.<br>مممومات

UNIVERSIDAD CARLOS III DE MADRID

working papers

Working Paper 08-19 Departamento de Economía Economic Series (11) Universidad Carlos III de Madrid June 2008 Calle Madrid, 126 28903 Getafe (Spain) Fax (34) 916249875

# Robust Methodology for Investment Climate Assessment on Productivity: Application to Investment Climate Surveys from Central America<sup>1</sup>

Alvaro Escribano\* J. Luis Guasch\*\*

### Abstract

 $\overline{a}$ 

Developing countries are increasingly concerned about improving country competitiveness and productivity, as they face the increasing pressures of globalization and attempt to improve economic growth and reduce poverty. Among such countries, Investment Climate Assessments (ICA) surveys at the firm level, have become the standard way for the World Bank to identify key obstacles to country competitiveness, in order to prioritize policy reforms for enhancing competitiveness. Given the surveys objectives and the nature and limitations of the data collected, this paper discusses the advantages and disadvantages of using different productivity measures. The main objective is to develop a methodology to estimate, in a consistent manner, the productivity impact of the investment climate variables. The paper applies it to the data collected for ICAs in four countries: Costa Rica, Guatemala, Honduras and Nicaragua. Observations on logarithms (logs) of the variables are pooled across three countries (Guatemala, Honduras and Nicaragua). Endogeneity of the production function inputs and of the investment climate variables is addressed by using a variant of the control function approach, based on individual firm information, and by aggregating investment climate variables by industry and region. It is shown that it is possible to get robust results for 10 different productivity measures. The estimates for the four countries show how relevant the investment climate variables are to explain the average level of productivity. IC variables in several categories (red tape, corruption and crime, infrastructure and, quality and innovation) account for over 30 percent of average productivity. The policy implications are clear: investment climate matters and the relative impact of the various investment climate variables indicate where reform efforts should be directed in each country. It is argued that this methodology can be used as a benchmark to assess productivity effects in other ICA surveys. This is important because ICA surveys are available now for more than 65 developing countries.

#### JEL Clasification: D24, L60, O54, C01.

Keywords: Total factor productivity, investment climate, competitiveness, firm level determinats of productivity, robust productivity impacts.

 $<sup>1</sup>$  We are indebted to Jorge Pena, Heisnam Singh and Rodolfo Stucchi for their excellent research assistance. This paper</sup> is an extension of Escribano and Guasch(2005). We have benefited from the suggestions and questions from Paulo Correa, Juan Miguel Crivelli, Pablo Fajnzylber, Luke Haggarty, Danny Leipziger, Eduardo Ley, Marialisa Motta, Jose Guillherme Reis, Isabel Sánchez and Stefka Slavova, and from participants at a World Bank seminars, CORE (UCL) seminar and the American Association meetings in Chicago, January 2006.

<sup>\*</sup> Telefónica-UC3M Chair on Economics of Telecommunications. Departamento de Economía, Universidad Carlos III de Madrid, Madrid 126, 28903 Getafe, Spain. Email: alvaroe@eco.uc3m.es. http://www.eco.uc3m.es/ \*\* World Bank and University of California, San Diego.

## **CONTENTS**



## LIST OF TABLES



## LIST OF FIGURES



## INTRODUCTION

As developing countries face the pressures and impacts of globalization, they are seeking ways to stimulate growth and employment within this context of increased openness. With most of these countries having secured a reasonable level of macroeconomic stability, they are now focusing on issues of competitiveness and productivity through microeconomic reform programs. From South East Asia to Latin America, countries are reformulating their strategies and making increased competitiveness a key priority of government programs.

A significant component of country competitiveness is having a good investment climate or business environment. The investment climate, as defined in the World Development Report (2005), is "the set of location-specific factors shaping the opportunities and incentives for firms to invest productively, create jobs and expand." It is now well accepted and documented, conceptually and empirically, that the scope and nature of regulations on economic activity and factor markets - the so-called investment climate and business environment - can significantly and adversely impact productivity, growth and economic activity (see Bosworth and Collins, 2003; Dollar et al., 2004; Rodrik and Subramanian, 2004; Loayza, Oviedo and Serven, 2004; McMillan, 1998 and 2004; OECD, 2001; Wilkinson, 2001; Alexander et al., 2004; Djankov et al., 2002; Haltiwanger, 2002; He et al., 2003; World Bank, 2003; and World Bank, 2004 a,b). Prescott (1998) and Parente and Prescott (2002) argue that to understand large international income differences, it is necessary to explain differences in productivity (TFP). His main candidate to explain those gaps is the resistance to the adoption of new technologies and to the efficient use of current operating technologies, which in turn are conditioned by the institutional and policy arrangements a society employs (investment climate variables). Recently, Cole et al. (2004) also have argued that Latin America has not replicated Western economic success due to the productivity (TFP) gap. They point to competitive barriers (investment climate variables in our analysis) as the promising channels for understanding the low productivity observed in Latin American countries.

Figures 1a to 1c plot the evolution of the GDP-per capita, of labor productivity and labor force participation in Costa Rica, Guatemala, Honduras and Nicaragua, relative to the values of the US. Since the relative labor force participation of each country is stable since 1975, the decline in GDP per capita is mainly due to the observed decline in labor productivity, indicating that the gap in both series, relative to the US, is increasing

through time (divergence). Therefore, it is clear that these countries have a serious productivity problem. In this paper we want to study the elements related to the investment climate of those three Caribbean countries in order to identify the bottlenecks for productivity growth in the areas of; infrastructure, red tape and corruption and crime, finance and corporate governance and, quality, innovation and labor skills.

Government policies and behavior exert a strong influence on the investment climate through their impact on costs, risks and barriers to competition. Key factors affecting the investment climate through their impact on costs are: corruption, taxes, the regulatory burden and extent of red tape in general, input markets regulation (labor and capital), the quality of infrastructure, technological and innovation support, and the availability and cost of finance.

For example, Kasper (2002) shows that poorly understood "state paternalism" has usually created unjustified barriers to entrepreneurial activity, resulting in poor growth and a stifling environment. Kerr (2002), shows that a quagmire of regulation which is all too common, is a massive deterrent to investment and economic growth. As a case in point, McMillan (1988) argues that obtrusive government regulation before 1984 was the key issue in New Zealand's slide in the world per-capita income rankings. Hernando de Soto (2002) describes one key adverse effect of significant business regulation and weak property rights: with costly firm regulations, fewer firms choose to register and more become informal. Also, if there are high transaction costs involved in registering property, assets are less likely to be officially recorded, and therefore cannot be used as collateral to obtain loans, thereby becoming "dead" capital.

Likewise, poor infrastructure and limited transport and trade services increase logistics costs, rendering otherwise competitive products uncompetitive, as well as limiting rural production and people's access to markets, which adversely affects poverty and economic activity (Guasch, 2004).

The pursuit of greater competitiveness and a better investment climate is leading countries -often assisted by multilaterals such as the World Bank - to undertake their own studies to identify the principal bottlenecks in terms of competitiveness and the investment climate, and to evaluate the impact these have, to set priorities for intervention and reform. The most common instrument used has been firm-level surveys, known as Investment Climate surveys (ICs), from which both subjective evaluations of obstacles and objective hard-data numbers with direct links to costs and productivity are elicited and imputed. Such surveys collect data at firm level on the following themes: infrastructure, bureaucracy and corruption, technology and quality, human capital, corporate governance, crime and security, and financial services.

While the ICs are quite useful in identifying major issues and bottlenecks as perceived by firms, the data collected is also meant to provide a quantitative assessment of the impact or contribution of the investment climate (IC) variables on productivity. In turn, that quantified impact is used in the advocacy for, and design of, investment-climate reform. Yet providing reliable and robust estimates of productivity estimates of the IC variables from the surveys is not a straightforward task. First, ICs do not provide balance panel-type data on all the variables. Second, the production function is not observed; and third, there is an identification issue separating Total Factor Productivity (TFP) from the production function inputs. When any of the production function inputs is influenced by common causes affecting productivity, like IC variables or other plant characteristics, there is a simultaneous equation problem. In general, one should expect the productivity to be correlated with the production function inputs and, therefore, inputs should be treated as endogenous regressors when estimating production functions. This demands special care in the econometric specification for estimating those productivity effects and in the choice of the most appropriate way of measuring productivity.

There is an extensive literature discussing the advantages and disadvantages of using different statistical estimation techniques and/or growth accounting (index number) techniques to estimate productivity or Total Factor Productivity in levels (TFP) or in rates of growth (TFPG). For overviews of different productivity concepts and aggregation alternatives see, for example, Solow (1957), Jorgenson, Gollop and Fraumeni (1987), Hall (1990), Olley and Pakes (1996), Foster, Haltiwanger and Krizan (1998), Batelsman and Doms (2000), Hulten (2001), Diewert and Nakamura (2002), Jorgenson (2003), Barro and Sala-i-Martin (2004) and Van Biesebroeck (2007).

In this paper we discuss the applicability of some of these techniques to the problem at hand and present adaptations and adjustments that provide a best fit for the described objective: estimating robust productivity impact of IC variables collected through firmlevel surveys across countries; investment climate surveys.

The development of a consistent econometric methodology to be used in most developing countries as a benchmark for evaluating the impact of IC variables on productivity at the firm level is the main objective of this paper. To illustrate its

applicability and usefulness, the methodology is used to assess the productivity impact in four different countries, Costa Rica, Guatemala, Honduras, and Nicaragua, with the ICs data collected for 2001 and 2002 (Guatemala, Honduras, and Nicaragua) and 2002, 2003 and 2004 (Costa Rica).

Using a common productivity methodology is essential for benchmarking and for cross country comparisons of the empirical results. This methodology is intended to give robust empirical results and aims at explaining the reasons why different research groups addressing common issues might reach opposite conclusions, even sharing the same data set. At the same time, in support of diversity and cross fertilization, having alternative econometric approaches should help identifying limitations, advantages or disadvantages of each approach. Those productivity results that are robust to different approaches should play a key role in the formulation of clear policy recommendations for developing countries. This robust econometric approach can be justified using the statistical sensitivity analysis discussed in Magnus and Vasnev (2007).

This paper is structured as follows. Section 2 introduces the concepts of productivity and discusses general productivity measures based on levels versus differences. We conclude that, given the fixed effect nature of IC variables obtained form ICs, it is better to analyze productivity in levels (or log-levels) rather than rates of growth of productivity. This section also introduces a consistent econometric methodology for the selection of IC and firm explanatory variables for different productivity measures. This econometric strategy is applied to study the investment climate determinants of productivity in Costa Rica, Guatemala, Honduras and Nicaragua. Section 3, describes in detail the estimation issues and presents the results. This section also suggests evaluating the country specific contribution of IC variables to average productivity, if we have estimated common elasticities by pooling the data from several countries. Section 4 compares our empirical results with the results form using other methods suggested in the literature to estimate production functions. Finally, section 5 presents a summary of the econometric methodology and of the main conclusions. All the figures and tables with the definitions of the variables used and with the panel data estimation results are included in the appendix.

## 1 Productivity and Total Factor Productivity Measures for the Analysis of the Productivity Impact of Investment Climate (IC) Variables

The econometric methodologies discussed in this paper are applied to study the productivity determinants of variables collected at the firm level. In particular, we consider the impact of investment climate (IC) variables and other firm control variables (C) on several productivity measures. We classify the IC variables into four broad categories: i) infrastructure, ii) red tape, corruption and crime, iii) finance and corporate governance and iv) quality, innovation and labor skills; see Tables 3a to 3d of the appendix.

Productivity (P), or multifactor productivity, refers to the effects of any variable different from the inputs --labor (L), intermediate materials (M) and capital services (K)--, affecting the production (sales) process. To be more specific, consider that the production function Q=F(L,M,K,  $\alpha$ ) and the productivity ( $P_{it}$ ) equation of the firm (i) at period (t) are given by:

$$
Y_{it} = F(L_{it}, M_{it}, K_{it}, \alpha_{F, it}) P_{it}
$$
 (1a)

$$
P_{it} = G(IC_{it}, C_{it}, \alpha_{IC.it}) \exp(u_{it})
$$
 (1b)

where u<sub>it</sub> is a random error term with properties that will be specified later on. The individual firms are indicated by the sub-index  $i = 1, 2, ..., N$ , where N is the total number of firms in the sample and by the sub-index time  $t = 1, 2, ..., T$ , where T is the total number of years in the sample. In the IC surveys, N is large and T is small.

When any of the input variables (L, M and K) is influenced by common causes affecting productivity, like IC variables or other firm characteristic variables (C), we have a simultaneous equation problem. (See Marschak and Andews, 1944, and Griliches and Mairesse, 1995). In general, we should expect productivity to be correlated with the inputs L, M and K, and therefore the inputs must be treated as endogenous regressors when estimating production functions. Blundell and Bond (2000) discuss a solution, System-GMM, to this endogenous regressors problem based on a generalized method of moments (GMM) approach, applied to persistent panel data. Olley and Pakes (1996),

Levinsohn and Petrin (2003) and Akerberg, Caves and Frazer (2007) suggest structural approaches to estimate production functions.

A specific solution to this endogeneity problem of the inputs L, M and K in (1a) will be presented in section 2.2 when estimation issues of production functions are discussed. Taking logarithms in (1a) and (1b),

$$
\log Y_{it} = \log Q_{it} + \log P_{it} \tag{2a}
$$

$$
logP_{it} = log G(IC_{it}, C_{it}) + u_{it}
$$
 (2b)

where  $\log P$  is the "residual" from equation (2a) and  $\log Q = \log F(L,M,K)$ . That is, the log of productivity (P) is the difference between the logarithm of output (Log Y) and the logarithm of aggregate input (log Q) formed by L, M and K. Differentiating (2a) and (2b) we get similar expressions for the rates of growth:

$$
d \log Y_{it} = d \log Q_{it} + d \log P_{it} \tag{3a}
$$

$$
dlogP_{it} = dlogG(IC_{it}, C_{it}) + du_{it}. \qquad (3b)
$$

From equations (3a) and (3b) it is clear that we would like to be able to assign to dlog $P_{it}$ all those changes different than  $L_{it}$ ,  $M_{it}$  and  $K_{it}$ , that shift the production function of firm i in period t, while associating the movements along the production function with changes in the aggregate input<sup>2</sup>, dlog $Q_{it}$ .

$$
d \log Y_{it} = \frac{\partial \log F_{it}}{\partial L_{it}} dL_{it} + \frac{\partial \log F_{it}}{\partial M_{it}} dM_{it} + \frac{\partial \log F_{it}}{\partial K_{it}} dK_{it} + \frac{\partial \log F_{it}}{\partial P_{it}} dP_{it}.
$$

 $\overline{a}$ 

If the "residual" or the weighted rate of growth of P<sub>it</sub>, which is  $\frac{\partial \log F_{it}}{\partial P_{tt}} dP_{it} = \alpha_{P,i} d \log P_{it}$ it  $\frac{F_{it}}{dt}dP_{it} = \alpha_{p_{it}}d\log P_{it}$  $\frac{\partial \log F_{it}}{\partial P_{it}} dP_{it} = \alpha$  $\frac{\partial \mathcal{L}_{S-u}}{\partial P_{it}} dP_{it} = \alpha_{P,it} d\log P_{it}$ , has

<sup>&</sup>lt;sup>2</sup> Consider the extended production function  $Y_{it} = F(L_{it}, M_{it}, K_{it}, P_{it})$ , where  $P_{it}$  is an aggregate productivity index which incorporates technological changes, recent innovations, etc., in the production of  $Y_{it}$ . In this general specification, any improvement in  $P_{it}$ , perhaps due to improvements in IC conditions, represents a movement along the production function as well as a shift of the production function.

elasticity  $\alpha_{p,i} = 1$  then dlogP<sub>it</sub>=dlogTFP<sub>it</sub>, where TFP refers to the Total Factor Productivity. However, when the separability conditions (Hicks neutral technical, etc.) are not satisfied, see Jorgenson, Gollop and Fraumeni (1987), what we are measuring by the "residual" is the rate of growth of productivity as a time varying weighted rate of growth of  $P_{it}$  and this might not be equal to the rate of growth of TFP. As we will see in the empirical section, those conditions are difficult to satisfy in most countries. So we call the "residual" productivity (P) and not TFP. Our productivity (P) concept is sometimes called *multifactor* productivity.

The next step is to discuss the advantages and disadvantages of using alternative measures of productivity for the evaluation of the impact of IC variables on productivity. From the above discussion is clear that we have two general approaches to measure productivity (P): a) based on the rate of growth of productivity or b) based on the level (or logs) of productivity.

From equations (3a) and (3b) and the comment of footnote 3 we can write (2a) and (2b) in term of their rates of growth<sup>3</sup> as:

$$
d \log Y_{it} = \alpha_{L,it} d \log L_{it} + \alpha_{M,it} d \log M_{it} + \alpha_{K,it} d \log K_{it} + d \log P_{it}
$$
\n(4a)

$$
d \log P_{it} = \alpha_{IC,it} d \log IC_{it} + \alpha_{C,it} d \log C_{it} + du_{it}
$$
\n(4b)

where the coefficients of equation<sup>4</sup> (4a)  $\alpha_{j, it}$  are the heterogeneous and time varying jinput-elasticities of the aggregate input Q,  $j = L$ , M, and K, of firm (i) in period (t). Which of the two approaches, a) or b), is more convenient to evaluate the impact of IC variables on productivity based on ICA surveys?

At first glance, the procedure based on productivity growth seems to be more general and more convenient because it does not require us to specify a particular functional form of the production function F(L,M,K). However, it has serious drawbacks arising from the quality of the data (measurement errors and missing firm observations from one year to the next). The common drawbacks of estimating equation in rates of growth are:

- (i) Measurement errors are enhanced by taking first differences,
- (ii) When the inputs are not strictly exogenous (or "exogenous") the standard simultaneous equation problems imply and least square estimators are inconsistent and biased. The most common solution requires the use of GMM estimators or instrumental variable (IV) estimators. However, equations with variables in differences suffer from the weak instruments problem which produces very poor parameter estimates (Chamberlain, 1982; Griliches and Mairesse, 1995). Recently, Blundell and Bond (2000) have

<sup>&</sup>lt;sup>3</sup> Notice that we are assuming that IC and C variables are scalar and not vectors. At this point this is done to simplify the notation. Later on and also in the empirical application we will consider both as vectors. <sup>4</sup> The coefficients of (4b) are also elasticities and are defined in a similar way.

proposed an alternative GMM estimator for variables that are slow mean reverting (persistent).

(iii) We only have information on IC variables for a single year. Therfore, if we compute rates of growth we lose all the unobservable fixed effects but also all the IC variables.

In order to estimate productivity growth based on equation (4a) we have to take two important decisions:

First. We have to approximate the continuous transformation of the variables, say dlog(Y<sub>it</sub>), by a discrete approximation based on first differences, say  $\Delta$ log(Y<sub>it</sub>) =  $log(Y_{i,t})$ -log( $Y_{i,t-1}$ ). This last approximation requires transforming (4a,) using the Tornqvist<sup>5</sup> (1936) index:

$$
\Delta \log Y_{it} = \overline{\alpha}_{L,i} \Delta \log L_{it} + \overline{\alpha}_{M,i} \Delta \log M_{it} + \overline{\alpha}_{K,i} \Delta \log K_{it} + \Delta \log P_{it}
$$
(5)

where  $\overline{\alpha}_{j,i,t} = \frac{1}{2} (\alpha_{j,i,t} + \alpha_{j,i,t-1})$  $\bar{\alpha}_{j,i,t} = \frac{1}{2} (\alpha_{j,i,t} + \alpha_{j,i,t-1})$  is average input-output elasticity of input j of firm i during the last two years (t and t-1) where  $j = L_{it}$ ,  $M_{it}$  and  $K_{it}$ .

Second. Since the heterogeneous and time varying input-output elasticities  $\alpha_{j}$  are unknown they can be measured by nonparametric procedures, index number techniques (see Solow 1957, Diewert and Nakamura 2002) or estimated by regression techniques, assuming that the input-output elasticity parameters are constant in some sense. In this paper, we will consider two possibilities: constant input-output elasticities by industry pooling and not pooling across countries, and constant elasticity parameters at the aggregate level pooling and not pooling countries.

To understand why the characteristics of World Bank investment climate surveys (ICs) favor the productivity analysis done in levels, we describe now the main ICs properties of these four Central America countries.

 $<sup>5</sup>$  Jorgenson and Griliches (1967), among others, suggested to use this Tornqvist index as an approximation to</sup> the continuous Divisia index.

## 1.1 Description of the Data

 $\overline{a}$ 

The data base of each country is a short unbalanced panel with temporal observations of most variables for 2001 and 2002 (T=2) in Guatemala Honduras, and Nicaragua and 2002, 2003 and 2004 (T=3) in Costa Rica. However, for the IC variables, which are listed in Tables 3a to 3d of the appendix, we have observations only for the year 2002 in Guatemala, Honduras, and Nicaragua and for the year 2004 for Costa Rica.

This raises the first question: should we only use cross-section data (say only for 2002 for the pool of countries and 2004 for Costa Rica) or, should we also use the recall data from the previous one or two years, even if we do not have information on the IC variables for those years? We assume that, unless there is an important structural break in the preceding, the IC variables at the firm level should not change much from one year to the next. In fact, what can change from one year to the next is the reaction of the firm facing a certain investment climate, but it requires time for the firm to implement the corresponding adjustments. Therefore, for each plant we repeat the values observed of each IC variable for the three years (observable fixed effects).

We are interested in keeping as many observations as possible to benefit from the law of large numbers and the central limit theorems. Hence, we suggest pooling observations across Guatemala, Honduras, and Nicaragua while treating separately Costa Rica<sup>6</sup> This is important because our observations are very unevenly distributed through time and across firms, precluding us from doing separate country analyses of each industry or sector. (See Table 4 of the appendix.) For example, if we conduct an industry analysis country by country, we will end up having in the textile sector of Honduras only nine observations, while if we pool the observations across the three countries we have at least 38 observations, giving more reliable statistical results.

In 2001, after pooling the observations across the three countries, we only have 440 observations while for 2002 we have 1,020 observations. Therefore, if we measure productivity in rates of growth we will end up with at most 440 firms, which is a very small sample size to study differences by industry and by country. However, doing the

<sup>&</sup>lt;sup>6</sup> Some other World Bank studies, see for example Haltiwanger and Schweiger (2005) take an alternative approach. They selected a very large pool of countries (say 30 countries) and estimate only a cross section. However, by doing that cross country analysis at the firm level, we generally loose a lot of firms from the sample because we do not have a large common set of IC variables for very different countries. This approach suffer important sample representation issues or sample selection biases. We believe that selecting a small group of countries with similar number of responses to the questions of the ICA surveys, increases the representativeness of the sample and the number of observations.

analysis in levels or logs we get 1,460 observations in total. From Table 4 of the appendix it is clear that the three countries have similar number of observations for the two-year period: Guatemala has 468 firms, Honduras 472 and Nicaragua 521.

In all the regressions we use several productivity measures, 11 dummy variables  $(D_r, r)$  $= 1, 2, ..., 11$ ) and a constant term (intercept). That is, we control for a constant industry effect of the nine industries (apparel, beverages, chemicals/rubber, food/tobacco, furniture/wood, leather/shoes, nonmetallic minerals, textiles, metal), by including only eight dummy variables, leaving out apparel to avoid having perfect multicolinearity with the constant term. Similarly, we add only one yearly dummy variable leaving out the corresponding dummy for the year 2001. Finally when we pool countries, to control for a constant country effect, we include two dummies, one for Honduras and the other for Nicaragua, with Guatemala omitted. In the case of Costa Rica we have enough observations to avoid pooling the ICs with the other three Caribbean countries but we also use 9 dummy variables (seven industry dummies and two dummies of year).

## 1.2 The level of firms' productivity

To estimate productivity in levels we have to specify a functional form of the production function. If the functional form F(L,M,K) is Cobb-Douglas, estimating productivity in levels requires estimation of the following well known equation,

$$
\log Y_{it} = \alpha_L \log L_{it} + \alpha_M \log M_{it} + \alpha_K \log K_{it} + \alpha_p + \log P_{it}.
$$
\n<sup>(6)</sup>

When the parametric functional form of the production function is Translog, the equation becomes:

$$
\log Y_{it} = \alpha_L \log L_{it} + \alpha_M \log M_{it} + \alpha_K \log K_{it} ++ \frac{1}{2} \alpha_{LL} (\log L_{it})^2 + \frac{1}{2} \alpha_{MM} (\log M_{it})^2 + \frac{1}{2} \alpha_{KK} (\log K_{it})^2 ++ \alpha_{LM} (\log L_{it}) (\log M_{it}) + \alpha_{LK} (\log L_{it}) (\log K_{it}) + \alpha_{MK} (\log M_{it}) (\log K_{it}) ++ \alpha_p + \log P_{it}.
$$
\n(7)

The third alternative considered in this paper is to use a nonparametric or index number approach based on cost-shares from Hall (1990) to obtain the Solow´s residual in levels (logs)

$$
\log P_{it} = \log Y_{it} - \overline{s}_L \log L_{it} - \overline{s}_M \log M_{it} - \overline{s}_K \log K_{it}
$$
\n(8)

where  $\overline{s}_j$  is the aggregate *average cost shares* from the last two years<sup>7</sup> given by  $,t \quad \text{or} \quad j, t-1.$  $\frac{1}{2}(s_{it}+s_{it-1})$  $\overline{s}_j = \frac{1}{2}(s_{j,t} + s_{j,t-1})$  for  $j = L$ , M and K. The advantage of the Solow residuals, Solow(1957), is that it does not require the inputs (L, M, K) to be exogenous nor the input-output elasticities to be constant nor heterogeneous. The drawback is that it requires to have constant returns to scale (CRS) and at least competitive input markets. Measuring productivity in levels (or in logs) it is less demanding in terms of:

- (i) data quality (since it allows to treat unbalanced panel without loosing many observations),
- (ii) measurement errors, and

 $\overline{a}$ 

(iii) allowing constant firm specific fixed IC variables (observable fixed effects).

This productivity approach in levels is in line with Hall and Jones (1999) when they say that "to explain differences in levels of long-run economic success across countries, one is forced to focus on more basic determinants: infrastructure, persistent barriers (why is technology and capital not moving fast across borders) ..." and continue saying that "Long-run determinants of economic success are factors that are changing slowly over time". Those determinants are associated in this paper with firm specific investment climate (IC) fixed effects.

Therefore, the estimation strategy suggested for productivity levels, can be justified from the following simplified structural simultaneous equations model which includes the following equations: a production function, a productivity equation, determinants of the unobserved firm specific time-fixed effects and the inputs demands of L, M and K (for simplicity we only write the equation for L in  $(9,d)$ ). That is,

 $<sup>7</sup>$  When there is only firm information about a single year we take the average cost share of the firms of</sup> that year.

$$
\log Y_{ii} = \alpha_L \log L_{ii} + \alpha_M \log M_{ii} + \alpha_K \log K_{ii} + \log P_{ii}
$$
\n(9.a)

$$
\log P_{j,i} = a_i + \alpha'_{Ds} D_j + \alpha'_{DT} D_t + \alpha_p + w_{ii}
$$
\n
$$
(9.b)
$$

$$
a_i = \alpha'_{IC} IC_{P,i} + \alpha'_{C} C_{P,i} + \varepsilon_i
$$
\n(9.c)

$$
LogL_{it} = \delta_{IC,L} IC_{L,i} + \delta_{Lw} log (wages)_{it} + v_{Lit}. \qquad (9. d)
$$

where, Y is firms' output (sales), L is employment, M denotes intermediate materials, K is the capital stock, IC and C are time-fixed effect vectors of investment climate and control variables, and  $D_i$  and  $D_t$  are the vectors of industry and year dummies.

The usually unobserved time fixed effects  $(a_i)$  of the TFP equation (9.b) are here proxy by the set of observed time fixed components IC, and C variables of (9.c) and a remaining unobserved random effects  $(\varepsilon_i)$ . The two random error terms of the system,  $\varepsilon_i$  and  $w_i$ , are assumed to be conditionally uncorrelated with the explanatory  $L$ ,  $M$ ,  $K$ ,  $INF$ ,  $IC$  and  $C$  variables<sup>8</sup> of equation (10),

$$
\log Y_{ii} = \alpha_L \log L_{ii} + \alpha_M \log M_{ii} + \alpha_K \log K_{ii} + \alpha'_{IC}IC_{P,i} + \alpha'_{C}C_{P,i} + \alpha'_{Ds}D_j + \alpha'_{DT}D_i + \alpha_P + u_{ii} \quad (10)
$$

Therefore, the regression equation (10) is representing the conditional expectation plus a composite random-effect error term equal to  $u_{it} = \mathcal{E}_i + w_{it}$  and should satisfy standard assumptions of random effects (RE) conditional models. That is,

$$
E\Big[\,w_{ii}\,\,/\text{log}\,L_{ii}\,,\text{log}\,M_{ii}\,,\text{log}\,K_{ii}\,,\,IC_{P,i}\,,\,C_{P,i}\,,\,D_{j}\,,\,D_{t}\,,\,\varepsilon_{i}\,\Big]=0
$$
\n
$$
E\Big[\,\varepsilon_{i}\,\,/\text{log}\,L_{ii}\,,\text{log}\,M_{ii}\,,\text{log}\,K_{ii}\,,\,IC_{P,i}\,,\,C_{P,i}\,,\,D_{j}\,,\,D_{t}\,\Big]=0
$$
\nand 
$$
Var\Big[\,\varepsilon_{i}\,\,/\text{log}\,L_{ii}\,,\text{log}\,M_{ii}\,,\text{log}\,K_{ii}\,,\,IC_{P,i}\,,\,C_{P,i}\,,\,D_{j}\,,\,D_{t}\,\Big]=\sigma_{\varepsilon}^{2}\,.
$$

Notice that we need to condition on the observable fixed effects (IC) to get the orthogonally condition of the inputs L, M and K. That is  $E\left[w_{it} / \log L_{it} \log M_{it} \log K_{it}, D_j, D_t\right] \neq 0$  and also  $E\left[a_i / \log L_{it} \log M_{it} \log K_{it}, D_j, D_t\right] \neq 0$ and therefore the correlation between the unobserved effects and the inputs come the time fixed IC variables. As will become clear later on, the fact that this conditional expectation of  $a_i$  is not equal to cero, invalidates one of the main assumptions of

<sup>&</sup>lt;sup>8</sup> Under this formulation (and other standard conditions) the OLS estimator of the productivity equation (4.2) with robust standard errors is consistent, although a more efficient estimator (GLS) is given by the random effects (RE) estimator that takes into consideration the particular covariance structure of the error term,  $\mathcal{E}_i + W_{it}$ , which introduces certain type of heteroskedasticity in the regression errors of (4.2).

section 4.4 where we discuss Wooldridge (2005) procedure of estimating Ackerberg et al (2007).

Equation (9.a) is the familiar Cobb-Douglas production function, but it is obvious that the argument applies to other functional forms, like the Translog. The second equation (9.b) is the usual firm level productivity equation of firm i in year t. Productivity depends on the unobserved firm specific effects, a<sup>i</sup> , a vector of firm control variables  $(C_{it})$ , industry, country and year dummies  $(D_r)$  and the productivity shocks  $(w_{it})$  which are assumed to be uncorrelated with the inputs (L, M and K).

Many of the usually unobserved firm specific fixed effects  $(a_i)$  are now observed at the micro level (firm level), due to the detailed firm specific information obtained from the ICA´s surveys. In equation (9.c) we add an extra random firm specific fixed effect term  $(\epsilon_i)$  which is the part of the unobserved time fixed effects not correlated with the IC variables  $(IC_i)$ . Notice, that since the number of available firm specific  $IC_i$  variables is very large (in our data base we used more than 50 time fixed effect terms) it is reasonable to assume that  $\varepsilon_i$ 's are uncorrelated with the inputs after conditioning in IC information. The last equation is the input demand equation derived from a competitive labor market $9$ . In particular, the demand for labor depends on wages but also on certain investment climate (IC) fixed effects that affects also the productivity equation.

From this simple structural simultaneous equation model, it is clear that a 2-step estimation approach, where we first estimate the single equation (9.a) to get a measure of productivity and second we use this estimated productivity measure to evaluate the impact of IC variables, will render inconsistent least squares estimations. The measurement error problem of the dependent variable  $(LogP_{it})$  of equation (9.b) is transmitted to rest of the parameters of the productivity equation. The reason is clear, the measurement error term of the dependent variable of equation (9b) includes the inputs (labor, etc.) which from (9.d) are correlated with the IC explanatory variables.

From this simple simultaneous equation model it is clear that direct applications of the production function estimation procedures proposed by of Olley and Pakes (1996), Levinsohn and Petrin (2003) and Akerberg, Caves and Frazer (2007) might generate inconsistent parameter estimates in their first step, derived from the correlation of the inputs with IC variables. Furthermore, these sophisticated estimation procedures require

<sup>&</sup>lt;sup>9</sup> For simplicity we omit the input demand equations of the other two inputs, intermediate materials (M) and capital (K). However, it is clear that IC variables will affect as well those input demands and the same argument applied to the estimation of those inputs-output elasticities.

at least two years of firm level data, and, as we pointed out before, we would loose many observations if we have to track the same firm for more than one year because usually panels based on IC surveys are usually very unbalanced.

The solution we propose to address the endogeneity of the inputs is to estimate an extended production function that incorporates the IC variables driving endogeneity. By joint estimation of the input-output elasticities and the rest of the parameters of the system (IC and C variables), the IC variables are used as proxies for the unobserved firm specific effects  $(a_i)$  and we are therefore controlling for the common cause of endogeneity.

Using similar arguments, we could consistently estimate by least squares, the following Translog extended production function,

$$
\log Y_{it} = \alpha_{L,j} \log L_{it} + \alpha_{M,j} \log M_{it} + \alpha_{K,j} \log K_{it} +
$$
  
+  $\frac{1}{2} \alpha_{LL,j} (\log L_{it})^2 + \frac{1}{2} \alpha_{MM,j} (\log M_{it})^2 + \frac{1}{2} \alpha_{KK,j} (\log K_{it})^2 +$   
+  $\alpha_{LM,j} (\log L_{it}) (\log M_{it}) + \alpha_{LK,j} (\log L_{it}) (\log K_{it}) + \alpha_{MK,j} (\log M_{it}) (\log K_{it}) +$   
+  $\sum_{r=1}^{q_{IC}} \alpha_{IC} \log IC_{r,it} + \sum_{r=1}^{q_{C}} \alpha_{C} \log C_{r,it} + \sum_{r=1}^{q_{D}} \alpha_{D,r} D_{r} + \alpha_{P} + u_{it}$  (11)

This general local functional approximation, allows us to check whether the technology (at the aggregate level or at the industry level) is Cobb-Douglas. Furthermore, with both parametric specifications of the production function we can test the constant returns to scale<sup>10</sup> (CRS) condition behind Solow's residuals (log  $P_i$ ), see equation (8). From equation (12) we can estimate the IC elasticities and semi-elasticities,

$$
\log P_{ii} = \sum_{r=1}^{q_{ic}} \alpha_{IC,r} \log IC_{r,i} + \sum_{r=1}^{q_{c}} \alpha_{C,r} \log C_{r,i} + \sum_{r=1}^{q_{b}} \alpha_{D,r} D_{r} + \alpha_{p} + u_{it}. \tag{12}
$$

Since there is no single salient measure of productivity  $(P_{it})$ , any empirical evaluation on the productivity impact of IC variables might critically depend on the way productivity is measured. Therefore, to get reliable empirical results for policy analysis, we suggest

 $10$  For example, if the coefficients of the inputs (L, M, and K) in the Cobb-Douglas specification of the production function add up to one. Similar but more complicated coefficient restrictions apply for a CRS Translog production function. Tables 8, 9 and 10 show the results for the pool of countries and for Costa Rica.

to look for robust empirical results using several productivity measures. This is the approach we will follow in the rest of the paper.

For this purpose, we use the 10 productivity measures (see section 3) that best fit with the characteristics of our data set: two levels of aggregation (countries and industries), with two parametric production functions (Cobb-Douglas and the Translog) and the Solow residuals for each level of aggregation.

Controlling for the largest set of IC variables and firm characteristics in equations (10) and (11) we can get, under standard regularity conditions, consistent and unbiased least squares estimators of the parameters of the production function and of the productivity equation. That is, we can run OLS from a one-step regression<sup>11</sup> based on the extended production function (10). In the empirical section we allow the errors  $(u_{it})$  from (10) and (11) to be heteroskedastic and therefore we will be using pooling OLS with robust standard errors and also random effects (RE) estimators (GLS).

## 1.3 Endogeneity of the IC Variables

 $\overline{a}$ 

Another econometric problem that we have to face in estimating (10), (11) and (12) is the possible endogeneity of IC variables and some C variables. The traditional instrumental variable (IV) approach is difficult to implement in this context, given that we only have IC variables for one year and therefore we cannot use the natural instruments like those provided by their on lags, and that it is difficult to find good and convincing instruments for them.

To control for the endogeneity of the IC variables, we use the region-industry average of the plant level investment climate variables ( $\overline{IC}$ ) instead of the crude IC variables. This is a common solution in panel data studies at the firm level. In the pool of countries we have, in total, 13 regions for the three countries and 9 industries for each country (See Table 1 for details). In Costa Rica, we have 7 regions and 8 industries (See Table 2). Taking region and industry averages instead of the individual IC variables, is also useful to mitigate the effect of missing individual IC observations. This is an important issue in most of the IC surveys.

 $11$  Alternatively, we could have used an equivalent two-step control function approach procedure where we first estimate by OLS a regression of each of the inputs on all the IC and C variables (partialling out) and then include the residuals of each estimated input equation, instead of the observed inputs, in the production function.

## 1.4 Strategy for IC Variables' Selection

The econometric methodology applied for the selection of the variables (IC, C and PE) goes from the general to the specific. The omitted variables problem that we encounter, starting from a too simple model generates biased and inconsistent parameter estimates. On the contrary, adding irrelevant variables (meaning starting from a very general model with some variables that are irrelevant) gives unbiased and consistent, but inefficient, estimates. Therefore, we start from a general model, such as equations (10) and (11) with all the variables of Tables 3a to 3d included at once, and we reduce this general model to a simpler one with relevant (significant) variables<sup>12</sup>. Note that the final estimated model is efficiently estimated once we have deleted insignificant or irrelevant variables.

In the reduction process we should not delete all insignificant variables at once. Due to multicolinearity, if we drop one variable that is highly correlated with others, some of the insignificant variables might become significant. An informative statistic for this purpose is the variation of the  $R^2$  of the regression (or the standard error of the regression). The  $R^2$  of the simplified model with only significant or relevant variables, see Table 11 for Guatemala, Honduras and Nicaragua and Table 12 for Costa Rica, is smaller but close to the initial  $R^2$  of the most general regression model. We applied this iterative procedure, eliminating the less significant variables leaving, for interpretive purposes, at least one IC variable from each broad category (infrastructure, bureaucracy/corruption, crime, technology and quality, human capital, corporate governance, etc.). The estimated explanatory variables of the regression models of Tables 11 and 12 of the appendix were selected in this way. We include in those tables the set of IC variables that were significant in at least one of the 12 specifications (pooling OLS or random effects). These regression results are consistent (with equal signs and a reasonable range of parameter values). The detailed empirical results are explained in the next section.

 $12$  Sometimes, in the final regression model, we leave IC variables that are not individually significant but are relevant for the model (jointly significant, affect the significance of other variables, etc.). When this happens it could be due to the presence of multicolinearity among some of the explanatory variables.

## 2 Robustness of the Estimated Productivity-IC Elasticities and Semi-elasticities

As we said before, for policy implications we would like the estimated *elasticities*, or semi-elasticities of IC variables to be robust among: 1) different functional forms of the production functions; 2) different consistent estimation procedures; 3) different productivity measures; and 4) different levels of aggregation (industry, country, pooling across countries, etc).



As mentioned in section 2, to reduce the simultaneous equation bias and the risk of getting reverse causality problems if the  $IC<sub>i</sub>$  variables are endogenous, we use their region-industry average ( $\overline{IC}$ ). The coefficients of investment climate ( $\overline{IC}$ ) variables and other plant-specific control  $(C_{it})$  variables are maintained constant for all the firms in Costa Rica and for all the firms in the pool of countries. However, we allow the production function elasticities, and therefore the productivity measures, to change for each functional form (Cobb-Douglas and Translog), and for each different aggregation levels (industry and countries). We consider two levels of aggregation: (i) Restricted

estimation (equal input-output elasticities among industries for the three countries) and (ii) unrestricted estimation (different input-output elasticities for each industry). Moreover, we consider two different estimators (pooling OLS and random effects, RE) for each productivity measure. The following table summarizes the productivity measures and the corresponding IC elasticities that we estimate.

Thus we obtain 10 different productivity measures  $(P_{it})$  and we evaluate the impact of IC variables on each of them based on two estimation procedures pooling OLS and RE. If the sign of the impact of certain IC variables on productivity changes, contingent on the productivity measure used, we would not have a robust or solid empirical result for policy implementation. However, as we will see later, it is possible to obtain robust and consistent results even when the correlations between the alternative measures of productivity differ dramatically. Tables 6 and 7 report the correlations between the log productivity measures obtained from the four single-step production function estimates and from the two Solow residuals. The correlations between the Solow residuals and the productivity measures that result from estimating restricted production functions are high, ranging from 0.87 to 0.98. However, when we allow for different input elasticities across industries (unrestricted production functions) the correlations are lower, ranging from 0.69 in the Cobb-Douglas case to 0.11 in the Translog case.

Figure 2, shows the kernel density of the 1o productivity measures. We observe that that are very different and therefore we might expect the IC elasticities on productivity to change depending on which one we are using. However, as we will se later on, it is possible to get very robust results with any of them. Therefore, it is no so important which one to use in practice if the goal is to estimate the IC elasticities, see section 3.3.

## 2.1 Restricted Coefficient Estimates (equal input-output elasticities)

### 2.1.1 Solow´s Residual (Two-step restricted estimation)

We first obtain the Solow residuals  $(P_{it})$  as in equation (8) and then estimate the impact of IC variables on  $P_{it}$  through regression techniques. This two-step approach overcomes the endogeneity problem for the inputs.

Table 8 shows that the cost share of labor is 0.36 in the pool of countries and 0.33 in Costa Rica. The cost shares of intermediate materials are 0.53 and 0.56, respectively,

and that of capital 0.11 and 0.11. The cost shares add up to one because we are imposing constant returns to scale (CRS).

The empirical results of estimating equation (12) by pooling the observations from the three countries and running OLS and random effects (RE) are in Table 11. Table 12 shows the same estimates for Costa Rica. We comment these results in section 3.3.

## 2.1.2 Cobb-Douglas and Translog Productivities (Single-step restricted estimation)

In this case, we consider that the coefficients of the three inputs  $(L, M, K)$  of the Cobb-Douglas (10) and Translog (11) production functions are constant for the whole manufacturing sector. Each of the two equations is estimated in a single step, meaning that the parameters of the production function are estimated jointly with the parameters of the IC, C and D variables. However, to make the empirical results more readable we present them in separate tables. Table 8 shows the elasticities of inputs and Tables 10 and 11 the elasticities and semi-elasticities of the IC variables.

In the pool of countries, the estimated labor elasticity of the Cobb-Douglas production function is 0.43 (OLS) and 0.48 (RE), the intermediate materials elasticity is 0.52 (OLS) and 0.45 (RE). Finally, the elasticity of capital is 0.07 for both OLS and RE. With both estimation procedures, we can not reject the constant returns to scale (CRS) hypothesis.

In the case of Costa Rica, the estimated input elasticities are as follows: (i) labor, 0.31 by OLS and 0.29 by RE, (ii) intermediate materials, 0.53 by OLS and 0.47 by RE, and (iii) capital, 0.12 by OLS and RE. In this case, the CRS hypothesis is rejected at any reasonable significance value in the case of RE and at 10% in the case of OLS (the pvalue is 0.0649).

The empirical results obtained assuming a Translog production function are also in Table 8. The Translog specification allows to test whether the production function is Cobb-Douglas. The Cobb-Douglas specification is rejected with a p-value of 0 both for the pool of countries and for Costa Rica. The CRS is not rejected at any reasonable significance level for the pool of countries and rejected at any significance level for Costa Rica.

## 2.2 Unrestricted Production Function Coefficients (by Industry)

In this case, the coefficients of the inputs  $(L, M, and K)$  in the production function vary by industry. Table 1 shows the definition of the industries for the pool of countries and Table 2 for Costa Rica.

### 2.2.1 Solow´s Residuals (Two-step unrestricted estimation)

First, the costs shares of each industry are reported in Table 9.a (pool of countries) and Table 9.b (Costa Rica). We can see that there is a certain homogeneity among the 9 sectors. Intermediate materials (M) always has the highest share, with almost 50%, followed by the cost share of labor, at nearly 40% and capital, around 10%.

Second, the empirical results from the OLS and the random effects estimates of equation (12) are included in Table 11 (pool of countries) and Table 12 (Costa Rica).

## 2.2.2 Cobb-Douglas and Translog Productivities (Single-step unrestricted estimation by industry)

In this case, the production function specifications derived in equations (10) and (11) become the production functions for each industry  $i$ ,  $j=1,2, \ldots, 9$ . Each equation is estimated by OLS and by random effects (RE). Once again, we separate the information on the production function elasticities from the information on the IC elasticities to make the tables more readable although all the parameters were jointly estimated.

Tables 9.a and 9.b show the Cobb-Douglas specification for the pool of countries and Costa Rica, respectively, and Tables 10.a and 10.b the Translog specification.

When estimating a Cobb-Douglas specification, in the pool of countries, the constant returns to scale (CRS) condition is non rejected in six of the nine sectors (Apparel, Food and Tobacco, Furniture and Wood, Nonmetallic minerals, Textiles and Metal Products). In the industry of Chemical and Rubber the hypothesis is strongly rejected and in the other sector the evidence is mixed.

For some sectors like leather/shoes, the estimated input-output elasticities are very different from the values obtained from the cost shares given by the two-step procedure with Solow residuals, meaning that the industries have certain heterogeneity in their input-output elasticities. Therefore, the corresponding productivity measures should differ in a significant way. Tables 6 and 7 and Figures 2 and 3 show that this is the case.

With the trasnlog specification the CRS hypothesis is only rejected in the Apparel sector. The evidence in the other industries is mixed in the sense that is rejected in the OLS and not rejected in the RE estimation.

In the case of Costa Rica the CRS hypothesis is not rejected when estimating a Cobb-Douglas specification in three out of eight industries and rejected two. (See Table 9.b.) The empirical results of the Translog production function parameters are included in Table 10.a. The CRS hypothesis is rejected in 5 industries and not rejected in one. The Cobb-Douglas specification is rejected in six out of eight sectors it was rejected. The industries that failed to reject the Cobb-Douglas specification also failed to reject CRS.

## 2.3 Empirical Results: The impact of the IC variables on firms' productivity

The question of interest is whether these new productivity measures yield similar elasticity and semi-elasticity estimates for the IC effects on productivity.

Before discussing the effects of different IC variables on productivity, it is important to take into account that the economic interpretation of each investment climate coefficient is contingent on the units of measurement of each IC variable and on the transformations performed on them (logs, fractions, percentages, qualitative constructions, etc.). Since productivity variables are always in logs, when the IC variable is also expressed in logs, the estimated coefficient is a constant *productivity-IC* elasticity; and when the IC variable is not expressed in logs, the estimated coefficient is generally described as a *productivity-IC semi-elasticity*<sup>13</sup>. While the constant productivity-IC elasticity measures the percentage change in productivity induced by a percentage change in the IC variable, the semi-elasticity coefficient multiplied by 100, measures the percentage change in productivity induced by a unitary change in the IC variable. A detailed explanation of the units of measurement of each variable is given Tables 11 and 12 with the estimated elasticities and semi-elasticities for the 10

<sup>&</sup>lt;sup>13</sup> While it is sometimes natural to express an IC variable in log form, for some types of IC variables it is more appropriate not to do so. For example, when an IC variables is a fraction or a percentage number with some data equal to 0 or close to 0. Notice however that expressing IC variables in fractions allow us to interpret also their coefficients as constant elasticities and not as semi-elasticities.

productivity measures. Table 11 shows the results for the pool of countries and Table 12 for Costa Rica.

As we mention before, Investment Climate (IC) variables were classified into five broad categories: (a) Red Tape, Corruption and Crime, (b) Infrastructure, (c) Quality, Innovation and Labor Skills, (d) Finance and Corporate Governance, and (e) Other control variables.

Within each group, all IC variables have the expected signs and the estimated elasticities or semi-elasticities are always within a reasonable range of values for the 10 productivity measures. In absolute terms, the highest elasticity values correspond to the Solow residual or to the Cobb-Douglas specification, while the lowest usually correspond to the Translog production function. Therefore, we observe a trade-off between the role played by inputs (labor, intermediate materials and capital) and the role played by the IC variables and other control variables. The robustness of these empirical results across productivity measures allows us to obtain *consistent evaluations* of the IC determinants of productivity.

The Translog results on the empirical estimates of the IC elasticities are the same in terms of signs but less number of parameters become significant now, see Table C5.2. The reason is clear: the Translog specification includes many nonlinear terms of the inputs variables of each sector and they compete with the explanatory power of IC variables or C characteristics. The important point is that all the signs of the coefficients of the IC and C variables are maintained<sup>14</sup>. Therefore, the results on the impact of IC variables on productivity are consistent and robust to different productivity measures, suggesting that we can use the signs and the range of estimated elasticities for policy analysis $^{15}$ .

Finally, we also present the individual estimates of the elasticities or semi-elasticities of IC variables on productivity in Figures 4 and 5.

<sup>&</sup>lt;sup>14</sup> We also considered the possibility of having nonlinear impacts of IC variables on productivity in equations (10), (11) and (12) by including linear terms as well as the square and cubic terms of the IC and C variables that appear in those equations. However, they were not significant.

<sup>&</sup>lt;sup>15</sup> Those elasticity and semi-elasticity parameter were also estimated for small and large firms as well as for young and old firms. The results are reported in Escribano and Guasch (2005).

## 2.4 The contribution of the IC variables to average productivity

To complement the evaluation of the impact of IC variables on TFP we will evaluate the regressions estimates at their corresponding sample means. Since the 10 productivity measures of Figure 2 are very different we will fist find their demean counterpart to makes them more similar. The results are presented in Figure 3. To make this productivity methodology a valid benchmark for cross-country comparisons form now on we will always evaluate the IC impacts on average TFP coming from the restricted Solow's residuals of each country.

Replacing each one of IC elasticity by its estimate in equation (12) using as a measure of TFP the aggregate Solow residual, and averaging across firms of each country, it is possible to evaluate country by country, the contribution of each IC variable to the average log of productivity.

This mean evaluation has two advantages: (i) the contribution of each variable can be obtained as a percentage and percentage can be added by groups of IC variables, and (ii) even when we estimate equal coefficients for all the firms in the pool of countries (Guatemala, Honduras and Nicaragua), we can average by country and therefore we can have the contribution of each IC variable by country.

Figure 6 shows the contribution of each IC variable to the average log of productivity in each country of the pool of countries (Guatemala, Honduras and Nicaragua) and Figure 7 shows the same for Costa Rica.

In all the countries the group of IC variables with larger contribution is Red Tape, Corruption and Crime. This group represents 41.1%, 36.6%, 36.6%, and 37.8% of the whole contribution of IC variables and C variables in Guatemala, Honduras, Nicaragua, and Costa Rica, respectively. The second group of variables with large contribution to the average log productivity is Infrastructures in Guatemala (30.5%), Honduras (32.3%), and Nicaragua (32.3%) and Finance and Corporate Governance in Costa Rica (25.3). In Costa Rica Infrastructures also has a large contribution (19.2%).

These Figures also show the contribution of each IC variable. In the group of Red Tape, Corruption and Crime, the variable with the largest contribution is the number of days spent in inspections and regulation related activities in Guatemala, Honduras, and Nicaragua and the percentage of sales that is declared for tax purposes in Costa Rica.

In the group of infrastructures the most important variables in Guatemala, Honduras, and Nicaragua are the number of days that a firm needs to clear customs when it imports and whether the firm uses internet to communicate with its clients or suppliers. In Costa Rica, is the number of days that a firm has to wait after asking for electricity.

The group of other control variables explains around 16% of the impact of the IC variables in Honduras and Nicaragua, 13% in Guatemala and 11% in Costa Rica. The most important variable in this group is the age of the firm that explain around 8% in the Guatemala, Honduras and Nicaragua. In Costa Rica the most important variable is the number of competitors that explain 7.9% of the impact of IC variables on firms' productivity.

The last group in order of importance in the four countries is quality, innovation and labor skills. The contribution of this group of variables is around 10%. In Guatemala, Honduras and Nicaragua, the factor with the largest contribution is training provided beyond "on the job". In Costa Rica, in this group of variables, there are many variables that resulted significant but none of them has a contribution larger than 2%.

### 3 Further Robustness

In this section, we estimate the production function considering structural procedures based on Olley and Pakes (1996). In particular, we consider the procedures of Levinshon and Petrin (2003) and Ackerberg, Caves, and Frazer (2007).

## 3.1 Olley and Pakes (OP)

 The Olley and Pakes (1996) estimation algorithm takes into account the attrition bias due to exiting firms, as well as the simultaneous equation problem already mentioned. Given that the IC surveys are not designed to address issues related to firms' survival we focus our attention on the simultaneous equation problem.

As we mention before, the production function can be written in logs as follows

$$
y_{it} = \alpha_L l_{it} + \alpha_M m_{it} + \alpha_K k_{it} + p_{it} + \varepsilon_{it} \tag{13}
$$

where y is the logarithm of firm's i output, l is labor, m denotes intermediate inputs and k is capital stock, all in logs. The sequence  $\{p_{it}: t=1, 2, ..., t\}$  is unobserved productivity and  $\{\varepsilon_{it}: t=1, 2, ..., t\}$  is a sequence of *i.i.d* unanticipated shocks.

In their structural model the investment in fixed assets is function of firm's productivity and firm's the capital stock, i.e.,  $i_t = h_t(p_t, k_t)$ . They show that  $i_{it}$  is strictly monotonous in  $p_{it}$  and therefore it is possible to invert it out obtaining  $p_{t} = h_{t}^{-1}(i_{t}, k_{t})$ . Substituting this expression into (13) we have

$$
y = \alpha_L l_{it} + \alpha_M m_{it} + \alpha_K k_{it} + h_t^{-1}(i_{it}, k_{it}) + \varepsilon_{it} \tag{14}
$$

This equation allows us to obtain estimates of the labor and materials coefficients, as well as, an estimation of the composite term,  $\hat{\phi}_{i} = \alpha_{k} k_{i} + h_{i}^{-1}(i_{i}, k_{i}) + \varepsilon_{i}$ .

The next step is related to the estimation of the capital coefficient in (13). Assuming that capital is a fixed input in the sense that it depends on the amount of capital in period t-1 and on the investment decisions taken also in period t-1, and assuming that productivity follows a first order Markov process, that is,  $\rho(p_{ii} | p_{ii-1}, p_{ii-2},..., p_{i0}) = \rho(p_{ii} | p_{ii-1})$ , we have the moment condition that allow us to identify the capital coefficient. That is,  $k_{it} = i_{it-1} + (1 - \delta)k_{it-1}$  with  $p_{it} = E[p_{it} | p_{it-1}] + \xi_{it}$ yields to  $E[k_{it} | \xi_i] = 0$ . The second step involves replacing the estimates of  $\alpha_L$ ,  $\alpha_M$ and  $\hat{\phi}_{it}$  in equation (14), i.e.,

$$
y_{it} - \hat{\alpha}_{L} l_{it} - \hat{\alpha}_{M} m_{it} = \alpha_{K} k_{it} + g(\hat{\phi}_{i,t-1} - \alpha_{K} k_{it-1}) + \mu_{it} + \varepsilon_{it}.
$$
\n(15)

To estimate this equation, g(.) is approximated by a third or fourth order series expansion on  $\phi_t$ , and  $k_{it-l}$ .

### 3.2 Levinsohn and Petrin (LP)

One possible pitfall of OP procedure is that in many data sets the investment variable takes many zero values. Levinshon and Petrin (2003) addressed this problem by using the intermediate inputs demand instead of the investment equation. Let

$$
m_{it} = f_t(p_{it}, k_{it}) \tag{16}
$$

be the intermediate inputs demand. If monotonicity holds, then this expression can be inverted and replaced in equation (13). Then, the resulting production function is given by

$$
y = \alpha_L l_{it} + \alpha_K k_{it} + \alpha_M m_{it} + f_t^{-1}(m_{it}, k_{it}) + \varepsilon_{it}.
$$
 (17)

As in the OP approach, it is possible to obtain an estimate of the composite term  $\hat{\phi}_{it} = \alpha_K k_{it} + \alpha_M m_{it} + f_t^{-1}(m_{it}, k_{it}) + \varepsilon_{it}.$ 

The timing assumption regarding inputs is important. LP assumes that materials are chosen in the moment that the production takes place and therefore, it is influenced by productivity. Additionally, they assume that labor is chosen in same point after materials materials election. If this assumption does not hold, then  $l_{it}$  would affect the optimal choice of  $m_{it}$ . Hence, given these assumptions, in the last step there are two coefficients to estimate and identification is provided by the next two moment conditions: (i)  $E[\xi_{it}(\alpha_K, \alpha_M) | k_{it}] = 0$ , and (ii)  $E[\xi_{it}(\alpha_K, \alpha_M) | m_{it-1}] = 0$ .

## 3.3 Ackerberg, Caves, and Frazer (ACF)

Ackerberg, Caves, and Frazer (2007) point out that productivity also affect the demand of labor and therefore it coefficient can not be identified in the first step. If labor is a function of productivity and capital,  $l_{ii} = \gamma_i(p_{ii}, k_{ii})$ , and intermediate inputs are used as proxy rather like in  $LP^{16}$ , then

$$
l_{ii} = \gamma_t(p_{ii}, k_{ii}) = \gamma_t(f_t^{-1}(k_{ii}, m_{ii}), k_{ii}) = h_t(m_{ii}, k_{ii}).
$$

Now, it is not possible to identify the labor coefficient in the first step and all the coefficients must be estimated in the second step.

In this case, the production function is given by  $y_{it} = \phi_t (m_{it}, k_{it}) + \varepsilon_{it}$ . ACF like OP and LP, also assume a first order Markov process for productivity and therefore the set of moment conditions that allows identification of the three parameters are: (i)

 $16$ <sup>16</sup> The procedure can also be implemented using investment as proxy.

$$
E[\xi_{ii}(\alpha_L, \alpha_K, \alpha_M) | k_{ii}] = 0, \qquad \text{(ii)} \qquad E[\xi_{ii}(\alpha_L, \alpha_K, \alpha_M) | m_{ii-1}] = 0, \qquad \text{and} \qquad \text{(iii)}
$$
  

$$
E[\xi_{ii}(\alpha_L, \alpha_K, \alpha_M) | l_{ii-1}] = 0.
$$

If labor is a dynamic input, i.e., the current choice of labor may affect future choices, then the expressions of intermediate materials and labor demand become  $m_{it} = f_t(p_{it}, k_{it}, l_{it-1})$  and  $l_{it} = \gamma_t(p_{it}, k_{it}, l_{it-1})$ , respectively. This yields to  $y_{it} = \phi_t (m_{it}, k_{it}, l_{it-1}) + \varepsilon_{it}$ , with an additional moment condition provided by  $E[\xi_{it}(\alpha_L, \alpha_K, \alpha_M) | l_{it-1}, k_{it}] = 0$ .

When labor is not a variable input, i.e., it is chosen in the moment t-b between t and t-1, the intermediate inputs and labor demand become  $m_{it} = f_t(p_{it}, k_{it}, l_{it})$  and  $l_{it} = \gamma_t(p_{it-b}, k_{it})$ , respectively. In this case, the production function is of the form  $y_{\mu} = \phi_t(m_{\mu}, k_{\mu}, l_{\mu}) + \varepsilon_{\mu}$  and the additional moment condition is as in the previous case  $E[\xi_{it}(\alpha_L, \alpha_K, \alpha_M) | l_{it-1}, k_{it}] = 0$ .

### 3.4 GMM estimation

Wooldridge (2005) proposed a computational improvement that can be used in the OP, LP and ACF procedures. In particular he proposed a GMM procedure to estimate to estimate  $\alpha_i$ ,  $\alpha_m$  and  $\alpha_k$ .

Assuming that in (13),  $E(\varepsilon_{ii} | l_{ii}, m_{ii}, k_{ii}) = 0$ , the expected value of the production function is given by

$$
E(y_{it} | l_{it}, m_{it}, k_{it}) = \alpha_0 + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it} + g(k_{it}, m_{it}) =
$$
  
=  $\alpha_0 + \alpha_l l_{it} + h(k_{it}, m_{it})$ 

for some unknown function  $p_{ii} = g(m_{ii}, k_{ii})$  and  $h(k_{ii}, m_{ii}) = \alpha_m m_{ii} + \alpha_k k_{ii} + g(k_{ii}, m_{ii})$ . Note that this equation is the first step of the LP and ACF estimation algorithms. The unanticipated productivity shocks follows a first order Markov process and its innovations are defined by  $a_{it} = p_{it} - E(p_{it} | p_{it-1})$ . The expected value of  $p_{it}$  conditional

on  $p_{it-1}$  is a function  $f(.)$  of  $m_{it-1}$  and  $k_{it-1}$ , i.e.,  $E(p_{it} | p_{it-1}) \equiv f[g(m_{it-1}, k_{it-1})]$ , then

$$
v_{it} = f[g(m_{it-1}, k_{it-1})] + a_{it}
$$
 (18)

Plugging (18) into (13) gives

$$
y_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it} + f[g(k_{it-1}, m_{it-1})] + a_{it} + \varepsilon_{it}
$$

If  $u_{it} = a_{it} + e_{it}$  then,

$$
y_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it} + f[g(k_{it-1}, m_{it-1})] + u_{it}.
$$
 (19)

Remember that the equation of the first step in OP, LP and ACF is given by

$$
y_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it} + g(k_{it-1}, m_{it-1}) + \varepsilon_{it}.
$$
 (20)

The orthogonality condition for equations (19) and (20) are given by

$$
E(u_{it} | m_{it}, k_{it}, l_{it-1}, m_{it-1}, k_{it-1}, \ldots, l_{it}, m_{it}, k_{it}) = 0, \qquad (21)
$$

$$
E(\varepsilon_{ii} | l_{ii}, m_{ii}, k_{ii}, l_{ii-1}, m_{ii-1}, k_{ii-1}, \ldots, l_{i1}, m_{i1}, k_{i1}) = 0,
$$
\n(22)

respectively.

The main concern in the estimation of  $\alpha_l$ ,  $\alpha_m$  and  $\alpha_k$  is that we have to deal with unknown functions  $g(.)$  and  $f(.)$ . An approach that has been found to work well is to use high order polynomials. Thus we have

$$
g(m_{it}, k_{it}) = \lambda_0 + \mathbf{c}(m_{it}, k_{it})\lambda , \qquad (23)
$$

for a 1XQ vector of functions  $c(.)$ . Further assume that  $f(.)$  can be approximated by a polynomial of degree G in c such that (19) and (20) becomes

$$
y_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it} + \mathbf{c}(k_{it}, m_{it})\lambda + \varepsilon_{it},
$$
\n(24)

and

$$
y_{it} = \delta_0 + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_k k_{it} + \rho_1 (\lambda c_{i,t-1}) + ... + \rho_G (\lambda c_{i,t-1})^G + u_{it}.
$$
 (25)

Given the moment conditions (21) and (22) it is possible to use an instrumental variables procedure for (24) and (25). The most straightforward choice of instruments for (24) is simply

$$
\mathbf{z}_{it1} = (1, l_{it}, k_{it}, \mathbf{c}_{it}^0), \tag{26}
$$

where  $c^0$  is c without k. Instruments for (25) would include

$$
\mathbf{z}_{ii2} = (1, k_{ii}, l_{ii-1}, \mathbf{c}_{it-1}, \mathbf{q}_{it-1}),
$$
 (27)

being **q** a set of non-linear functions of **c** (e.g. low order polynomials).

A simple estimation approach is to choose, for each i, a matrix of instruments as

$$
\mathbf{Z}_{it} = \begin{pmatrix} (l_{it} \mathbf{\mathbf{c}_{it}}, \mathbf{z}_{it2}) & 0 \\ 0 & \mathbf{z}_{it2} \end{pmatrix}, t = 2, ..., T \tag{28}
$$

GMM estimation in (24) and (25) is now straightforward. For each  $\geq 1$  define a residual function as

$$
\mathbf{r}_{ii}(\boldsymbol{\theta}) = \begin{pmatrix} r_{ii1}(\boldsymbol{\theta}) \\ r_{ii2}(\boldsymbol{\theta}) \end{pmatrix} = \begin{pmatrix} y_{ii} - \alpha_0 - \alpha_l l_{ii} - \alpha_m m_{ii} - \alpha_k k_{ii} - \lambda \mathbf{c}_{it} \\ y_{ii} - \delta_0 - \alpha_l l_{ii} - \alpha_m m_{it} - \alpha_k k_{ii} - \rho_1 (\mathbf{c}_{i,t-1} \lambda) - \ldots - \rho_G (\mathbf{c}_{i,t-1} \lambda)^G \end{pmatrix}
$$
(29)

so that,

$$
E[\mathbf{Z}_{it}^{+} \mathbf{r}_{it}(\mathbf{\theta})] = 0, t = 2, ..., T
$$
\n(30)

This T-1 conditions can be stacked for each i and standard GMM estimation can be used.

## 3.5 Further empirical results

Table 8, panel B, shows the estimates of the input elasticities for the LP and ACF procedures in the case of Costa Rica. We apply these procedures only to Costa Rica because the panels of Guatemala, Honduras and Nicaragua are very unbalanced and these procedures use the lag of the inputs as instruments. For the procedure of ACF we use the Wooldridge (2005) GMM procedure with heteroskedastic standard errors. We use a polynomial of degree 3 to approximate equation (23), i.e.,  $Q = 3$ , and a polynomial of degree 1 to approximate function  $f(.)$ , i.e. G=1. As expected, in Table 8 panel B, the input-output elasticity of capital obtained by L&P or by ACF are too low, 0.08 and 0.09 respectively. This is not solved by estimating equation (9a) by fixed effects (FE), without controlling for IC variables since the estimated elasticity of capital is 0.07. However, remember that when controlling for IC variables a simple OLS with robust standard errors, or a random effects estimators, provide an elasticity of capital equal to 0.12, see Table 8, panel B. A question of interest for further research is how to extend O&P, L&P and ACF procedures to control for IC variables.

However, the robustness of IC elasticities in TFP is preserved estimating also by these procedures. With the estimated input elasticities (from O&P and ACF) we estimated firms' productivity (TFP) and in a second step we evaluated the impact of the

investment climate variables selected in section 2 from equation (12). The results are shown in Table 15. For comparative purpose, the first column shows the results obtained using Solow residual. As can be seen, the IC results on productivity are still robust. None of the IC variables change signs and the magnitudes of the coefficients are similar.

## 4 Conclusion

There is not a single salient measure of productivity. For the analysis of the investment climate (IC) determinants of productivity in Costa Rica, Guatemala, Honduras and Nicaragua, productivity is considered to be that part of the production of goods (sales) that is not explained by the main inputs (labor, intermediate materials and capital). This productivity concept is sometimes called total factor productivity (TFP) or multifactor productivity (MFP).

Several measures are used to evaluate what is broadly understood as productivity and a methodology is developed that produces robust estimates regardless of the measure used. We show that it is possible to get consistent and robust estimates (elasticities) of investment climate determinants of productivity. This is so no matter whether we use productivity measures with a low correlation coefficient, such as 0.11 (very different), or a high one, such as 0.98 (similar).

The main requirement of this econometric methodology for internal consistency is that the policy implications must be robust: 1) among different functional forms of the production functions, 2) among different consistent estimation procedures, 3) among different productivity measures and 4) among different levels of aggregation (industry, country, pooling countries, etc.). In our case, all the signs of the estimated coefficients are as expected. Obviously, the numerical values of those elasticities parameters vary from one productivity measure to the next, but the range of values is reasonable and significant in most cases.

The analysis is undertaken without transforming the variables into rates of growth. There are good reasons explaining that decision: (a) the IC variables are available for only one year; (b) the panel data for Guatemala, Honduras and Nicaragua is very unbalanced with many more observations in 2002 than in 2001, hence computing rates of growth for the non IC variables implies loosing many observations; and (c)

measurement errors are enhanced by taking first differences. Therefore, variables in levels are used with logarithmic (logs) transformation of output, labor, intermediate materials and capital.

Productivity is estimated as the residual of the production function. To get consistent least squares estimates of the input-output elasticities it is necessary that all inputs are uncorrelated with productivity. But this is almost never the case with annual data sets, like the IC surveys, since the investment climate (IC) variables affect both the inputs and the productivity. This condition invalidates any two-step least squares procedures where first the productivity variable and then its investment climate determinants are estimated, unless you control in both steps by IC variables. This problem also affects procedures like Olley and Pakes (1996), Levinsohn and Petrin (2003) or Ackerberg et al. (2007).

Given that good instrumental variables are difficult to find for the IC variables, we suggest a single-step least squares estimation procedure where the parameters of the production function (input-output elasticities) are jointly estimated with the coefficients of the IC determinants of productivity.

A valid two-step approach is also used when the input-output elasticities are obtained, following Solow (1957), as cost-shares, since there is no erogeneity requirement of the inputs. Once productivity is measured as the Solow residual in levels (logs), the IC determinants of productivity can be consistently estimated in a second step.

The possible endogeneity of the IC variables is reduced by taking their region-industry averages. To correct for heteroskedasticity (heterogeneity) of the individual unobserved terms, we estimate by least squares (pooling OLS) with robust standard errors and by random effects. The results obtained are very similar.

For policy analysis there is no need to use a single value for the elasticity or semielasticity of each IC variable. In fact, it is more interesting to perform a sensitivity analysis based on the range of parameter values obtained for several productivity measures.

Four important categories of investment climate (IC) variables are identified: (a) Infrastructure, (b) Read Tape, Corruption and Crime, (c) Finance and Corporate Governance and (d) Quality, Innovation and Labor Skills. Within each group, all the IC variables always have the expected signs and the estimated elasticities or semielasticities are always within a reasonable value range for the ten productivity measures considered. In absolute terms, the higher values of the IC elasticities correspond to the

Solow residual or to the Cobb-Douglas specification, while the lowest usually correspond to the Translog production function. Therefore, we observe a trade-off between the role played by the inputs (labor, intermediate materials and capital) and the role played by the IC variables and other control variables.

In summary, the robustness of these empirical results across 10 productivity measures allows us to obtain consistent empirical evaluations of the IC determinants of productivity. The estimates show consistently the high impact of investment climate on productivity. Overall, it accounts for over 30 percent of productivity. In Guatemala, Honduras and Nicaragua, the two most impacting categories are red tape, corruption and crime, and infrastructure, accounting respectively for about 12 and 9 percent of productivity.

Although more sophisticated econometric techniques could be applied, to take into account that the inputs are not used at full capacity, firms might not be at the frontier of the production possibility frontiers, etc., we plan to apply this simple and robust procedure to several developing countries. The objective is to identify, at the firm level, basic robust empirical regularities on the main bottlenecks on productivity and to make cross county comparisons. Those empirical results could be used later on as a benchmark for further improvements.

The policy implications from this simple analysis are clear. Investment climate matters enormously and the relative size of the impact of the various investment climate variables indicates where the efforts of reform should be placed.

## 5 References

- Ackerberg, D., K. Caves, and G. Frazer (2007). "Structural Identification of Production Functions," mimeo.
- Alexander, W. Robert J., Bell, John D., and Knowles, Stephen (2004). "Quantifying Compliance Costs of Small Businesses in New Zealand". Discussion paper, University of Otahgo.

http://www.business.otago.ac.nz/econ/research/discussionpapers/DPO406.pdf.

- Arellano M. (2003). Panel Data Econometrics. Advanced Texts in Econometrics, Oxford University Press.
- Barro R. J. and X. Sala-i-Martin (2004). Economic Growth. The MIT Press, second edition, Cambridge, Massachusetts.
- Bartelsman E. J. and M. Doms (2000). "Understanding Productivity: Lessons from Longitudinal Microdata". Journal of Economic Literature, Vol. 38, Nº 3, 569-594.
- Basu S. and J. Fernand (2001). "Why is Productivity Procyclical? Why do we Care?". In Ch. R. Hulten, E.R. Dean and M. J. Harper (eds.) New Developments in Productivity Analysis, The University of Chicago Press, 225-301.
- Blundell R. and S. Bond (2000). "GMM Estimation with Persistent Panel Data: An Application to Production Functions". Econometric Reviews, 19 (3), 321-340.
- Blundell R. and J. L. Powell (2003). "Endogeneity in Nonparametric and Semiparametric Regression Models" In Advances in Economics and Econonometrics: Theory and Applications, Eighth World Congress, Vol. II, M. Dewatripont, L.P. Hansen and S.J. Turnovsky, eds. Cambridge: Cambridge University Press, 313-357.
- Bosworth, Barry and Susan Collins (2003). "The Empirics of Growth: An Update". The Brookings Institution. Washington, D.C. Processed.
- Cole, H. L., L. E. Ohanian, A. Riascos and J. A. Schmitz Jr. (2004). "Latin America in the Rearview Mirror". National Bureau of Economic Research WP #11008, December.
- De Soto, Hernando (2002). "The Mystery of Capital: Why Capitalism Triumphs in the West and Fails Everywhere Else". New York: Basic Books Press.
- Diewert W. Erwin and Alice O. Nakamura (2002) "The Measurement of Aggregate Total Factor Productivity Growth". J. J. Heckman and E. E. Leamer (eds.). Handbook of Econometrics, Vol. 6, forthcoming.
- Djankov, Simeon, La Porta, Rafael, Lopez-de-Silanis, Florencio, and Shleifer, Andrei (2002). "The Regulation of Entry". Quarterly Journal of Economics 117, February 2002. 1-37.
- Dollar, David, Anqing Shi, Shuilin Wang and L. Colin. Xu (2004). "Improving City Competitiveness through the Investment Climate: Ranking 23 Chinese Cities". Washington, D.C., World Bank.
- Dollar, David, Mary Hallward-Driemeier and Taye Mengistae (2004). "Investment Climate and International Integration". Washington, D.C., World Bank.
- Dollar, David, Mary Hallward-Driemeier and Taye Mengistae (2003). "Investment Climate and Firm Performance in Developing Economies". Washington, D.C., World Bank.
- Escribano Alvaro and J. Luis Guasch (2005). "Assessing the Impact of the Investment Climate on Productivity using Firm Level Data: Methodology and the Cases of Guatemala, Honduras and Nicaragua". Policy Research Working Paper # 3621, The World Bank, June.
- Escribano Alvaro and J. Luis Guasch (2004). "Econometric Methodology for Investment Climate Assessments (ICA) on Productivity using Firm Level Data: The Case of Guatemala, Honduras and Nicaragua". Mimeo World Bank, June.
- Escribano Alvaro and Jorge Pena (2004). "Productivity in Levels or in Differences: Evaluation of the Impact of ICT from Firm Level Data on the Spanish Manufacturing Sector". Mimeo, Universidad Carlos III de Madrid.
- Foster L., J. Haltiwanger and C.J. Krizan (1998). "Aggregate Productivity Growth: Lessons from Microeconomic Evidence". NBER Working Paper W6803.
- Griliches Z. (1996). "The Discovery of the Residual: A Historical Note". Journal of Economic Literature, 34, 1324-1330.
- Griliches Z. and J. Mairesse (1997). "Production Functions: The Search for Identification". In S. Strom (ed.) Essays in Honor of Ragnar Frisch, Econometric Society Monograph Series, Cambridge University Press, Cambidge.
- Guasch, J. Luis. (2004). "An Assesment of Logistic Costs and of their Impact on Competitiveness", World Bank, Washington, DC.
- Hall, R. E. (1988). "The Relationship between Price and Marginal Cost in U.S. Industry". Journal of Political Economy, 96, 5, 921-947.
- Hall, R. E. (1990). "Invariance Properties of Solow´s Productivity Residual". In Peter Diamond (ed.). Growth, Productivity, Employment. Cambridge: MIT Press, 1- 53.
- Hall, R. E. and C.I. Jones (1990). "Why Do Some Countries So Much More Output per Worker than Others?" The Quarterly Journal of Economics, 114, 1, 83-116.
- Haltiwanger, John (2002). "Understanding Economic Growth". The Need for Micro Evidence". New Zealand Economic Papers 36 (1), 33-58.
- He, Kathy S., Morck, Randall, and Yeung, Bernard (2003). "Corporate Stability and Economic Growth". William Davidson Working Paper No. 553.
- Hulten Ch. R. (2001). "Total Factor Productivity: A Short Biography". In Ch. R. Hulten, E.R. Dean and M. J. Harper (eds.) New Developments in Productivity Analysis, The University of Chicago Press, 1-47.
- Im, K.S., M.H. Pesaran and Y. Shin (2003). "Testing for Unit Roots in Heterogenous Panels". Journal of Economics, 115, 53-74.
- Johnson, Simon, McMillan, John, and Woodruff, Christopher (2002). "Property Rights and Finance". American Economic Review 92, 1335-56.
- Jorgenson D.W. (2001). "Information Technology and the U.S. Economy," The American Economic Review, Vol. 91, 1, 1-32.
- Jorgenson D.W., F. Gollop and B. Fraumeni (1987). "Productivity and U.S. Economic Growth," Cambridge: Harvard University Press.
- Jorgenson D.W. and Z. Griliches (1967). "The Explanation of Productivity Change," Review of Economic Studies, 34, 249-280.
- Kasper, Wolfgang, (2002), "Losing Sight of the Lodestar of Economic Freedom: A Report Card on New Zeland's Economic Reform," NZ Business Roundtable.
- Kerr, Roger (2002). "The Quagmire of Regulation," NZ Business Roundtable. http://www.nzbr.org.nz/documents/speeches/speeches-200/the quagmire of regulation.pdf.
- Klapper, Leora, Laeven, Luc, and Rajan, Raghuram (2004). "Business Environment and Firm Entry". NBER paper 10380. http://papers.nber.org/papers/W10380.
- Levinsohn J. and A. Petrin (2003). "Estimating Production Functions Using Inputs to Control for Unobservables". Review of Economic Studies, 70, 317-341.
- Loayza, N.V., A. M. Oviedo and Luis Serven (2004). "Regulation and Macroeconomic Performance", World Bank, Washington DC.
- Marschak J. and W. H. Andrews (1944). "Random Simultaneous Equations and the Theory of Production". Econometrica, 12 (3,4), 143-205.
- McMillan, John, (1998), " Managing Economic Change: Lessons from New Zeland", The World Economy 21, 827-43.
- Mc Millan, John (2004), "A Flexible Economy? Entrepeneurship and Productivity in New Zeland", Working Paper, Graduate Scholl of Business, Stanford University, Stanford, CA.
- Olley G. S.and A. Pakes (1996). "The Dynamics of Productivity in the Telecommunications Equipment Industry". Econometrica, Vol. 64, 6, 1263- 1297.
- Organization for Economic Cooperation and Development (2001). Businesses' Views on Red Tape, Paris, OECD. http://www1.oecd.org/publications/ebook/4201101E.PDF.
- Prescot, Edward C. (1998) "Needed: A Theory of Total Factor Productivity". International Economic Review, 39, 525-552.
- Rodrik, Dani, and Arvind Subramanian (2004). "From 'Hindu Growth to Productivity Surge: The Mystery of the Indian Growth Transition". Harvard University, Cambridge, Mass. Processed.
- Solow R. M. (1957). "Technical Change and the Aggregate Production Function" The Review of Economics and Statistics, 39 (3), 312-320.
- Stiroh K.J. (2002). "Information Technology and the U.S. Productivity Revival: Whta Do the Industry Data Say?" The American Economic Review, Vol. 92, 5, 1559- 1575.
- Tornqvist L. (1936). "The Bank of Finland´s Consumption Price Index". Bank of Finland Monthly Bulletin, 10, 1-8.
- Wooldridge J. M. (2002). Econometric Analysis of Cross Section and Panel Data. The MIT Press. Cambridge, Massachusetts.
- World Bank 2003. "Doing Business in 2004" Understanding Regulation. Washington, D.C. World Bank.
	- \_\_\_\_\_\_\_\_\_\_ 2004. "Doing Business in 2005: Removing Obstacles to Growth". Washington, D.C. World Bank.

\_\_\_\_\_\_\_\_\_\_ 2004. "2003 Annual Review of Development Effectiveness: The Effectiveness of Bank Support for Policy Reform. Report 28290". Washington, D.C.: World Bank Operations Evaluation Department.

2005. "World Development Report 2005: A Better Investment Climate for Everyone". World Bank and Oxford University Press. Washington, D.C.

Wilkinson, Bryce (2001). "Constraining Government Regulation". NZ Business Roundtable. http://www.nzbr.org.nz/documents/publications/publications-2001/constraining\_govt.pdf.

# Appendix: Tables and Figures





## Table 2: General information at plant level and production function variables: Costa Rica



## Table 3.a: Investment climate (IC) variables: Infrastructures



## Table 3.b: Investment climate (IC) variables: Red Tabe, Corruption and Crime



## Table 3.c: Investment climate (IC) variables: Finance and Corporate Governance



## Table 3.d: Investment climate (IC) variables: Quality innovation, and labor skills



## Table 3.e: Investment climate (IC) variables: Other Control Variables





## Table 4: Total number of observations used in the IC regressions by country and industry

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

## Table 5: Total number of observations used in the IC regressions by year and industry



### A. Guatemala, Honduras and Nicaragua

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

#### B. Costa Rica



Source: Authors' elaboration with Investment Climate Surveys (ICs) data.



#### Table 6: Correlation matrix among productivity measures: Guatemala, Honduras, and Nicaragua

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

#### NOTES:

a) Solow residuals in levels are obtained as sales (in logarithms or logs) minus a weighted average of labor, materials, capital (all in logs) where the weights are given by the share in total costs of each of the inputs.

(1) Restricted case: the cost shares are calculated as the averages of the plant-level cost shares across the entire sample in 2001 and 2002.

(2) Unrestricted by Industry case: the cost shares are calculated as the averages across plant-level cost shares in years 2001 and 2002. for each of the nine industries.

(3) Outlier plants were defined as those which had ratios of materials to sales larger than one or had ratios of labor costs to sales larger than one.

b) Estimated Productivity in levels is obtained from Cobb-Douglas and Translog production functions of sales with inputs labor, materials, and capital estimated by OLS and random effects under two different environments:

(1) Restricted: a single set of production function coefficients is obtained using data on plants in the three countries, for all industries in years 2001 and 2002 (excluding outliers).

(2) Unrestricted by Industry: a set of production function coefficients is obtained for each of nine industries using data on all plants for the three countries in years 2001 and 2002 (excluding outliers).



#### Table 7: Correlation matrix among productivity measures: Costa Rica

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

#### NOTES:

a) Solow residuals in levels are obtained as sales (in logarithms or logs) minus a weighted average of labor, materials, capital (all in logs) where the weights are given by the share in total costs of each of the inputs.

(1) Restricted case: the cost shares are calculated as the averages of the plant-level cost shares across the entire sample in 2002, 2003 and 2004.

(2) Unrestricted by Industry case: the cost shares are calculated as the averages across plant-level cost shares in years 2002, 2003 and 2004 for each of the nine industries.

(3) Outlier plants were defined as those which had ratios of materials to sales larger than one or had ratios of labor costs to sales larger than one.

b) Estimated Productivity in levels is obtained from Cobb-Douglas and Translog production functions of sales with inputs labor, materials, and capital estimated by OLS and random effects under two different environments:

(1) Restricted: a single set of production function coefficients is obtained using data on plants in the three countries, for all industries in years 2002, 2003 and 2004 (excluding outliers).

(2) Unrestricted by Industry: a set of production function coefficients is obtained for each of nine industries using data on all plants for the three countries in years 2002, 2003 and 2004 (excluding outliers).



#### A. Guatemala, Honduras and Nicaragua

#### B. Costa Rica



Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

NOTES:

(a) Fixed effect estimation.

(b) Ackerberg, Caves and Frazer's (2007) procedure using the GMM estimation method of Wooldridge (2005) without IC variables.

(c) Levinsohn and Petrin's (2003) estimation procedure.

(1) Significance is given by robust standard errors.\* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

(2) The cost shares of labor, materials and capital are calculated as average (excluding outliers) of the plant-level cost shares of labor, materials and capital across all plants in years 2001 and 2002 (Guatemala, Honduras, and Nicaragua) and 2002, 2003 and 2004 (Costa Rica).

(3) The sample generating the sets of production function coefficients is constituted by all plants (excluding outliers) in years 2001 and 2002 (Guatemala, Honduras, and Nicaragua) and 2002, 2003, and 2004 (Costa Rica).

## Table 9.a: Production Function Parameters from the Unrestricted Estimation by Industry, Cobb-Douglas specification: Guatemala, Honduras, and Nicaragua



Source: Authors' elaboration with Investment Climate Surveys (ICs) data. NOTES:

(1) Significance is given by robust standard errors. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

(2) The cost shares of labor, materials and capital are calculated as averages of the plant-level cost shares of labor, materials and capital for each industry using all plants for years 2002, 2003 and 2004 (excluding outliers).

## Table 9.b: Production Function Parameters from the Unrestricted Estimation by Industry, Cobb-Douglas specification: Costa Rica



Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

NOTES:

(1) Significance is given by robust standard errors. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%. (2) The cost shares of labor, materials and capital are calculated as averages of the plant-level cost shares of labor, materials and capital for each industry using all plants for years 2002, 2003 and 2004 (excluding outliers).



### Table 10.a: Production Function Parameters from the Unrestricted Estimation by Industry, Translog specification: Guatemala, Honduras, and Nicaragua

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

**NOTES:**  $\frac{1}{1}$  p-values.

Significance is given by robust standard errors. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%..<br>The cost shares of labor, materials and capital are calculated as averages of the plant-level cost shares outliers).

	L	M	$\mathbf K$	L2	M <sub>2</sub>	K2	L*M	L*K	$M*K$		Test for $CD^1$ Test for $CRS^1$
Food & Beverages											
Pool OLS	0.56	$1.03***$	0.00	$-0.03$	$0.06***$	$-0.03**$	$-0.11***$	$0.16***$	$-0.06**$	0.000	0.000
RE	0.10	$1.18***$	$0.00\,$	$-0.01$	$0.07***$	$-0.04**$	$-0.12***$	$0.17***$	$-0.07**$	0.000	0.000
<b>Textiles</b>											
Pool OLS	$-1.32***$	1.19	$0.70***$	$0.17***$	$0.08*$	$0.01*$	$-0.17$	$0.004**$	$-0.07$	0.000	0.000
RE	$-1.11$	1.03	0.15	$0.14**$	0.09	$0.01*$	$-0.17$	$0.03**$	$-0.06$	0.000	0.199
<b>Apparels</b>											
Pool OLS	1.43	$1.69*$	$-1.12***$	$-0.16***$	0.05	$0.03**$	$-0.04*$	0.25	$-0.18***$	0.000	0.000
RE	1.05	1.63	$-1.18***$	$-0.15***$	$0.02**$	$0.01*$	$-0.01**$	0.24	$-0.14$	0.000	0.007
Wood & furniture											
Pool OLS	0.13	$0.04*$	0.25	$-0.17*$	$0.003*$	$-0.04$	$0.17**$	0.18	$-0.11$	0.033	0.000
<b>RE</b>	0.17	$-0.60**$	0.26	$-0.09$	0.05	$-0.02$	0.09	0.10	$-0.08$	0.008	0.000
Paper & edition											
Pool OLS	0.71	1.21	$-0.17$	0.01	0.02	$0.02*$	$-0.07$	$0.02*$	$-0.03$	0.083	0.425
RE	0.17	1.96	$-0.54*$	0.09	0.05	$0.06***$	$-0.16$	$0.005***$	$-0.07$	0.015	0.320
Chemicals, rubber & plastics											
Pool OLS	0.92	$0.32*$	0.08	$-0.05$	0.04	$-0.01$	$-0.03$	$0.06**$	$-0.03$	0.000	0.008
<b>RE</b>	0.88	0.51	$-0.24$	$-0.07$	$0.02*$	$0.003**$	$0.01*$	$0.07**$	$-0.04$	0.004	0.047
<b>Non-metallic Products</b>											
Pool OLS	0.18	0.73	0.06	$0.11*$	0.1	$0.04**$	$-0.18$	$-0.04**$	$-0.04$	0.000	0.269
RE	$-0.43$	0.5	1.18	0.12	0.01	$-0.04$	$-0.07$	$-0.09**$	0.06	0.322	0.088
Mach. & Equip. - Metallic Prod.											
Pool OLS	0.72	1.32	$-0.72***$	0.03	0.06	$0.00*$	$-0.17$	0.09	$-0.02$	0.000	0.000
<b>RE</b>	0.41	0.7	$-0.21$	0.03	0.04	$-0.01$	$-0.12$	$0.04*$	$-0.02*$	0.054	0.004

Table 10.b: Production Function Parameters from the Unrestricted Estimation by Industry, Translog specification: Costa Rica

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

**NOTES:**  $\frac{1}{1}$  p-values.

Significance is given by robust standard errors. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.<br>The cost shares of labor, materials and capital are calculated as averages of the plant-level cost shares outliers).

## Table 11: Estimation of IC elasticities and semi-elasticities on productivity controlling for observable fixed effects: Guatemala, Honduras, and Nicaragua



Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

NOTES: (AV) means that the variable enters the regression in form of industry-region average. Significance is given by robust standard errors (very similar results by robust cluster errors). \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%. The regressions include a constant, industry dummies and year dummies.



### Table 12: Estimation of IC elasticities and semi-elasticities on productivity controlling for observable fixed effects: Costa Rica

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

NOTES: (AV) means that the variable enters the regression in form of industry-region average. Significance is given by robust standard errors (very similar results by robust cluster errors). \* significant at 10%; \*\* signif significant at 1%. The regressions include a constant, industry dummies and year dummies.

## Table 13: IC elasticities and semi-elasticities with respect to productivity without controlling for other IC variables: Guatemala, Honduras, and Nicaragua



Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

NOTES: (AV) means that the variable enters the regression in form of industry-region average. LIGHT GREY means that the variable changes in significance and magnitude with respect to the full estimation of Table 2. DARK GR

<b>Blocas</b> of IC variables	<b>Explanatory IC variables</b>		<b>Restricted estimation</b>							<b>Inrestricted by industry estimation</b>					
			Two steps <b>Solow residual</b>		Single step				Single step Two steps						
					Cobb-Douglas Translog			<b>Solow residual</b>		Cobb-Douglas		Translog			
			R.E	<b>OLS</b>	R.E	<b>OLS</b>	R.E	<b>OLS</b>	R.E	<b>OLS</b>	R.E	<b>OLS</b>	R.E		
Infrastruc-	Average number of days to clear customs for exports (logs) (AV)	$-0.06$	$-0.066$	$-0.073**$	$-0.071$	$-0.058*$	$-0.06$	$-0.080**$	$-0.085$	$-0.062$	$-0.074$	$-0.031$	$-0.052$		
tures	Average duration of power outages Hours per day (logs) (AV)		$-0.012$	$-0.011$	$-0.013$	$-0.009$	$-0.013$	$-0.014**$	$-0.013$	$-0.018**$	$-0.020**$	$-0.014*$	$-0.020**$		
	Total number of water outages (logs) (AV)		$-0.156$	$-0.131**$	$-0.146$	$-0.077**$	$-0.095$	$-0.156**$	$-0.167$	$-0.102*$	$-0.118$	$-0.068$	$-0.087$		
	Average days waiting for an electricity supply (logs) (AV)	$-0.109***$	$-0.112**$	$-0.108***$	$-0.117**$	$-0.096***$	$-0.104**$	$-0.101***$	$-0.103**$	$-0.084***$	$-0.097**$	$-0.077**$	$-0.073*$		
Red corruption and	tape, Percentage of sales declared to IRS for tax purposes (% of total sales) (AV)	$0.004**$	0.004	$0.004**$	0.003	0.001	0.001	$0.004**$	0.004	$0.004**$	0.003	0.001	0.002		
crime	Vumber of days spent in Inspection and Regulation related work Days (logs)	$-0.018$	$-0.018$	$-0.070*$	$-0.014$	$-0.031$	$-0.005$	$-0.027$	$-0.026$	$-0.075*$	$-0.054$	$-0.084**$	$-0.086$		
	Dummy for payments to obtain a contract with the government $(0 \text{ or } 1)$ (AV) 0.156		0.18	0.143	0.185	0.02	0.05	0.185	0.21	0.053	0.134	$-0.142$	$-0.044$		
	$-0.015***$ Percentage of sales never repaid (percentage of total sales) (AV)		$-0.015**$	$-0.012**$	$-0.018**$	$-0.006$	$-0.012*$	$-0.016***$	$-0.016**$	$-0.011**$	$-0.015**$	0.002	$-0.002$		
	Number of days lost due to absenteeism (logs)		$-0.022$	$-0.024$	$-0.021$	$-0.014$	$-0.015$	$-0.032**$	$-0.027$	$-0.007$	$-0.009$	$-0.005$	$-0.014$		
Finance and $\mathop{\mathrm{corporate}}$ governance	Dummy for firm belonging to a trade association $(0 \text{ or } 1)$ $(AV)$		$0.366**$	$0.252***$	$0.425**$	$0.265***$	$0.307*$	$.321***$	$0.331*$	$0.251**$	$0.369**$	0.14	0.168		
	Dummy for credit line $(0 \text{ or } 1)$		0.117*	$0.083**$	$0.145**$	0.051	0.093	$0.126***$	$0.118*$	0.039	0.049	0.055	0.062		
	Dummy for debts with creditors $(0 \text{ or } 1)$ $(AV)$	0.16	0.196	0.126	0.149	0.037	0.116	0.143	0.182	0.089	0.096	$-0.015$	$-0.029$		
	Firm's profits after taxes as a percentage of total sales $%$ of total sales) (AV)	$-0.006**$	$-0.005$	$-0.003$	$-0.006$	$-0.004$	$-0.008*$	$-0.007**$	$-0.007$	$-0.005$	$-0.008*$	$-0.004$	$-0.007$		
	Dummy for firm owning almost all the lands in which the plant operates (0 or 1)	$-0.135***$	$-0.132**$	$-0.182***$	$-0.152**$	$-0.170***$	$-0.144**$	$-0.120***$	$-0.117*$	$-0.176***$	$-0.147**$	$-0.190***$	$-0.154**$		
Quality,	Dummy for ISO certification (0 or 1)		$0.545***$	$0.502***$	$0.707***$	$0.427***$	$0.513***$	.549***	$0.542***$	$0.394***$	$0.518***$	$0.387***$	$0.423***$		
	innovation and Dummy for new technological license $(0 \text{ or } 1)$ (AV)	$0.198**$	0.184	0.039	0.218	$-0.004(a)$	.109	$0.207**$	0.195	$-0.039(a)$	0.147	$-0.079$	.069		
labor skills	Percentage computer-controlled machinery of total machinery (% of total machinery) 0.005***		$0.005***$	$0.004***$	$0.006***$	$0.004***$	$0.005***$	$0.005***$	$0.005***$	$0.004***$	$0.006***$	$0.003***$	$0.004***$		
	Number of plant's employees dealing with engineering and design (logs) (AV)	$0.036***$	$0.036*$	$0.028**$	$0.041*$	$0.020**$	0.029	$0.038***$	$0.038*$	0.017	0.03	0.003	0.012		
	Percentage of immigrant workers (perc. of total staff) (AV)	$-0.256***$	$-0.258**$	$-0.245***$	$-0.244**$	$-0.166***$	$-0.188*$	$-0.283***$	$-0.283**$	$-0.124*$	$-0.109$	$-0.109$	$-0.137$		
	Percentage of unskilled workers receiving training (perc. of unskilled workers) (AV) $-0.001(a)$		$-0.002(a)$	$-0.001$ (a)	$-0.003$ (a)	0.002	0.001	$-0.002(a)$	$-0.002(a)$	0.001	$-0.001(a)$	$0.004**$	0.003		
	Percentage of staff using computer at job (perc. of total staff)	$0.006***$	$0.006***$	$0.005***$	$0.006***$	$0.004***$	$0.005***$	$.005***$	$0.005***$	$0.005***$	$0.006***$	$0.004***$	$0.004***$		
	Other controlDummy for foreign direct investment (0 or 1)	$0.395***$	$0.387***$	$0.312***$	$0.464***$	$0.225***$	$0.297***$	$0.393***$	$0.384***$	$0.297***$	$0.467***$	$0.196***$	$0.279**$		
variables	Total number of competitors in plant's main market (logs) (AV)	0.021	0.018	0.027	0.009	0.044	0.034	0.023	0.019	0.032	$-0.001$	0.019	0.022		
	Dummy for benefit from free trade agreements with signed by the government (0 or $0.268***$		$0.264***$	$0.197***$	$0.337***$	$0.144**$	$0.228***$	$0.246***$	$0.242***$	$0.141**$	$0.276***$	$0.184***$	$0.239***$		
	Percentage of capacity utilization (percentage)	$0.003***$	$0.003**$	$0.003***$	$0.004**$	$0.004***$	$0.004***$	$003***$	$0.003**$	$0.003***$	$0.004***$	$0.003***$	$0.003**$		
	Dummy for importer firm $(0 \text{ or } 1)$		$0.303***$	$0.277***$	$0.445***$	$0.246***$	$0.344***$	$0.310***$	$0.304***$	$0.248***$	$0.380***$	$0.259***$	$0.317***$		

Table 14: IC elasticities and semi-elasticities with respect to productivity without controlling for other IC variables: Costa Rica

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.<br>NOTES: (AV) means that the variable enters the regression in form of industry-region average. Significance is given by robust standard errors. \* sign changes the direction of the effect, although statistically insignificant.



## Table 15: Further robustness: Costa Rica

NOTES: (1) (AV) means that the variable enters the regression in form of industry-region average.

(2) Significance is given by robust standard errors. \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%.

(3) Two steps estimation, inputs elasticities restricted by industry.

(4) The regressions include a constant, industry dummies and year dummies.

Source: Authors' elaboration with Investment Climate Surveys (ICs) data.

(5) Ackerberg, Caves and Frazer's (2007) GMM estimation method of Wooldridge (2005) without IC variables.

## Figure 1: Decomposition of per capita income from 1950 to 2004: Guatemala, Honduras, Nicaragua, and Costa Rica



(a) Real Gross Domestic Product per capita (Relative to US)











A. Restricted Estimation: Equal input-output elasticities for all the firms in the sample



B. Unrestricted by industry estimation: equal input-output elasticities for all the firms in the same industry (sector)



B.1 Unrestricted by industry Solow residual; B2 Single step-unrestricted-Cobb-Douglas-OLS TFP; B3 Single step-unrestricted-Translog-OLS TFP; B4 Single step-unrestricted-Cobb-Douglas-RE TFP; B5 Single step-unrestricted-Translog-RE TFP.

A.1 Restricted Solow residual;

A2 Single step-restricted-Cobb-Douglas-OLS TFP; A3 Single step-restricted-Translog-OLS TFP;

A4 Single step-restricted-Cobb-Douglas-RE TFP;

A5 Single step-restricted-Translog-RE TFP.

**Source:** Authors' elaboration with Investment Climate Surveys (ICs) data.

### Figure 3: Kernel density of productivity measures: Costa Rica



A. Restricted Estimation: Equal input-output elasticities for all the firms in the sample

A.1 Restricted Solow residual;

A2 Single step-restricted-Cobb-Douglas-OLS TFP;

A3 Single step-restricted-Translog-OLS TFP;

A4 Single step-restricted-Cobb-Douglas-RE TFP;

A5 Single step-restricted-Translog-RE TFP.

**Source:** Authors' elaboration with Investment Climate Surveys (ICs) data.





B.1 Unrestricted by industry Solow residual; B2 Single step-unrestricted-Cobb-Douglas-OLS TFP; B3 Single step-unrestricted-Translog-OLS TFP; B4 Single step-unrestricted-Cobb-Douglas-RE TFP; B5 Single step-unrestricted-Translog-RE TFP.



Figure 4: IC and C elasticities and semi-elasticities with respect to productivity: Guatemala, Honduras, and Nicaragua

**Source:** Authors' elaboration with Investment Climate Surveys (ICs) data.



#### Figure 5: IC and C elasticities and semi-elasticities with respect to productivity: Costa Rica

**Source:** Authors' elaboration with Investment Climate Surveys (ICs) data.

## Figure 6: Relative IC effects to average log productivity: Guatemala, Honduras, and Nicaragua

### (a) Guatemala



### (b) Honduras



## (c) Nicaragua

![](_page_65_Figure_6.jpeg)

![](_page_66_Figure_0.jpeg)

## Figure 7: Relative IC effects to average log productivity: Costa Rica