THREE ESSAYS ON THE MACROECONOMICS

OF HUMAN CAPITAL AND GROWTH

by

MERCY LAITA PALAMULENI

B.S., Wake Forest University, 2008

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

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Manhattan, Kansas

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Abstract

This dissertation encompasses three essays on the macroeconomics of human capital and economic growth. Below are the individual abstracts for each essay.

Essay 1: Does Public Education Spending Increase Human Capital?

I investigate the effect of public education spending on the quality of human capital as measured by international student test scores in science and mathematics, conditional on the efficiency of a country's governance. Combining World Bank country level data on government efficiency with rich micro data from the OECD PISA-2009, I estimate a human capital production function from student level data. Prior work suggests that public education expenditures are inconsequential for student achievement. I illustrate that public education spending matters for student test scores when one uses student level data instead of aggregate country level data. These results are robust to controlling for governance measures such as corruption control and regulatory quality. An implication is that less efficient government does not preclude improving test scores through education spending.

Essay 2: Inequality of Opportunity in Education: International Evidence from PISA.

I provide lower-bound estimates of inequality of opportunity in education (IEO) using micro-data from the Programme for International Student Assessment (PISA). The measure represents variation in student mathematics test scores which can be explained by predetermined circumstances (including parental education, gender, and additional community variables). I explore the heterogeneity of the measure at the top and bottom of the test score distribution, and demonstrate that IEO accounts for 10 percent of the variation in test scores for students at the top and bottom of the test score distribution. Using this inequality measure I establish three main conclusions. *(1)* IEO decreases overall in response to an increase in preprimary enrollment rates.

An implication here is that improvements in early childhood education might mitigate the effects of IEO factors for some students. *(2)* IEO increases in a manner which relates to overall inequality. This indicates the possibility of a more general persistence to inequality factors. An implication is that equity-based education policies can be a key tool for reducing income inequality. *(3)* There is evidence of an equity-efficiency tradeoff in education. An implication here is that public education policies aimed at reducing IEO might hinder overall education efficiency, in that it decreases academic achievement for some groups of students.

Essay 3: Public Education Spending and Economic Growth: The Role of Governance.

Although the theoretical literature often connects public education spending to growth, individual empirical findings sometimes conflict. In this paper I propose that inefficiencies in public education spending might explain these inconsistencies. Using a dataset from both developed and developing countries observed over the period of 1995 to 2010, I demonstrate that the efficiency of public education spending on growth depends on a country's level and quality of governance. I also find evidence that increasing educational spending is associated with higher economic growth only in countries that are less corrupt. These findings have important implications for the formation of effective education policies in developing countries. They illustrate that efficient public education spending augments economic growth in a way that increased spending alone does not match.

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Table of Contents

List of figures

List of tables

Acknowledgements

"Education is the great engine of personal development [. . .]. It is what we make out of what we have, not what we are given, that separates one person from another."

--by Nelson Mandela

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Dedication

I dedicate this dissertation to my parents: Mrs. Anne A. Palamuleni
and Mr. Grement G. Palamuleni (late)

Essay 1: Does Public Education Spending Increase Human Capital?

1.1 Introduction and problem identification

Ample empirical studies show that the accumulation of human capital strongly relates to individual labor market outcomes. A large part of the literature on economic growth presumes that these individual outcomes aggregate such that human capital accumulation fuels long run growth. This opens the possibility of increased growth through enhancing the production of human capital.

Around the world much of the funding for education is provided by governments. To some extent this spending is motivated by the hope of exploiting the relationship between human capital and growth. The question of whether these expenditures lead to improved growth and other development outcomes has been extensively explored. However, the empirical results are conflicting. Hanushek and Kimko (2000), for example, find a robust relationship between human capital, as measured by test scores, and economic growth. However, they find no relationship between expenditures and test scores. Stating it differently, human capital matters for growth but public education spending does not matter for human capital.

This has an important policy implication. It suggests one must look beyond government education funding to improve human capital. One feature of Hanushek and Kimko (2000) is that they use aggregate data. In this paper, I show that their results are not robust to using student level data. I find that public expenditures do matter for test scores when one estimates an education production function at the student level.

I use a dataset on international student test scores in mathematics and science from the Programme for International Student Assessment 2009 and data on country level variables from the World Bank. One advantage of using student level data is that it contains information on a student's family and the school she attends. This enables a further analysis to identify other institutional features and family characteristics that are important in improving student test scores. Thus, this helps in identifying other avenues, beyond expenditures, that a government can pursue to improve human capital. For instance, I find that time spent learning a subject and parental educations are associated with high student test scores. An implication is that governments can influence these features in order to improve the quality of human capital.

Another advantage of estimating a human capital production function at the student level along with country education spending is that it mitigates the endogeneity problems that are common when using cross country data. For example, the public education expenditures at the student level are exogenous to student decisions because they are determined by the government. Using cross-country student level data in the estimation process is one way of addressing the long run relationship between public spending and student test scores.

Considering that most of the data is from countries with high income and good governance, I analyze whether the results only hold for countries with better governance. I use data on different dimensions of governance organized by Kauffman, Kraay and Mastruzzi (2004) from the Worldwide Governance Indicators. After controlling for country level governance measured by control of corruption and regulatory quality, I find robust evidence that increasing public education spending improves students' test scores. Additionally, similar to Rajkumar and Swaroop (2008), I include an interaction term between public education spending and governance in order to assess the effectiveness of public education spending. I still find that public education spending improves student scores. I also find that the marginal effect of public education spending on test scores is lower in countries with better governance. One implication of these results is that less efficient government does not prevent public education spending from improving test scores. Moreover, the results suggest a possibility of diminishing marginal productivity of public education spending on student test scores.

Overall, these results are useful for education policy decisions and cast light on some key policy questions. They advocate that public education spending improves students' test scores, and hence a country's level of human capital. Moreover, these results have implications in the economic growth literature that investigates the effectiveness of government education spending and find inconclusive results. They suggest that the effect of public spending and economic outcomes such as growth might depend on the level of governance.

I organize the remainder of this essay as follows. Section 1.2 provides a literature review. Section 1.3 presents the conceptual framework based on the education production function. Section 1.4 describes the data and the empirical methodology. Section 1.5 analyzes the empirical results and discussion. Section 1.6 contains concluding remarks.

1.2 Literature review

The economics literature emphasizes the importance of skills and knowledge in promoting labor market outcomes (see e.g. Mincer and Polachek (1974), Mincer (1974), Zhang (2005)) and economic growth (see e.g. Mankiw, Romer and Weil (1992), Lucas (1988), Hanushek and Woessmann (2007)). In general, the concept of skills and knowledge are embedded in the notion of human capital. Finding explicit measures of human capital has been challenging throughout the literature. Numerous studies have used education levels and schooling measures to proxy for society's quantity and quality of human capital.

There is a significant consensus of the positive effects of education on growth regardless of the measure. However, the debate in the literature dwells on whether to focus on the quality of human capital, such as test scores, or quantity of human capital, such as average years of schooling, or both. One drawback of using quantitative measures of education in a growth regression is that quantitative measures assume that the amount of human capital gained from one year of schooling is equal across countries (Hanushek and Kimko, 2000). However, there exist considerable differences in the quality of schooling across countries. This has led to usage of the qualitative measures of human capital literacy rates and tests score in the empirical growth literature (see e.g. Hanushek and Kimko (2000) and Hanushek and Woessmann (2007)).

Because human capital, as measured by international test scores, is a key to growth, the stakes are high in identifying the paths to improved student achievement. Economists agree that the quality of institutions plays a significant role in improving education outcomes and hence human capital (Hanushek, 2003). Governments around the world invest in the education system in order to promote the quality of schools, and subsequently the quality of human capital. Thus, it is essential to disentangle the role of government involvement in facilitating human capital production.

Since I investigate the effectiveness of public education spending on student achievement, two strands of literatures are relevant. The first examines the effect of public education spending on education outcomes and the second investigates the effect of governance and institutional corruption on economic outcomes and education spending.

The use of public funds to facilitate the production of development outcomes has remained a key policy issue. Many studies have analyzed the effect of public spending on development outcomes such as economic growth (see e.g. Kneller, Bleaney and Gemmell (1999), Blankenau, Simpson, Tomljanovich (2007)); health (see e.g. Gupta, Verhoeven and Tiongson (2002, 2003), and Filmer and Pritchett (1999a)) and education (see e.g. Rajikumar and

Swaroop (2008), and Hanushek (2003)). The empirical results are conflicting, although the theoretical literature posits the role for public spending to promote these development outcomes. For example, most empirical studies find that public education spending has no impact on education outcomes. Hanushek (1986, 1989, 1995, and 2003) provides summaries of the literature. He shows that most empirical studies, based on education production function, find no empirical support for the effect of increasing public education spending on education outcomes. A common explanation of this - is that public education spending crowds out private investments in education and distorts individual incentives (Blankenau and Camera, 2009).

On the other hand, other studies suggest that inefficiencies in the allocation of school resources might have a significant impact in explaining this observed failure of public education spending in improving education achievement (see e.g. Hanushek (1995), Rajikumar and Swaroop (2008)). Thus, rather than focusing on the level of spending on education outcomes, these studies emphasize the effectiveness of resource allocation. These studies suggest that improved resource management can improve the development outcomes of government expenditures on education and health (see e.g. Hanushek (1995), and Rajikumar and Swaroop (2008)). Additionally, studies from international organizations such as the World Bank and the International Monetary Fund have suggested that public spending might not yield desirable results on economic outcomes because of the presence of inefficiencies in governments' budget formulation and implementation. This argument has been used to explain why developing countries find it difficult to translate public funds into services that promote development outcomes, such as education and health. The latter explanation suggests the role of government efficiency and not just levels of spending in improving student achievement.

The second strand of literature relevant to my current study is the literature that examines the effect of governance and corruption on economic outcomes and public spending allocation. In general, the empirical literature concludes that corruption and poor governance are detrimental to economic growth (see e.g. Mauro (1995), Hall and Jones (1999), Fisman and Gatti (2002), and Fisman and Svensson (2007)). One channel through which poor governance might discourage growth is by influencing the allocations of government spending to development outcomes. This can be possible if government officials mismanage funds or if they allocate more funds to budget categories that allow them to have private gains. Thus, in the education sector, students may perform poorly if not all resources reach them.

Even though many studies have analyzed the governance-growth relationship, only a few studies have analyzed the direct effect of governance and institutional quality on public spending. Mauro (1998) is among the early studies that analyze the effect of corruption on government spending composition. After controlling for GDP per capita, he demonstrates that countries which are more corrupt allocate a smaller share of public spending to education. These results are similar to the findings by Delavallade (2006), who reports that corruption decreases public health and education spending. This suggests the possibility that if public spending is a productive input in generating quality institutions that produce human capital, controlling for corruption would improve the effectiveness of public spending in promoting development outcomes. In this paper, I proceed with providing empirical support of the effect of governance on student test scores; and hence, the quality of human capital.

1.3 The theoretical framework

The most straightforward way to model academic achievement is to use an education production function. The production function expresses education outcomes as a function of inputs such as students' characteristics, school quality and school resources. Equation (1.1) below is an example of an education production function:

$$T_{isc} = Z_c \, I_{isc}^{\theta} F_{isc}^{\alpha} \, Q_{sc}^{\eta}, \tag{1.1}$$

where subscript i denotes the student, s denotes school and c denotes country.[1] Equation (1.1) states that a student's test score, T, depends on country institutional features, Z, her individual characteristics, I, her family background information, F, and the quality of school she attends, Q. For illustrative purposes I parsimoniously choose to use the Cobb-Douglas production function. In this case α, θ and η are the elasticities of a student's achievement with respect of her family background information, her characteristics and school quality respectively.

Typically studies that analyze education production functions within countries assume that the institutional structure, Z, is constant. This assumption might not be entirely accurate when analyzing an international education production function. Thus, one might consider Z to be similar to the total factor productivity (similar to total factor product in a macro context).[2]

One can decompose the institutional quality to depend on average public education expenditure in a country, E_c, and all other school characteristics, X_{sc}, such as:

$$Q_{sc} = X_{sc}^{\delta} E_c^{\phi}. \tag{1.2}$$

As stated in the literature review, numerous studies conclude that public spending does not systematically influence a student's test scores. This would be the case if $\phi = 0$. Otherwise if $\phi > 0$, then public education expenditures affect institutional quality and hence a student's test

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[1] I use this notation in order to be consistent with the structure of the data I use for estimation. For example, countries nest schools and schools nest students.

[2] See also argument by Hanushek, Link and Woessmann (2012). During the estimation, I include institutional features in a form of country level of governance and the level of income.

score. I conjecture that the effectiveness of public education spending on the quality of institutions depends on the level of government efficiency. Similar to Pritchett (1996), this can be achieved by having the elasticity of institutional quality with respect to public education spending depend on the level of governance, G_c, such as $\phi(G_c)$. For simplicity, I assume that the relationship is linear and can be expressed as:

$$\phi(G_c) = \phi_0 + \phi_1 G_c. \tag{1.3}$$

Combining equations (1.1-1.3) yields the following education production function:

$$T_{isc} = Z_c \, I_{isc}^{\theta} F_{isc}^{\alpha} (X_{sc}^{\delta} E_c^{\phi_0+\phi_1 G_c})^{\eta}. \tag{1.4}$$

Taking the natural log of equation (1.4) yields the following linear specification of the education production function:

$$\begin{aligned} ln(T_{isc}) = ln(Z_c) + \theta ln(I_{isc}) + \ \alpha\, ln(F_{isc}) + +\delta\eta\, ln(X_{sc}) + \eta\phi_0\, ln(E_c) \\ + \eta\phi_1\, ln(E_c) * G_c. \end{aligned} \tag{1.5}$$

If the institutional quality is a productive input in the education production function e.g. $\eta > 0$ and better governance leads to public education spending efficiency, $\phi_1 > 0$, then I expect that $\eta\phi_1 > 0$. An implication is that if G_c is measured such that higher values represents better outcomes then increasing governance improves public educating spending efficiency. In this paper, I provide empirical evidence in line with this hypothesis. I therefore, proceed with estimating an education production function similar to equation (1.5). It is important to note that the objective of the paper is to determine the public education spending efficacy in improving education outcomes and not recovering the structural parameters. Furthermore, it is important to notice that if one defines $ln(T_{isc}) = t_{isc}$ and the variables in (1.5) in a similar manner, the education production function can be expressed in levels as:

$$t_{isc} = z_c + \theta i_{isc} + \ \alpha f_{isc} + \delta\eta x_{isc} + \eta\phi_0 e_c \tag{1.6}$$

$$+ \eta\phi_1 e_c * G_c.$$

This is similar to the regression that I estimate.[3]

1.4 Data and the empirical strategy

1.4.1 Data

The primary data for the econometric analysis comes from the 2009 wave of Program of International Student Assessment (PISA) and country level data comes from the World Bank.

1.4.1.1 PISA Dataset

The Organization for Economic Cooperation and Development (OECD) organizes the PISA dataset. PISA is a system of international student assessment that focuses on testing a student's reading, mathematics and science skills. It emphasizes testing individual skills of young adults as they approach the end of compulsory education (OECD). Thus, it focuses on fifteen year old students. Furthermore, unlike other international achievement tests (such as the Trends in International Mathematics and Science Study (TIMSS)) the PISA assessment does not focus on a specific type of learning curriculum or grade level. This ensures that testing is independent of the structure of a country's school system.

The PISA testing program began in 2000 and every three years students from participating countries sit for the test. The 2009 dataset covers 72 countries and territories. For the empirical analysis, I use the data on 60 countries of which I have information on public education spending and also governance.[4] Occasionally, some countries sample students from

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[3] I did not transform the data, but for illustrative purposes I rewrite the education production function in levels.

[4]The Appendix 1.1A contains the list of all countries used in this essay.

specific territories. I assign the same average education spending per student per capita to territories from the same country.

Similar to other international achievement tests, the PISA survey follows a two-stage stratified sampling protocol in which schools are the primary sampling unit. It assesses 35 fifteen year old students from each of the selected schools. In each one of the participating countries approximately 150 or more schools are sampled based on the population size of fifteen year old students regardless of their grade in school.

The student sample size varies from 329 students (Liechtenstein) to 38,250 students (Mexico) per country. This is as a result of some countries failing to meet the targeted sample size, and other countries taking advantage of the PISA survey to collect data on their education systems. The total sample is approximately 515,948 students. However, I drop all the observations with missing data on my control variables. I have 237,896 observations for the science test score and 256,708 observations for the math test score.[5]

The PISA survey contains complimentary questionnaires for the selected schools, selected students and their parents. Compared to other international achievement tests, PISA provides more detailed information about family background, such as parental highest education level of parents and information on the availability of resources at home. Having this information is significant because it enables one to control for home inputs that can influence a student's achievement. Extensive efforts were made to deal with issues of data comparability across

[5]The reduction in the sample size can bias the population estimates. Statisticians suggest using imputed data. However, typical imputation methods might also bias population estimates. For example, numerous studies show that the use of mean score replacement, distorts the estimated coefficients and standard errors (see e.g. Little and Rubin, (1987)). Perhaps a possible future analysis should involve comparing the results from this essay to estimates of education production function that uses data with some missing observations.

countries and cultures. Unlike using cross country aggregated data, which lacks direct information on a student's family background, PISA micro-dataset provides information on family background and school administrative information. Having this information mitigates the measurement error associated with using aggregated proxy measures of family and school inputs in the human capital production function. Table 1-1 provides the descriptive statistics of the data I use for the empirical analysis. Table 1-1 shows that the average test scores of my sample are 464.421 for science and 453.742 for math. About 86 percent of the students are born within the country and their families have at least two children. As it pertains to parental education about 64% of the students have mothers with at least a high school diploma and the highest education level of a student's guardian is secondary school. Table 1-1, also shows that about 35% of students are from rural areas with population of less than 10,000.

1.4.1.2 Data from the World Bank

I merge the PISA-2009 student level data with country level data from the World Bank. The country level dataset consists of GDP per capita from 2008 (measured in constant purchasing power parity), public education spending per student in secondary as a percentage of GDP per capita, and the governance measures. My sample size includes 60 countries mainly countries from middle income to high income countries. The average per student public education spending is 20% of the income per capita.

One notable empirical challenge is that governance is unobservable and has to be estimated using subjective views and perceptions. Thus, the measures are prone to measurement error despite the extensive efforts used to standardize them. However, to my knowledge there are no objective country level governance measures, nor is there a cross country corruption and governance measure specific to the education sector.

I consider governance measures in the form of the control of corruption and regulatory quality. Kaufman et al. (2004) describes these dimensions of governance as follows: the control of corruption measures the extent to which public power is exercised for private gain. The regulatory quality measures the perceptions of the ability of the government to formulate and implement sound policies and regulations. The original governance indicators are set between -2.5 and 2.5. The governance indicators are oriented such that the highest number is associated with better outcomes. For instance, control of corruption reflects corruption abetment. For my sample, the average control of corruption measure is 0.593 and the average regulatory quality measure is 0.404.

1.4.2 Empirical specification

In order to assess the effectiveness of public education spending on student test scores, I use a modified linear specification similar to equation (1.6). This can be expressed as:

$$T_{isc} = Z_c\, \beta_{41} + I_{isc}\beta_2 + F_{isc}\beta_3 + X_{sc}\beta_4 + \beta_5 E_c + \beta_6 G_c * E_c + \varepsilon_{isc,} \qquad (1.7)$$

where T_{isc} is the science or the mathematics test score; I_{isc} is a vector of individual characteristics that includes variables such as a student's gender; F_{isc} is a vector of a student's family background information and includes variables such as parental education and number of children at home; X_{sc} is a vector of school characteristics such as school size, class size, school community location, instructional time per week, and a measure of school autonomy; Z_c is a vector of country level variables such as GDP per capita and the level of governance G_c; E_c is the measure of government education spending and ε_{isc} is the error term which captures all unobservable characteristics that affect student's scores.[6]

[6] This linear specification has been widely used by numerous studies such as Woessmann (2003), Fuch and Woessmann (2007), Woessmann et al. (2009), West and Woessmann (2010), and Woessmann (2011).

Student achievement is likely to be influenced by a variety of a student's characteristics and socioeconomic factors. I include a number of control variables in the regression to minimize the problem of omitted variables. I chose the control variables based on the empirical and theoretical literature on education production function. For example, the education literature documents that students' characteristics, such as gender, affect individual economic outcomes. Moreover, some studies that assess intergenerational transfers of ability and wealth find that family background information such as parental education, resources at home, and family social economic status affect an individual's economic outcomes.

Most of the human capital literature emphasizes the role of institutions and school resources in affecting a student's educational outcome. Thus, I include measures such as school type, public expenditure, and a measure of school autonomy in order to control for institutional quality and features. Table 1-1 reports the detailed data description for all the variables used in the empirical analysis.

I estimate the parameter vectors from equation (1.7). This specification is restrictive because it only enables me to estimate the average effect of each variable and I assume that the estimated coefficients are the same in all countries and in all schools. While it might be interesting to analyze the heterogeneity at all levels (within schools, between schools, within countries and between countries) by using a multi-level model or a fixed effect model, the specification from equation (1.7) serves the purpose in answering the present question. Moreover, Woessmann (2003) demonstrates that on average using this specification or a multilevel model yields similar results.

Throughout the estimation I consider the complexity of the PISA dataset and I acknowledge that the error structure ε_{isc} is non-traditional. For instance, with the stratified and clustered nature of the dataset, one cannot dismiss the possibility of the error terms being correlated at the school level and country level.

The appropriate error term is given by:

$$\varepsilon_{isc} = \vartheta_c + \eta_{sc} + \epsilon_{isc},$$

where ϑ_c is the error term at a country level, η_{sc} is the error term at a school level, and ϵ_{isc} is the student specific error term. The next section describes the data adjustments necessary for minimizing the estimation bias for both the parameter estimates and their corresponding standard errors.

1.4.3 Adjustments for non-standard data

PISA data collection involves two-stage clustered complex survey design, which complicates the data analysis. The simple random sampling assumptions, for calculating the mean and the standard deviations of the estimates no longer apply, even in a simple regression analysis.

The first complexity is that schools were sampled first based on the population size of fifteen years old students within each country. Consequently, students from smaller schools might have had a higher probability of being included in the sample. In some countries, such as Canada, students from small provinces were intentionally over-sampled. Therefore, estimation without taking into account this survey design effect might bias population parameters. To overcome this problem, PISA-2009 provides survey design weights which represent the probability of students being selected both at a country level and within each school. I use these weights during estimation in order to obtain population estimates.

The second complexity of the dataset comes from the reported test scores, which are standardized in a way that the mean score is 500 and the standard deviation is 100 (OECD, 2009a). However, the PISA test scores for a specific test is not simply the share of correct answers, but a set of five computed scores for each subject, called plausible values. The dataset includes these five imputed test scores because each student completes only a subset of questions. These plausible values are generated using Item Response Theorem (IRT).[7]

After IRT identifies patterns of correct, incorrect, and omitted responses in the subset of questions completed in a particular test, statistical models are used to predict the probabilities of a student answering correctly to the non-completed set of questions as a function of the student's proficiency in the completed questions. Thus, these reported plausible values represent the distribution of potential scores for all students in the population with similar patterns of item response (OECD, 2009a). To obtain an unbiased estimate for any analysis with the plausible value, the PISA-2009 manual suggests using all five plausible values for each analysis. And thus the appropriate statistical estimate is the average of five. This can be represented as:

$$\beta_b = \frac{1}{5}\sum_{j=1}^{5} \hat{\beta}_{bj} \, ,$$

Where $b,$ is the index of the parameter of interest from equation (1.7) such that b =1, 2, 3, 4, 5, 6 and therefore β_b is the the estimated coefficient of interest and $\hat{\beta}_{bj}$ is the estimated parameter obtained using the j^{th} plausible value and a student's final sample design weight.[8] As it pertains to obtaining standard errors, there are a few more complexities that I considered while using this PISA-2009 dataset. One complexity arises due to the clustered and stratified nature of the dataset. Ignoring this design feature of PISA-2009 dataset might result in underestimation of the

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[7] The IRT identifies patterns of correct, incorrect, and omitted responses in the subset of questions completed on a particular test.

[8] It is important to note that even the mean of the plausible values are computed using all five plausible values and the final weight. On the other hand the means for students' attributes at school and country characteristics are computed by only using the final weight.

standard errors. This affects the hypothesis testing and results in wrong conclusions regarding the significance of the estimated parameters. Another complexity that arises when computing standard errors is due to the fact that countries differ in the way they created strata, even though they use schools as primary sample unit (PSU).

There are several ways to overcome the complex survey design nature of the PISA dataset in order to obtain more efficient standard errors. The most common approaches can be grouped into two methods. The first method typically involves using the Taylor Series Linearization (TSL) such as the "sandwich" approaches, in which the variance covariance matrix is adjusted for clustering and weighting. The second method uses replication procedures which involve drawing multiple (sub) samples from the original full sample, re-computing the parameter estimates for each replicate, and the full sample, and then computing the variance as squared deviations of these replicate estimates from the full-sample estimate. The most common replication based approaches include bootstrapping, the Jackknife method and the Balanced Repeated Replication (BRR) method. These methods differ in how subsamples are generated.[9] The BRR method is a variation of the Jackknife method. Unlike the Jackknife method, the BRR approach generates replications by selecting one school for removal from each stratum, and doubles the weights for schools that remain. PISA-2009 uses the BRR method with a Fay's adjustment of 0.5 and reports replication weights which are required to use when estimating variance.[10] PISA-2009 BRR method uses 80 replicates and thus reports 80 replication weights. I

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[9] For example, with bootstrapping method if one has a sample of *n* observations, one simply draws *n* samples of observations with replacement and generates *n* replicates. The Jackknife is similar to bootstrapping method, but instead of sampling *n* subjects with replacement, the analyst draws *n* replicate samples of *n-1* units.

[10] The Fay's adjustment is used to correct for biases from selecting schools in a small strata.

use these replication weights along with the final design sample weight to get unbiased estimates of the sampling variance.

It is advantageous to use these replication weights when conducting any empirical analysis with the dataset because the reported replication weights contain information on post-stratification adjustments and accounts for non-respondents. As expressed earlier, although all participating countries used two-stage sampling designs with two primary sample units (PSUs) per stratum, countries differed in how they stratify the data.[11]

Some countries used regions, provinces, and sometimes used private and public schools for stratification. However, the variables used for specifically used for stratification are not entirely given nor are all the PSUs available with the public use data. Thus, using the provided replication weights controls for this sample design feature.

Even though using the replication weights can be computationally involved, an advantage is that one doesn't have to make a strong assumption that the higher order terms of the objective functions of the TSL are negligible. Thus, all the analytical derivations of the estimates required when using Taylor series approximation are avoided. Kish and Frankel (1974) is one of the earliest studies to demonstrate that on average the results from TSL methods and the replication approaches are similar. Additionally, Rust (1995) provides further details, and shows how the replication method takes both the stratification and clustering into account.

Because PISA-2009 reports 80 replication weights, one needs to run 405 regressions in order to an unbiased sample. The sample variance is computed using the following formula:

$$\sigma^2_{\beta_{b,sample}} = \frac{1}{5}\left(\frac{1}{80(1-0.5)^2}\right)\sum_{k=1}^{80}\sum_{j=1}^{5}(\beta_{bjk} - \hat{\beta}_{bj}),$$

[11] The same number of students is drawn from each school in all countries.

where $\sigma^2_{\beta_{b,sample}}$ represents the sampling variance for estimated β_b, 80 is the number of replication weights, β_{bjk} is the estimated coefficient obtained from using the j^{th} plausible value and the final weight, β_{bjk} is the estimated coefficient(s) obtained from using j^{th} plausible value and the k^{th} replication weight, and 0.5 is the Fay's Adjustment for all PISA dataset (OECD, 2009b).

Moreover, in order to obtain the standard error one has to also considering the imputed variance from using the plausible values. This imputed variance can be expressed as:

$$\sigma^2_{\beta_{b,imputed}} = \frac{1}{4}\sum_{j=1}^{5}(\hat{\beta}_{bj} - \beta_b)^2,$$

where $\sigma^2_{\beta_{b,imputed}}$ is the imputed variance. Thus the final computed variance $\sigma^2_{\beta_b}$ for the coefficient(s) is given by:

$$\sigma^2_{\beta_b} = \sigma^2_{\beta_{b,sample}} + (1.2)\sigma^2_{\beta_{b,imputed}},$$

and 1.2 is the deft adjustment.

1.4.4 Cross country identification and potential endogeneity problems

I do not ignore the endogeneity problem that might arise when estimating equation (1.7). One source of bias is due to the problem of omitted variables at the student level and the selection bias of students or teachers into schools and class rooms. Additionally, there is no consensus as to which variables to include in the education production function (Hanushek, 1986).

The main concern arises when there is a correlation between the unobserved or the omitted variables and the error term in equation (1.7). One solution is to use a panel or a value-added- specification, when one estimates the reduced form education production function in first differences. However, the cross sectional structure of the PISA 2009 does not permit this approach. I minimize the problem by including more explanatory variables both at the student and school levels.

Another concern arises when there is a reverse causality relationship between the explanatory variables and the dependent variable or when the relationship between the explanatory variables and the dependent variable changes over time. This identification problem can bias the parameter estimates from equation (1.7). I use similar identification assumptions as Woessmann (2003) and Fuchs and Woessmann (2007). Firstly, it is obvious that a student's individual and family background information are exogenous to her test score. Moreover, it is reasonable to assume that family background information does not rapidly change over time. Thus, including family and individual control variables when estimating equation (1.7) in levels, does not bias the parameter estimates of the equation. Furthermore, the family information recorded in PISA data represents the characteristics of the family even from the recent past. Explanatory variables at a school level are exogenous and time invariant, because institutional changes are typically gradual. I consider the school features presented in the PISA dataset as consistent indicators of past characteristics of schools a student might have attended. For instance, this assumption holds when one assumes that on average students and parents might not choose to switch between countries when estimating the international production function. However, the possibility of selection bias within countries is possible. This calls for focusing on between country variations when estimating the international human capital production function. Moreover, one should be cautious when interpreting the causal relationship between test scores and institutional features.

Nonetheless, school resources at a country level may change over time. For example, studies show that public education spending changes over time (see e.g. Fuchs and Woessmann, 2007). I use a five year average of public education spending per student as a fraction of GDP per capita to instrument for public education spending. Additionally, it is reasonable to assume that the country level public education spending is exogenous to the performance of a student, because a country's government policy determines the public education spending allocation. A last identification concern when estimating the international education production involves omitted variable bias that arises when there is a correlation between country level unobserved characteristic and the country level control variables or the student achievement. For instance, cultural differences might influence both students' performance on standardized tests and citizens perceptions of how government monitors resources. One way to overcome this cultural bias is to restrict the identification variation to groups of countries that are culturally more identical. However, another way is to incorporate continental fixed effect effects and re-estimate equation (1.7) with continental fixed-effect effects. I proceed with this analysis in the robustness section. In general, there are no solutions to all other identification concerns that arise when estimating the education production function using cross country data. Thus, one needs to be cautious when interpreting the empirical results.

1.5 Estimation

I begin the discussion of empirical results by providing preliminary results on the bivariate correlations between the tests scores and the main explanatory variables including the level of income, public education expenditures and different dimensions of governance. I report the bivariate correlations in Table 1-2.

Table 1-2 demonstrates that there is a positive correlation between the test scores and these explanatory variables. More specifically, the correlation between public education spending and the test scores is positive. This indicates that using this sample, increasing expenditures should be associated with high student test scores. However, these bivariate correlations might not depict the entire story of the relationship between test scores and the explanatory variables. One reason for this that perhaps it might be the case that countries with better governance actually spend more on education or that the relationship between the governance and public education spending might depend on the level of income. Figure 1.1 shows that the relationship between corruption control and the average public education spending per student as a percentage of GDP per capita after controlling for income level.

In Figure 1.1, the first panel includes data from all the countries in my study, the second panel includes data from high income countries, and the last panel is data from the rest of the countries.[12] This Figure 1.1 demonstrates that the positive association between good governance and public education spending only holds for the high income countries. This exemplifies that the correlation between public education spending and governance might depends on the income level. Additionally, this correlation pattern between corruption control and public education spending slightly holds when I group the countries between OECD members and non-OECD members. These results are suggestive that perhaps the relationship between test scores and public education spending or governance should also depend on income level. Thus, I control for income levels in all the regressions to ensure that income level does not drive the relationship public education spending and test scores.

1.5.1 Empirical results

Table 1-3 and Table 1-4 include the estimation results of the relationship between public education spending and test scores. The dependent variables are the science test score and the

[12] I describe high income countries and all other groups of income levels based on the definition from the World Bank. The evidence from Figure 1.1 also holds when I plot the relationship between public education spending and the regulatory quality measure.

math test scores, respectively. From each table the estimated model (1) is the baseline model which does not include any governance measure. The estimated model; (2) and (3), includes governance measures in a form of control of corruption and regulatory quality. The last two models (4) and (5), represent the models that include the interaction term between spending and the governance measures. The main estimation results can be summarized better in categories.

Demographics: There is a positive relationship between test scores and being a native born for both science and math test scores. Moreover, consistent with the literature that analyzes the effect of gender on test scores, I find female students perform lower than male students, on average. Students who live in rural areas perform poorer than students from urban areas. Based in results from Table 1-3 and Table 1-4, students from rural communities with a population of less than 10,000 perform lower that students from urban areas, but the results are always statistically insignificant.

One advantage of using a student level micro dataset is that it contains information on family background, which might not be available when using aggregated data. Controlling for family background is necessary because students not only learn in schools, but also at home while they associate with their parents and relatives. I find a positive relationship between student test scores and the highest education level of her parents in years, whether her mother has at least a secondary school education and whether one of her parents works full time. For example, students with mothers with at least a secondary education score 25 points (23 points) higher in science (mathematics) than their counterparts. This confirms that differences in student tests scores and hence the labor force quality can be attributed to differences in family inputs. These results suggest that there exist inequality in opportunity, more especially from the literature that measure inequality of opportunity as inequality that results from circumstances beyond one’s control. These results suggest that the long-run education policy should focus on promoting female education and reducing inequality at family levels. Interestingly, I find consistently find that students from families with many children at home perform lower than students from small families, and these results are not significant in all specifications for both tests.

School features: Schools play a crucial role in producing human capital for a nation. However, I find inconclusive support of effects of most institutional characteristics on student test scores. This partially supports the argument for the failure of input based theories that suggest that school resources do no significantly influence student achievement (Hanushek, 2003). For instance, there is a growing literature that analyzes the effect of increasing class size on student achievement and results from the empirical studies are still conflicting (Hanushek, 2003). The results from Table 1-3 and Table 1-4 illustrate that large class size as instrumented by student-teacher ratio lowers student's test scores. However, the coefficient on student teacher ratio is statistically insignificant. One would hypothesize that improving the quality of instruction in schools, such as improving the proportion of certified teachers, would improve test scores. Although, I find that increasing the proportion of certified teachers is associated with higher student test scores, the results are consistently insignificant. Students from schools that report to have a shortage of teachers as a problem perform lower in both subjects, and the results are consistently not statistically significant in all specifications. Furthermore I find that students from schools that administer standardize exams perform better and the results are not statistically significant. As it pertains to school autonomy, the results illustrate those students from schools that have the authority to hire or fire teachers, tend to perform better. However, the results are not statistically significant in both tests except for models (2) and (3) in Table 1-4. Thus, contrary to Woessmann (2009), I do not find a systematic relationship between school autonomy and student outcomes.

The only school input that is consistently significant in improving student test scores, even at a one percent level, is the amount of learning time in both subjects. I show that a one percentage increase in instruction time in minutes per work, increases student test scores by 19.992 points for science and 14.630 points for math in the baseline model and approximately 14.400 in the models that include the governance measures for both tests. These results are suggestive, that perhaps schools should focus on increasing learning time along with other strategies.

Income: Studies show that education spending does not matter for student outcomes when one takes into account the income level (see e.g. Roberts (2003) and Filmer and Pritchett (1999b)). In order to avoid the possibility of income levels driving the results, I include the logarithm of GDP per capita in all of my specifications. Furthermore the inclusion of the income measures controls for the average level human capital and student's peer effects, which are typically difficult to control for when estimating an education production function. Similar to previous studies, I find evidence that having higher income per capita is associated with higher test scores in math and science. Consistent with empirical studies that uses the PISA test score, Students from countries with high GDP per capita perform better on PISA test. A one percentage increase in GDP per capita leads to an average 42.000 points increase in science test scores. The argument supporting this evidence is straightforward, because the results suggest that high income countries might perhaps also have more resources allocated to the education sector. However, as mentioned in the introduction, studies have continuously demonstrated that resources alone do not determine student achievement.

Public education spending and governance: Based on results from Table 1-3 and Table 1-4, I find demonstrate that education spending increases student test scores in all specifications. Estimates from the baseline models show that a standard deviation increase in public education spending per capita improves students' science test scores by approximately 28.000 points and the math test scores by 14.832. These results are significant even at the one percent level. These results are contrary to conclusions from Hanushek and Kimko (2000). Moreover, these results also hold after controlling for income. Considering that most of the countries are from countries with better governance, I control for governance in regressions with the inclusion of governance measures. I find consistent evidence in both subjects that better governance in the form of control of corruption and regulatory quality, leads to better student test scores. An implication is that improving the quality of resource regulation or corruption abatement is associated with high student test scores for both math and science. However, the estimated effect of control of corruption on math test scores is not statistically significant even at a 10 percent level.

It is important to also note the estimated results show a positive association between public education spending and institution quality as measured by better control of corruption and resource regulation. However, the magnitudes of the estimated effects are smaller than the effects from family back ground such as parental education.

1.5.2 Interpretation of marginal effects

In order to assess the role of public education spending efficiency in improving student test scores, I use a similar approach to Rajikumar and Swaroop (2008). I include an interaction term between governance and public education spending. Models (4) and (5) of both Table 1-3 and Table 1-4, report the results for this exercise. First, the results consistently show that on average high public education spending is associated with higher test scores. However, these results need to be interpreted with care as there is an interaction between the public spending and the governance level. In these specifications, the effectiveness of public education spending also depends on the governance level, and the marginal effect of governance also depends on the public education spending level. For instance, the marginal effect of public education spending on a student's achievement can be expressed as: $\beta_5 + \beta_6 G_c$ based on equation (1.7).

The term $\beta_6 G_c$ represents the effect of public education spending on student achievement after controlling for governance measures. In these models the estimate for β_6 is always negative and statistically significant, except for the model (5) in Table 1-4. This shows that there is a negative relationship between the marginal effects of spending and the governance measure. Improving public education spending improves students' tests scores in countries with poor governance. An implication is that improvements in the control of corruption and regulatory quality reduce the effectiveness of education spending on student achievement. This suggests the possibility of diminishing marginal productivity of education spending on a student's tests score. Thus, public education spending is associated with high student achievement scores in countries with poor governances. Meanwhile, the marginal effect of better governance can be interpreted in an analogous way. Increasing public education spending reduces the marginal effects of governance on test scores.

1.5.3 Robustness check

To check the sensitivity of the results, I first exclude countries with fewer than 500 students. Moreover, in order to avoid a specific country or a group of countries that over sampled students, such as Mexico, Spain and Italy, to influence the results. I remove these countries both individually and as a group. I do not report the results from this exercise. However, I find evidence that the empirical results from this exercise are not different from that of using the entire dataset. Thus, I dismiss the possibility that a particular country or group of countries drives the results.

The second analysis in the robustness check involves verifying if the results vary with the inclusion of continental fixed effects. Table 1-5 reports the results from estimating equation (1.7) with the inclusion of continental fixed effects for the science test scores.

From Table 1-5, the baseline model still shows that increasing education spending improves test scores. From the baseline model in Table 1-5, a one standard deviation increase in public education spending per student as a share of GDP per capita increases the test score 9.376 and the results are statistically significant at a one percent level. Moreover, controlling for governance in terms of control of corruption enhances the effectiveness of public education spending on student test scores. In contrast with the results from Table 1-3 and Table 1-4 without fixed effects, Table 1-5 provides robust evidence of the effect of public education spending on student test scores.[13] Moreover, as it pertains to governance, models 2 and 3 of Table 1-5 show a positive correlation between that good governance and test scores. However, the results are consistently statistically insignificant. The marginal effects of public education spending and governance exhibits the same pattern with the inclusion of the continental fixed effects.

1.5.4 Data limitations and future research

The results from this study have to be interpreted with care due to several data limitations. Data issues arise from the fact that extremely poor countries, such as those in sub-Saharan Africa, did not participate in any waves of PISA testing. And also those students who are 15 years old and

[13] These results are also consistent with using math test scores as the dependent variable.

below 6^{th} grade are not in the sample. Therefore, the students sampled were not fully representative of all fifteen-year-old students in the world. There is a need of analyzing the quality of human capital from developing countries.

Another data limitation pertains to the measures of public education spending which is expressed as the averaged public education spending per student in a particular country. This measure is overly aggregated as it contains both direct education costs such as payments on education resources such as books and indirect costs such as administrative pays. A better extension is to use disaggregated data on education expenditures and determine which aspects affects economic wide education acquisition.

As for estimation, currently there is still no consensus in the literature as to what determines student achievement, and how the determinants are related to student achievement. Thus, I include more explanatory variables in order to avoid biases that might arise due to omission of variables. However, I have not considered any nonlinearity that might arise when estimating an education production function. In addition, I have assumed that student's efforts are the same on average in all countries. This might not be true as student effort might vary both within and between countries. However, the analysis at hand provides insight into the current question and I leave the above mentioned shortcomings for future work.

1.6 Conclusion

The main objective of this essay has been to understand whether public education spending improves student test scores, and hence, the quality of human capital. Prior studies find little role of public spending improving student achievement. I use student level data from the OECD and country level data from the World Bank, to estimate an international human capital production function. The international student level data enables one to capture the long run relationship between education spending and student achievement. Moreover, the student level data contains information on a student's family and schools she attends. This enables a possibility of identifying other channels through which governments can influence student tests scores. For example, I find that a student's mother's education is highly associated with her achievement. These results are suggestive that perhaps future long run education policy should target female education. After controlling for student characteristics and institutional features I find evidence that increasing public spending improves test scores. These results are contrary to studies that find that public expenditures are inconsequential to student test scores such as Hanushek and Kimko (2000). Thus, this study demonstrates that there is a relationship between education spending and the quality of human capital as measured by student test scores.

Considering that most countries in my study are from high income countries and have good governance, I control for the role of government efficiency. I include governance measures such as of corruption control and quality of regulation. I find a positive relationship between corruption abatement and test scores. I also find that improving regulatory quality improves test scores. In order to measure government efficiency, I include an interaction term between public education spending and governance. I demonstrate that spending still matters for test scores. I find that the marginal effects of public education spending falls with better governance. These results imply that government in efficiency does not prevent education public spending in improving test scores. Moreover, they also suggest the possibility of diminishing marginal productivity of public education spending on student test score.

Overall, the results from this study advocate the role of government in improving student test scores, and hence human capital. In particular, public education spending improves the quality of human capital, even after controlling for government efficiency. One acknowledgeable shortcoming is that the governance measures used in this study are from subjective perceptions. Moreover, the governance indices are aggregated measures that use different sources. Thus, a future possible research direction is to search for governance measures specific to the education sector.

Table 1-1. Descriptive statistics.

	Science		Math			
	Mean	Std. Dev	Mean	Std. Dev	Min	Max
Science	464.412	135.000			30.530	863.240
Math			453.742	124.900	42.460	901.860
Female	0.508	0.004	0.511	0.003	0	1
Native born	0.866	0.001	0.865	0.001	0	1
Highest parental education	12.225	0.037	12.212	0.035	3	18
Number of children	2.320	0.007	2.316	0.007	1	6
Mother has high school	0.638	0.005	0.656	0.005	0	1
A parent works full-time	0.771	0.003	0.772	0.003	0	1
School is in rural area	0.367	0.010	0.355	0.009	0	1
Student teacher ratio	15.887	0.119	16.258	0.191	5	126
Standardized test	0.786	0.009	0.772	0.003	0	1
Shortage of teachers	0.592	0.011	0.605	0.010	0	1
School chooses firing	0.485	0.012	0.470	0.011	0	1
ln(instructional time)	5.278	0.011	5.361	0.004	2.708	6.908
Ratio of certified teachers	0.819	0.006	0.807	0.007	0	1
Public	0.801	0.008	0.796	0.008	0	1
ln(GDP per capita)	9.688	0.012	9.693	0.011	7.887	11.860
Expenditure	19.781	0.058	19.829	0.052	6.568	36.445
Control of corruption	0.592	0.001	0.409	0.009	-1.372	2.478
Regulatory quality	0.404	0.010	0.602	0.008	-2.406	1.902

Table 1-2. The bivariate correlation matrix.

	Science	Math	Expenditure
Expenditure	0.294	0.378	1
Corruption control	0.313	0.332	0.339
Regulatory quality	0.314	0.331	0.433
ln(GDP per capita)	0.350	0.381	0.311

Table 1-3. Public spending and science test scores.

	(1)	(2)	(3)	(4)	(5)
Female	-0.381	-0.406	-0.635	-0.406	-0.353
	(1.019)	(1.019)	(0.983)	(0.989)	(0.983)
Native born	20.700***	21.827***	21.556***	21.847***	20.551***
	(3.266)	(3.277)	(3.291)	(3.285)	(3.287)
Parental highest education	4.804***	4.873***	4.876***	4.874***	4.876***
	(0.196)	(0.193)	(0.192)	(0.193)	(0.192)
Number of children	-0.499	-0.406	-0.380	-0.406	-0.378
	(0.389)	(0.396)	(0.398)	(0.396)	(0.398)
Mother has high school	19.864***	23.768***	23.506***	23.737***	23.702***
	(1.392)	(1.399)	(1.391)	(1.149)	(1.410)
A parent has full time job	18.011***	18.359***	18.615***	18.352***	18.614***
	(1.172)	(1.121)	(1.121)	(1.121)	(1.122)
School is in rural area	-2.271	-2.038	-2.012	-2.041	-2.016
	(2.792)	(2.656)	(2.639)	(2.656)	(2.640)
Student teacher ratio	-0.052	-0.037	-0.036	-0.037	-0.036
	(0.086)	(0.081)	(0.082)	(0.081)	(0.082)
Standardized tests	1.360	3.133	3.121*	3.148*	3.135*
	(2.309)	(2.196)	(2.176)	(2.191)	(2.547)
Teacher shortage	-4.365*	-3.317*	-3.382*	-3.345*	-3.376*
	(2.543)	(2.554)	(2.545)	(2.556)	(2.547)
School chooses firing	2.353	3.197	3.334	3.204	3.340
	(2.608)	(2.605)	(2.606)	(2.607)	(2.609)
ln(instructional time)	19.992***	14.602***	14.429***	14.251***	14.400***
	(1.265)	(0.829)	(1.357)	(1.348)	(1.360)
Ratio of certified teachers	0.929	0.829	0.776	0.836	0.929
	(2.691)	(2.640)	(2.640)	(2.650)	(2.638)
Public	-0.319	-0.402	-0.402	-0.397	-0.442
	(2.359)	(3.223)	(3.223)	(3.220)	(3.213)
ln(GDP per capita)	48.673***	41.273***	44.941***	41.060***	44.697***
	(1.309)	(1.572)	(1.443)	(1.537)	(1.352)
Expenditure	1.440***	0.701***	0.793***	0.710***	0.851***
	(0.115)	(0.120)	(0.122)	(0.133)	(0.187)
Control of corruption		2.972***		4.213***	
		(0.885)		(2.825)	
Expenditure*corruption				-0.054***	
				(0.019)	
Regulator quality			20.772**		1.106***
			(0.800)		(0.265)
Expenditure*regulatory					-0.073
					(0.184)
Adjusted R2	0.379	0.357	0.357	0.357	0.357

Note: Each regression uses data from 60 countries and 237,896 students. Standard errors are in parenthesis. The superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.
Public is a dummy variable of whether a school is public school =1 or private school=0.

Table 1-4. Public spending and mathematics test scores.

	(1)	(2)	(3)	(4)	(5)
Female	-10.788***	-10.788***	-10.635***	-10.479***	-10.715***
	(1.079)	(1.079)	(0.983)	(1.077)	(1.483)
Native born	16.118***	16.118***	14.469***	15.962***	14.483***
	(3.266)	(3.098)	(3.291)	(3.127)	(3.116)
Parental highest education	4.804***	4.811***	4.812***	4.808***	4.799***
	(0.174)	(0.793)	(0.173)	(0.173)	(0.171)
Number of children	-0.509	-0.507	-0.482	-0.514	-0.484
	(0.367)	(0.367)	(0.368)	(0.367)	(0.367)
Mother has high school	23.419***	23.419***	23.323***	23.562***	23.370***
	(1.288)	(1.287)	(1.281)	(1.302)	(1.297)
A parent work full time	18.191***	18.205***	18.538***	18.237***	18.542***
	(1.203)	(1.204)	(1.121)	(1.203)	(1.198)
School is in rural area	-2.827	-2.822	-2.861	-2.810	-2.855
	(2.425)	(2.245)	(2.398)	(2.422)	(2.395)
Student teacher ratio	-0.026	-0.026	-0.022	-0.025	-0.021
	(0.785)	(0.780)	(0.780)	(0.785)	(0.784)
Standardized tests	2.125	2.128	2.251	2.060	2.025
	(2.294)	(2.292)	(2.251)	(2.289)	(2.245)
Teacher shortage	-1.109	-1.109	-1.190	-1.134	-1.202
	(2.475)	(2.475)	(2.447)	(2.471)	(2.447)
School chooses firing	3.585	3.595	3.713	3.564	3.701
	(2.452)	(2.455)	(2.451)	(2.607)	(2.453)
ln(Instructional time)	14.630***	14.625***	14.846***	14.846***	14.414***
	(1.369)	(1.370)	(1.376)	(1.376)	(1.375)
Ratio of certified teachers	1.879	1.882	1.690	1.849	1.677
	(2.879)	(2.879)	(2.730)	(2.883)	(2.880)
Public	-0.894	-0.899	-0.892	-0.926	-0.905
	(3.013)	(3.012)	(3.223)	(3.016)	(2.965)
ln(GDP per capita)	43.191***	43.413***	47.249***	44.369***	47.731***
	(1.376)	(1.689)	(1.547)	(1.693)	(1.461)
Expenditure	0.748***	0.756***	0.805***	0.626***	0.8689***
	(0.122)	(0.119)	(0.122)	(0.133)	(0.175)
Control of corruption		0.329		5.855***	
		(1.010)		(2.644)	
Expenditure*corruption				-0.242**	
				(0.104)	
Regulator quality			6.960**		10.245***
			(0.965)		(3.905)
Expenditure*regulatory					0.144
					(0.172)
Adjusted R2	0.363	0.363	0.365	0.363	0.363

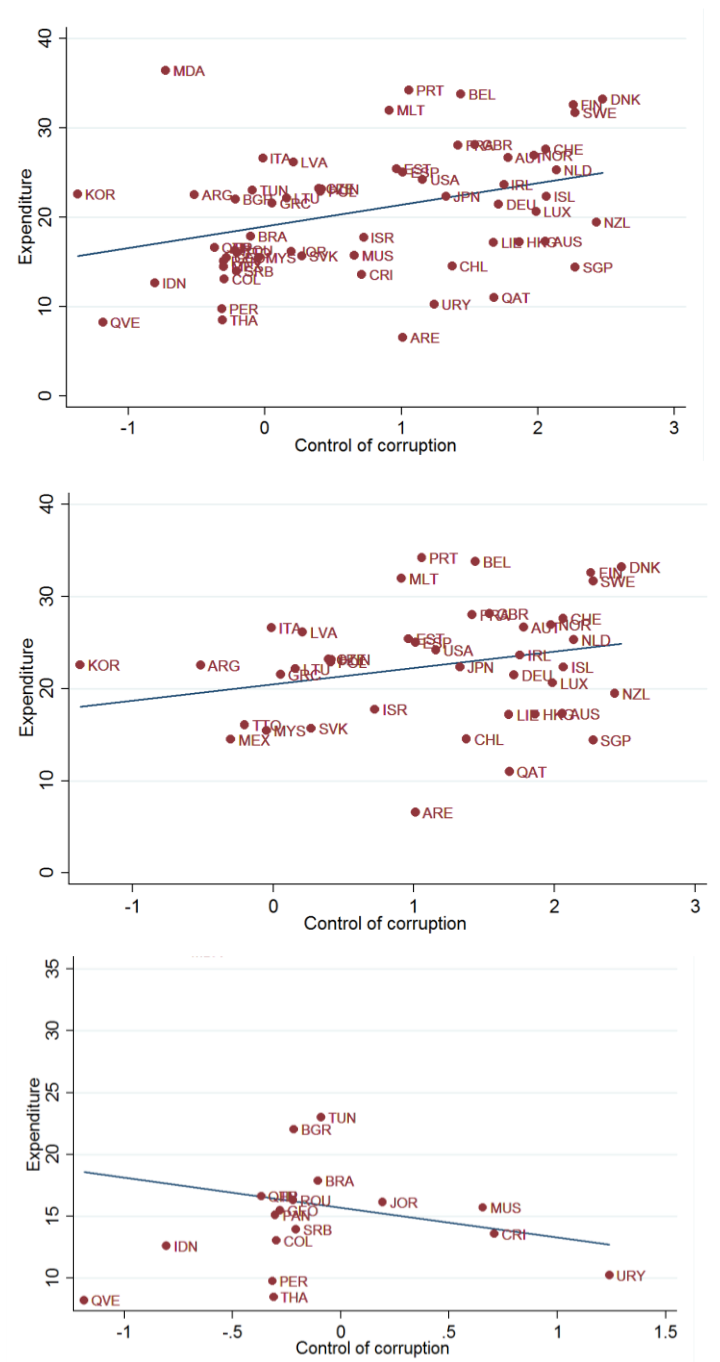
Note: Each regression uses data from 60 countries and 237,896 students. Standard errors are in parenthesis. The superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.
Public is a dummy variable of whether a school is public school =1 or private school=0.

Table 1-5. Public spending and science test scores: Robustness and continental fixed effects

	(1)	(2)	(3)	(4)	(5)
Female	-0.553	-0. 311	-0.323	-0.323	-0.543
	(1.040)	(1.955)	(0.955)	(0.955)	(1.047)
Native born	21.915***	22.173***	22.183***	22.101***	21.752***
	(3.098)	(3.074)	(3.074)	(3.075)	(3.106)
Parental highest education	4.608***	4.719***	4.719***	4.716***	4.605***
	(0.204)	(0.7201)	(0.201)	(0.202)	(0.205)
Number of children	-0.556	-0.469	-0.466	-0.404	-0.544
	(3.366)	(0.411)	(0.412)	(0.317)	(0.405)
Mother has high school	20.218***	21.051***	21.075***	20.146***	20.049***
	(1.366)	(1.365)	(1.366)	(1.377)	(1.379)
A parent work full time	17.422***	17.109***	17.140***	17.418***	17.447***
	(1.137)	(1.087)	(1.087)	(1.133)	(1.138)
School is in rural area	-2.470	-2.658	-2.656	-2.473	-2.493
	(2.895)	(2.758)	(2.3759)	(2.894)	(2.895)
Student teacher ratio	-0.039	-0.007	-0.007	-0.039	-0.039
	(0.085)	(0.082)	(0.082)	(0.085)	(0.085)
Standardized tests	1.578	1.596	1.597	1.598	1.603
	(2.419)	(2.278)	(2.278)	(2.415)	(2.416)
Teacher shortage	-4.309	-4.159	-4.158	-4.307	-4.313
	(2.533)	(2.434)	(2.434)	(2.535)	(2.410)
School chooses firing	2.498	2.289	2.305	2.511	2.507
	(2.714)	(2.664)	(2. 717)	(2.717)	(2.540)
ln(Instructional time)	21.714***	18.470***	18.481***	21.430***	21.391***
	(1.354)	(1.359)	(1.394)	(1.366)	(1.072)
Ratio of certified teachers	-1.084	-0.848	-0.837	-1.069	-1.072
	(2.266)	(2.672)	(2.673)	(2.663)	(1.359)
Public	0.740	0.120	-0.115	0.747	0.775
	(3.261)	(3.165)	(3.163)	(3.265)	(2.660)
ln(GDP per capita)	54.107***	53.849***	53.152***	52.922***	52.817***
	(1.509)	(1.625)	(1.526)	(1.575)	(1.364)
Expenditure	0.474***	0.249***	0.239***	0.527***	0.818***
	(0.139)	(0.147)	(0.154)	(0.144)	(0.186)
Control of corruption		0.171		2.301***	
		(0.982)		(0.209)	
Expenditure*corruption				-0.119***	
				(0.019)	
Regulator quality			0.461		10.254***
			(1.003)		(4.256)
Expenditure*regulatory					-0.478***
					(0.175)
Adjusted R2	0.389	0.378	0.378	0.3389	0.399

Note: Each regression uses data from 60 countries and 237,896 students. Standard errors are in parenthesis. The superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.
Public is a dummy variable of whether a school is public school =1 or private school=0.

Figure 1.1: The correlation between public expenditures and a country's level of control of corruption.



Note: Figure 1.1 shows the relationship between public education spending and control of corruption after controlling for the income level. The first panel includes all the countries I use in my empirical analysis. The second panel has high income countries only and the last panel includes only lower to middle income countries.

Essay 2: Inequality of Opportunity in Education: International Evidence from PISA

2.1 Introduction and problem identification

Recent attention in the inequality literature has shifted towards examining the inequalities inherent in an individual's access to opportunity.[14] This change of focus is a consequence of recently developing views from egalitarian philosophers, who suggest that distinguishing inequality by source and type might be fruitful. Roemer (1998) is among the most recent influential researchers to interpret the philosophical view of inequality of opportunity in a manner that it can be empirically measured. He suggests dividing inequality into fair and unfair inequalities, as judged by whether or not the inequality is due to environmental conditions that an individual can control. In the human capital context, fair (or "legitimate") inequalities can include, for example, an individual's personal academic motivation. Conversely, unfair sources of inequality are based on circumstances (whether positive or negative from an academic standpoint) that are beyond a person's control.

In this essay, I apply this philosophical view and provide a measure of inequality of opportunity in education (IEO). I implement a modified parametric method for quantifying inequality proposed by Ferreira and Gignoux (2011). After computing IEO, I proceed with predicting the role of educational policies and various economic environments in determining IEO. In the analysis I also examine whether equity-efficiency tradeoff in education.

Availability of an international student level dataset (which allows for reliable comparisons across different countries) provides the framework to construct an IEO measure. I

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[14] See for example Corak (2013), Lafranc, Pistolesi and Trannoy (2008), Marrero and Rodriguez (2013), Ferreira and Gignoux (2011), among others.

use student-level data from PISA for the years 2003, 2006, and 2009. For each country and year, I measure IEO as a variation in student achievement explainable by predetermined circumstances in terms of gender, whether a student is a native born, family background (parental education) and school location characteristics. The measured IEO represents the lower-bound estimate of the actual IEO. This is because I only have access to a subset of circumstances that affect a student's achievement; those available in the PISA data across time. Thus, the inclusion of other relevant variables would improve the magnitude of the measure. It is important to note that the approach has several advantages. First, in contrast with other inequality measures, the IEO measure in this paper makes more extensive use of available predetermined factors. Second, the reported IEO is a relative measure of inequality, and so satisfies the axioms of inequality measures.[15] Furthermore, since it is a relative measure of inequality this allows meaningful cross-country comparisons.

This paper contributes to the current education and public policy literatures in several useful ways. Most notably, I quantify IEO by focusing on predetermined characteristics of students and their families, which enables me to use a relatively larger set of circumstances to quantify IEO. This is in contrast to previous researchers in the education literature, who only measure the effect of a single family factor on student outcomes in their representations of IEO. For example, Woessmann (2004) and Shueltz, Ursprung, and Woessmann (2008) measure IEO as an effect of the number of books at a student's home. They defend their choice of measure by explaining that the number of books at home is a robust at explaining international differences in student achievement. It is important to note that this measure is in some ways inadequate,

[15] This measure is thus similar in computation to other approximate relative measures of inequalities, such as the coefficient of variation or even the Gini coefficient.

because it excludes other predetermined home factors which might influence a student's achievement. Therefore, I contribute to the literature by diverting from the exising on one-dimensional standards.

In addition, I contribute to the literature by constructing a relative measure of IEO which is conditional upon a student's test score distribution. This is achieved through the quintile regression analysis. This allows me to evaluate how educational systems affect students at different levels of academic achievement.

Finally, by taking advantage of several waves of PISA data, I construct a panel dataset at the international level. I use the panel dataset to provide fixed-effect (FE) estimates on the effect of the education system on IEO (which is indirectly the effect of education system on student achievement) as well as estimates of the education policy question of equality and efficiency trade-off. One notable disadvantage of the fixed-effect analysis is the inability to estimate the effects of a country's non-invariant education system characteristics, such as student tracking.[16] The main advantage of using the panel data FE estimation is that it enables direct control of cross-country heterogeneity, which is impossible in cross-sectional studies.

The main findings are consistent with the findings from other studies that use the PISA dataset. Predetermined circumstances explain differences in student achievement within and between countries, as well as across the student test score distribution. IEO also accounts for 10% of the variation in test scores of students at the top and bottom of the test score distribution.

The FE estimates show that overall economy-wide inequality (as measured by the GINI coefficient) explains cross-country differences in IEO. This has implications in addressing the

[16] The appropriate method to compensate for this issue is the difference-in-difference approach. I leave this for future work and only focus on continuous measures of the education system.

roles of educational policy and economic activity on academic achievement. They suggest that perhaps policy should focus on combating overall economic disparities as a way of reducing inequality in education. The results also suggest that equity-based education policies can be a key tool for reducing income inequality

The results also demonstrate that access to preprimary education reduces IEO for students at the top of the test score distribution. An implication here is that improvements in early childhood education (such as increasing the average enrollment rate for all children in a country) can mitigate inequality in education opportunity.

Important to education policy is the discussion of the equity-efficiency tradeoff of any existing or planned program. I find a non-robust equity-efficiency tradeoff exists in education sector. The tradeoff is evidenced especially for students at the middle of the test score distribution. This suggests that policies aimed at promoting equality in education opportunity might actually hinder the overall efficiency of a system by decreasing academic achievement for some groups of students. There is also evidence that IEO at the bottom of the test score distribution is positively related to higher average test scores.

I organize the rest of this essay as follows. Section 2.2 includes a brief literature review on the application of inequality of opportunity. Section 2.3 describes the analytical framework used to compute IEO. Section 2.4 describes the data set used for the purposes of empirical analysis. Section 2.5 reports the findings and investigates potential uses for this measure. Section 2.6 contains concluding remarks.

2.2 The concept of Inequality of education opportunity (IEO)

Does an individual's achievement predominantly depend on effort, or on the predetermined circumstances of that individual's life? This question has challenged researchers, philosophers, and policy makers all over the world. As it pertains to education literature in the United States, the question of inequality of opportunity in education began to gain popularity as early as the 1960's, when James Samuel Coleman and his concluded that the education gap between certain groups could be traced to family resources, rather than to resource deficiencies between schools (Coleman *et at,* 1966). This observation spurred debates not only on how differences in resources matter for student achievement, but also over questions of education policy in influencing individual student outcomes.

In the past 15 years most of the developments in understanding the nature of inequality of opportunity have resurfaced due to works such as Roemer (1998), who first formalized the concept and originally coined the term "inequality of opportunity". According to Roemer, the best way to understand inequality of opportunity is to view it as differences in outcome which can be attributed to circumstances beyond one's control. At this juncture, it is also important to distinguish inequality of opportunity from inequality of outcome in the education context (which is a common measure of inequality in human capital). Although these concepts might be correlated and both represent inequality, they differ conceptually. The common measurement of inequality of outcome is the variance of the outcome (or other measures of spread).[17] The fundamental focus of inequality of opportunity measure is on quantifying the disparities in opportunities to achieve a goal rather than disparities in outcome. In case of academic

[17] The human capital-growth literature documents both positive and negative effects of human capital inequality on economic growth. For example, Hanushek and Woessmann (2008) show that the variance of student outcome as a measure of inequality of human capital is a strong predictor of economic growth. However, Castello and Domenech, (2002) demonstrate that inequality in human capital hinders economic growth. This implies that inequalities in human capital represent both production efficiencies and production inefficiencies.

achievement this may include factors such as such as gender, level of parental education, and school community.

In general, the concept of inequality of opportunity is motivated by the principles of compensation and natural reward. The principle of compensation attributes inequality of opportunity to the differences in outcomes as a result of factors beyond an individual’s control (and therefore, calls for social compensation to address this issue). From this perspective, inequalities of opportunity demand a response such as focused government intervention which can "level the playing field" for those individuals who suffer because of unfortunate personal circumstances. On the other hand, the principle of natural reward states that responsible effort on the part of an individual should be encouraged and rewarded.

Even though the concept of inequality of opportunity is established, much of the empirical literature differs on the empirical methodology to measure it. For the literature following Roemer (1998) philosophy, the primary goal is to decompose the inequality in outcomes into inequality that results from circumstantial factors and inequality resulting from other factors (individual choice, talent, and luck) which is usually called effort. The current literature differs on the usage of parametric approach or non-parametric approach for estimation purposes. Both approaches have their own advantages and limitations. For instance, the main advantage of using non-parametric approaches is that one needs not to specify a direct functional relationship between outcomes and circumstances (or efforts). However as Ferreira and Gignoux (2011) point out, these approaches suffer from data insufficiency when the number of circumstances is large. On the other hand, the parametric approaches are able to include a relatively large set of circumstance, and one can decompose the partial effects of individual circumstances.[18] The major disadvantage of the parametric approach is that one has to assume the functional forms of the relationship between outcomes and circumstances. To this end, the literature generally views the non-parametric and parametric approaches as complementary to each other and not as substitutes for one another (for specific examples, see arguments made by Checchi and Peragine (2010) and Ferreira and Gignoux (2008)). I proceed in the next section by presenting a parametric approach which I adapt in order to quantify the inequality of opportunity in education.

2.3 An analytical framework for quantifying IEO

My framework is based on a modified parametric approach to an inequality of opportunity measurement proposed by Ferreira and Gignoux (2011). This method is also closely related to the parametric approaches discussed by Bourguignon, et al. (2007), as well as Checchi and Peragine (2010) and Fernando et al. (2012). Although most of these authors use the method to approximate inequality of opportunity in income or health, I focus on describing how it can be used to estimate the inequality of opportunity in education.

The general framework begins with an assumption that each population contains individuals such as the students in my case, which can be indexed by $i \in \{1, \ldots, N\}$. Each person's outcome, (each student's test score in mathematics)[19], denoted by T_i, depends on a set of circumstances, C_i, and an amount of effort[20], E_i, in addition to other environmental factors μ_i, such that:

[18] This requires a clear identification of coefficients and is left for future work.
[19] I focus on results from students' mathematics scores because it has been shown that the results from mathematics examinations are the most easily comparable internationally.

[20] It is common in the literature to treat choices and luck which might determine outcomes as effort.

$$T_i = f(C_i, E_i, \mu_i). \tag{2.1}$$

In the education context, circumstances are weakly exogenous to a student's test outcome because they are predetermined and cannot be influenced by his or her decisions. However, circumstances can influence a student's effort. For instance, a student's academic effort might depend on her family's social economic status. Thus a reduced form of equation (2.1) can be expressed as:

$$T_i = f(C_i, E_i\,(C_i), \mu_i). \tag{2.2}$$

Once the individual circumstances for a student are defined and identified, students can be partitioned into homogenous groups of circumstance. The most fundamental question in defining inequality is establish the benchmark of equality and measure inequality as overall (or relative) deviations from the equality. In the literature, there are two basic approaches for defining benchmarks of equality in opportunity (thus inversely measuring the inequality of opportunity). An ex-ante approach uses evaluations of the opportunities available to each group, and compares the evaluation to an ideal equality of opportunity that would exist if all sources of IEO were hypothetically eliminated. For example, one can use the mean value of a nation's opportunity set as the standard, then argue that equality of opportunity is achieved when there is no difference in the means across the various subgroups in a that nation (Fleurbaey and Paragine, 2013). Thus inequality in opportunity can be represented by the between-type inequality, (or differences between students who would otherwise have the same characteristics in a given system).

On the other hand, ex-post approaches also offer unique insight into ways by which one may define the benchmarks of equality of opportunity. The ex-post methodology follows directly from the Roemer (1998, 2001) philosophical body, which argues that equality of opportunity is achieved only when individuals who exert the same effort achieve the same outcome. Thus, inequality of opportunity is expressed as the sum of inequalities within subgroups that exert the same effort. Although the two approaches both approximate inequality of opportunity, they differ in quantifying the degree of inequality.[21]

Similar to Ferreira and Gignoux (2011), who build on the models by Bourguignion et al., 2007 and Checchi and Peragine (2010), I adopt the ex-ante approach which allows for computation of the lower bounds of the inequality of opportunity. This between-type inequality of opportunity (IO) can be approximated using non-parametric procedures. However, Ferreira and Gignoux (2011) point out that this can be data-intensive, especially when the vector of circumstances is large (more than three circumstances). Ferreira and Gignoux (2008) present a parametric method based on regression estimates, and use the variance to measure inequality. The procedure involves assuming a relationship between outcome (such as student achievement) and circumstances. Specifically, a simple linear reduced form specification for equation (2.2) can be expressed as:

$$T_i = C_i'\beta + \varepsilon_i. \tag{2.3}$$

As it pertains to education literature, equation (2.3) represents a typical "education production function". This linear specification has been widely used by numerous studies such as Woessmann (2003), Fuch and Woessmann (2007), Hanushek et al. (2011), Woessmann et al. (2009), West and Woessmann (2010), and Woessmann (2011). In this case a student's test score T_i is regressed on a vector of predetermined circumstances at a student level C_i. I include the following circumstance based on the education production function literature and their comparable availability in the three waves of the PISA dataset: gender, whether a student is a

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[21] Fleurbaey and Paragine, (2013) provides additional analysis comparing these two methods, and their respective strengths.

native born, family background (parental education, average index of social economics status), and school location characteristics (whether it is located in a rural area with population of less than 10,000 or urban and average social economic status of students).

The last term, ε_i, represents the error term. The coefficient estimates of β in equation (2.3) capture the cumulative effect of predetermined circumstances, namely the effects which comes directly from circumstances and indirectly through a student's effort. Thus, it does not represent the causal effect of each particular circumstance on student outcome.

The predicted value of equation (2.3) (i.e. $c_i'\widehat{\beta}$, where $\hat{\beta}$ is the vector of estimated coefficients of interest) represents the smoothed distribution of student outcomes, drawing from the assumption that students with similar circumstances have the same conditional average test scores. As suggested by Ferreira and Gignoux (2011), it is possible to use variance as the inequality index. In this case, the measure of inequality of education opportunity can be expressed as:

$$IEO = \frac{Var(C_i'\,\widehat{\beta})}{Var(Y_i)}. \qquad (2.4)$$

The index from equation (2.4) is simply the variation of student achievement, explained by these predetermined circumstances. In addition to the benefit of this method's simplicity, the measure also satisfies the three general axioms for measuring inequality proposed in previous literature: symmetry, continuity, and transfer principle axioms.[22]

There are numerous advantages to using equation (2.4) as a measure of IEO. First from an econometric standpoint, the measure is simply the coefficient of determination or an *R2* value

[22] Ferreira and Gignoux (2011) provide formal proofs.

from a linear regression model.[23] Thus, it represents lower bounds of the actual measure of IEO, owing to the fact that data limitations restrict the number of circumstances that can be used in the estimation process.[24] In comparison to studies such as Schultz et al. (2008) and Woessmann (2004)[25], this measure contains more information about family background effects. Furthermore, unlike studies that choose a coefficient of circumstance (such as parental education or parental income) to represent the measure of IEO, this measure does not require the justification of a single variable to represent all inequality in opportunity. Finally, this IEO measure can also be used to represent a measure of intergenerational persistence as it applies to education, because it can be decomposed by each individual circumstance (or group of circumstances) that strictly relates to family income.

It is important to note that I obtain my IEO measurements based on the average effects of circumstance on student test scores, and also at different levels of score distribution. In other words, in addition to using the Ordinary Least Squares (OLS) estimates of $\hat{\beta}$, I also obtain the

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[23] $R^2 = 1 - \frac{\sum_i (T_i - C_i' \hat{\beta})}{\sum_i (T_i - \bar{T})}$

[24] Refer to Ferreira and Gignoux (2011) for formal proofs and arguments. However the simple econometric argument is that the addition of relevant variables to the model will only improve the fit of the model. Therefore R^2 should be increasing and hence the measured IEO rises.

[25] This is in contrast with other studies that choose the effect of one of the family factors on student outcome. For example, Woessmann (2004) and Shultz et al. (2008) uses the effect of number of books at home as a measure of IEO. They defend their choice of measure by illustrating that numbers of books at home were robust at explaining international differences in student achievement. One can argue that the measure is inadequate because it undermines other home factors that influence a student's achievement. This measure can also be sensitive to the chosen dataset. Using one coefficient of circumstance from regression (2.3) undermines the information available in datasets such as PISA.

estimates of $\hat{\beta}$ at different levels of the test score distribution based on the quantile regression analysis proposed by Koenker and Hillock (2001) and Koenker and Bassett (1978).[26]

The quantile regression of equation (2.3) can be expressed as:

$$Q_q(Y_i \mid C_i) = C_i'\beta_q + \mu_{i,q}.$$

In this context, $q \in (0, 1)$ represents the proportion of a population achieving a test score below the quantile level *1-q*. The estimation process is similar to OLS, with the main assumption being that the error term at each quintile, $\mu_{i,q}$, is independently distributed. The difference here is that instead of minimizing the residual sum of squares to obtain coefficient estimates (as would be done in OLS), the quintile regression attempts to minimize the weighted sum of these residuals.

2.4 Data

The primary data source for my econometric analysis the 2003 to 2009 waves of Programme for International Student Assessment (PISA) dataset.[27] All country level data comes from educational statistics generated by the World Bank, except for my data on income inequality which is drawn from the United Nations' World Income Inequality Database.

2.4.1 PISA dataset

The PISA dataset is organized by the Organization for Economic Cooperation and Development (OECD). PISA tests assess students' skills at the age of fifteen (an age at which most children worldwide are approaching the end of their compulsory education). Unlike other international achievement tests, such as the Trends in International Mathematics and Science Study (TIMSS),

[26] An advantage of using quantile regression is that it reduces the possibility of biases prone to OLS estimates from outcomes that have a skewed distribution.

[27] The 2001/2002 datasets could not be retrieved at the time this paper was prepared.

the PISA assessment does not focus on a specific type of learning curriculum or grade level. The assessment is in the primary subject areas of mathematics, reading, and science. The OECD has administered the survey triennially since 2000. The number of countries participating in the test has grown over the years, with 65 nations taking part in 2009.[28]

Similar to other international achievement tests, the PISA survey uses a complex procedure which follows a two-stage stratified sampling protocol. This allows both private and public schools to serve as the primary sampling unit. It then assesses 35 students from each of the selected schools. In each one of the participating countries approximately 150 schools are sampled, drawing from the total number of fifteen-year-old students in school, regardless of their grade level.[29]

The student sample size varies across countries and years, in part because some countries fail to meet the targeted sample size while others take more active advantage of the PISA survey to collect data on their own education systems. The PISA survey contains complimentary questionnaires for the selected schools, selected students, as well as for the parents. Compared to other international achievement tests, PISA provides more detailed information about family background, even addressing aspects such as the highest education level of each parent, and a number of home resource considerations. I take advantage of this family information to quantify IEO.

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[28] There are 72 total territories that were assessed for the 2009 wave. More populous countries such as China and India sampled several regions within the country separately.

[29] It is important to consider that this sample does not represent all 15 year olds in a country, because dropouts from school are not available for testing in this manner.

PISA provides five plausible values for each subject area. It is important to note that the plausible value rendered is not the actual score of a student on a particular assessment. Plausible values, rather, are random draws from the distribution of scores that could be reasonably assigned to a student with a specific testing pattern. The primary goal of reporting plausible values is to avoid biases caused by students answering only a subset of questions on a particular test. Because students only answer a fraction of all possible questions, these imputation methods are employed by PISA in order to assess how well students would have performed had they answered all the questions. Thus, instead of reporting a single raw test score, a distribution of scores (with associated probabilities) is generated for each individual student.

2.4.2 Estimation adjustments while using PISA dataset

Although the reported plausible values are neatly standardized such that the mean test score is 500 and the standard deviation is 100, this standardization also complicates parameter estimates. To obtain an unbiased estimate for any analysis using plausible values, the PISA 2009 manual suggests using all five plausible values for each analysis. Thus, the appropriate statistical estimate is the average of these five. This can be represented as:

$$\beta = \frac{1}{5}\sum_{j=1}^{5}\hat{\beta}_{ij},$$

Where β is the estimated coefficient of interest and $\hat{\beta}_{ij}$ is the estimated parameter obtained using the j^{th} plausible value. A final weight accounts for the fact that a student from a small school is more likely to be sampled.[30]

[30] Sample design weights are used to obtain population estimates. The computation of standard errors is not straightforward due to the two-stage clustered sampling design of the PISA dataset.

2.5 Empirical results

The first stage of the empirical analysis involves computing IEO measures based on the theoretical model described in section (2.3)[31]. In the second stage of the empirical analysis, I provide evidence of the connections between IEO and relatable factors, such as the overall level of economic development, income inequality, and investment in human capital (as well as other forms of institutional structure).

2.5.1 IEO estimates

I estimate IEO (using OLS and quantile regression analyses for quantile values 0.2, 0.5, and 0.8) as a relative variation in student test scores which is explainable by a set of circumstances at an individual level, for each country and for each year.

These estimates of the IEO represent the lower bounds of the actual IEO because the estimation might not include all possible family situations.[32] Table 2-1 displays the averages of the estimated results of IEO, and demonstrates substantial cross-country heterogeneity in these values. Territories such as Hong-Kong and Panama have family background information explaining approximately 30% and 37% (respectively) of the difference in student scores on average. In the majority of Scandinavian countries, these same predetermined family factors only

[31] For each country I estimate a linear relationship of the mathematics test score and circumstances in the form of a dummy variable for whether a student's mother has completed high school education (mother has at least high school education =1), parental highest level of education, index of cultural possessions) and the school's average of the index of social economic status. To avoid the results being influenced by gender, school location and whether or not a student is a native born I include, a dummy variable for gender dummy (female =1), whether a student is a native born dummy variable (Native=1), whether a student lives in rural area (with population less than or equal to 10000), These variables were chosen based on the education production literature and on their availability in all three waves of PISA used in the empirical analysis.

[32] I present a list of all included circumstances and their definitions in the appendix.

explained about 17% of the variation in student test scores. And Azerbaijan had the lowest measure of IEO of around 2%.

Table 2-2 summarizes the estimated IEO measure by year. On average, predetermined circumstances explain about 18.3%, 17.4%, and 17.7% of the variation in student test scores for the years 2003, 2006, and 2009 (respectively). Moreover, family circumstances explain nearly 10% of variation in student test scores at each quantile.

In order to assess the trends in IEO for each country, I have plotted the measure for selected countries. Figure 1.1 represents national trends of the IEO measures for OECD countries. It shows that the OLS estimates overstate the IEO in comparison to the quantile regression estimates. Moreover, there is no clear trend of IEO over time, indicating that the computed measure is stable within each of these countries. Countries such as Greece, Hungary, Turkey, and Luxemburg yield an IEO that appears to decline between 2006 and 2009. Another observation is that measured IEO for students at the top of the test score distribution is greater than the IEO measure for the students at the bottom of the test score distribution. An implication for this finding is that intergenerational persistence of certain factors within the educational context might be greatest for students at the top of the score distribution.

2.5.2 Application 1: How does institutional structure relate to IEO?

After constructing a comparable measure of IEO, another objective of this paper is to find sources of international differences in IEO. This investigation sheds light on educational policy and the structure behind student achievement, as well as on how these forces affect the quality of the labor in a country. It is important to note that understanding the relationship between IEO and existing institutional structures also provides a preliminary understanding of the intergenerational persistence of inequality.

Since there is no definitive theory for how educational policies and institutional structure influence IEO, I estimate the relationship on the pooled cross-section of countries using the following equation:

$$IEO_{q,ct} = X'_{ct}\alpha_1 + \sum_t \tau_t\, \delta_t + \vartheta_{ct}. \tag{2.5}$$

The dependent variable, IEO^{q}_{ct}., is the imputed IEO at quantile q, in country *c*, and at time *t*. [33] The vector of presumed determinants of IEO; X'_{ct}, includes measures of the education system such as average education spending per student (as a percentage of GDP per capita), preprimary enrollment rates, average class size (as measured by the average student teacher ratio), average productivity of the labor force (as measured by GDP per capita at constant PPP), and overall inequality (as measured by a country's average GINI coefficient). I denote α_1 as a vector of the parameters of interest. I also include δ_t as a variable to control for time-fixed effects. The error term is denoted with ϑ. Besides the pooled cross-section, I also estimate the relationship between IEO and its determinants by using a panel model with country fixed-effects. This estimation takes the form of:

$$IEO_{q,ct} = X'_{ct}\alpha_1 + \sum_t \tau_t\, \delta_t + \sum_c \theta_c\ Z_c + \xi_{ct}. \tag{2.6}$$

In equation (2.6) Z_c represents country specific fixed-effects and ξ_{ct}.represents an idiosyncratic error term. I report the estimation results of equation (2.5) and equation (2.6) in Tables 2.4 -2.7. I organize Tables 2.4 -2.7 such that the dependent variable for each table is a different measure of IEO for each. The first regression in each table is the baseline model. It demonstrates the

[33] Note that I also use a similar regression, for the average imputed IEO. The difference is that the IEO at a given quantile is replaced with the IEO measure I obtain from using OLS.

relationship between overall economic inequality and the level of IEO which is conditional on economic development, as measured by average income level per capita. The second regression includes the institutional features. The third regression is similar to the second regression, except that it accounts for the possibility of a non-linear effect from preprimary education. Models (1-3) in each table represent pooled cross-sectional regression estimates, and models (4-6) represent the fixed-effect estimates. The results are best summarized by variable.

Financial resources: All Tables 2.4 -2.7 show that financial measures such as expenditures per student and resource endowment (as measured by GDP per capita) do not robustly impact IEO. Increasing GDP per capita is associated with higher IEO for students with average test scores or whose scores are in the middle of the test score distribution. However, the association disappears when one analyzes the relationship at the top of the test score distribution. These results are consistent with the findings that the level of economic development explains the cross country differences in student achievement on average. As it pertains to the role of education expenditures, there is no clear support that financial resources impact IEO. These results are in line with the literature, which uses aggregated data and finds no clear relationship between student outcomes and education spending (see e.g. Hanushek and Kimko (2000), Hanushek (2003) and Pritchett (2006)).

Income inequality: Both pooled cross-sections and FE estimates demonstrate that income inequality impacts IEO significantly at all quantile levels, except in the case of FE, at the top of the student test score distribution. On average, a single percentage point increase in the GINI coefficient is associated with about a 0.3% increase in IEO at the top, middle, and bottom of the test score distribution. These results suggest that inequalities from parents can translate to unequal opportunities for students from poor families. Of course, these results do not imply causation; it might also be the case that increased IEO translates to increased overall inequality in society. This is an example of a “vicious circle” theory from economic development.

Class size: There is no consensus regarding how a reduction in class size affects IEO and hence student test scores. One might argue that small classes should produce higher test scores because students can interact more with their teacher. On the other hand, students in larger classes might outperform students in smaller classes because of other externality effects from their peers. From a policy perspective it is interesting to investigate whether class size reduction reduces IEO. For this reason, I included student-teacher ratio in the analysis. Only FE estimates demonstrate that class size impacts the IEO of average scores and the IEO of scores at the bottom of distribution. The results show that increasing class size by one unit increases IEO by about a tenth of a percentage.

Preprimary enrollment rate: Schuetz et al. (2008) emphasize the role of preprimary education in influencing the effect of family background on student achievement. In general, it is not clear how the accessibility of preprimary education can influence IEO. On one hand, preprimary education can level the playing field of students if it is made accessible to students coming from disadvantaged families. On the other hand, it can increase IEO if the accessibility to preprimary education is dependent on economic status. This can cause the students from advantaged families to attend preprimary education more exclusively, thus exacerbating IEO. Schuetz et al. (2008) provides a theoretical model (and empirical evidence) that shows a non-linear relationship between preprimary education and IEO. More specifically, using cross-sectional data from TIMSS, they find an inverted-U relationship to be present between these factors. In this case, increasing enrollment rates increases student outcomes initially, but eventually the especially high enrollment rates result in lower student outcomes. I include the preprimary enrollment rate in models (2) and (5) of Tables 2.4-2.7. To test for the possibility of non-linearity, I also include the square of this in models (3) and (6) of Tables 2.4-2.7. Consistent with the findings of Schuetz et al. (2008), my models predict that there is an inverted-U relationship between these variables. However, these results are only statistically significant for the pooled-regression results of IEO at the top of the student score distribution. This suggests that accessibility to preprimary education initially increases IEO, but then eventually lowers IEO overall, most particularly for the students at the top of the test score distribution. The lack of clear evidence from FE estimates makes interpreting results from the cross-sectional (international) dataset unsubstantial.

Robustness check: These results are not robust for the samples from the OECD and non-OECD countries in Tables 2.8-2.11and Tables 2.12-2.15 respectively. For example, both the pooled cross-section regression and panel data FE estimates from Tables 2.8-2.11 show that financial resources do not predict IEO at various student levels of test score distribution. However, it does seem that increased income inequality leads generally to increased IEO.

2.5.3 Application 2: To what extent does an equity-efficiency tradeoff in education exist?

Always relevant to education policy discussions is an evaluation of whether attempts to improve education efficiency (such as efforts to increase student test scores) come at a cost of unintentionally exacerbating the existing inequalities in education. Education policy evaluations should also involve analysis of the extent to which policies intended to reduce IEO might in turn decrease overall student achievement. For these reasons, I investigate here whether there is an equity-efficiency tradeoff in education. I report the pooled correlation between the average test score in mathematics and associated IEO measurements which are conditional on a student's test score in Figure 2.2. The first graph of Figure 2.2 represents the relationship between mean mathematics test scores and the average IEO based on ordinary least squares. The other graphs represent the relationship between mean mathematics test scores and IEO at the 20th, 50th, and 80th quintiles.

The scatter plots in Figure 2.2 show no definitive tradeoff between equality and efficiency in education, but the fitted correlation at the top of student score distribution is suggestive of a possible tradeoff in some cases. One possible explanation of the absence of the equity-efficiency tradeoff is that the plots do not control for features that might influence IEO (such as the level of economic development).

I resolve this issue by estimating the equity-efficiency tradeoff through a pooled cross-section model in the form of:

$$\bar{T}_{ct} = \varphi_1 ln\ (GDP\ per\ capita)_{ct} + \sum_q \varphi_q\, IEO_{q,ct}\ + \sum_t \tau_t\, \delta_t + u_{ct}. \qquad (2.6)$$

In this case $\bar{T}_{ct}$ deNote the average student test score in mathematics for country c in year t. The natural log of GDP per capita in constant PPP is included in order to control for the level of economic development.[34] The imputed inequality measure at each quantile $IEO_{q,ct}$, is included to capture and measure the tradeoff, and thus φ_q is the parameter of interest. I also include time dummies in order to control for time fixed effects that are common to all countries, denoted with δ_t. The last term, u_{ct}, is the error term.

[34] Since the first application showed strong relationship between GINI coefficient and my IEO, I do not control form the overall inequality in this model. Furthermore, controlling for overall inequality yields similar qualitative conclusions. However I control for the level of economic development or human capital quality as measured by GDP per capita because I previously (in essay 1) found robust evidence that students from high income countries perform relatively better than those from low income countries.

Besides reporting results from the pooled cross-section model presented in equation (2.8), I also employ a panel fixed-effect model expressed as:

$$\bar{T}_{ct} = \varphi_1 Ln(GDP\ per\ capita)_{ct} + \sum_q \varphi_q\, IEO_{q,ct} + \sum_t \tau_t\, \delta_t + \sum_c \theta_c\ Z_c + u_{ct}. \tag{2.9}$$

Equation (2.9) differs from equation (2.8) in that it includes country dummies, Z_c, in order to control for country specific fixed-effects. I present pooled-regression and panel fixed-effect results in Table 2-16.

Table 2-16 show results from the pooled regressions (models 1-3) and for the fixed-effect estimates (models 4-6). The first regression in Table 2-16 is a baseline model for the pooled regression. It includes the logarithm of GDP per capita in order to control for average productivity. The second regression includes the average measure of IEO, and the third regression includes the disaggregated measures of IEO at the top, middle, and bottom of the test score distribution. The estimated results show that, on average, a single percentage increase in GDP per capita increases average mathematics test scores by 56 points, and that the results are statistically significant for all of the pooled regressions.

As for the relationship between IEO and student achievement, the results don't show robust equity-efficiency tradeoff at either levels of the student test score distribution. This is in line with the findings of Woessmann (2004), who used the TIMSS dataset and found no clear evidence of tradeoff between a country's mean test scores and inequality. However, model 3 shows that a percentage increase in IEO at the top of student test score distribution lowers the average math achievement by 6.515 points. An implication from the pooled regressions is that the equity-efficiency tradeoff exists for some groups of students.

The fixed-effect estimates which takes into account the cross country heterogeneity are presented in models (4-6) of Table 2-16. They show a different outlook of the equity-efficiency tradeoff. First, they show no evidence that initial economic conditions matter for the average student test score. Furthermore, model (6) of Table 2-16 demonstrates that an increase in IEO for a student at the bottom of the score distribution actually improves the average mathematics test scores, and that the results are statistically significant at a 1% level. On the other hand, model (6) also demonstrates that the equity-efficiency tradeoff for IEO exists at the middle of the test score distribution. The results show that at lower levels of the score distribution, high levels of IEO are associated with higher levels of math test scores. In contrast to Woessmann et al. (2008) and Woessmann (2004), which find no clear evidence of the tradeoff on average, the fixed-effect estimates suggest that the tradeoff exists when one considers the inequality measure at different points of the test score distribution, and especially for students at the middle of the distribution.

Keep in mind while interpreting results from Table 2-16 that not every country participated in all three waves of PISA. This results in an unbalanced panel of nations. In Table 2-17 and Table 2-18, I present the results from non-OECD and OECD member countries. Most OECD countries in my sample participate in all three waves of PISA.

The results from Table 2-17 and Table 2-18 are similar to the observed results from Table 2-16. The main difference is that for both pooled-OLS estimates and fixed-effect estimates, the averaged measure of overall IEO negatively relates to average mathematics test scores and results are not statistically significant.

Consistent with results from Table 2-16, model (6) of Table 2-17 and Table 2-18 shows that there is an equity-efficiency trade off, but only for IEO of students at the middle of the test score distribution. This exemplifies the way in which predetermined circumstances can influence educational outcomes, even at the national level.

2.5.4 Data limitations and future research

This study has several limitations. Data collection issues arise from the fact that extremely poor countries, such as those in sub-Saharan Africa, did not participate in any waves of PISA testing. Therefore, the students sampled were not fully representative of all fifteen-year-old students in the world, and the country-level panel dataset in this study only describes middle and higher-income countries. It would be interesting to analyze education policy factors in developing countries, and to monitor their influence on inequality of opportunity in the education sector.

In addition, data limitations restrict the extent of family background information that can be included in approximations for the effect that these factors have on achievement. As a result, the estimates of IEO are lower bounds values, and the regression results used to derive IEO should be interpreted with care. Additionally, there is still no consensus in the literature as to what determines IEO, or how predetermined family background variables affect student achievement. To this end, I have not considered any nonlinearity that might arise while defining the effect of predetermined circumstance on student outcomes.

On a more technical note, the PISA dataset does not include individuals who repeated grades such that they are not in grade 6 or higher by the age of fifteen, nor does it include dropouts. The reported measure should be interpreted only for students who did not leave school or repeat multiple grades. The reported IEO should not be interpreted, therefore, as representing IEO for all 15-year-old students in a country. The provided IEO does, however, usefully demonstrate how the effect of family background information varies across countries. Finally, there is no underlying and established theory behind the determinants of IEO. For this reason, omission of unconsidered variables might worsen the endogeneity problem in the second stage of my estimates. However, the results from fixed-effect estimates (which account for heterogeneity between countries) help to control this endogeneity problem. A notable disadvantage of the fixed-effect analysis is that reliable estimations relating to a country's non-invariant education system characteristics (such as student tracking) cannot be generated. An appropriate response to this issue would be to use a difference-in-difference approach. My focus, however, is on more conscious measures of the education system, and so I reserve such investigation for future works.

2.6 Conclusion

The results from the Program for International Student Assessment (PISA) have triggered serious debate about the efficacy of various educational systems. One important finding is that inequality of education opportunity (IEO), as measured by the effect of a student's family background on test scores, is a demonstrable force in influencing educational outcomes. Numerous hypotheses seek to explain this phenomenon, with most policy makers primarily showing interest in understanding the extent to which a nation's education system affects IEO. To this end, I investigate the role of both education policy and implemented educational systems towards explaining international differences in IEO.

The availability of international microeconomic data on student achievement in the past decade enables a much deeper investigation of cross-country differences in IEO. A few studies have recently used panel data techniques to analyze the role of education systems in influencing IEO at different levels of students' test score distribution. I add to this body of research by examining the specific role of policy with regards to cross-country differences in the presence of IEO.

I use quantile regressions analysis to construct measures of IEO for countries that have participated in the PISA assessment since 2003. I construct the measure of IEO as a relative variation in student test scores that can be explained by predetermined circumstances. The main advantage of this measure is that it allows for simple parametric estimations, and that it makes more substantial use of family background information. This is in contrast to studies such as Woessmann (2004), and Schuetz et al. (2008), which only examine family background according to the value of a single metric.

Constructed IEO varies greatly across international borders (and sometimes even within countries) at different points in the students' score distribution. I show thatthat overall inequality in society strongly predicts IEO. Additionally, increasing preprimary enrollment rates also seems to reduce the IEO measure at the top of the test score distributions. One implication for these findings is that improvements in early childhood education can mitigate the deleterious effects of IEO for some students.

Additionally there is an equity-efficiency tradeoff in education, especially for students at the middle of the test score distribution. Policies aimed at reducing inequality of education opportunity also risk harming efficiency in other ways, such as by lowering academic achievement for certain groups of students.

One acknowledged shortfall associated with using fixed-effect estimation is that one cannot approximate the effects of non-invariant education system characteristics, such as student tracking in schools. An appropriate method to mitigate this issue would be to use a difference-in-difference approach. Analysis in this vein may prove productive for future projects.

This paper can also be extended in several ways. The provided measure of education inequality may be used to critically analyze the role of IEO on economic growth and earnings.

Additionally, one could disaggregate inequality of opportunity in human capital development, and analyze the effects. Finally, with an increased availability of data from developing countries (such as those in sub-Saharan Africa), it is now possible to analyze the roles of aid policy, trade, and financial remittance in explaining IEO. It may even be fruitful to deconstruct IEO by source, and thereby obtain even more accurate estimations of intergenerational persistence in IEO.

Table 2-1. Decade averages of IEO as measured by variation in mathematics test scores explained by predetermined circumstances in non-OECD countries.

Non-OECD	IEO-OLS	IEO-q50	IEO-q20	IEO-q80
Argentina	25.150	12.839	12.796	14.913
Azerbaijan	1.933	1.639	2.615	2.496
Brazil	22.993	11.876	9.384	15.697
Bulgaria	26.600	14.688	13.622	15.925
Colombia	21.633	11.540	10.628	12.168
Costa Rica	13.000	7.388	7.264	8.843
Croatia	15.567	8.375	8.724	8.291
Georgia	20.500	12.880	12.740	9.218
Hong-Kong China	33.500	19.480	19.327	11.603
India	11.200	5.546	5.401	7.710
Indonesia	11.878	6.354	5.553	9.326
Jordan	12.100	7.040	6.883	7.158
Kazakhstan	14.633	8.078	7.517	9.851
Kyrgyzstan	14.367	7.290	6.512	8.926
Latvia	14.047	7.481	8.080	7.837
Republic of Moldova	16.350	7.827	7.279	10.155
Romania	17.550	9.290	8.354	10.375
Russian Federation	12.116	6.472	6.456	6.856
Lithuania	20.083	12.080	11.262	9.070
Macao-China	9.300	5.091	5.260	5.729
Malaysia	17.400	10.274	10.106	10.180
Malta	18.500	10.406	10.137	10.685
Mauritius	17.400	9.278	9.142	9.370
Panama	37.500	20.020	19.887	16.100
Peru	17.100	9.830	9.798	11.188
Qatar	16.300	8.978	8.865	8.623
Serbia	14.967	8.559	8.356	8.558
Thailand	14.296	7.581	5.753	11.692
Uruguay	23.791	13.665	12.800	11.854

Note: The IEO is measured as R^2*100.

Table 2-2. Decade averages of IEO as measured by variation in mathematics test scores explainec by predetermined circumstances in OECD countries.

OECD	IEO-OLS	IEO-q50	IEO-q20	IEO-q80
Austria	19.044	10.979	11.423	9.491
Belgium	22.807	13.093	13.836	9.794
Chile	26.700	13.868	12.163	16.288
Czech Republic	17.329	9.297	8.873	8.778
Estonia	11.967	6.219	6.256	7.526
Finland	12.989	7.155	6.981	7.252
France	14.100	9.046	9.039	6.753
Greece	15.273	8.233	7.861	10.278
Hungary	21.916	11.995	11.306	12.035
Italy	13.400	7.520	7.524	7.362
Japan	12.002	6.613	6.179	6.960
Mexico	18.330	10.082	9.470	9.941
New Zealand	16.484	9.011	8.606	10.348
Poland	17.971	10.041	10.081	10.730
Portugal	21.960	12.080	11.988	11.865
Slovak Republic	21.069	12.000	11.621	10.564
Slovenia	19.267	10.880	9.906	10.075
Spain	16.540	9.093	9.092	8.599
Sweden	17.500	9.665	9.449	8.496
Turkey	20.669	10.281	8.623	13.717
United Kingdom	17.973	10.131	9.945	10.974
United States	20.933	11.503	10.770	12.747

Note: The IEO is measured as R^2*100.

Table 2-3. Average IEO values for 2003, 2006, and 2009.

Year 2003	Mean	Std. Dev	Min	Max
IEO-OLS	18.315	6.341	1.933	37.500
IEO-q50	10.124	3.547	1.639	20.020
IEO-q20	9.610	3.608	1.942	19.887
IEO-q80	10.035	2.809	2.496	16.288

Year 2006	Mean	Std. Dev	Min	Max
IEO-OLS	17.368	6.159	1.467	37.500
IEO-q50	9.493	3.475	0.851	20.020
IEO-q20	8.937	3.094	3.305	19.887
IEO-q80	9.800	3.069	3.053	17.850

Year 2009	Mean	Std. Dev	Min	Max
IEO-OLS	17.727	6.362	2.400	37.500
IEO-q50	9.832	3.523	2.426	20.020
IEO-q20	9.776	3.570	1.811	19.887
IEO-q80	10.221	3.136	1.256	17.025

Note: The IEO is measured as R^2*100.

Table 2-4. The determinants of IEO on average.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	2.167**	2.208*	1.683	5.384**	4.112*	4.687*
	(0.920)	(1.099)	(1.134)	(2.151)	(2.340)	(2.397)
GINI	0.251***	0.310***	0.252**	0.188***	0.197**	0.197**
	(0.093)	(0.104)	(0.112)	(0.069)	(0.082)	(0.083)
ln(Expenditure)		3.178	3.168		3.944	3.815
		(2.660)	(2.625)		(2.713)	(2.690)
Class-Size		-0.010	-0.009		0.007	0.009
		(0.011)	(0.011)		(0.006)	(0.007)
Preprimary enrollment rate		-0.014	0.638		-0.087	0.510
		(0.137)	(0.474)		(0.143)	(0.583)
Preprimary enrollment rate squared			(0.016)			(0.016)
			(0.010)			(0.015)
N	162	141	141	162	141	141
R2	0.143	0.174	0.197	0.084	0.108	0.116
F	4.455	2.931	2.357	4.072	1.764	1.696

Note: The dependent variable is IEO-0LS. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a fraction of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-5. The determinants of IEO at the middle of the test score distribution.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	1.263**	1.314*	1.028	3.198**	3.136**	3.464**
	(0.546)	(0.653)	(0.681)	(1.243)	(1.395)	(1.510)
GINI	0.123**	0.160***	0.129**	0.0969**	0.105**	0.106**
	(0.051)	(0.056)	(0.062)	(0.039)	(0.049)	(0.049)
ln(Expenditure)		1.444	1.438		1.191	1.117
		(1.498)	(1.478)		(1.628)	(1.633)
Class-Size		-0.007	-0.006		0.003	0.005
		(0.006)	(0.006)		(0.004)	(0.004)
Preprimary enrollment rate		-0.024	0.331		0.002	0.343
		(0.077)	(0.273)		(0.087)	(0.393)
Preprimary enrollment rate squared			-0.009			-0.009
			(0.006)			(0.009)
N	162	141	141	162	141	141
R2	0.126	0.162	0.184	0.079	0.101	0.108
F	3.976	2.898	2.490	3.454	2.288	2.060

Note: The dependent variable is IEO-q50. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-6. The determinants of IEO at the bottom of the test score distribution.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	1.235**	1.424**	1.187*	2.703*	3.069**	3.129**
	(0.545)	(0.652)	(0.685)	(1.371)	(1.338)	(1.438)
GINI	0.101*	0.137**	0.111*	0.103***	0.111***	0.111***
	(0.052)	(0.059)	(0.063)	(0.037)	(0.039)	(0.040)
ln(Expenditure)		1.316	1.312		1.019	1.006
		(1.384)	(1.372)		(1.406)	(1.427)
Class-size		-0.010*	-0.010*		0.001	0.001
		(0.006)	(0.006)		(0.004)	(0.004)
Preprimary enrollment Rate		-0.027	0.267		0.053	0.114
		(0.070)	(0.244)		(0.050)	(0.298)
Preprimary enrollment rate squared			-0.007			-0.002
			(0.005)			(0.007)
N	162	141	141	162	141	141
R^2	0.110	0.164	0.179	0.088	0.123	0.123
F	4.826	3.919	3.119	5.827	3.309	2.866

Note: The dependent variable is IEO-q20. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-7. The determinants of IEO at the top of the test score distribution.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	0.649*	0.535	0.164	1.048	(0.935)	(0.659)
	(0.381)	(0.476)	(0.506)	(1.046)	(1.224)	(1.320)
GINI	0.150***	0.162***	0.121***	0.060	0.045	0.045
	(0.036)	(0.040)	(0.042)	(0.038)	(0.045)	(0.045)
ln(Expenditure)		1.281	1.274		1.415	1.353
		(1.276)	(1.251)		(1.340)	(1.336)
Class-size		-0.003	-0.002		0.000	0.001
		(0.005)	(0.005)		(0.003)	(0.004)
Preprimary enrollment rate		0.023	0.483**		-0.125	0.162
		(0.067)	(0.218)		(0.082)	(0.280)
Preprimary enrollment ate squared			-0.011**			-0.008
			(0.005)			(0.007)
N	162	141	141	162	141	141
R^2	0.181	0.192	0.242	0.023	0.062	0.068
F	6.481	4.028	3.361	1.120	1.386	2.278

Note: The dependent variable is IEO-q80. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-8. The determinants of IEO on average in OECD countries.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	1.679	2.523	3.531	4.522	7.570	17.420
	(1.423)	(2.608)	(2.772)	(13.560)	(13.300)	(13.450)
GINI	0.055	0.176*	0.109	0.623*	0.334	0.343
	(0.092)	(0.100)	(0.096)	(0.347)	(0.338)	(0.322)
ln(Expenditure)		2.483	3.584		18.560	12.690
		(5.290)	(5.014)		(22.870)	(19.740)
Class-Size		0.022	0.026		-0.006	-0.025
		(0.019)	(0.020)		(0.021)	(0.021)
Preprimary enrollment Rate		(0.250)	1.539*		(0.542)	-4.650**
		(0.162)	(0.858)		(0.352)	(1.971)
Preprimary enrollment Rate squared			-0.0461**			0.0943**
			(0.021)			(0.045)
N	62	54	54	62	54	54
R^2	0.173	0.213	0.308	0.305	0.374	0.439
F	12.330	12.040	14.870	7.173	9.389	5.565

Note: The dependent variable is IEO-0LS. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a fraction of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-9. The determinants of IEO on the middle of the test score distribution in OECD countries.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	-0.483	-1.298	-1.906	3.559	4.721	11.070
	(0.785)	(1.481)	(1.548)	(7.896)	(7.828)	(7.459)
GINI	0.003	0.066	0.026	0.315	0.163	0.169
	(0.049)	(0.064)	(0.059)	(0.186)	(0.187)	(0.174)
ln(Expenditure)		2.477	3.142		11.070	7.292
		(2.947)	(2.765)		(13.190)	(11.230)
Class-size		0.010	0.012		-0.006	-0.019
		(0.012)	(0.012)		(0.013)	(0.014)
Preprimary enrollment Rate		-0.094	0.985**		-0.252	-2.900**
		(0.098)	(0.458)		(0.210)	(1.117)
Preprimary enrollment rate squared			-0.028**			0.0608**
			(0.011)			(0.025)
N	62	54	54	62	54	54
R^2	0.146	0.178	0.291	0.292	0.383	0.471
F	12.470	14.040	14.780	6.433	8.042	7.083

Note: The dependent variable is IEO-q50. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-10. The determinants of IEO at the bottom of the test score distribution in OECD countries.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	-0.271	-1.036	-1.695	7.590	5.124	11.140
	(0.763)	(1.317)	(1.298)	(7.048)	(7.804)	(7.526)
GINI	(0.017)	0.049	0.005	0.222	0.083	0.089
	(0.049)	(0.068)	(0.065)	(0.180)	(0.176)	(0.167)
ln(Expenditure)		3.186	3.906		5.902	2.321
		(2.834)	(2.517)		(14.860)	(12.730)
Class-Size		0.005	0.007		-0.008	-0.020
		(0.011)	(0.012)		(0.011)	(0.013)
Preprimary enrollment Rate		-0.079	1.089**		-0.124	-2.631**
		(0.106)	(0.428)		(0.233)	(1.106)
Preprimary enrollment Rate squared			-0.0301***			0.0576**
			(0.011)			(0.025)
N	62	54	54	62	54	54
	0.118	0.143	0.271	0.263	0.266	0.350
F	7.155	3.232	3.726	5.371	3.652	2.795

Note: The dependent variable is IEO-q20. All regressions include time fixed effects. For the Pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-11. The determinants of IEO at the top of the test score distribution in OECD countries.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	-0.719	-0.920	-1.535	3.042	8.207	13.760
	(1.002)	(1.539)	(1.469)	(12.510)	(13.250)	(13.310)
GINI	0.113*	0.164***	0.123***	0.255	0.103	0.108
	(0.057)	(0.047)	(0.036)	(0.246)	(0.279)	(0.258)
ln(Expenditure)		(1.022)	(0.350)		9.644	6.340
		(2.940)	(2.606)		(10.550)	(9.875)
Class-size		0.012	0.014		-0.007	-0.017*
		(0.009)	(0.010)		(0.011)	(0.009)
Preprimary enrollment Rate		-0.157	0.935**		-0.448*	-2.76**
		(0.092)	(0.355)		(0.230)	(1.249)
Preprimary enrollment rate squared			-0.028***			0.0531*
			(0.008)			(0.027)
N	62	54	54	62	54	54
R^2	0.161	0.292	0.399	0.076	0.275	0.342
F	4.279	14.050	22.540	2.217	9.338	6.200

Note: The dependent variable is IEO-q80. All regressions include time fixed effects. For the Pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-12. The determinants of IEO on average in non-OECD countries.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	2.954	3.786	(3.531)	4.522	7.570	17.420
	(1.973)	(2.547)	(2.772)	(13.560)	(13.300)	(13.450)
GINI	0.313***	0.334***	0.109	0.623*	0.334	0.343
	(0.090)	(0.111)	(0.096)	(0.347)	(0.338)	(0.322)
Ln(Expenditure)		5.326	3.584		18.560	12.690
		(3.818)	(5.014)		(22.870)	(19.740)
Class-size		-0.037	0.026		-0.006	-0.025
		(0.025)	(0.020)		(0.021)	(0.021)
Preprimary enrollment Rate		0.233	1.539*		-0.542	-4.650**
		(0.223)	(0.858)		(0.352)	(1.971)
Preprimary enrollment rate squared			-0.0461**			0.0943**
			(0.021)			(0.045)
N	64	56	54	62	54	54
R^2	0.229	0.309	0.308	0.305	0.374	0.439
F	5.433	4.827	14.870	7.173	9.389	5.565

Note: The dependent variable is IEO-0LS. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a fraction of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-13. The determinants of IEO on the middle of the test score distribution in OECD countries.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	1.813	2.337	-1.906	3.559	4.721	11.070
	(1.175)	(1.545)	(1.548)	(7.896)	(7.828)	(7.459)
GINI	0.158***	0.174***	0.026	0.315	0.163	0.169
	(0.050)	(0.061)	(0.059)	(0.186)	(0.187)	(0.174)
ln(Expenditure)		2.483	3.142		11.070	7.292
		(2.207)	(2.765)		(13.190)	(11.230)
Class-size		-0.022	0.012		-0.006	-0.019
		(0.015)	(0.012)		(0.013)	(0.014)
Preprimary enrollment Rate		0.107	0.985**		-0.252	-2.900**
		(0.131)	(0.458)		(0.210)	(1.117)
Preprimary enrollment rate squared			-0.0278**			0.0608**
			(0.011)			(0.025)
N	64	56	54	62	54	54
R^2	0.221	0.288	0.291	0.292	0.383	0.471
F	5.445	4.330	14.780	6.433	8.042	7.083

Note: The dependent variable is IEO-q50. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-14. The determinants of IEO at the bottom of the test score distribution in non-OECD countries.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	1.955	2.557	-1.695	7.590	5.124	11.140
	(1.157)	(1.538)	(1.298)	(7.048)	(7.804)	(7.526)
GINI	0.127**	0.139**	0.005	0.222	0.083	0.089
	(0.049)	(0.057)	(0.065)	(0.180)	(0.176)	(0.167)
ln(Expenditure)		2.181	3.906		5.902	2.321
		(2.095)	(2.517)		(14.860)	(12.730)
Class-size		-0.020	0.007		-0.008	-0.020
		(0.017)	(0.012)		(0.011)	(0.013)
Preprimary enrollment rate		0.084	1.089**		(0.124)	-2.631**
		(0.120)	(0.428)		(0.233)	(1.106)
Preprimary enrollment rate squared			-0.0301***			0.0576**
			(0.011)			(0.025)
N	64	56	54	62	54	54
R^2	0.261	0.322	0.271	0.263	0.266	0.350
F	7.430	4.938	3.726	5.371	3.652	2.795

Note: The dependent variable is IEO-q20. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-15. The determinants of IEO at the top of the test score distribution in non-OECD countries

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per	0.483	0.275	-1.535	3.042	8.207	13.760
capita)	(0.761)	(0.863)	(1.469)	(12.510)	(13.250)	(13.310)
GINI	0.177***	0.183***	0.123***	0.255	0.103	0.108
	(0.047)	(0.060)	(0.036)	(0.246)	(0.279)	(0.258)
ln(Expenditure)		2.158	(0.350)		9.644	6.340
		(1.676)	(2.606)		(10.550)	(9.875)
Class-size		-0.010	0.014		-0.007	-0.0174*
		(0.007)	(0.010)		(0.011)	(0.009)
Preprimary enrollment rate		0.103	0.935**		-0.448*	-2.761**
		(0.103)	(0.355)		(0.230)	(1.249)
Preprimary enrollment rate squared			-0.028***			0.0531*
			(0.008)			(0.027)
N	64	56	54	62	54	54
R^2	0.207	0.276	0.399	0.076	0.275	0.342
F	4.593	5.464	22.540	2.217	9.338	6.200

Note: The dependent variable is IEO-q80. All regressions include time fixed effects. For the pooled-OLS regressions, the regressions are clustered by country. Expenditure is measured as public education expenditure per student in secondary school, as a percentage of GDP per capita. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-16. The equity-efficiency tradeoff

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	56.00***	56.74***	51.37***	3.302	3.296	1.559
	(9.352)	(9.373)	(10.28)	(5.290)	(5.300)	(4.984)
IEO-OLS		-1.517*			-0.0819	
		(0.786)			(0.210)	
IEO-q20			4.295			2.778***
			(3.032)			(0.872)
IEO-q50			-1.656			-2.854***
			(3.052)			(0.999)
IEO-q80			-6.515***			0.429
			(2.307)			(0.644)
N	174	174	174	174	174	174
R^2	0.516	0.541	0.593	0.00367	0.00481	0.119
F	35.86	18.79	51.80	0.390	0.255	3.842

Note: The dependent variable is the mean student test score in mathematics. The pooled-OLS regressions are clustered by country. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-17. The equity-efficiency tradeoff, evidence from non-OECD countries.

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	47.50**	50.16**	37.92*	0.180	-1.301	-10.24
	(20.150)	(22.000)	(22.230)	(13.190)	(15.790)	(13.230
IEO-OLS		-1.120			0.196	
		(1.449)			(0.632)	
IEO-q20			4.507			6.018***
			(4.413)			(1.695)
IEO-q50			0.851			-5.131***
			(5.455)			(1.771)
IEO-q80			-9.732**			-0.349
			(3.804)			(1.741)
N	58	58	58	58	58	58
R^2	0.358	0.376	0.520	0.00000571	0.00214	0.349
F	5.559	2.600	15.37	0.000186	0.0602	5.819

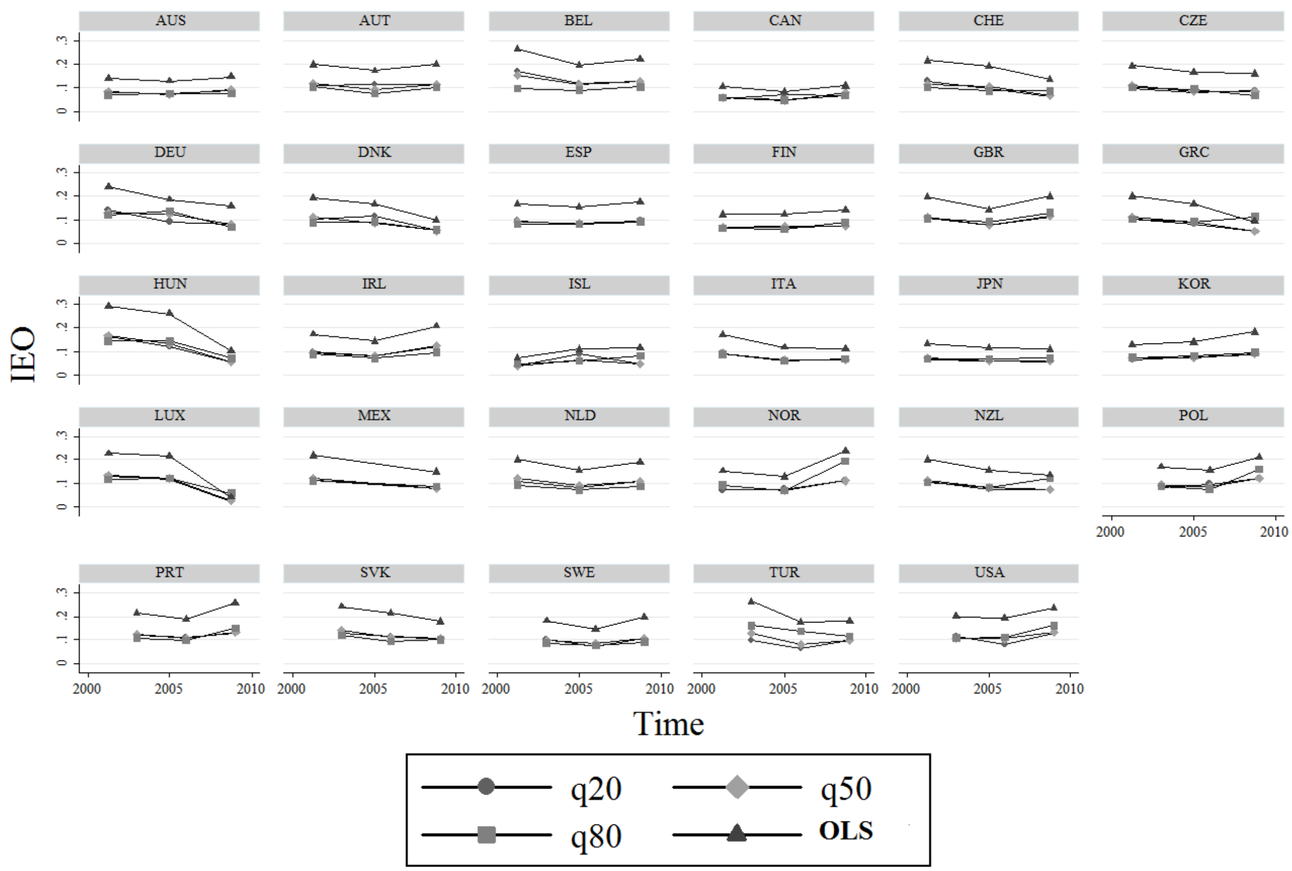
Note: The dependent variable is the mean student test score in mathematics. The pooled-OLS regressions are clustered by country. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Table 2-18. The equity-efficiency tradeoff, evidence from OECD countries

	Pooled-OLS			FE		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP per capita)	42.94**	40.87**	37.89**	-5.169	-9.390	-17.24
	(16.420)	(16.490)	(15.560)	(17.030)	(17.110)	(17.490)
IEO-OLS		-0.788			-0.175	
		(0.701)			(0.251)	
IEO-q20			1.539			1.096
			(2.141)			(0.806)
IEO-q50			0.505			-1.980**
			(2.455)			(0.825)
IEO-q80			-3.906***			0.869
			(1.391)			(0.596)
N	87	87	87	87	87	87
R^2	0.296	0.308	0.365	0.00195	0.0105	0.0674
F	6.840	4.114	5.789	0.0921	0.334	1.694

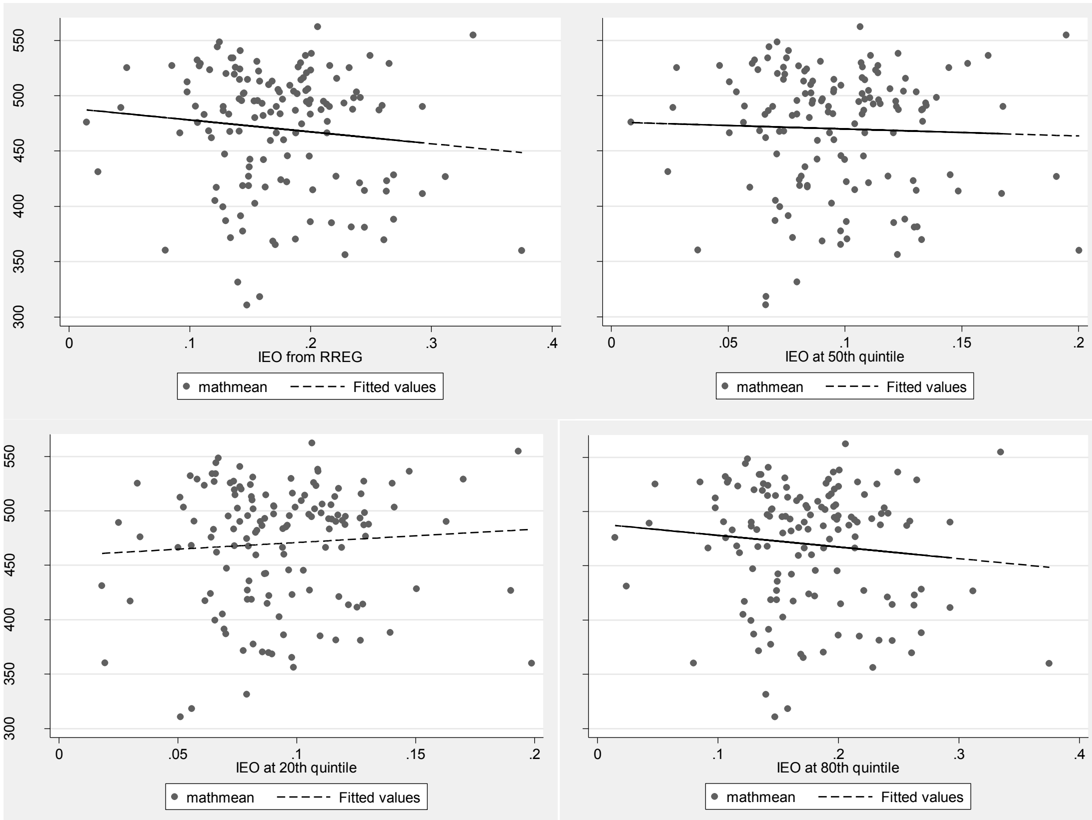
Note: The dependent variable is the mean student test score in mathematics. The pooled-OLS regressions are clustered by country. Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % level.

Figure 2.1: IEO trends for OECD countries from 2003 to 2009



Note: I report results for OECD countries because these countries participated in all three waves of the PISA mathematics test. For most countries it is evident that the IEO measure was stable since there is no clear trend on average as well as conditional on the student test score distribution.

Figure 2.2: Equity-efficiency tradeoff in education



Note: This above graphs shows the pooled average equity-efficiency tradeoff in education as well as the tradeoff at the bottom, middle, and top of the conditional test score distribution. The fitted values are based on pooled correlations between the average math test score in a particular quintile against the computed inequality of opportunity in education measure.

Essay 3: Public Education Spending and Economic Growth: The Role of Governance

3.1 Introduction and problem identification

Numerous studies document the substantial economic benefits of education at an individual level. The economic growth literature presumes that these individual benefits aggregate, and thereby spur growth. Indeed, a large body of empirical literature demonstrates that both the quality of human capital (including student test scores and literacy rates) and the quantity of human capital measures (such as enrolment rates) are associated with high economic growth. These results are documented in studies such as (Barro, 1991), Hanushek(1995), Mankiw, Romer and Weil (1992), and Temple (2001). The effect of human capital quality on economic growth is also documented in studies such as Romer (1990), Hanushek and Kimko (2000) and Hanushek and Woessmann (2008). This evidence partially motivates governments and policy makers to encourage investments in education, in order to improve the quality and quantity of human capital. However, the empirical results supporting this link between public education spending and growth is mixed. I argue that inefficiencies in resource allocation, management, and implementation hinder the positive effects of public education spending on economic growth. To my knowledge this paper is among the early studies that empirically links public education spending, governance, and economic growth.

The main objective of this paper is to empirically analyze the role of governance (as measured by the level of corruption control, government effectiveness, and regulatory quality) in determining the efficiency of public education spending on economic growth. I take advantage of the endogenous growth models such as Barro (1990), Devarajan, Swaroop and Zou (1996), which assign a role for public spending in promoting economic growth. Barro (1990) is among the early studies that include government spending on the production of technology to assess the effect of fiscal policy on economic growth. On the other hand, Devarajan al. (1996), while analyzing the effect of public expenditure composition on economic growth, extends the Barro (1990) approach to include both productive and unproductive public expenditures in the production technology. I further modify the Barro (1990) and the Devarajan et al. (1996) models to include governance in the allocation of government spending as well as production technology. This modification is motived by empirical studies that demonstrate the detrimental effects of poor governance on public human capital investments (see e.g. Mauro (1998) and Delavallade (2006)).

I contribute to the empirical growth literature in several ways. First, the literature currently tends to engage two significant areas of investigation separately: the relationship between economic growth and public spending, and the relationship between economic growth and governance. My work bridges this gap by demonstrating the extent to which these three aspects are interlinked, and also showing that some forms of governance do influence the effectiveness of public education spending. Second, this study defines governance as a multidimensional entity, instead of attempting to work with governance as a single, simplified measure. This disaggregation of the phenomenon enables a deeper understanding of what aspects of governance influence the efficacy of public spending on economic growth.

This study closely relates to recent research by Rajkumar and Swaroop (2008), which demonstrates that government efficiency positively influences development outcomes (in this case, school enrollment rates and mortality rates). However, I differ from Rajkumar and Swaroop

(2008) by focusing on the effectiveness of public education spending in promoting economic growth.

Using a panel dataset consisting of both developed and developing countries from the World Bank Development Indicators (WDI), and the governance measures from the World Bank Governance Indicators (WGI), I demonstrate that public education spending is effective at promoting economic growth in countries with "good" governance (as measured by the degree of control over corruption). In particular, I demonstrate that educational spending is more effective at promoting growth in countries that reduce incidences of corruption. These results are robust for analysis of developing countries. I find no consistent evidence that other dimensions of governance (such as the regulatory quality of state institutions) consistently improve the effectiveness of public education on growth. These empirical results have important policy implications, especially for developing countries. They suggest that growth-enhancing policies should focus predominantly on spending efficiency, rather than on increasing the quantity of expenditures alone.

I organize the rest of this paper as follows. Section 3.2 provides the motivation behind this current research by briefly discussing the literatures that relates public spending to economic growth, as well as governance to economic growth. Section 3.3 includes the theoretical model I use to formulate the empirical specifications for my analysis. Section 3.4 details my empirical methodology. Section 3.5 discusses the results. Section 3.6 includes the concluding remarks

3.2 Literature Review

3.2.1 Public education spending and economic growth

Ample studies show that human capital accumulation can fuel economic growth.[35] One way a country can influence the quality and quantity of its human capital is through education. Governments world-wide invest resources into education through publicly funding primary and secondary education, in order to exploit this human capital-growth relationship.

While theoretical literature often emphasizes the role of public education expenditures to promote economic growth, the results from the empirical literature based on cross-country regressions are conflicting. For example Baldacci, Clements, Gupta, and Cui (2008), and Blankenau, Simpson and Tomljanovich (2007), both find a positive association between education spending and economic growth, but Devarajan et al. (1996) uses a sample of 43 countries to demonstrate a statistically insignificant relationship between public spending on education and economic growth. Hanushek and Kimko (2000) conclude that since there is no link between public education spending and the quality of human capital (as measured by student test scores in mathematics and science), public education spending should not influence economic growth.

Several phenomena may explain why the presence of a link between education spending and improved growth is not yet clear from the empirical literature. First, there is a possibility that general equilibrium adjustments might undo the positive effects of public human capital investment on economic growth. Blankenau and Simpson (2004) theoretically illustrate that the positive effects of public education spending might disappear in the presence of general

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[35] See for example Romer (1990), Barro (1991), Hanushek (1995), Mankiw et al. (1992), Temple (2001), Hanushek and Kimko (2000) and Hanushek and Woessmann (2007).

equilibrium growth determinants which are negatively affecting economic growth at the same time. For example, when governments use high taxes to finance public education, the increased tax rates might decrease economic growth to a greater extent than the simultaneous increase in growth from better public education. This causes the net effect of public education spending on economic growth to be nonexistent or even negative (Blankenau and Simpson, 2004). Using a sample of 23 developed countries, however, Blankenau et al. (2007) provides empirical support that high public education spending can be associated with high economic growth.

Another explanation of the apparent inconsistencies in previous data focuses on empirical methodology, more specifically on econometric misspecification of the empirical growth models. For instance, Kneller, Bleaney and Gemmell (1999) demonstrates that most empirical studies are incapable of supporting endogenous growth model theories about fiscal policies, mainly because these studies ignore the role of complete specification regarding budget constraints during estimation. By using data from 22 developed countries and considering the governments' various budget constraints, their study demonstrates that productive expenditures (such as public education investment) positively influence economic growth. This finding also supports the argument that empirical analysis is sensitive to small changes in model specification (see e.g. Levine and Renelt (1992)).

A third explanation of these observed empirical inconsistencies relates to inefficiencies in resource allocation, management, and implementation. Indeed, empirical studies that find no clear or significant evidence for public education spending's effects on growth suggest that policy inefficiencies are indeed the main cause. For example, Devarajan et al. (1996) attribute the observed negative effect of public spending on growth to problems with service delivery. Moreover, studies from international organizations such as the World Bank suggest that many developing countries fail to translate public investment into positive development outcomes, predominantly due to poor management of resources. Stated another way, public investments in developing countries may fail to produce development outcomes not because projects are underfunded, but instead because the financing of these projects is poorly executed.

This third line of argument suggests that mismanagement of public education investments results in resources not reaching intended targets, such as schools and students. Thus, public education spending might not always generate additional human capital, and may eventually lead to slower growth overall. This suggests that better policy formulation and implementation schemes both improve the effectiveness of public expenditures. Therefore, empirical studies to consider the role of governance on the effectiveness of public education spending (especially as it relates to economic growth) would be a fruitful future endeavor.

3.2.2 Surveying governance and economic growth

Before analyzing the role of governance (as measured by corruption control, government effectiveness, and regulatory quality), and its subsequent effect on public expenditures, it is important to understand how governance affects economic growth (both directly and indirectly) through investments. There is no conclusive evidence as to whether good governance consistently leads to better economic outcomes. Ugur (2013) is among the recent studies that summarize the literature, which demonstrate that most studies find conflicting results of a correlation between improved governance and better economic outcomes. Some studies posit that poor governance (as measured by level of corruption) facilitates economic growth because it "greases the wheels" of economic growth and development. For example, this argument is generally supported by the views that corruption might facilitate beneficial trades or other economic activities that would otherwise not have taken place. Yet other studies claim the opposite: that poor governance actually “sands the wheels of economic growth” instead (Mauro, 1995) and is believed to play a critical role in generating poverty traps (Blackburn, Bose and Haque (2006), and Blackburn and Sarmah (2008)).

Intuitively, it seems straightforward that improved governance can result in efficiency gains, which in turn may lead to growth. And it is also true that poor governance (including high incidences of corruption) can have a plainly detrimental effect on economic growth. However, poor governance can directly decrease the productivity of existing resources through resource misallocations, or by distorting optimal input mixtures. Poor governance can negatively influence the efficiency of production technology, and thereby hinder growth.

On the other hand, poor governance can indirectly influence economic growth by reducing investments in both physical and human capital, which in turn influences the effectiveness of these inputs in promoting economic growth. Gyimah-Brempong (2002), while using a sample of African countries, shows that corruption negatively influences economic growth because it reduces investment in physical and human capital. Mauro (1998), by analyzing the effect of corruption on government spending composition, shows that corruption corresponds to lower government spending levels in education. He argues that in societies with high incidences of corruption, government officials are likely to divert money to sectors that they can easily control with bribes. This increases spending to corruptible sectors, and often depletes finances from education as a result. This further justifies the position that governance does impact the allocation of public spending. Delavallade (2006) supplements this result by using data from a sample of 64 developing countries, and finding evidence that corruption specifically tends to distort government spending in a way that reduces support for education and health infrastructure.

Perhaps the most common explanation for empirical inconsistencies on governance-growth relationship dwells in the complex nature of governance. In general, it is difficult to define and quantify governance. Kaufmann, Kraay, and Zoido-Lobadino (2002) defines governance as the "traditions and institutions by which authority is exercised in a country." According to Kaufmann et al. (2002), these traditions involve the process through which governments formulate and implement policy, in addition to how governments are selected and replaced. Governance affects the social, economic, and political structures of institutions. Therefore, any analysis that involves the role of governance on economic performance must consider that governance is highly multidimensional.

3.2.3 Public education spending, governance, and predictions of economic growth

The evidence that poor governance is associated with lower public human capital investments suggests that public education spending, governance, and economic growth are all interlinked (see e.g. Delavallade (2006) and Mauro (1998)). So far, the literature focusing on education-growth relationships (and governance-growth linkages) fails to capture the overall connection between public education spending, governance, and economic growth. The recent availability of comparable governance indices has resulted in empirical analysis emphasizing the role of governance in influencing the effectiveness of public investment spending on various development outcomes. Rajkumar and Swaroop (2008) are among the most recent to focus on governance and public spending efficiencies in both health and education. I differ from Rajkumar and Swaroop (2008) by focusing on developmental outcomes, as measured in terms of economic growth.

3.3 The theoretical framework

In order to motivate the empirical specification, I extend the Barro (1990) and Devarajan et al. (I996) models to include governance. Barro (1990) and Devarajan et al. (1996) each extend the Ramsey economic growth model to incorporate additional factors: government and the composition of government expenditures, respectively.

3.3.1 Utility

The model begins with a representative agent, who maximizes her own utility by choosing her optimal amount of consumption.[36] This agent produces a single product that can be consumed, accumulated as capital (either physical or human), and paid as income tax. In each time period, the agent's main objective is to choose optimal consumption that maximizes her discounted sum of utilities, such as:

$$\underset{C}{Max} \int_0^\infty U(C)\, exp^{-\rho t} dt. \tag{3.1}$$

In this case, C represents the amount of consumption and $\rho > 0$ is the subjective discounting rate. In order to obtain an analytical solution, I assume that the utility function is characterized by constant elasticity of substitution, such as:

$$U(C) = \frac{C^{1-\theta} - 1}{1-\theta}. \tag{3.2}$$

In this case, $\frac{1}{\theta} > 0$ is the elasticity of substitution between consumption at any two periods. The representative agent maximizes her utility subject to a budget constraint:

$$\dot{K} \ = (1-\tau)Y - C, \tag{3.3}$$

[36] For simplicity, I eschew using the time subscript, except in cases where the utility function is a lifetime utility.

where $\dot{K}$ is the amount of savings which represents capital evolution, τ is the flat-rate income tax, and Y is income. Therefore, equation (3.3) demonstrates that an agent's disposable income is divided between consumption and savings.

3.3.2 Production technology

The production function for y depends on capital and public expenditures. Using a similar model to the one described in Devarajan et al. (I996), the expenditures can be decomposed to include public education expenditures, e, and all other public expenditures, s, (which may include both productive and unproductive public inputs). The production technology is given by:

$$Y = AK^{\alpha}E^{\beta}S^{\eta}. \tag{3.4}$$

In this case, in addition to public expenditures, output (Y) depends on the level of efficiency enhancing technology, A, and a broad definition of capital (which includes both physical and human capital), K. Parameters $\alpha, \beta, \eta \in (0,1)$, are elasticity of production inputs with respect to their output. For simplicity, these elasticities are assumed to be less than one so that the production function exhibits diminishing marginal product with respect to each factor. I assume that $\alpha + \beta + \eta = 1$, so that the production function exhibits constant returns to scale.

3.3.3 Government budget constraint

In order to avoid financing issues, I assume that the government balances its budget, using all tax revenue (τY) to finance all public spending. This can be expressed as follows:

$$\tau Y = E + S. \tag{3.5}$$

Furthermore, let $\delta_e \in (0,1)$ denote the share of total government expenditure; G, that is devoted to education and let $\delta_s \in (0,1)$ denote the share of government expenditures devoted to all other public sector. Therefore, government expenditures can be expressed as,

$$\tau Y = \delta_e\, G + \delta_s\, G. \qquad (3.6)$$

i assume that $\delta_s = 1 - \delta_e$, so that $\tau Y = G$.

3.3.4 Model solution

Given government policy variables, $\tau, \delta_e,$ and δ_s, and the initial level of capital, K, the objective of the representative agent is to maximize her lifetime utility function (3.1), subject to her budget constraints (3.3).[37] Solving the agent's optimization problem and simplifying the first order conditions yields the following steady state growth equation of consumption:

$$\frac{\dot{C}}{C} = \gamma = \frac{1}{\theta}\left[\alpha(1-\tau)\frac{Y}{K} - \rho\right] \qquad (3.7)$$

In this case, γ, represents the growth rate of consumption. Substituting in the production technology yields the following steady state growth equation:

$$\gamma = \frac{1}{\theta}\left[(1-\beta-\eta)(1-\tau)\frac{AK^{\alpha}E^{\beta}S^{\eta}}{K} - \rho\right]. \qquad (3.8)$$

Considering that along the balanced growth the ratios of aggregates will either be constant or grow at a constant rate, and the marginal tax rate (τ) are constant, the growth rate equation can be transformed to its intensive form by defining $\frac{K}{Y} = k, \frac{C}{Y} = c, \frac{G}{Y} = g, \frac{S}{Y} = s, \frac{E}{Y} = e$. Therefore, the growth rate of equation (3.8) can be simplified further and expressed as a function of shares of public spending such that:

$$\gamma = \frac{1}{\theta}\left[(1-\beta-\eta)(1-\tau)(Ae^{\beta}s^{\eta})^{\frac{1}{\alpha}} - \rho\right] \qquad (3.9)$$

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[37] Similarly to Devarajan et al. (I996), I do not explicitly analyze decision mistakes made by the government. I rather assume that the government chooses the marginal tax rate optimally and balances its own budget, and so also probably choses the spending allocations made to different government sectors.

Considering the budget constraint this can be simplified further such that $G=\tau Y$, then $g=\tau$. The growth rate equation can be re-written as:

$$\gamma = \frac{1}{\theta}\left[(1-\beta-\eta)(1-g)A^{\frac{1}{\alpha}}\delta_e^{\frac{\beta}{\alpha}}(1-\delta_e)^{\frac{\eta}{\alpha}}g^{\frac{\beta+\eta}{\alpha}} - \rho\right]. \qquad (3.10)$$

There are several ways through which governance can affect growth. Authors, such as Pritchett (1996) suggest that governance affects the elasticity of output with respect to individual factors of production. And yet other authors suggest that governance influence economics growth by affecting the total factor product, *A,* (Barro 1990 and Mauro 1998) or the shared of public expenditures such as δ_e (Delavallade (2006) and Mauro 1998). Under any of these assumptions, specifying the steady state growth rate in the form of equation (3.9) or equation (3.10) is important because it illustrates that the growth depends directly on public expenditures, governance, and their mutual interaction.

3.3.5 Comparative statics

Proposition: If a government balances its budget such that $\delta_e + \delta_s = 1$, then the growth effect on the share of government expenditure which is devoted to education depends on the relative shares of expenditures, and their relative elasticities in terms of output.

Verification: if $\delta_e + \delta_s = 1$, then differentiating the steady state growth equation (3.10) with respect to the share of government spending on education can be rendered as follows:

$$\frac{\partial\gamma}{\partial\delta_e} > 0, if\ \frac{\delta_e}{1-\delta_e} < \frac{\beta}{\eta}. \qquad (3.11)$$

Equation (3.11) implies that increases in public education spending tend to be growth-enhancing under certain conditions. More specifically, growth is predicted when the relative share of public education spending compared to the other sectors ($\frac{\delta_e}{1-\delta_e}$), is below these sectors' relative output elasticities ($\frac{\beta}{\eta}$).

3.4 Empirical specification and data

3.4.1 Empirical specification

The growth regression for the empirical analysis follows from equation (3.9) and is a dynamic model taking the form of:[38]

$$\gamma_{i,t} = \phi_0 y_{i,t-1} + \phi_1 e_{i,t-1} + \phi_2 s_{1,i,t-1} + \phi_3 s_{2,i,t-1} + \sum_n \phi_{n,4} g_{n,i,t-1} + \sum_n \phi_{n,5} e_{i,t-1} * g_{n,i,t-1} + \sum_n \phi_{n,6} s_{1.i.,t-1} * g_{n,i,t-1} + \sum_n \phi_{n,7} s_{2,i,t-1} * g_{n,i,t-1} + x_{i,t}{}'\phi_8 + \varepsilon_{i,t}. \qquad (3.11)$$

The dependent variable γ_{it} represents the growth rate of GDP per capita of country *i,* at time period t, with *i=1,. . .,N* and *t=1,. . .,T.* The parameters $\{\phi_0, \phi_1, \phi_2, \phi_3\}$ and associated vectors of parameters $\{\phi_{n,4}, \phi_{n,5}, \phi_{n,6}, \phi_{n,7}, \phi_8\}$ are coefficients of interest corresponding to each of the explanatory variables. The variables of interest in equation (3.11) are: public spending on education as a fraction of GDP (denoted by e), public health spending education as a fraction of GDP (denoted by s_1), public military spending education as a fraction of GDP (s_2) and different dimensions of governance, g_n.[39] I include the governance measures in the form of the level of control of corruption (*corr*), government effectiveness (*gove*) and regulatory quality (*rege*).

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[38] This is similar to studies such as Barro (1991), Levine and Renelt (1992), and Devarajan et al. (1996).

[39] For my empirical analysis I assume that overall measures of governance are representative in all sectors.

In addition to the above variables, I have also included a vector of explanatory variables ($x_{i,t}$) and a lagged explanatory variable ($y_{i,t-1}$), a natural log of GDP per capita, based on the literature. The vector of this explanatory variable $x_{i,t}$ includes the level of human capital as measured by secondary school enrollment rate (h)[40], the level of other private investments (k), the population growth rate (v), and the current size of a government, as measured by government consumption in relative shares of GDP (Gov).

In line with the established empirical growth literature, I include a lagged value for the output, $y_{i,t-1}$, in order to control for the initial economic conditions of each country, and to capture the speed at which income levels adjusts to equilibrium.[41] It is important to note that negative values of the coefficient for the lagged value of output, ϕ_0, represent that countries starting out with lower levels of income per capita grow faster than countries with relatively higher starting values.

In order to capture the effectiveness of education spending on economic growth, I include the interaction terms between public education spending and different dimensions of governance, $e * g_n$. Without the loss of generality that comes with ignoring the time and country subscripts (based on equation (3.11)), the marginal effect of government education spending on economic growth can be expressed as:

$$\frac{\partial \gamma}{\partial e} = \phi_1 + \sum_n \phi_{n,5} * g_n.$$

[40] Refer to the literature initiated by Barro (1991) and Mankiw et al. (1992), which found evidence that human capital matters significantly for economic growth.

[41] See for example Levine and Renelt (1992), Mankiw et al. (1992), and Devarajan et al. (I996), as well as others that include a lagged dependent variable in their growth regressions.

The value ϕ_1 measures the direct effect of public education spending on economic growth and the value $\sum_n \phi_{n,5} * g_n$ represents the indirect effects of education spending, which are conditional on different dimensions of governance, *n*.[42] Therefore, the marginal effect of public health and military expenditures can be expressed in a similar manner as: $\frac{\partial \gamma}{\partial s_1} = \phi_2 + \sum_n \phi_{n,6} * g_n$, and $\frac{\partial \gamma}{\partial s_2} = \phi_3 + \sum_n \phi_{n,7} * g_n$, respectively.

Analogously, the marginal effects of each level of governance can be found by using the following equation:

$$\frac{\partial \gamma}{\partial g_n} = \phi_{n,4} + \phi_{n,5} e_1 + \phi_{n,6} s_1 + \phi_{n,7} s_{21}.$$

In this case $\phi_{n,4}$ represents the direct marginal effect of different dimensions of governance on economic growth. The final component represents the marginal effect of governance that varies with government spending policies.

The last term in equation (3.11), ε_{it} is the error term, which includes country-specific characteristic, μ_i, time fixed effects, λ_t, and an idiosyncratic error term, ξ_{it},. This describes the unobserved characteristics that may also influence a country's growth rate. The country-specific effect, μ_i, is included to capture the heterogeneity among countries, such as differences in the initial level of technological efficiency, and other constant factors which might affect a country's economic growth (but are not already included in the growth regression). These factors may include specific geographic and demographic characteristics. On the other hand, the time-specific effects, λ_t, are incorporated to capture the economic conditions that are common to all countries (such as common productivity shocks). Therefore, the error term can be expressed as:

$$\varepsilon_{i,t} = \mu_i + \lambda_t + \xi_{i,t}. \tag{3.12}$$

Combining equations (3.11) and (3.12) yields the following growth regression:

$$\gamma_{i,t} = \phi_0 y_{i,t-1} + X_{i,t}{}'\phi + \mu_i + \lambda_t + \xi_{i,t}, \tag{3.13}$$

Where $X_{i.t}' = [e_{i,t-1}, s_{1,i,t-1}, s_{2,i,t-1}, g_{n,i,t-1}, s_{1,i,t-1} * g_{n,i,t-1}, s_{2,i,t-1} * g_{n,i,t-1}, x_{i,t}]'$ and $\phi = [\phi_0, \phi_1, \phi_2, \phi_3, \phi_{n,4}, \phi_{n,5}, \phi_{n,6}, \phi_{n,7}, \phi_8]$.[43] In section 3.5, I proceed with explaining how to derive the parameter estimates based on equation (3.13).

3.4.2 Data

I use data from the World Bank Development Indicators (WDI) and World Wide Governance spanning from 1995 to 2010. I have a total of 16 years of unbalanced panel data because some countries missed certain observations in various years. Because the estimation procedure involves using differences, the total sample shrinks as countries with missing data are excluded from the estimation procedure.

The dependent variable here is the growth rate of real GDP per capita (γ).The explanatory variables include public expenditures in: education (e), health (s_1), and military (s_2), private investment in physical capital (k), current government consumption (Gov), population growth rate (ν), and human capital as measured by net secondary school enrollment rate (h). All expenditure variables are expressed as a fraction of GDP based on purchasing power parity, and their values are expressed in natural logarithmic terms.[44]

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[43] Equation (13) can be re-written in a more compact form (similar to Equation (15)). This provides a simple dynamic growth regression, which allows for easier derivation of the dynamic panel estimates.

[44] Although it might be interesting to analyze the determinants of economic growth exhaustively, as is examined in Sala-i-Martin (1995), the goal of this paper is more specifically to determine the effectiveness and role of educational spending in promoting economic growth.

As expressed in the literature review section, it is difficult to quantify governance as it has no precise international definition, and what might constitute good or bad governance would not be the same for different countries. The empirical literature has relied on using indicators rather than direct measures. To this end, I use the governance indexes organized by Kauffmann et al. (2009) in the forms of control of corruption (*corr*), government effectiveness (*gove*), and regulatory quality (*rege*).

Kauffman et al. (2009) defines these indicators as:

Control of corruption (corr) -- measures the extent to which public power is exercised for private gain (including both petty and grand forms of corruption).

Government effectiveness (gove) -- measures the quality of public services, the quality of civil services, and the degree of government independence from political pressures. It also refers to the quality of policy formulation and implementation, and to the credibility of the government's commitment to such policies.

Regulatory quality (rege) -- measures the ability of the government to formulate and implement sound policies, as well as the quality of regulations that permit and promote private sector development.

Each of these governance indicators is generated by combining data from numerous sources, including polls of experts as well as surveys of government officials and businesses. Additionally, they are based on average perceptions of each dimension of governance. Since these samples also capture the perceptions of the government process, this might exacerbate endogeneity factors and reverse causality issues which are common in the empirical economic growth regression analyses. These measures are reported on a scale of 0 to 100, with larger numbers representing improved outcomes.

Before proceeding with more specific presentations of my results, it is important to note that many empirical growth studies use period averages in their estimations. Averaging the data in this way is intended to minimize the biases associated with the data series (such as business cycle effects which might otherwise go unnoticed). It is still unclear in the existing growth literature whether the use of these averaged datasets provides substantial information about the long-run or medium-run nature of the growth. However, one noticeable disadvantage of using average data is that one loses information and degrees of freedom while estimating the growth regression (Devarajan et al. (I996), Kneller et al. (1999), and Bleaney Gemmell and Kneller (2001) provides similar arguments). Moreover, Bleaney et al. (2001), while testing the endogenous growth theory hypothesis (pertaining to the role of fiscal policy in spurring economic growth), argues that inconsistencies in the literature are not due to the use of annual data or period averages. This research demonstrates that using period averages does not capture the long-run growth, mainly because using period averaged data or annual data produced similar results. To this end, there is no established and definitive theory behind choosing period averaged data, annual data, or even the initial values for estimation. Due to the problem of missing data, I use four-year averages for the purposes of empirical estimation. However, using two-year average data also yields similar qualitative results.

3.5 Empirical estimation and results

3.5.1 *The dynamic panel estimates*

The main objective of this study is to obtain unbiased and consistent coefficient estimates of the effectiveness of public education spending in promoting economic growth. In order to achieve this, standard estimation procedures require that:

1) All explanatory variables of equation (3.13) be exogenous (e.g. $E(X_{it}, \varepsilon_{it}) = 0$ and $E(y_{i,t-1}, \varepsilon_{it}) = 0$). Stating this another way, there should be no endogeneity issue.
2) The individual errors are independent and identically distributed (e.g. $\varepsilon_{it} \sim i.i.d\ (0, \sigma^2)$). Alternatively, there should be no serial correlation or heteroskedasticity.

The nature of the error term of equation (3.13) does not prevent the possibility of violating one of the above conditions. Several econometric problems may arise when estimating a dynamic model from equation (3.13). Endogeneity issues are of the foremost concern; it may be the case that countries with high growth rates simply spend more on education and other public services. Countries with high growth rates may also instead have a higher quality of institutional infrastructure. If this is the case, there is a chance of reverse causality complication. This leads to an inability to clearly define the relationship between growth and public spending, or between growth and governance. Kneller et al. (1999) argues that most explanatory variables, including the lagged explanatory variable, investments, institutional features, and public policy variables, might not all be strictly exogenous to growth. To avoid these simultaneity problems (and the associated reverse causality problems they can bring), I assume that public education spending and governance do not affect economic growth contemporaneously, but rather influence the rate of economic growth rate only with a lag.

Additionally, from an econometric point of view, the presence of a lagged explanatory variable violates the second assumption made above. It is obvious that country fixed effects are correlated with initial income levels, i.e. $E\left(y_{i,t-1}, \mu_i\right) \neq 0$. Thus, static panel estimates as well as ordinary least squares (OLS) estimations of equation (3.13) are biased and inconsistent.[45]

[45] Within the empirical growth literature it is common to assume that the country-specific effects are fixed. Hence, they are often omitted when estimating the growth regression from OLS results. These omitted variables, however, can also bias estimates.

Arellano and Bover (1995) demonstrate that the presence of the lagged endogenous variable $y_{i,t-1}$, causes the OLS estimate of ϕ_0 to be biased towards incorrectly high values. On the other hand, the fixed effect estimates of ϕ_0 is biased in the opposite direction, even in the absence of serial correlation in the idiosyncratic error term. This is because numbers from fixed effects estimates are based on within-group transformation. In such a case, it is impossible to dismiss the possible correlation between the transformed error term ($\varepsilon_{it} - \overline{\varepsilon_{i,\iota}}$) and the lag of the endogenous variable ($y_{i,t-1}$), especially when the time period is small (Nickell, 1981). In order to overcome the aforementioned challenges, my solution involves removing the country-specific fixed effects (μ_i) from equation (3.13). Furthermore, the between-group transformation of the model removes these fixed effects. However, the estimates produced from these methodologies are still not ideally consistent because the time period is fixed (Nickell, 1981).

Another possible way to circumvent these issues is to take the first difference for the dynamic equation (3.13), such that:

$$\begin{gathered}(y_{i,t} - y_{i,t-1}) = \varphi(y_{i,t-1} - y_{i,t-2}) + \left(X_{it} - X_{i,t-1}\right)'\phi + (\lambda_t - \lambda_{t-1}) + \\ (\xi_{i,t} - \xi_{i,t-1}).\end{gathered} \tag{3.14}$$

Similarly,

$$\gamma_{i,t} = \varphi\, \gamma_{i.t-1} + \Delta X_{i,t}{}'\phi + \Delta\lambda_t + \Delta\xi_{i,t},$$

where $\varphi = \phi_0 + 1$.

Although this transformation removes the country fixed characteristics, static panel data estimates and OLS estimates of equation (16) are still biased and violate the exogeniety assumption described earlier. From equation (3.14), it is clear that $E((y_{i,t-1} - y_{i,t-2}), (\varepsilon_{it} - \varepsilon_{it-1})) \neq 0$. By using an instrumental variable approach, it is possible to address this endogeneity problem in a satisfactory way. In general, an instrument, *Z*, is valid if it satisfies the following two conditions: first, it is an exogenous variable and not part of the explanatory variable (e.g. $E(Z, (\varepsilon_{it} - \varepsilon_{it-1})) = 0$); and second, the instrument is highly correlated with the endogenous variable, (in our case e.g. $E(\, y_{i.t-1}, Z) \neq 0$).

In the empirical growth literature, finding valid instruments for endogenous variables is challenging. For example, as it pertains to the endogeneity of governance, Mauro (1995) and other studies have used ethno-linguistic fragmentation as an instrument for measuring corruption. However, it is still debated in the literature whether ethno-linguist fragmentation is a valid instrument, as it might itself affect economic growth (see for example arguments by Acemoglu, Johnson, and Robinson (2001)).

Literature pertaining to dynamic panel data proposes several solutions to this issue. Anderson and Hsiao (1982) show that consistent unbiased estimates can be obtained by using the lagged levels of the first differenced endogenous variable as instruments. Their methodology uses a related variant of equation (3.13) in this paper. For example, supposing that *t=3*, equation (3.14) can be expressed as:

$$(y_{i3} - y_{i,2}) = \varphi(y_{i,2} - y_{i,1}) + \left(X_{i,3} - X_{i,2}\right)'\phi + (\lambda_3 - \lambda_2) + (\xi_{i,3} - \xi_{i,2}). \qquad (3.15)$$

When estimating equation (3.15), one can use $y_{i,1}$ to serve as an instrument for $(y_{i,2} - y_{i,1})$, because under the assumption of no serial correlation, $E\big((y_{i,2} - y_{i,1}),\ (\xi_{i3,} - \xi_{i2})\big) = 0$, and it is obvious that $E((y_{i,2} - y_{i,1}), y_{i,1})) \neq 0)$. Similarly, $y_{i,2}$ and $y_{i,1}$ can be used as instruments for *t=4*. This argument can also be applied to all of the predetermined variables. At times when *t>s*, one can use $X_{i,1}, \ldots, X_{i,s-1}$ as a valid instrument.

Anderson and Hsiao (1982) suggest using a two-stage least-squares estimator (2SLS) in order to obtain effective parameter estimates. However, in the past decade, the empirical growth literature has adopted the Generalized Method of Moments (GMM) techniques for data approximation, which use more instruments and can produce asymptotic efficiency estimates. The literature suggests two main GMM approaches. First, there is the first differenced-GMM approach proposed by Arellano and Bond (1991) and Arellano and Bover (1995). The authors combined the 2SLS of Anderson and Hsiao (1981) and the GMM of Hansen (1982) to estimate a regression similar to equation (3.14). The consistency of the first differenced-GMM estimates relies on the assumption that the lagged values of the endogenous variable in the levels equation are valid instruments for the endogenous variable in first differences, such as equation (3.14) does.

Evidence suggests that using these lagged values or predetermined variables in level assessments may be poor instruments for the first differenced *regressors* (Blundell and Bond, 1998). This is especially true when the series are persistent, as this implies that the predetermined variables do not explain much about the future changes. Blundell and Bond (1998) have shown that this occurs in cases where an empirical model features only a small time period, which is unfortunately the case with many dynamic growth models.

In order to mitigate the inefficiencies and biases that might arise from using these weak instruments, Arellano and Bover (1995) and Blundell and Bond (1998) both suggest a system GMM approach. The system GMM derives coefficient estimates by using both the equation in levels (such as equation (3.13)) and the equation in first differences (such as equation (3.14)) as a system together. The addition of the equation in levels increases the number of instruments for the endogenous variables in the first differences. The system GMM uses the lag levels of the explanatory variables as instruments for the endogenous variables in the first difference, and the lag differences as instruments for the endogenous variables in the levels equation. This approach increases efficiency. Blundell and Bond (2000) provide further evidence that when there is no serial correlation or endogenous variable, the system GMM produces consistent and less biased estimates than the first-differenced GMM.

I make use of the system GMM because of the efficiency gains described above, and also because the instruments are valid and useful in this context. Furthermore it is more suitable for estimating marginal effects than the first-differenced GMM, because my endogenous explanatory variables might be persistent (and therefore their lagged levels might be weak instruments).

After addressing this endogeneity problem by selecting between first-differenced GMM and system GMM, a researcher is confronted with the choice between using one step or two step estimation for standard errors. The one-step estimator assumes homoscedastic errors while the two-step estimator assumes that the errors are heteroskedastic, and uses the first-step errors to construct heteroskedastic-consistent standard errors (Arellano and Hahn, 2007). Although two-step estimators are asymptotically more efficient, they present standard errors estimates that are severely downward-biased. However, it is possible to solve this problem by using the finite-sample correction to the two-step covariance matrix derived by Bond and Windmeijer (2002).With this it is possible to make two-step robust GMM estimates more efficient than one-step robust ones, especially for system GMM models (Roodman, 2009).

It is also important to note that Roodman (2009) cautions against instrumental variable proliferation. The main problem of having too many instruments is that endogenous variables can be over-fit, and this may weaken the strength of the joint validity of the instrumental variables (Roodman, 2009). It is also debatable whether predetermined variables, which are weakly exogenous, are good instruments for the endogenous variable. If the instruments used are not valid, the estimated coefficients are biased and hence the OLS or the traditional fixed-effect estimates might be preferred instead.

In spite of these potential estimation shortcomings, I report my results from the system GMM methods, with two-step robust standard errors. These have been shown to produce more efficient and consistent results than the OLS or Fixed-Effects estimates.

3.5.2 Preliminary results

To obtain a general overview of the correlation between governance, public education spending, and economic growth, I present bivariate correlations in Table 3-1 using four year period averages.[46] From this table there is evidence of a negative correlation between growth and all tested measures of governance and public expenditures. This evidence is in line with previous studies that use OLS to estimates the effect of public education spending on economic growth (such as Devarajan et al. 1996). As it pertains to the governance indicators in my study, the negative correlation relationship with growth supports the argument that corruption "sands the wheels of economic growth" (Mauro, 1995).

Another interesting observation from the bivariate correlation analysis is that all measures of governance are positively correlated with education and health spending. These results suggest that human capital investments tend to be high in countries with better governance. On the other hand, the negative correlation between governance and military spending suggests that countries with poor governance spend more on their military forces. Perhaps it is not surprising in many cases that exorbitant military spending and poor governance seem to go hand-in-hand.

[46] I draw similar qualitative conclusions when I use two year period averages.

As expected there is strong positive correlation between governance measures. This suggests the possibility of these measures being compliments of one another. This has crucial implication in the literature that analyzes the role of institution quality on economic outcomes. For instance, chances of high levels corruption prevalence are high if societies are poorly governed and their luck of poor resource management and regulation.

In general the resulting bivariate correlations show only whether or not variables are highly related, and do not capture the full picture of the efficacy of public spending and governance towards promoting economic growth. I provide results for this in the next section.

3.5.3 Main results

Because I have no instruments to account for all endogenous variables, I take advantage of the system-GMM estimation approach to obtain estimates of equation (3.13). The approach uses the lag levels of the explanatory variables as instruments for the endogenous variables in the first difference. Likewise, the lag differences are useful as instruments for the endogenous variables in the levels equation.[47] I present the estimation results for the system GMM in Table 3-2, using all available data.

In Table 3-2, the dependent variable is the growth rate of real GDP per capita. I treat public expenditures, governance measures, and the interaction term between public expenditures and the levels of governance as endogenous variables. I express all explanatory variables except for the population growth rate (v) in natural logarithmic form. Thus, their estimated coefficient are elasticities.

[47] The past values of the endogenous regressors are viable instruments because they are correlated with the explanatory variables, and do not affect economic growth contemporaneously. As a result, predetermined variables can be considered weakly exogenous.

Model (1) in Table 3-2 is a benchmark; it supports the theory of conditional convergence. The coefficient of the initial level of GDP per capita is negative and statistically significant even at a 1% level. One implication is that countries that start out with low income levels grow faster than those that initially have higher levels of income. Model (1) also provide support of the relationship between private investments (or government consumption) and growth. However, it does show that the growth rate of GDP per capita positively relates to human capital, although the results themselves are statistically insignificant. This model also suggests that the economic growth and population growth rates are negatively related to each other. This result is consistent with the predictions from most endogenous and exogenous growth theories.

Model (2) in Table 3-2 is similar to the benchmark except in that it also includes public spending in health, military, and education. This model does not show any evidence of the conditional convergence as indicated by the positive correlation between economic growth and initial income levels. However, unlike the benchmark model, this model does support views advocating increases in government spending as a way of stimulating growth. However, the results are statistically insignificant. An indication of luck of clear evidence supporting the hypothesis that increasing government consumption directly increases economic growth. Model (2) also suggests that private investment hinders growth.

As it pertains to public investments in human capital (more specifically public health and education spending), Model (2) of Table 3-2 demonstrates a negative relationship with statistically significant results. These results are in line with studies such as Devarajan et al. (1996), which demonstrate that economic growth and public human capital investments (especially in education) are negatively related.

Model (3) of Table3.2 is similar to model (2), except in that I include different dimensions of governance. Public investments in both health and education seem to lower growth. The results are statistically significant at the 1% level. As for different dimensions of governance, the results are statistically significant only for government effectiveness and for political stability. A possible implication here is that politically stable countries provide better public services, leading to faster growth.

In model (4), I include the interaction term between different dimensions of governance and public investment (including health, military, and education). This interaction term measures the effectiveness of public spending on economic growth. Based on the theoretical model, if better governance *improves* the effectiveness of public education expenditures on economic growth, the coefficient estimates of the interaction term should be positive. Only the coefficient for educational spending and corruption control has the correct sign and is statistically significant. I present this marginal effect in Figure 3.1.

Figure 3.1 illustrates that the marginal effects of public education spending increases with the level of corruption control. The average imputed marginal effect is 0.270 (with a computed standard deviation of 1.230), which occurred when the corruption control level was 53.677. This means that, in a country with an average corruption control level, a 1% increase in public education spending per student (as a percent of GDP per capita) increases GDP growth rate by 0.279. Countries whose control of corruption is at least within the 54th percentile experience a positive effect from public education spending on economic growth. This finding contrasts with previous studies, which that argue education spending has little to no effect on growth. An implication to consider is that corruption abatement improves the effectiveness of public education spending, at least in terms of in translating these investments into measurable economic growth.

It is interesting to note that the model does not show clear evidence regarding the individual and combined roles of public spending in health, military, and education in enacting predictable economic growth. As for the dimensions of governance alone, political stability does tend to correlate positively with economic growth.[48]

3.5.4 Robustness check

In order to assess whether these results vary significantly by country group and by level of economic development, I render empirical estimations for both developing and developed countries. I categorize included countries according to their World Bank's Income classification ratings. The results are reported in Tables 3-3 and Table 3-4. In Table 3-3, the results are consistent with the entire dataset. They suggest that in developing countries the effectiveness of public education spending on economic growth depends significantly upon a country's level of corruption control. The computed elasticity of public education spending on economic growth demonstrates that on average a 1% increase in public education spending per student (as a share of GDP per capita) lowers the growth rate of GDP by 0.136 with a computed standard deviation of 3.34. These results are similar to the findings by Devarajan et al. (1996), except that improvements in corruption control are now understood to offset some of the negative direct growth effects of public education spending. Thus, developing countries with better governance have the potential to translate public investments into significant development outcomes such as positive economic growth.

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[48] It is important to note that the coefficient magnitudes of these interaction terms are unrealistically large. One reason for this might be due to inefficiencies in how governance indicators are measured.

It is important to note that there is no clear evidence that increasing education spending in developed countries with good governance directly guarantees to economic growth. The results in Table 3-4 (although similar in magnitude to values found by using a sample of developing countries) are statistically insignificant. This evidence can be attributed to the fact that most developed countries have established institutions with relatively less systemically poor governance.

3.6 Conclusion

In this paper, I analyze the role of governance in determining the efficiency of public education spending on economic growth. I cast light on the links between public education spending, quality of governance, and the resulting economic growth. Using a large cross-section of data from both developed and developing countries between 1995 and 2010 (and also considering the endogeneity of public education spending and governance), I show that public spending affects economic growth in countries with better governance. More specifically, I demonstrate how this growth depends upon a country's level of corruption control. The results are robust to a sample of developing countries.

My results contribute to the understanding of the role of public education spending on economic growth, by demonstrating that that public education growth is positively related. I demonstrate that efficiencies in resource allocation and management (and conversely, misuses of public funds due to corruption) explain many previous inconsistencies in the literature. These results are important to future development policy. They suggest that countries should focus more on the effectiveness of public spending, particularly by working to enforce good governance. These results are especially relevant to developing countries, in which debates on how to achieve Millennium Development Goals continue to wage back and forth. My findings suggest that mere increases in spending are a poor substitute for institutional improvements and growth-enhancing public policy.

Table 3-1. Bivariate correlation matrix: growth, public expenditures, and governance.

	γ	E	s_1	s_2	*corr*	*gove*
e	-0.231	1				
s_1	-0.383	0.366	1			
s_2	-0.101	0.128	0.030	1		
corr	-0.227	0.4449	0.602	-0.082	1	
gove	-0.202	0.3763	0.534	-0.059	0.953	1
rege	-0.166	0.2947	0.579	-0.147	0.922	0.946

Table 3-2. Table 3- Public education spending, governance, and economic growth.

	(1)		(2)		(3)		(4)	
y_{t-1}	-1.502***	(0.455)	0.271	(0.367)	0.326	(0.361)	0.0391	(0.236)
Gov_{t-1}	-1.955	(1.209)	1.204	(1.006)	0.740	(0.700)	2.286***	(0.704)
k_{t-1}	-2.580	(1.933)	-3.045***	(0.875)	-1.723**	(0.712)	-2.077***	(0.407)
h_{t-1}	0.783	(1.574)	-1.043	(1.191)	-0.862	(0.688)	-0.551	(0.413)
v_{t-1}	-1.461***	(0.376)	-2.180***	(0.266)	-1.864***	(0.155)	-0.955***	(0.130)
$s_{1,\ t-1}$			-6.767***	(1.006)	-6.154***	(0.801)	-2.715	(1.758)
$s_{2,\ t-1}$			-0.908*	(0.500)	-0.976***	(0.306)	-2.804***	(0.467)
e_{t-1}			-3.028***	(1.033)	-2.581***	(0.556)	-6.578***	(2.268)
$corr_{t-1}$					-0.0106	(0.0238)	-0.174***	(0.0541)
$gove_{t-1}$					0.0202	(0.0332)	0.0443	(0.0820)
$rege_{t-1}$					-0.0264	(0.0173)	0.137**	(0.0667)
$s_{1,\ t-1}$* $corr_{t-1}$							-0.0246	(0.0379)
$s_{1,\ t-1}$* $gove_{t-1}$							0.00674	(0.0598)
$s_{1,\ t-1}$* $rege_{t-1}$							-0.0877**	(0.0407)
$s_{2,\ t-1}$* $corr_{t-1}$							0.0103	(0.00964)
$s_{2,\ t-1}$* $gove_{t-1}$							-0.0327	(0.0276)
$s_{2,\ t-1}$* $rege_{t-1}$							0.0707***	(0.0209)
e_{t-1}* $corr_{t-1}$							0.128***	(0.0272)
e_{t-1}* $gove_{t-1}$							-0.00322	(0.0330)
e_{t-1}* $rege_{t-1}$							-0.0206	(0.0216)
N	218		218		218		218	
Hansen	0.00625		0.164		0.142		0.961	
ar1p	0.109		0.118		0.0833		0.0741	
J	25		38		53		98	

Note: Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % levels. All estimations are done by two step system-GMM.I used 1 lag difference as instruments. All equations include year dummies and a dummy variable =1, for sub-Saharan Africa.

Table 3-3. Public education spending, governance, and economic growth: evidence from developing countries.

	(1)		(2)		(3)		(4)	
y_{t-1}	2.340**	(0.895)	0.453	(0.405)	0.692*	(0.356)	-1.020*	(0.517)
Gov_{t-1}	3.860*	(1.950)	1.619*	(0.959)	1.452*	(0.757)	1.295	(0.962)
k_{t-1}	3.280	(2.222)	-1.682	(1.320)	0.595	(0.738)	-1.340*	(0.729)
h_{t-1}	-3.875**	(1.552)	-1.995**	(0.932)	-0.808*	(0.445)	0.0221	(0.648)
v	-3.339***	(0.390)	-2.708***	(0.391)	-1.901***	(0.203)	-1.208***	(0.295)
$s_{1, t-1}$			-4.511***	(1.426)	-3.239***	(1.016)	5.115**	(2.205)
$s_{2, t-1}$			-0.0396	(0.460)	-0.715**	(0.316)	-1.571**	(0.604)
e_{t-1}			-2.428*	(1.212)	-2.953***	(0.515)	-6.911**	(1.661)
$corr_{t-1}$					-0.0383*	(0.0207)	-0.0895	(0.0969)
$gove_{t-1}$					0.0322	(0.0270)	0.0314	(0.166)
rege					-0.0297**	(0.0130)	0.252	(0.188)
$s_{1, t-1}$*$corr_{t-1}$							-0.0571	(0.0529)
$s_{1, t-1}$* $gove_{t-1}$							0.0190	(0.0843)
$s_{1, t-1}$* $rege_{t-1}$							-0.150*	(0.0882)
$s_{2, t-1}$* $corr_{t-1}$							-0.0144	(0.0152)
$s_{2, t1}$* $gove_{t-1}$							0.0533	(0.0487)
$s_{2, t-1}$* $rege_{t-1}$							0.00124	(0.0379)
e_{t-1}* $corr_{t-1}$							0.126***	(0.0356)
e_{t-1}* $gove_{t-1}$							-0.0506	(0.0703)
e_{t-1}* $rege_{t-1}$							0.0350	(0.0390)
N	154		154		154		154	
Hansenp	0.303		0.142		0.380		0.999	
ar1p	0.00764		0.0524		0.0276		0.0301	
J	25		38		53		98	

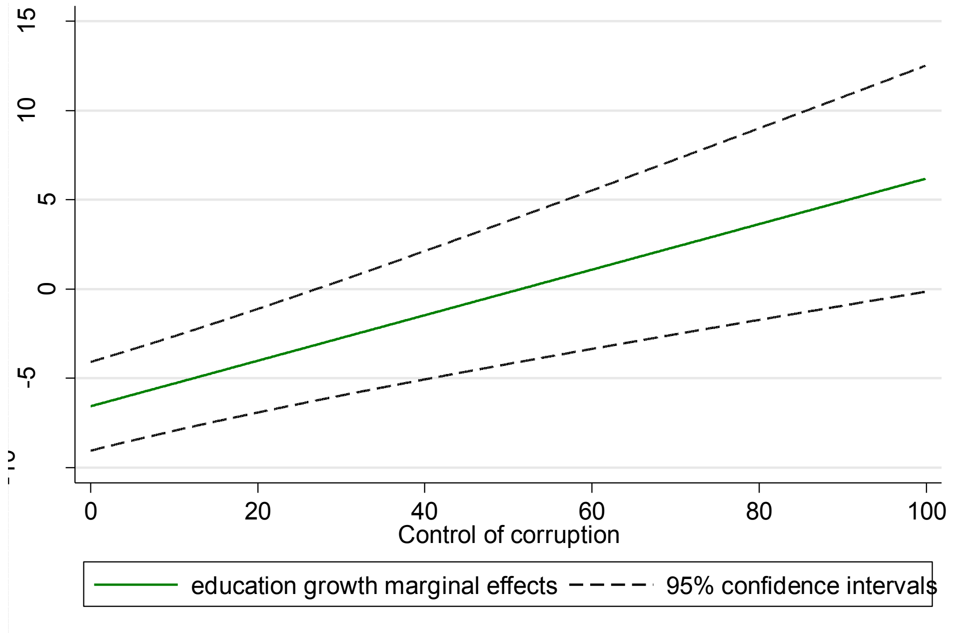
Note: Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % levels. All estimations are done by two step system-GMM.I used 1 lag difference as instruments. All equations include year dummies and a dummy variable =1, for sub-Saharan Africa.

Table 3-4. Public education spending, governance, and economic growth: evidence from developed countries.

	(1)		(2)		(3)		(4)	
y_{t-1}	-1.141**	(0.510)	-0.294	(0.834)	-1.329	(2.424)	-2.467	(8.712)
Gov_{t-1}	1.185	(0.777)	4.895	(3.996)	-2.218	(2.732)	-6.522	(13.09)
k_{t-1}	-2.189*	(1.201)	-0.0142	(2.483)	-3.357	(2.919)	-6.530	(6.954)
h_{t-1}	-0.636	(2.798)	-6.953	(5.248)	2.964	(8.269)	-4.034	(24.09)
v_{t-1}	-0.289***	(0.0678)	-0.552**	(0.241)	-0.342	(0.334)	-0.457	(1.098)
$s_{1, t-1}$			-2.911*	(1.664)	-1.308	(2.505)	79.79	(142.1)
$s_{2, t-1}$			0.109	(0.654)	1.133*	(0.593)	-21.43	(45.06)
e_{t-1}			-0.371	(1.907)	2.089	(1.256)	-6.50	(8.825)
$corr_{t-1}$					0.0295	(0.135)	0.539	(1.890)
$gove_{t-1}$					0.00937	(0.112)	0.171	(2.195)
$rege_{t-1}$					0.0644	(0.0764)	0.299	(1.662)
$s_{1, t-1}$* $corr_{t-1}$							-0.488	(0.667)
$s_{1, t-1}$* $gove_{t-1}$							-0.135	(0.887)
$s_{1, t-1}$* $rege_{t-1}$							-0.343	(1.578)
$s_{2, t-1}$* $corr_{t-1}$							-0.00877	(0.652)
$s_{2, t-1}$* $gove_{t-1}$							0.308	(0.209)
$s_{2, t-1}$* $rege_{t-1}$							-0.0116	(0.142)
e_{t-1}* $corr_{t-1}$							0.361	(1.242)
e_{t-1}* $gove_{t-1}$							0.125	(0.970)
e_{t-1}* $rege_{t-1}$							0.268	(1.427)
N	64		64		64		64	
hansenp	0.388		0.987		1.000		1	
ar1p	0.226		0.373		0.186		0.768	
j	25		37		52		64	

Note: Robust standard errors are in parenthesis and the superscript (*; **; ***) indicates significance at the (10, 5, 1) % levels. All estimations are done by two step system-GMM.I used 1 lag difference as instruments. All equations include year dummies and a dummy variable =1, for sub-Saharan Africa.

Figure 3.1: The marginal effects of public education spending.



Note: In order to obtain the marginal effects of increasing education on economics, $\frac{\partial \gamma}{\partial e} = \phi_1 + \phi_{corr,5} * corr$. Knowing that the corruption control measure as a percentile ranking ranges from 1-100, I generate a vector containing 1000 numbers that range from 0-100. I then proceed with computing the marginal effects using the formula above. In order to obtain the confidence interval bands, I use that the following formula: $\frac{\partial \gamma}{\partial e} = var(\phi_1) + var\left(\phi_{corr,5}\right) * corr^2 + 2\, cov(\phi_{corr,5} * \phi_1) * corr^2)$. I obtain the variances of the parameter estimates from the variance-covariance matrix

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Appendix

1A. Countries used in the empirical analysis in essay 1.

United Arab Emirates, Argentina, Australia, Austria, Belgium, Bulgaria, Brazil, Switzerland, Chile, Colombia, Costa Rica, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Georgia, Greece, Hong, Hungary, Indonesia, Ireland, Iceland, Israel, Italy, Jordan, Japan, Korea, Liechtenstein, Lithuania, Luxembourg, Latvia, Republic Macedonia, Mexico, Malta, Mauritius, Malaysia, Netherlands, Norway, New Zealand, Panama, Peru, Poland, Portugal, Qatar, India (Himachal), Sri Lanka (Tamil), Venezuela (Miranda), Romania, Singapore, Serbia, Slovak Republic, Sweden, Thailand, Trinidad and Tobago, Tunisia, Uruguay, United States.

2A. A list of country codes and associated country names for Essay 1 and Essay 2.

Country Code	Country Name	Country Code	Country Name
ALB	Albania	LVA	Latvia
AZE	Azerbaijan	LTU	Lithuania
ARG	Argentina	MAC	Macao-China
AUS	Australia	MYS	Malaysia
AUT	Austria	MLT	Malta
BEL	Belgium	MUS	Mauritius
BRA	Brazil	MEX	Mexico
BGR	Bulgaria	MDA	Republic of Moldova
CHL	Chile	NLD	Netherlands
COL	Colombia	NZL	New Zealand
CRI	Costa Rica	NOR	Norway
HRV	Croatia	PAN	Panama
CZE	Czech Republic	PER	Peru
DNK	Denmark	POL	Poland
EST	Estonia	PRT	Portugal
FIN	Finland	QAT	Qatar
FRA	France	ROU	Romania
GEO	Georgia	RUS	Russian Federation
GRC	Greece	SRB	Serbia
HKG	Hong-Kong China	SVK	Slovak Republic
HUN	Hungary	SVN	Slovenia
IND	India	ESP	Spain
IDN	Indonesia	SWE	Sweden
ISR	Israel	CHE	Switzerland
ITA	Italy	THA	Thailand
JPN	Japan	TUR	Turkey
KAZ	Kazakhstan	GBR	United Kingdom
JOR	Jordan	USA	United States
KGZ	Kyrgyzstan	URY	Uruguay

3A. The Ramsey Model with productive and non-productive government inputs in production and governance.

The Model:

The optimization problem begins with a representative agent maximizing her life time consumption such as:

$$Max \int_{t=0}^{\infty} U(C)\, exp^{-\rho t} dt, \tag{3A.1}$$

where $\rho > 0$ is the subjective discounting rate. I assume that the utility function has Constant Elastisticity of Substitution (CES) which can be expressed as:

$$U(C) = \frac{C^{1-\theta} - 1}{1-\theta}, \tag{3A.2}$$

where $\theta \geq 1$. In this case, $\frac{1}{\theta} > 0$ is the elasticity of substitution between consumption at any two periods. The agent's problem is to maximize consumption expressed by equation (3A.1) at each time period, subject to her budget constraint and given public policies. These constraints are:

$$\begin{aligned} \dot{K} &= (1-\tau)Y - C, \\ y &= AK^{\alpha}E^{\beta}S^{\eta}, \\ \tau Y &= E + S, \end{aligned} \tag{3A.3}$$

Given $1 < \alpha, \beta, \eta < 1$ and $\alpha + \beta + \eta = 1.$

For interior solution, I assume that the production function to exhibit diminishing returns with respect to each factor and constant returns to scale such as $1 < \alpha, \beta, \eta < 1$ and $\alpha + \beta + \eta = 1$, respectively. Now, assuming that education spending is proportional to total government spending (G) such public education spending can be expressed as

$\delta_e G = E,\ \delta_e \in (0,1)$. In a similar manner public education spending to all other sectors is $\delta_s G = S$ and $\delta_s \in (0,1)$. without loss of generality we can assume $\delta_s = 1 - \delta_e$ can and the government budget constraint be expressed as follows:

$$\tau Y = \delta_e G + (1 - \delta_e) G \text{ or}$$
$$G = \tau Y \tag{3A.4}$$

Model solution:

Simplifying the first order necessary conditions yields the following growth regression.

$$\frac{\dot{C}}{C} = \gamma = \frac{1}{\theta}\left[\alpha(1-\tau)\frac{Y}{K} - \rho\right]. \tag{3A.5}$$

Substituting the production technology and government policies into the above equation (3A.5) yields the following:

$$\gamma = \frac{1}{\theta}\left[\alpha(1-\tau)\frac{AK^{\alpha}E^{\beta}S^{\eta}}{K} - \rho\right], \tag{3A.6}$$

$$\gamma = \frac{1}{\theta}\left[(1-\beta-\eta)(1-\tau)\frac{AK^{\alpha}E^{\beta}S^{\eta}}{K} - \rho\right],$$

Considering that along the balanced growth the ratios of aggregates will either be constant or grow at a constant rate, and the marginal tax rate (τ) are constant, we can convert the solution to its intensive, by defining $\frac{K}{Y} = k,\ \frac{C}{Y} = \text{c},\ \frac{G}{Y} = g,\ \frac{S}{Y} = s,\ \frac{E}{Y} = e$. Therefore, the growth regression of equation 3A.5 can be simplified further and expressed as a function of shares of public spending and governance. This can be illustrated by first focusing on simplifying the production function on steady state to depend on the shares of spending as a fraction of income per capita, such as:

$$\frac{Y}{Y} = \frac{AK^{\alpha}E^{\beta}S^{\eta}}{Y},$$

$$1 = A\left(\frac{K}{Y}\right)^{\alpha}\left(\frac{E}{Y}\right)^{\beta}\left(\frac{S}{Y}\right)^{\eta}$$

$$1 = A\left(\frac{K}{Y}\right)^{\alpha} e^{\beta} s^{\eta}$$

$$\frac{Y}{K} = (Ae^{\beta}s^{\eta})^{\frac{1}{\alpha}}, \qquad (3A.7)$$

Combining equations (3A.6) and (3A.7) yields the following growth regression:

$$\gamma = \tfrac{1}{\theta}\left[(1-\beta-\eta)(1-\tau)(Ae^{\beta}s^{\eta})^{\frac{1}{\alpha}} - \rho\right],$$

Considering the budget constraint this can be simplified further such that if *G=τY*, then *g=τ*.

Therefore the first order condition can be re-written as:

$$\gamma = \frac{1}{\theta}\left[(1-\beta-\eta)(1-g)A^{\frac{1}{\alpha}}\delta_e^{\frac{\beta}{\alpha}}(1-\delta_e)^{\frac{\eta}{\alpha}}g^{\frac{\beta+\eta}{\alpha}} - \rho\right] \qquad (3A.8)$$

The empirical analysis of essay 3 involves estimating thegrowth regression similar to equation (3A.8). The growth effect on the share of government expenditure which is devoted to education depends on the relative shares of expenditures, and their relative elasticities in terms of output. And the effect for governance on economic growth cannot be determined unambiguously. Therefore this requires data to empirically determine how human capital public expenditures and governance interacts in determining economic growth.

3B First differencing the dynamic model: equation 3.13 to 3.14

Beginning with the following growth regression from equation (3.13):

$$\gamma_{i,t} = \phi_0 y_{i,t-1} + X_{i,t}{}'\phi + \mu_i + \lambda_t + \xi_{i,t}, \qquad (3B.1)$$

where $X'_{i.t} = \left[e_{i,t-1}, s_{1,i,t-1}, s_{2,i,t-1}, g_{n,i,t-1}, s_{1,i,t-1} * g_{n,i,t-1}, s_{2,i,t-1} * g_{n,i,t-1}, x_{i,t}\right]$ is the vector of endogenous variables,

$\phi = \left[\phi_0, \phi_1, \phi_2, \phi_3, \phi_{n,4}, \phi_{n,5}, \phi_{n,6}, \phi_{n,7}, \phi_8\right]$ are the model parameters and the last term is the error term which includes country fixed effects (μ_i), time fixed effects (λ_t) and the idiosyncratic error term ($\xi_{i,t}$). The explanatory variables are as described in the paper. The key to dynamic panel model estimation is to obtain consistent estimates of the parameters. The obvious endogeneity issue arises due to the presence of the lagged dependent variable, since it is correlated with the country fixed effects. First differencing equation 3B.1 wipes out the country specific fixed effects and yields the following dynamic model:

$$\begin{aligned} \gamma_{i,t} - \gamma_{i,t-1} = \phi_0(y_{i,t-1} - y_{i,t-2}) + (X_{i,t} - X_{i,t-1})'\phi + (\mu_i - \mu_i) \\ + (\lambda_{i,t} - \lambda_{i,t-1}) + (\xi_{i,t} - \xi_{i,t-1}) \end{aligned} \tag{3B.2}$$

The country fixed effects cancel out. And noticing that $\gamma_{i,t} = (y_{i,t} - y_{i,t-1})$ and $\gamma_{i,t-1} = (y_{i,t-1} - y_{i,t-2})$, equation (3B.2) can be expressed:

$$\begin{aligned} (y_{i,t} - y_{i,t-1}) - (y_{i,t-1} - y_{i,t-2}) = \phi_0(y_{i,t-1} - y_{i,t-2}) + (X_{i,t} - \\ X_{i,t-1})'\phi + (\lambda_{i,t} - \lambda_{i,t-1}) + (\xi_{i,t} - \xi_{i,t-1}), \end{aligned} \tag{3B.3}$$

Adding $(y_{i,t-1} - y_{i,t-2})$ to both sides yields the following:

$$\begin{aligned} (y_{i,t} - y_{i,t-1}) = (y_{i,t-1} - y_{i,t-2}) + \phi_0(y_{i,t-1} - y_{i,t-2}) + (X_{i,t} - \\ X_{i,t-1})'\phi + (\lambda_{i,t} - \lambda_{i,t-1}) + (\xi_{i,t} - \xi_{i,t-1}). \end{aligned} \tag{3B.4}$$

Similary:

$$\gamma_{i,t} = \varphi\, \gamma_{i,t-1} + (X_{i,t} - X_{i,t-1})'\phi + (\lambda_{i,t} - \lambda_{i,t-1}) + (\xi_{i,t} - \xi_{i,t-1}).$$

where $\varphi = 1 + \phi_0$. This is similar to equation 3.14.

3C. A list of countries used in the empirical analysis in the third essay.

Developing Countries		Developed Countries
Angola	Malawi	Australia
Armenia	Malaysia	Austria
Bangladesh	Mauritania	Belgium
Belize	Mauritius	Canada
Bolivia	Mexico	Cyprus
Brazil	Moldova	Denmark
Bulgaria	Morocco	Finland
Burkina Faso	Mozambique	France
Cambodia	Namibia	Germany
Cameroon	Nepal	Greece
Cape Verde	Nicaragua	Ireland
Chad	Pakistan	Israel
Colombia	Paraguay	Italy
Congo, Republic	Peru	Japan
Croatia	Philippines	Netherlands
Czech	Poland	New Zealand
Djibouti Republic	Romania	Norway
Dominican Republic	Russian Federation	Portugal
Ecuador	Rwanda	Singapore
El Salvador	Saudi Arabia	Slovenia
Eritrea	Sierra Leone	Spain
Estonia	Slovak Republic	Sweden
Gambia	South Africa	Switzerland
Guatemala	Swaziland	United Arab Emirates
Hungary	Syrian Arab, Republic	United States of America
India	Tajikistan	
Indonesia	Thailand	
Kazakhstan	Tunisia	
Kenya	Turkey	
Korea Republic	Uganda	
Kyrgyz Republic	Ukraine	
Lebanon	Yemen, Rep.	
Lesotho	Zambia	
Lithuania		

3D. Descriptive statistics for data used in the growth regression.

Variable	Obs	Mean	Std. Dev.	Min	Max
γ	461	2.560	2.809	-6.764	10.436
y	458	9860.599	14027.680	133.010	66123.220
k	461	22.177	6.229	4.271	63.974
Gov	420	15.921	6.393	4.335	48.413
v	305	65.321	27.921	33.412	99.855
n	463	1.380	1.283	-2.003	10.341
corr	463	51.019	28.068	2.927	100.000
gove	463	52.318	28.050	3.171	100.000
rege	463	49.851	28.365	2.392	99.761
s_1	463	6.361	2.401	2.177	19.830
s_2	463	2.372	2.538	0.159	28.769
e	463.	4.447	1.775	1.109	14.383

Note: all data are in their level form.