India	2003
Malaysia	2009
Iran	2007
Iraq	2004
Jordan	2007
Algeria	2007
Burundi	2004
Cameroon	2008
Ghana	2009
Kenya	2001
Mozambique	2011
Namibia	2008
Swaziland	2006
Uganda	2004
France	2009
Luxembourg	2008
Albania	2003
Guatemala	2007
Honduras	2003
Argentina	2009
Bolivia	2000

Table 4.1 Countries for which 2010 STEM degree data were not available, and the most recent year for which data were collected instead.

Additionally, a panel data set for S&E first university degrees, by 15 selected Western or Asian country/economy and field is reported for the 2000–2010 period. The countries are as follows: Australia, Canada, China, France, Germany, Italy, Japan, Mexico, Poland, South Korea, Spain, Taiwan, Turkey, United States, United Kingdom. It is important to note that data on “All S&E Fields” are not available for France (2010) and Canada (2001, 2002, 2003). **Table 4.2** on the following page reports Summary Statistics for the panel data, averaged over the relevant period.

Country	S&E Degrees	Real GDP in bilions US$	Population (in millions)	Labor Force	Capital Stock in billions US$	Price Level of Capital Stock	Human Capital
Australia	44,057	812.56	20.44	9.73	2807.32	0.97	3.48
Canada	60,948	1281.69	32.33	16.43	3972.24	0.88	3.58
China	789,597	8584.64	1305.53	752.74	23412.98	0.31	2.27
France	108,817	2173.35	63.03	26.49	7262.42	1.06	2.97
Germany	90,273	2995.74	81.2	39.49	10201.14	1.03	3.61
Italy	80,615	2002.09	58.51	24.18	8237.27	0.77	2.88
Japan	346,257	4324.21	126.78	64.86	15006.12	1.04	3.42
Mexico	107,493	1473.2	110.22	42.22	3497.31	0.72	2.51
Poland	98,235	627.15	38.49	14.56	1318.78	0.58	3.12
South Korea	116,852	1320.41	47.63	22.59	4688.28	0.56	3.33
Spain	65,470	1367.51	43.8	19.27	5131.83	0.81	2.72
Taiwan	76,307	813.29	22.72	9.98	1982.32	0.45	2.92
Turkey	69,063	884.03	67.78	18.97	1853.07	0.49	2.1
United States	461,659	14570.96	296.36	142.68	44021.08	0.89	3.63
United Kingdom	108,270	2282.52	60.48	28.56	6850.93	1.06	3.61
Universal	**174,928**	**3034.22**	**158.35**	**82.18**	**9349.54**	**0.77**	**3.08**

Table 4.2 Summary Statistics for 15 Western/Asian Countries averaged over the 2000-2010 period.

This study will utilize both data sets on STEM education as it is reported in the 2014 *NSF* publication in an effort to harness the benefits of using panel data. Sianesi and Reenen (2002) discuss these benefits. They reveal that, at the time of their report, there was a prevailing use of cross-country variation when looking at returns to education; that is to say, cross-sectional data were used most often in macro regression analyses. However, around this time, some more forward-looking studies were trying to exploit time-series information for countries in a panel approach. Such pooled cross-country time-series data can be used to explain both the cross-country differences in growth as well as the evolution of economic performance over time in each country. Some benefits to this approach include the possibility of controlling for endogeneity biases and unobserved or omitted variables that are constant over time but may be correlated with some regressors (like existing human capital).

III. REPORT AND ANALYSIS OF PANEL RESULTS

When estimating the model using panel data, an unbalanced panel is built using data on the above-mentioned variables over 11 periods (years) and 15 cross-sections (countries). 165 observations are sampled from the Cohen and Soto (2007) estimation and 161 from the estimations corresponding to Equations (1) and (2) from Chapter Three. The results are summarized in **Table 4.3**. Because development level is measured as initial GDP per worker, which is a single period observation (year t-1) for each country, aggregate growth cannot be regressed on it in a panel estimation. In an effort to still capture time-invariant, country-specific characteristics in the estimation, fixed cross-section effects are specified. This serves as a reasonable proxy for level of development and eliminates the omitted variable bias that would potentially result from not including initial GDP per worker in the regression. Note: the coefficients on all variables are more significant and the adjusted R-value is higher when cross-section fixed effects are specified.

Estimating the basic model provided by Cohen and Soto (2007), the results are significant for all coefficients and the adjusted R-squared value indicates that approximately 72% of the variation in this sample's GDP per labor force can be explained by the regression results. An interpretation of the coefficient on physical capital is, on average, each additional ten percentage points increase in real capital stock per worker is associated with an approximate 6.6 percentage point increase in annualized GDP per labor force, ceteris paribus. Looking at the coefficient on human capital, an additional percentage point increase in the index of human capital per person is associated with 1.2 percentage point increase in annual per-worker growth, on average and ceteris paribus.

Estimating Equation (1) from Chapter Three, the results are significant for all coefficients. Coefficients on physical capital and human capital are positive, as expected. The coefficient on STEM can be interpreted as, on average, for each additional ten percentage points increase in number of first university STEM degrees per worker, one can expect an approximate 2.4 percentage point increase in annualized GDP per labor force, ceteris paribus. Importantly, nearly 99% of the variation in GDP per labor force in this sample can be captured by the regression results. This indicates that an estimation considering STEM education, specifically, is a better fit than the general Cohen and Soto (2007) estimation when regressing growth on education.

Estimating Equation (2), which includes an interaction term between index of human capital per person and augmented human capital in the form of per-worker STEM degrees, the results are significant for all coefficients. Coefficients on physical capital and human capital are positive, as expected. Furthermore, nearly 99% of the variation in the dependent variable can be explained by the regression results. The coefficient on STEM education remains positive and significant. It indicates that, on average, each additional ten percentage points increase in STEM degrees is correlated with an approximate 2.2 percentage point increase in annualized GDP per worker, ceteris paribus; however, considering the presence of the interaction term, which captures the effect of additional STEM education on growth given existing human capital, the true interpretation is: for each additional ten percentage points increase in first university STEM degrees per worker, one can expect a 2.9 percentage point increase in annualized GDP per worker given countries' existing human capital, on average, all else equal.

Some calculation is necessary to explain the magnitude of this interpreted effect on growth. Corresponding to Equation (2), the regression results can be translated as:

$$\log (y) = \hat{\beta}_0 + \hat{\beta}_1 \log (x_1) + \hat{\beta}_2 \log (x_2) + \hat{\beta}_3 \log (x_2) * \log (x_3)$$

Where: y = GDP per labor force
$x_1 = k$ = physical capital per labor force
$x_2 = s$ = first university STEM degrees
$x_3 = h$ = index of human capital per person

Focusing on the interaction term, we can derive:

$$\frac{\frac{\partial y}{\partial t}}{y} = \% \,\Delta\, y = \ldots + \hat{\beta}_3 \% \,\Delta\, x_2 \log (x_3) + \hat{\beta}_3 \% \,\Delta\, x_3 \log (x_2)$$

Essentially, the effect of the percentage change in *s* depends on *h*, and vice versa. Mathematically, this means the effect of per-worker first university STEM degrees on per-worker annualized growth is a matter of both the estimated coefficient on log(*s*) and on the interaction term, the latter multiplied by the average index of human capital per person. In this case, the average used was the universal one on human capital denoted in **Table 4.2**, which is 3.08. Ultimately: 2.2 + (0.06 * ln(3.08) * 10) = 2.9.

The significance of existing human capital in this study supports the findings of Marginson et al. (2013), which state that agendas for STEM economic policy are driven first and foremost by the need to improve the general quality of the human capital supply, which is necessary for then cultivating the high-skill subset of workers who are able to innovate and adapt to technological change. For this reason, national STEM projects are not solely focused on the R&D system, except in relation to the training of knowledge workers. Rather, they focus primarily on STEM in terms of human capital—that is, human learning, knowledge and skills—and their applications in the labor market.

Continuing with an estimation of Equation (3), the coefficients on all variables are statistically significant and over 99% of the variation in GDP per labor force in this sample can be captured by the results. Coefficients on physical capital and human capital are positive, as expected. The coefficient on STEM education indicates that, on average, for each additional percentage point increase in number of first university STEM degrees per worker, you can expect an approximate 2 percentage point increase in annual GDP per labor force, ceteris paribus. However, the coefficient on STEM squared must be considered. The negative value of the coefficient indicates that there are decreasing returns to STEM education, or that increases in STEM degrees per worker lead to smaller and smaller increases in GDP per worker. For this reason, the net effect of each additional percentage point increase in number of first university STEM degrees per worker is, on average, an approximate 1.9 percentage point increase in annualized per-worker growth, ceteris paribus. Note: this is the net of the coefficients on $\log(s)$ and $[\log(s)]^2$.

Lastly, estimating Equation (4) yields results that are also significant for each coefficient and which explain over 99% of the variation in the dependent variable. Once again, the coefficients on physical capital and human capital are positive. The effect of STEM education on growth, with considerations of coefficients on both the interaction term and on the quadratic term, can be interpreted as follows: on average, an additional percentage point increase in first university STEM degrees per worker is correlated with an approximate 2.1 percentage point increase in annual GDP per labor force given countries' existing human capital, all else equal. Note the underlying calculation:

$2.0 + (-0.13) + (0.21 * \ln(3.08)) = 2.1$.

Table 4.3 Panel Data Estimation Regression Results

DEPENDENT VARIABLE: ANNUALIZED CHANGE IN LOG GDP PER WORKER

Estimation	***Cohen and Soto (2007)***	***Equation (1)***	***Equation (2)***	***Equation (3)***	***Equation (4)***
log(k)	0.655***	0.104***	0.139***	0.036*	0.058***
	(.052)	(.026)	(.025)	(.022)	(.023)
log(s)		0.240***	0.215***	2.013***	2.022***
		(.028)	(.053)	(.209)	(.226)
log(h)	1.229***	1.147**		2.020***	
	(.150)	(.301)		(.267)	
log(h)*log(s)			0.057*		0.208***
			(.034)		(.034)
$[\log(s)]^2$				-0.118***	-0.131***
				(.014)	(.016)
R-squared	*.72*	*.99*	*.99*	*.99*	*.99*
Durbin-Watson	*.08*	*.41*	*.45*	*.50*	*.46*
Observations	*165*	*161*	*161*	*161*	*161*

Notes: k is physical capital per labor force, s is first university STEM degrees per worker, h is index of human capital per person, fixed cross-sectional effects specified as proxy for development level. Standard errors in parentheses, coefficients significant at 1% (***), 5% (**) and 10% (*).

IV. TOTAL FACTOR PRODUCTIVITY

As discussed in the preceding sections, Total Factor Productivity (TFP), represented for the purposes of this study as *A*, represents the Solow Residual or contribution to aggregate growth that cannot be accounted for by the traditional input units. This is often considered to be exogenous technological progress. Atkinson and Mayo (2010) discuss the importance of including TFP in growth regressions, concluding in their results that differences in total factor productivity per worker explain 90 percent of the cross-country variation in the growth rate of income per worker. Because the growth regressions in this study focus on STEM education, the contributions of innovation—which, in the U.S. for one, appears responsible for 55 percent or more of productivity growth from 1959 to 2005, according to Marginson et al. (2013)—are partially accounted for by the inclusion of a STEM education variable (*s*).

Below are calculations of TFP based on coefficients reported in **Table 4.3** and the growth rates displayed in **Table 4.4** for the U.S. Ultimately, they show that by adding the *s* variable to the specifications of this study's enhanced growth model, the measure of the Solow residual (i.e., what regressions fail to account for) is reduced.

Variable	Rate of Growth (%)
Real GDP	1.52
Real GDP per worker	1.37
Real Capital Stock	0.94
Real Capital Stock per worker	0.80
Index of Human Capital per person	0.34
First University STEM Degrees per worker	2.65

Table 4.4 Average Annual Rates of Growth corresponding to data collected for the United States over the 2000-2010 period.

Recalling from Chapter Three:

$$\mathbf{y = A\, k^{\alpha}\, h^{a(1-\alpha)}\, s^{b(1-\alpha)}}$$

Which can be specified as:

$$\mathbf{\log (y) = \log (A_{it}) + \alpha \log (k_{it}) + a(1-\alpha) \log (h_{it}) + b(1-\alpha) \log (s_{it}) + \varepsilon}$$

Let: $a(1-\alpha) = \beta$, $b(1-\alpha) = \gamma$

To derive:

$$\mathbf{\%\,\Delta\, y = \alpha\ \%\,\Delta\, k + \beta\ \%\,\Delta\, h + \gamma \%\,\Delta\, s}$$

Cohen and Soto (2007):

$$A = \%\,\Delta\, y - (\alpha\,\%\,\Delta\, k + \beta\,\%\,\Delta\, h)$$

$$A = 1.37 - (0.66 * 0.80 + 1.23 * 0.34)$$

$$\mathbf{A = 0.42}$$

Equation (1) from Chapter Three:

$$A = \%\,\Delta\, y - (\alpha\,\%\,\Delta\, k + \beta\,\%\,\Delta\, h + \gamma\%\,\Delta\, s)$$

$$A = 1.37 - (0.10 * 0.80 + 1.15 * 0.34 + 0.24 * 2.65)$$

$$\mathbf{A = 0.26}$$

The TFP calculations above indicate that the measure of the Solow residual (A) is reduced by adding the s variable (approximately half of the TFP value in the Cohen and Soto (2007) model can be explained by the s variable). In other words, the enhanced model developed in this study, which includes a measure of STEM educational attainment, has explanatory power.

V. REPORT AND ANALYSIS OF CROSS-SECTIONAL RESULTS

When estimating the model using cross-sectional data—that is, using data on the above-mentioned variables over a single period (2010 or most recent year) and 87 cross-sections (countries)—81 observations are included in the Cohen and Soto (2007) estimation and 80 observations are included in the estimations corresponding to Equations (1) and (2) from Chapter 3. The results are summarized in **Table 4.5**.

Running the first estimation, in accordance with Cohen and Soto (2007), the coefficients are positive and statistically significant on both physical and human capital variables. The results indicate that 91% of the variation in GDP per labor force in this sample can be explained by the regression. The coefficient on physical capital stock per worker indicates that, on average, each additional ten percentage points increase in real capital stock per worker is associated with an approximate 7.4 percentage point increase in annualized GDP per labor force, ceteris paribus. Additionally, the coefficient on index of human capital per person indicates that, on average, an additional percentage point increase in the index of human capital per person correlates with a 1.35 percentage point increase in annual productivity, all else equal.

Estimating Equation (1) from Chapter Three, the results are significant with respect to all coefficients. Furthermore, approximately 92% of the variation in GDP per labor force in this sample can be captured by the regression results. Coefficients on physical capital and human capital are positive, as expected. It is important to note that the coefficient on first university STEM degrees per worker is significant at the 10% level, but negative, indicating that additional STEM education is correlated with a decrease in annual growth. Of course, this seems counterintuitive based on existing research.

Estimating Equation (2) yields results that are statistically significant for all coefficients; the results indicate that approximately 91% of the variation in growth in this sample can be captured by the regression. Again, the coefficient on STEM degrees is negative and significant; however, the coefficient on the interaction term between STEM degrees and index of human capital it positive. Taken together, the coefficients indicate that for each additional ten percentage points increase in first university STEM degrees per worker, one can expect an approximate 0.5 percentage point decrease in annualized GDP per worker given countries' existing human capital, on average, all else equal. Note: -1.6 + (0.10 * ln(3.08) * 10) = -0.5.

With the addition of quadratic term $[\log(s)]^2$ in the following two estimations, the coefficient on s becomes positive, which satisfies prior expectations. Given that the coefficient on $[\log(s)]^2$ is negative and significant in both estimations, this supports the idea that a relationship of decreasing returns exists between STEM education and growth.

An estimation of Equation (3) produces coefficients that are statistically significant for all variables and that captures over 92% of the variation in GDP per labor force in the sample. Coefficients on physical capital and human capital are positive, as expected. The net effect of each additional percentage point increase in number of first university STEM degrees per worker is, on average, an approximate 1.4 percentage point increase in annualized per-worker growth, ceteris paribus.

Estimating Equation (4) yields results that are, similarly, significant for all coefficients and which explain over 92% of the variation in the dependent variable. Again, coefficients on physical capital and human capital are positive. The effect of STEM education on growth, with considerations of coefficients on both the interaction term and on the quadratic term, can be interpreted as follows:

all else equal, an additional percentage point increase in first university STEM degrees per worker is correlated with an approximate 1.9 percentage point increase in annual GDP per labor force given countries' existing human capital, all else equal. Note:

$1.8 + (-0.07) + (0.10 * \ln(3.08)) = 1.9.$

Table 4.5 Cross-Sectional Estimation Regression Results

Dependent Variable: Annualized Change in Log GDP Per Worker

Estimation	***Cohen and Soto (2007)***	***Equation (1)***	***Equation (2)***	***Equation (3)***	***Equation (4)***
log(k)	0.735***	0.744***	0.764***	0.739***	0.752***
	(.043)	(.043)	(.043)	(.042)	(.041)
log(s)		-0.083*	-0.163***	1.483**	1.843***
		(.048)	(.057)	(.706)	(.703)
log(h)	1.353***	1.548***		1.481***	
	(.172)	(.202)		(.199)	
log(h)*log(s)			0.103***		0.100***
			(.014)		(.014)
[log(s)]^2				-0.055**	-0.070***
				(.025)	(.025)
R-squared	*.91*	*.92*	*.91*	*.92*	*.92*
Durbin-Watson	*1.50*	*1.59*	*1.63*	*1.52*	*1.53*
Observations	*81*	*80*	*80*	*80*	*80*

Notes: k is physical capital per labor force, s is first university STEM degrees per worker, h is index of human capital per person. Standard errors in parentheses, coefficients significant at 1% (***), 5% (**) and 10% (*).

VI. A RE-ESTIMATION OF THE CROSS-SECTIONAL REGRESSIONS

When running estimations using a diverse sample of cross-sections, it is important to consider the presence of outliers that may skew regression results. A look at some of the group statistics in Appendix A shows that there are, indeed, some outlying countries for which the regression is not as good of a fit as it is for the majority. The first grouping of per-worker GDP and human capital per person (logs taken) shows the general relationship between the two variables, which is positive, as expected. The outliers in this case are Qatar, Brunei and Saudi Arabia, which all lie above the regression line. This indicates a positive relationship of greater magnitude between human capital and growth than exists for other countries in the sample. Considering a broader context, this is likely because these outlying countries are major oil produces—and Brunei's geographic location makes it a major trading post—that have large GDPs relative to their population sizes (particularly Qatar and Brunei, which are very small in size). Additional outliers include Kyrgyzstan and Madagascar, which fall below the regression line.

In the second grouping of per-worker GDP and per-worker STEM degrees (logs taken), the relationship is positive, following lines of existing evidence; however, there are some significant outliers. These outlying countries include Qatar, Brunei, Luxembourg and Madagascar. Evidently, there is some overlap between outliers in both groupings providing support for re-estimating the regression with these countries excluded.

Furthermore, a third grouping between per-worker GDP and per-worker physical capital stock (logs taken) presents a positive correlation and less apparent outlier; however, Burundi lies distinctly below the regression line as it has in other groupings, and for this reason it, too, is excluded during re-estimation.

In addition to group statistics, residual diagnostics offer an overview of how well each country was captured by the regression results. The residual plot in Appendix B reveals the following, most prominent outliers: Mongolia, Ghana, Madagascar and Mozambique. Again, there is some overlap with the group statistics. These countries are also excluded from the re-estimation.

Table 4.6 below presents the regression results from a re-estimation with the following countries excluded: Brunei, Burundi, Ghana, Qatar, Kyrgyzstan, Luxembourg, Madagascar, Mongolia, Mozambique and Saudi Arabia. Across all estimations, coefficients on physical capital stock per labor force and on index of human capital per person are positive and significant, and over 91% of the variation in annual GDP per labor force in this sample is explained by the regression results. Notice the coefficient on STEM education is negative in the first two of this study's estimations and statistically insignificant in the estimation of Equation (1).

Focusing on the estimations of Equations (3) and (4), for which the coefficient on STEM education is positive and significant: the coefficient on the quadratic term is statistically significant and negative—again, supporting a relationship of decreasing returns between STEM education and growth; according to the estimation of Equation (3), the net effect of an additional percentage point increase in number of first university STEM degrees per worker is, on average, an approximate 1.9 percentage point increase in annualized per-worker growth, all else equal; according to the estimation of Equation (4), which considers coefficients on both the interaction term and on the quadratic term, ceteris paribus, an additional percentage point increase in first university STEM degrees per worker is correlated with an approximate 2.4 percentage point increase in annual GDP per labor force given countries' existing human capital, all else equal. Note:

$2.4 + (-0.09) + (0.11 * \ln(3.08)) = 2.4$

Overall, with the exclusion of outliers in a re-estimation of the cross-sectional regressions, the net effect of STEM education on annualized growth increases in magnitude for both estimations of Equations (3) and (4).

Table 4.6 Cross-Sectional Re-Estimation Regression Results

Dependent Variable: Annualized Change in Log GDP Per Worker

Estimation	***Cohen and Soto (2007)***	***Equation (1)***	***Equation (2)***	***Equation (3)***	***Equation (4)***
log(k)	0.743***	0.753***	0.770***	0.743***	0.752***
	(.049)	(.050)	(.051)	(.048)	(.047)
log(s)		-0.070	-0.146**	1.979***	2.377***
		(.058)	(.080)	(.721)	(.719)
log(h)	1.483***	1.648***		1.587***	
	(.187)	(.231)		(.220)	
log(h)*log(s)			0.108***		0.108***
			(.016)		(.015)
$[\log(s)]^2$				-0.072***	-0.089***
				(.025)	(.025)
R-squared	*.92*	*.92*	*.91*	*.93*	*.93*
Durbin-Watson	*1.46*	*1.59*	*1.63*	*1.41*	*1.41*
Observations	*69*	*69*	*69*	*69*	*69*

Notes: k is physical capital per labor force, s is first university STEM degrees per worker, h is index of human capital per person. Standard errors in parentheses, coefficients significant at 1% (***), 5% (**) and 10% (*). Countries excluded from the sample are Brunei, Burundi, Ghana, Qatar, Kyrgyzstan, Luxembourg, Madagascar, Mongolia, Mozambique and Saudi Arabia.

VII. A DISCUSSION OF DEVELOPMENT LEVEL

In addition to interpreting the variables related to STEM education, it is relevant to discuss the control variable for level of development, or initial Real GDP per worker (y_{t-1}). According to the principle of Economic Convergence, low- and middle-income economies are expected to grow faster than high-income economies, eventually converging with high-income countries over time. This is to say, if one country's initial GDP level is below another one's, it is expected to have a higher rate of growth. A priori, we would expect a negative coefficient on initial Real GDP, indicating its negative correlation with annualized growth.

Islam, Ang and Madsen (2014) are among many who offer evidence of this. In their regression, they specify an interaction between human capital quality and distance to the frontier (DTF), which they state is important given the role that human capital plays in allowing the transfer of technology from the frontier. In their results, they report the coefficient on initial income (as a measure of DTF, intended to represent existing levels of development) to be significant and of the right sign when using an extended Solow specification (that includes a measurement of human capital). The sign of this coefficient is negative.

The cross-sectional regression results, as displayed in **Tables 4.5** and **4.6**, do not report the coefficient on initial level of GDP. This is because, unlike in the panel section, data on variables in the cross-sectional estimations are collected for one year and the relevance of the Economic Convergence phenomenon *over time* does not apply. It is worth mentioning that, when included in the cross-sectional regressions, initial GDP has a coefficient that is, indeed, statistically insignificant across estimations. Interestingly, however, when included in the specifications involving s^2, the coefficient becomes negative (despite remaining insignificant), which seems in line with existing theories and empirical evidence like that mentioned above. This seems to offer further support that the relationship between STEM education and growth is best characterized as positive but diminishing in its effect.

VIII. POLICY IMPLICATIONS

To reiterate a key finding by Marginson et al. (2013), it is assumed by nearly all nations that the quantity and quality of STEM competences, as they put it, affects productivity. The issue, however, is that, despite this prevalent assumption, most national programs focus less on the links between education in STEM than on the take-up of STEM skills in labor markets. Across countries, the discussion about STEM is promoted in terms of remedying shortages of high skill labor. But this concentration is narrow in scope. STEM education equips graduates with a broad range of skills that extend beyond preparation for STEM-specific occupations, contributing to competiveness and management in various economic sectors. The results of this study—in particular, the robust results of the panel data estimation, which establish a consistent, significant and positive correlation between STEM education and growth—corroborate the emerging area of consideration in productivity research, which advocates for the importance of policy programs geared towards, first and foremost, enhancing the education of workers in STEM disciplines in order to generate long-term innovation and wideranging labor market influences.

Not only do the results of this study call for policy which focuses on promoting STEM educational programs, it specifically adds to a need for regard at the higher education level. A further conclusion of Marginson et al. (2013), in their international STEM comparison, is that most government effort and public attention is targeted at schools, rather than universities. Their report is similar to many others looking at STEM education in that it calls for policy related to improving curriculum, pedagogy, student motivation, and teaching at the primary school level, but lacks a demand for proposals to deal with similar issues at the post-secondary level. This study supports the significance of STEM education at the undergraduate, post-secondary level as an influence on productivity. It highlights a rising need to center on STEM higher education in forward-looking growth studies, as well as, importantly, in policy initiatives that seek to reform and improve the quality of innovation-stimulating education.

A final implication of this study's results is that policy makers ought to support research that investigates when to stop investing in STEM education. The consistently negative, significant coefficient on $[\log(s)]^2$ suggests that there are diminishing returns to STEM educational attainment as it affects productivity. For this reason, it is important for countries to determine at which point the returns to STEM education begin to decrease—or, essentially, how much STEM educational attainment would be too much—in which case resources might be better allocated elsewhere.

IX. CONCLUSION

Overall, the results of this study, with the exception of a couple of cross-sectional estimation results, indicate that a significant, positive relationship exists between STEM educational attainment (of first university degrees, specifically) and annualized growth across countries. However, it is important to acknowledge the possibility of some estimation issues. In models of the type studied in this thesis, there is always the possibility of reverse causality. That is, for example, a situation in which STEM educational attainment drives growth but, in turn, economic growth drives an increase in STEM educational attainment, and similarly for capital stock and human capital in general. Due to this potential endogenity issue, the magnitude of coefficients could be biased; however, it is unlikely that signs or significances would be much affected.

CHAPTER FIVE

CONCLUSION

I. SUMMARY OF FINDINGS

In summary, the augmented Solow neoclassical growth models specified in this study, which further enhanced the model proposed by Cohen and Soto (2007) to include STEM education as a particular form of human capital, significantly capture the effects of innovation-fueling STEM education on macroeconomic growth. The panel estimation produces results that are statistically significant, make intuitive sense and are consistent across estimations. This is to say, the results are robust with respect to different specifications. The hypothesis regarding the positive effects of STEM education on growth—when physical capital stock, human capital and development level are considered—is supported. The results of the cross-sectional estimation are less consistent and capture a slightly lesser percentage of the variation in annualized growth (averaging 92% as opposed to the panel estimation's 99%); however, the specifications including a quadratic term provide statistically significant evidence of the positive impact of STEM education on annualized growth across different countries. This quadratic term is significant and negative across all panel and cross-sectional estimations, indicating the diminishing returns to STEM degrees per worker, or the fact that as countries increase the number of first university STEM degrees, the effect of each additional degree on productivity decreases.

II. SUGGESTIONS FOR FUTURE RESEARCH

Recalling from the review of literature in Chapter Two that most studies examining the effect of human capital on growth only account for average years of education, an area for further research would be investigating more thoroughly the returns to various, distinct kinds of education, as this study has begun by looking at STEM education (and not simply general educational attainment). This has important policy implications according to the OECD (1998), which affirms that the contribution of human capital to growth depends on the efficiency with which it is being accumulated. Countries that allocate their educational resources inefficiently gain little from their investments in human capital in terms of growth.

Another idea for future research would be including an account of informal knowledge acquisition, which may broaden existing findings (OECD 1998). Primarily, literature that examines returns to human capital—specific forms or otherwise—is based on formal educational attainment only, without a consideration of the wider definitions of human capital investment that include on-the-job training, experience and learning-by-doing (Sianesi and Reenen 2002). Efforts to capture these additional effects, coupled perhaps with mechanisms for measuring the extent of education's spillover benefits at the macro level, would likely elucidate an even more profound effect of various types of education—and I would postulate especially STEM-related education, for the reasons this study has set forth—on productivity.

Turning towards areas of future research with STEM, there is far more to investigate beyond the effects of undergraduate, post-secondary STEM education. As mentioned in preceding chapters, national STEM projects focus mainly on STEM in terms of human learning and knowledge at the primary and secondary levels. This study broadens this scope by collecting data on first university STEM degrees; however, examining returns to all post-secondary levels of education could produce similarly significant findings, which would contribute to the importance of having policy considerations of STEM at the higher education level. Furthermore, most studies, like this one, focus on the connection between STEM and human capital (via education), which then manifests as skill in the labor market. Moving forward, it would be interesting to target the connections and mutual effects between human capital and STEM education with direct measures of R&D, as they all impact productivity. Of course, it is up to such future studies to build on this one and correct for potential endogeniety issues, perhaps using an instrumental variables technique to come up with proper instruments for more accurate coefficients.

Lastly, building on the policy implications section of the preceding chapter, another area of future research would be looking at the retention of not only students in STEM educational programs, but also of STEM graduates in related labor market positions. This could be particularly interesting alongside a very important consideration of gender divides, which Maginson et al. (2013) touch upon in their discussion of how the human capital of women who have undertaken training in STEM and left their careers prematurely is considered to be a wasted economic resource, and a quite prevalent one at that.

III. CONCLUDING REMARKS

Ultimately, the results of this study corroborate current assumptions that improvements in STEM performance have the ability to enhance human capital and innovation, thereby promoting countries' R&D, competiveness, management/other expert skills and overall economic growth. The findings in this thesis regarding the significant effects of STEM education at the undergraduate level contribute to the (limited) research today, which supports the existence of a vital intersection between education, innovation and growth. Moving forward, more attention ought to be paid to STEM education, especially at the higher education level, and policy should focus on developing strategies for attracting and retaining students (i.e., high-skill human capital) in STEM educational programs.

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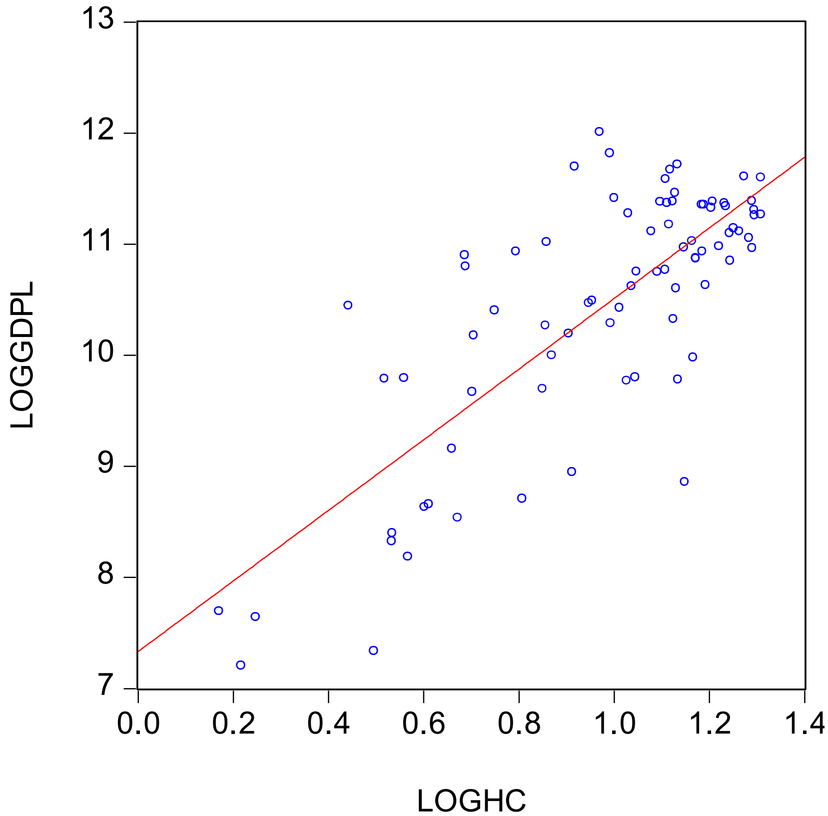
APPENDIX A

Group Statistics for the Cross-Sectional Series



Outliers:

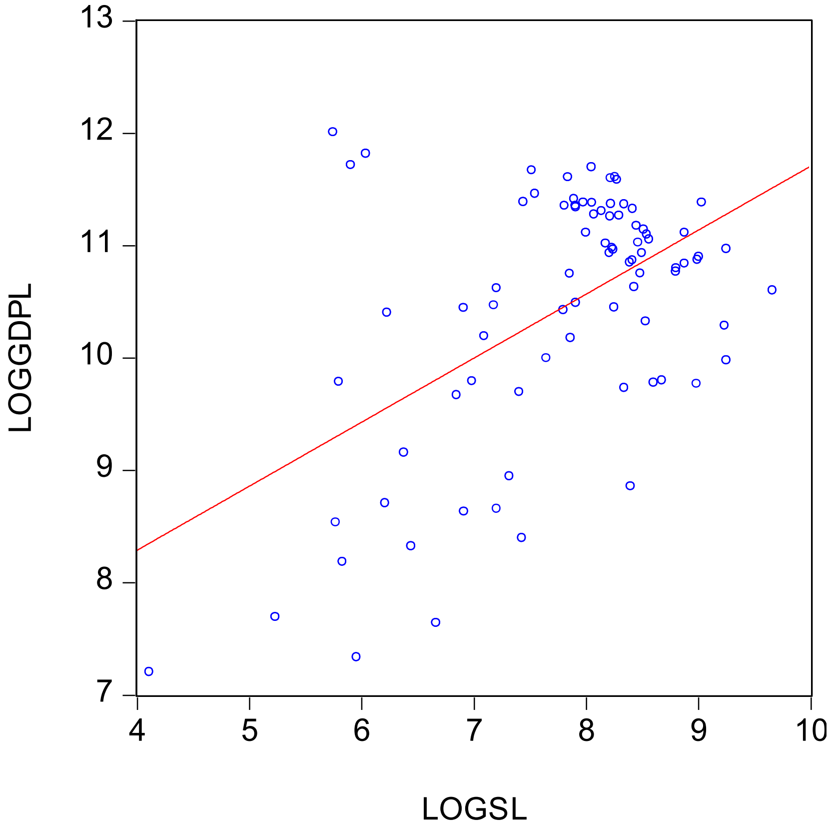
Qatar (0.97, 12.0)

Brunei (0.99, 11.8)

Saudi Arabia (0.92, 11.7)

Kyrgyzstan (1.15, 8.9)

Madagascar (0.5, 7.3)



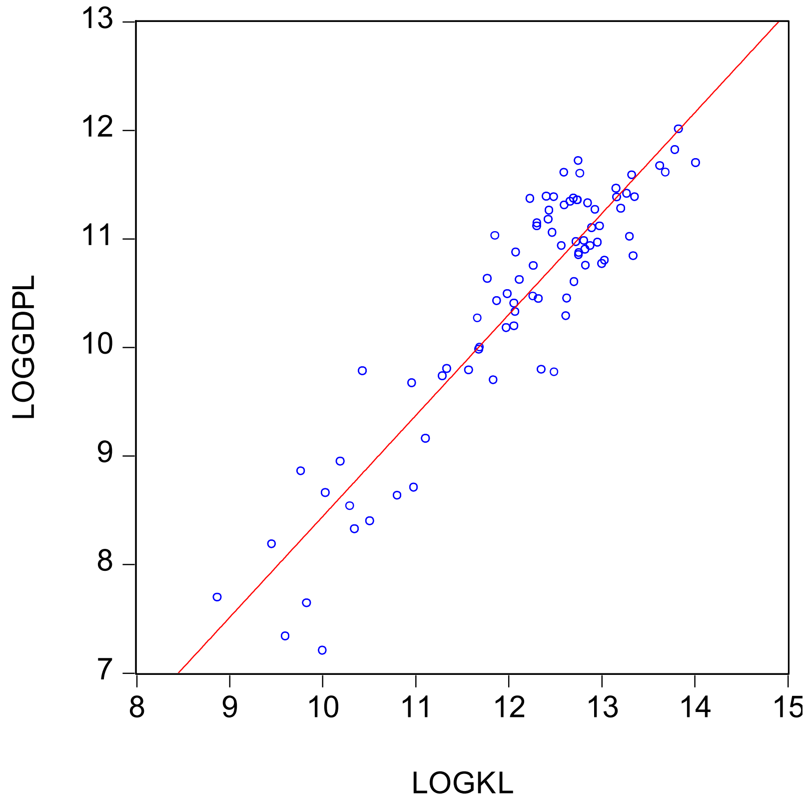
Outliers:

Qatar: (5.7, 12.0)

Brunei: (6.0, 11.8)

Luxembourg (2008): 5.9, 11.7

Madagascar: (6.0, 7.3)



Outliers:

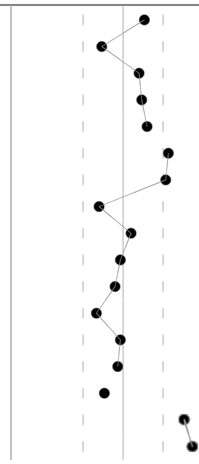
Burundi (10.0, 7.2)

APPENDIX B

Residuals for the Cross-Sectional Series

obs	Actual	Fitted	Residual
Russian Federation	10.6276	10.4516	0.17599
Ukraine	9.97526	10.1465	-0.17123
Canada	11.2558	11.1350	0.12087
Mexico	10.4889	10.3452	0.14363
United States	11.5966	11.3970	0.19958
El Salvador	9.66585	9.30076	0.36509
Guatemala (2007)	9.78347	9.44346	0.34002
Honduras (2003)	9.15415	9.34726	-0.19311
Panama	10.4225	10.3618	0.06071
Argentina (2009)	10.6154	10.6342	-0.01877
Bolivia (2000)	8.94375	9.01853	-0.07478
Brazil	10.1898	10.4025	-0.21271
Chile	10.7454	10.7601	-0.01468
Colombia	9.99294	10.0324	-0.03949
Uruguay	10.4647	10.6099	-0.14519
Australia	11.3640	10.8665	0.49747
New Zealand	11.0239	10.4620	0.56189

Residual Plot



(continued on next page)

obs	Actual	Fitted	Residual	Residual Plot
Armenia	9.77789	9.33615	0.44174	
Bangladesh (2003)	8.39625	8.68588	-0.28964	
Brunei	11.8136	11.8029	0.01065	
Cambodia (2009)	8.32315	8.59492	-0.27177	
China	9.69453	10.1368	-0.44230	
India (2003)	8.63065	9.03501	-0.40436	
Japanc	11.1411	10.9152	0.22582	
Kyrgyzstan	8.85527	8.91242	-0.05715	
Malaysia (2009)	10.7495	11.0050	-0.25552	
Mongolia	9.76760	10.6092	-0.84163	
Singapored	11.6668	11.8432	-0.17644	
South Korea	11.0971	11.3306	-0.23348	
Taiwan	11.3807	11.3809	-0.00022	
Iran (2007)	10.8969	10.3445	0.55242	
Iraq (2004)	10.1764	9.97428	0.20208	
Israel	11.1092	10.8485	0.26072	
Jordan (2007)	10.2827	10.5828	-0.30008	
Qatar	12.0058	11.7764	0.22938	
Saudi Arabia	11.6941	11.7650	-0.07083	
Turkey	10.9292	10.4374	0.49176	
Algeria (2007)	10.7950	10.5559	0.23906	
Burundi (2004)	7.20365	7.52833	-0.32469	
Cameroon (2008)	8.65548	8.46177	0.19371	
Ethiopia	7.63846	7.79388	-0.15542	
Ghana (2009)	8.70638	9.46518	-0.75879	
Kenya (2001)	8.53434	8.72561	-0.19128	
Madagascar	7.33492	7.96873	-0.63381	
Morocco	9.79058	10.1133	-0.32276	
Mozambique (2011)	7.68975	6.86385	0.82590	
Namibia (2008)	10.4002	10.1758	0.22436	
Swaziland (2006)	10.4413	9.91956	0.52176	
Uganda (2004)	8.18078	7.95770	0.22308	
Austria	11.3510	11.2453	0.10572	
Belgium	11.4592	11.5087	-0.04955	
Bulgaria	10.3216	10.5513	-0.22973	
Cyprus	11.4110	11.3648	0.04623	
Czech Republic	10.9620	11.5062	-0.54422	
Denmark	11.3376	11.2574	0.08017	
Estonia	10.8471	11.2594	-0.41232	
Finland	11.3230	11.2677	0.05533	
France (2009)	11.3687	11.0543	0.31438	
Germany	11.3037	11.2670	0.03671	
Greece	11.1098	11.2484	-0.13859	
Hungary	10.9305	11.2980	-0.36754	
Ireland	11.5804	11.5023	0.07807	
Italy	11.3756	11.4016	-0.02600	
Latvia	10.7647	11.1544	-0.38971	
Lithuania	10.9676	10.8883	0.07927	
Luxembourg (2008)	11.7120	11.2350	0.47696	
Netherlands	11.3492	11.2566	0.09262	
Poland	10.8720	10.5188	0.35318	
Portugal	11.0132	11.1341	-0.12085	
Romania	10.5988	10.7230	-0.12425	
Slovak Republic	11.0515	11.0737	-0.02227	
Slovenia	10.9769	11.2974	-0.32051	
Spain	11.2744	11.3340	-0.05962	
Sweden	11.3785	11.0801	0.29833	
United Kingdome	11.2639	11.5035	-0.23962	
Albania (2003)	9.79753	9.85785	-0.06032	
Croatia	10.8665	11.1498	-0.28329	
Iceland	11.1719	10.8163	0.35556	
Norway	11.6058	11.2763	0.32952	
Switzerland	11.3847	11.2059	0.17876