Understanding multilevel interactions in economic development [*]

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Abstract

National framework conditions mediate the effect of technological capabilities of firms on their productivity. Although this has been recognized in the literature for a long time, a quantitative test that explicitly considers this hypothesis has been lacking. Using a World Bank datasets of about 19,000 firms in 42 countries, most of which are developing, we estimate a multilevel production function with effects of firm's technological capabilities nested in the national framework conditions. Our results confirm that various facets of firm's technological capabilities and national economic, technological and institutional conditions influence total factor productivity of firms. Furthermore, we find that the effects of the national conditions and firm's technological capabilities are closely intertwined with each other. Adherence to international standards, formal training of workers and access to technology through foreign ownership make more difference for productivity of firms in less developed countries, while R&D capabilities on the contrary boost significantly more performance of firms in countries at the technological frontier. Different features of the national framework are shown to be responsible for this.

Keywords: Productivity, innovation, technological capability, institutions, multilevel modeling.

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1. Introduction

Economic development is a multilevel problem. Many factors at various levels of aggregation chip in. Firms invest in research and development (R&D), adopt new technologies and train their workers how to use them productively. Governments design policies aimed to, at least in an ideal world, provide infrastructure, incentives, stability and other framework conditions that boost innovation and ultimately economic growth. Still other factors often out of reach for firms or even governments, such as deeply rooted institutional, social or cultural context, play a role too. The main proposition of this paper is that none of these is likely to be the dominant, or sufficient, driver of economic development alone, that factors operating at the different levels intertwine with each other, and therefore their effects should be studied in an integrated multilevel framework. To show how this can be done, we construct and estimate a hierarchical model that allows us to examine these multilevel interactions in a more complete way than the literature on economic development has been able to do so far.

Since Schumpeter (1934, 1939 and 1943), economists have been challenged to study how the "micro, mezzo and macro" spheres of the economy jointly evolve in the process of economic development. Endogenous growth models have gone a long way to elaborate the thesis of increasing returns driven by knowledge spillovers between firms and other organizations (Romer 1986, Grossman and Helpman 1990, Aghion and Howitt 1992). Even broader framework conditions have been emphasized in the literature on technological catching up (Abramovitz 1986, Fagerberg 1987 and Verspagen 1991). Neo-Schumpeterian perspectives on long waves drew attention to the (mis)match between the techno-economic system and socio-institutional characteristics in diffusion of new technologies (Perez, 1983). Nevertheless, these contributions are distinctly macroeconomic, with implicit micro foundations, but focusing solely on the national patterns. Not much has been said, in contrast to Schumpeter's affection for the entrepreneur, about the multilevel interactions in this literature.

Explicitly micro-founded is the thesis about survival of firms propelled by innovation, but determined by the environment, which is at the core of growth modeling in evolutionary economics (Nelson and Winter 1982). Here the focus is on dynamic interactions between heterogeneity of firms given by their technology, selection environment given by markets and innovation. But in this approach the interaction goes one-way, it is predominantly bottom-up in the sense that the macro patterns become derived as aggregations of micro outcomes, so that distinctly macro phenomena are lacking. As Castellacci (2007) rightly laments, understanding of how behavior of firms is shaped by specific characteristics of the macro environment, even though often called for, remains limited. Econometric evidence on these models also remains quite rare in this tradition.

Multilevel thinking about economic development, at least at the conceptual level, has become emblematic for systemic approaches to innovation (Lundvall 1992, Nelson 1993 and Edquist 1997). At the core of this perspective figures a firm as the basic unit of the analysis, but the firm is not seen in isolation, the firm is embedded in a national innovation system. Innovation and therefore development is portrayed as a collective problem, which cannot be fully understood by focusing at a single level of analysis. According to this approach, performance of firms is affected by the framework conditions, which in turn feeds back to the aggregated level, so forming the essential link between micro and macro patterns. Synergies, feedbacks and interactions between private and public actors within complex macrostructures naturally become the main focus of these studies. Needless to say, formal modeling of relations like these proves to be difficult, especially in a dynamic framework, which prevented the systemic perspective to be fully formalized into mathematical models yet.

Studies of technological upgrading in developing countries have long argued for a need to recognize not only capabilities at the firm level, but also the role of national environment for technological change (Kim, 1980; Dahlman, et al, 1987 and Lall, 1992). Lessons from industrialization in South-East Asia, the most favorite subject of these studies, offer a particularly strong practical support for the multilevel perspective. It is well known that development efforts of firms (and their groups, networks or associations) on one hand and the government on the other hand have been purposefully coordinated in Japan, later the Asian Tigers or more recently China, which generated some of the most spectacular development spurts, while dusty infrastructure, excessive bureaucracy and macroeconomic, social and political instability have bulldozed upgrading efforts of firms elsewhere. Similarly to the systemic perspective, however, this literature has not been forged into formalized models and econometric testing of the underlying hypotheses is therefore extremely rare.

All too many questions remain unanswered, because an integrated framework to quantitatively analyze the multilevel interactions in economic development is lacking. Could it be that returns on technological capabilities developed by firms critically depend on national economic, technological, institutional and other framework conditions? Does it pay off for firms to invest in their own R&D capabilities in a country with poor technological infrastructure? Should on the other hand governments design, sequence and prioritize policies according to what the firms are capable of doing? Should governments in developing countries maintain public R&D infrastructure, even if there are very few incumbent firms with noticeable R&D capabilities to benefit from it? Should they rather use their limited resources to improve basic education, because this bears fruits for a broad stratum of firms? Should they insist on price stability, much in line with IMF's recommendations, or is this rather superficial, perhaps except of hyperinflation, for productivity of firms? Can we find support for such multilevel interactions in econometric analysis based on hard data? Can we model this in a concise way?

Econometric estimates using micro data to investigate the relationship between R&D, innovation and productivity have become increasingly synchronized to use the same model on datasets from different countries, so that the results can be directly compared between them (Lööf, et al. 2003, Griffith, et al. 2006, Raffo et al., 2008, OECD 2009). Some researchers have even been able to pool micro data from different countries (Janz, et al. 2004, Mohnen, et al. 2006, Goedhuys et al. 2008a), which allowed them to include dummies to capture the country effects. Using these conventional methods, however, we are able to detect whether the national differences matter, which is often the case, but we can only speculate what exactly drives them. Moreover, the effect of firm's technological efforts on their productivity is likely to differ by country too, but we have learnt very little from these studies about the mechanisms how the micro and macro effects interact with each other. To find out what lurks behind these differences, and to estimate their correct standard errors, one needs to use the method of multilevel modeling, which has been tailored to handle hypotheses identified at different levels like these (Goldstein 2004).

A multilevel model, sometimes also called a 'hierarchical', 'random coefficient' or 'mixed-effect' model is a statistical model that relates the dependent variable to predictor variables at more than one level (Luke 2004). If a hierarchical structure of data exits, the major assumption of standard models that observations are independent from each other is likely to be violated. By relaxing this assumption, multilevel models allow us to properly estimate the extent to which differences between the higher-level units, such as countries, are accountable for performance at the micro level, in this case the productivity of firms. In addition, in a more complex model, we can examine whether the country conditions interact with the technological efforts the firms undertake individually to raise productivity, in other words to reveal the contextual effects that reinforce or weaken the link between firms' technological capabilities and their productivity level.

The aim of the paper is to address exactly this kind of questions. To illuminate the multilevel interactions, we need micro data from many countries and a set of macro indicators that capture the salient aspects of the nation framework conditions, in which the firms operate. For this purpose, we pool micro data from 42 countries, derived from the Productivity and Investment Climate Survey (PICS) organized by the World Bank (2003), which provides harmonized information on technological capabilities of firms and their performance, such as value added, capital stock and employment, that are necessary to estimate production function. In addition we collect from various sources a battery of macro indicators, which capture not only the overall level of development, but also direct measures of the quality of research infrastructure, education system, institutional framework and macroeconomic stability, and test their explanatory power in the multilevel framework. More specifically, we estimate a multilevel specification of Cobb-Douglas production function, to explain differences in total factor productivity as a function of firm-level capabilities, national framework conditions and a combination thereof.

As far as we know, this is the first time multilevel modeling is used to study how much the various macro factors affect productivity of firms. So far multilevel modeling has been applied in education studies, health science, human geography and biology, but rarely in the field of economics, innovation or development studies; with the exception of the recent papers by Srholec (2008, 2009), which used this methodology to study national and regional effects on innovativeness of firms, but not their productivity. Clearly, the enormous requirement on scale and scope of data to estimate a multilevel model has been a major reason for a lack of such evidence, because one needs micro data with significant variation across countries, but also a sufficient number of observations per country to run meaningful inferences. Since new sources of data emerge from national statistical offices and international organisations, however, multilevel modeling becomes a viable method to econometrically study those more complex relationships that have been hypothesized in the theoretical literature for quite some time.

The structure of the paper is as follows. Section 2 reviews theoretical arguments for studying productivity of firms and their technological efforts in a multilevel framework, particularly in research on technological catching-up. Section 3 explains multilevel modeling, outlines a multilevel production function with effects of firm's technological capabilities nested in the national environment and debates relevant methodological issues. Section 4 introduces the PICS micro dataset. Section 5 brings in measures of the national framework conditions. Section 6 delineates the empirical model and presents results of the econometric estimates. Section 7 concludes.

2. A multilevel production function of firms nested in countries

Assume a 2-level structure, with firms at level-1, nested in countries at level-2. A standard 1-level regression model would be the following:

(1) $$y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + e_{ij}$$

where y_{ij} is the dependent variable, such as in our case firm's productivity, x_{ij} is the firm-level explanatory variable (or a vector of variables), β_{0j} is the usual intercept, β_{1j} is the usual slope coefficient, e_{ij} is the standard residual error term, i is the firm ($i = 1\ldots m$) and j is the country ($j = 1\ldots n$). Note that by putting subscript j, we allow for more than one country in the analysis, but formulate the equation separately for each of them, generating different intercepts and different slope coefficient per country. If we are interested only in this relationship, we can estimate the n models independently, resulting in different parameters for each country and a common intra-country residual variance.

Since the intercept and slope coefficients vary across countries, they can be referred to as 'random coefficients', with a certain mean value, variance and distribution, which can be explicitly modeled in a multilevel framework. By constructing a multilevel model, in other words, we allow the firm-level relationships to differ by countries and aim to explain (at least some of) the variance by introducing country-level predictors. A 2-level model with explanatory variables at both firm and country levels thus emerges, if we let the intercept β_{0j} and slope β_{1j} become random variables:

(2) Level-1 model:

$$y_{ij} = \beta_{0j} + \beta_{1j}x_{ij} + e_{ij}$$

Level-2 model:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}z_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}z_j + u_{1j}$$

where z_j is the level-2 or country predictor (or a vector thereof) and u_{0j} and u_{1j} are normally distributed residual terms for each level-2 equation, which are independent from the level-1 residual e_{ij}. Since the country effects are identified by the subscript j, we have a hierarchical system of regression equations, where we are allowing each country to have a different average outcome represented by the intercepts (β_{0j}) and a different effect of the level-1 predictor (β_{1j}) on the outcome. Although a different level-1 model is estimated for each country, as apparent from the j subscripts in the level-1 parameters, the level-2 equation is defined for all of them and the γ coefficients are not assumed to vary across countries.

By substituting β_{0j} and β_{1j} into the level-1 model and rearranging we can write the entire model in a single equation:

(3) $$y_{ij} = \gamma_{00} + \gamma_{01}z_j + \gamma_{10}\, x_{ij} + \gamma_{11}z_jx_{ij} + (u_{0j} + u_{1j}x_{ij} + e_{ij})$$

where in brackets is the random part and the rest contains the fixed part of the model. As discussed by Goldstein (2003), the presence of more than one residual term makes the traditional estimation procedures such as ordinary least squares inapplicable and therefore specialized maximum likelihood procedures must be used to estimate these models. For more details on these estimators see Raudenbush, et al. (2004).

A major assumption of single-level models is that the observations are independent from each other. If a nested structure of data exits, units belonging to the same group tend to have correlated residuals and the independence assumption is likely to be violated. By relaxing this assumption, multilevel modeling provides statistically more efficient estimates, which are more “conservative”, as Goldstein (2003) puts it, than those ignoring the hierarchical nature of data[1]. Statistically significant relationships that have been established in the literature by using the standard methods may come out not significant in the multilevel analysis. A lot that we have learned empirically about the link between technological capabilities and productivity from research on data identified at a single level might appear different in the multilevel framework.

A partial solution to account for the compositional effects, as already noted above, is to ignore the random variability associated with the higher-level factors and include into the estimate fixed effect dummies that correspond to the hierarchical structure of the data, such as dummies for location of firms in different countries. Using dummies might be a useful quick-fix solution, if the purpose only is to control for the compositional effects, but it is of a little help if the prime interest is in effects of the higher-level factors or cross-level interactions themselves. Although we may detect rough patterns of the structure, a dummy is a “catch-all” variable for which we can only speculate what it really represents. After all, if the country dummies significantly improve the predictive power of the model, which is typically the case in econometric estimates, a multilevel analysis should be chosen.

More specifically, we analyze how productivity of firms is influenced by firms’ own technological capabilities and how this link is affected by national framework conditions. We use a Cobb Douglas framework as point of departure. Firm i in country j ‘s value added Y_{ij} is a function of the traditional factors of production, physical capital K_{ij} and labour $L_{ij.}$ The total output that is produced with these inputs depends on the firms level of productivity, captured by parameter α, which is a function of the activities the firms undertake to build up technological capabilities and firm specific knowledge:

$$Y_{ij} = A(T_{ij})\, K_{ij}^{\delta 1j} L_{ij}^{\delta 2j}\, e_{ij}$$

[1] It should be noted, however, that not only multilevel modeling relaxes the standard independence assumption on residual terms Spatial autocorrelation techniques have been developed to produce valid statistical inferences if errors tend to be correlated regionally (Fotheringham et al. 2000). Also survey design and analytical tools recognize the need to take into account the hierarchical structure of the population (Skinner et al. 1989) Although these procedures are deemed to be necessary to obtain efficient estimates, the higher-level effects typically do not merit a serious interest themselves. Only multilevel modeling allows us to look closely at the patterns and consequences of hierarchical structure of the phenomena in question

Here δ_{1j} and δ_{2j} denote marginal productivities of physical capital and labour, respectively, T_{ij} represents technological capabilities of firms. The stochastic term e_{ij} summarizes other unobservable factors affecting firms output. Taking the log-linear form of this equation, and simplifying the notation, we get the following specification:

$$y_{ij} = \alpha_{0j} + \sum_{t=1} \beta_{tj} T_{ijt} + \delta_{1j}\, k_{ij} + \delta_{2j}\, l_{ij} + e_{ij}$$

where $y_{ij}=\ln Y_{ij}$; $k_{ij}=\ln K_{ij}$; $l_{ij}=\ln L_{ij}$; T_{ijt} is a vector of t variables that are hypothesised to be related to TFP_{ij}, such as proxies for technological capabilities or foreign ownership. These variables are of major interest in this study along with their corresponding vector of coefficients β_{tj}. The main aim is to find out to which extent they differ by countries and whether we can explain these differences by country variables. Therefore, what is specific to our analysis it that we let the intercept α_{0j} and the slopes of the technological T_{ijt} variables β_{tj} become random variables, in the following way:

$$\alpha_{0j} = \gamma_{00} + \sum_{n=1} \gamma_{0n}\, NATION_j + u_{0j}$$

$$\beta_{tj} = \gamma_{t0} + \sum_{n=1} \gamma_{tn}\, NATION_j + u_{1j}$$

where $NATION_j$ is a vector of n variables that capture specific aspects of the national framework conditions given, for example, by research infrastructure, educational system, regulation or macroeconomic stability. Instead of controlling for these effects by country dummies, we investigate how relevant are these specific national factors for explaining TFP_{ij} of firms. Also we allow the slopes of the technological variables to vary with national conditions; in other words, we allow the link between technological capabilities or ownership of firms and their productivity to be different along different national settings. Finally, u_{0j} and u_{1j} are normally distributed residual terms for each equation that represent other unobserved national factors.

3. Micro data

One reason why multilevel modeling has not been widely applied in this field so far is the demanding requirement on the scope and quality of data. To properly estimate a multilevel model, we need micro data for a number of higher level units, such as countries, with a reasonable number of observations within each of them. For a long time a dataset that would allow this type of analysis has not been around. But this has changed with the recent availability of micro data from the Productivity and Investment Climate Survey (PICS) organized by the World Bank, which has been rarely used in research on technological catching-up so far; except the recent papers by Goedhuys (2007a,b), Goedhuys et al (2008a, 2008b), Almeida and Fernandes (2008) and Srholec (2008). About 19,000 observations from 42 countries can be used in our analysis.

Firms were asked about various aspects of their business activity, including information on financial variables and a set of questions on technological capabilities, in a questionnaire harmonized across many developing countries (for more details on methodology of the survey see World Bank 2003). To estimate the production function, we need a measure of output, capital and labor. Y_{ij} refers to value added, measured by the difference between sales (turnover) and sum of material, electricity and energy costs. The capital stock, K_{ij} , is measured by the sum of the net book value - the value of assets after depreciation - of machinery and equipment (including vehicles), land and buildings at the end of fiscal year. Labor input, $L_{ij,}$ is measured as the sum of full-time permanent and seasonal (temporary) employees. Both Y_{ij} and K_{ij} are expressed in constant USD according to Purchasing Power Parity (PPP) derived from World Bank (2007). All of these variables are used in logs in the following, denoted by small caps, as explained in the previous section.

Besides the traditional production function variables, the dataset provides information on industry, foreign ownership and technological variables. Sectors were difficult to identify because somewhat different classifications had been used in the various national datasets. For this reason we can distinguish only between 9 broad sectors as follows: 1) Agro, food and beverages; 2) Mining, energy, water and recycling; 3) Apparel, garments, leather and textiles; 4) Chemicals; 5) Wood, paper, non-metal materials and furniture; 6) Metallurgy, machinery, electronics and transport equipment; 7) Construction and transport; 8) Retailing; and 9)

Services n.e.c. (including wholesale, hotels and restaurants, tourism, repairing, real estate, information technology and other services). Sectoral dummies IND_i are further introduced in the econometric estimate to control for the sectoral patterns with “Metallurgy, machinery, electronics and transport equipment” as the base category.

Equally essential to take into account are resources of firms directly devoted to search, absorption and generation of new technology. Research and development (R&D) is the traditional, and for a long time the only, seriously considered indicator. $R\&D_{ij}$ is defined as a dummy with value 1 if the firm devotes expenditure on this activity. The aim of this variable is to capture a general commitment to R&D. An important insight of the aforementioned literature on innovation in developing countries, however, is the broad and multifaceted nature of technological capabilities (Bell and Pavitt, 1993). Arguably, innovation is about much more than just spending on R&D, so that we need to keep an eye on these broader aspects of capabilities as well. It is very fortunate for our purpose that the survey contains a battery of variables that may be used to gauge their various facets

Besides the R&D variable, the dataset provides information on adherence to ISO norms, use of internet in the business and formal training of employees. ISO_{ij} is a dummy with value 1 if the firm has received ISO (e.g. 9000, 9002 or 14,000) certification and thus reflects a capability to conform to international standards. ICT_{ij} is a dummy with value 1 if the firm regularly uses a website in its interaction with clients and suppliers, which captures the potential for user-producer interactions mediated by the internet. $SKILL_{ij}$ is a dummy with value 1 if the firm provides formal (beyond “on the job”) training to its permanent employees. And finally, the variable FOR_{ij} refers to share of foreign ownership, which is important to take into account, because foreign-owned firms benefit from access to technologies developed by the parent company abroad.

It is interesting to note that many of these facets of technological capabilities, such as the use of information technologies, quality control and training, have been emphasized as particularly relevant but under-measured in the context of developing countries in the third edition of the Oslo Manual (OECD, 2005, pp. 141-144). Along these lines the PICS data provide much richer evidence as compared to what can be derived from most of the innovation surveys that have been conducted in developing countries so far.

A basic overview of the dataset is given in Table 1. The sample comprises about 19,000 firms with non-missing information.[2] A quick look at the composition of the sample reveals widely different firms in terms of size, endowments and ownership. Averages of the variables reflecting technological capabilities are self-explanatory, and will be examined in more detail later in the econometric framework.

Table 1: Overview of the micro sample

Variable	Obs.	Mean	Std. Dev.	Min	Max
y_{ij}	19,219	13.55	2.14	3.74	24.12
k_{ij}	19,219	13.18	2.24	4.03	22.59
l_{ij}	19,219	3.71	1.58	0	11.08
$R\&D_{ij}$	19,219	0.30	0.46	0	1
ICT_{ij}	19,219	0.45	0.50	0	1
ISO_{ij}	19,219	0.21	0.40	0	1
$SKILL_{ij}$	19,219	0.42	0.49	0	1
FOR_{ij}	19,219	0.07	0.24	0	1

[2] It should be mentioned that about 50 observations have been already excluded at this point, because they have been identified as major multivariate outliers on the base of Mahalanobis distance computed for sales per employee, costs per employee and capital stock per employee.

4. Macro data

A natural starting point to examine the cross-country differences is to look at patterns of the micro dataset by country, which is revealed in Table 2. Surveys conducted in 42 countries are included, most of which are developing. A particularly thorny issue is whether the data are representative. Since we fully acknowledge this concern, we have included into the sample only national datasets with a reasonable number of observations given size and structure of the country. Even these could be seen as a relatively low numbers by some observers; in particular by those in developed countries who have the fortune to analyze large datasets. Nevertheless, most of the sample comes from developing countries for which micro data (particularly on technological capabilities) are extremely scarce, so that we should not judge this dataset by standards of the most advanced countries. In fact, one can find plethora of papers in the literature based on samples of a few hundreds of firms, which at least implicitly claim to be representative to the context in question. Indeed, much more extensive micro data on technological capabilities of firms in a reasonably large number of developing countries is not likely to emerge anytime in the near future.[3]

[3] Some developing countries have conducted surveys based on the CIS methodology (UNU-INTECH 2004), but access to micro data from these surveys remains limited, which prevents pooling them together for the purpose of multilevel analysis.

Table 2: Overview of the sample by country

Country	Year	exp($GDPCAP_j$)	Obs.	y_{ij}	k_{ij}	l_{ij}
Algeria	2006	7,101	96	13.42	12.94	3.38
Argentina*	2005	10,027	344	14.49	13.60	3.93
Bangladesh*	2006	1,071	1,173	12.76	12.90	4.58
Bolivia*	2005	3,672	163	13.17	13.50	3.59
Brazil*	2002	7,960	1,432	14.00	13.10	4.04
Chile*	2005	11,646	320	14.07	13.36	3.74
China	2002	2,888	1,114	14.44	14.31	4.49
Colombia*	2005	5,682	196	13.49	13.12	3.60
Costa Rica*	2004	8,399	196	12.16	12.08	2.77
Ecuador	2005	6,394	225	13.89	13.30	3.64
Egypt*	2003	4,304	716	12.43	13.12	3.60
El Salvador	2005	5,103	295	13.41	12.73	3.88
Ethiopia*	2005	575	205	12.90	13.28	4.26
Germany	2004	29,922	1,047	13.97	13.37	2.95
Greece	2004	27,137	428	13.33	12.83	2.30
Guatemala*	2005	4,042	259	13.02	12.28	3.56
Honduras*	2005	3,171	189	12.89	12.35	3.36
Hungary	2004	15,563	326	13.58	13.67	3.11
India*	2004	1,941	1,503	12.43	12.29	3.28
Indonesia*	2002	2,795	306	14.39	14.36	5.25
Ireland	2004	35,814	386	14.05	13.61	3.02
Korea	2004	19,787	392	14.42	14.02	2.96
Madagascar	2004	790	115	14.40	13.31	4.12
Mexico*	2005	11,142	731	13.43	12.85	3.47
Morocco*	2002	3,107	636	13.67	12.98	4.22
Nicaragua*	2005	2,237	204	12.11	11.64	3.03
Pakistan*	2001	1,917	802	12.90	12.77	3.45
Paraguay*	2005	3,772	90	13.33	13.11	3.52
Peru*	2005	6,159	232	13.75	12.95	3.82
Philippines*	2002	2,650	450	13.18	12.48	4.41
Poland	2004	12,488	586	12.96	12.75	2.59
Portugal	2004	19,950	391	13.80	12.98	2.79
Romania	2004	8,356	214	13.38	12.84	3.55
Saudi Arabia	2004	19,881	558	14.71	14.33	4.35
South Africa	2002	7,577	420	15.64	14.48	4.80
Spain	2004	26,294	408	13.99	13.30	2.87
Thailand*	2002	5,865	604	14.58	14.32	4.85
Turkey*	2004	9,068	448	14.31	14.01	4.09
Ukraine	2004	4,833	176	13.62	13.19	3.63
Uruguay*	2005	8,581	142	13.24	12.41	3.26
Vietnam	2004	1,888	414	13.21	13.27	3.64
Zambia*	2006	1,188	287	12.17	11.71	3.40
TOTAL	..	8,875	19,219	13.55	13.18	3.71

*Note: *Manufacturing firms only.*

Since we use a multilevel model, we need data for specific country-level variables that capture the salient features of the national framework conditions. To reduce the influence of shocks and measurement errors occurring in specific years, we use these indicators in the form of three-year averages over a period prior to the year when the survey was conducted, if not specified otherwise below.[4] This also limits the extent of missing data, which is crucial in a sample containing many developing countries. Still missing information had to be estimated for some countries, which is explained for the particular indicators below.

As a all-encompassing variable, before turning to more specific indicators of the national conditions, we use log of GDP per capita (in PPP, constant 2000 international USD), denoted by $GDPCAP_j$, which represents the general level of economic development. This variable is a strong correlate to most other relevant variables such as proxies for quality of the science, research and educational systems, institutional framework or macroeconomic stability. Therefore, we first – in a basic specification of the model – include only this predictor at the macro level in an attempt to find out whether the overall development level matters for the firm-level link between technological capabilities and productivity. In other words, is it more rewarding for firms to engage in R&D, invest in ICT and training or obtain an ISO certificate in an economically more (or less) developed country? Some previous empirical studies have revealed that technological variables have limited effect on productivity of firms in the least developed countries, but that rather other factors that are related to the business environment and are beyond the control of the firm are more relevant (Goedhuys et al, 2008a, Goedhuys et al 2007, Eifert, Gelb and Ramachandran, 2005). It is thus interesting to investigate the effect of $GDPCAP_j$ on the slope coefficients of the capability variables.

For the more specific characteristics of the national framework, a natural starting point is to consider the quality of the national science, research and educational systems (Nelson, 1993). Availability of research infrastructure, like universities, R&D labs and a pool of researchers in the labor force, reduce costs and uncertainties associated with firm's innovative activities, and are likely to generate positive externalities in the economy. Although some part of these resources is devoted to basic research, most research in developing countries is arguably geared toward fostering the capacity to assimilate knowledge from abroad rather than to

[4] Since the surveys were conducted in different years, we computed averages over the three-year periods prior to the reference period of the particular survey.

generate new knowledge at the frontier. We measure this aspect of the national conditions by the $GERD_j$ variable, which refers to general expenditure on research and development as % of GDP. Information for this variable has been gathered from various sources, including UNESCO, RICYT and World Bank (2007).

Education, which is at the heart of what Abramovitz (1986) would refer to as “social capabilities”, and which Baumol et al. (1989), Verspagen (1991) and many others have shown to be a crucial variable for explaining successful technological catching up, is a must to take into account. We represent this aspect of the national framework conditions by literacy. $LITERA_j$ refers to the literacy rate in adult population (% of people ages 15 and above), and has been derived from UNESCO. Since there is a relatively low frequency of this indicator, we use data from the latest year available, and complement the information in few cases by estimates from various issues of the Human Development Report.[5]

Another relevant feature of the institutional framework is regulation of business, for which data from the “Doing Business” project of the World Bank - following Djankov, et al. (2002), Djankov, et al. (2003) and Botero, et al. (2004) - come very handy. $REGUL_j$ is the composite “Ease of doing business index”, which refers to scores of countries on ten topics covered in the Doing Business dataset (starting a business, employing workers, registering property, enforcing contracts, etc.), and is supposed to represent the ease (or difficulty) to do business in the country given the existing regulatory burden on the firms; for more details see World Bank (2005). Lower scores indicate more business-friendly regulations and vice-a-versa. Unfortunately, data for the index exist only from 2005 onwards, so that we do not compute the three-year averages for this indicator, and use only the earliest period available. But scores on this index tend to be highly stable in short term ($R = 0.928$ between 2005 and 2007 in our sample of 42 countries).

Macroeconomic instability has always been an essential part of the economic picture in developing countries, and in the recent period, turbulences along these lines are also worrisome for more advanced economies. Because innovation is very uncertain venture in

[5] It would have been perhaps preferable to have data on educational attainment of the population by primary, secondary and tertiary levels, but this information is not available for many countries in the sample. Similarly, data on science and engineering education, which would have been interesting to take into account, is unfortunately not widely available.

itself, characteristics of the environment that further increase for firms the uncertainty of returns on their innovation projects, such as symptoms of macroeconomic volatility, should hinder technological catching up and slows down productivity. We use the rate of inflation to capture the macroeconomic conditions. $INFLAT_j$ reflects price stability, which is measured by geometric average of inflation indicated by the consumer price index derived from World Bank (2007).

An overview of the macro variables is given in Table 3. There is a lot of variety in the sample, ranging from the least developed countries (Ethiopia, Bangladesh and Madagascar) to advanced European economies (Germany, Ireland and Spain). Some of them rank among the most technologically intensive countries in terms of $GERD_j$ (Germany and Korea), while many others maintain negligible technological infrastructure. $LITERA_j$ may not be very relevant indicator in studies confined to develop countries, because virtually all of them maintain close to complete literacy, but this sample contains a lot of diversity along this dimension, including several countries with more than a third of illiterate population (Ethiopia, Pakistan, Bangladesh, Morocco and India). As far as the $REGUL_j$ variable is concerned, there are countries with fairly liberalized economies (Ireland and Thailand), as well as those with a relatively tight grip of the government on the business sector (Egypt, India and Ukraine). $INFLAT_j$ is limited to single digits in most countries and moderate levels elsewhere (Romania, Turkey and Zambia), but fortunately there are no countries in the sample with rampart inflation rates that would make them major outliers. It should be noted, finally, that correlation between these variables is quite modest, except of the overlap with the $GDPCAP_j$ variable that is included separately, so that the regression estimates do not suffer from multicollinearity problems (see Appendix 2 for the correlation table).

Table 3: Overview of the macro sample

Variable	Obs.	Mean	Std. Dev.	Min	Max
$GDPCAP_j$	42	8.65	1.00	6.36	10.49
$GERD_j$	42	0.50	0.58	0	2.67
$LITERA_j$	42	84.84	16.04	35.90	99.66
$REGUL_j$	42	85.74	39.39	10	164
$INFLAT_j$	42	5.43	3.55	-0.15	16.31

5. Estimation and results

By adding these variables and sector dummies to the multilevel production function outlined above, the estimated equation becomes:

Firm-level model:

$$y_{ij} = \alpha_{0j} + \beta_{1j}\,R\&D_{ij} + \beta_{2j}\,ICT_{ij} + \beta_{3j}\,ISO_{ij} + \beta_{4j}\,SKILL_{ij} + \beta_{5j}\,FOR_{ij} +$$

$$\delta_0\,k_{ij} + \delta_1\,l_{ij} + \sum_{m=1}\delta_{2m}\,IND_i + \sum_{m=1}\delta_{3m}\,IND_i\,k_{ij} + \sum_{m=1}\delta_{4m}\,IND_i\,l_{ij} + e_{ij}$$

Country-level model:

$$\alpha_{0j} = \gamma_{00} + \sum_{n=1}\gamma_{0n}\,NATION_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \sum_{n=1}\gamma_{1n}\,NATION_j + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + \sum_{n=1}\gamma_{2n}\,NATION_j + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + \sum_{n=1}\gamma_{3n}\,NATION_j + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + \sum_{n=1}\gamma_{4n}\,NATION_j + u_{4j}$$

$$\beta_{5j} = \gamma_{50} + \sum_{n=1}\gamma_{5n}\,NATION_j + u_{5j}$$

where i is a firm, j is a country, $IND_i = 1 \ldots m$ is the set of sector dummies and $NATION_j = 1 \ldots n \in GDPCAP_j \wedge (GERD_j, LITERA_j, REGUL_j, POLITY_j, INFLAT_j)$.

From this follows that α_{0j} is the conditional productivity level of firms operating in country j, in other words average of their total factor productivity (TFP_{ij}), which is indentified by the estimated grand intercept γ_{00} and the various country effects $\sum_{n=1}\gamma_{0n}$ on the total factor productivity. In a similar fashion, effects of the capability variables β_{1j}, β_{2j} ... β_{5j} are allowed to differ by country, because they are given not only by the estimated means of the slope coefficients γ_{10}, γ_{20} ... γ_{50} across countries, but also by the cross-level interactions between the firm- and country-level predictors $\sum_{n=1}\gamma_{1n}$, $\sum_{n=1}\gamma_{2n}$ ... $\sum_{n=1}\gamma_{5n}$. Residuals u_{0j} for the intercept and u_{1j}, u_{2j} ... u_{5j} for the slope coefficients indicate that these effects vary not only as a function of the predictors but also as a function of unobserved country effects (assumed to be sampled from a normal distribution with expected zero mean and variance = σ^2_u). Finally, δ_0, $\delta_{1,}$ δ_{2m}, δ_{3m} and δ_{4m} indicate the usual fixed effects in the production function framework and e_{ij} is the firm-level residual.[6]

To improve interpretability of the results, we centre the production function predictors k_{ij} and l_{ij} and their cross-products with IND_i by deducting mean, so that these variables enter the estimation with zero mean. We standardize the country-level predictors $NATION_j$ by deducting mean and dividing by standard deviation, so that these enter the estimation with zero mean and standard deviation equal to one. All of the predictors, including the proxies for firm-level technological capabilities, therefore have meaningful zero-points, which greatly simplifies interpretation of the estimated parameters.[7] In addition, we can directly compare the magnitude of the estimated country-level effects, because the standardization procedure transforms the predictors to units of standard deviation and the unobserved random effects are measured in standard deviation too. Since the firm-level capability variables are dummies, the magnitude of their coefficients is comparable by definition.

Table 4 gives the first set of results. [8] Fixed effects are reported in the upper part, while random effects are in the lower part of the table. For the sake of space, we do not report the estimated fixed effects of IND_i and their interaction terms with k_{ij} and l_{ij}, though they are included in these estimates. First, we consider a "basic" model with only firm-level explanatory variables, but allow the estimated intercept and slope coefficients of the technological variables to vary across countries by including the respective random effects. Second, we examine a so-called "intercept-as-outcome" model, which adds the country-level predictor $GDPCAP_j$ only for the intercept. Third, we estimate a full "slopes-as-outcomes" model, which relates the country-level predictor $GDPCAP_j$ to both the intercept and slopes of the firm-level technological variables. $GDPCAP_j$ is used as the only country-level predictor

[6] δ_0, $\delta_{1,}$ δ_{2m}, δ_{3m} and δ_{4m} can be allowed to differ by country by adding another 2 + 3*m equations to the country-level layer of the model, but this would consume too many degrees of freedom and prohibit us from estimating robust standard errors of the multilevel interaction effects that are the main focus of this paper. Unfortunately, there is a narrow limit to how many country-level parameters we can estimate in a sample consisting of 42 countries.

[7] For instance, the intercept α_{0j} becomes the outcome of a firm that is characterized by average capital and labour (k_{ij}, l_{ij} = 0), fully domestic-owned (FOR_{ij} = 0), without technological capabilities ($R\&D_{ij}$, ICT_{ij}, ISO_{ij}, $SKILL_{ij}$ = 0), operating in the base industry (IND_i) and in an average country ($NATION_j$ = 0); e_{ij} and u_{1j}, u_{2j} ... u_{5j} have mean of zero by definition.

[8] A specialized statistical software Hierarchical Linear and Non-linear Modeling (HLM) version 6.04 was used to estimate the equations. See Raudenbush et al. (2004) for details on the estimation procedure.

for now, leaving the other national factors for more detailed investigation below, in order to avoid problems of multicollinearity.

Results of the basic model are presented in the first column in Table 4. Even though there are no country-level predictors, the random effects reveal to which extent the intercept (TFP_{ij}), returns on the capability variables and the effect of foreign ownership differ by country. [9] Overall, there is a lot of variability in the average level of firm's productivity across countries. It can be easily calculated that for 67% of the countries, TFP_{ij} lies in the range of [12.55, 13.55] and for 95% of the countries average TFP_{ij} lies in the range of [12.05, 14.05]. [10] All of the firm-level fixed effects come out statistically significant and with the expected signs. But also the estimated coefficients of the capability and ownership variables appear widely distributed around the mean highlighting their sensitivity to the national framework conditions.

$R\&D_{ij}$ boosts value added for given inputs by 0.15, confirming that this aspect of technological capabilities is relevant in the context of most developing countries. However, a closer look at distribution of this coefficient reveals that for 68% of the countries the effect of R&D on productivity lies in the range of [0.03, 0.27], which indicates that for firms in countries with the least favorable conditions the positive effect of R&D on productivity does not hold, while in countries with the most enabling environment R&D is a strong productivity enhancing activity. For 95% of the countries the coefficient lies in the range of [-0.09, 0.39], so that the effect of R&D on productivity is estimated to be even negative in a small number of countries. Normally, this is difficult to envisage, but in extremely adverse conditions, for instance during a steep slump of aggregate demand, the negative relationship may start to kick in.

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[9] Since the HLM (version 6.04) package assumes that the variances may not be normally distributed, a chi-square test of the residuals is performed (Raudenbush, et al. 2004). Nevertheless, this should be interpreted with caution because the variances are bounded at zero by definition, while we generally expect the residuals to be non-zero, so that the meaning of their statistical significance is not the same as for an ordinary variable.

[10] A useful characteristic of the standard deviation is that with normally distributed observations, about 68% of the observations lie less than one standard deviation from the mean, and about 95% of the observations lie between two standard deviations below and above the mean. Thus, for the grand mean TFP, 68% of countries have average TFP lying in the range [13.05-0.50, 13.05+0.50] or [12.55, 13.55], while 95% of countries have mean TFP lying in the range [13.05-2*0.50, 13.05+2*0.50] or [12.05, 14.05]. In a similar way, the slope coefficients vary across countries and the distribution of the coefficients can be analysed. It illustrates how the effect of capabilities on productivity varies across countries.

As compared to the other capability variables, the magnitude of the $R\&D_{ij}$ coefficient is similar to the effect of $SKILL_{ij}$, but almost half of the estimated effect of ICT_{ij} and ISO_{ij}. R&D matters for firms in many countries, but it is not the only and even not necessarily the most important aspect of technological capabilities, especially if we consider the joint effect of the other variables. Similarly their effects are significantly distributed around the mean. For 68% of the countries, the coefficient is estimated in the range of [0.13, 0.37] for ICT_{ij}, [0.14, 0.34] for ISO_{ij} and [0.04, 0.22] for $SKILL_{ij}$. Hence, adoption of ICT solutions and adherence to ISO norms seem to be a relatively safe bet for firms, even if they have to operate in quite difficult national environment, while investment into R&D facilities and formal training of employees require supporting conditions to make a tangible difference for productivity.

FOR_{ij} has an even larger coefficient, which confirms the prevailing productivity gap between foreign- and domestic-owned firms, because the foreign affiliates benefit from access to technology developed by the parent company. The mean effect is a rise of TFP_{ij} by 0.40, but within a large range of [-0.06, 0.86] in 95% of the countries; in other words from a fairly dual economy that is typical for most developing countries to roughly equal productivity in both groups of firms that is commonplace in advanced economies, from where most of the leading multinational companies originate. It is clear that overall, the national differences clearly matter for performance of firms, indeed an encouraging finding for the more detailed analysis below, in which we attempt to pin down specific characteristics of the national framework conditions with which these effects vary.

Table 4: Econometric results along the level of economic development

	(1)	(2)	(3)
Fixed effects:			
For Intercept$_{ij}$ (α_{0j})			
Intercept$_{ij}$ (γ_{00})	13.05 (0.27)***	13.06 (0.25)***	13.05 (0.25)***
GDPCAP$_j$ (γ_{01})	..	0.40 (0.07)***	0.39 (0.07)***
For R&D$_{ij}$ slope (β_{1j})			
R&D$_{ij}$ (γ_{10})	0.15 (0.04)***	0.15 (0.04)***	0.14 (0.04)***
GDPCAP$_j$ (γ_{11})	..	..	0.05 (0.02)**
For ICT$_{ij}$ slope (β_{2j})			
ICT$_{ij}$ (γ_{20})	0.25 (0.03)***	0.25 (0.03)***	0.24 (0.03)***
GDPCAP$_j$ (γ_{21})	..	..	0.03 (0.03)
For ISO$_{ij}$ slope (β_{3j})			
ISO$_{ij}$ (γ_{30})	0.24 (0.04)***	0.24 (0.04)***	0.25 (0.04)***
GDPCAP$_j$ (γ_{31})	..	..	-0.08 (0.02)***
For SKILL$_{ij}$ slope (β_{4j})			
SKILL$_{ij}$ (γ_{40})	0.13 (0.03)***	0.13 (0.04)***	0.13 (0.03)***
GDPCAP$_j$ (γ_{41})	..	..	-0.04 (0.02)*
For FOR$_{ij}$ slope (β_{5j})			
FOR$_{ij}$ (γ_{50})	0.40 (0.07)***	0.40 (0.07)***	0.41 (0.06)***
GDPCAP$_j$ (γ_{51})	..	..	-0.09 (0.05)*
k_{ij} (δ_0)	0.33 (0.05)***	0.32 (0.05)***	0.33 (0.05)***
l_{ij} (δ_1)	0.64 (0.11)***	0.64 (0.11)***	0.64 (0.11)***
IND$_i$ (δ_{2m})	Yes	Yes	Yes
IND$_i$ k_i (δ_{3m})	Yes	Yes	Yes
IND$_i$ l_i (δ_{4m})	Yes	Yes	Yes
Random effects:			
Intercept$_{ij}$ (u_{0j})	0.50 (2,294)***	0.32 (728)***	0.32 (737)***
R&D$_{ij}$ slope (u_{1j})	0.12 (102)***	0.13 (103)***	0.12 (99)***
ICT$_{ij}$ slope (u_{2j})	0.12 (84)***	0.12 (83)***	0.13 (85)***
ISO$_{ij}$ slope (u_{3j})	0.10 (62)**	0.10 (62)	0.08 (49)
SKILL$_{ij}$ slope (u_{4j})	0.09 (65)**	0.10 (65)**	0.08 (59)**
FOR$_{ij}$ slope (u_{5j})	0.23 (96)***	0.23 (96)***	0.21 (87)***
e_{ij}	1.059	1.058	1.058
Deviance	57,013	56,981	56,962
Level-1 observations	19,219	19,219	19,219
Level-2 groups	42	42	42

Note: Linear unit-specific model; full maximum likelihood estimate; coefficients and robust standard errors in brackets reported for the fixed effects; standard deviation and Chi-square in brackets reported for the random effects; *, **, *** denote significance at the 10, 5 and 1 percent levels.

Next, in the second column in Table 4, we present the intercept-as-outcome model, which incorporates the $GDPCAP_j$ variable into the model as a predictor of the intercept, but lets the firm-level effects remain “unconditional” at the country level. The main hypothesis is that firms located in more advanced countries achieve higher productivity with given inputs, because they benefit from all sorts of geographically bounded advantages (or even external economies) thanks to the fact of being embedded in more supportive (but also demanding) environment. This prediction is firmly supported by the results, because the effect of $GDPCAP_j$ on the intercept is positive and highly significant, even after controlling for the firm-level effects and allowing for the random country differences in the multilevel framework. Moreover, the random country effect for the intercept has decreased by about one third to a magnitude slightly lower than the estimated effect of one standard deviation difference in $GDPCAP_j$, which shows that a healthy part of the cross-country variety is related to the overall level of development, but also that substantial part of the picture remains unexplained by this variable.

Even more interesting is to investigate whether the estimated slopes of the $R\&D_{ij}$, ICT_{ij}, ISO_{ij}, $SKILL_{ij}$ and FOR_{ij} firm-level predictors vary along the development level of the country, which is the purpose of the last estimate presented in Table 4. In other words, the “slopes-as-outcomes” model examines not only whether $GDPCAP_j$ directly affects the intercept, but also whether the level of development has an indirect impact on the total factor productivity by mediating the respective firm-level relationships. Given the large random differences across countries detected above, the idea is to test whether the capability and ownership effects on productivity vary with the level of development of the country.

The main result is, first, a positive and fairly significant interaction between the $GDPCAP_j$ and $R\&D_{ij}$ variables, which signals that the effect of internal R&D activity of firms increases with the development level of the country. Hence, firms benefit more from their R&D activity if located in an advanced environment with superior quality of the science base, technological infrastructure, education and other complementary assets to their own innovative efforts. Second, a highly statistically significant cross-level interaction has been detected between $GDPCAP_j$ of the country and adherence to ISO_{ij} standards at the firm-level. The negative sign of this interaction term indicates that, in contrast to the previous case, the ISO certificate contributes relatively more to productivity of firms in less developed countries. This indicates that the ability to adhere to international quality standards makes more difference in an environment, where most other firms are not readily able to meet these requirements. In addition, the respective random effect ceased to be statistically significant at the conventional levels, though the Chi-square significance test of the random effects should be interpreted with caution, as already noted above. After all, the magnitude of the random effects remains quite high for all of the coefficients.

Similar conclusions with regards to the sign can be drawn from the interaction between $GDPCAP_j$ and $SKILL_{ij}$ variables, although this terms is only weakly statistically significant. Formal training of the work force is more important for raising productivity in less developed countries than in more advanced economies, pointing at failures of the educational system in the former. Also negative, but only weakly significant, is the interaction between $GDPCAP_j$ and FOR_{ij}, which confirms that the productivity gap between foreign- and domestically-owned firms tends to narrow with higher levels of development of the country. The interaction term of $GDPCAP_j$ and ICT_{ij} did not come out statistically significant, so that the effect of using internet for interaction with clients and suppliers seems to be of a truly global nature, regardless of whether the country is advanced or not.

In sum, while the firm-level technological capability variables seem to be strongly positively correlated with productivity levels, the magnitude of these effects differs markedly for countries at different levels of development, with adherence to ISO standards and formal training of workers to be the driving forces for productivity in less developed countries, while R&D activity is shifting productivity of firms upwards more in advanced economies. Foreign ownership makes a big difference for productivity, but mainly in developing countries. Admittedly, these broad patterns are relevant for introducing the debate, but not very useful for deriving concrete insights about characteristics of the environment that hinder or boost productivity of firms. Hence, in the next step, we turn to the more detailed country-level predictors.

Table 5 gives the results. Since $GDPCAP_j$ tends to be highly correlated to most of the more detailed indicators, we do not include these in the model at the same time, but replace the $GDPCAP_j$ predictor by the $GERD_j$, $LITERA_j$, $REGUL_j$ and $INFLAT_j$ variables. First, we estimate the full specification of the model. However, the number of parameters to be estimated becomes far too large to generate robust standard errors, so that in the second column we simplify the model by not controlling for the interaction terms between capital, labor and industry dummies $IND_i\ k_i$ and $IND_i\ l_i$, which solves the problem without changing the key results. Finally, in the last column, we use the backward stepwise selection procedure to eliminate those effects involving the country-level predictors that do not significantly contribute to predictive power of the model.[11] Exactly half of them have been ruled out this way, which gives noticeably more concise specification used for deriving predictions of the model below.

[11] At the beginning of this procedure, we estimate the full model, and then stepwise eliminate the least statistically significant effects of the country-level predictors, including their cross-level interactions, until arriving at a model that includes only effects significant at a chosen level. $GERD_j$ and $SKILL_{ij}$ interaction is significant at 12% level, so that we keep this effect, because it reasonable contributes to predictive power of the model. It should be noted that none of the other eliminated effects appeared significant at more than 20% level.

Table 5: Econometric results with detailed indicators of national framework conditions

	(1)	(2)	(3)
Fixed effects:			
For Intercept$_{ij}$ (α_{0j})			
Intercept$_{ij}$ (γ_{00})	13.06 (0.12)***	13.27 (0.09)***	13.27 (0.09)***
GERD$_j$ (γ_{01})	0.10 (0.07)	0.10 (0.05)*	0.12 (0.04)**
LITERA$_j$ (γ_{02})	0.17 (0.06)**	0.17 (0.07)**	0.18 (0.07)***
REGUL$_j$ (γ_{03})	-0.16 (0.07)**	-0.16 (0.07)**	-0.15 (0.06)**
INFLAT$_j$ (γ_{04})	-0.06 (0.06)	-0.06 (0.08)	..
For R&D$_{ij}$ slope (β_{1j})			
R&D$_{ij}$ (γ_{10})	0.15 (0.03)***	0.16 (0.04)***	0.15 (0.04)***
GERD$_j$ (γ_{11})	0.06 (0.03)**	0.06 (0.02)***	0.06 (0.02)***
LITERA$_j$ (γ_{12})	0.03 (0.03)	0.03 (0.02)	..
REGUL$_j$ (γ_{13})	0.02 (0.03)	0.02 (0.03)	..
INFLAT$_j$ (γ_{14})	0.01 (0.03)	0.02 (0.03)	..
For ICT$_{ij}$ slope (β_{2j})			
ICT$_{ij}$ (γ_{20})	0.25 (0.03)***	0.26 (0.03)***	0.26 (0.03)***
GERD$_j$ (γ_{21})	0.01 (0.03)	0.01 (0.04)	..
LITERA$_j$ (γ_{22})	0.03 (0.03)	0.03 (0.03)	0.04 (0.02)*
REGUL$_j$ (γ_{23})	-0.01 (0.03)	0.00 (0.03)	..
INFLAT$_j$ (γ_{24})	0.00 (0.03)	0.01 (0.05)	..
For ISO$_{ij}$ slope (β_{3j})			
ISO$_{ij}$ (γ_{30})	0.26 (0.03)***	0.26 (0.04)***	0.26 (0.04)***
GERD$_j$ (γ_{31})	-0.02 (0.03)	-0.02 (0.02)	..
LITERA$_j$ (γ_{32})	0.00 (0.03)	0.00 (0.02)	..
REGUL$_j$ (γ_{33})	0.08 (0.03)***	0.08 (0.03)***	0.08 (0.02)***
INFLAT$_j$ (γ_{34})	-0.01 (0.03)	-0.01 (0.02)	..
For SKILL$_{ij}$ slope (β_{4j})			
SKILL$_{ij}$ (γ_{40})	0.11 (0.02)***	0.12 (0.03)***	0.12 (0.03)***
GERD$_j$ (γ_{41})	0.03 (0.02)	0.03 (0.02)*	0.03 (0.02)
LITERA$_j$ (γ_{42})	-0.05 (0.02)**	-0.05 (0.02)*	-0.04 (0.02)*
REGUL$_j$ (γ_{43})	0.05 (0.02)**	0.05 (0.02)**	0.06 (0.02)**
INFLAT$_j$ (γ_{44})	-0.05 (0.02)**	-0.05 (0.03)*	-0.05 (0.02)**
For FOR$_{ij}$ slope (β_{5j})			
FOR$_{ij}$ (γ_{50})	0.39 (0.05)***	0.39 (0.06)***	0.40 (0.06)***
GERD$_j$ (γ_{51})	0.00 (0.05)	0.01 (0.04)	..
LITERA$_j$ (γ_{52})	0.04 (0.06)	0.04 (0.05)	..
REGUL$_j$ (γ_{53})	0.11 (0.06)**	0.11 (0.06)**	0.09 (0.04)**
INFLAT$_j$ (γ_{54})	-0.06 (0.05)	-0.06 (0.05)	-0.09 (0.04)**
k_{ij} (δ_0)	0.32 (0.01)***	0.29 (0.02)***	0.29 (0.02)***
l_{ij} (δ_1)	0.64 (0.02)***	0.71 (0.06)***	0.71 (0.06)***
IND$_i$ (δ_{2m})	Yes	Yes	Yes
IND$_i$ k_i (δ_{3m})	Yes	No	No
IND$_i$ l_i (δ_{4m})	Yes	No	No

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Random effects:			
$Intercept_{ij}$ (u_{0j})	0.36 (902)***	0.36 (896)***	0.36 (926)***
$R\&D_{ij}$ slope (u_{1j})	0.09 (82)***	0.08 (78)***	0.09 (82)***
ICT_{ij} slope (u_{2j})	0.13 (86)***	0.13 (88)***	0.13 (88)***
ISO_{ij} slope (u_{3j})	0.07 (44)	0.07 (40)	0.06 (40)
$SKILL_{ij}$ slope (u_{4j})	0.05 (41)	0.05 (42)	0.05 (42)
FOR_{ij} slope (u_{5j})	0.20 (80)***	0.21 (81)***	0.21 (82)***
e_{ij}	1.058	1.061	1.061
Deviance	56,949	57,026	57,029
Level-1 observations	19,219	19,219	19,219
Level-2 groups	42	42	42

Note: Linear unit-specific model; full maximum likelihood estimate; coefficients and robust (except of the first column) standard errors in brackets reported for the fixed effects; standard deviation and Chi-square in brackets reported for the random effects; *, **, *** denote significance at the 10, 5 and 1 percent levels.

$GERD_j$ comes out with a significantly positive coefficient for the intercept, if robust standard errors are estimated, which supports the existence of knowledge spillovers and other broadly beneficial effects for total factor productivity of firms located in countries with superior research infrastructure. Since $GERD_j$ significantly interacts with the $R\&D_{ij}$ and $SKILL_{ij}$ variables defined at the firm level, there seems to be credible evidence that these beneficial effects become substantially reinforced, almost jointly doubled in magnitude, for firms with their own R&D and formal training capabilities. In other words, firms gain considerably more from their own R&D investment if located in countries with high concentration of R&D activity, which underlines the role of absorptive capacity for firms to benefit from this source of localized external economies. Likewise, the training capabilities of firms seem to enhance this kind of benefits, although their contribution appears less significant. From the policy perspective, this result suggests that investment in research infrastructure yields tangibly positive effects on a broad stratum of firms indeed, though these resources become much more productive if the local firms come forward with nurturing appropriate absorptive capacity by themselves. Governments certainly should not neglect research infrastructure, but firms have their job to do too.

$LITERA_j$ seems to exert even stronger direct influence on productivity of firms, through the effect on the intercept. As can be expected, the literacy rate has a positive effect, suggesting that all kinds of firms greatly benefit from access to educated labor force. Here, we should emphasize, that this result should be really interpreted as a joint effect of basic education, because most other relevant indicators tend to be highly correlated to the literacy rate. $LITERA_j$ seems to boosts the effect of ICT_{ij} capabilities, which is natural because important synergic effects should be in play here, even though this cross-level interaction comes out only weakly statistically significant in the last specification. Nevertheless, the interaction term between $LITERA_j$ and $SKILL_{ij}$ comes out significantly negative, which indicates that these national- and firm-level capabilities substitute rather than complement each other. To achieve desired productivity levels, firms tend to leverage deficiencies of national education systems by establishing their own training programs. Arguably, this regularity in the data is a strong policy finding, because this highlights a systemic failure of governments in developing countries to furnish incumbent firms with educated people they demand to produce effectively. General education must be clearly a priority for every government serious about economic development.

Excessive regulation of business, given by a high score on the $REGUL_j$ variable, directly cripples total factor productivity of firms, and triggers complex interaction effects with their characteristics. Admittedly, the direct negative effect on the intercept can be easily attributed to extra costs, delays and friction induced by the regulatory burden, which makes doing business generally less efficient. Both of the significant interaction terms with firm's capabilities come out with a positive coefficient, suggesting that these variables shift productivity in the same direction. In other words, ISO_{ij} and $SKILL_{ij}$ capabilities pay off more for firms operating in more regulated environment. Stricter regulatory framework may directly require firms to obtain the certificates to access certain markets, such as rules for public procurement, environmental protection, etc., which may not make a difference for productivity in more liberal environment. Just to keep up with the numerous regulations, firms may also need to train their employees more often than elsewhere. Moreover, a quality certificate signals to other contracting parties that the firm is a high-performer on quality management issues (Terlaak and King, 2006, Swann, et al. 1996), which is especially beneficial when information asymmetries are large and when firms fear opportunistic behavior of their partners (King, et al. 2005). To the extent that the $REGUL_j$ variable can be understood as a proxy for quality of the broader institutional framework, such as lack of trust, erratic informal relations or general "culture" of regulation in the whole economy, firms that can demonstrate their credentials with the quality certificate naturally come out more competitive.

$REGUL_j$ also comes out with a strongly positive interaction with the FOR_{ij} variable for foreign ownership of firms. Since domestic-owned firms appear to be much more severely exposed to the adverse effects of regulation, this result provides evidence that the existing regulatory frameworks produce unfair competitive environment between the different modes of ownership. Foreign-owned firms manage to escape the curse of excessive bureaucracy in one way or another. Examples of why this is the case are abound, including exceptions from regulations, such as from red tape, labor code, customs or tax breaks, granted to foreign affiliates as a form of investment incentives used by governments in many developing countries to attract foreign direct investment. On the other hand, this can be given by the ownership advantage itself, because foreign firms might be on average better equipped to deal with the regulatory requirements, perhaps thanks to a superior administrative capacity, access to better legal services and/or stronger lobbyist power to leverage the unproductive regulations. In any case, policymakers should take this result as an opportunity to rethink the discriminatory regulations that contribute to the productivity gap between foreign- and domestic-owned firms. It is interesting to notice in this context that the FOR_{ij} effect seems to be largely independent of the $GERD_j$ and $LITERA_j$ framework conditions, in other words of those most intimately related to the technological level of the country, which signals that ceteris paribus these benefit firms regardless of the ownership divide.

Macroeconomic instability, represented by the $INFLAT_j$ variable, does not seem to have a strong direct effect on the total factor productivity of firms, but comes out with a couple of significant interaction terms. This indicates that this aspect of the framework conditions matters more for a certain kind of firms than others, which is consistent with the macroeconomic literature that has recognized for a long time that the effects of inflation tend to be distributed unevenly. As far as the effect on productivity of firms is concerned, we find that inflation thwarts returns on formal training and affects foreign-owned firms more negatively than their domestic counterparts. Generally speaking, a stable macroeconomic environment should facilitate returns on technological capabilities, because unpredictable fluctuations in market conditions undermine particularly returns on long-term investment of this kind, so that the negative interaction with the training capability of firms comes out in line with expectations. Foreign-owned firms benefit from easier access to technology, market and credit from abroad, which mirrors in their generally superior productivity, but this also makes them more exposed to instability of the local currency. Domestic-owned firms, on the other hand, tend to be relatively less integrated in the global economy, which turns out to be beneficial for them in times of macroeconomic instability. It is acknowledged that volatility rather than the level of inflation might be more relevant to take into account, but these effects tend to be closely correlated in this sample, and therefore not possible to distinguish in the estimate. It should be also noted that strong threshold effects are likely to be involved here, because hyperinflation has obviously disastrous effects on the economy. As already noted above, however, this sample includes only countries with relatively modest rates of inflation, which is fortunate for us, because we do not have to wrestle with influence of major outliers on the estimates.

So much for what we have been able to explain. But equally insightful in the context of multilevel modeling is the residual variance. Many of the random effects remain relatively strong, except perhaps of those for the ISO_{ij} and $SKILL_{ij}$ slope coefficients, which indicates that a noticeable part of the diversity across countries has not been accounted for by the country-level predictors. As already emphasized above, however, we had to constrain ourselves to a relatively small set of national predictors, because of the limited number of countries in the sample. At the same time, other relevant indicators of the national framework conditions that one may rightly point out to be potentially relevant, such as those for the financial system, governance, political system, globalization and last but not least aggregate demand conditions, could not have been included in the estimates, because these tend to be excessively correlated to the incumbent variables, and we therefore leave them for more detailed examination in future multilevel research. Besides other relevant country-level variables that may exist, the unexplained differences could be related to idiosyncratic national factors, which certainly should not be neglected in cross-country comparative research given these results. Although we have been able to identify quite strong regularities, there is arguably a limit to how much we can explain by quantitative methods. To illuminate the rest is a task for more detailed qualitative research, which can dive even more deeply into the specific national context.

How much are these results robust? Not much has changed in estimates of the firm-level effects, which confirms that these are remarkably robust to specification of the country-level part of the model. It should be noted that an inspection of both the firm-level and country-level residuals has not revealed a major problem with outliers in either of the estimates. Yet some countries might be outliers with regards to the more detailed national conditions.

Mahalanobis distance based on the $GERD_j$, $LITERA_j$, $REGUL_j$ and $INFLAT_j$ variables has identified the following countries as multivariate outliers: Turkey (10%; $INFLAT_j$); Ethiopia (10%; $LITERA_j$); Germany (1%; $GERD_j$) and Korea (1%; $GERD_j$); statistical significance of the distance and the main outlining indicator in brackets. Korea and Germany come out as the main outliers, because the sample is predominantly composed of developing countries. $GERD_j$ amounts to 2.67% and 2.50% in Korea and Germany respectively, but there are only three other countries in the sample with more than 1.00% (Ireland, Spain and Ukraine) and the sample average is 0.50% only. Not surprisingly, the effects of $GERD_j$ are most sensitive to exclusion of Korea and Germany from the sample.[12] But these countries are not outliers in technological intensity when compared to other developed countries. Even though both of them rank quite high on the global technology ladder, there are at least two dozens other countries with similar (or even higher) technology intensity of their economies (Fagerberg, et al. 2007). If more developed countries were included in the sample, Korea and Germany would most likely not come out much different from the main pack, so that there would be more robust support for making inferences in this tail of the distribution. It well might be, therefore, that the effects of $GERD_j$ based on the full sample are credible, because these results will be confirmed in estimates on datasets including more developed countries in the future.

To demonstrate implications of the multilevel model, we compare the predicted productivity of firms in various situations. As already anticipated above, we base these predictions on the most concise specification of the model in the last column of Table 5, which has been derived from the backward stepwise selection procedure. Table 6 shows the predictions. Horizontally, we alter characteristics of the firm, where we put forward scenarios with increasing levels of firm's technological capabilities $T_{ij} \in (R\&D_{ij}, ICT_{ij}, ISO_{ij}, SKILL_{ij})$ from the minimum (all equal to zero), mean values observed in the population, to the maximum (all equal to one) for a fully domestic-owned firm (FOR_{ij}=0), and we compare them to a situation of a fully foreign-owned firm (FOR_{ij}=1) with the mean level of capabilities. Vertically, there are different combinations of the national framework conditions given by both the observed (fixed) and unobserved (random) country effects. For the unobserved country effects, we compute predictions for one standard deviation into the positive territory, mean country (all

[12] If we estimate the simplified specification of the model used in the second column in Table 5, but exclude Korea and Germany from the sample, the $GERD_j$ effect on the intercept and its interaction term with $R\&D_{ij}$ come out significant only at 20% level, while its interaction term with $SKILL_{ij}$ turns out insignificant at the conventional levels. Estimates of the other effects change only marginally.

equal to zero) and one standard deviation into the negative territory. For the fixed country effects, we differentiate between countries with their best, mean (all equal to zero), and worst combination. In other words, we rank countries according to the prediction for each situation given their observed country predictors, which reveals either Korea (FOR_{ij}=0) or Germany (FOR_{ij}=1) at the top with the best combination and Ethiopia in every case at the bottom with the worst conditions. All other effects remain constant at zero. Since each of the predictors has a meaningful zero point thanks to their normalization, this means that the prediction always refers to a firm with average capital and labor (k_{ij}, l_{ij} = 0) in the base industry (IND_i) and with mean firm-level residual (e_{ij} = 0). The predicted productivity of firms is expressed in terms of $\exp(y_{ij})$, hence in constant USD in PPP, relatively to a representative "average" case of a fully domestic owned firm ($FOR_{ij}=0 \vee$ all else equal to zero = 100).

Table 6: Predictions of $\exp(y_{ij})$ based on the backward stepwise selection estimate (the reference firm=100)

	$\mathrm{Min}(T_{ij})$ FOR_{ij}=0	$\mathrm{Mean}(T_{ij})$ FOR_{ij}=0	$\mathrm{Max}(T_{ij})$ FOR_{ij}=0	$\mathrm{Mean}(T_{ij})$ FOR_{ij}=1
<u>+1 st. dev. of country random effects:</u>				
Top country fixed effects	256	400	903	686
Mean (zero) country fixed effects	110	161	336	297
Bottom country fixed effects	57	83	170	149
<u>Mean (zero) country random effects:</u>				
Top country fixed effects	179	248	453	344
Mean (zero) country fixed effects	77	100	169	149
Bottom country fixed effects	40	51	85	75
<u>-1 st. dev. of country random effects:</u>				
Top country fixed effects	125	153	227	173
Mean (zero) country fixed effects	53	62	85	75
Bottom country fixed effects	28	32	43	38

Note: All else hold constant at zero (k_{ij}, l_{ij}, IND_i, e_{ij} = 0); $T_{ij} \in$ ($R\&D_{ij}$, ICT_{ij}, ISO_{ij}, $SKILL_{ij}$).

At this point, interpretation of the predictions should be clear. Firm-level technological capabilities offer a substantial premium for productivity. All else equal to average, firms armed with the full set of capabilities are estimated to achieve 2.2 times (169/77) higher productivity than those without them. Foreign ownership of firms, as already obvious from the estimated coefficient, makes a real difference too. But this is not the full story, because the national framework conditions have powerful implications for productivity of firms. Holding all other effects to average, a firm located in Korea with the best combination of the fixed country effects is estimated to be 2.5 times (248/100) more productive than a firm with the same characteristics in a hypothetical "average" country and even 4.9 times (248/51) more productive than an otherwise same firm operating in Ethiopia with the worst observed conditions. If we factor into the equation the unobserved (random) country effects, the productivity differences become even more dramatic, simulating in the far corners of the table productivity gaps of a factor of 20 and more between the advanced and least developed countries. Overall, the national framework conditions have a substantial effect on performance of firms, but at the same time much also depends on what firms are capable of doing themselves. One can at least partly compensate for the other, but the most powerful forces shifting productivity materialize in their joint effects. Arguably economic development is not about achievements of the government on one side and firms on the other, but essentially about what they accomplish in concert.

6. Conclusions

Using a multilevel framework, we estimated a model of firm's productivity with effects of their technological capabilities nested in national framework conditions. Our results confirm the important role of the national factors for explaining differences in performance of firms. Furthermore, the estimates reveal significant indirect influence of the national framework conditions on productivity of firms through interaction with the various proxies for firm's technological capabilities. Indeed, while on average the firm-level technological capability variables seem to be positively correlated with their productivity, the magnitude of these effects differs markedly across countries. Here we find that training of workers, adherence to standards and foreign ownership are important driving forces for productivity in less developed countries, R&D on the contrary is shifting productivity more in advanced economies. Different features of the national framework come out to be responsible for this.

Multilevel modeling appears to be a promising new item in the tool box of research on technological capabilities, which may allow us to formally test complex predictions of the contextual perspectives on economic development. Although we have constrained ourselves only to 2-level multilevel model in this paper, there is a variety of specifications of the model that in principle could be estimated. A straightforward extension would be to take into account a more complicated hierarchical structure. For example, we can specify 3-level models with firms in regions within countries or so-called cross-classified models with firms simultaneously nested in sectors and countries, which take into account the sectoral differences even more seriously than we have been able to do. All that matters is access to suitable data, which unfortunately remains scarce, especially for the least developed nations.

A major weakness of this paper that needs to be flagged is that to the extent that firms are mobile across countries, in other words their location is endogenously determined, the results cannot be interpreted in terms of showing causal relations. One can discuss how much are the firms under consideration really mobile, except of course the foreign-owned strata of the sample, which is actually quite limited, because the average share of foreign owners is less than 10% in this sample of firms. Nevertheless, from methodological point of view this is something that is well taken and certainly should be one of the priorities to clarify in future research. Arguably, however, this is "the chicken or the egg" type of causality dilemma, which is very difficult to resolve without extensive panel data, which is unfortunately not likely to become available anytime soon.

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Appendix 1: Correlation matrix between the firm-level predictors (N=19,219)

	k_{ij}	l_{ij}	$R\&D_{ij}$	ICT_{ij}	ISO_{ij}	$SKILL_{ij}$	FOR_{ij}
k_{ij}	1.00						
l_{ij}	0.65	1.00					
$R\&D_{ij}$	0.26	0.33	1.00				
ICT_{ij}	0.28	0.22	0.19	1.00			
ISO_{ij}	0.35	0.37	0.23	0.22	1.00		
$SKILL_{ij}$	0.33	0.35	0.25	0.26	0.31	1.00	
FOR_{ij}	0.22	0.23	0.07	0.11	0.19	0.16	1.00

Appendix 2: Correlation matrix between the country-level predictors (N=42)

	$GDPCAP_j$	$GERD_j$	$LITERA_j$	$REGUL_j$	$INFLAT_j$
$GDPCAP_j$	1.00				
$GERD_j$	0.54	1.00			
$LITERA_j$	0.71	0.37	1.00		
$REGUL_j$	-0.58	-0.44	-0.32	1.00	
$INFLAT_j$	-0.30	-0.25	-0.08	0.29	1.00