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Foreign Direct Investment, Inequality and Human Capital Accumulation

By

Luseni Kamara

B.S., St. John's University, 1994

M.A., St. John's University, 1995

M.A., Fordham University, 2001

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Chapter 1

The Introduction

Evolution of Inequality

The literature about inequality, growth and technical progress has been growing fast in the last decade. This survey should give a flavor for the complex interactions between income distribution, human capital and technological change (which is associated with foreign direct investment). It should also underline the importance of a broad understanding of these topics for both macroeconomic theory and economic policy.

Adam Smith, David Ricardo and Karl Marx argued that capital accumulation and technological change are the main determinants of the functional income distribution. In order to avoid going into too much detail, the discussion of the classical and Marxian perspective is restricted to their pioneering works, and refers only to the most essential features of the relationship between inequality and growth their theories imply.

The Classical View

Both Smith (1776, reprinted 1937) and Ricardo (1821, reprinted 1965) distinguished between the three production factors labor, capital and land. Ricardo explicitly aimed to explain changes in the functional income distribution, i.e. he viewed the labor share, the capital share and the land rent share of total income as endogenous variables. In his work (1965,), Ricardo stated that " The produce [...] is divided among three classes of the community, namely, the proprietor of land, the owner of the stock or capital necessary for its cultivation, and the labourers. But in different stages of the society, the proportion of the whole produce of the earth which will be allotted to each of these classes, under the names of rent, profit, and wages, will be essentially different; depending mainly on the fertility of the soil, on the accumulation of capital, and on skills, ingenuity, and the instrument employed in agriculture".

Smith, as Ricardo, saw capital accumulation as a necessary condition for an increase in labor productivity, mainly through its effect on the "division of labor". According to Smith, "as the accumulation of stock must, in the nature of things, be previous to the division of labour, so labour can be more and more subdivided in proportion only as stock is previously more and more accumulated." (Smith, 1937, p. 260).

However, both writers argued that the long run real wage rate would not depend on the productivity of labor. Rather, there would be a "natural price of labour which is necessary to enable the labourers [...] to subsist," (Ricardo, 1965, pp.52). Smith viewed this wage level as "subsistence wage" in the physiologic sense, i.e., as one which ensures survival. In contrast, Ricardo pointed out that the natural price of labor would vary at different times in the same country, and would materially differ in different countries. That is, rather than being fixed, the real wage depends on the habits and customs of the people (Ricardo, pp. 54-55). Thus, over time, real wages would change due to changes in workers' subjective view about the subsistence level of wages.

Labor demand would crucially depend on the capital stock, i.e. on food, clothing, tools, raw materials, machinery, etc. which would be necessary to give effect to labor (p.53). As capital accumulates, real wages would rise only in the short run. In the long run, there would be "a greater addition [...] to the population such that the market price of labour will sink to its natural price" (p. 54). According to Ricardo, labor supply is perfectly elastic. Labor demand curve shifts rightwards to a new point after an increase in the capital stock which induces a real wage increase from the original subsistence wage to a new and higher wage. This causes the working population to increase, yielding a new labor supply curve. Thus, the new full employment equilibrium wage is, again, given by the original wage. Unlike Smith who makes no reference to the point, Ricardo believed in the law of diminishing returns. That is, labor productivity would decline with an employment expansion unless there would be technological progress. Thus the main implication of Ricardo's theory for functional income distribution is as follows. Unlike in the neoclassical theory, the marginal product of labor (which is smaller than the average product), is not equal to the wage rate. Rather, the marginal product of labor times total employment is equal to the sum of the wage-bills and profit. The remaining residual of the "whole produce" (i.e. the difference between the average and the marginal product of labor times total employment) is equal to the rent appropriated by owners of land. Moreover, with constant real wages and a declining average productivity of labor, the share of labor increases with capital accumulation. Ricardo was probably the first economist to acknowledge a crucial impact of social factors on economic variables. Unfortunately, he was not explicit about the underlying mechanism how the wage demands by the workers are shaped.

Theory of Karl Marx

Unlike Smith and Ricardo, Marx (reprinted 1965) did not distinguish between the return to capital and land. The value-added in the production which is not paid in wages is called the "surplus value". According to Marx, capitalism is inevitably characterized by a struggle between the ruling class (all those who live off surplus value) and the producing class (workers). The theory of Marx differs from the classical perspective in several other ways. Whereas capital accumulation in the classical theory is determined by its rate of return only, in the theory of Marx, capital accumulation is inherent in a capitalistic society. This is due to the following reasons. First, Marx argued that for capitalists, capital accumulation would be an end itself rather than a means to raise profits. According to his view, it is inherent in a capitalistic economy that capitalists accumulate capital in order to gain social esteem. In this sense, status-seeking by capitalists has an impact on growth via its impact on capital accumulation. Second, Marx presumed economies of large scale production, implying that competition among capitalist would foster accumulation and would lead to large concentration processes.

Unlike classical writers, Marx left not doubt about strong adverse effects of capital accumulation on both the income share of labor and the level of employment. As Kaldor (1956, p.88) summarizes: "On the Marxian model the share of wages in output must necessarily fall with every increase in output per head". Moreover, Marx argued that "any piece of capital equipment actually in operation requires fixed amount of labor to work with. Thus, as the supply of labor is inelastic if the wage is not lower than a subsistence level, unemployment is due to an inelastic labor demand which depends on the total stock of capital. As a result, the labor market does not clear and the wage is equal to a subsistence level. Does that imply that unemployment decreases over time when capital accumulates? This ceteris paribus implication of a fixed capital-labor ratio is strongly denied by Marx, because of two countering effects. First, (exogenous) population growth and second, technological change.

For a general evaluation of Marx's work, one may follow Adelman (1961, p.93) in concluding that " his system lends itself quite easily to an investigation of the relationship between the character of technological change, the distribution of income through time, capital accumulation, and economic growth". The inherently dynamic nature of Marx's models provides an excellent example of the power and importance of dynamic analysis.

Furthermore, his notion of an increasing substitution of capital for labor is actually very similar to what is discussed today under the label of labor-saving technological progress, at least as far as low-skilled workers (in the manufacturing sector) are concerned.

Foreign Direct Investment

Depending on the economy's starting point, technical progress and growth can be based on creation of entirely new knowledge, or adaptation and transfer of existing foreign technology. Since it is less costly to learn to use existing technology than to generate new technology, developing countries have the potential to grow faster than developed economies for any given level of investment or R&D spending. However, this potential for convergence is conditional on the economy's level of human capital. More specifically, as noted by many authors it is the quality of the labor force, its accumulated experience and human capital, its education system, and so on, that determines an economy's ability to create new ideas and adapt old ones. Consequently, improvements in education and human capital are essential for absorbing and adapting foreign technology, and to generate sustainable long-run growth.

Along with international trade, the most important vehicle for international technology transfer is foreign direct investment (FDI). It is well known that multinational corporations (MNCs) undertake a major part of the world's private R&D efforts and produce, own, and control most of the world's advanced technology. When a MNC sets up a foreign affiliate, the affiliate receives some amount of the proprietary technology that constitutes the parent's firm- specific advantage and allows it to compete successfully with local firms that have superior knowledge of local markets, consumer preferences, and business practices. This leads to a geographical diffusion of technology, but not necessarily to any formal transfer of technology beyond the boundaries of the MNC: the establishment of a foreign affiliate is, almost per definition, a decision to *internalize* the use of core technology. However, MNC technology may still leak to the surrounding economy through external effects or spillovers that raise the level of human capital in the host country and create productivity increases in local firms.

In many cases, the effects operate through forward and backward linkages, as MNCs provide training and technical assistance to their local suppliers, subcontractors, and customers. The labor market is another important channel for spillovers, as almost all MNCs train operatives and managers who may subsequently take employment in local firms or establish entirely new companies. This way, FDI may be a particularly valuable source of new technology, it not only introduces new ideas but it also strengthens the human capital base needed to adapt these ideas to the local market. It is therefore not surprising that attitudes towards inward FDI have changed considerably over the last couple of decades, as most countries have liberalized their policies to attract all kinds of foreign investment. Numerous governments have even introduced various forms of investment incentives to encourage foreign MNCs to invest in their jurisdiction.

However, productivity and technology spillovers are not automatic consequences of FDI. Instead, FDI and human capital interact in a complex manner, where FDI inflows create a potential for spillovers of knowledge to the local labor force, at the same time as the host country's level of human capital determines how much FDI it can attract and whether local firms are able to absorb the potential spillover benefits. It is likely that that the relationship between FDI and human capital is highly non-linear, and that multiple equilibria are possible. For instance, host economies with relatively high levels of human capital may be able to attract large amounts of technology intensive foreign MNCs that contribute significantly to the further development of labor skills. At the same time, economies with weaker initial conditions are likely to experience smaller inflows of FDI, and those foreign firms that enter are likely to use simpler technologies that contribute only marginally to local learning and skill development.

This paper focuses on the relationship between foreign direct investment, human capital, inequality and economic growth. Here we investigate correlation not only between economic growth and human capital as many economists in this area of study have done. However, this work contributes further to this area by investigating the relationship between human capital, wage inequality and FDI. The assertion here is that FDI increases economic growth and secondary school enrollment. We also investigate the correlation between FDI and return on education. Finally, we look at the causal relationship, between FDI and GDP, FDI and schooling, and growth and schooling.

CHAPTER 2

REVIEW OF THE LITERATURE

How Inequality Is Expected To Affect Growth

Economists have long focused on the relationship between income distribution and efficiency, rather than on the relationship between inequality and growth. Economists have emphasized both efficiency goals and distribution function of the state. A tradeoff between efficiency and equality has been the center of debate in the theory of optimal income taxation

In contrast, macroeconomic theory did not address the personal income distribution in the 1970s and 1980s. In particular, the relationship between inequality and growth has not been examined before the early 1990s. In the early 1990s a negative impact of income inequality on the rate of growth was observed (using cross-country regression analysis) by Persson and Tabellini (1994). Growth models with heterogeneous agents addressing this relationship belong to the "new growth theory" in which growth is either driven by positive external effects of investment in physical and human capital or by endogenous technological change.

The theories mainly used to assess the macroeconomic relations between inequality and economic growth can be classified into four categories matching the main feature emphasized: political economy, capital market imperfections, social unrest and saving rates.

Political Economy Approach

Without considering growth, Meltzer and Richard (1981) showed that income inequality, measured by ratio of median to average income, leads to a higher linear income tax rate which is redistributed lump-sum among the individuals in a voting model. In this model, given the specific assumption linear income tax, the median income earner is also the median voter who is pivotal under the majority voting rule. Thus the (relatively) poorer the median voter is, the higher his or her preferred level of redistribution, Bertola (1993), Persson and Tabellini (1994). In these models, endogenous growth arises because of a positive externality of capital accumulation, yielding socially non-decreasing returns to capital. Under the assumptions of perfect capital markets and infinitely living consumers, a capital-poor median voter demands a high level of redistribution capital income taxation which in turn depresses the rate of economic growth. The distribution of the (physical or human) capital endowment is exogenous and some inequality remains even after redistribution. This is because voters take the adverse growth effects of capital income taxation into account. In Bertola (1993), redistribution raises the level of wages and lowers the return to capital, and the growth rate of wages depends on the rate of capital accumulation. In Persson and Tabellini (1994), capital income is proportionally taxed and redistributed lump-sum to the individuals. Persson and Tabellini (1994) consider a model in which capital income taxes are levied to finance productive public investment expenditures. Thus, in their model taxation of capital may even enhance growth, but only for sufficiently small capital income tax rates. Taxation has an indirect redistributive effect on the level of wages which depends on the quality of the publicly provided infrastructure.

Political economic models linking inequality to redistribution can only be analysed under given specifications of the tax scheme. But the choice of the tax scheme determines whether or not redistribution, i.e. a reduction in inequality, is harmful to growth. Thus, by assuming growth-reducing taxation to be voted on, the result of political economic growth models outlined above is not at all surprising in light of the result of Meltzer and Richard (1981). Moreover, it has been criticized that the result critically depends on the assumption of perfect capital markets and infinitely living agents. Relaxing the infinite horizon assumption, Bertola (1996) show that shifting taxes from labor income to (human or physical) capital income (holding the tax revenue share in aggregate income constant) may even increase growth. The reason is that, in the absence of bequests, newly born individuals have to rely on labor income in order to build a capital stock, i.e. capital income solely accrues to the old. Thus, taxing capital income more heavily and cutting the tax rate on labor income leaves young agents with more income out of which to save, such that the overall impact on capital accumulation may indeed be positive.

Capital Market Imperfections

In the last decade there has been a series of prominent papers, indicting that redistribution of wealth towards the poor (i.e. a reduction in both wealth and income inequality) may have a growth-promoting effect if capital markets are imperfect. Moreover, these models address the question whether or not inequality declines in the process of development, i.e. in the process of endogenous wealth accumulation as suggested by Kuznets (1955). Most models assume that a fixed capital outlay is necessary for an individual to start a production activity, e.g. to open or to finance secondary schooling. However, Benabou (1996) have shown that this assumption is not necessary to obtain the result that inequality may be harmful to growth if capital markets are imperfect. The latter result also turns out not to be sensible to the source of capital market imperfection. Persson and Tabellini (1994) assume that effort (which is individually costly, but positively affects the probability that investment will yield a positive return) is not observable for lenders and borrower's repayment of his or her lender cannot exceed his or her future income. This give rise to a moral hazard problem, implying that poor individuals are credit constrained. Thus, redistribution may stimulate total investment since more individuals become able to borrow. In both models inequality may eventually decline as the economy grows. In Persson and Tabellini (1994) capital markets are imperfect in the sense that the rate at which individuals can borrow exceeds the lending interest rate. Due to the high costs of borrowing, an investment in human capital is only optimal for individuals with sufficiently high amount of inherited wealth. In the long run, if the wedge between the borrowing and the lending rate is sufficiently large, some dynasties will always invest whereas others will never invest to become skilled workers. The authors also show that some descendants of skilled workers will eventually become unable to invest in human capital. In this sense, inequality increases as the economy grows. Benabou (1996) assume that a loan market simply does not exist, again implying that redistribution may foster growth. Both authors derive a voting equilibrium with respect to a given tax-transfer scheme. That is, they assume in a political economic growth model that capital markets are imperfect. The crucial assumption in Benabou (1996) is that individual marginal returns to education are decreasing. Since the additional output of a marginal increase in human capital for a poor individual exceeds the output loss of the reduced after-tax income of the rich individual, a tax increase may be growth enhancing.

Saving Rates

Some economists believe that individual saving rates rise with the level of income. If true, then a redistribution of resources from rich to the poor tends to lower the overall rate of saving in the economy. Through this channel, a rise inequality tends to raise investment. According to Barro (1989), this effect arises if the economy is partly closed, so that domestic investment depends, to some extent, on desired national saving. In this case more inequality would enhance economic growth at least in a transitional sense.

Learning

Arrow (1962) conceptualized learning as an unintended byproduct of production. As new types of capital are produced this accumulated knowledge is embodied in the capital stock and learning builds on this embodied knowledge stock. Hence the cumulated production of capital goods and not the current levels of investment is the source of growth. Later, other authors extended this concept to include, for example, investment, R&D, etc.

According to Arrow, learning makes the production process more transparent and allows for a better division of labor. In this sense, it is reminiscent of Adam Smith's conceptualization of technical progress. Specialization would allow workers to build up product specific skills and increase their value. Product cycle theory suggest the possibility that learning by doing in fact is low skill biased. As products mature and capital designed to produce them develops, low-skilled labor tends to become more important as a factor of production. On the other hand, one could argue that by being embodied in capital goods, learning captures the increased efficiency following from introducing new capital goods and therefore is most likely to exhibit a capital bias which would, through capital-skill complementarity, imply a bias towards skilled labor.

Or, alternatively, that learning possibilities change over the product cycle. In early phases, high-skilled workers can learn how to design capital goods and production practices and in a later stage, low-skilled workers can come in to learn how to operate and refine such machines.

Whatever the exact direction of the bias, one would conjecture, there is little attention to the possibility that learning may cause biases in technical change in the empirical literature. In part, this can be explained because learning by doing is difficult to capture empirically. It is clear that experience is an important element in any wage equation, however, the separation of seniority, tenure and productivity effects is a difficult issue.

Human Capital Formation

In models that link economic growth to human capital accumulation, the skill level of a worker is endogenous. Typically, technology is assumed constant and there are no diminishing returns to the accumulation of knowledge. This knowledge is usually assumed to be embodied in the worker and thus human capital accumulation cannot cause a factor bias at the production unit level. In these models, wage divergence due to biases in technical change will ultimately cause the level of investment in human capital to go up or down and the relative supply of educated workers would adjust. This may be an adequate representation of the economy in the long run, however, other models are needed in helping researchers locate sources of factor and sector biases in production technology changes. The responsiveness of relative labor supply to price signals an empirical question frequently addressed in the literature and of importance for the policies to be designed. If skills supply is relatively price elastic or can be made more elastic, this may present another efficient way to improve the less-educated labor market position in addition to trying to change biases in technical change.

What underlies wage gap?

What underlies the wage gap—that difference in wages between educated and uneducated workers. In reality, of course, there is a continuum of worker education, and while economic models can accommodate this concession to reality, the intuition is clearer in a simpler model. Suppose then that there are just two types of workers, educated and uneducated. Each type of worker is paid according to the value of their marginal product. To keep things simple while still allowing the ideas to get across, assume that there is just one product produced and that production of this product requires educated and/or uneducated labor. The two types of labor are substitutable for one another although high and low skilled workers are not perfect substitutes. Assuming skilled workers can produce more, they earn more. The education premium is just the wage of the educated workers relative to the wage of the uneducated workers. The larger the wage of educated workers relative to uneducated workers, the bigger will be wage premium. But what will wage premium depend on? It will be a function of the marginal productivity of educated worker, the marginal productivity of uneducated worker, and the elasticity of substitution between the two types of labor.

Wages depend on the marginal productivity of the different types of labor. A higher marginal product means a higher wage. Technology matters here in that technology enhances the productivity of workers. If there is no education-bias to technology, the marginal productivities of educated and uneducated workers are equally impacted by a new technology. If the change in technology makes educated workers more productive relative to what it does for uneducated workers, then there is an education-biased technical change. The degree to which educated and uneducated workers can substitute for one another also is going to matter when we think about what education biased technical change will do to relative wages. In the usual case, educated and uneducated workers will be imperfect substitutes for one another (so what economists call the elasticity of substitution between worker types is greater than one.)

Human capital externalities

One important motivation for looking at the cross-country data is the possible presence of externalities to human capital. As we have seen, however, the empirical growth literature gives rather imprecise answers about the social returns to education. Many authors have written about the benefits of human capital in economic growth but have not actually linked inequality to education. In this section, we will briefly review theoretical work on this topic, and then discuss some innovative recent evidence based on microeconomic data sets.

Interest in human capital externalities was revived by Lucas (1993). One of his arguments was that, in the absence of such externalities, it is difficult to reconcile observed pressures for migration from poor to rich countries with the absence of massive capital flows in the other direction.

In more recent work, Acemoglu (1998) has provided an ingenious justification for the presence of externalities. His theory is based on microeconomic foundations, and so is particularly worthy of attention. In his model, firms and workers make investments in physical capital and human capital respectively, before production begins. Production requires a partnership between a firm and a worker, but when firms or workers make their respective investments, they do not know the identity of their future partner. A key assumption of the model is that firms and workers are then brought together via a matching process that is imperfect, perhaps because searching for partners is costly.

Acemoglu shows how the structure of the model yields an important result: an increase in the average level of human capital can have a positive effect on the private return to human capital, at least over some region. The intuition is as follows: say that a subset of workers decide to acquire more human capital. This will raise average human capital, and anticipation of this encourages firms to make greater investments in physical capital. Since the matching process is inefficient, the firms that have invested more are not necessarily matched with the workers who have invested more in human capital. As a result, some of the other workers will gain from the increase in average human capital, since they are matched with firms using more physical capital than before; and in this sense the average level of human capital has an external benefit.

Work of this kind has helped to motivate the recent search for externalities, using survey data sets that include individuals who live in different cities or regions. The idea is to estimate human capital earnings functions in the normal way, but including a new variable, the average level of schooling in each individual's city or region. The central idea is that, if there are significant externalities to human capital, individuals should earn more when they work in those cities with a higher average level of schooling. The exercise will miss externalities that work at the national level, perhaps through social structures or institutions, but it remains of considerable interest.

Unfortunately, as Ciccone et al. (1999) point out, there is an important argument against interpreting the observed wage premium as solely driven by externalities. Differences in average years of schooling across cities are likely to be associated with differences in the relative supplies of skilled and unskilled labor. These relative supply effects may give rise to an apparent wage premium for average schooling even in the absence of externalities.

The empirical work of Ciccone et al. (1999) supports this proposition. When they follow Rauch and do not allow for relative supply effects, they are able to obtain a high and precise estimate of the social return to education. In a more general approach, which builds in a role for supply effects, the measured externalities are greatly reduced; indeed it is not possible to reject the hypothesis that externalities are absent altogether. Related work by Acemoglu (1998) also indicates that the overall social returns to education may be close to the private returns, this time using the variation in average schooling across US states to capture the effects of externalities.

Inequality

Summaries of the empirical literature that tests relationships between income inequality and growth in a cross section of countries are provided by Benabou (1996) and Perotti (1993). The majority of this literature finds a negative impact of inequality on growth whereby a one standard deviation decrease in inequality increases the annual growth rate of per capita GDP by between 0.5 to 0.8 points. This is too little to account for the outstanding performance of East Asian economies, but it is clearly of relevance and could lead to significant differences in longer-term performance across economies. The use of better data that allow incorporation of panel aspects (using 5-year averages) suggests, however, that the empirical relationship weakens considerably (and may actually be reversed). This led to fear that the *empirical regularity* of a negative inequality-growth relationship may be similar to the famous Kuznets curve – very robust in a cross section but disappearing once country level fixed effects were introduced. (Deininger and Squire 1998). Forbes (2000) uses fixed effects, random effects, and the Arrellano-Bond estimator with 5-year periods for 35 countries, generally obtaining a positive and significant relationship between income inequality and growth. This relationship is robust to variations in samples, inclusion of different variables or different measures of inequality, and divisions of the sample by region, initial income, and other specification tests. Barro (1989) based on a panel estimator using an expanded sample with ten-year averages, suggests that the negative impact of inequality on growth may depend on a country's wealth level, although even then the overall effects are weak and the relationship lacks robustness. However, other studies suggest that income inequality may have an impact on growth.

Economist such as Simon Kuznets argued that there is a tradeoff between reducing inequality and promoting growth. In the post-World War period, however, many East Asian economies had relatively low levels of inequality (for countries of comparable income levels) and grew at unprecedented rates. In sharp contrast to this experience, many Latin American countries had significantly higher levels of inequality and grew at a fraction of the average East Asian rate. These trends prompted a surge of interest in the relationship between inequality and growth, and in particular, a reassessment of how a country's level of income inequality predicts its subsequent rate of economic growth. Over the past five years, many economists have attempted to measure this relationship by adding inequality as an independent variable to some variant of Robert J. Barro's cross-country growth regression. This line of research has received such widespread support that a recent survey of this work concludes: "These regressions, run over a variety of data sets and periods with many different measures of income distribution, deliver a consistent message: initial inequality is detrimental to long-run growth."(Roland Benabou, 1996, pp. 13). This message has been so widely accepted that it has recently motivated a series of papers explaining the specific channels through which inequality might affect economic growth. While most of these papers focus on theories establishing a negative effect of inequality on growth, a careful reading of this literature suggests that this negative relationship is far less definitive than generally believed. In many models, the negative relationship depends on exogenous factors, such as aggregate wealth, political institutions, or the level of development. Many of these papers also predict multiple equilibria, so that under certain initial conditions, inequality could have a positive relationship with economic growth. Moreover, several recent papers have developed models that predict a positive relationship between inequality and growth. Benabou (1996) develops a model based on heterogeneous individuals and shows that if the degree of complementarity between individuals' human capital is stronger in local than global interactions, then segregated and more unequal societies can experience higher rates of growth (at least in the short-run). Oded Galor and Daniel Tsiddon (1997) develop two theories of why inequality and growth could be positively related. In one model, a home environment externality helps determine an individual's level of human capital, and if this externality is strong enough, a high level of inequality may be necessary for growth to "take-off" in a less-developed economy. In a second model, Galor and Tsiddon argue that inequality increases during periods of major technological inventions, which, by enhancing mobility and the concentration of high-ability workers in technologically-advanced sectors, will generate higher rates of technological progress and growth. These theoretical papers predicting a positive relationship between inequality and growth have received less attention in this branch of literature due to the fact that all empirical work has reported a negative relationship between these variables. There are, however, a number of potential problems with this empirical work. First, many of the estimates of a significant negative effect of inequality on growth are not robust. When any sort of sensitivity analysis is performed, such as when additional explanatory variables are included, the coefficient on inequality often becomes insignificant (although it usually remains negative). Deininger and Squire (1998, pp. 269) emphasize this point which leads them "...to question the robustness and validity of the negative association between inequality and growth."

Second, all of these studies have two potential econometric problems: measurement error in inequality and omitted variable bias. Random measurement error could generate an attenuation bias and reduce the significance of results. Potentially more problematic, however, systematic measurement error could lead to either a positive or negative bias, depending on the correlation between the measurement error and the other variables in the regression. For example, if more unequal countries tend to underreport their inequality statistics and also tend to grow more slowly than comparable countries with lower levels of inequality, this could generate a negative bias in cross-country estimates of the impact of inequality on growth.

Omitted variable bias could be equally problematic, although it is impossible to predict the direction of this bias in a multivariate context. If there are strong univariate correlations between an omitted variable, inequality, and growth, however, these relationships could outweigh any multivariate effects and generate a significant, predictable bias. For example, if a country's degree of capitalism, support for entrepreneurship, and/or amount of labor market flexibility is omitted from the growth equation (and each of these variables tends to be positively correlated with both inequality and growth), this could generate a positive bias on estimated inequality coefficients. On the other hand, if the level of corruption (which tends to be positively correlated with inequality and negatively correlated with growth) is omitted from the growth equation, this could generate a negative bias on the estimated inequality coefficient. Given the numerous variables which are difficult to measure and include in a growth regression, it is difficult to predict a priori how omitted variables could affect estimates of the relationship between inequality and growth. A third issue with this cross-country work on inequality and growth is that it does not directly address the important policy issue of how a change in a country's level of inequality will affect growth within that country. The cross-country regression results show the long-term pattern that countries with lower levels of inequality have tended to grow more quickly. This has been interpreted to imply that governments which undertake policies to reduce inequality could simultaneously improve long-term growth performance. Although the cross-country results support this interpretation, they do not directly address this issue of how a change in inequality within a given country is related to growth within that country. The direct way of estimating this relationship is to utilize panel estimation. Panel techniques can specifically estimate how a change in a country's level of inequality predicts changes in that country's growth rate.

In this paper, using five-year average panel data and Arellano-Bond GMM estimation technique, we inequality (wage) is positively correlated with growth.

Chapter 3

Foreign Direct Investment and Wage Inequality

The common aim of FDI studies has been to identify the various costs and benefits of FDI. Productivity externalities were discussed together with several other indirect effects that influence the welfare assessment, such as those arising from the impact of FDI on government revenue, tax policies, terms of trade, and the balance of payments. The fact that spillovers were included in the discussion was generally motivated by empirical evidence from case studies rather than by comprehensive theoretical arguments. Yet, the early analyses made clear that multinationals may improve allocative efficiency by entering into industries with high entry barriers and reducing monopolistic distortions, and induce higher technical efficiency if the increased competitive pressure or some demonstration effect spurs local firms to more efficient use of existing resources. They also proposed that the presence may lead to increases in the rate of technology transfer and diffusion. More specifically, case studies showed that foreign MNCs may: contribute to efficiency by breaking supply bottlenecks (but that the effect may become less important as the technology of the host country advances); introduce new know-how by demonstrating new technologies and training workers who later take employment in local firms; either break down monopolies and stimulate competition and efficiency or create a more monopolistic industry structure, depending on the strength and responses of the local firms; transfer techniques for inventory and quality control and standardization to their local suppliers and distribution channels; and, force local firms to increase their managerial efforts, or to adopt some of the marketing techniques used by MNCs, either on the local market or internationally.

Although this diverse list gives some clues about the broad range of various spillover effects, it says little about how common or how important they are in general. Similar complaints can be made about the evidence on spillovers gauged from the numerous case studies discussing various aspects of FDI in different countries and industries. These studies often contain valuable circumstantial evidence of spillovers (see Blomström, et al., 2003 for a survey), but often fail to show how significant the spillover effects are and if the results can be generalized. For instance, many analyses of the linkages between MNCs and their local suppliers and subcontractors have documented learning and technology transfers that may make up a basis for productivity spillovers or market access spillovers. However, these studies seldom reveal whether the MNCs are able to extract all the benefits that the new technologies or information generate among their supplier firms. Hence, there is no clear proof of spillovers, but it is reasonable to assume that spillovers are positively related to the extent of linkages. Similarly, there is much written on the relation between MNC entry and presence and market structure in host countries, and this is closely related to the possible effects of FDI on competition in the local markets. There are also case studies of demonstration effects, technology diffusion, and labor training in foreign MNCs.

However, although these studies provide much detailed information about the various channels for spillovers, they say little about the overall significance of such spillovers. The statistical studies of spillovers, by contrast, may reveal the overall impact of foreign presence on the productivity of local firms, but they are generally not able to say much about how the effects come about. These studies typically estimate production functions for locally owned firms, and include the foreign share of the industry as one of the explanatory variables. They then test whether foreign presence has a significant positive impact on local productivity (or productivity growth) once other firm and industry characteristics have been accounted for. Although the data used in these analyses are often limited to few variables, aggregated to industry level rather than plant level, and in several cases of a cross-section rather than time-series or panel character, they do provide some important evidence on the presence and pattern of spillover effects.

Almost all of the statistical analyses of spillovers have focused on intra-industry effects, but there are a few exceptions. One of them is Katz (1998), who notes that the inflow of foreign capital into the Argentine manufacturing sector in the 1950s had a significant impact on the technologies used by local firms. He asserts that the technical progress did not only take place in the MNCs. Own industries, but also in other sectors, because the foreign affiliates forced domestic firms to modernize .by imposing on them minimum standards of quality, delivery dates, prices, etc. in their supplies of parts and raw materials. Haddad, M. and Harrison, A.E., (1993) include some discussion about inter-industry effect in Venezuelan manufacturing, and argue that forward linkages generally brought positive spillover effects, but that backward linkages appeared to be less beneficial because of the foreign firms high import propensities (although there were differences between industrial sectors).

The earliest statistical analyses of intra-industry spillovers include studies for Mexico by Blomström (1983). These authors examine the existence of spillovers by testing whether foreign presence has any impact on labor productivity in local firms in a production function framework. Foreign presence is simply included among other firm and industry characteristics as an explanatory variable in a multiple regression. All three studies conclude that spillovers are significant at this aggregate level, although they cannot say anything about how spillovers take place.

Some more recent studies also claim that inward investment has made an important and significant contribution to economic growth in the recipient countries. Blomström tried to determine the size of these effects by asking whether the spillovers in the Mexican manufacturing sector were large enough to help Mexican firms converge toward US productivity levels during the period 1965-1982. Their answer is affirmative: foreign presence seems to have a significant positive impact on the rates of growth of local productivity.

On the other hand, there are several studies that find negative effects of the presence of multinationals on domestic firms. For instance, Haddad and Harrison (1991 and 1993), in a test of the spillover hypothesis for Moroccan manufacturing during the period 1985-1989, conclude that spillovers do not take place in all industrial sectors. Like Blomström (1983), they find that foreign presence lowers the average dispersion of a sector's productivity, but they also observe that the effect is more significant in sectors with simpler technology. This is interpreted to mean that foreign presence forces local firms to become more productive in sectors where best practice technology lies within their capability, but that there are no significant transfers of modern technology. Furthermore, they find no significant effects of foreign presence on the rate of productivity growth of local firms, and interpret this as additional support to the conclusion that technology spillovers do not occur.

Aitken and Harrison (1999) use plant-level data for Venezuelan manufacturing between 1976 and 1989 to test the impact of foreign presence on total factor productivity growth. They conclude that domestic firms exhibited higher productivity in sectors with a larger foreign share, but argue that it may be wrong to conclude that spillovers have taken place if MNC affiliates systematically locate in the more productive sectors. In addition, they are also able to perform some more detailed tests of regional differences in spillovers. Examining the geographical dispersion of foreign investment, they suggest that the positive impact of FDI accrued mainly to the domestic firms located close to the MNC affiliates. However, effects seem to vary between industries.

So the results on the presence of spillovers seem to be mixed. However, recent studies suggest that there is a systematic pattern where various host industry and host country characteristics influence the incidence of spillovers. For instance, the foreign affiliates' levels of technology or technology imports seem to influence the amount of spillovers to local firms. The technology imports of MNC affiliates, in turn, have been shown to vary systematically with host country characteristics. These imports seem to be larger in countries and industries where the educational level of the local labor force is higher, where local competition is tougher, and where the host country imposes fewer formal requirements on the affiliates' operations.

Some recent studies have also addressed the apparent contradictions between the earlier statistical spillover studies, with the hypothesis that the host country's level of technical development or human capital may matter as a starting point. In particular, foreign MNCs may sometimes operate in enclaves, where neither products nor technologies have much in common with those of local firms. In such circumstances, there may be little scope for learning, and spillovers may not materialize. Conversely, when foreign affiliates and local firms are in more direct competition with each other, spillovers are more likely.

Examining data for Mexican manufacturing, Blomström finds that spillovers are positively related to the host economy's capacity to absorb them.

While most of the studies mentioned above have focused on differences between industries in a given host country, Blomström *et al.* (1994) have examined the role of the host country's overall development level as a determinant of spillovers. The results of their comprehensive cross-country study of 101 economies suggest that spillovers are concentrated to middle-income developing countries, while there was no evidence of such effects for the poorest developing countries. Just as the analyses of individual host countries, these findings highlight the importance of local competence and competition for spillovers. Few local firms in the poorest countries are in direct competition with foreign MNCs, and few of these countries possess the technical skills needed to absorb modern MNC technologies. Similar results are reported in Balasubramanyam (1998). He concluded that FDI can be a potent instrument of development, but only in the presence of a threshold of human capital, well developed infrastructure facilities, and a stable economic climate. Thus, FDI is a good for rich countries and that only the most advanced developing countries are able to benefit from FDI.

Thus, it seems clear from these studies that host country and host industry characteristics determine the impact of FDI, and that systematic differences between countries and industries should therefore be expected. There is strong evidence pointing to the potential for significant spillovers benefits from FDI, but also ample evidence indicating that spillovers do not occur automatically. Whether these potential spillovers will be realized or not depends on the ability and motivation of local firms to engage in investment and learning to absorb foreign knowledge and skills. Competition and education are key requirements to achieve this.

FDI and Human Capital Development

The transfer of technology from MNC parents to its affiliates and other host country firms is not only embodied in machinery, equipment, patent rights, and expatriate managers and technicians, but is also realized through the training of local employees. This training affects most levels of employees, from simple manufacturing operatives through supervisors to technically advanced professionals and top-level managers. Types of training range from on-the-job training to seminars and more formal schooling to overseas education, perhaps at the parent company, depending on the skills needed. The various skills gained through the relation with the foreign MNCs may spill over directly when the MNCs do not charge the full value of the training provided to local firms or over time, as the employees move to other firms or set up their own businesses.

According to our findings, FDI increase schooling and returns to schooling. The intuition here is that FDI is education-biased as many economists argue, however, it is this very education-bias that that prompts people to enroll in school in order to improve their human capital. Schooling provides skill premium that increase one wages.

Many governments desire to attract Foreign Direct Investment for the effect it can have on productivity through technology and skills, on exports through access to networks, and on employment and the balance of payments. There is now an increased interest in examining the social effects of Foreign Direct Investment, notably on wage inequality and poverty.

Foreign ownership and wage inequality: micro level

Te Velde and Morrissey (2001) survey the empirical evidence on foreign ownership and wages at the micro level. They find that

- Foreign-owned firms pay more to their workers than local firms. Wage differentials can be up to 60 per cent (Indonesia), but more often are more modest.
- Studies that do not control fully for other effects (size, location, industry etc.) overstate the effect of foreign ownership on wages.
- Studies that distinguish between average wages in two separate education categories find that wage differentials are greater for non-production (relatively educated) workers than for production (less educated) workers.

Differences in wage differentials by education level are found in micro studies for several economies. Lipsey (1981) examine wage differentials between foreign owned and local plants in a survey of over 14000 manufacturing plants in Indonesia in 1996. They find that foreign owned plants pay 12 per cent more to blue collar and 22 per cent more to white collar workers.

Work on China mirrors the importance of segmented labor markets in determining how foreign ownership affects the wages of educated and uneducated workers. Wu (2001) examines wages in a sample of 5345 state owned firms and 188 foreign owned firms taken from the Chinese economy as a whole in 1996. The returns to education and skills are twice as high in foreign owned firms as in state owned firms. It is argued that this is consistent with high labor mobility costs and the segmentation of the Chinese labor market into a privileged sector (state) and an unprivileged sector (non state). The Chinese use education to access the privileged sector. In order to poach educated workers from the privileged sector foreign firms need to pay educated workers more, while uneducated workers are available as a much lower or even negative wage premium.

Other work provides indirect evidence for the effects of foreign ownership on the returns to skill. Blomström, et al., 2003 uses panel establishment and identified an increase over the period 1977-1995 period in the employment of highly skilled professionals, managers and technician workers. He finds support for the hypothesis that technological change proxied by total factor productivity growth (TFP) is skill-biased for the most highly skilled group of managers and technician workers. The skills-biased technological change hypothesis also finds strong empirical support using an alternative technology measure—use of new information and communications technologies (IT). Tan also found that foreign firms are more likely to be using most types of IT, followed by joint-ventures, then by local firms. This implies that foreign firms introduce technologies that are associated with skill up grading.This brings out a more general point that foreign ownership is often associated with skill-biased technical progress leading to faster growth but also to an improvement in the relative position of skilled workers.

Emphasizes on the technology transfer aspect of FDI are often made, but there are other routes through which FDI can affect the market for skills. First, the effects of FDI comprise a composition effect (foreign firms may have different skill intensities from domestic firms) pushing up the average skill intensity. Traditional trade theory (the

Heckscher-Ohlin model) would suggest that FDI in developing countries with abundant low-skilled workers is located in low-skill sectors such as garments and simple assembly operations. New trade models also based on Heckscher-Ohlin foundations consider cases where Transnational Corporations transfer activities abroad, which are less-skilled compared to the home average but more-skilled compared to the host-country. In addition, new trade models have been developed where TNCs locate abroad because of firm-specific assets (Markusen and Venables, 1997) and TNCs are assumed more skill intensive than local firms. The latter appears to be the case for FDI in relatively complex production processes and in particular sectors using above average skills (electronics, chemicals, etc.), bringing up the national average employment of skilled labor.

Secondly, FDI could induce faster productivity growth of educated and/or uneducated labor in domestic firms (spillover effect). Thirdly, the approach includes a potential sector bias of FDI, if FDI causes a relative expansion of skill intensive sectors, leading to a higher relative wages for skills (Te Velde, 2001). Fourthly, while the many derived models assume perfect competition, others can be derived under a situation of imperfect competition, where FDI affects the relative bargaining position of educated workers. In fact, other variables can be included that allow for imperfect wage-setting, such as a measure of the relative scarcity of educated labor in to allow for pressure on the relative wage of educated workers if educated labor is relatively scarce. Finally, FDI may affect the supply of skills through training and contributions to general education (see Te Velde, 2001).

Transnational Corporations as carriers of FDI are often at the leading-edge of using new technology. They are often more skill-intensive than local firms, requiring workers with knowledge of technical subjects such as engineers .The growth in FDI would thus lead to a growing demand in skilled workers. This will lead to an increase in the relative scarcity of skilled workers, who can exploit this by demanding a higher wage, unless the education system provides appropriate and good quality workers that can be employed in sectors where FDI is locating. Good quality and appropriate education is this context requires at least a good educational basis (at least secondary education) on which TNC and their training systems can build as well as provision of tertiary technical education.

Chapter 4

Return to Schooling

Education has numerous consequences for individuals and society. For many people, there is some consumption value from the educational process. Human beings are curious creatures, and they enjoy learning and acquiring new knowledge. Education also has considerable investment value. Those who acquire additional schooling generally earn more over their lifetimes, achieve higher levels of employment, and enjoy more satisfying careers. Education may also enable people to more fully enjoy life, appreciate literature and culture, and be more informed and socially involved citizens. An important distinction is that between the private and the social returns to education. Private returns refer to benefits received by the individual who acquires the additional schooling. These include economic benefits such as higher lifetime earnings, lower levels of unemployment, and greater job satisfaction. They may also include consequences such as improved health and longevity. Social returns refer to positive (or possibly negative) consequences that accrue to individuals other than the individual or family making the decision about how much schooling to acquire. They are therefore benefits (possibly also costs) that are not taken into account by the decision-maker. If such "external benefits" are substantial, they could result in significant under-investment in education in the absence of government intervention.

The discount rate that equalizes the discounted costs and discounted benefits of a project is its internal rate of return. It is a standard means of ranking the profitability of investment projects in a well-functioning capital market and yields a unique ordering of projects if large costs are not incurred at the end of an asset's life, as when disposal costs are substantial. This does not seem to be a limitation of the rate of return concept when used to evaluate human resource investments.

There are often costs and benefits associated with a human resource investment that are not borne by the investor. Consequently, a private rate of return that is relevant to the private investor's maximization of expected wealth may not be the social rate of return that is relevant to the social planner. The critical criterion for the social planner is that the suitably discounted surplus of social over private benefits must exceed the social costs that are not borne by the private family. Consequently, the social planner must first satisfy the private return criterion to have private individuals invest in or use the human resource program, and then satisfy the requirement that social returns justify social costs.

Most economic analysis of human resources has focused on the returns to education. In the 1950s and 1960s economists sought to explain sources of economic growth that were not accounted for by the traditional measures of labor and capital inputs (Kuznets, 1955). Becker (1964) attributed the difference in average earnings between workers with a four-year college degree and those with only a twelve-year high school degree to their attending college. He compared the discounted value of this age-earnings stream of benefits to the opportunity cost of the earnings a student forgoes to attend college plus the direct costs of college tuition, materials, and fees. After additional adjustments and refinements in his working assumptions, Becker computed what private internal rate of return a U.S. male high school graduate might expect to receive from his investment in college education, based on age-earnings cross-tabulations from the 1940 and 1950 U.S. Censuses. The average percentage increment in wages associated with an extra year of schooling is a reasonable approximation for the private internal rate of return to that year of schooling, given the simplifying assumptions that the cross section predicts lifecycle returns and that the opportunity costs of not working for a year approximate the private cost of completing a year of schooling (Mincer, 1974).

Mincer (1974) then hypothesized how returns on postschooling experience or on-the-job training accumulated over the lifecycle, which helped him explain the upward sloping profile of earnings with age after an individual leaves school. Many subsequent studies have replicated these patterns, finding in general that the slope of the wage function with respect to years of schooling experience is steeper in countries that have invested more heavily in schooling and in which economic growth has been more rapid.

The policy implications of these returns to schooling training are less clear than those related to the returns to schooling, because the cost of the training cannot be directly measured and the transferability of the training to a new job is uncertain. In the case of schooling, the period of attendance in years can be inferred with or without adjustment for repetition, even though this neglects length of school year, the student's attendance, and school quality. There is no consensus on how to measure the share of a worker's time invested in on-the-job training or schooling investment. Nor is it easy to distinguish between firm-specific human capital, which is specific to the worker-firm match, from general human capital, which can be readily transferred to another job. Only general human capital should be paid for entirely out of the worker's gross wage, since it is embodied in the worker, whereas the cost of firm-specific human capital should be shared by worker and employer, possibly through some form of long-term employment contract. The gap between actual net wages paid the worker and gross labor productivity, which could provide the incentive for such long-term contracts, is, unfortunately, empirically elusive.

Mincer (1974) provided a conceptual framework for empirically summarizing wage differences across persons of different education levels and durations of schooling experience. His approach has become the standard form for log-linear wage regressions in which the estimated coefficient on completed years of education could, under certain simplifying assumptions, be interpreted as the private rate of return to an additional year of schooling. For two decades this wage function has been modified, extended, and generalized in many ways to assess whether the particular functional form, empirical specification, or estimation method proposed by Mincer leads to biased estimates of private returns to full-time schooling.

With large representative household surveys now available from most countries of the world, the empirical patterns found between schooling and wages have shown themselves to be robust, suggesting private wage returns to schooling are substantial in virtually all countries. Returns are particularly evident in countries experiencing a minimum of stable macroeconomic conditions, a mobile market for workers, and an economy open to international trade and competitive pressures created by technical change in the world economy. Some simplifications such as constant returns to different levels of education are readily relaxed by allowing the proportionate effect on wages of years of schooling to vary across levels of schooling, even non parametrically. Mincer (1974). The omission of wage-determining variables representing the ability of workers, or family wealth, was initially thought to bias upward Mincer's estimates of the returns to education, whereas efforts to include these variables in the wage function can be shown to bias downward estimates of schooling returns, because they worsen the problem of errors-in-measurement of education (Griliches, 1969). Several decades of searching for improved specifications of the wage function have not fundamentally altered the early interpretation of the data, insofar as it suggests basic levels of schooling earn a handsome return for the private individual and, undoubtedly, contribute to more rapid aggregate economic growth.

It is often noted that, as a rule, private returns appear to decline at higher levels of schooling within a particular country, and, at a specific level of schooling, e.g., secondary returns are generally lower in more advanced countries where a larger fraction of the population has acquired that level of schooling. However, since the return on an investment in skills is not only a function of the relative supply of workers with that skill, but also the derived demand for those skills in the domestic economy, there are many exceptions to the above empirical regularities.

Estimation Methods of the Returns to Schooling

In our estimation results for tables 8 through 12 we use the OLS estimation. Estimates of returns to education may suffer from several drawbacks. These include omission of relevant variables and endogeneity of schooling. Although several approaches to these problems have been developed, this study does not fully benefit from them due to data limitations.

Omission of unobserved characteristics such as ability can bias conventional OLS estimates. Including ability proxies tends to lower the estimated returns to schooling indicating that OLS estimates are biased upwards. Knight and Sabot, 1990 have used panel data for twins to estimate returns to schooling. The idea behind this approach is that differencing eliminates the effects of common ability and family-background so that the estimates are purged of these time-invariant effects. Studies using this approach display varying results, with some reporting slightly lower and others reporting slightly higher educational return estimates as compared to conventional OLS estimates. Using data on workers in Kenyan and Tanzanian urban enterprises, Knight and Sabot (1990) test whether human capital (measured as cognitive skill) has an independent effect on earnings or if it simply signals inborn ability (measured by ability test scores). They find that, though ability might have a role in wage formation, controlling for it does not diminish the effect of human capital on earnings.

OLS estimates of the effect of education on earnings are consistent only if, for example, unobserved variables are not correlated with both education and earnings. However, if an unobserved characteristic, say 'ability' has a positive effect on earnings and schooling, then OLS estimates of the returns to schooling will be biased upwards. Another source of bias is measurement error in schooling. This may generate a negative correlation between the earnings and schooling equation error terms and induce a negative bias in OLS estimates.

A negative bias could also arise if workers with low schooling have a higher earnings capacity (and higher returns to schooling), but curtailed their education due to higher discount rates. This negative correlation is implied in the Becker model of human capital investment in which schooling is acquired until the marginal return to schooling equates the discount rate (see Card, 1995).

Other studies find that family background such as parent's education and income (another commonly omitted set of characteristics) has a positive impact on wages and that returns to education decline when family background variables are included in the earnings regressions (e.g., Knight and Sabot, 1990). Knight and Sabot, 1990 examined how parental education interacted with employees' earnings in establishments located in Nairobi, Kenya and Dar es Salaam, Tanzania. They find that the private return to secondary education increased monotonically with parental education. Wambugu (2003) using data on Kenyan manufacturing firm employees, finds that controlling for parental education in the earnings function reduces the level of returns to workers education only by a small percentage.

The data set used in this study does not provide information that can be used to control for ability, family background, or personal discount rates. Also, as is the case in most developing countries, panel data of workers is not available. However, we make the assumption that though unobserved ability might have a role in wage formation, it does not significantly diminish the effect of human capital on earnings (e.g., see Knight and Sabot, 1990). In this study it is not possible to control for unobserved ability or eliminate its effect using panel data. This may bias our OLS estimates upwards. However, we are not trying to determine return to education, given above mention variables. Instead, you are trying to determine the effect on foreign direct investment on returns to education so these biases are not expected in our results.

Chapter 5
Model and Data Description

Education and other forms of training that enhance worker's productivity are valuable in the sense that they increase the individual's earnings. In other words, individuals who decides to accumulate more education or skill, will increase the earning over those who do not. This human capital affects growth indirectly the foreign direct investment which in this paper, is argued to be the source of technological transfer. To better understand this relationship, we use a modified version of Bils and Klenow's models of schooling and growth.

We start with the production function $Y(t) = K(t)^{\alpha}\left[A(t)H(t)\right]^{1-\alpha}$ (1)

With Y representing the flow of output, K, being the stock of physical capital, A representing foreign direct investment (source of technology index), and H being the stock of human capital. The total stock of human capital is the sum of human capital stocks of working cohorts in the economy. To further clarify the role of human capital, we shall suppose that all cohorts go to school from 0 to age s, with s representing the years of schooling attained and work form age s to age T. So we have

$$H(t) = \int_{s}^{T} h(a,t)L(a,t)da \qquad (2)$$

In the above equation, $L(a,t)$ represents the number of workers in the cohort a at time t and $h(a,t)$ is their level of human capital. Note the efficiency units assumption that different levels of human capital are perfectly substitutable, and we generalize that s and T differ across cohorts.

So we can say that a person's human capital stock follows

$$h(a,t) = h(a+n,t)^{\phi} e^{f(s)+g(a-s)} \forall a > s \tag{3}$$

In the above equation, $\phi \geq 0$ takes into account, the influence of teacher human capital with the cohort of n years older being the teachers. If ϕ is great than 0, then one can say that the quality of school is increasing in the human capital of teachers. In equation (3), (s) captures the years of schooling and $(a-s)$ captures experience, with $f^{'}(s) > 0$ and $g^{'}(a-s) > 0$ being the percentage gains in human capital from each year. Something to keep in mind is that the teachers' influence h, is not only at school, but on the job as well. The case that $\phi = 1$, h grows from cohort to cohort even if years of schooling attained are constant (see Sergio Rebelo, 1991). And when $\phi < 1$, then growth in h from cohort to cohort requires rising s and or T.

Equation 3 reduces to the common Mincer (1974) specification when $\phi = 0$, $f(s) = \theta s$, and $g(a-s) = \gamma_1(a-s) + \gamma_2(a-s)^2$. The specification implies that a persons wage is linearly related to the person's years of schooling, years of experience and years of experience squared. Equation (3) shows the direct effect of human capital on output in equation 1, and also shows that human capital may affect output by affecting FDI (the level of technology. This can be seen in equation 4, where the growth rate of technology for country i follows

$$g_{A_i}(t) = -\eta \ln \frac{A_i(t)}{\bar{A}(t)} + \beta \ln h_i(t) + \xi_i(t) \tag{4}$$

with $\bar{A}$ being the exogenously growing FDI technology frontier and $h_i(t) = H_i(t) / L_i(t)$ being the average level of human capital in country i. If $\eta > 0$, the closer the country's technology to the FDI technology frontier the slower the country's growth rate. If $\beta > 0$, the higher the country's human capital the faster the country's growth rate. One has to keep in mind that the one motivation for $\beta > 0$ is that human capital may speed technology adoption, and another motive is that human capital may be necessary for technology use. Integrating equation (4) over time, one finds that the level of FDI in a country should be a positive function of its current and past human capital stocks. In the empirical section, we report that there is ample evidence that the level of FDI (A constructed from equation 1) and the level of human capital (constructed using equation 3) are positively correlated across countries. However, it can be possible that FDI is not positively correlated with past human capital. When this is the case, this could mean that η is very high so that transition dynamics are rapid and economies are close to their steady state paths. This may suggest higher level of human capital that allows a higher level of technology use: $\ln A_i(t) = \beta \ln h_i(t) + \ln \bar{A}(t) + \xi_i(t)$ (5)

$\Rightarrow$

$$\Rightarrow g_{A_i}(t) = \beta g_{h_i}(t) + g_{\bar{A}}(t) + \varepsilon_i(t)$$

(6)

What equation (6) implies is that growth in human capital contributes to economic growth indirectly through FDI and not just directly through stock of human capital is equation (1). It important to take notice of the fact that since h in this model is measured to be consistent with Mincerian private returns estimate in equation (3), the indirect effect of human capital on FDI is an externality that is not captured by individual workers. One reason why externalities arise might be because the introduction of FDI (a source of advanced technology) is based on the amount of human capital in the country as a whole.

The Effect of Schooling On Growth

To look at the effect of schooling on growth, we will use equations (1) through (6). Imagine a competitive open economy facing a constant world real interest rate r. With price of output in the world normalized to one each period, firms first order conditions from equation (1) are $\alpha Y(t)/K(t) = r + \delta$ (7)

and $(1-\alpha)Y(t)/H(t) = w(t)$ (8)

with δ representing physical capital depreciation rate and w being the wage rate per unit of human capital. Combining equations (1), (6) and (8), it can be shown that

$$w(t) \propto A(t) \tag{9}$$

Equation (9) means the wage per unit of human capital grows at the rate g_A.

In this economy, individuals can choose a consumption profile and years of schooling to maximize $\int_0^T e^{-\rho t} \frac{c(t)^{1-1/\sigma}}{1-1/\alpha} dt + \int_0^s e^{-\rho t} \zeta \, dt$ (10)

Where c is consumption and ζ is the flow of utility from going to school.

The individuals budget constraint is

$$\int_s^T e^{-rt} w(t)h(t)dt \geq \int_0^T e^{-rt} c(t)dt + \int_0^s e^{-rt} \mu w(t)h(t)dt \tag{11}$$

with $\mu > 0$ being the ratio of schooling tuition to opportunity cost of student time. Individuals go to school until age s and work from age s through age T.

Using equation (3), (10) and (11), the first order condition for an individual's schooling choice is

$$(1-\mu)w(s)h(s) = \zeta c(s)^{1/\sigma} + \int_s^T e^{-r(t-s)} \left[f'(s) - g'(t-s) \right] w(t)h(t)dt \tag{12}$$

This equation equates the sum of tuition and the opportunity cost of student time for the last year spent in school (the left hand side) to the sum of the utility flow from attending plus the present value of future earning (the right hand side). The gap between human capital gained from education and that gained from experience $\left[f'(s)-g'(t-s)\right]$ enters because staying in school means foregoing experience.

Privately optimal quantity of education is generally not an explicit function of the model's parameters. To show this point, consider a special case in which $f'(s)=\theta s$, $g(a-s)=\gamma(a-s)$, and $\zeta>0$. Using $h(t)=h(s)e^{\gamma(t-s)}\forall t>s$, $w(t)=w(s)e^{g_A(t-s)}$ from equation (9) and first-order condition (12), the privately optimal education is

$$s=T-\left[\frac{1}{r-g_A-\gamma}\right]X\ln\left[\frac{\theta-\gamma}{\theta-\gamma-\mu(r-g_A-\gamma)}\right]. \tag{13}$$

The above equation shows the channel by which higher expected growth in FDI can induce more schooling. The interest rate r and growth rate g_A enter schooling decision Through their difference $(r-g_A)$. This implies that the comparative statics of schooling decision with respect to g_A mirror those of r, with opposite sign. Here, higher growth rates puts more weight on future human capital, it encourages more schooling. We can also say that the higher growth in FDI, raises the private return to investment in schooling.

To analyze the cross-country pattern of schooling growth, we focus on whether high enrollments in 1960 are associated with rapid subsequent growth because high enrollments generate rapid growth in human capital or productivity. Therefore, we proceed to net off the contribution of growth in labor supply and physical capital per capita to arrive at a measure of the combined growth in and for each country. To do this, we use equation (1) to isolate the combined growth in h and A for the countries as

$$g_h + g_A = \frac{1}{1-\alpha}(g_y - \alpha g_k)$$

where h is human capital per person, A is a productivity index, y is GDP per capita, and is physical capital per worker. We estimate using investment rates from world development indicators dataset.

In quantify the growth in human capital for a cross section of countries in we look various specifications of the production of human capital designed to be consistent with Mincer (1974) wage equations that have been estimated for many countries. To calibrate the production function for human capital, use equation (3) and $g(a-s) = \gamma_1(a-s) + \gamma_2(a-s)^2$ - a quadratic term in experience, as a standard in empirical literature on wages – a worker of age a will possess a natural log of human capital given by $\ln[h(a)] = \phi \ln[h(a+n)] + f(s) + \gamma_1(a-s) + \gamma_2(a-s)^2$ (14)

A time subscript is implicit here. For as many countries as possible, Bils and Klenow construct human capital stocks for individuals of each age between 20 and 59, using (13) and incorporating schooling, experience, and teacher human capital specific to each age. We can then calculate average human capital stocks for each country in 1960 and 1990 by weighting each age's human capital stock by the proportion of that age group in the total population of the country in that year (using population data from United Nations, 1994).

Basing the returns to education and experience on the estimates of the sources of wage differences (Mincer equations) we use equation (14) come up with the canonical

Mincer regression estimates returns to education and experience for a cross section of individuals $(i's)$ $\ln(w_i) = \lambda_0 + \lambda_1 s_i + \lambda_2 (age - s_i) + \lambda_3 (age - s_i)^2 + \varepsilon$ (15)

With 6 being the years of enrollment

For $f(s)$ Bils and Klenow posit $f(s) = \dfrac{\theta}{1-\psi} s^{1-\psi}$. (16)

They contemplate $\psi > 0$ because diminishing Mincerian returns to schooling appear to exist when they compared micro-Mincer estimates across countries. To estimate in (16), we exploit the fact that estimated Mincerian returns to education, λ_1 in (15), equal $f'(s) = \phi / s^{\psi}$. Using Bils and Klenow's reports estimates of Mincerian returns to schooling, together with mean years of schooling in the sample, we will use a sample of 52 countries to regress country Mincerian return estimates on country levels of schooling as follows

$$\ln(\hat{\lambda}_1) = \ln(\theta) - \psi \ln(s) + \left[\ln(\hat{\lambda}_1) - \ln(\lambda_1) \right]. \quad (17)$$

We add FDI to the above equation in order to find the effect of FDI on return to schooling. We also add inequality, proxied by wage and income inequality, to find the effect of inequality on returns to schooling

Data Description

As we are aware, data availability creates not only potential measurement errors, but also for omitted variable bias. However, data used in this paper have been painstakingly compiled by its sources. The data for GDP growth from the Summers-Heston data set, version 6.0. Education data is from Barro-Lee schooling data set at NBER and from Bils and Klenow data set. Wage inequality data set is from the Theil index of University of Texas. Data for Foreign direct investment, net inflows (% of GDP), School enrollment, secondary (% gross). Average per capita growth, Openness in current prices SH 6.0, Public spending on education, total (% of GDP). Gross capital flows (% of GDP), Fertility rate, total (births per woman), Per capita income, Primary school enrollment, Male (% of gross) are all from the world development indicator. Data for Foreign direct investment is for Darryl Mcleod's dataset. The variables are taken at five-year averages from 1960 to 2000.

Data for the returns to schooling is from Bils and Klenow's dataset and are taken for specific years. (see Appendix D for dataset).

It is important to note that the first data is divided into two categories. First, we have all countries (developed and least developed) in the sample, then we use the same equations to estimates the effects of FDI on schooling and growth using only least developed countries.

Inequality Statistics Based on Industrial Data

Recent explorations of Inequality Project using the Theil's T, a statistic measuring the dispersion or degree of inequality of data, have provided inequality measures for countries around the world, using readily available manufacturing wage and employment data. The value of the Theil measure is that it can be easily decomposed because of the additive property of logarithms. The Gini is popular for its clarity and is easily represented graphically by areas under a unit line compared with those under a □orenz curve; a theoretical cumulative distribution curve of income to population based on the notion that laborers earn differential amounts of more or less income as compared with one another. Both are good measures: the Theil is a more mathematically elegant measure of inequality, while the Gini offers a more easily interpretable picture of inequality.

The Theil Index.

The Theil Index is derived from information theory, which says that maximum information is learned when the least probable events occurs. If we follow Theil's logic as it applies to incomes, we see that a distribution of income is analogous to a certain level of entopy, given by H(y) as in equation A, where y_i represents a share of income which sums to the total income as given by equation (B).

$$\sum_{i=1}^{N} y_i = 1 \qquad y_I \geq 0 \qquad I = 1, \ldots, N \tag{A}$$

$$H(y) = \sum_{i=1}^{N} y_i \log \frac{1}{y_i} \tag{B}$$

The level of entropy is really a statement of the relative difference of information or values in the set, so that the smaller the difference, the smaller the entropy and the greater the equality. If we are interested in creating a measure of inequality, we follow Theil's derivation and subtract a given entropy from the maximum value of log N (the number of individuals in the population) as shown in equation C.

$$\text{Log } N - H(y) = \sum_{i=1}^{N} y_i \log N y_i = \log \frac{1}{\theta} = \log \frac{1}{\left(\frac{M}{N}\right)} \tag{C}$$

In this simplified form, we can examine measures of inequality in elementary cases. Take, for example, the case where you have two individuals, but one having all the income. The measure reduces to log 2 or 0.301.

Now suppose that there are now ten individuals, one, again, having all the income. It would make sense if the inequality measure reflected this greater imbalance. And indeed it does. This time the mathematical measure for inequality from equation C reduces to log 10 or 1; considerably more than the first one.

If we maintain the same proportion of income between group members, inequality measure stays the same. In realty, an income distribution looks more the case some individuals making more than others, but most having some amount of income. Note that a more realistic distribution between ten individuals requires the added complexity of a summation to calculate the Theil Index.

Actually, as Henri Theil was well aware, industrial data has the rough form just described. But in order to use it to measure inequality, you must separate the variation in inequality into two parts: a between-group measure and a within-group measure as described in equation (D).

$$T = \sum_{i=1}^{N}\left(p_i \frac{\mu_i}{\mu}\right)\log\left(\frac{\mu_i}{\mu}\right) + \sum_{i=1}^{N}\left(p_i \frac{\mu_i}{\mu}\right)T_i \qquad \text{(D)}$$

Where

$$p_i = \frac{e_i}{\sum_{i=1}^{N} e_i}$$

$(\mu_I = w_i)$

$$\mu = \frac{\sum_{i=1}^{N} e_i w_i}{\sum_{i=1}^{N} e_i}$$

But within-group variations are unknown, leading to an abbreviated form (for the sake of practicality) of the Theil Index based on available data. Each of the ten individuals in the example given earlier is representative of a larger population divided vertically by similar wage or income groups. The finer the dissaggregation of wage grouping, the more unknown within-group variations can be minimized. In any case, after decoupling, we are left with T′; a crude approximation of the total inequality, but one that appears to have merit predicting the overall inequality as shown in equation (E).

$$T' = \sum_{i=1}^{N}\left(p_i \frac{\mu_i}{\mu}\right)\log\left(\frac{\mu_i}{\mu}\right) \qquad \text{(E)}$$

Wage Structure-Derived Gini Index

If they are able to collect enough specific data on a regular basis, they are able to create a somewhat accurate Lorenz curve and derive a better Gini. The Gini is basically defined as the value of the area between the curve and the diagonal line, divided by the entire area beneath the diagonal line. As implied above, the ratio may vary between 0 (equality) and 1 (complete inequality).

With good mathematical skills, one can also derive a Gini from wage and employment data, because wages are proportional to income on an individual basis. The process involves sorting industrial wage groups by standard industrial classification (SIC) codes from those earning the smallest to the largest hourly wage based on existing group structure. There are many ways to calculate the area under the Lorenz Curve for wage and employment data. Here the method of Summing triangles and rectangles by rows.

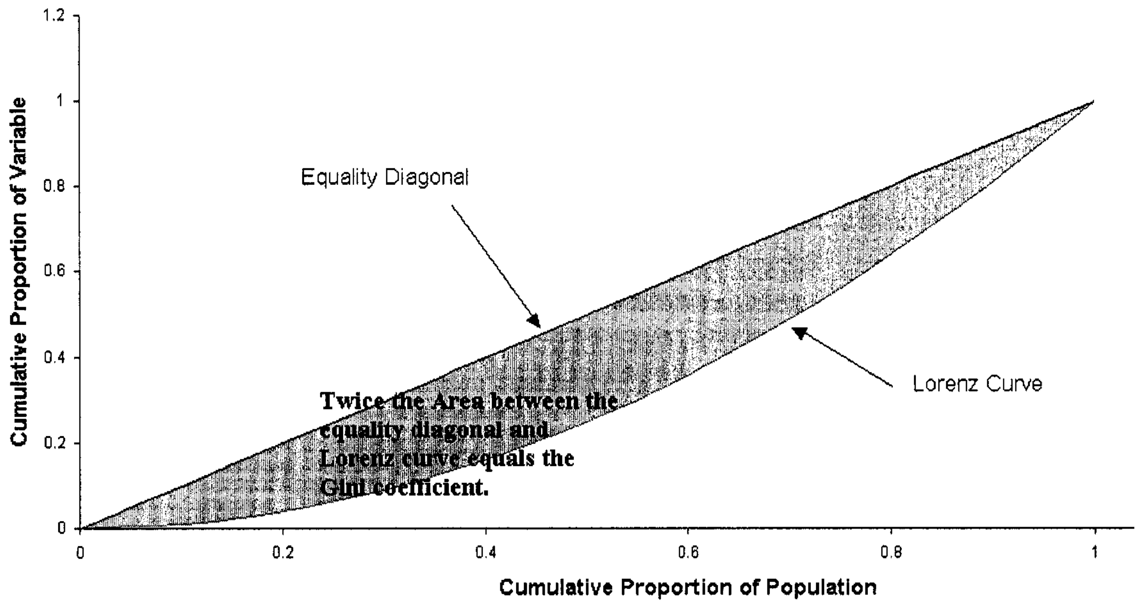
The triangle-rectangle method of summing areas is used to determine the total area under the Lorenz Curve. It is assumed that each group has an even distribution of wages with the group such that the maximum wage earning is simply the product of the wage and employment values for that particular group. Each group's collective wage earnings serve as the bases for the successive groups until we reach the highest income earner group. In aggregate then, Area B is subtracted from the larger area (A+B), then divided by the total area (A+B) to make the statistic range between zero (perfect equality) and one (complete inequality). The result is given by the equation E, labeled as G_W:

$$G_W = \frac{\frac{1}{2}\left[\sum_{i=1}^{N} e_i w_i\right]\left[\sum_{i=1}^{N} e_i\right] - \sum_{i=1}^{N}\left[\frac{1}{2}e_i^2 w_i + \sum_{\substack{k=i+1 \\ i \le N-1}}^{N} e_k . e_i w_i\right]}{\frac{1}{2}\left[\sum_{i=1}^{N} e_i w_i\right]\left[\sum_{i=1}^{N} e_i\right]}$$

$\forall I \in (1,N)$

$$\text{s.t. } w_1 \le w_2 \le w_3 \ldots w_N \qquad \text{(F)}$$

Graphical Representaion of the Gini Coefficient



In the graph above, the Gini coefficient compares this cumulative frequency and size curve to the uniform distribution that represents equality. The diagonal line represents perfect equality, and the greater the deviation of the Lorenz curve from this line, the greater the inequality. The Gini coefficient is double the area between the equality diagonal and the Lorenz curve, bounded below by zero (perfect equality) and above by one (the case when a single member of the population holds all of a resource).

Chapter 6

Foreign Direct Investment and Economic Growth: Does One Granger Cause the Other

As we have suggested in this work, FDI plays an important role for technology to host countries. FDI by multinational corporations (MNCs) is suggested as a vehicle of international diffusion of technology. The effectiveness and magnitude of technology diffusion from MNCs on host country's economy can be measured by analyzing the level of adaptation of new technology in the host country. In light of this, it is therefore important to test for a causal relationship between FDI and economic growth.

Regarding causality of FDI and economic growth, it is still and ongoing debated issue. Hansen and Rand (2004) analyze the causal link between FDI and GDP and the causal of these two variables by looking at a sample of 31 developing countries in Asia, Latin America and Africa for the period of 1970-2000. They conclude that "when allowing for country-specific heterogeneity of all parameters, a strong casual link from FDI to GDP exists" (Hansen and Rand, 2004, p.18). Their empirical research points out that FDI promotes capital accumulation and that a higher ration of FDI in gross capital formation creates a positive effect on GDP growth.

However, Hansen and Rand (2004) suggest that there is no variance of impact of FDI on GDP: "on average, FDI has a significant long run impact on GDP irrespectively on the level of development" (Hansen and Rand, 2004, p.18). According to their findings, the impact of FDI does not vary across region including Asia, Africa, and Latin America. This conclusion completely contrast the results obtained by Blomstrom. As discussed, there is an inconsistency in the results of causality between FDI and economic growth in the literatures. Whereas previous empirical studies support the conventional view of the role of FDI as a critical factor for economic growth, Carkovic and Levine (2002) argue that there is no statistical evidence of this positive view on FDI for economic growth. Through the combination of the microeconomic approach analysis of FDI on productivity growth which measures the total factor productivity (TFP), and does not have a positive influence on TFP or GDP. They argue that FDI cannot be viewed as an independent variable for economic growth while disregarding other economic growth determinant factors.

Carkovic and Levine (2002) claim that "previous macroeconomic studies do not fully control for endogeneity, country-specific effects, and the inclusion of lagged dependent variables in the growth regression" (p.13). Thus, these uncontrolled factors result in inaccuracy in the statistical tests. By correcting the factors that used to be uncontrolled in other studies, they perform the simple ordinary least squares (OLS) regressions and dynamic panel procedure with data averaged over five-year periods on 72 countries over the years 1960-1995. Carkovic and Levive (2002) conclude that while FDI flows may go hand-in-hand with economic success, they do not tend to exert an independent growth effect. This finding disputes generally accepted views on the positive influence of FDI on economic growth.

Choe (2003) also examines causality of FDI and Gross Domestic Investment (GDI) and economic growth by applying the panel VAR model. He argues the GDI rates and FDI inflows play catalyst roles for economic growth through capital accumulation, which is necessary for long-run growth. He analyzed GDI rates and FDI inflows in terms of their relationship to economic growth. In his empirical study, he tests for Granger causality between FDI inflows and GDI rates and GDP growth. From a sample of 80 countries comprising of high income OECD countries and developing countries over the period of 1971-1995, he concludes that the overall causality of FDI and GDI are bi-directional. However, more significant effects are observed from economic growth rather than from FDI to economic growth.

In sum, the correlation and causality of FDI and economic growth are heterogeneous across countries, and an application of different econometric methodologies creates variation in test results. In addition, there are still many other variables that can effect the results of empirical studies due to country specification. Therefore, it is critical to understand these variations when examining the relationship and causality between FDI and economic growth.

Causality Test Methodology

This section of this paper measures the level of impact of FDI on GDP growth and vice versa in order to determine the causal relationship of these two variables by using several econometric methodologies: the granger causality test and the vector autoregressive representation (VAR) approach. The data used for these tests are GDP annual growth rate and FDI gross as a percent of GDP taken at five year averages from 1960 to 2000. Data for the granger causality test is from the World Development Indicators 2003 that is published by the World Bank .

The same test will be performed for FDI and human capital (measured as school attainment and school enrollment), and GDP and human capital. The countries of this study included in the study are: Poland, Sweden, Greece, Italy, Austria, Hungary, Canada, China, Denmark, Israel, India, Australia, Netherlands, Tanzania, Switzerland, Bolivia, Germany West, Dom. Rep, Ireland, Venezuela, Peru, Kenya, Uruguay, Thailand, USA, Malaysia, Portugal, El Salvador, UK, Pakistan, Nicaragua, Cyprus, Ecuador, Paraguay, Costa Rica, Korea, Argentina, Singapore, Philippines, Chile, Botswana, Panama, Spain, Mexico, Guatemala, Colombia, Brazil, Indonesia, Honduras, Jamaica.

Granger Causality Test

In economics you may often have that all variables in the economy reacts to some unmodeled factor and if the response of one variable and another is staggered in time you will see Granger causality even though the real causality is different. There is nothing we can do about that (unless you can experiment with the economy) - Granger causality measures whether one thing happens before another thing and helps predict it - and nothing else. Of course we all secretly hope that it partly catches some "real" causality in the process. In any event, you should try and use the full term Granger causality if is not obvious what you are referring to.

The definition of Granger causality did not mention anything about possible instantaneous correlation between two variables. If the innovation to one variable and the innovation to the other are correlated we say there is *instantaneous causality*. You will usually (or at least often) find instantaneous correlation between two time series, but since the causality (in the \real" sense) can go either way, one usually does not test for instantaneous correlation. However, if you do find Granger causality in only one direction you may feel that the case for \real" causality is stronger if there is no instantaneous causality, because then the innovations to each series can be thought of as actually being generated from this particular series rather than part of some vector innovations to the vector system. Of course, if your data is ampled with a long sampling period, for example annually, then you would have to explain why one variable would only cause the other after such a long lag (you may have a story for that or you may not, depending on your application). Granger causality is particularly easy to deal with in VAR models. Assume that our data can be described by the model.

In each of the following, suppose that y_{1t} and y_{2t} have vector autoregressive representation (VAR) with lag length of p. These equations can be written as follows:

$$y_{1t} = \mu_{10} + \pi_{11.1} y_{1t-1} + \ldots.. + \pi_{11.p} y_{1t-p} + \pi_{12.1} y_{2t-1} + \ldots.. + \pi_{12.p} y_{2t-p} + \varepsilon_{1t} \tag{a}$$

$$y_{2t} = \mu_{20} + \pi_{21.1} y_{1t-1} + \ldots.. + \pi_{21.p} y_{1t-1} + \pi_{22.1} y_{2t-1} + \ldots.. + \pi_{22.p} y_{2t-p} + \varepsilon_{2t} \tag{b}$$

Each equation, y_{1t} and y_{2t} show the systematic dependences on lags of itself and lags of the other variables. In other words, y_{1t} depends on lags of itself and lags of y_{2t}, and y_{2t} depends on itself and lags of y_{1t}. Each equation assumes that $E\{\varepsilon_{it}\} = 0$ and $E\{\varepsilon_{it}{}^2\} = \sigma_i^2$ for i = 1, 2 and $E\{\varepsilon_{it}\varepsilon_{is}\} = 0$ for $t \neq s$ and for $i = 1, 2$. Another assumption that should be made for VAR model is that there is no serial correlation between the two y_{1t} and y_{2t}, which can be expressed as $E\{\varepsilon_{it}\varepsilon_{is}\} = 0$ for $t \neq s$.

Equations (a) and (b) can be written in matrix form in the following way:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \mu_{1t} \\ \mu_{2t} \end{pmatrix} + \begin{bmatrix} \pi_{11.1} & \pi_{12.1} \\ \pi_{21.1} & \pi_{22.2} \end{bmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \ldots$$

$$\ldots..+ \begin{bmatrix} \pi_{11.p} & \pi_{12.p} \\ \pi_{21.p} & \pi_{22.p} \end{bmatrix} \begin{pmatrix} y_{1t-p} \\ y_{2t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{c}$$

The above matrix from of VAR can be written in another form as follows:

$$y_t = \mu + \Pi_1 y_{t-1} + \ldots.. + \Pi_p y_{t-p} + \varepsilon_t \tag{d}$$

where $y_t' = (y_{1t}, y_{2t})$, $\mu_t' = (\mu_{1t}, \mu_{2t})$, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ and Π_i are 2 x 2 matrix defined above in equation (c).

Applying the VAR model with the lag lengths of two, we test for Granger causality between FDI and GDP growth. We use tow lags because we are using five-year averages and it takes about five to ten years to truly experience any effect of one variable on the other. Therefore, each equation of y_{1t} and y_{2t} in which the lag length runs from 1 to 2 can be written as follows:

$$y_{1t} = \mu_{10} + \pi_{11.1}y_{1t-1} + \pi_{11.2}y_{1t-2} + \pi_{12.1}y_{2t-1} + \pi_{12.2}y_{2t-2} + \varepsilon_{1t} \quad \text{(a)'}$$

$$y_{2t} = \mu_{20} + \pi_{21.1}y_{1t-1} + \pi_{21.2}y_{1t-1} + \pi_{22.1}y_{2t-1} + \pi_{22.2}y_{2t-2} + \varepsilon_{2t} \quad \text{(b)'}$$

In addition, the general matrix from of the VAR model (c) which has the lag length p can be written as the following VAR model with lag length 2 that is used in this paper.

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \mu_{1t} \\ \mu_{2t} \end{pmatrix} + \begin{bmatrix} \pi_{11.1} & \pi_{12.1} \\ \pi_{21.1} & \pi_{22.2} \end{bmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \dots$$

$$\dots\dots + \begin{bmatrix} \pi_{11.2} & \pi_{12.2} \\ \pi_{21.2} & \pi_{22.2} \end{bmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \quad \text{(c)'}$$

In the Granger causality in a bivariate system where lag length runs from 1 to through p, hypotheses can be written as follows:

$$H_O : \pi_{12.1} = \pi_{12.2} = \dots = \pi_{12.p} = 0 \quad \text{(e)}$$

$$H_A : \text{At least one } \pi_{12.i} \neq 0 \quad \text{(f)}$$

If H_O (e) is rejected, it implies that y_{2t} does Granger cause y_{1t}. If Ho is not rejected, it implies that y_{2t} does not Granger cause y_{1t}.

$$H_O : \pi_{21.1} = \pi_{21.2} = \dots = \pi_{21.p} = 0 \quad \text{(g)}$$

H_A : At least one $\pi_{21.i} \neq 0$ (h)

If Ho (g) is rejected, it implies that y_{1t} does Granger cause y_{2t}. If Ho is not rejected, it implies that y_{1t} does not Granger cause y_{2t}.

$H_O : \pi_{12.1} = \pi_{12.2} = \ldots = \pi_{12.p} = 0$ and $H_O : \pi_{21.1} = \pi_{21.2} = \ldots = \pi_{21.p} = 0$ (i)

H_A : At least one $\pi_{12.i} \neq 0$ and at least one $\pi_{21.i} \neq 0$ (j)

If Ho (i) is rejected, it implies that y_{2t} does not Granger cause y_{1t} and y_{1t} does not granger cause y_{2t}.

Since the Granger causality tests in this paper use VAR model with a lag length of 2, the above hypothesis can be written as follows:

$Ho : \pi_{12.1} = \pi_{12.2} = 0$ (e)'

H_A : At least one $\pi_{12.i} \neq o$ for $i = 1 \, and \, 2$ (f)'

$Ho : \pi_{21.1} = \pi_{21.2} = 0$ (g)'

H_A : At least one $\pi_{21.i} \neq o$ for $i = 1 \, and \, 2$ (h)'

$Ho : \pi_{12.1} = \pi_{12.2} = 0$ and $Ho : \pi_{21.1} = \pi_{21.2} = 0$ (i)'

H_A : At least one $\pi_{12.i} \neq o$ and at least one $\pi_{21.i} \neq 0$ for $i = 1 \, and \, 2$ (j)'

By applying the VAR models described above, this paper performs hypothesis test and uses coefficients and standard errors of the wald test with 5% and 10% significant levels. The test involves the addition of one extra lag of each of the variables to each equation and the use of a standard Wald test to see if the coefficients of the lagged variables are jointly zero in the equation. The results of the Wald test are in Tables 13 to 18 in Appendix A.

In table 13 wald test results does not suggest that FDI granger causes GDP in the sample countries selected for this study.

When the same test is performed for foreign direct investment and school attainment (see table 14), the results suggest that FDI and school attainment do granger-cause each other. The implications of this result is very significant since we are arguing in this paper that FDI does increase schooling in a host country. The same result is obtained when we test for a granger causality between FDI and school enrollment (see table 15). This may suggest that not only does higher levels of schooling encourage inflow in foreign direct investment and vice-versa, FDI also may lead people to enroll in school. Finally, we find that school enrollment (both at the primary and secondary levels) granger-cause economic growth.

No causality relationships were found between FDI and growth by our results even at the 10% level of significance. We provide two possible explanations to this outcome. First, one must consider the nature of investment flows. Wang (2002), disaggregating the nature of investment flows entering a country found that at least for the 12 Asian countries she examined, only FDI in the manufacturing sector had a significant and positive impact on these countries' economic growth. Second, as de Mello (1996) pointed out, "FDI is very sensitive to balance of payments constraints and factors related to the macroeconomic performance and institutional features of the recipient economy such as open economy performance variables, and domestic policy variables." It is possible that many of the countries in the study have, unfortunately, neglected the importance of attracting foreign investments into their country. Quoting a study done by the East Asia Analytical Unit of the Department of Foreign Affairs and Trade of

Australia; "...poor economic policies and political instability meant growth stagnated and real incomes actually fell for most part of the past three decades...The Philippines failed to participate in East Asia's growth because it pursued inward-looking protectionism, intrusive government driven industry policies and politically driven expansionist fiscal policies. It neglected infrastructure, over taxed agriculture and mining and discouraged foreign investment."

Chapter 7

GMM Estimation Technique

In this paper, we briefly review the problems with the first-differenced GMM estimator for autoregressive linear regression models estimated from short panels in the presence of unobserved individual-specific time-invariant ('fixed') effects. We explain why large finite sample biases can be expected when the individual series are highly persistent. In this paper, we use 'system' GMM estimator developed by Arellano and Bover (1995).

First-differenced GMM

We first look at the first-differenced GMM approach. For simplicity, consider an AR(1) model with unobserved individual-specific effects

$$y_{it} = \alpha y_{it,t-1} + \eta_i + \upsilon_{it} \qquad |\alpha| < 1 \tag{1}$$

for i = 1, ...,N and t = 2, ..., T, where $\eta_i + \upsilon_{it} = u_{it}$ has the standard error components structure

$$E[\eta_i]=0,\ E[v_{it}]=0,\ E[v_{it}\eta_i]=0 \text{ for } i=1,...,N \, and \, t=2,...,T. \tag{2}$$

We assume that the transient errors are serially uncorrelated

$$E[v_{it}v_{is}]=0 \, for \, i=1,...,N \, and \, s \neq t \tag{3}$$

and that the initial conditions y_{it1} are predetermined

$$E[y_{it1}v_{it}]=0 \, for \, i=1,...,N \, and \, t=2,...,T \tag{4}$$

Together, these assumptions imply the following m = 0.5(T − 1)(T − 2) moment restrictions

$$E\left[y_{1,t-s}\Delta v_{it}\right]=0 \, for \, t=3,...T \, and \, s \geq 2 \tag{5}$$

which can be written more compactly as

$$E(Z_i^{'}\Delta v_i)=0 \tag{6}$$

where Z_i is the (T − 2) × m matrix given by

$$Z_i = \begin{bmatrix} y_{i1} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & y_{i1} & y_{i2} & \dots & 0 & \dots & 0 \\ . & . & . & \dots & . & \dots & . \\ 0 & 0 & 0 & \dots & y_{i1} & \dots & y_{i,T-2} \end{bmatrix} \tag{7}$$

and Δv_i is the (T − 2) vector $(\Delta v_{i3}, \Delta v_{i4}, \dots, \Delta v_{iT})^{'}$. These are the moment restrictions exploited by the standard linear first-differenced GMM estimator, implying the use of lagged levels dated $t-2$ and earlier as instruments for the equations in first-differences (cf. Arellano and Bond, 1991). This yields a consistent estimator of α as $N \to \infty$ with T fixed.

However, this first-differenced GMM estimator has been found to have poor finite sample properties, in terms of bias and imprecision, in one important case. This occurs when the lagged levels of the series are only weakly correlated with subsequent first-differences, so that the instruments available for the first-differenced equations are weak (Blundell and Bond 1998). In the *AR(1)* model of equation (1), this occurs either as the autoregressive parameter (α) approaches unity, or as the variance of the individual effects (η_i) increases relative to the variance of the transient shocks (v_{it}).

Simulation results reported in Blundell and Bond (1998) show that the first-differenced GMM estimator may be subject to a large downward finite-sample bias in these cases, particularly when the number of time periods available is small.

This suggests that some caution may be warranted before relying on this method to estimate autoregressive models for a series like per capita GDP from samples containing five or six time periods of five-year averages. It may be that the presence of explanatory variables other than the lagged dependent variable, and more particularly the inclusion of current or lagged values of these regressors in the instrument set, will improve the behavior of the first-differenced GMM estimator in particular applications. But some investigation of this in the context of empirical growth models would seem to be in order.

How can we detect whether serious finite sample biases are present? One simple indication can be obtained by comparing the first-differenced GMM results to alternative estimates of the autoregressive parameter α. In the AR(1) model of equation (1), it is well known that OLS levels will give an estimate of α that is biased upwards in the presence of individual-specific effects (see Hsiao, 1986, for example), and that Within Groups will give an estimate of α that is seriously biased downwards in short panels (see Nickell, 1981). Thus a consistent estimate of α can be expected to lie in between the OLS levels and Within Groups estimates. If we observe that the first-differenced GMM estimate is close to or below the Within Groups estimate, it seems likely that the GMM estimate is also biased downwards in our application, perhaps due to weak instruments.

These simple bias results have been extended to models with other regressors only in the special case when all the regressors except the lagged dependent variable are uncorrelated with η_i and strictly exogenous with respect to v_{it}. Nevertheless it may still be useful to compare first-differenced GMM results to those obtained by OLS levels and Within Groups. A finding that the first-differenced GMM estimate of the coefficient on the lagged dependent variable lies close to the corresponding Within Groups parameter estimate can be regarded as a signal that biases due to weak instruments may be important. In these cases, it may be appropriate to investigate the quality of the instruments by studying the reduced form equations for $\Delta y_{i,t-1}$ directly, or to consider alternative estimators that are likely to have better finite sample properties in the context of persistent series.

System GMM

Now consider one estimator that may have superior finite sample properties. To obtain a linear GMM estimator better suited to estimating autoregressive models with persistent panel data, Blundell and Bond (1998) consider the additional assumption that

$$E(\eta_i \Delta y_{i2}) = 0 \ for \ i = 1, \ldots, N. \tag{8}$$

This assumption requires a stationarity restriction on the initial conditions y_{i1}. Condition (8) holds if the means of the y_{it} series, whilst differing across individuals, are constant through time for periods 1, 2,..., T for each individual. Combined with the AR(1) model set out in equations (1) to (4), this assumption yields $T - 2$ further linear moment conditions

$$E(u_{it} \Delta y_{i,t-1}) = 0 \ for \ i = 1, \ldots, N \ and \ t = 3, 4, \ldots, T. \tag{9}$$

These allow the use of lagged first-differences of the series as instruments for equations in levels, as suggested by Arellano and Bover (1995).

We can then construct a GMM estimator which exploits both sets of moment restrictions (5) and (9). This uses a stacked system of (T − 2) equations in first-differences and (T − 2) equations in levels, corresponding to periods 3, ..., T for which instruments are observed. The instrument matrix for this system can be written as

$$Z_i^+ = \begin{bmatrix} Z_i & 0 & 0 & \ldots & 0 \\ 0 & \Delta y_{i2} & 0 & \ldots & 0 \\ 0 & 0 & \Delta y_{i3} & \ldots & 0 \\ . & . & . & \ldots & 0 \\ 0 & 0 & 0 & \ldots & \Delta y_{i,T-1} \end{bmatrix}$$

where Z_i is given by equation (7). The complete set of second-order moment conditions available given assumption (8) can be expressed as

$$E(Z_i^{+'} u_i^+) = 0 \qquad (10)$$

where $u_i^+ = (\Delta v_{i3}, \ldots, \Delta v_{iT}, u_{i3}, \ldots, u_{iT})'$.

The system GMM estimator thus combines the standard set of equations in first-differences with suitably lagged levels as instruments, with an additional set of equations in levels with suitably lagged first-differences as instruments. Although the levels of y_{it} are necessarily correlated with the individual-specific effects (η_i) given model (1), assumption (8) requires that the first-differences Δy_{it} are not correlated with η_i, permitting lagged first-differences to be used as instruments in the levels equations. As an empirical matter, the validity of these additional instruments can be tested using standard Sargan tests of over-identifying restrictions, or using Difference Sargan or Hausman comparisons between the first-differenced GMM and system GMM results (see Arellano and Bond, 1991).

The calculation of this system GMM estimator is discussed in more detail in Blundell and Bond (1998). They also report evidence from Monte Carlo simulations that compare the finite sample performance of the first-differenced and system GMM estimators. For an AR(1) model, this shows that there can be dramatic reductions in finite sample bias and gains in precision from exploiting these additional moment conditions, in cases where the autoregressive parameter is only weakly identified from the first-differenced equations.

Chapter 8
Regression Results and Conclusion

One prediction of our model is that FDI is positively associated with growth. To test this first implication of our model, we estimate specifications of the following type:

$$Growth_{it} = \alpha_0 + \beta_1 GDP_{it-1} + \beta_2 FDI_{it-1} + \beta_3 X_{it-1} + u_{it}$$

Where, *i* denote a country and t a time-period (measured in terms of five-year averages). α_i is a country-specific parameter. $Growth_{it}$ and GDP_{it-1} represent the rate of growth of GDP growth, while X_{it} is a matrix of other growth determinants. A key issue in the use of panel data is how the country-specific effect is treated and consequently how the parameters should be estimated. There are two ways of estimating this equation using panel data: the fixed effects method and uses OLS and GMM estimation. Both procedures provide consistent estimates. The results are provided in tables in appendix A for the fixed effects method, and for the Arellano–Bond system-GMM.

Our model also predicts that it is especially in those economies that education affects growth through FDI. To test this we look at the equation below:

$$Growth_{it} = \alpha_0 + \beta_1 GDP_{it-1} + \beta_2 FDI_{it-1} * HC_{it-1} + \beta_3 X_{it-1} + u_{it}$$

In order to evaluate whether our model is correctly specified, we use system-GMM with the Sargan test . If the model is correctly specified, the variables in the instrument set should be uncorrelated with the error term . The *J* test is the Sargan test for overidentifying restrictions, which, under the null of instrument validity, is asymptotically distributed as a chi-square with degrees of freedom equal to the number of instruments less the number of parameters. The FDI test is asymptotically distributed as a standard normal under the null of no second-order serial correlation of the differenced residuals.

The results of the GMM estimates are presented in column 4 of Table 1, 2 and 3. We can see that coefficients associated with the variables FDI and human capital (which are measured as school enrollment and school attainment) are positive and precisely determined. In accordance with our model, this suggests that the positive and significant relationship between FDI, human capital and growth. The Sargan test does not indicate any problem with the choice of the instruments or the specification of the model. The results obtained by estimating the above equation using a OLS fixed-effects specification are reported in columns 1, 2, and 3 of Tables 1, 2 and 3. We can see that, as predicted by the model, there is a strong positive association between FDI and growth.

Estimating the above equation using a fixed-effects specification is likely to lead to biased estimates as growth and FDI might be simultaneously determined, and more specifically all right-hand side variables might be endogenous. This is why we re-estimate variantes of the equation using a system-GMM estimator. Arellano and Bover (1995) and Blundell and Bond (1998) have shown that where there is persistence in the data such that the lagged levels of a variable are not highly correlated with the first difference, also estimating the levels equation with a lagged difference term as an instrument offers significant gains, countering the bias due to weak instruments. Because growth equations are particularly likely to suffer from the latter bias, we use the system-GMM estimator rather than the simple first-difference estimator. We use FDI and GDP annual growth variables lagged two as instruments in the differenced equation, and first-differences of the same variables lagged once as instruments in the levels equation. The estimates of the equation undertaken using the system-GMM estimator are reported in columns 4 and 5 of tables 1, 2, 4, 5, 6, 7 and 8. We can see that FDI remains positively associated with growth. The Sargan test suggests that there are no problems present in the model. Extending the growth equation and controlling other variables does not significantly affect the result. In each case, results suggest once again that FDI and growth are positively related and that human capital, measured as school attainment and school enrollment, are positively and significantly related to growth. This result is consistent with previous studies. Barro, 1989 found a positive and significant effect of the secondary school enrollment rate, when used as a proxy for human capital.

Contrary to previous works like Barro (1989), Perotti (1994), wage inequality is positively associated with changes growth (see Table 1, column 4).It is important to note that the coefficients in Tables 1, column 4 are interpreted differently than in previous work on this subject. First of all the used income inequality and here we are using wage inequality, also they used instrumental variables (IV) to estimate some variant of the standard cross-country growth regression. The resulting estimates of a negative coefficient on inequality suggested that countries with lower levels of inequality tend to have higher steady-state levels of income. These estimates do not directly assess a potentially more relevant question: how are changes in a country's level of inequality related to changes in that country's growth performance? The Arellano and Bond fixed-effects estimator, however, specifically addresses this question. It controls for a country's unobservable, time-invariant characteristics or "fixed effect," and instead of analyzing differences in inequality and growth across countries, focuses on changes in these variables within each country across time. The resulting coefficient on inequality can therefore be interpreted as measuring the highly relevant relationship of how inequality is related to changes in growth within a given country. Another difference between the interpretation of this paper's results and that of earlier work is the time period under consideration. The standard cross-country growth regression estimates how initial inequality is related to growth over the next 25 or 30 years, thereby assessing a long-run relationship. Since this paper utilizes five-year panels, however, the coefficients reflect a short or medium-run relationship.

As suggested by the model, human capital may be affected by growth and FDI and this relation can be seen in Table 4 and 5 changes in FDI are positively related with changes in secondary school enrollment. This does not come as a surprise since the model suggests that individuals with human capital benefit from FDI. Individuals may choose to enroll in school in order to acquire the human capital necessary to benefit from FDI. The results in Tables 4 and 5 are also estimated using system GMM and the sargan test is applied. Results in columns 4 of the tables (the GMM estimates) are consistent with the OLS results, and the sargan test of the GMM estimation suggests that that is not problem with the instruments. The model implies that FDI effects wage inequality, so we test for this effect and report it in Table 6. The results in this table shows that FDI is positively associated with changes in wage inequality. The table also shows that changes in FDI are positively correlated with changes in wage inequality. Even when we control for other variables that may affect wage inequality, we still find that the relationship remains positive and significant. We re-estimate the same equation using system GMM (see columns 6.1A, 6.2A and 6.3A) and see that the results are consistent with the OLS fixed effects estimation. The sargan test also suggest that the choice of instrument have no problem.

The positive correlation between FDI schooling and economic growth persists even when the samples of countries only included developing ones.

Table 2 shows that changes in secondary school enrollment is positively related to changes in FDI and we also see that changes in fertility rate is positively related to changes in FDI. The results in this equation are re-estimated using system GMM, which as presented in column 12.3 are consistent with the OLS fixed effect estimation. Again, the sargan test result shows no sign of problems with the instruments used.

Returns To Education

As predicted in the model, Tables 9, 10, 11 and 12 show that change in foreign direct investment and lagged FDI are positively correlated with returns to education. This implies that higher FDI increases the return to education. The suggestion here is that FDI introduces production processes that are education intensive and in order for individual to engage in this production process, the individual must spend more time acquiring education, therefore increase their return. This explanation is inline with the model.

In tables 9 column 9.3, we fine a positive and significant correlation between wage inequality and returns to education. Part of the hypothesis advanced here explains the increased earnings inequality in many developed and developing and countries, the most persuasive appears to be that it is caused by an increased rate of education-biased technological change, whose transmission to through FDI to host countries may have been facilitated by the increased openness of those economies. The increased earnings inequality is associated closely with a higher dispersion of the average wages received by workers with different schooling attainment. This had the consequence, in turn, of raising the of return to higher levels of education.

Interestingly enough, when past secondary school enrollment rates are negatively associated with returns to education (See Table 9), however, primary school enrollment rates are positively and significantly associated with returns to education (see Table 11).

In Table 17, we see that wage inequality and income inequality are positively associated with returns to education.

Causality Results

This paper explores the plausibility of foreign direct investment as a catalyst for human capital accumulation. Given the large body of literature dedicated to the positive effects of education and training on growth, human development and income equality, their drivers merit exploration. On a micro level, there is a large body of literature that explores the returns to schooling and numerous other factors as driving forces behind an individual's decision to pursue schooling.

Numerous studies within the growth literature empirically explore the effects of human capital on economic growth. For most, the expansion of the definition of capital in the neoclassical growth model to include human capital set off a series of examinations into the correlation between human capital and growth. While demonstrating a convincing correlation between human capital and growth, these studies are not necessarily convincing about the causality. More recent studies such as those by Bils and Klenow (1998) question the assumed direction of causality from education to economic growth. In fact, Bils and Klenow postulate and present a convincing argument, using micro analysis, that anticipated economic growth (functioning through observed present and past growth) leads to faster human capital accumulation.

In this paper, the results suggest a granger causality between FDI and gross domestic product (see Table 18). Also, we find in Table 19 that school attainment granger causes FDI. This result is not too surprising since a level of education is necessary in the host country in order to attract FDI. But when the measure of human capital was replace with school enrollment, we see in Table 20 that there is a two way granger causality between FDI and school enrollment when we use two lags. One explanation for this might be that since FDI increases wage inequality by increasing the wages of those with human capital, individuals may want to enroll in school in order to capture the human capital required to benefit from FDI that is associated with higher wages.

In Table 16, results suggest growth of gross domestic product does not granger cause school attainment, however, school attainment granger causes growth in gross domestic product. Similar causality result is obtained when we replace school attainment with school enrollment. Here again, we see that with two lags, school enrollment granger causes gross domestic product growth.

Conclusion

In many countries, attracting foreign direct investment has been a strategic economic policy adopted to upgrade technology and boost economic growth. The development of special economic boom and the tax break for joint ventures and wholly foreign owned subsidiaries have made a significant contribution to the rapidly increase of FDI inflows into these in the past decades. Firms with FDI have contributed to many of these countries' growth. Meanwhile, wage inequality is becoming a more and more important issue for social stability.

Indeed, multinational firms with relatively skill intensive technologies can be responsible for rising inequality in recipient countries as studied in Wu (2001). These FDIs have pushed up the relative wage of skilled labor and hence the wage in those relatively education intensive sectors, which is consistent with the sectorial wage data presented in Wu (2001). Although FDI from well developed countries is increasing, a higher percentage of recipient country's FDI is still from newly developed countries/regions with mostly relatively labor biased technologies, which can reduce the wage gap by increasing returns to education

On the one hand, foreign direct investment introduces more advanced technology, increases the recipient country's competitiveness in the high-end product markets, especially in the high-tech sector, and facilitates gradual movement from exporting low value added products to high value added products and hence its potential economic growth. On the other hand, such a technology transfer will intensify the social tension between educated and those that are not.

Being aware of this trade-off, countries can encourage small scale foreign direct investment with relatively biased technologies. For example, computer software industry is knowledge intensive, but can operate on a relative small scale with only several employees. This can maximize gains from FDI in upgrading technology and the profit margin of its exports while minimizing the potential risk of rising inequality between educated and those without education across the country.

Therefore, as long as countries keep a balanced inward FDI with both knowledge and labor biased technologies in either relatively knowledge or labor intensity sectors, inward FDI will facilitate recipient country's technology development, increase its competitiveness in the world market of both low- and high-end products, and induce a balanced wage increase for both skilled and unskilled workers.

Wage Inequality and Returns to education

As can be seen in table 12 , wage inequality is positively correlated with returns to education. This result is expected given the model presented in this work. In short, what these results suggest is that the wage inequality, which is associated with rewards differences in education, increases returns to education.

Overall wage inequality expanded in many countries over the 1980s and 1990s. Changes in the wage structure along two primary dimensions played a major role in this process. First, there was an increase in between-group wage inequality mainly driven by rising returns to education. Second, there was an increase in within-group wage inequality. The returns to education likely played also a role to increase the latter type of inequality.

In the analysis of in the model, we see that if some people choose to spend more time accumulating human capital and others do not, can lead to increase in wage inequality between individuals who choose to go school.

This paper develops a unified model with an endogenous determination of technological progress in which the evolution of technological change through FDI, and wage inequality is consistent with the observed pattern in many countries in the last decades. The evolution of the economy and its impact on wage inequality is based upon three central elements that appear consistent with empirical evidence. First, the state of transition brought about by technological change raises the rate of return to skills (ability and education). Second, the increase in the return to skills induces an increase are associated with increases in foreign direct investment. Third, that foreign direct investment increases economic growth. These three elements generate a dynamic path characterized by a positive feedback loop that permits a persistent increase in the rate of technological progress in a transition to a steady-state equilibrium with a constant positive rate of technological progress. The increase in the return to ability and education that stem from the increase in the rate of technological progress brings about a rise in wage inequality within as well as between groups in the transition to a steady-state. In the long run, an increase in the average education level of the workforce induces investment in new knowledge, which leads to knowledge biased technological progress.

Wage inequality between skilled and unskilled workers has increased sharply in the 1990 in many countries. Apparently, the steady increase of the relative supply of knowledged workers, which compresses wage differentials, has been more than offset by the increase in relative demand, which increases wage differentials. The economic literature has given a number of explanations for this phenomenon. In this paper, we have illustrated that and most dominant explanation for the rise in wage inequality is so called knowledge- biased technological change. educated workers are more complementary with new technologies than uneducated workers. Consequently, new technologies increase the relative demand for educated workers.

In this paper, we see that secondary school enrollment reduces wage inequality. Perhaps there is a role for government in reducing wage inequality. Perhaps the role for the government to reduce wage inequality by means of education subsidies. The argument is based on the idea that increasing the incentives to enroll in higher education, stimulates the relative supply of skilled workers, and reduces wage inequality as a consequence. If equity is valued in society, then there is a possibility for the government to use education policies to reduce wage inequality.

So how do we deal with FDI which we have linked to education - biased technical change, hence increase in returns to education and increase in wage inequality?

Results in this paper are similar to the results of other authors who test for the relation ship between FDI and growth. Aitken and Harrison, 1993 do find positive relations. Most econometric work on the effects of FDI on development tends to ignore economic and policy factors affecting the link between FDI and development. It is often shown that FDI is correlated with growth and productivity, but this masks the fact that different countries with different policies and economic factors tend to derive different benefits and costs of FDI. Whether the positive effects of FDI outweigh the negative effects will depend on the economic and policy factors in the host country as well as the sector and the strategies of multinational affiliates.

One of the objectives of this paper is to test the robustness of the conjectured causal relationship between foreign direct investment, output growth and human capital. The relationships were tested for bi-directional Granger causality using a multivariate vector auto regression model. The results of this paper have led me to observe the following: (1) past values of FDI do have a predictive ability in determining present values of economic growth in some countries; (2) past values of economic growth do have a predictive ability in determining present values of foreign direct investments in others; (3) it is possible that other economic policies and schooling polices may be driving the growth of both the economy and foreign investments. The results of this paper, also, show that this bi-directional granger causality exists between FDI and schooling and economic growth and schooling.

Our results to show a causal relationship between FDI and growth, however, may be attributed to three major things. First, the nature of these flows may play an important role on whether a causal relationship will exist for the variables. Studies show that FDI in the manufacturing sector alone contribute positively to economic growth. Second, as de Mello (1996) pointed out, the direction of causality depends on the recipient economy's trade regime, open economy performance variables, and domestic policy variables. These countries' policies on foreign direct investment may be a reason why the relationship was not observed.

Lastly, caution must be taken in interpreting the results of this paper. Causality tests in particular and VAR models in general lack any formal theory behind their formulation. As Greene (2000) pointed out, these causality tests are predicted on a model that may be missing either intervening variables or additional lagged effects that should be present but are not. We must bear in mind that Granger causality alone cannot be used as a basis to conclude that one variable causes the other. While it is a possibility, we must note that the results simply indicate the predictive ability of past values of one variable in determining the present values of another variable.

However, this author believes that in view of the importance of this topic in the literature, further research using more sophisticated techniques and theoretically-based models is warranted to assert a convincing argument on the relationship between FDI growth and output growth.

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Appendix A

Results

Table 1: Change in Gross Domestic Product, FDI and Wage Inequality

	Dependent Variable: Change in Gross Domestic Product Growth			
	1.1	**1.2**	**1.3**	**1.4**
Estimation Methods	OLS	OLS	OLS	SYS-GMM
Constant	**3.38** *(9.24)*	**5.19** *(3.16)*	**0.66** *(0.29)*	
Gross Domestic Product Growth - Lagged	**-1.08** *(-15.21)*	**-1.13** *(-15.01)*	**-1.21** *(12.04)*	**-0.25** *(-10.69)*
Foreign Direct Investment - Lagged	**0.26** *(2.25)*	**0.26** *(2.17)*	**0.29** *(1.71)*	**0.29** *(6.01)*
Gross Private Capital Flows - Lagged		**-0.35** *(-1.04)*	**-0.01** *(-1.41)*	**-0.01** *(-1.16)*
Public Spending on Education total (Percentage of GDP)			**-0.03** *(-0.09)*	**-0.36** *(-7.35)*
Fertility rate, total (births per woman)			**0.89** *(2.33)*	**1.03** *(15.32)*
Wage Inequality - Lagged			**10.04** (0.72)	**11.44** *(3.64)*
Number of Observations	222	203	203	136
Adjusted R^2	0.51	0.52	0.56	
F-Statistics	6.00	5.00	5.00	
Sargan Test				0.54

t-statistics in parenthesis and italics. Stepwise Regression

Table 2: Change in Gross Domestic Product, FDI and Human Capital

Dependent Variable: Change in Gross Domestic Product Growth						
	2.1	**2.2**	**2.3**	**2.4**	**2.5**	**2.6**
Estimation Methods	OLS	OLS	OLS	OLS	SYS-GMM	SYS-GM
Constant	**0.32**	**-0.29**	**0.24**	**0.38**		
	(-2.44)	*(-2.22)*	*(0.49)*	*(1.35)*		
Gross Domestic Prodcut Growth - Lagged	**-0.69**	**-0.48**	**-0.51**	**-0.59**	**-0.44**	**-4.11**
	(-4.33)	*(-6.72)*	*(-5.20)*	*(-4.01)*	*(-6.52)*	*(-7.51)*
Foreign Direct Investment -Lagged * Secondary school attainment (15+) - Lagged	**0.21**		**0.18**		**0.55**	
	(2.00)		*(3.46)*		*(4.92)*	
Foreign Direct Investment - level	**0.17**	**0.11**	**0.21**	**0.18**	**0.24**	**0.22**
	(1.98)	*(2.11)*	*(1.99)*	*(2.66)*	*(2.01)*	
Foreign Direct Investment -Lagged * Secondary school enrollment - Lagged		**0.19**		**0.01**		**0.04**
		(2.13)		*(2.43)*		*(4.12)*
Gross Private Capital Flows - Lagged			**0.01**	**0.002**	**-0.001**	**-0.001**
			(0.13)	*(0.17)*	*(-0.28)*	*(-0.59)*
Fertility rate, total (births per woman)			**0.91**	**0.85**	**-2.09**	**-0.82**
			(2.01)	*(2.06)*	*(-4.07)*	*(-3.17)*
Number of Observations	170	170	170	170	163	163
Adjusted R^2	0.26	0.22	0.26	0.31		
F-Statistics	29.00	24.00	15.00	18		
Sargan Test					0.51	0.54

t-statistics in parenthesis and italics. Stepwise Regression. (*) means multiply

Table 3: Gross Domestic Product Growth and Human Capital

Dependent Variable: Gross Domestic Product Growth						
	3.1	**3.2**	**3.3**	**3.1A**	**3.2A**	**3.3A**
Estimation Methods	OLS	OLS	OLS	SYS-GMM	SYS-GMM	SYS-GM
Constant	**2.97**	**8.37**	**8.03**			
	(1.42)	*(3.37)*	*(4.48)*			
Gross Domestic Prodcut Growth - Lagged	**-1.02**	**-1.01**	**-1.02**	**-0.89**	**-0.88**	**-0.91**
	(-18.49)	*(18.49)*	*(-17.66)*	*(-4.51)*	*(-7.73)*	*(-3.31)*
Secondary School enrollment - Lagged	**-0.01**	**-0.02**	**-0.01**	**-0.01**	**-0.04**	**0.01**
	(-0.70)	*(-1.23)*	*(-1.02)*	*(-0.98)*	*(-3.53)*	*(-0.09)*
Public spending on education, total (percentage of GDP)	**-0.45**	**-0.51**	**-0.49**	**-1.01**	**-1.12**	**-1.77**
	(-1.68)	*(-1.79)*	*(-1.76)*	*(-9.16)*	*(-8.62)*	*(-11.71)*
Share of education in top quintile - Lagged	**9.02**			**9.27**		
	(1.75)			*(7.43)*		
Share of education in middle quintile - Lagged		**-3.05**			**-16.51**	
		(-1.05)			*(-5.46)*	
Share of education in lower quintile - Lagged			**-7.16**			**-3.34**
			(-1.94)			*(-1.29)*
Number of Observations	257	257	257	208	208	208
Adjusted R^2	0.44	0.42	0.43			
F-Statistics	5.00	5.00	5.00			
Sargan Test				0.51	0.56	0.52

t-statistics in parenthesis and italics. Stepwise Regression. (*) means multiply

Table 4: Change in secondary school enrollment and FDI

	Dependent Variable: Change in school enrollment, secondary (gross)			
	4.1	**4.2**	**4.3**	**4.4**
Estimation Methods	OLS	OLS	OLS	SYS-GMM
Constant	**5.59**	**5.28**	**5.26**	
	(9.97)	*(8.32*	*(7.66)*	
Change in foreign direct investment	**0.52**	**0.56**	**0.66**	**3.89**
	(2.75)	*(2.83)*	*(2.87)*	*(5.01)*
Change in gross private capital flows (percentage of GDP)		**0.02**	**0.04**	**-0.32**
		(0.71)	*(1.05)*	*(-1.93)*
Change in public spending on education, total (percentage of GDP)			**0.19**	**-3.16**
			(0.67)	*(-1.71)*
Change in fertility rate, total (births per woman)			**-2.97**	**-4.29**
			(-1.25)	*(-3.35)*
Number of Observations	241	241	210	191
Adjusted R^2	0.03	0.03	0.05	
F-Statistics	8.00	4.00	3.00	
Sargan Test				0.599

t-statistics in parenthesis and italics. Stepwise Regression

Table 5: Secondary school enrollment, FDI and Inequality

	Dependent Variable: School enrollment, secondary (gross)			
	5.1	**5.2**	**5.3**	**5.4**
Estimation Methods	OLS	OLS	OLS	SYS-GMM
Constant	**57.09**	**59.34**	**68.91**	
	(11.38)	*(10.43)*	*(28.01)*	
Change in foreign direct investment	**1.42**	**1.70**	**2.84**	**5.55**
	(7.49)	*(7.35)*	*(4.71)*	*(4.73)*
Change in gross private capital flows (percentage of GDP)	**-0.01**	**-0.01**	**-0.02**	**-0.05**
	(-0.28)	*(-0.29)*	*(-0.49)*	*(-0.31)*
Change in public spending on education, total (percentage of GDP)		**-0.49**	**-0.64**	**5.21**
		(-0.96)	*(-1.18)*	*(4.75)*
Change in wage inequality			**8.96**	**-0.30**
			(0.46)	*(-0.11)*
Change in fertility rate, total (births per woman)			**8.48**	**-5.58**
			(2.29)	*(-1.76)*
Number of Observations	358	358	315	257
Adjusted R^2	0.91	0.91	0.89	
F-Statistics	45.00	36.00	31.00	
Sargan Test				0.68

t-statistics in parenthesis and italics. Stepwise Regression

Table 6: Change in Wage Inequality and Foreign Direct Investment

	Dependent Variable: Change in wage inequality					
	6.1	**6.2**	**6.3**	**6.1A**	**6.2A**	**6.3A**
Estimation Methods	OLS	OLS	OLS	SYS-GMM	SYS-GMM	SYS-GM
Constant	**0.12**	**0.21**	**0.61**			
	(6.24)	*(9.39)*	*(4.22)*			
Change in wage inequality - Lagged	**0.02**	**-0.17**	**0.15**	**-0.02**	**0.45**	**0.02**
	(0.21)	*(-1.61)*	*(4.79)*	*(-0.03)*	*(2.37)*	*(0.19)*
Change in gross private capital flows (percentage of GDP) - Lagged	**-0.05**	**-0.21**	**-0.36**	**-0.20**	**-0.01**	**-0.06**
	(-1.75)	*(-1.33)*	*(-10.77)*	*(-1.06)*	*(-7.21)*	*(-1.18*
Opennes in current prices	**-0.03**		**-0.04**	**0.21**		**-0.05**
	(-4.85)		*(-3.24)*	*(3.21)*		*(-0.85)*
Foreign Direct Investment -Lagged			**0.12**			**0.19**
			(6.91)			*(2.16)*
School enrollment, secondary - Lagged	**-0.09**			**0.01**		
	(-6.76)			*(0.79)*		
Change in foreign direct investment	**0.30**					
	(4.92)					
Change in foreign direct investment - Lagged		**0.77**			**0.96**	
		(5.79)			*(3.38)*	
Export of goods and services (annual percetage of GDP) - Lagged		**-0.40**			**0.16**	
		(-1.27)			*(2.13)*	
Average per capita growth (from the WDI) Lagged		**-0.31**			**-0.11**	
		(-4.34)			*(-5.11)*	
Number of Observations	216	152	172	138	135	138
Adjusted R2	0.31	0.69	0.59			
F-Statistics	5.00	5.00	5.00			
Sargan Test				0.61	0.55	0.54

t-statistics in parenthesis and italics. The number of observations change from one column to the other because the system countries without full samples.

Table 7: Change in Gross Domestic Product, FDI and Wage Inequality

	Dependent Variable: Change in Gross Domestic Product Growth			
Least Developed Countries Only	**7.1**	**7.2**	**7.3**	**7.4**
Estimation Methods	OLS	OLS	OLS	SYS-GMM
Constant	**0.25** *(5.09)*	**0.022** *(1.52)*	**0.023** *(1.45)*	
Gross Domestic Product Growth - Lagged	**-0.01** *(-3.41)*	**-0.01** *(-3.01)*	**-0.02** *(-2.08)*	**-0.53** *(-2.76)*
Foreign Direct Investment - Lagged	**0.03** *(4.13)*	**0.033** *(3.91)*	**0.05** *(3.97)*	**0.01** *(4.26)*
Gross Private Capital Flows - Lagged		**-0.51** *(-0.77)*	**-0.55** *(-0.83)*	**-0.31** *(-0.11)*
Public Spending on Education total (Percentage of GDP)			**-0.85** *(-1.98)*	**-0.61** *(-2.45)*
Fertility rate, total (births per woman)			**1.42** *(5.12)*	**1.44** *(3.21)*
Wage Inequality - Lagged			**0.93** (1.66)	**074** *(1.78)*
Number of Observations	152	152	152	146
Adjusted R^2	0.41	0.43	0.42	
F-Statistics	11.01	11.52	11.91	
Sargan Test				0.59

t-statistics in parenthesis and italics. Stepwise Regression. Only LDCs are included in this sample.

Table 8: Change in Gross Domestic Product, FDI and Human Capital

Dependent Variable: Change in Gross Domestic Product Growth						
Least Developed Countries Only	**8.1**	**8.2**	**8.3**	**4.4**	**5.5**	**6.6**
Estimation Methods	OLS	OLS	OLS	OLS	SYS-GMM	SYS-GM
Constant	**0.05**	**0.049**	**0.05**	**0.43**		
	(1.86)	*(2.19)*	*(2.04)*	*(2.54)*		
Gross Domestic Prodcut Growth - Lagged	**-0.001**	**-0.001**	**-0.001**	**-0.003**	**-0.001**	**-0.001**
	(-2.92)	*(-3.22)*	*(-2.65)*	*(-1.98)*	*(-1.91)*	*(-1.64)*
Foreign Direct Investment -Lagged * Secondary school attainment (15+) - Lagged	**0.13**		**0.15**		**0.11**	
	(4.04)		*(4.22)*		*(3.94)*	
Foreign Direct Investment - level	**0.5**	**0.61**	**0.52**	**0.59**	**0.34**	**0.31**
	(3.01)	*(3.47)*	*(3.88)*	*(2.99)*	*(3.44)*	*(-3.14)*
Foreign Direct Investment -Lagged * Secondary school enrollment - Lagged		**0.82**		**0.71**		**0.62**
		(4.17)		*(3.68)*		*(3.01)*
Gross Private Capital Flows - Lagged			**-0.02**	**-0.02**	**-0.001**	**-0.001**
			(-1.81)	*(-1.71)*	*(-1.12)*	*(-1.31)*
Fertility rate, total (births per woman)			**-0.31**	**-0.26**	**-0.19**	**-0.24**
			(-3.91)	*(-2.82)*	*(-2.55)*	*(-2.65)*
Number of Observations	152	152	152	152	129	129
Adjusted R^2	0.44	0.45	0.41	0.47		
F-Statistics	31.00	32.00	28.00	29		
Sargan Test					0.61	0.56

t-statistics in parenthesis and italics. Stepwise Regression. (*) means multiply

Table 9: Gross Domestic Product Growth and Human Capital

Dependent Variable: Gross Domestic Product Growth						
Least Developed Countries Only	**9.1**	**9.2**	**9.3**	**9.1A**	**9.2A**	**9.3A**
Estimation Methods	OLS	OLS	OLS	SYS-GMM	SYS-GMM	SYS-GM
Constant	**0.04** *(1.87)*	**0.049** *(2.07)*	**0.05** *(1.52)*			
Gross Domestic Prodcut Growth - Lagged	**-0.001** *(-2.92)*	**-0.001** *(-2.11)*	**-0.002** *(-2.06)*	**-0.001** *(-1.37)*	**-0.001** *(-1.33)*	**-0.001** *(-1.81)*
Secondary School enrollment - Lagged	**0.001** *(0.55)*	**0.001** *(0.76)*	**0.001** *(0.97)*	**0.002** *(0.66)*	**0.001** *(0.57)*	**0.01** *(1.11)*
Public spending on education, total (percentage of GDP)	**-0.12** *(-2.78)*	**-0.11** *(-2.46)*	**-0.14** *(-2.52)*	**-0.11** *(-3.44)*	**-0.10** *(-2.25)*	**-0.01** *(-2.46)*
Share of education in top quintile - Lagged	**0.10** *(2.22)*			**0.07** *(1.98)*		
Share of education in middle quintile - Lagged		**-0.09** *(-2.11)*			**-0.13** *(-2.17)*	
Share of education in lower quintile - Lagged			**-01.18** *(-3.61)*			**-0.92** *(-2.13)*
Number of Observations	147	147	147	129	129	129
Adjusted R^2	0.38	0.39	0.41			
F-Statistics	28.00	26.00	29.00			
Sargan Test				0.54	0.61	0.59

t-statistics in parenthesis and italics. Stepwise Regression. (*) means multiply

Table 10: Change in secondary school enrollment and FDI

	Dependent Variable: Change in school enrollment, secondary (gross)			
Least Developed Countries Only	**10.1**	**10.2**	**10.3**	**10.4**
Estimation Methods	OLS	OLS	OLS	SYS-GMM
Constant	**0.59**	**-0.52**	**-0.55**	
	(0.91)	*(-1.54)*	*(-1.19)*	
Change in foreign direct investment	**1.01**	**0.98**	**0.68**	**0.56**
	(4.33)	*(4.01)*	*(3.59)*	*(2.97)*
Change in gross private capital flows (percentage of GDP)		**-0.15**	**-0.13**	**-0.22**
		(-2.11)	*(-1.29)*	*(-0.97)*
Change in public spending on education, total (percentage of GDP)			**-0.45**	**-0.33**
			(-2.66)	*(-2.23)*
Change in fertility rate, total (births per woman)			**-0.99**	**-0.87**
			(-3.65)	*(-2.58)*
Number of Observations	172	172	172	129
Adjusted R^2	0.21	0.21	0.23	
F-Statistics	15.00	15.00	18.00	
Sargan Test				0.51

t-statistics in parenthesis and italics. Stepwise Regression

Table 11: Secondary school enrollment, FDI and Inequality

	Dependent Variable: School enrollment, secondary (gross)			
Least Developed Countries Only	**11.1**	**11.2**	**11.3**	**11.4**
Estimation Methods	OLS	OLS	OLS	SYS-GMM
Constant	**2.33**	**1.95**	**1.86**	
	(3.46)	*(5.38)*	*(5.48)*	
Change in foreign direct investment	**0.24**	**0.29**	**0.31**	**0.18**
	(4.88)	*(3.38)*	*(3.77)*	*(2.59)*
Change in gross private capital flows	**-0.12**	**-0.11**	**-0.15**	**-0.11**
(percentage of GDP)	*(-2.19)*	*(-1.82)*	*(-1.01)*	*(-1.15)*
Change in public spending on education,		**-1.11**	**-1.09**	**-0.94**
total (percentage of GDP)		*(-2.14)*	*(-1.88)*	*(-2.01)*
Change in wage inequality			**-0.63**	**-0.51**
			(-2.61)	*(-3.18)*
Change in fertility rate,			**0.26**	**0.10**
total (births per woman)			*(1.99)*	*(0.91)*
Number of Observations	148	148	148	122
Adjusted R^2	0.72	0.72	0.77	
F-Statistics	31.00	32.00	33.00	
Sargan Test				0.51

t-statistics in parenthesis and italics. Stepwise Regression

Table 12: Change in Foreign Direct Investment and Human Capital

Dependent Variable: Change in Foreign Direct Investment	12.1	12.2	12.3
Estimation Methods	OLS	OLS	SYS-GMM
Constant	**0.77**	**1.79**	
	(3.15)	*(4.25)*	
Change in foreign direct investment Lagged	**0.08**	**-0.02**	**-0.73**
	(0.41)	*(-0.08)*	*(-7.92)*
Change in gross domestic product growth - Lagged	**0.09**	**0.08**	**0.02**
	(1.08)	*(0.99)*	*(0.66)*
Change in secondary school enrollment	**0.09**	**0.09**	**0.09**
	(3.21)	*(3.31)*	*(5.59)*
Change in fertility rate, total (births per woman)		**2.89**	**5.91**
		(4.03)	*(6.75)*
Number of Observations	162	162	162
Adjusted R^2	0.13	0.17	
F-Statistics	9.00	10.00	
Sargan Test			0.52

t-statistics in parenthesis and italics.

Table 13: Return on Education and Foreign Direct Investment

Dependent Variable: Return On Education			
	13.1	**13.2**	**13.3**
Estimation Methods	OLS	OLS	OLS
Constant	**0.2**	**0.20**	**0.23**
	(3.64)	*(3.62)*	*(4.80)*
Share of education in the lower quintiles Lagged	**-0.25**	**-0.26**	**-0.26**
	(-2.06)	*(-2.12)*	*(-2.52)*
Foreign direct investment one lag minus Foreign direct investment, two lags	**0.01**	**0.004**	**0.01**
	(2.39)	*(1.61)*	*(3.24)*
Foreign direct investment - Lagged		**0.002**	**0.001**
		(3.00)	*(1.66)*
Per capita income			**-0.003**
			(-5.43)
Number of Observations	39	39	39
Adjusted R^2	0.06	0.06	0.45
F-Statistics	3.00	3.00	9.00

t-statistics in parenthesis and italics.

Table 14: Return on Education, FDI and Wage Inequality

Dependent Variable: Return On Education	14.1	14.2	14.3
Estimation Methods	OLS	OLS	OLS
Constant	**0.12** *(9.08)*	**0.13** *(9.07)*	**0.10** *(3.72)*
Secondary scholl enrollment - Lagged	**0.001** *(-3.06)*	**-0.001** *(-3.35)*	**-0.0003** *(-1.30)*
Foreign direct investment - Lagged		**0.001** *(1.30)*	**0.004** *(1.71)*
Wage Inequality			**0.56** *(2.40)*
Number of Observations	49	41	37
Adjusted R^2	0.16	0.22	0.31
F-Statistics	10.00	7.00	6.00

t-statistics in parenthesis and italics. Stepwise regression.

Table 15: Return on Education, FDI and Income Inequality

Dependent Variable: Return On Education	15.1	15.2	15.3
Estimation Methods	OLS	OLS	OLS
Constant	**0.12** *(9.08)*	**0.13** *(9.07)*	**-0.03** *(-0.85)*
Secondary scholl enrollment - Lagged	**-0.001** *(-3.06)*	**-0.001** *(-3.35)*	**-0.0001** *(-0.45)*
Foreign direct investment - Lagged		**0.001** *(1.31)*	**0.004** *(1.92)*
Income Inequality			**0.003** *(4.01)*
Number of Observations	49	41	37
Adjusted R^2	0.16	0.22	0.38
F-Statistics	10.00	7.00	8.00

t-statistics in parenthesis and italics. Stepwise regression.

Table 16: Return on Education, FDI and Human Capital

Dependent Variable: Return On Education	16.1	16.2	16.3
Estimation Methods	OLS	OLS	OLS
Constant	**0.09**	**-0.01**	**-0.02**
	(12.66)	*(-0.24)*	*(-0.47)*
Foreign direct investment - Lagged	**0.002**		**-0.0001**
	(2.65)		*(-0.45)*
Primary school enrollment - Lagged		**0.001**	**0.001**
		(3.01)	*(2.54)*
Number of Observations	48	48	42
Adjusted R^2	0.07	0.09	0.09
F-Statistics	5.00	5.00	8.00

t-statistics in parenthesis and italics. Stepwise regression.

Table 17: Return on Education, Inequality

Dependent Variable: Return On Education	17.1	17.2	17.3
Estimation Methods	OLS	OLS	OLS
No Peru	**0.07**	**-0.08**	**0.11**
	(9.64)	*(-2.03)*	*(11.42)*
Wage Inequality - Lagged	**0.61**		
	(5.59)		
Income Inequality - Lagged		**0.004**	
		(4.23)	
Income per capita			**-0.0003**
			(-3.11)
Number of Observations	48	48	42
Adjusted R^2	0.08	0.07	0.09
F-Statistics	6.00	6.00	8.00

t-statistics in parenthesis and italics. Stepwise regression.

Causality Tests Results

Table 18: Causality Test Between Foreign Direct Investment and GDP Growth

Dependent Variables:	FDI	GDP
Lagged FDI	**0.512**	**0.736**
	0.43	*0.003***
Lagged GDP	**0.645**	**0.489**
	*0.012**	*0.24*
# of Ctys	50	50
# of Obs	170	170

Using Two Lags For independent Variables, Standard Errors of Wald Test in italics

Table 19: Causality Test Between FDI and School attainment (25 and over)

Dependent Variables:	FDI	School Attainment (25 and over)
Lagged FDI	**0.91**	**0.970**
	0.08	*0.013**
School Attainment (25 and over)	**0.021**	**0.298**
	*0.011**	*0.16*
# of Ctys	50	50
# of Obs	173	173

Using Two Lags For independent Variables, Standard Errors of Wald Test in italics

Table 20: Causality Test Between FDI and School enrollment (25 and over)

Dependent Variables:	FDI	School Enrollment (25 and over)
Lagged FDI	**0.571**	**0.921**
	0.39	*0.04**
Lagged School Enrollment (25 and over)	**0.033**	**0.862**
	*0.009***	*0.084*
# of Ctys	50	50
# of Obs	162	162

Using Two Lags For independent Variables, Standard Errors of Wald Test in italics

Table 21: Causality Test Between FDI and School Attainment (15 and over)

Dependent Variables:	GDP	School Attainment
Lagged GDP	**0.523** *0.93*	**0..024** *0.010**
Lagged School Attainment	**-0.131** *0.13*	**0.883** *0.14*
# of Ctys	48	48
# of Obs	228	228

Using Two Lags For independent Variables, Standard Errors of Wald Test in italics

Table 22: Causality Test Between FDI and School enrollment (15 and over)

Dependent Variables:	GDP	School Enrollment (15 and over)
Lagged GDP	**-0.078** *0.09*	**0.806** *0.036**
Lagged School Enrollment	**0.499** *0.099*	**0.033** *0.06*
# of Ctys	48	48
# of Obs	228	228

Using Two Lags For independent Variables, Standard Errors in italics

Appendix B.

Table 23: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Observations
FDI	2.968417	3.884363	0.00077	22.26236	No. obs. 276 Cross Sections: 50
Growth	4.100921	2.940321	-3.629758	18.23247	No. obs. 338 Cross Sections: 50
Secondary Sch. enrollment	59.01159	30.02765	2.853886	154.5477	No. obs. 341 Cross Sections: 50
Education attainment, 15+	5.894404	2.50304	0.074	12.05	No. obs. 445 Cross Sections: 50
Wage Inequality	0.044746	0.036007	0.001695	0.29175	No. obs. 334 Cross Sections: 50
Income Inequality	40.01085	6.621121	25.07787	54.57325	No. obs. 331 Cross Sections: 50
Gross private capital flows	15.49779	30.82047	0.112084	315.4444	No. obs. 282 Cross Sections: 50
Fertility	3.79435	1.848936	1.18	8.12	No. obs. 282 Cross Sections: 50
Spending on education	4.251829	3.803038	0.88	47	No. obs. 380 Cross Sections: 50
Return on education	0.095635	0.047271	0.024	0.28	No. obs. 50

Notes: FDI is defined as gross inflows of direct foreign investment as a percentage of GDP. Growth is the annual percentage GDP growth. Secondary sch. enrollment is school enrollment, secondary as percentage of gross. Education attainment, 15+ is defined as educational attainment of the total population aged 15 and over. Wage inequality is measured using the Theil index. Gross private capital flows (% of GDP). Fertility is the fertility rate, total (births per woman).

Part of the data used for Tables 13 through 17

Countries	yr	Return on education	Income Inequality	Wage Inequality	Secondary school enrollment	Foreign direct investment
POL	86	2.40%	29.56	0.0061341	81.5	1.7
SWE	81	2.60%	27.30	0.0033713	90.8	5.0
GRC	85	2.70%	40.96	0.0302781	90.5	1.2
ITA	87	2.80%	36.92	0.0169224	82.8	0.9
AUT	87	3.90%	34.60	0.0182846	103.7	1.4
HUN	87	3.90%	28.62	0.0073757	78.6	5.5
CAN	81	4.20%	34.50	0.0150863	98.8	2.8
CHN	85	4.50%	33.00	0.0041903	39.7	1.0
DNK	90	4.70%	29.88	0.0072788	109.2	3.4
ISR	79	5.70%	40.49	0.0557547	72.9	0.8
IND	81	6.20%	50.60	0.1100462	37.9	#N/A
AUS	82	6.40%	32.45	0.009168	80.1	5.2
NLD	83	6.60%	33.91	0.0088345	117.1	6.4
TZA	80	6.70%	44.95	0.0369483	3.3	#N/A
CHE	87	7.20%	#N/A	#N/A	99.1	4.6
BOL	89	7.30%	48.32	0.0681181	36.6	2.6
DEU	88	7.70%	32.31	0.0109251	98.3	1.5
DOM	89	**7.80%**	48.28	0.0910356	40.2	2.4
IRL	87	7.90%	39.03	0.0275518	100.5	3.3
VEN	89	8.40%	43.68	0.0422939	34.7	2.5
PER	90	8.50%	52.39	0.1583259	67.3	3.1
KEN	80	8.50%	48.37	0.0733996	19.6	0.4
URY	89	9.00%	39.81	0.0355884	81.3	#N/A
THA	71	9.10%	52.57	0.14077	28.8	0.8
USA	89	9.30%	37.17	0.0270566	93.1	2.2
MYS	79	9.40%	39.71	0.0222819	47.7	3.7
PRT	85	9.40%	39.35	0.0363261	57.3	2.2
SLV	90	**9.60%**	51.80	0.1307411	26.4	#N/A
GBR	72	9.70%	29.93	0.0142394	83.5	3.5
PAK	79	9.70%	47.56	0.059957	14.2	0.3
NIC	78	9.70%	38.97	0.0121776	40.7	#N/A
CYP	84	9.80%	39.41	0.0346062	87.0	1.7
ECU	87	9.80%	44.90	0.0411425	55.3	2.4
PRY	89	10.30%	40.11	0.0133108	30.9	1.4
CRI	89	10.50%	40.52	0.0329084	41.6	2.7
KOR	86	10.60%	47.27	0.0263791	89.8	0.8
ARG	89	10.70%	45.74	0.0708553	71.1	2.0
SGP	74	11.30%	40.01	0.0781124	59.9	9.2
PHL	88	11.90%	47.85	0.0751321	73.2	2.0
CHL	89	12.10%	47.76	0.0832588	73.5	1.7
BWA	79	**12.60%**	46.75	0.0532373	18.8	15.0
PAN	89	12.60%	47.81	0.0730068	62.6	3.4
ESP	90	13.00%	39.52	0.0292035	104.1	2.7
MEX	84	14.10%	41.05	0.0199726	56.5	#N/A
GTM	89	14.20%	48.18	0.0745804	23.1	0.8
COL	89	14.50%	44.19	0.0379813	49.8	2.4
BRA	89	15.40%	45.22	0.0610148	38.4	0.6
IDN	81	17.00%	49.53	0.0863567	41.3	0.6
HND	89	17.20%	43.52	0.0496236	20.9	1.2
JAM	89	28.00%	55.10	0.300087	65.3	3.3

A.2 Abstract

Luseni Kamara

BS, St. John's University

MA, St. John's University

MA, Fordham University

Foreign Direct Investment, Inequality and Human Capital Accumulation

Dissertation directed by Darryl McLeod, PhD

In recent years, a considerable amount of literature on the links between foreign direct investment, schooling, inequality and growth has flourished. The emerging consensus is that equality enhances growth, also, that foreign direct investment and schooling enhance growth, but disagreement exists on the underlying mechanisms. In this paper, we aim to provide the reader with new empirical evidence from a panel analysis of countries. First, we try to improve upon the accuracy of previous empirical models by using new data on inequality extracted from University of Texas. Second, we test the relevance of the theoretical models proposed in the literature to explain the FDI, schooling, inequality and growth relationships. Finally, using multivariate vector auto regression model, the paper further uses data from fifty countries to empirically examine the causality between foreign direct investment and gross domestic product, foreign direct investment and human capital, and gross domestic product and human capital

Results suggests that FDI is positively associated with economic. We also find a positive association between returns on education with FDI, and a positive relationship between FDI and inequality. In the model presented in this paper, the role of human capital endowment and FDI are important if not crucial, since the distribution of income and wages may be given by the distribution of human capital and FDI. Interestingly enough, we find that inequality is positively associated with growth as suggested by Kristin J. Forbes (2000). Also, findings suggest that FDI granger-causes economic growth and growth granger causes FDI. Further investigations suggest that there is also bi-directional granger causality between FDI and schooling, and economic growth and schooling.

A.3 VITA

Luseni Kamara, son of Musu C. Redd, was born on October 24, 1967 in Fairo, West Africa. Upon graduating from Bo Government Secondary School in Sierra Leone, I came to United States of America in 1991. I earned my B.S. in Criminal Justice and M.A. Government and Politics at St. John's University in 1995, and M.A. at Economics at Fordham University in 2001.