Health Costs, Factor Productivity and Foreign Direct Investment Inflows

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Abstract

In this study, we evaluate the effects of health costs on FDI (foreign direct investment) inflows based on a two-stage panel data model using both low- and middle-income and high-income countries data from 1995 to 2010. We hypothesize that total health expenditure is a proxy of direct cost of health and TFP (total factor productivity) is a proxy of indirect cost of health. We first estimate TFP based on an estimation of Cobb-Douglas production function. Then in the first stage model, we obtain the health elasticity of TFP, that is, the effect of health on TFP. In the second stage model, we regress FDI inflow on total health expenditure and TFP after controlling for other factors. The effect of direct cost of health on FDI inflow is captured by the coefficient estimate of total health expenditure. The effect of indirect cost of health on FDI inflow is obtained by multiplying the elasticity of FDI inflow with respect to TFP and the health elasticity of TFP. Our results suggest that overall both direct and indirect cost of health have significant and positive impact on FDI inflows. A 1% increase in health expenditure is associated with a 1.8% increase in FDI inflow and a 1% increase in life expectancy is associated with FDI inflow increase of 1.4%. But differences do exist among low- and middle-income countries and high-income countries.

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Chapter 1

Introduction

Foreign direct investment (FDI) plays an important role in a country's economic growth. A recent example is China – its economy grows at an average 10% per year in the past 30 years – and it went from a sleepy lion lying in the east that nobody cares about to a new dreamland that every smart investor wants to have a share in. Before that, people attribute the economic miracle of Four Asian Tigers (Taiwan, South Korea, Singapore, and Hong Kong) also to foreign investment. Brazil can be added to the list too if we look back at their economic performance and fast growth of foreign direct investment. We have numerous other examples.

A host of researchers study the relationship between FDI and characteristics of a country, for example, openness of trade, geographical location and labor supply (Blomstrom and Kokko, 2003; Blonigen 2005). However, few studies consider the role of population health in FDI formation. A report published by the World Health Organization (Report of the Commission on Macroeconomics and Health, 2001) asserts: ‘‘a healthy workforce is important when attracting foreign direct investment (FDI).’’ Similar comments have been made by several other international organizations and agencies, all confirming the importance of health in attracting FDI.

As an integral part of human capital, good health raises productivity and spurs economic growth. Other things being equal, better health translates to higher human capital and a workforce with higher human capital will make a country more attractive to foreign investors. Moreover, healthier workers are physically and mentally more energetic and robust. They are more productive in working environment (Bloom, Canning and Sevilla, 2003). They are also less likely to be absent from work because of illness, which will greatly reduce investors' cost on health, thus reducing the overall production cost. Again, this contributes to attracting FDI.

It is reasonable to assume that the derived demand for labor by multinational firms is a function of the anticipated cost of the labor resource. Given a choice from among alternative foreign locations, it may be reasonable to assume that the FDI decision process involves a form of cost minimizing behavior where an investing company chooses to locate where it can best reduce the costs of its economic activities. For convenience we can think of the direct costs of labor as being those incurred by foreign investors as part of their financial outlays to hire workers in the host country. The corresponding indirect costs of labor are those associated with expected labor productivity gains and losses, i.e., factor productivity. These costs are likely to vary from one country to another due to several demographic and economic variables. Thus, labor-related health costs are one factor which foreign investors may take into account when formulating their international investment strategies.

Population health has been found to have a positive and statistically significant real labor productivity effect on economic growth (Bloom, Canning and Sevilla, 2004; Bloom and Canning, 2003). Specifically, Bloom, Canning and Sevilla model the direct effect of life expectancy on total factor productivity (TFP) for a panel of developing countries. They find that increasing average life expectancy by one year generates about a 4% annual average rate of GDP growth.

Ashraf, Lester & Weil (2008) suggest that the effects of health on GDP growth may be conditional on the particular change in health that is being evaluated. They explore two exogenous changes in health: increases in life expectancy and eradication of diseases. Increased life expectancy might significantly raise per capita income in the long run, yet the complete eradication of diseases like malaria and tuberculosis will likely have much smaller effect on income. These latter effects will vary widely also depending on the type of disease and the demographic group of the population that is affected. In this paper we will assume that the direct and indirect effects of health on productivity and growth are both of importance when assessing the impact of health on investment decisions.

We take the approach of a foreign investor where the problem is to evaluate the effect of health on the cost of the investment strategy. Analogous to Rosen *et al*. (2003), there are two cost categories for the health costs that a business might bear – the direct costs and the indirect costs. Direct costs are linked to seeking and obtaining medical treatment for a disease, including medical care expenses, health benefits payments, and insurance premiums. Indirect costs refer to the implied production losses that are incurred by higher rates of absenteeism and lower productivity of sick workers. Logically, as the health status of employees improves, investors will pay less to cover the health care needs of their employees and related health expenses. Better health status will also imply higher labor productivity. If foreign investors can obtain higher productivity from a healthier work force and limit the extra replacement cost of sick workers, they might be motivated by good population health to locate in some countries and not in others.

1.1 Foreign Direct Investment Trends

Foreign direct investment (FDI) by multinational firms has grown rapidly in recent decades, and developing countries have attracted an increasing share of it: $334 billion in 2005 or more than 36% of all inward FDI flows (World Investment Report, 2006). In 2011, flows to developed countries reached $748 billion, increased by 21 per cent compared to 2010. In developing countries FDI increased by 11 per cent, to a record $684 billion, almost within reach to the level of develop countries'. United Nations Conference on Trade and Development (UNCTAD) has a separate statistical category for "transition" economies and FDI in this group increased by 25% to $92 billion in 2010 (World Investment Report, 2012). When combined, developing and transition economies accounted for 51% (45% and 6%, respectively) of global FDI in 2010. This is a remarkable achievement. The importance of FDI for developing countries has also increased from an average of barely 1% of GDP in the 1970s to about 2.5% of GDP on average by 2000.

Yet, the magnitude of the inflow- and outflow of foreign direct investment varies greatly across countries (regions) and over time. Figure 1 provides a categorization of FDI inflows by country.

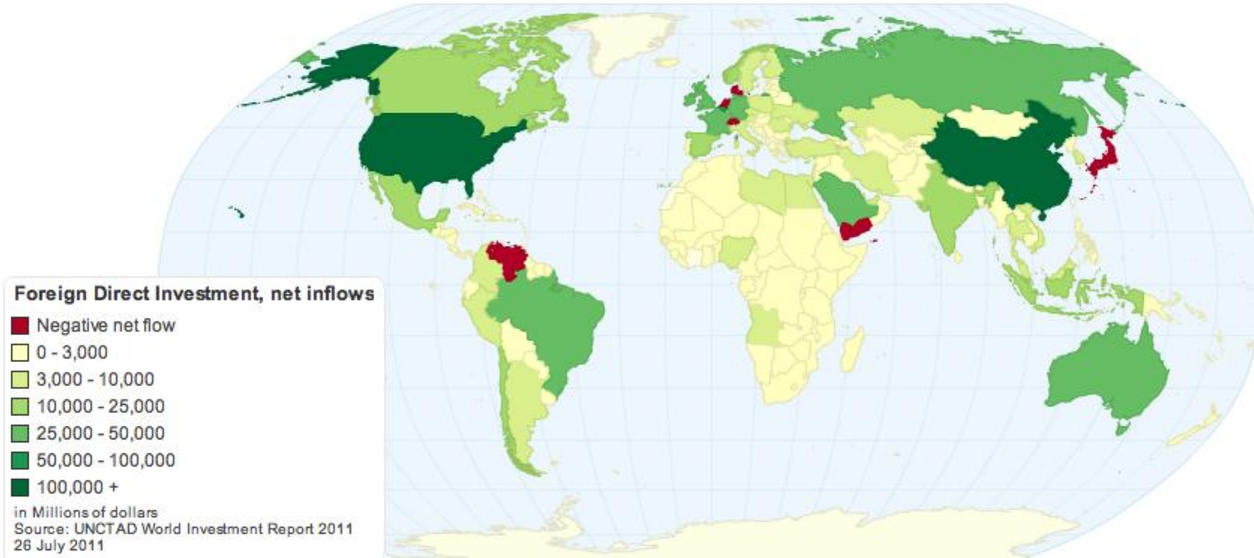

Figure 1. FDI net inflows (in millions of dollars), 2010.

This GIS map, based on 2010 UNCTAD data, offers a direct view on worldwide FDI net inflows. The U.S. and China took the lead, while South Asia, Middle East and Central Africa attracted significantly less foreign investment. A more detailed look at each region can be found in Appendix A.

1.2 Population Health and Health Cost

Health is a crucial part of human capital and is a complex social and economic concept. To a large extent, better population health status means a healthier workforce, better productivity and lower labor cost. It also implies less investment that investors need to make in improving workforce health status.

Population health status is positively associated with economic development and growth. The best example may be Sub-Saharan Africa countries in recent decades. Scarred by years of domestic wars, turmoil and violence, those countries have seen a decline in population health conditions and stagnancy in economic development and growth, despite the aid and various development programs received and initiated by international humanitarian organizations and countries. The spread of AIDS and other severe diseases such as Ebola virus (EBOV), also contributes to the regional economic inactivity as it adds to firm labor cost both directly and indirectly and slows economic growth (Rosen *et al*., 2003).

Just like FDI, population health cost varies a lot across countries (see Appendix B, Figures B.1 and B.2). Among OECD countries, the U.S. leads in both health expenditure as a share of GDP and in per capita terms. Interestingly, the difference between other countries is much smaller (see Figure B.1 and B.2 in Appendix B for details).

The GIS map in Figure 2 from the World Health Organization is based on 2010 Global Health Observatory data (Global Health Observatory, 2012). It provides per capita total expenditure on health worldwide. The map confirms that the U.S. outspends other countries on health by far. Canada, Europe, Australia and New Zealand follow the lead. Countries in South Asia, Middle East and Central Africa spend the least on health.

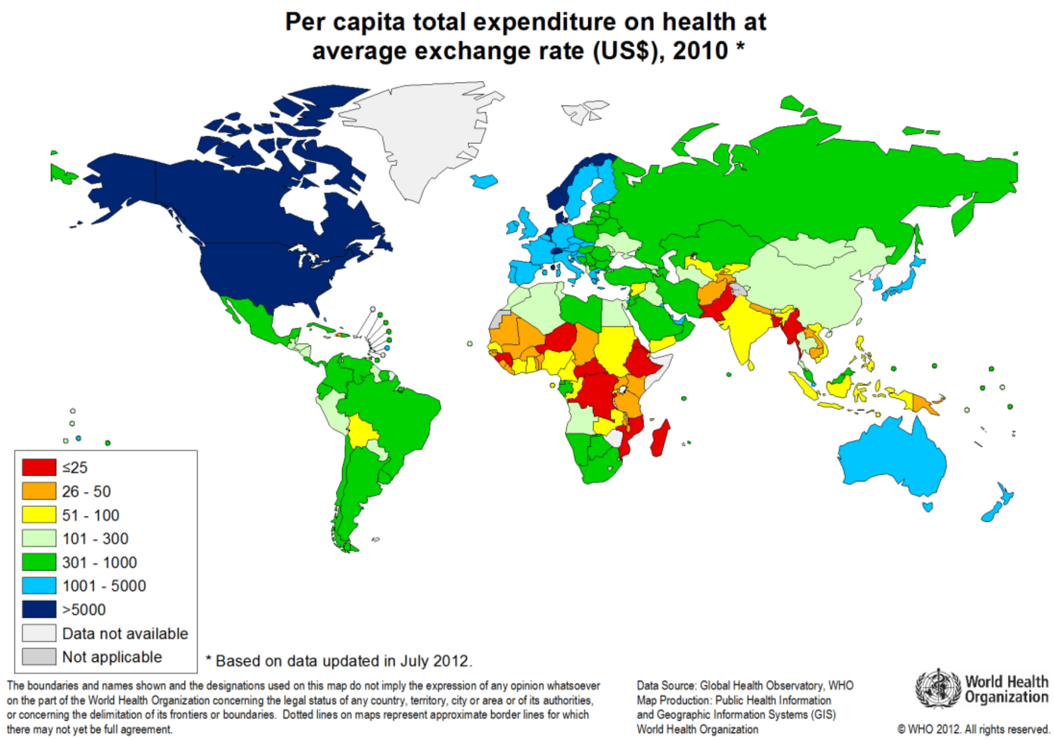

Figure 2. Per capita total expenditure on health at average exchange rate (in US$), 2010

1.3 FDI and Health

Evolving patterns of foreign investment suggest that variations in labor availability and productivity are important factors in attracting foreign direct investment (FDI) inflows to developing countries. As evidence of this, service industries have gained from the recent surge in FDI where there has been an increasing demand for an adequate and high quality labor force (World Investment Report, 2006). It is also notable that many countries that suffer from the poorest health attract the least amount of foreign direct investment.

It has been established in the literature that labor cost is one of the most important elements in an investor's decision making process regarding where to invest. Wage, as a big part of labor cost, has been constantly mentioned as the decisive factor in attracting investment (Feenstra and Hanson, 1997, Lipsey 2001). Health or health cost also plays a big role. However, it does not always attract as much attention.

We suggest that health affects investment decision through direct and indirect ways. Investors take into consideration the expenses that poor health of workers may impose on the business and these are the direct costs of health. For instance, employee healthcare (in the form of medical care expenses, health benefits payments, and insurance premiums) can sometimes be costly so that it may greatly add to the total labor cost or even affect the normal operation of a business. For instance, employee healthcare cost is typically in the 1.25 to 1.4 times the base salary range in the United States (Hadzima 2005). We will assume that total health-related expenditure is a good proxy for the direct cost of health in this analysis.

Table 1. Health cost to a company

Direct costs	Indirect Costs
• Insurance premiums • Medical care expenses • Benefits payments due to illness and disabilities • Accidents due to ill worker and inexperienced replacement workers	• Production disruptions and reduction due to employee's absence • Loss of experience workers and reduced productivity while replacement worker leans the job • Management's time in dealing with productivity losses

Source: Adapted from Rosen *et al.* (2003).

Indirect cost of health can include production disruptions and reduction due to employee absence, or in some cases loss of experienced workers, and reduced productivity while replacement worker learns the job. In Table 1 we list several examples of direct costs and indirect costs.

Indirect costs of labor are those associated with expected labor productivity gains and losses, i.e., factor productivity. Although estimates of the indirect cost of health data are not readily available, these costs can be approximated by estimating labor factor productivity.

1.4 Research Objective

Our first research objective is to determine whether the direct and indirect costs of health have significant effects on attracting FDI inflows among high-income and low-to-middle-income countries. We take the approach of a foreign investor where the problem is to evaluate the effect of health on the cost of the investment strategy. Our second objective is to explore the economic implications of country-level health disparities for foreign investors and host countries.

Foreign direct investment is recognized in most countries as a positive and important source of employment opportunity and economic growth, as it contributes to the development of a country. Success stories of some giant firms in the past twenty to thirty years have demonstrated that investing in foreign countries is a viable way to grow, expand and sustain a business. For example, the electronics designer and manufacturer, Apple Inc. has been constantly cited as one of the most successful firms. In addition governments actively develop policies to attract foreign investors and multinational businesses. Some countries form special taskforces aimed at bringing in investment from foreign investors. A couple examples are the Department of Investment Services in the Ministry of Economic Affairs in Taiwan and the Bureau of Economic and Business Affairs in Korea. This research may offer a new point of view that health cost also matters in attracting FDI. In the past, infrastructure and labor cost (wage in particular) are the focus for many countries to improve their business environment to bring in foreign investment. Capital and other resources have been directed to improve infrastructure in order to attract investors (those in the manufacturing industry in particular) to utilize a competitive advantage such as low labor cost. As illustrated by cases in which businesses move to new host countries from traditional FDI destinations, more factors come into play in determining FDI attractiveness. Health or health cost is one of them.

For investors who are looking for new investment opportunities overseas, this research may identify important characteristics of a country worth considering when choosing where to invest. If they have never thought about the cost of health as a component in their decision, our research may bring some new ideas. For investors who have already made investments in foreign countries who are looking to improve their investments, it may be worthwhile to review their current investment practices and determine if health cost contributes to their success. For example, health may be the underlying reason of the high worker turnover rate or even though the wage is low in the host country, the overall cost when taking into account health cost may be a significant burden on the investment.

Since indirect cost of labor is not readily available, to attain these objectives we build a two-stage regression model to investigate the relationship between FDI and health cost. In the first stage, we first estimate total factor productivity based on a Cobb-Douglas production function. After obtaining estimated total factor productivity that is measured by residual terms we regress it on life expectancy (population health indicator) and other country characteristics using both fixed effects panel data model to estimate the effect of health on factor productivity. In the second stage of the analysis, we estimate the effect of direct and indirect costs of health on FDI inflows by using total factor productivity as a proxy for indirect costs along with a host of country characteristic variables. The estimated equations produce estimates of the elasticity of FDI inflows with respect to both direct costs of health and indirect costs of health.

1.5 Thesis Outline

In Chapter 2 we reviews the relevant literature on health costs, FDI and factor productivity. In Chapter 3 we discuss model building and selection. In Chapter 4 we describe the data source and methodology. In Chapter 5 we report and interpret the estimation results. In Chapter 6 we provide a set of conclusions.

Chapter 2

Literature Review

We conjecture that health, or health cost has a potentially big impact on foreign investment. We study the effect of health on FDI by analyzing the impact of both direct cost of health and indirect cost of health on FDI in a two stage regression model. We first obtain the elasticity of FDI inflow with respect to average life expectancy, our health status indicator, to capture the effect of indirect cost of health. Then in the second stage, we study the effect of direct cost of health and indirect cost (through TFP) on FDI inflow.

This chapter review literature with regards to the main topic of this thesis, the relationship between health and FDI, and also some details in the sub-sections, for example, different approach to estimating TFP, selection of independent variables in the regressions in both stages.

2.1 Health and FDI

A number of empirical studies have examined the effect of human capital on FDI inflows. For example, Farhard and Alberto (2001) investigated effect of human capital on FDI inflows in the developing countries using three human capital indicators, secondary school enrollment, number of accumulated years of secondary education present in the working age population and number of accumulated years of secondary and tertiary education in the working age population, all three being educational indicators. Their empirical findings are: (a) human capital is a statistically significant and one of the most important determinants of FDI; and (b) its importance has become increasingly greater through time. Lucas (1990) recognizes that lack of human capital discouraged foreign investment in less-developed countries and his human capital indicator is level of education. Dunning (1988) argues that the leve of education and skills in the work force can influence both the volume of FDI inflows and the activities that firm undertake in a country.

As an important component of human capital, health seems to attract less attention. One of the major publications studying the effect of health on FDI is the paper by Alsan, Bloom & Canning (2006). They demonstrate by empirical evidence that FDI inflow is strongly and positively influenced by population in low- and middle income countries. Life expectancy is used as proxy for health in their study to estimate the effect of health on FDI. They further suggest that a healthy workforce will attract foreign investment.

In the literature, however, health is rarely studied from the perspective of cost. It's reasonable to assume that a business decision by a multinational firm regarding investment locations involves a cost-minimizing process. Among all related costs, health cost, is an easily ignored though important cost category. Rosen et al. (2003) specifically point out that there are two kinds of health cost that a business might bear—the direct costs and the indirect costs. Direct costs are linked to seeking and obtaining medical treatment for a disease, including medical care expenses, health benefits payments, and insurance premiums. Indirect costs refer to the implied production losses that are incurred by higher rates of absenteeism and lower productivity of sick workers. Logically, as the health status of employees improves, investors will pay less to cover the health care needs of their employees and related health expenses.

Alsan, Bloom & Canning (2006) identify population health as a determinant of FDI inflows. They propose a conceptual model of FDI inflows based on a profit function approach. Assuming constant returns to scale, profit maximization, and competitive markets, FDI inflows are hypothesized to occur up to the point investors equalize the profitability of investment across countries. The implicit function for FDI inflows is specified as a function of worldwide variables (profitability of investment, world price of output produced, world cost of capital), selected country specific variables (FDI absorptive capacity, local cost of inputs), and other factors (distance to markets, tariffs, and corruption in the host country) which represent barriers to trade and may add to the cost of production. In the investment equation, they suggest that GDP per capita captures the combined effects of absorptive capacity of the country and input cost effects. The health variable (average life expectancy) appears in the FDI inflows equation, so that the direct effect of population health status is captured in the estimated model. They acknowledge that indirect effects of health exist, but that they are captured by the other variables in the model. They find that population health has a positive and significant effect on FDI, but the effect varies between low-to-middle-income countries (where it is significant) and high-income countries (where no effect is observed). The implication is that worker productivity effects of health differentials appear only in lower income developing countries. While they argue that companies may need to spend more on health care in countries where health infrastructure and personnel are lacking, they do not explicitly model these costs or, more importantly, the indirect costs of health.

Cole and Neumayer (2006), on another front, innovatively study the effect of health on Total Factor Productivity (TFP). They first estimate TFP based on a Cobb-Douglas production function and then estimate the determinants of TFP in a fixed effects regression model using a 52 country panel data set, paying particular attention to three indicators of health: malnutrition, malaria and water borne diseases. They find the impact of poor health on TFP to be significant and negative.

Xu (2008) studies health as a determinant of foreign direct investment in a two stage country-level analysis similar in framework to our research. She measures the indirect cost of health through GDP. In the first stage, she captures the elasticity of GDP with respect to life expectancy, the health variable. Then in the second stage, she obtains the effect of both direct cost of heal and indirect cost of health (through elasticity of FDI with respect to GDP). In her study, however, an endogeneity issue seems hard to avoid. In the second stage, GDP is correlated with the other independent variables included in the empirical estimation.

Those three studies, to a large extent, motivate this research. We connect the dots by innovatively linking the indirect cost of health with FDI through TFP in a two stage model. Cole and Neumayer (2006) has demonstrated the significant effect of health on TFP and in a number of studies (for example, Roy 2009 and Baltabaev 2012), TFP has been identified as an important contributing factor in attracting FDI. Hence, we adopt the same theoretical framework in Xu (2008) and build a two stage regression model. In the first stage of the mode, we obtain the health-elasticity of TFP. In the second stage, we study the effect of both direct cost of health and indirect cost of health. The effect of direct cost of health will be captured by the regression coefficients of direct health expenditure and the effect of indirect cost of health will be captured by the TFP-elasticity of FDI.

2.2 Estimating TFP

The concept of TFP (total factor productivity) was first introduced by Solow (1957)[1] in his seminal paper. Total factor productivity has since gained much attention of economists and has been recognized as an important source of economic growth for a long time (Kim 2009). It is defined as the ratio of real product and real factor inputs. It accounts for effects in aggregate output not explained by traditionally measured inputs, for example, capital and labor.

Generally speaking, there are two approaches to measuring TFP (Chen 1997): the econometric estimation approach and the growth accounting or national income approach.

We'll discuss some of the widely used parametric econometric methods to estimate TFP. Van Biesebroeck (2007) provides a detailed review of several non-parametric methods.

Estimation of a Cobb-Douglas production function is the most commonly used and widely accepted method for estimating TFP (Cole and Neumayer, 2006). This approach is used in many key productivity studies, such as Bernard and Jones (1996), Hall and Jones (1999) and Miller and Upadhyay (2000).

If the data is cross section time series (or panel) data set and there is an unobserved but time-invariant panel effect, fixed effects modes is the most widely accepted and used method in the production function literature, and in fact they were introduced to economics in this context (Hoch, 1962).

[1] Now many believe that Tinbergen (1942) first introduced it in an article written in German.

An alternative method to fixed effects is instrumental variable (IV). At the firm level, an "endogeneity of inputs" issue or simultaneity bias, defined as the correlation between the level of inputs chosen and unobserved productivity shocks (De Loecker, 2007), may cause the coefficient estimates to be inconsistent. By instrumenting the independent variables (i.e. the inputs in the production function) that cause the endogeneity problems by regressors that are correlated with these production inputs, but uncorrelated with unobserved productivity, the endogeneity issue may be resolved. To achieve consistency of this IV estimator, three requirements have to be met (ABBP, 2007). First, instruments need to be correlated with the endogenous regressors (inputs). Second, the instruments cannot enter the production function directly and finally, instruments need to be uncorrelated with the error term (Ackerberg et al., 2007). One of the shortcomings of this technique obviously is the lack of appropriate instrumental variables in many data sets.

Some semi-parametric methods also appear in the literature. Van Beveren (2012) has an excellent review of those methods, including Olley-Pakes estimation algorithm, Levinsohn-Petrin estimation algorithm and the extensions of the Olley-Pakes methodology.

2.3 Determinants of TFP

As pointed out by Moral-Benito (2012), although there is general consensus that productivity growth is a crucial source of output growth, very limited research is available on its determinants from an empirical standpoint. Although our primary focus is the impact of health on TFP, we also try to take into account some other potential determinants of TFP that have been discussed in the literature.

Inflation: A number of studies (Miller and Upadhyay, 1997; Chen, 1997; Loko and Diouf, 2009) argue that greater instability at the macroeconomic level—in particular, a high inflation rate—tends to negatively affect a country's economic performance. Hence, we use inflation as an indicator of macroeconomic stability.

Government size: The size of government, measured as the share of public expenditures in GDP, has been identified in the literature as a significant indicator to explain TFP variation. A few studies argue that to certain extent, government spending may promote productivity growth because as a result of the spending, legal and administrative institutions or rule of law may get strengthened or infrastructure may get improved, and those improvements will undoubtedly positively affect productivity. Ghali (1998), for example, supports this theory. However, the majority contents that because of government inefficiencies, distortions provoked by interventions to free markets and tax burdens, excessively and unnecessarily large government spending may actually hinder productivity growth and these negative impacts may well offset and often beat the positive externalities brought by good government spending. Most empirical studies (Barro, 1991; Atul A. Dar, Sal Amir Khalkhali, 2002) present strong evidence that a large government does not product higher productivity.

Market Size: Market size has been recognized as a significant TFP determinant in a fair number of empirical studies. At the industry level, Boppart and Weiss (2012)'s findings based on US data suggest that a 1 percent increase in market size leads to an increase of about 0:25 percentage points of the TFP growth rate. At the aggregate level, Klenow (1996) identifies market size as one of the key driving forces of the difference in productivity growth and R&D intensity across U.S. manufacturing industries. In his "systematic attempt" to search for main determinants of total factor productivity growth using nonparametrics and model averaging methods, Moral-Benito (2012) also finds market size to be significant. Some other studies (Ericson and Pakes, 1995; Geroski, 1998) find that even at the firm level, size still matters. The underlying theory is that when an economy (or industry) grows, more resources will be put together to invest and innovate and thus promoting productivity growth.

Some other variables are used in some empirical studies too, for example, Miller and Upadhyay (1997) construct local price deviation from purchasing power parity by measuring local price of an identical basket of goods for all countries relative to the price in the U.S. They also build up a volatility measure as an index of the combined volatility in inflation, terms of trade and openness of trade.

2.4 Determinants of FDI

In addition to direct cost of health and indirect health cost, other factors will certainly have impact on FDI too. Here is a list of some of the main variables and how they appear in the literature.

Trade Openness: Measured mostly by the imports plus exports as share of GDP, trade openness has been the single most widely accepted as a significant FDI inflow determinant in the empirical studies we have reviewed. The underlined hypothesis is: the relative importance of international trade in an economy will have an important role in attracting FDI. It's not hard to imagine that in a trade-oriented economy, a lot of resources will be directed to serve trade related industries, for example, improve infrastructure to reduce transportation cost, thus making it more attractive to foreign investment. Kravis et al (1982), Culem (1988) and Edwards (1990) all report a statistically significant positive effect of openness on FDI. Mody et al (1992) observed strong evidence to support the hypothesis in the manufacturing industries.

Corruption: Every business needs to deal with the local government in the host country, be it getting a license, setting up a factory, hiring local workers or clearing custom. Whether this process is smooth or not can sometimes even decide the success of an investment, especially in a lot of developing countries, where setting up any sort of business from scratch can be a pain. Hence, a measure of the quality of the investment host country's government or of the easiness to do business is necessary. World Bank publishes an "ease to do business index" annually, which serves as a perfect measure in this case. However, it only started since 2004. Including this index as an independent variable in our models will render half of our data unused. In this study, instead, we use the Corruption Perceptions Index (CPI) published by the Germany based NGO, Transparency International, since 1990. It provides a consistent measure ranking countries "by their perceived levels of corruption, as determined by expert assessments and opinion surveys" (Transparency International, 2011). The CPI generally defines corruption as "the misuse of public power for private benefit." It ranks countries on a scale from 100 (least corrupt) to 0 (highly corrupt) and we will use this as our indicator of a country's corruption level and easiness to do business. Other similar indicators of political environment that appear in the literature includes economics freedom index, political rights index.

Infrastructure: Infrastructure has been found by numerous studies to be a crucial determinant of FDI flows. Alsan (2006) and Xu (2008) use numbers of telephones as the measure of infrastructure and both find it to be significant and positively associated with FDI inflows. Walsh and Yu (2010) come up with an infrastructure quality index in their empirical estimation of FDI inflows. Theoretically, good infrastructure will enhance the competitiveness of an economy in attracting foreign investment since it not only reduces the transportation cost for business, it also provide access to more customers. The positive effect of infrastructure on FDI has been confirmed by other studies, including Coughlin et al (1991), while examining the determinants of FDI inflow to the U.S. for 1981-1983, finds that extensive transportation infrastructures contributes to increased FDI. Mody and Wheeler (1992) find that the quality of infrastructure is very important for developing countries seeking to attract FDI from the U.S., but is less important for those developed countries that already enjoy high quality infrastructures.

Other variables including exchange rate, taxes and wage also have been mentioned and used in several empirical studies in the literature.

Chapter 3

Model

Direct cost of health might be measured as the total health expenditure. Its effect on FDI inflow can be measured as after controlling other factors.

In order to obtain the indirect (productivity) cost, we assume that poor health of the work force affects foreign investment decisions by lowering the expected level of human capital and firms interpret poor health as a threat to labor productivity. In this sense, the effect of population health status on productivity could be measured by estimating the total factor productivity of labor. This approach to the indirect costs of health implies that there is a measurable elasticity of factor productivity of labor in response to changes in health status. To model these indirect costs we use the approach suggested by Cole and Neumayer (2006). We identify and measure the link between health and aggregate production through innovations in total factor productivity of labor, and then we study the effect of health cost, both direct and indirect, on foreign direct investment inflows.

3.1 Production Function and Factor Productivity

We first need a measure of factor productivity of labor in order to examine the impact of health on FDI. Although some commonly estimated growth equations in the literature (for example, Barro and Sala-i-Martin, 1995; Mankiw et al., 1992; Islam, 1995) can be used to provide information on aggregate productivity, their primary focus is on the convergence of national income or to test the convergence hypothesis (Miller and Ypadlhyay, 2002) and a variety of independent variables have been included in the models. We adopt the most commonly used and widely accepted method for calculating

TFP, namely the estimation of a Cobb-Douglas production function. This is the approach used in many key productivity studies, such as Hall and Jones (1999), Bernard and Jones (1996) and Miller and Upadhyay (2000).

The measurement of total factor productivity requires the estimation of a production function from which we derive the total factor productivity measure. We adopt the Cobb-Douglas production function to estimate total factor productivity.

Whether or not to include human capital in the Cobb-Douglas production function is a question here. Mankiw, Romer and Weil (1992) advocate including human capital both theoretically and empirically. They build a cross-section regression model and obtain a better fit with human capital being included as an independent variable. Islam (1995) advocates and implements a panel data approach to study growth. He tests the Mankiw-Romer-Weil specification using a panel data set. However, he finds that human capital is not significant in explaining the output variable. He suggests that human capital, as a contributing factor, significantly affects total factor productivity.

Benhabib and Spiegel (1994) studies the role of human capital in economic development with aggregate cross-country data on physical and human capital stocks. They build a log difference model to estimate the production function, incorporating human capital as a factor. They only discover human capital to be insignificant in explaining per capita growth rate. They then consider the more complex situation where the growth rate of total factor productivity depends on human capital stock level (i.e., adding an interaction term). Test of the alternative model suggest a positive role of human capital. They conclude that though human capital is not significant as a direct input in production function, it does influence growth through its effect on total factor productivity.

Our production function is specified as

$$Y = AK^{\alpha}H^{\delta}L^{\beta} \tag{1}$$

where Y denotes real GDP, A is the index of total factor productivity, K is the total stock of physical capital, H is the stock of human capital measured by average years of schooling and L is the total labor force. The sum of (α + β + δ) is not restricted to one to allow for increasing or decreasing returns to scale.

We convert the production function to a per worker form by dividing (1) by total labor force (L) to get

$$\frac{Y}{L} = \frac{AK^{\alpha}H^{\delta}L^{\beta}}{L}$$

$$y = \frac{AK^{\alpha}H^{\delta}L^{\beta}}{L}$$

$$y = \frac{A(\frac{K}{L})^{\alpha}(\frac{H}{L})^{\delta}L^{\beta} * L^{\alpha} * L^{\delta}}{L}$$

$$y = A(\frac{K}{L})^{\alpha}(\frac{H}{L})^{\delta}L^{\beta} * L^{\alpha} * L^{\delta} * L^{-1}$$

$$y = Ak^{\alpha}h^{\delta}L^{\beta} * L^{\alpha} * L^{\delta} * L^{-1}$$

$$y = Ak^{\alpha}h^{\delta}L^{\alpha+\beta+\delta-1} \tag{2}$$

where y represents real GDP per worker, k is the stock of physical capital per worker, h is human capital per worker, and L is still total labor force. This production function will display increasing, constant, or decreasing returns to scale as (α + β + δ) is greater than, equal to, or less than one, respectively.

Rewriting (2) in natural logarithms yields

$$\ln y = \ln A + \alpha \ln k + \delta \ln h + (\alpha + \beta + \delta - 1) \ln L. \quad (3)$$

Whether the coefficient of ln L equals zero will reveal the result of the test for constant returns to scale.

Denoting country (i) and period (t), we rewrite (3) as an estimating equation,

$$\ln y_{i,t} = \theta_i + \alpha \ln k_{i,t} + \delta \ln h_{i,t} + (\alpha + \beta + \delta - 1) \ln L_{i,t} + \epsilon_{i,t} \quad (4)$$

where (θ + ε) is the measure of total factor productivity and it is equivalent to the coefficient on ln A in (3).

We can estimate (4) using fixed and random effects to obtain estimates of total factor productivity.

3.2 First Stage Regression

In this first stage regression, we use the estimated total factor productivities from (4) to estimate the effects of health and other country characteristics on factor productivity in (5) by regressing

$$TFP = f(Health,\ Z) \quad (5)$$

where H represents a country level measure of health status, Z represents a vector of country characteristics that are hypothesized to influence total factor productivity over time. Following the approach suggested by Cole and Neumayer (2006) and to obtain the indirect (productivity) cost of health, we assume that poor health of the work force affects foreign investment decisions by lowering the expected level of human capital. In this sense, the effect of population health status on productivity could be measured indirectly using total factor productivity. This approach to the indirect costs of health implies that there is a measurable elasticity of total factor productivity in response to changes in health status. To model these indirect costs we use this approach to identify and measure the link between health and aggregate production through innovations in total factor productivity.

We choose life expectancy as our country-specific health status indicator following the overwhelming majority of previous studies. Bloom Canning and Sevilla (2004) provides a detailed list of papers that include health as an explanatory variable in growth regressions (e.g., Barro, 1996 ; Barro and Lee, 1994; Hamoudi and Sachs, 1999; Gallup and Sachs, 2000).

Over the last few decades, several researchers have tried to identify the determinants of TFP. While there is general consensus that total factor productivity contributes output growth, agreement has not yet been reached on what actually determines TFP from an empirical standpoint.

In addition to human capital, Benhabib and Spiegel (2002) include a dummy indicating Sub-Saharan African nations, tropics, a variable measuring the share of land area subject to a tropical climate, life expectancy and trade openness (an indicator of the degree to which domestic policy favors free trade). Miller and Upadhyay (1997) explore the effects of trade openness and orientation on total factor productivity in a selection of developed and developing countries. Kneller and Stevens (2006) study the impact of the differences in human capital and Research and Development in OECD on cross-country divergences in total factor productivity growth. A systematic attempt has been made by Danquah, Moral-Benito and Ouattara (2012) to search for the main determinants of total factor productivity. They conjecture that "any of the potential determinants of GDP growth considered in the literature might have a direct effect on total factor productivity" and hence in the regression explore a rich set of potential explanatory variables from a pure empirical perspective, including population, trade openness, urban people share, government spending share, life expectancy, civil liberties and political rights. However, since their entire analysis is based on a nonparametric Bayesian model, the result is of little use to us in this context. All in all, little consensus has been reached so far in the literature regarding the determinants of total factor productivity.

Here Z is the vector of country characteristics. Upon a thorough review of literature and as a result of data availability, we include population, inflation and government size (spending share as % of GDP) as country characteristics. We write this in estimation form as

$$TFP_{i,t} = \varphi_i + Life_{i,t} + Pop_{i,t} + Infl_{i,t} + Govt_{\ i,t} + \epsilon_{i,t} \tag{6}$$

where Life is life expectancy, Pop is total population, Infl is inflation rate and Govt is government spending share as % of GDP. φ_i is the country-specific fixed effects and $\epsilon_{i,t}$ is error term.

Transform (7) in log form, we get:

$$lnTFP_{i,t} = \varphi_i + \alpha Life_{i,t} + \beta lnPop_{i,t} + \gamma lnInfl_{i,t} + \delta Govt_{\ i,t} + \epsilon_{i,t} \qquad (7)$$

and this is the regression model we estimate in the first stage. We expect that life expectancy will have positive impact on TFP. Our hypothesis is that increased life expectancy indicates a healthier population and work force. As a result, overall productivity gets improved.

3.3 Second Stage Regression

In the second stage of the model we can estimate the effect of direct and indirect costs of health on the FDI inflows. The conceptual model is as follows

$$FDI = f(HEXP,\ TFP,\ X) \qquad (8)$$

where FDI is gross FDI inflows, HEXP is total expenditures on health as the indicator of direct cost of health, TFP is the total factor productivity estimated from (4) as a proxy for indirect cost of health, and Z captures other country-level effects (openness of economy, infrastructure and government corruption).

We can rewrite the investment model in log form as

$$lnFDI_{i,t} = \varphi_i + \alpha lnHEXP_{i,t} + \beta ln\,TFP_{i,t} + \gamma Open_{i,t} + \delta Corr_{i,t} + \theta ln\ Rail_{i,t} + \epsilon_{i,t} \quad (9)$$

where HEXP and TFP again represent direct and indirect cost of health, Open is trade openness, Corr is corruption index, Rail is railway length measured in km, φ_i is the country-specific fixed effects and $\epsilon_{i,t}$ is the error term. The estimated parameters in (9) are interpreted as elasticity of FDI inflows with respect to each of the independent variables. Specifically, α is the effect of direct cost of health on FDI inflow. β is the estimated elasticity of FDI inflows with respect to TFP. After incorporating the health elasticity of TFP in (7) we will get the effect of indirect cost of health on FDI inflow, which is given by β (in (9)) * α (in (7)).

We expect that both the direct and indirect cost of health will have a positive impact on FDI inflow. We hypothesize that increased spending in health will produce a healthier population and work force. This potentially reduces a foreign investor's health-related cost, which is attractive to cost-minimizing investors. As a result, that will bring in more foreign direct investment. Similarly, if a country's overall health status improves, productivity loss due to poor health condition in the work force will likely reduce and hence the overall cost of investment is lowered, which further encourages foreign investors to make investments.

In both stage one and stage two regressions, after we obtain the overall effect of the direct and indirect cost of health on FDI inflow, we divide the sample into two groups: low- and middle-income countries and high-income countries and run the same regressions using these two sub-sets of our data to see if there is any difference in terms of the effect of the direct and indirect cost of health on FDI inflow in these two groups of countries. We will discuss the results in Chapter 5.

Chapter 4

Data

The data used in previous studies date back to the 1990s. For example, Bloom, Canning and Sevilla (2004) construct a panel of courtiers observed every 10 years during 1960-1990. Cole and Neumayer (2006) use data of 52 developed and developing countries at five-year intervals during 1965-1995. Alsan, Bloom and Canning (2006) get up to two observations per country, one for 1980-1990 and the other for 1990-2000. Xu (2008) uses a panel data set that covers 1990-2000.

We construct a panel data set for 59 counties across all regions covering 1995-2010. The data set covers countries in all continents— Africa (10 countries), Caribbean, Central America, and North America (6), South America (10), Asia (13), Europe (18), and Oceania (2), and across different income group—high, medium and low income. A list of countries is in the Appendix C.

The selection of countries takes into account various factors, including regions, income levels and most importantly the availability of capital stock data. The gross capital formation data is from the World Bank WDI data set. A number of techniques could be used to fill in missing values, but we refrain from doing so because of questionable accuracy of those techniques. We prefer to use a slightly smaller, but still representative selection of countries.

Due to limited data availability, our panel data covers 1995-2010 in five year intervals. This time series reflects the fact that our source data for human capital (Barro and Lee,

2013) only reports five-year observations. In total we have 236 data points.

Data in TFP Estimation

We first estimate TFP based on a Cobb-Douglas production function in equation (1) – (4). We use GDP and labor force data from The World Bank's World Development Indicators (WDI) data set. To make estimated TFP comparable among different countries, we choose GDP in constant dollar. Human capital stock is in the form of average years of schooling attained and comes from the most recent update (2013 09 April version) to the classic Barro and Lee dataset. It is the detailed definition of educational attainment for the population aged 15 and over.

Capital Stock

For a few countries (U.S., U.K., Japan, and Germany) the capital stock series is created and updated by the government. But it is not readily available for most other countries. Following Hall and Jones (1999) we use the perpetual inventory method to construct capital stock series based on gross capital formation time series data from World Bank's WDI data set.

The perpetual inventory method uses

$$K_t = K_{t-1} - \delta K_{t-1} + GFK_t = (1-\delta)K_{t-1} + GFK_t \quad (10)$$

where K is capital stock and GFK is gross capital formation; t and t-1 are subscripts indicating different time periods and δ is the depreciation rate (assumed constant over time). Hence, K_t is the capital stock level at time t and GFK_t is the gross capital formation at time t-1.

We use this equation in the following way. Suppose we set the initial year as 1900 and the initial capital stock level is equal to $1000, the rate of depreciation is equal to 10%, the new investment level in the next year, 1901, is $200 (i.e., K_{1900} = 1000, GFK_{1900} = 200 and δ = 0.1), then the capital stock in 1901 is equal to

$$K_{1901} = (1 - \delta)K_{1900} + GFK_{1900}$$

$$= (1 - 0.1)1000 + 200$$

$$= 1100$$

If gross fixed capital formation in 1901 is equal to $250, then the capital stock in 1902 is equal to

$$K_{1902} = (1 - \delta)K_{1901} + GFK_{1901}$$

$$= (1 - 0.1)1100 + 250$$

$$= 1240$$

Capital stock in the later years can be calculated using the same formula.

Note that we need three pieces of information to calculate a series of capital stock: initial capital stock, depreciation rate, and time series data on gross fixed capital formation. Since gross fixed capital formation data is available from the WDI data set, we need to calculate the initial capital stock and the depreciation rate.

In the above example, we assigned a value to K_{1900}, the initial capital stock to create the capital stock series for 1901 and 1902. In most cases, an initial capital stock level is not readily available. The question is, how should we estimate the initial capital stock? Hall and Jones (1999) used the following formula to calculate initial capital stock.

$$K_0 = \frac{GFK_0}{\delta + g_{GFK}} \qquad (11)$$

Here, K_0 is initial capital stock, GFK_0 is the level of gross fixed capital formation in the initial period, δ is the depreciation rate and g_{GFK} is the rate of growth in gross fixed capital formation. Given equations (10) and (11), the only unknown is δ, the depreciation rate. Following Hall and Jones (1999) we assume a depreciation rate of 6 percent.

Since the panel data set we use for this paper spans from 1995 to 2010, to serve the purpose of the analysis in this paper, we set the initial year as 1990, i.e., $K_0 = K_{1990}$, $GFK_0 = GFK_{1990}$.

Other Variables

In addition to capital stock, the other variables entering the production function estimation are GDP per worker (as dependent variable), average years of schooling as human capital stock and total labor force.

Note that as we demonstrated in Chapter 3, here the GDP variable is GDP per worker instead of GDP per capita.

The wide variety in GDP, capital stock, years of schooling and labor force is confirmed by the summary statistics in table 4.1. The lowest GDP per worker value was in Rwanda in 1995 ($387) and the highest, $125325, happened in 2010's Norway. The pattern-developed countries in Europe and North America enjoy a high GDP per worker while the lowest GDP per worker happens in sub-Saharan African countries-is consistent across the entire time period covered in this data set. The same pattern holds in capital stock and average years of schooling too, for example, Mozambique, Mali and Rwanda rank the lowest consistently in 1995, 2000, 2005 and 2010 in average years of schooling (1.81, 2.38 and 3.96 years respectively in 2010), while in Australia, Canada, New Zealand and United States, people receive more than 12 years education on average.

Table 4.1 Summary Statistics for Full Sample (59 countries) in TFP Estimation

Variable	Mean	Std.Dev.	Min	Max
GDP per worker	29134	31997	387	125325
Capital Stock per worker	72811	86628	463	340935
Avg Years of Schooling	7.98	2.57	0.92	13.09
Total Labor Force	3.63E+07	1.11E+08	4.88E+05	8.12E+08

Data in Stage One Regression

In the first stage, we regress estimated TFP from (4) on a country level health status indicator (life expectancy) and a vector of country characteristics including GDP per capita, inflation and government size.

Life expectancy, GDP per capital and inflation data comes from World Bank's World Development Indicator data set. Government size is expressed as government spending as share of GDP.

Table 4.2 Summary Statistics of Variables in Stage One Regression

Variable	Mean	Std.Dev.	Min	Max
Life Expectancy	70.69	10.15	30.47	82.84
Population	55369	15832	819	1090693
Inflation	7.072	12.10	-0.95	96.09
Government Size	14.92	5.17	4.58	28.95

Table 4.2 lists the summary statistics for the variables in the regression in this stage. Note that the dependent variable, TFP, is estimated from the Cobb-Douglas production function as specified in equation (4) and a detailed list of estimated TFP by country is available in Appendix D. As we have discussed in Chapter 3, in addition to life expectancy (the health status indicator variable), population, inflation and government size all have been found significant in association with TFP in the literature. Given the fact that various countries of different regions a wide range of income levels are included in our sample, we are not surprised to see the variations in the data. Life expectancy, for example, ranges from lower 30s back in 1990s in some African countries that have long been scarred by domestic wars to 80s in Japan in 2010, where its Human Development Index has been consistently ranked top 10 in the world (0.912 in 2012). Government spending as share of GDP also varies from country to country and across different years with the maximum value (28.95%) six times that of the minimum (4.58%).

All variables enter the regression model in logarithm form.

Data in Stage Two Regression

In our stage two regression model, we estimate the effect of direct cost and indirect cost of health on FDI inflows (see equation 9).

FDI inflow data, measured in US Dollars at current prices in millions, comes directly from United Nations Conference on Trade and Development (UNCTAD)'s UNCTADSTAT data set (UNCTADSTAT, 2012). TFP is estimated from the production function in stage one. Country level total health expenditure, here representing direct health cost, comes from WDI data set. Railway length in km is also from WDI data set. Trade openness, is constructed as the sum of import and export as percentage of GDP. Import as percentage of GDP and export as percentage of GDP data again is retrieved from WDI data set.

$$\text{Trade Openness} = \frac{Import+Export}{GDP} * 100\% \quad (13)$$

Among which, import and export data also comes from WDI data set. Corruption Index comes from Transparency International. It is a measure of the corruption level in the surveyed countries. An index score of 10 indicates the least corrupt. Table 4.3 reports the summary statistics for stage two regression.

Table 4.3 Summary Statistics of Variables in Stage Two Regression

	Mean	Std.Dev.	Min	Max
FDI inflow	10833.99	28333.80	2.00	197905.00
Total Health Expenditure	48.71	193.88	0.28	2055.41
Trade Openness	76.10	54.70	16.03	429.90
Railway Length	16994.84	34727.62	261.00	228999.00
Corruption Index	5.12	2.53	1.70	10.00

Chapter 5

Estimation and Results

In this chapter, we report and discuss the estimation results. It is organized in the same order as in previous chapters—first we report the result of TFP estimation, followed by the result of stage one regression, and finally stage two regression result.

5.1 TFP Estimation

We start with the estimation of TFP. Table 5.1 provides the fixed effects estimation results of equation (4). The random effects estimation yields similar coefficients and same signs as the fixed effect model. Since the Hausman test rejects the random effects specification at the 1 per cent level, we only report the result of fixed effects model.

Table 5.1 Production Function Estimation Results

VARIABLES	Log GDP per worker
Log Capital Stock per worker	0.42***
	(0.03)
Log Avg Years of Schooling	0.61***
	(0.10)
Log Labor Force	-0.17**
	(0.09)
Observations	231
Number of countries	59
R-squared	0.72

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficient estimate of ln L is -0.17. It is significant at the 1 percent level and indicates that the Cobb-Douglas production function exhibits slightly decreasing returns to scale. This is similar to what Miller and Upadhyay (1997) obtain. The coefficient estimate of ln k (Log Capital Stock per worker), representing output elasticity with respect to the physical capital stock, is 0.42. Output elasticity with respect to human capital stock is estimated at 0.61. Since the three coefficients respectively represent α, δ and $(\alpha + \beta + \delta - 1)$ in (4), we can calculate the estimate β, the output elasticity with respect to labor force, as 0.14. All three coefficient estimates are significantly different from zero: the coefficients of physical capital stock and human capital stock are both significant at the 1 per cent level while the coefficient of labor force is significant at the 5 per cent level.

The elasticity of output with respect to physical capital stock, labor force and human capital stock is evaluated at 0.42, 0.14 and 0.61 respectively. This result is similar to Miller and Upadhyay (1997) and Mankiw, Romer and Weil (1992).

5.2 Stage One Regression

In table 5.2 we present the empirical estimation results for Log TFP between 1995 and 2010 for 59 countries. We use two specifications (with and without the government size variable) and three samples (full sample, only low- and middle-income countries and high-income countries). In total we run six fixed effects regressions.

Table 5.2 Stage One Regression Results

Dependent Variable: Log TFP (estimated)

VARIABLES	(1) All Countries	(2) All Countries	(3) Low- and Middle-Income Countries	(4) Low- and Middle-Income Countries	(5) High-Income Countries	(6) High-Income Countries
Life Expectancy	0.009**	0.009**	0.008**	0.007*	0.020**	0.031***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)
Log Population	0.046**	0.058***	0.068**	0.076***	-0.035	-0.024
	(0.020)	(0.020)	(0.027)	(0.027)	(0.032)	(0.031)
Log Inflation	-0.291***	-0.285***	-0.352***	-0.332***	-0.130	-0.226
	(0.093)	(0.091)	(0.116)	(0.115)	(0.236)	(0.223)
Government size		-0.010***		-0.009*		-0.017***
		(0.004)		(0.005)		(0.005)
Observations	231	231	137	137	94	94
R-squared	0.651	0.723	0.707	0.811	0.499	0.605
Number of countries	59	59	35	35	24	24

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0

We begin by estimating TFP as a function of three determinants in Model (1), Life Expectancy, Population, Inflation and Government size using the full sample of our data set. Here GDP and Inflation are in log form. All variables are signed in accordance with our prior expectations and statistically significant at the 5% level. Most notably, the average life expectancy is a positive determinant of TFP. Adding government size to the model doesn't change the result substantially—signs don't change and the coefficients only change by a tiny bit. We then divide the full sample into two groups: low- and middle-income countries and high-income countries (for detailed criteria see Appendix C, List of Countries). We run the regressions with the same specifications as in the full sample model.

All specifications except Model (5) pass the significance test at 1% level. Model (5), using high-income countries data without government size variable, passes the significant test at the 10% level. The model also appears to be robust across all specifications—adding government size variable, measured by the share of government spending in GDP doesn't affect the significance of the model or regression coefficients significantly.

Our main variable of interest is life expectancy. It is statistically significant across all 6 model specifications. This confirms our expectation that life expectancy is positively associated with TFP and a healthier population contributes to TFP accumulation. When using all sample data, given a one year increase of life expectancy, we expect TFP to increase by 0.9% with or without government size variable included in the model. In the low- and middle-income countries specifications and given one year increase of life expectancy, TFP is expected to increase by 0.8% with government size variable included and 0.7% without it in the model. In the high-income countries group and given one year increase of life expectancy, TFP is expected to increase by 2% and 3.1% respectively. As a general pattern, the health elasticity of TFP, or the effect of indirect cost of health on FDI, is higher in high-income countries and lower in low- and middle-income countries. This result is similar to what Cole and Neumayer (2006) obtain in their estimations using three other indicators of health: undernourishment, incidents of malaria and access to safe water, where the effect of health on TFP is generally larger in Africa than non-Africa countries.

Population is our measure of market size in the model. This variable acts differently in low- and middle-income and high-income countries. While it is highly significant and is positively associated with TFP in the low- and middle-income countries, it’s not significant in high-income countries. One explanation is that since most of the low- and middle-income country’s economies are labor intensive, the increase of labor supply will contribute substantially to productivity. In a developed economy that is built mostly on capital intensive industries, increase of labor supply may not matter so much to productivity growth. Similaly, the inflation variable is significant in models using low- and middle-income countries data and insignificant in models using high-income countries data, although the coefficients share the same negative signs. As an indicator of macroeconomic environment, inflation tends to have much bigger fluctuation in low- and middle-income countries than in high-income countries. For example, in our data set, while we see a 100% inflation rate in Ecuador and Brazil, we never see an inflation rate greater than 5% in high-income countries. Since most of those high-income countries enjoy a stable inflation rate and macroeconomic environment and focus their productivity growth on technology and R&D, inflation may not be a crucial determinant of TFP. However, in the less developed countries, due to political turmoil, government failure or other reasons, an extremely high inflation may significantly impacts production and productivity. A most recent example is Argentina in 2005. Government size appears significant and a negative determinant of TFP in all three models. As we have discussed in Chapter 2, because of government inefficiencies, failure and distortions and, large government spending may actually hinder productivity growth. Our result is similar to most empirical studies (Barro, 1991; Atul A. Dar, Sal Amir Khalkhali, 2002).

In general, we find the impact of health on TFP is significant, positive and robust across a variety of models and specifications. The effect of health on TFP is our measure of indirect cost of health on FDI. It is estimated to be 0.9% in association with a one year increase in life expectance.

5.3 Stage Two Regression

In this stage, we investigate the effect of direct cost of health and indirect cost of health on FDI. Total health expenditure is the proxy of direct cost of health and estimated TFP is the proxy of indirect cost of health. Other variables include trade openness (measured as the share of import and export in GDP), corruption index (the easiness of doing business indicator), and railway length (the infrastructure indicator). All these variables serve as controls in the model. In each model, we first estimate FDI inflow as a function of Health Expenditure, TFP and Trade Openness. Then we add Corruption Index and Railway Length to the model. Health Expenditure, TFP and Railway Length appear in the model in log form.

Table 5.3 Stage Two Regression for Log FDI Inflow (Full Sample)

VARIABLES	(1)	(2)	(3)	(4)
Log Health Expenditure	1.846***	1.542***	1.894***	1.810***
	(0.461)	(0.493)	(0.460)	(0.499)
Log TFP	1.590**	1.876**	1.509*	1.683*
	(0.937)	(0.989)	(0.933)	(0.977)
Trade Openness	0.017***	0.015**	0.017***	0.017***
	(0.007)	(0.006)	(0.007)	(0.006)
Corruption Index		0.251		0.221
		(0.159)		(0.157)
Log Railway Length			0.032**	0.508**
			(0.020)	(0.019)
Observations	220	185	220	185
R-squared	0.655	0.701	0.741	0.756
Number of countries	59	59	59	59

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The regression result using full sample data is reported in Table 5.3. All four models are significant at the 1% level. Health expenditure, TFP and railway length are significant predicators, but corruption is statistically insignificant. In Model (1), the coefficient of log health expenditure indicates that after controlling for other factors, a 1% increase in health expenditure is associated with an increase of FDI inflow by 1.8%. That is the effect of direct cost of health on FDI. Similarly, the coefficient of log TFP indicates that a 1% increase in TFP is associated with FDI inflow increase by 1.6%. That is the effect of indirect cost of health on FDI. Trade openness also significantly contributes to FDI inflow: A one percent increase in trade openness, the share of import and export in GDP, is associated with an increase in FDI inflow by approximately 1.7%.

Adding the measure of government corruption (corruption index published by

Transparency International yearly) and a proxy for infrastructure development (railway length in kilometers) doesn't change the overall significance of the model and does not affect the coefficient estimates significantly. We notice that corruption index doesn't seem to be statistically significant in either Model (2) or Model (4). Railway length appears to be significant, which confirms our expectation that investing in infrastructure or infrastructure improvement is likely to help attract FDI inflow.

Like the first stage, we then divide the sample and run regressions using low- and middle-income countries only and high-income countries only with the same specifications.

Table 5.4 Stage Two Regression for Log FDI Inflow (Low- and Middle-Income Countries)

VARIABLES	(5)	(6)	(7)	(8)
Log Health Expenditure	3.005***	2.328***	2.967***	2.373***
	(0.602)	(0.671)	(0.608)	(0.661)
Log TFP	4.195**	4.485**	3.387*	3.691*
	(1.860)	(2.024)	(2.007)	(2.111)
Trade Openness	0.012*	0.017**	0.012*	0.017**
	(0.008)	(0.008)	(0.008)	(0.008)
Corruption Index		0.168		0.164
		(0.218)		(0.214)
Log Railway Length			0.013**	0.373**
			(0.024)	(0.021)
Observations	132	101	132	101
R-squared	0.733	0.795	0.819	0.836
Number of countries	35	35	35	35

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 5.4 we present the result of the models using low- and middle-income countries data only. The significance of health expenditure stays the same. It is still highly significant and the estimated coefficient indicates that it has a larger effect on FDI inflow. A 1% increase in total health expenditure now produces a 3% increase in FDI inflow. This effect is robust to different model specifications. The proxy for indirect cost of health, TFP also stays significant with a larger effect on FDI inflow. It is expected to increase by 4% given a 1% increase in TFP. Openness of trade still positively contributes to FDI inflow- and it is also highly significant and the magnitude of effect on FDI is similar to that in other models. Corruption index carries the expected positive sign but it stays statistically insignificant. Railway length is significant and it has a positive effect on FDI inflow, same as in the full sample model.

In high-income countries, the result is different. The effect of direct cost of health on FDI inflow is still significant but with a smaller magnitude. A 1% increase in health expenditure now is associated with 0.34% increase in FDI inflow in the default specification (Model (9)) and 0.7% increase when adding the government corruption variable and the infrastructure variable in Model (10) and (11). The proxy of indirect cost of health, TFP is not significant across all specifications. It does have the expected positive sign with much smaller effect compared to the results obtained for low- and middle-income countries. The corruption index is still not significant while trade openness is significant in two specifications and railway length is significant in one specification. This indicates that government corruption, measured by corruption index, does not have a significant impact on FDI inflow but trade openness and infrastructure do significantly impact FDI inflow.

Table 5.5 Stage Two Regression for Log FDI Inflow (High-Income Countries)

VARIABLES	(9)	(10)	(11)	(12)
Log Health Expenditure	0.338**	0.717**	0.703**	1.252**
	(0.558)	(0.654)	(0.655)	(0.779)
Log TFP	0.440	0.516	0.437	0.430
	(1.054)	(1.063)	(1.058)	(1.047)
Trade Openness	0.022**	0.011	0.026**	0.015
	(0.010)	(0.011)	(0.011)	(0.012)
Corruption Index		0.222		0.179
		(0.227)		(0.233)
Log Railway Length			0.035	0.921*
			(0.043)	(0.049)
Observations	88	84	88	84
R-squared	0.442	0.556	0.502	0.602
Number of countries	24	24	24	24

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, the variables have expected signs and are mostly statistically significant at the 5% level. As expected, direct cost of health is positively associated with FDI inflow—a 1% increase in health expenditure links to a 1.8% increase in FDI inflow. It confirms our hypothesis that large health spending or health investment will lead to a healthier population and work force. This potentially reduces a foreign investor's health-related cost, which is attractive to cost-minimizing investors. Indirect cost of health is also significant and robust. As we have discussed in the previous chapters, it is measured indirectly through estimated TFP. We first obtain the health elasticity of TFP, which is the elasticity of TFP with respect to health status, and then the elasticity of FDI with respect to TFP, thus approximately the effect of indirect cost of health on FDI. Using the full sample data, health elasticity of TFP is estimated to be 0.9 while the elasticity of FDI with respect to TFP is estimated to be 1.59. So overall, the effect of indirect cost of health on FDI inflow is approximately 1.4%.

We find different patterns in low- and middle income countries and high-income countries. While the effect of direct cost of health on FDI inflow is significant in both groups, it is much bigger in low- and middle income countries than in high-income countries. In the models with both the government corruption variable and infrastructure variable, the effect in low- and middle income countries is twice that of high-income countries.

Although TFP has the expected signs in the second stage model for high-income countries, it is not statistically significant. This indicates that indirect cost of health does not have significant impact on FDI inflow. In the low- and middle-income countries, the impact of indirect cost of health on FDI is significant and positive. That is, health does have a measurable labor productivity effect on FDI inflow.

These results confirm our catch-up theory. That is, high-income countries have maintained a high level of both population health status and spending on health for a long time while in most low- and middle-income countries, the health status is improving, more investment is being directed to health and they are catching up. Hence, the health effect in attracting FDI inflow is more obvious in the low- and middle-income countries. For instance, the average life expectancy in OECD countries is 79 years in 2010 (OECD, 2010) while in Africa, it is only 56 (WHO, 2011); The U.S. has been consistently spending more than 15% of GDP on health for more than a decade while some Sub-Sahara countries spend less than 1% of GDP.

We also spend efforts trying to adjusting for time in the TFP estimation stage. In a new set of regressions, we include time variable t (it takes the value of 1, 6, 11, 16 to indicate the four years 1995, 2000, 2005 and 2010) in the TFP estimation stage and then run stage one and stage two models again based on the same model with same specifications. Although this small change in model specification does not substantially affect the overall regression estimates, we include this set of regression results in Appendix E.

First of all, time does appear to be significant. Adjusting for time in the TFP estimation equation does not change the overall significance level of the model and the explanatory power of the model substantially. The signs of regression coefficients do not change either. The change in actual coefficient estimates is very limited.

In stage one and stage two regressions, the effect of including a time variable in the TFP estimation stage is also very limited. In the first stage, the overall significance level of the model, R square, signs of coefficient estimates and actual coefficient estimates almost stay the same. The change in terms of our main interest in this stage, the effect of life expectancy on TFP, is that it is no longer significant in high-income countries model.

The change in the second stage regression is mainly the magnitude of the coefficient estimate of health expenditure, our indicators of direct cost of health and the significance level of TFP, our indicator of indirect cost of health. After adjusting for time in TFP, now the direct health cost effect on FDI is approximately 0.8 in the full sample model (see table E.3), which is to say, a 1% increase in health expenditure is associated with 0.8% increase in FDI inflow. Compared to the result in the original specification, which is 1.8%, the direct health cost effect is lowered by approximately 1%. TFP becomes not significant in the full sample model, however, same as in the model without time adjustment, it is still significant in the low- and middle-income countries model, with a smaller coefficient estimate.

Overall, the effect of adjusting for time is limited.

Chapter 6

Conclusion

We analyze and discuss the impact of the effects of both direct and indirect cost of health on FDI inflow in this study based on a two-stage model using a panel data set of 59 countries from 1995 to 2010. We first estimate TFP based on a Cobb-Douglas production function estimation. Then in the first stage regression model, we regress estimated TFP on average life expectancy (population health indicator) and control for other country level variables to obtain the effect of health on TFP (health elasticity with of TFP). In the second stage, we model FDI inflow by countries' total expenditure on health (measure of direct cost of health) and TFP (proxy for indirect cost of health) to obtain the effect of both direct cost of health and indirect cost of health (through health elasticity of TFP) on FDI inflow.

We find that overall both direct cost of health and indirect cost of health has significantly positive effect on FDI inflow. A 1% increase in health expenditure results in a 1.8% increase in FDI inflow. This is the effect of direct cost of health on FDI inflow. Health elasticity of TFP is estimated to be 0.9 in the first stage while the elasticity of FDI with respect to TFP is estimated to be 1.59. So overall, the effect of indirect cost of health on FDI inflow is approximately 1.4%. When we run the regression using low- and middle-income countries and high-income countries separately, the results differ. We find different patterns in low- and middle income countries and high-income countries. While the effect of direct cost of health on FDI inflow is significant and positive in both groups, it is much bigger in low- and middle income countries than in high-income countries.

Indirect cost of health does not have statistically significant impact on FDI inflow in high-income countries while in low- and middle-income countries it still has a significantly positive impact on FDI inflow.

These results confirm our hypothesis that large health spending or health investment will lead to a healthier population and work force. This potentially reduces a foreign investor's health-related cost and productivity loss due to health issues, both which is attractive to cost-minimizing investors.

That fact that low- and middle-income countries and high-income countries exhibit different patterns in terms of health effects on FDI inflow can be explained by catch-up theory. That is, high-income countries have maintained a high level of both population health status and spending on health for a long time while in most low- and middle-income countries, the health status is improving, more investment is being directed to health and they are catching up. Hence, the health effect in attracting FDI inflow is more obvious in the low- and middle-income countries.

Our results are consistent with findings from Alsen et al (2006) and Xu (2008). Both find health cost has significant and positive impact on FDI inflows in low- and middle-income countries. While Xu also finds health cost is a significant determinant of FDI inflow in high-income countries, Alsen et al does not find evidence to support that.

Many governments have recognized foreign direct investment as a positive and important source of growth and development for a long time and have developed various special policies (e.g., tax credit, R&D funds) to attract foreign investments. Some East Asian countries have even taken the steps to set up special agencies or taskforces aimed at bringing in investment from foreign investors. The results of this research offer some evidence to those FDI-seeking governments that investing in health may also be a good idea to attract foreign investors. It certainly entails a long term plan, but its effect may be significant. Invest more in health will likely give investors confidence that the health cost out of their pocket may be lower and as a result of a potentially healthier workforce, the productivity loss (for example, production disruptions and reduction due to employees' absence or sickness) may also be lower. Hence, it will reduce the overall cost of their investment. In this sense, when making policies to attract FDI, governments may also consider expanding their investment in health, especially of those who are still at their working age.

For investors who are looking for new investment opportunities overseas, this study identifies health as one of the important characteristics of a country worth considering when choosing where to invest. Our research offers a new perspective that health cost, both direct and indirect, has a significant positive impact on FDI inflow. For investors who have already made investments in foreign countries but are looking to improve their investments, it may be worthwhile to review their current investment practices and determine if health cost contributes to or undermines their success. For both investors, it is worth even more attention if they choose to invest in low- and middle-income countries. Our research shows that the effect of health costs on FDI inflow is more significant and larger in those counties than in high-income countries. Many investors prefer low- and middle-income countries because of their stock of low-wage workers, but we argue that direct health cost and associated indirect health cost as a result of productivity loss are also an important aspect of cost and when adding those costs to the existing cost formula, it may not be a good investment destination any more.

One thing we would like to improve in this study and also one of the limitations of this study is data availability, which probably applies to all cross country time series studies. We'd like to include more years so that we can also capture the transitions those now high-income countries went through in terms of population health status and health expenditure, and compare it to the low- and middle-income countries to possibly get a clearer picture of the health effect, both direct and indirect, on FDI.

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Appendix A

FDI Development by Region

Over the past 20 years, Europe was the single region that attracted the most foreign direct investment. With steady growth since the beginning of 1990s and a big boom in the mid and late 1900s, it reached its first peak in 2000, at $725 billion. The following years witnessed a sharp decline as the result of the burst of internet bubble and a series of labor market crises. In 2004, Europe's FDI inflow bottomed out to reach its lowest point in almost a decade. As the economy recovered, FDI again started to grow steadily and the pre-financial crisis years had definitely been the best years as far as foreign direct investment is concerned for Europe as a whole. In 2007, Europe reached an all-time high with FDI inflows of nearly $900 billion, registering a 20% increase over its previous 2007 peak. The global financial crisis undoubtedly played an important role in explaining the free-fall in FDI since 2008. Some signs of weak recovery gave a lot of hope in 2010 but the double dip in countries like Greece, Italy, Portugal and Spain (see Table 1 below), all of which were trapped by their debt problems and unemployment, made it hard for the region to see positive FDI growth.

East Asia

Due to its low labor cost and in some cases, fairly good infrastructure, East Asia has long been a success story in attracting foreign direct investment, which in turn, made a huge contribution to economic growth. We see the impact of the 1999-2000 crisis and 2007 global financial crisis on East Asia's FDI inflow, but soon overcome by its vast growth potential and economic attractiveness. Overall, FDI inflows grew steadily over the past 20 years with the 2010 level almost 25 times of that in 1990.

North America

North America follows the same pattern as Europe with the overall trend smoother and a stronger recovery after the 2007 financial crisis. Similarly, the two crises had a huge impact on FDI inflows and the years leading to the crisis were the best years.

South America

In addition to East Asia, South America has been another success story in attracting foreign direct investment. In 2011, FDI flows to South America increased by 165 to a record high $217 billion. Thanks to the size of its domestic market and rate of return, Brazil attracted $67 billion FDI, an increase of 37% (55% of South America's FDI inflows), and it remained by far the largest FDI target in the region.

Africa

Africa has received double digit growth FDI growth in the past. However, it has been continuously falling since 2008, due to the global crisis and recent regional turmoil in North Africa. However, this overall declining trend in FDI, does not reflect the situation across all parts of the continent. Sub-Saharan Africa and South Africa both recovered in recent years.

In Figure 1 we can see the overall FDI inflow trend by region. Being the two biggest FDI destinations and sharing very similar patterns, Europe and North America have gone through the ups and downs parallel to their economic booms and downturns. The developing world, in particular East Asia, despite the impact of the recent disastrous financial crisis, is showing a strong upward trend and high growth potential.

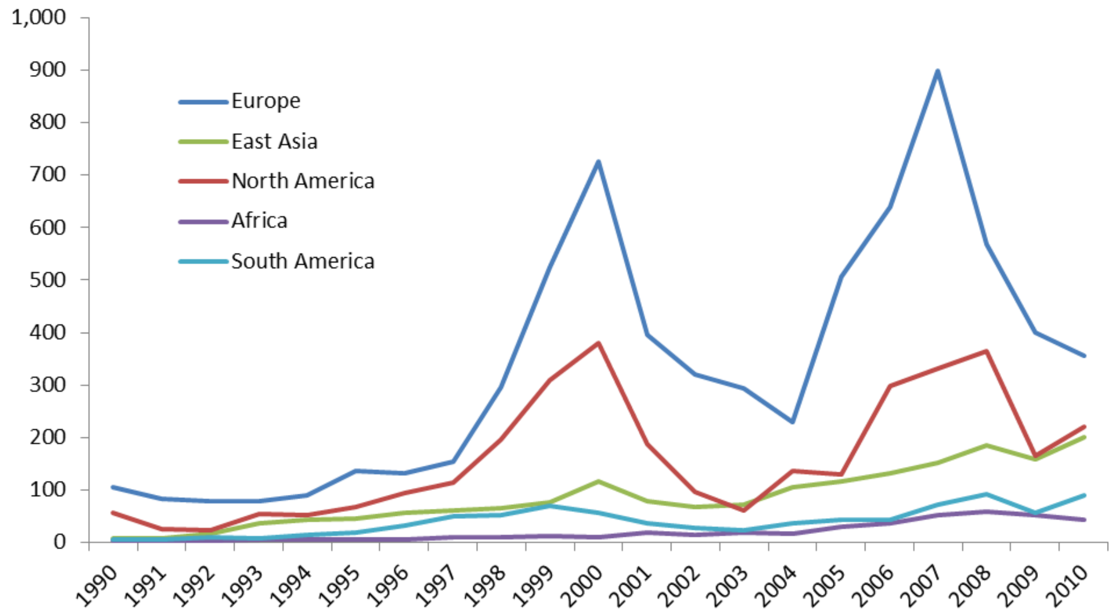


Figure A.1. FDI inflows, by region and economy (billions of dollars), 1990-2010

Appendix B

OECD Health Expenditure by Country

Figure B.1. Health expenditure as a share of GDP in OECD countries, 2010

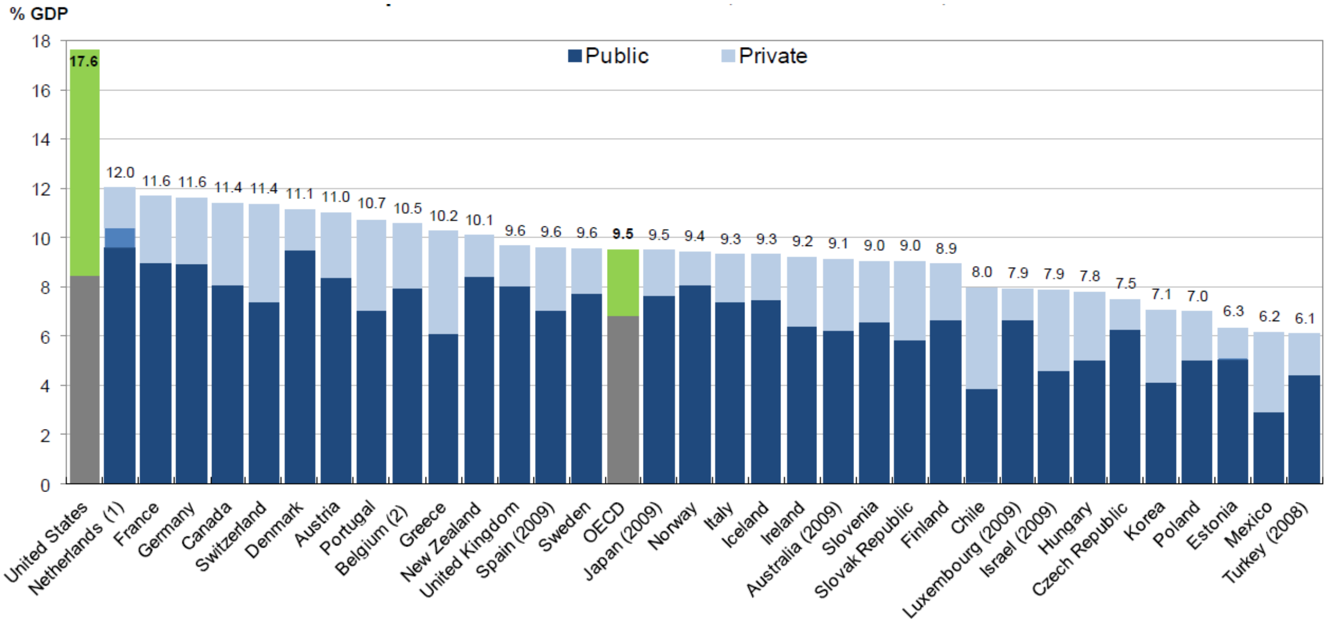
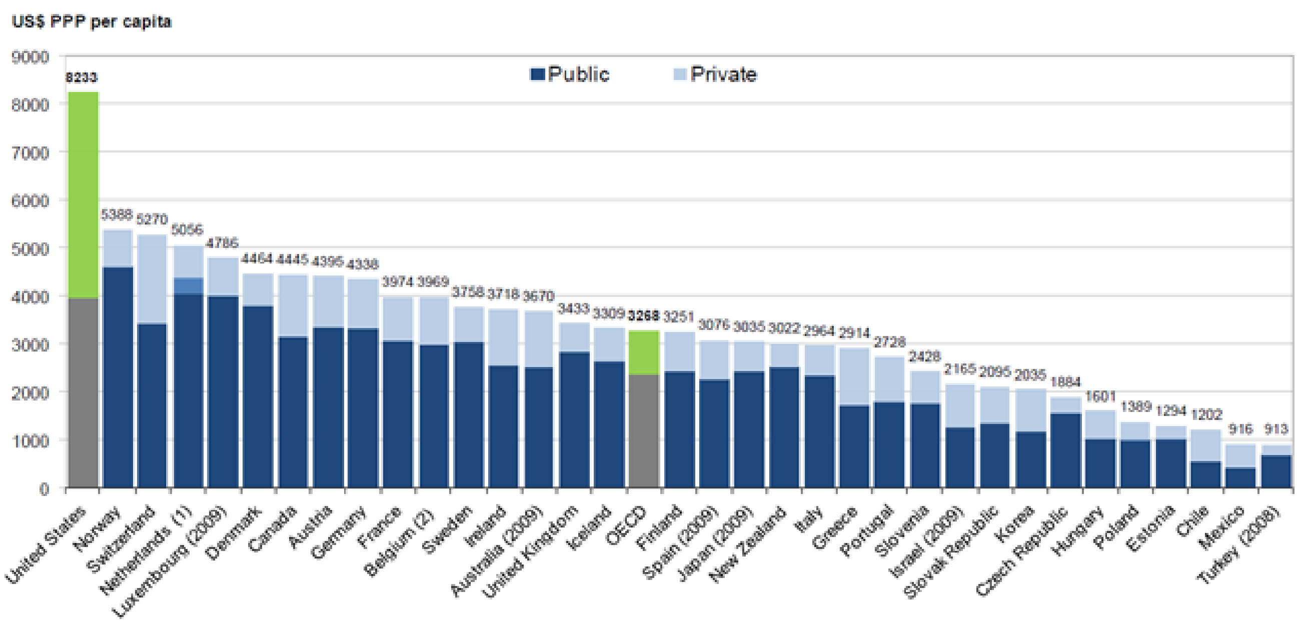


Figure B.2. Health expenditure per capita, public and private, OECD countries, 2010



Appendix C

List of Countries in Sample

High-income Countries	Low- and Middle-income Countries	
Australia	Argentina	Peru
Austria	Bolivia	Philippines
Belgium	Brazil	Rwanda
Canada	China	Senegal
Switzerland	Cameroon	El Salvador
Chile	Costa Rica	Thailand
Denmark	Dominican Republic	Turkey
Spain	Algeria	Uganda
Finland	Ecuador	Venezuela
France	Guatemala	South Africa
United Kingdom	Indonesia	Zambia
Greece	India	
Ireland	Iran	
Italy	Jordan	
Japan	Kenya	
Netherlands	Sri Lanka	
Norway	Mexico	
New Zealand	Mali	
Portugal	Mozambique	
Singapore	Mauritius	
Sweden	Malaysia	
Trinidad and Tobago	Nicaragua	
Uruguay	Pakistan	
United States	Panama	

Appendix D

Countries in Sample Ranked by Average Estimated TFP 1995-2010

Country	Rank	TFP	Country	Rank	TFP
United States	1	2939.47	China	31	709.00
United Kingdom	2	2660.11	India	32	706.41
France	3	2241.71	Algeria	33	703.99
Italy	4	2093.51	Iran, Islamic Rep.	34	700.32
Norway	5	1908.65	Malaysia	35	689.35
Japan	6	1772.20	Dominican Republic	36	660.91
Canada	7	1770.91	Indonesia	37	592.61
Denmark	8	1736.05	Peru	38	569.08
Netherlands	9	1729.31	Costa Rica	39	566.94
Switzerland	10	1674.22	Panama	40	547.32
Spain	11	1626.17	Uruguay	41	538.05
Ireland	12	1622.05	El Salvador	42	535.54
Belgium	13	1611.86	Ecuador	43	531.96
Sweden	14	1602.47	Mali	44	527.52
Australia	15	1568.81	Mozambique	45	509.29
Austria	16	1534.01	Pakistan	46	508.37
Turkey	17	1520.75	Thailand	47	480.61
Finland	18	1415.10	Mauritius	48	463.09
Singapore	19	1360.13	Jordan	49	415.65
Greece	20	1330.93	Philippines	50	395.84
Mexico	21	1297.01	Cameroon	51	390.38
Portugal	22	1165.53	Kenya	52	303.46
Brazil	23	1092.56	Senegal	53	298.37
South Africa	24	1065.74	Zambia	54	296.73
New Zealand	25	1065.59	Sri Lanka	55	294.91
Venezuela, RB	26	1017.21	Nicaragua	56	291.06
Chile	27	924.95	Bolivia	57	267.69
Trinidad and Tobago	28	760.69	Uganda	58	246.11
Argentina	29	759.39	Rwanda	59	242.78
Guatemala	30	723.77			

Appendix E

Results for Alternative Specification (add t in the TFP estimation stage, everything else in the same fashion as in thesis)

E.1 TFP Estimation

Table E.1 Production Function Estimation Results

VARIABLES	Log GDP per worker
Log Capital Stock per worker	0.37***
	(0.04)
Log Avg Years of Schooling	0.53***
	(0.10)
Log Labor Force	-0.41***
	(0.10)
t	0.01***
	(0.00)
Observations	231
Number of countries	59
R-squared	0.74

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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E.2 Stage One Regression

Table E.2 Stage One Regression Results

Dependent Variable: TFP (estimated)

VARIABLES	(1) All Countries	(2) All Countries	(3) Low- and Middle-Income Countries	(4) Low- and Middle-Income Countries	(5) High-Income Countries	(6) High-Income Countries
Life Expectancy	0.007**	0.007**	0.009**	0.009**	0.002	0.010
	(0.003)	(0.003)	(0.004)	(0.004)	(0.009)	(0.009)
Log Population	0.028	0.044**	0.060**	0.069***	-0.017	-0.004
	(0.020)	(0.019)	(0.026)	(0.026)	(0.031)	(0.029)
Log Inflation	-0.207**	-0.199**	-0.305***	-0.285**	-0.056	-0.165
	(0.091)	(0.087)	(0.111)	(0.110)	(0.228)	(0.210)
Government size		-0.014***		-0.010**		-0.020***
		(0.004)		(0.005)		(0.005)
Observations	223	223	132	132	91	91
R-squared	0.488	0.533	0.583	0.585	0.149	0.222
Number of countries	59	59	35	35	24	24

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

E.3 Stage Two Regression

Table E.3 Stage Two Regression for Log FDI Inflow (Full Sample)

VARIABLES	(1)	(2)	(3)	(4)
Log Health Expenditure	0.868***	0.618***	0.863***	0.560***
	(0.115)	(0.120)	(0.204)	(0.185)
Log TFP	1.222	1.131	1.661	2.085
	(0.879)	(0.974)	(1.600)	(1.486)
Trade Openness	0.016***	0.015**	0.029***	0.021**
	(0.006)	(0.006)	(0.010)	(0.010)
Corruption Index		0.271*		0.180
		(0.151)		(0.209)
Log Railway Length			0.313	0.541
			(0.480)	(0.502)
Observations	220	185	220	185
R-squared	0.335	0.292	0.333	0.316
Number of countries	59	59	59	59

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.4 Stage Two Regression for Log FDI Inflow (Low- and Middle-Income Countries)

VARIABLES	(5)	(6)	(7)	(8)
Log Health Expenditure	1.087***	0.781***	1.415***	0.897***
	(0.132)	(0.132)	(0.291)	(0.234)
Log TFP	3.954*	4.266*	5.356*	4.978*
	(2.042)	(2.222)	(2.755)	(2.843)
Trade Openness	0.027***	0.019*	0.042***	0.039**
	(0.010)	(0.010)	(0.015)	(0.016)
Corruption Index		0.270		0.162
		(0.232)		(0.263)
Log Railway Length			0.152	0.302
			(1.183)	(1.217)
Observations	132	101	132	101
R-squared	0.455	0.417	0.479	0.546
Number of countries	35	35	35	35

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.5 Stage Two Regression for Log FDI Inflow (High-Income Countries)

VARIABLES	(9)	(10)	(11)	(12)
Log Health Expenditure	0.417*	0.500**	0.556	0.523
	(0.221)	(0.231)	(0.334)	(0.341)
Log TFP	0.083	-0.279	-2.519	-0.735
	(0.947)	(0.993)	(2.233)	(1.868)
Trade Openness	0.010	0.011	0.021	0.010
	(0.007)	(0.007)	(0.014)	(0.011)
Corruption Index		0.218		-0.082
		(0.190)		(0.390)
Log Railway Length			0.092	0.520
			(0.536)	(0.523)
Observations	88	84	88	84
R-squared	0.242	0.262	0.314	0.320
Number of countries	24	24	24	24

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1