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A Multilevel Analysis of Innovation in Developing Countries*

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Abstract

Innovation is a multilevel phenomenon. Not only attributes of firms but also the framework conditions within which firms operate matter. 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 large sample of firms from many developing countries, we estimate a multilevel model of innovation which connects micro and macro levels of analysis in an integrated framework. National economic, technological and institutional framework conditions are shown to directly predict the likelihood of firms to innovate. More specifically, general education, taxation of income and democratic political institutions turn out to be highly relevant, while macroeconomic stability is somewhat less relevant. But what tends to be perceived as "good" governance and the extent of public research infrastructure do not seem to make much difference. The latter result is interpreted as indicating that what matters is not how much money governments spend on the research infrastructure but rather how effectively these resources are used to leverage innovation. Nevertheless, the results also draw attention to the limits of the existing models, methods and data.

Keywords: innovation, technological capability, multilevel modeling, institutions, developing countries.
JEL Classification: O12, O14, C39, O31, O43.

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Abstrakt

Úspěch firem v inovačním procesu záleží nejen na nich samotných, ale do značné míry rovněž na charakteristikách prostředí, ve kterém podnikají. Ačkoliv tato víceúrovňová podstata inovací je v literatuře diskutována dlouhou dobu, kvantitativní analýzy, které se explicitně zaměřují na tuto hypotézu, chybějí. S použitím velkého souboru firemních dat sesbíraných v mnoha rozvojových zemích jsou v této práci prezentovány výsledky víceúrovňového modelu, který propojuje mikro a makro faktory inovativnosti firem. Národní ekonomické, technologické a institucionální prostředí se ukazují jako velmi důležité. Jako nejvýznamější vychází všeobecná vzdělanost pracovní síly, míra zdanění vysokých příjmů a demokratické politické zřízení. Makroekonomická stablita se ukazuje jako relevantní, ale podstatně méně důležitý faktor. Na druhou stranu na souboru institucí, které jsou obecně považovány za známku dobrého vládnutí v dané zemí, a na rozsahu veřejné výzkumné infrastruktury oproti předpokladům příliš nezáleží. Posledně jmenovaný výsledek podtrhuje, že pro inovace ve firmách není rozhodující, jaký objem veřejných zdrojů vlády směrují do vědy a výzkumu, ale jak účinně jsou tyto prostředky používány. Nicméně je třeba zmínit, že tato studie rovněž upozorňuje na řadu omezení stávajících modelů, metod a dat.

1. Introduction

Early on, Schumpeter understood the role of context for innovation (Schumpeter, 1934). At the most abstract level, the idea about the survival of firms propelled by innovation, but determined by the environment, is developed in evolutionary economics (Nelson and Winter, 1982). Less abstract but all the more grounded is the argument about the sensitivity of innovation to local conditions that is integral to the literature on technological capabilities in developing countries (Kim, 1980; Dahlman, et al., 1987 and Lall, 1992). Arguing along somewhat similar lines, the need to develop favorable framework conditions for innovation has been entertained in technology gap models (Fagerberg, 1987; Verspagen, 1991) and by the literature on social capabilities (Abramovitz, 1986, 1994). Explicitly multilevel is the systemic approach to the study of innovation (Lundvall, 1992; Nelson, 1993 and Edquist, 1997) according to which firms need to be understood as embedded in broader innovation systems.

Yet, econometric research on innovation continues to use single-level models, which are not suitable for handling multilevel hypotheses. Single-level models assume that observations are drawn from a homogenous population and, therefore, are independent from each other. If a nested structure of data exits, however, the independence assumption is likely to be violated (Hox, 2002; Goldstein, 2003 and Luke, 2004). By relaxing this assumption, multilevel modeling provides a tool for an analysis of firms grouped along various lines. Even more importantly, a proper recognition of data hierarchies allows us to examine new lines of questions in a concise way that could not be done otherwise. Unlike any other method, multilevel modeling accounts for the unobserved contextual factors providing us with a framework that properly illuminates the extent to which specific differences between relevant contexts, such as national economic, technological or institutional framework conditions, are accountable for outcomes at the firm level.

The aim of this paper is to demonstrate how research on innovation can benefit from using multilevel modeling to examine the contextual effects more explicitly than the existing studies have been able to do. Section 2 debates the multilevel approach in the light of the literature on innovation and economic development. Do the national framework conditions matter for innovation? How do these factors relate to technological capabilities developed by firms themselves? How have these issues been addressed in the empirical literature so far? Should we just insert into the model dummies for the contextual effects? Are there better methods to study relations defined at different levels?

Until relatively recently, questions like these must have been jumped over in the econometric research on innovation because suitable data for examining multilevel hypotheses did not exist. But opportunities for doing this kind of analysis have improved considerably with the increasing availability of large micro datasets from multiple countries with information about the innovation activities of firms. Section 3 introduces micro data of this kind derived from the Productivity and Investment Climate Survey (PICS) organized by the World Bank, which provides a rich set of indicators for almost 15,000 firms from 32 developing countries, and because we are going to estimate a multilevel mode, this section also brings in various measures of national framework conditions.

Section 4 delineates the binomial logit multilevel model of innovation that combines firm- and country-level effects in an integrated framework. Because of a relatively small number of countries, in the empirical model we concentrate on the direct effects of the country-level predictors and leave more complex specifications involving various cross-level interaction terms for future research on more extensive datasets. Section 5 presents the results of the econometric estimates. Apart from various characteristics of firms, several broad facets of the national framework conditions have been confirmed to directly affect their propensity to innovate. But there remains considerable heterogeneity among countries that we have not been able to pin down, drawing attention to unobservable differences between countries, limits of the existing indicators, measurement errors and, last but not least, to the need to properly accommodate them in the multilevel framework because otherwise the results tend to be grossly biased. Finally, Section 6 discusses policy implications and outlines opportunities for future research.

2. Toward the Multilevel Modeling of Innovation

Sociologists, geographers and even biologists have recognized for several decades that many kinds of data have a hierarchical structure and, therefore, should be analyzed in a multilevel framework (Burstein, 1980; Van den Eeden and Hüttner, 1982; Blalock, 1984 and Draper, 1995). Offspring from the same parents and environment tend to be more alike than those chosen at random from the population. School performance is not only given by the amount of study time of a child, but also by higher-level factors such as characteristics of the class, school or national educational system. Similarly, innovation should be modeled as a multilevel phenomenon, because not only individual characteristics and capabilities of firms, but also the environment within which firms operate matters for their success in the innovation process.

Schumpeter clearly pointed to the significance of the social context for innovation (Schumpeter, 1934). New ways of doing things face resistance not only driven by the forces of habit imprinted within an individual but also by the way the society is organized. Entrepreneurs, therefore, need to possess special qualities, or "capabilities" in the contemporary terminology, that allow them to overcome the obstacles to innovation. Schumpeter most vividly articulated this insight by stating: "the reaction of the social environment against one who wishes to do something new… manifests itself first of all in the existence of legal or political impediments" (Schumpeter, 1934, pp. 86–87). Schumpeter perhaps emphasized the resistance too much, because there are forces in individuals, firms and the society at large that facilitate innovation, too.

As has been understood for a long time, emerging from behind represents a great "promise" for a technological catch-up, but the exploitation of this potential needs to be backed by a favorable environment (Gerschenkron, 1962). At the macro level, the idea that catching up requires a certain capacity of the society has been formalized in technology gap models of growth (Fagerberg, 1987 and Verspagen, 1991). Arguing along similar lines but without quantitative measurement or modeling of this relationship, Abramovitz (1986, 1994) entertained the idea that various "social capabilities" matter for economic development. For us the important insight of this literature, at least implicitly, is that besides the resources of individual firms there are factors that in this respect operate distinctly at the national level, so that these can be summoned to explain the innovativeness of firms in multilevel econometrics.

Explicitly micro-founded is the thesis that the survival of firms is driven by innovation but determined by the selection environment, which is at the core of growth modeling in evolutionary economics (Nelson and Winter, 1982). Here the focus is on dynamic interactions between the heterogeneity of firms given by their technology, the selection environment represented by markets and the capability of firms to innovate. But this approach 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, an understanding of how the behavior of firms is shaped by national capabilities, although often called for, remains limited in this literature.

Studies of technological upgrading in developing countries have long argued for a need to understand technological capabilities at the firm level, but also to recognize the importance of the national factors (Kim, 1980; Dahlman, et al., 1987; Lall, 1992; Bell and Pavitt, 1993 and Hobday, 1995). Kim (1980) emphasized the role of the external environment represented by customers, suppliers, competitors, the government and, last but not least, local research institutions and technical information centers for the ability of local firms to import, adapt and improve foreign technologies. Lall (1992) in an early attempt to integrate the micro and macro perspectives further elaborated on the role of national capabilities emphasizing that the latter refer to more than just the simple sum of capabilities of individual organizations developed in isolation, because of synergies, externalities and interlinkages between them. Nevertheless, research in this tradition has been seldom translated into formal modeling, which would replicate these insights with quantitative research on large firm-level datasets.

Needless to say, this concurs with the systemic perspective on innovation (Lundvall, 1992; Nelson, 1993 and Edquist, 1997). A central argument underlying this literature, which is explicitly multilevel, is that innovation is determined by factors operating at different levels. The spatial concentration of relevant actors and resources, as well as dense linkages between them and other environmental factors conducive to learning are expected to boost the innovative performance of firms. In other words, a firm embedded in a vibrant innovation system might become a successful innovator, while the very same firm in a considerably less favorable environment may fail in this endeavor. Such systems can be analyzed at different hierarchical levels and relevant variables can be defined at each of them. But the firm, around which this concept is organized, should always remain the ultimate unit of analysis because only micro data allow us to study how the system affects the performance of firms. Aggregate analyses might be insightful in their own right, but they can never illuminate the mechanisms through which firms interact with the national framework conditions in the innovation process.

Nevertheless, most of the existing literature has used exclusively macro data to gauge differences in innovation performance across countries (Furman et al., 2002; Archibugi, Coco, 2004 and Fagerberg and Srholec, 2008). Some studies using micro data have been performed for more than one country, though the contextual factors have been at best represented by a set of country dummies (Mairesse and Mohnen, 2002; Janz, et al., 2004; Mohnen and Röller, 2005; Mohnen, et al., 2006; Griffith, et al., 2006; Goedhuys, et al., 2008 and Srholec, 2009). Using dummies might be a useful quick-fix solution if the purpose is only to control for contextual effects, but it is of a little help if the prime interest is in the effects of the national conditions themselves. Although we might detect rough patterns of the hierarchical structure of the data, a dummy is a "catch-all" variable for which we can only speculate what it really represents. Not much can therefore be concluded from these studies on how the technological, economic and social environment influences the innovation process in firms.

Even if specific national predictors have been recently included in econometric estimates based on large micro datasets from numerous countries (Almeida and Fernandes, 2008; Lederman, 2010), the random variability associated with the national conditions has not been properly accounted for. In other words, the major assumption of single-level models that the observations are independent from each other remains imposed on the data. If a nested structure of data exits, however, units belonging to the same group tend to have correlated residuals, as a result the independence assumption is likely to be violated and the results are spurious. By relaxing this assumption, multilevel modeling provides statistically more efficient estimates, correct standard errors, and therefore more "conservative" results, as Goldstein (2003) puts it, than those ignoring the hierarchical nature of data. Statistically significant relationships that have been detected in the literature by using the standard methods may prove to be irrelevant. Much that we have learned empirically about innovation might appear quite different in the multilevel framework.

Apart from these statistical consequences, the proper recognition of data hierarchies allows us to examine new lines of questioning. Not only does the multilevel approach enable the researcher to properly explore the extent to which specific differences between countries are accountable for outcomes at the firm level, but also to investigate the mechanics by which the national factors operate at the firm level and the extent to which these effects differ for different kinds of firm. In addition, estimates of random variability across countries indicate to what extent the effects of the respective micro predictors depend on the national framework conditions. For example, we might quantify the extent to which returns on firms' capabilities in terms of innovation output differ by country and which national factors explain these differences. Such research questions can be straightforwardly examined by multilevel modeling, but can be neither easily nor correctly examined by the standard methods.

After all, the theoretical arguments established in the innovation literature outlined above implicitly predict the nested structure of micro data. Hence, the basic assumption of the standard regression models on independent residuals is expected to be violated from the outset. Empirical research that uses single-level models to study how framework conditions influence innovation therefore suffers from a methodological contradiction. The abundance of theoretical reasoning about the role of context is in sharp contrast with the general lack of quantitative work aimed at properly validating these hypotheses. On this front, multilevel modeling has much to offer. Such a perspective is particularly suitable for research on technological catching-up, because there is a considerable variety in the contextual factors among developing countries. To show how this can be done is the main purpose of the following sections.

3. Data

At the firm level we use a large micro dataset derived from the Productivity and Investment Climate Survey (PICS) organized by the World Bank. Firms were asked about various aspects of their business activities, including a set of questions on innovation and learning, in a questionnaire distributed in many developing countries. For more details on the methodology of the survey see World Bank (2003).

INNPDT, which provides direct evidence on innovation, is a dummy with value 1 for firms that answered positively to the question of whether they "developed a major new product line" during the reference period of the survey, which broadly corresponds to the concept of product innovation.[4] It is important to bear in mind that these innovations are new to the firm, but not necessarily new to the market or to the world. As demonstrated below, this is pivotal for the interpretation of the data in the context of developing countries.

Besides the evidence on innovation, the dataset provides information on size, age, foreign ownership, industry and various facets of the firm's technological capabilities. SIZE is the natural logarithm of the number of permanent employees in the initial year of the reference period. Apart from scale economies, size is important to control for due to the definition of INNPDT, which is the dependent variable in the econometric estimate. Since this is a dummy for introducing at least one innovation, larger firms

[4] Apart from being rather short, the PICS definition does not explicitly refer to a "technologically" new product. One can argue, however, that a more detailed question would be feasible to use in developing countries where awareness about the "technological" aspects of innovation is often limited. Simpler questions might be better in this context, at least as far as the response rate and the comparability of the answers are concerned. Furthermore, while the 2nd revision of the Oslo Manual (OECD, 1997) emphasises the "technological" nature of innovation, the 3rd revision of the Oslo Manual (OECD, 2005) does not explicitly refer to "technologically new developments" anymore, which in this sense makes the idea about innovation in these manuals somewhat closer to the more general definition used here.

should be more likely to report a positive answer because they often comprise multiple products under a single roof. AGE is the natural logarithm of the number of years since the firm began operations in the country. On the one hand older firms tend to have more accumulated knowledge and other resources to capitalize on, but on the other hand newly established, younger firms might appear more innovative because they introduce new products when they launch their business. FOR stands for the share of private foreign ownership, which is important to control for, because foreign subsidiaries may have privileged access to the technology of the parent company.

Sectors are difficult to identify because somewhat different classifications are used in the national datasets. For this reason we can distinguish only 13 broad sectors as follows: 1) Food and beverages; 2) Apparel, garments, leather and textiles; 3) Chemicals; 4) Wood, paper, non-metal materials and furniture; 5) Metal; 6) Machinery, electronics and automobiles; 7) Construction; 8) Hotels and restaurants; 9) Trade; 10) Transport; 11) Real estate and rental services; 12) Other industry (mining, energy, water, recycling); and 13) Other business services. Sector dummies denoted by the SEC acronym are used in the econometric estimate to control for the sectoral patterns with "Agro, food and beverages" as the base category.

Structural patterns like these are necessary to control for, but even more important is to include proxies for capabilities and the resources of firms directly devoted to the search for, absorption of and generation of new technology. Research and development (R&D) is the traditional and for a long time has been the only seriously considered indicator of technological capabilities. R&D is defined as a dummy with value 1 if the firm devotes expenditure to this activity. The aim of this variable is to capture a general commitment to R&D.[5] Nevertheless, it cannot be emphasized enough that innovation is about much more than just spending on R&D, especially in the context of developing countries (Bell

[5] Although most of the national questionnaires include information on the actual value of R&D expenditure and sales, we refrain from using this information to compute a measure of R&D intensity. The reasons are missing data for at least one of these variables in several thousand firms and concerns about the quality of the reported amount of R&D expenditure, which is often based on rough estimates. The dummy variable on whether a firm spends on R&D or not is more robust in this respect.

and Pavitt, 1993), so that we need to keep an eye on much broader aspects of technological capabilities.

For this purpose the dataset provides information on the structure of employment by occupation, adherence to ISO norms, the use of the internet in the business and the formal training of employees. PROF is a variable that refers to the share of professionals in permanent employment, which includes specialists such as scientists, engineers, chemists, software programmers, accountants and lawyers, and reflects the extent of highly qualified human capital.[6] ISO 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 of production. WWW 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. Finally, SKILL is a dummy with value 1 if the firm provides formal (beyond "on the job") training to its permanent employees.

Many of these broader facets of technological capabilities such as training, human resources, quality control and use of information technologies 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 provides much richer evidence than most of surveys of innovation (CIS) based on these (and derived) manuals. Another major advantage of PICS is that all of the information, including the R&D, PROF, ISO, WWW and SKILL variables, is available for both firms that innovated as well as for those that did not, whereas only the innovators answer most (and the most interesting part) of the CIS questionnaire. Since we actually do not know much about those that do not innovate, this design of the CIS questionnaire severely limits inferences that can be made about the factors behind the success of the innovation process in studies based on data from these surveys. If the

[6] Since some versions of the PICS questionnaire did not distinguish between professionals and managers, the PROF variable also covers the latter category, but excludes those involved in shop floor supervision. As often happens to variables of this kind, several dozen firms mistakenly reported employing more professionals than the total number of employees. In this case the PROF variable was changed to missing.

more detailed information from CIS data is used, the results suffer from a potential sample selection bias, which is difficult to identify precisely due to the lack of information. But robustness with regards to the identification of the selection equation is seldom discussed in studies based on this data, although arguably the results are often sensitive to specification of the exclusion restriction.

A basic overview of the dataset is given in Table 1. After deleting firms with missing information, the dataset includes 14,681 observations. As many as 41% of them answered positively to the question about INNPDT in the survey. It might seem surprising that such a high share of firms innovated in developing countries; however, one needs to keep in mind that these are "new to the firm" innovations which often reflect the diffusion of existing technology, as discussed in more detail below. About a fifth of the sample consists of micro firms with less than 10 employees, whereas large firms with more than 250 permanent employees account for roughly a tenth of the sample. The typical age of a firm is 14 years, around a tenth of them did not operate for more than 5 years, and about a fifth of them were older than 25 years. A quick look at the composition of the sample by ownership reveals that on average foreigners own a tenth of the equity, only about one in twenty firms have minority share of foreign owners, but almost a tenth of the sample consists of foreign affiliates with more than a 50% share of foreign ownership. The averages of the variables reflecting technological capabilities are self-explanatory and will be examined in more detail later in relation to the propensity to innovate in the econometric framework.

Table 1: Overview of micro data

Variable	Obs.	Mean	Std. Dev.	Min	Max
INNPDT	14,681	0.41	..	0.00	1.00
SIZE	14,681	3.59	1.55	0.00	9.93
AGE	14,681	2.61	0.76	0.00	6.43
FOR	14,681	0.10	0.27	0.00	1.00
R&D	14,681	0.25	..	0.00	1.00
PROF	14,681	0.15	0.18	0.00	1.00
ISO	14,681	0.21	..	0.00	1.00
WWW	14,681	0.41	..	0.00	1.00
SKILL	14,681	0.43	..	0.00	1.00

Source: Author's computations based on World Bank (2003).

Table 2 reveals the composition of the sample by country. Surveys conducted in 32 developing countries between the years 2002 and 2007 are included. Although the surveys are meant to be harmonized under the aegis of the World Bank, there are differences between the national datasets that need to be addressed. For example, a closer look at the national questionnaires reveals some subtle modifications in the phrasing of the questions in different waves of the survey. To account for these differences we assign countries into three groups denoted by the GP variable in the third column of the table and include dummies for these groups into the regression estimate.[7]

[7] Only countries with rather minor differences in the questionnaire were allowed to enter the analysis. For example, INNPDT refers to the question whether the firm has "developed a major new product" in GP 1, "developed successfully a major new product line/service" in GP 2 and "developed a major new product line" in GP 3. And this variable refers to the period over the last three years in GPs 1 and 2, but over the last two years in GP 3. Unfortunately, a large group of countries mostly from Latin America, where the survey was conducted in 2006 and later, is not included because this version of the questionnaire used much less restrictive phrasing of this question. Similarly, data from earlier surveys conducted in Brazil, the Philippines and China had to be excluded, and with a heavy heart, because the questionnaire was strictly speaking not comparable for various reasons. It should also be noted that the surveys included variations on the question whether the firm "substantially changed the way the main product is produced", which broadly refers to process innovation. But the particular phrasing of this question differs to an extent that arguably makes the data incomparable and, therefore, we refrain from using this information. Note that Almeida and Fernandes (2008) and Lederman (2010) entirely ignored these differences.

Table 2: Overview of the micro data by country

Country	Year	GP	Obs.	INNPDT
Armenia	2005	2	242	0.46
Benin	2004	1	154	0.34
Cambodia	2003	1	405	0.54
Chile	2004	3	896	0.47
Ecuador*	2003	1	290	0.53
Egypt*	2004	3	918	0.14
El Salvador*	2003	1	275	0.62
Guatemala	2003	1	437	0.52
Honduras*	2003	1	323	0.48
Hungary	2005	2	360	0.29
India*	2005	3	1,712	0.40
Indonesia*	2003	3	566	0.38
Kazakhstan	2005	2	347	0.26
Lebanon	2005	3	337	0.60
Madagascar	2005	1	217	0.66
Malawi	2005	3	121	0.57
Malaysia	2007	3	903	0.37
Mali	2003	1	103	0.49
Mauritius	2005	3	123	0.43
Morocco*	2003	1	598	0.24
Nicaragua*	2003	1	386	0.46
Poland	2005	2	639	0.35
Romania	2005	2	338	0.30
Saudi Arabia	2005	3	474	0.55
South Africa	2003	1	434	0.71
Tajikistan	2005	2	155	0.35
Tanzania	2003	1	158	0.34
Thailand*	2003	3	1,172	0.59
Turkey*	2005	3	817	0.35
Uzbekistan	2005	2	154	0.17
Vietnam	2005	2	496	0.21
Zambia	2002	1	131	0.45

Note: * denotes firms in industry (10-41 codes of ISIC, rev. 3 classification) only.

Another thorny issue is whether the data is representative. Since we fully acknowledge this concern, we have included into the sample only national datasets with a reasonable number of observations given the size of the economy. Yet, even these could be seen as relatively low numbers by some observers, in particular by those who have the fortune to analyze a large CIS dataset. However, we should not judge this by European standards because this data comes from developing countries for which micro data on innovation is extremely scarce. In fact, one can find a plethora of papers in the literature based on samples of a few hundred firms, which at least implicitly claim to be representative of the context in question. More extensive micro data on innovation from many developing countries is not likely to become available anytime in the near future.[8]

Let us look more closely at the distribution of the INNPDT variable. Less than 25% of the firms innovated in Egypt, Uzbekistan, Vietnam and Morocco, but more than 60% of them claimed to introduce a major new product in Lebanon, El Salvador, Madagascar and South Africa. What accounts for these patterns across countries? Why do firms innovate substantially less in Egypt than in South Africa? And why do firms in some of the least developed countries appear among the most innovative according to this data? Such questions are at the core of the interest of this paper.

As already noted above, an important reason for the relatively high frequency of innovation in many developing countries is that the INNPDT variable refers to products "new to the firm", but not necessarily new to others. Since firms in developing countries can benefit from the diffusion of technologies developed in frontier countries, all else equal, they should be more likely to introduce more "new to the firm" innovations as compared to firms operating in more advanced environments (and therefore markets). In other words, a large part of what is captured by the INNPDT variable may reflect what Kim (1997) called "innovation through imitation". Of course, this does not at all make this information less relevant economically, quite the opposite. But let us leave a more detailed explanation of the national patterns to the econometric estimates.

Since we are going to estimate a multilevel model, we need data for specific macro variables that can capture the salient aspects of the national framework conditions. To limit the influence of shocks and measurement errors occurring in specific years, we use the national indicators in the form of three-year averages over the period prior to the year when the survey was conducted, if not specified otherwise below. [9] Also the use of

[8] 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 modeling.

[9] Since the surveys were conducted in different years—see the third column in Table 2—we kept this in mind when constructing the macro variables, so that we computed averages over different three-year periods depending of the timing of the survey in the particular country.

three-year averages limits the extent of missing data, which is crucial in a sample containing developing countries. Still, missing information at the country level had to be estimated in several cases, which is also explained in more detail below.

As an overall measure of development, we use the information on GDP per capita in PPP (constant 2000 international USD) denoted by Y that was derived from World Bank (2009). Since the propensity of firms to the "new to the firm" innovation has been hypothesized to be inversely related to the potential for the diffusion of technology from abroad and, hence, to increase with distance vis-a-vis the frontier country, the GAP variable used in the estimates refers to $\ln(Y^{*}/Y)$, where Y^{*} denotes the most developed economy in the sample and Y the respective country. GAP is the natural logarithm of the distance, because there is likely to be a non-linear relationship as commonly assumed in the literature.

Arguably, the potential for imitation is relevant, but certainly not the only and perhaps not even the main explanation, because as argued above whether this "great promise" becomes realized depends on various conditional factors. A natural starting point is to consider the national research capabilities (Nelson, 1993). The availability of research infrastructure such as universities, R&D labs and a pool of researchers in the labor force presumably reduces cost and uncertainty associated with a firm's innovative activities. Although some part of these resources is devoted to basic research, most research in developing countries is geared toward fostering the capacity to assimilate knowledge from abroad rather to generate new knowledge at the frontier. For example, Kim (1997) was well aware of this fact, and used the notions of technological capability and absorptive capacity interchangeably in the Korean context.

As a measure of the national research infrastructure, we use the PUBRD variable, which refers to expenditures on R&D performed in the government, higher education and private non-profit sectors as a percentage of GDP, i.e. performed in organizations that constitute the public infrastructure. PUBRD has been derived from UNESCO (2009) and from national sources in several cases.[10] BERD, which stands for expenditures on R&D performed in the sector of business enterprises as percent of GDP is not taken into account for three main reasons. First, and this is the practical reason, there does not exist credible data for BERD in 15 countries, hence, almost a half of the sample, which was deemed too many to estimate. BERD is less available than PUBRD, because of the need to survey firms for the former, whereas a good deal of the latter is financed by the government for which there is much better oversight. Second, and this is the technical reason, there is likely to be an excessively strong reverse causality between BERD and INNPDT because the propensity of firms to innovation naturally correlates with the BERD intensity of the economy for which we have not been able to find relevant instruments. As further discussed below, the other country-level predictors might suffer from the endogeneity bias too, but in our view to a much lesser extent than this variable. Finally, BERD is correlated with some of the other predictors to an extent that triggers serious multicollinearity problems.

Education is at the heart of what Abramovitz (1986) would refer to as social capabilities. As a general proxy for the system of basic education stands the LITERA variable derived from World Bank (2009), which refers to the literacy rate in the adult population (percent of people age 15 and above). Since there is relatively low frequency for data on literacy, for this indicator we use information from the year nearest to the reference period of the survey available. It would have been preferable to have data on the educational attainment of the population, but this information is not available for many countries in the sample. Similarly, data specifically on science and engineering education is, unfortunately, not widely available.

[10] Missing data for PUBRD had to be filled in for 8 countries. For countries for which there exists data for the total R&D expenditures but not details by the sector of performance, namely Egypt, Nicaragua, Saudi Arabia and Mauritius, we assumed that PUBRD equals the total figure because the existing evidence shows that BERD accounts for a very small share of the national total in most developing countries. But no information on R&D expenditure exists for Benin, Mali, Malawi and Tanzania for which the PUBRD data has been estimated by sample average imputation of 0.22%, which happens to be very close to the regional average of the total R&D intensity of 0.25% in Sub-Saharan Africa, excluding South Africa, over 1999–2004 in UNESCO (2009) and consistent with the educated estimate of Gaillard (2008) that the R&D intensity of economies in this region is around or less than 0.3% of GDP.

A salient aspect of the national framework conditions that certainly concerns every profit-seeking entrepreneur is the income tax rate, which has direct implications for net (after-tax) rewards from innovation. Since the detrimental effect increases with more progressive taxation, the TAX variable for which data was also obtained from World Bank (2009) refers to the highest marginal income tax rate. It would be more relevant to use the "effective" tax rate because tax deductions may offset the nominal tax rate, but this information is not readily available for most developing countries.

Another relevant feature of the institutional framework is the quality of governance, for which the indicators developed in the "Governance Matters" project in the World Bank come in very handy. Kaufmann et al. (2009) explains in more detail the definitions, methodology and sources. Since individual governance indicators are highly correlated, we use factor analysis to identify the common variance in the data. Only one factor score, labeled GOVERN, with an eigenvalue higher than one has been detected, explaining 79.7% of the total variance (factor loadings in brackets): Voice and Accountability (0.81), Political Stability and Absence of Violence/Terrorism (0.76), Government Effectiveness (0.94), Regulatory Quality (0.95), Rule of Law (0.94), Control of Corruption (0.93). All of the underlying indicators have high loadings, and so the single measure generated by this procedure can be used to represent the overall quality of governance.

Furthermore, we take into account the general "rules of the game" formalized in the national constitution. An overall measure of this condition is the POLITY2 index developed by Marshall and Jaggers (2009), henceforth the POLITY variable, which measures the degree of democracy versus autocracy on a Likert scale with 20 degrees (from -10 for an autocratic constitution to +10 for a democratic constitution). To make a long story short, countries with a "western" political system rank high, while countries with constitutions that do not conform to the democratic ideals of the west get a low mark. Fagerberg and Srholec (2008) showed that this feature of the institutional framework should not be confused with the quality of governance, because good scores on the latter could be achieved by countries with very different political systems and vice versa.

Although inflation is not a serious matter of concern in most advanced countries, at least in the recent period, the extent of macroeconomic (in)stability is an essential feature of the framework conditions in developing countries. Because innovation activity is quite an uncertain venture by itself, the characteristics of the environment that further increases the uncertainty of returns from the innovation projects, including macroeconomic turbulences, should hinder the appetite of firms for introducing new products on the market. INFLAT reflects the stability of prices measured by the annual average rate of inflation. The GDP deflator obtained from World Bank (2009) has been used to compute this variable.

Finally, as a control variable, we include POP, which stands for the size of the country given by the log of population from World Bank (2009). The size of the country has been cited as a relevant classification factor in the empirical literature, because of the wide range of possible effects that *ceteris paribus* being small might have on the economy, including a limited internal market, less resources (in absolute terms) available for developing national research and other relevant institutions and relatively less autonomy in national policy making.

Table 3 presents the macro variables. As far as GAP is concerned, the sample includes the least developed countries in Sub-Saharan Africa, but there is also a number of emerging economies at substantially higher levels of development. Similarly the PUBRD, LITERA, TAX, GOVERN and POLITY variables indicate that there is a lot of variety along these lines. INFLAT is limited to single digits in most countries and moderately high levels elsewhere, but there are no major outliers with rampant inflation rates over the relevant period. Some of the countries rank among the most populous in the world, whereas others are quite small. It should be noted, however, that the Mahalanobis distance did not indicate the presence of multivariate outliers in these characteristics, so that in this regard the regression estimates do not suffer from a major problem.

Table 3: Overview of macro data

Variable	Obs.	Mean	Std. Dev.	Min	Max
GAP	32	1.72	0.99	0.00	3.46
PUBRD	32	0.22	0.16	0.03	0.58
LITERA	32	79.30	19.53	19.04	99.51
TAX	32	31.02	9.25	0.00	44.00
GOVERN	32	0.00	1.00	-1.89	2.60
POLITY	32	3.74	6.17	-10.00	10.00
INFLAT	32	9.42	8.37	0.02	29.04
POP	32	16.74	1.30	14.02	20.79

Source: Marshall and Jaggers (2009), UNESCO (2009), World Bank (2009) and national sources.

Of course, there are many other relevant indicators that could have been taken into account, such as those used by Faberberg and Srholec (2008), but too many of them tend to be prohibitively correlated to the GAP on one hand or the framework conditions for exploiting the potential for diffusion that are already taken account on the other hand. Some of the incumbent variables are modestly correlated too, which raises concerns about multicollinearity in the regression estimates, although this fortunately does not pose a serious problem for the results, as further discussed below.

4. A Logit Multilevel Model of Firms Nested in Countries

A multilevel model, also known as a hierarchical, random coefficient, variance component or mixed-effects model, is a statistical model that relates a dependent variable to explanatory variables at more than one level (Luke, 2004). Assume a two-level structure with firms at level-1 nested in countries at level-2. A standard one-level model is the following:

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

where y_{ij} is the dependent variable, x_{ij} is the level-1 explanatory variable, β_{0j} is the standard intercept, β_{1j} is the standard slope coefficient, e_{ij} is the standard error term, i is the firm ($i = 1\ldots m$) and j is the country ($j = 1\ldots n$). Although we allow for more than one country in the analysis, the equation is formulated separately for each. If we are interested only in this relationship, we can estimate the n models separately, assuming different parameters for each country and a common intra-country residual variance. A linear two-level model with explanatory variables at both the firm and country levels emerges if we let the intercept β_{0j} and slope β_{1j} become random variables:

(2) Level-1 linear 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 predictor and u_{0j} and u_{1j} are normally distributed random (or error) terms for each level-2 equation, which are independent from the level-1 residual e_{ij} and from each other. Since the level-2 effects are identified by the subscript j, we have a hierarchical system of regression equations where we allow each country to have a different average outcome (β_{0j}) and a different effect of the level-1 predictor on the outcome (β_{1j}). Although a different level-1 model is estimated for each country, the level-2 equation is defined for all of them. By substituting β_{0j} and β_{1j} in the level-1 model and rearranging the equation 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 the random part is in brackets and the rest contains the fixed part of the model. As discussed by Goldstein (2003), the presence of more than one residual term makes 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).

So far we have assumed that the dependent variable is continuously distributed. If the dependent variable is binary, we need to specify a non-linear multilevel model. For this purpose, we assume a binomial sampling model and use a logit link function to transform the level-1 predicted values. Only the level-1 part of the model differs from the linear case and the binomial logit multilevel model is delineated as follows:

(4) Level-1 logit model:

$$E\ (y_{ij} = 1 \mid \beta_j) = \varphi_{ij}$$

$$\text{Log}\ [\varphi_{ij} / (1 - \varphi_{ij})] = \eta_{ij}$$

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

Level-2 model:

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

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

where η_{ij} is the log of the odds of success such as, for example, the propensity of a firm to introduce innovation. Although φ_{ij} is constrained to the interval (0, 1), the logit transformation allows η_{ij} to take any value and, therefore, can be substituted for the structural model. From this follows that the predicted log-odds can be reversed to odds by $exp(\eta_{ij})$ and to the predicted probability φ_{ij} by $exp\{\eta_{ij}\}/(1+exp\{\eta_{ij}\})$.[11]

$INNPDT_{ij}$ is the dependent variable. $SIZE_{ij}$, AGE_{ij}, FOR_{ij} and the vector of the firm's capabilities $R\&D_{ij}$, $PROF_{ij}$, ISO_{ij}, WWW_{ij} and $SKILL_{ij}$ are the firm-level predictors,

[11] Note that there is no term for the level-1 residual in the binomial logit model because for binary dependent variables the variance is completely determined by the mean and thus a separate error term is not estimated; for a more detailed explanation see Luke (2004, pg. 55).

while the potential for diffusion given by the distance of the economy where the firm is nested from the frontier GAP_j and the vector of national factors that presumably determine whether this potential is exploited $PUBRD_j$, $LITERA_j$, TAX_j, $GOVERN_j$, $POLITY_j$, $INFLAT_j$ and POP_j are the country-level predictors. In addition, we control for sectoral patterns and differences in the questionnaire, as explained above, by including two sets of the respective dummy variables SEC_{ik} and GP_{il}. The full specification of the model with a complete set of fixed and random effects is as follows:

(5) Level-1 logit model:

$$E\,(INNPDT_{ij} = 1 \mid \beta_j, \delta_k, \delta_l) = \varphi_{ij}$$

$$\text{Log}\,[\varphi_{ij} / (1 - \varphi_{ij})] = \beta_{0j} + \beta_{1j}SIZE_{ij} + \beta_{2j}AGE_{ij} + \beta_{3j}FOR_{ij} + \beta_{4j}R\&D_{ij} + \beta_{5j}PROF_{ij} + \beta_{6j}ISO_{ij} + \beta_{7j}WWW_{ij} + \beta_{8j}SKILL_{ij} + \sum_{k=1} \delta_{0k}\, SEC_{ik} + \sum_{l=1} \delta_{1l}\, GP_{il}$$

Level-2 model:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}GAP_j + \gamma_{02}PUBRD_j + \gamma_{03}LITERA_j + \gamma_{04}TAX_j + \gamma_{05}GOVERN_j + \gamma_{06}POLITY_j + \gamma_{07}INFLAT_j + \gamma_{08}POP_j + u_{0j}$$

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

$$\beta_{2j} = \gamma_{20} + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + u_{4j}$$

$$\beta_{5j} = \gamma_{50} + u_{5j}$$

$$\beta_{6j} = \gamma_{60} + u_{6j}$$

$$\beta_{7j} = \gamma_{70} + u_{7j}$$

$$\beta_{8j} = \gamma_{80} + u_{8j}\,,$$

where there are firm-level fixed effects ($\gamma_{00}\ldots\gamma_{80}$), country-level fixed effects for the intercept ($\gamma_{01}\ldots\gamma_{08}$) and random (or residual) effects ($u_{0j}\ldots u_{8j}$) of which γ_{00} is the estimated grand average of the log-odds of firms to innovate across countries, $\gamma_{10}\ldots\gamma_{80}$ are the estimated averages of the firm-level slopes across countries, $\gamma_{01}\ldots\gamma_{08}$ are the estimated effects of the country-level predictors, $u_{0j}\ldots u_{8j}$ tell us that the respective coefficients vary not only as a function of the predictors, but also as a function of unobserved country effects.

Note that this is the so-called "intercept-as-outcome" multilevel model with only the intercept as a function of the country-level predictors. By focusing on this specification, we test the hypothesis that the national framework conditions directly influence the likelihood of firms to innovate, which is the main research question of this paper. A large number of cross-level fixed effects could emerge in a more complex specification if the country-level predictors were added in equations of the slope coefficients ($\beta_{1j}\ldots\beta_{9j}$) too. Given the relatively limited number of countries in this paper, which constrains the number of parameters that can be estimated, this is not viable because of concerns about degrees of freedom, multicollinearity and reduced parsimony. Also, we do not allow the set of SEC_{ik} and GP_{il} dummies to vary across countries because it greatly reduces the number of random effects to be estimated without losing much content.

Another major limitation that needs to be emphasized is that the model does not address the potential problems of endogeneity because valid instruments proved hard to find for the variables of interest. Obviously, the firm-level relationships are quite likely to be endogenously determined, but the reverse causality cannot be ruled out for some of the country-level effects either if, for example, one considers the possibility that innovating firms pressure governments to devote more resources to the national research infrastructure, provide better education to their employees or decrease the marginal income tax rate. Any interpretation of the estimated coefficients in terms of causality should therefore be put forward with caution. Needless to say, it remains an important challenge for future research to tackle this deficit if more suitable data become available.

5. Econometric Analysis

To improve the interpretability of the results we standardize the firm-level predictors $SIZE_{ij}$ and AGE_{ij}, and all of the country-level predictors, by deducting the mean and dividing by standard deviation, so that these variables enter the estimate with a mean of zero and standard deviation equal to one. After this transformation, the predictors have meaningful zero points, which greatly simplifies the interpretation of the estimated parameters, especially for the intercept (Hox, 2002; Goldstein, 2003 and Luke, 2004). An additional advantage is that we can directly compare the magnitude of the estimated country-level effects because the standardization procedure transforms these predictors to a common scale of units of standard deviation, i.e. the so-called beta coefficients are reported for the fixed effects, and because in addition the unobserved random effects are measured in standard deviation by definition.

Table 4 gives the results. [12] Fixed effects are reported in the upper part, separately for the intercept and slopes, while random effects are in the lower part of the table.[13] First, we consider a "basic" model with only the firm-level predictors, but allow the estimated coefficients to vary across countries by including the random effects. Second, we estimate the "intercept-as-outcome" model, which adds the country-level predictors for the intercept. Third, we revert to what would be the conventional specification of the model by excluding the random effects in order to examine how this affects the results. Finally, we use a backward stepwise selection procedure to eliminate redundant predictors, which leads to the most concise specification.

[12] A specialized statistical software Hierarchical Linear and Non-linear Modeling (HLM) version 6.06 was used to estimate the equations. Since there is a relatively low number of countries in the sample, we use the restricted maximum likelihood procedure, which is more robust to reduced degrees of freedom than the full maximum likelihood estimate. See Raudenbush, et al. (2004) for details.

[13] For the sake of space, we do not report the estimated fixed effects of the SEC_{ik} and GP_{il} dummies, which do not merit much interest here, but we indicate in the table whether these are included or not.

Table 4: Econometric results

	(1)	(2)	(3)	(4)
Fixed Effects:				
For intercept$_{ij}$ (β_{0j})				
Intercept$_{ij}$ (γ_{00})	-1.27 (0.12)***	-1.29 (0.14)***	-1.23 (0.04)***	-1.19 (0.15)***
GAP$_j$ (γ_{01})	..	0.37 (0.10)***	0.29 (0.02)***	0.30 (0.09)***
PUBRD$_j$ (γ_{02})	..	0.03 (0.06)	0.01 (0.01)	..
LITERA$_j$ (γ_{03})	..	0.24 (0.06)***	0.26 (0.02)***	0.19 (0.07)**
TAX$_j$ (γ_{04})	..	-0.28 (0.06)***	-0.30 (0.01)***	-0.27 (0.05)***
GOVERN$_j$ (γ_{05})	..	0.12 (0.08)	0.06 (0.02)***	..
POLITY$_j$ (γ_{06})	..	0.38 (0.05)***	0.27 (0.01)***	0.42 (0.05)***
INFLAT$_j$ (γ_{07})	..	-0.10 (0.05)*	-0.10 (0.01)***	-0.11 (0.04)**
POP$_j$ (γ_{08})	..	-0.03 (0.08)	-0.09 (0.01)***	..
For slopes$_{ij}$ ($\beta_{1j} \ldots \beta_{8j}$)				
SIZE$_{ij}$ (γ_{10})	0.11 (0.03)***	0.11 (0.03)***	0.14 (0.01)***	0.11 (0.03)***
AGE$_{ij}$ (γ_{20})	-0.09 (0.03)***	-0.09 (0.03)***	-0.09 (0.01)***	-0.09 (0.03)***
FOR$_{ij}$ (γ_{30})	0.01 (0.08)	-0.02 (0.09)	0.02 (0.03)	..
R&D$_{ij}$ (γ_{40})	0.67 (0.07)***	0.66 (0.07)***	0.69 (0.02)***	0.65 (0.07)***
PROF$_{ij}$ (γ_{50})	0.44 (0.20)**	0.37 (0.17)**	0.17 (0.05)***	0.37 (0.17)**
ISO$_{ij}$ (γ_{60})	0.47 (0.11)***	0.48 (0.11)***	0.36 (0.02)***	0.46 (0.11)***
WWW$_{ij}$ (γ_{70})	0.38 (0.06)***	0.38 (0.07)***	0.42 (0.02)***	0.38 (0.06)***
SKILL$_{ij}$ (γ_{80})	0.34 (0.06)***	0.35 (0.06)***	0.34 (0.02)***	0.34 (0.06)***
SEC$_{ik}$ (δ_{0k})	Yes	Yes	Yes	Yes
GP$_{il}$ (δ_{11})	Yes	Yes	Yes	Yes
Random effects:				
Intercept$_{ij}$ (u_{0j})	0.62 (266)***	0.52 (149)***	..	0.50 (165)***
SIZE$_{ij}$ slope (u_{1j})	0.11 (55)***	0.12 (55)***	..	0.11 (56)***
AGE$_{ij}$ slope (u_{2j})	0.13 (65)***	0.13 (64)***	..	0.12 (63)***
FOR$_{ij}$ slope (u_{3j})	0.28 (50)**	0.30 (50)**	..	..
R&D$_{ij}$ slope (u_{4j})	0.30 (70)***	0.30 (70)***	..	0.29 (70)***
PROF$_{ij}$ slope (u_{5j})	0.83 (54)***	0.62 (53)***	..	0.61 (55)***
ISO$_{ij}$ slope (u_{6j})	0.48 (98)***	0.52 (100)***	..	0.51 (96)***
WWW$_{ij}$ slope (u_{7j})	0.27 (57)***	0.28 (57)***	..	0.26 (55)***
SKILL$_{ij}$ slope (u_{8j})	0.24 (57)***	0.22 (56)***	..	0.21 (57)***
Index of dispersion	0.991	0.992	..	0.992
ML	-20,848.80	-20,856.49	-8,923.30	-20,847.77
Level-1 firms	14,681	14,681	14,681	14,681
Level-2 countries	32	32	32	32

Note: Non-linear unit-specific model with the logit link function. Restricted maximum likelihood (PQL) 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. *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.

The results of the "basic" model are presented in the first column of Table 4. Most of the firm-level predictors, except FOR$_{ij}$ only, are statistically significant. As already discussed above, in addition to other conceivable advantages of scale, SIZE$_{ij}$ has a positive sign because larger firms with many product lines are by principle more likely to innovate with at least one of them. Similarly, the negative coefficient of AGE_{ij} follows from the definition of the dependent variable because younger firms are more likely to experiment with "new to the firm" products when they start their business. FOR_{ij} does not seem to make a difference, so the presumable advantages of foreign ownership do not hold up, at least as far as the other relevant effects are properly accounted for. $R\&D_{ij}$ appears with a positive and highly significant coefficient, showing that this aspect of technological capabilities is fairly relevant in the context of developing countries. But $PROF_{ij}$, ISO_{ij}, WWW_{ij} and $SKILL_{ij}$ matter a great deal too, especially if we consider their joint effect, so that the broad nature of technological capabilities is firmly supported by the results.

All of the random effects are statistically significant at the conventional levels. This indicates that there are sizeable differences across countries in the likelihood of firms to innovate and in the way the firm-level effects affect this propensity.[14] Even though there are no country-level predictors in this model, the random effects expressed in units of standard deviation show how widely the intercept and slope coefficients are distributed around the estimated mean by country. For example, the fixed effect of $R\&D_{ij}$ is 0.67, but the respective random effect reveals that for 68% of the countries this effect lies in the range of [0.37, 0.97] and for 95% of the countries in the range of [0.07, 1.27].[15] In other words, this predicts that for firms nested in countries with the least favorable environment the productivity of their R&D in terms of the success in innovation falls very close to zero. Similarly, these intervals of the other capability variables spread quite widely across countries. Some of them are even estimated to stretch into negative territory, which is admittedly difficult to comprehend, unless in extremely adverse conditions.

[14] A chi-square test of the residuals can be performed (Raudenbush et al., 2004). Nevertheless, the meaning of this significance test is not the same as for an ordinary variable, which needs to be kept in mind when interpreting the results.

[15] Since the random effects are assumed to be normally distributed, about 68% of the observations lie less than one standard deviation from the mean and about 95% of the observations less than two standard deviations from the mean.

So far we have been able to show that there is considerable diversity by country, but we do not know what drives these differences. Next, in the second column of Table 4, we therefore attempt to explain the central tendency of firms to innovate by integrating the country-level variables into the model as predictors of the intercept. The advantages of latecomers for "innovation through imitation" represented by the GAP_j variable prove to be an essential part of the explanation. For every standard deviation of GAP_j the probability of a firm to introduce a product "new to the firm" is predicted to increase by roughly 7 percentage points, which in this sample of countries means that, all else equal to average, a firm nested in the least developed country is estimated to have about 25 percentage points higher probability to innovate than the same firm in a frontier country thanks only to the higher potential for imitation. Nevertheless, this is certainly not the full story, because the factors conditional for exploiting this potential appear equally, if not even more, relevant.[16]

$LITERA_j$, which refers to the adult literacy rate, has a significantly positive effect, suggesting that firms tangibly benefit from access to an educated labor force in the innovation process. Education is a staple variable in the empirical research on innovation, and so this effect hardly needs further explanation. But it should be perhaps noted that this result needs to be interpreted as a joint effect of the general quality of the national educational system because other relevant (and available) indicators in this domain such as the primary, secondary and tertiary enrollment rates tend to be highly correlated with this predictor.

Furthermore, the detrimental effect of TAX_j that stands for the highest marginal income tax rate is firmly backed by the estimate. Even though the government obviously needs to collect taxes in order to finance public services, including those supportive to innovation, what exactly gets taxed is an entirely different matter. Governments should primarily tax the "circular flow" segment of the economy in terms of Schumpeter (1934), but stay away from imposing taxes that reduce net (after tax) returns and hence incentives of firms to innovate. For example, governments

[16] GAP_j has a coefficient close to zero, if it is included into the model without the other country-level predictors, which supports the hypothesis of "conditional" diffusion in the sense of Fagerberg (1987) and Verspagen (1991).

could tax consumption rather than income and/or avoid steeply progressive income tax rates. Even more targeted instruments might do a better job, but it is an open question whether R&D tax credits that have been recently implemented in many advanced countries can effectively serve this purpose here, because R&D is not necessarily the main, and certainly not the only, source of innovation in developing countries.

A high score of the country on the $POLITY_j$ variable, indicating a democratic political system, is very favorable for innovation. Generally speaking, autocracy not only inhibits the diversification of knowledge and, therefore, the creation of new ideas, but, even more importantly, autocracy also inhibits the diffusion of knowledge in the society. Autocratic regimes tend to be more stable in terms of who rules, but not more durable as a system of government (Marshall and Jaggers, 2009). All too many autocratic governments crumble in chaos, when the ruling elite gets under pressure, whereas a democratic system among other things entails legal, transparent and peaceful transition of power, therefore decreasing political uncertainty over the long run. If government decisions require a broad consensus, there is less danger of arbitrary changes in the sense of Henisz (2000). A democratic constitution also carries a bandwagon of related safeguards, including adherence to basic freedoms, civil liberties, human rights and judicial independence. Fagerberg and Srholec (2008) did not find robust support for the direct effect of democracy on economic development. But this result suggests that the way a political system is organized has powerful indirect effects through innovativeness of firms. All in all, anchoring the general "rules of the game" in a democratic framework seems to be of great importance.

A much lower, although still statistically significant, coefficient was obtained for the $INFLAT_j$ variable. Anybody who has ever attempted to make a budget for an innovation project, which often requires a rather long horizon, in times of macroeconomic turmoil should understand what this is about. But price instability does not appear to be the key element of the framework conditions, at least not in this group of countries over this period. $INFLAT_j$ might be only weakly significant perhaps because in this respect expectations matter much more for the innovative behavior of firms than the historical record of inflation, but the former variable is hard to pin down. Nevertheless, macroeconomic conditions should certainly not be neglected in the innovation literature.

Equally intriguing is to see which of the country-level variables do not appear relevant. Somewhat surprisingly, $PUBRD_j$, which is cited by many as the key attribute of the national framework conditions, does not appear even remotely statistically significant. Admittedly, this outcome reflects the insufficient systemic interactions between the industry and the public research sector that has been pointed out in the literature on innovation systems in developing countries (Lundvall et al., 2009). Size does not seem to really matter here. Even if the government maintains a quite noticeable research infrastructure such as in Hungary, India or Turkey in this sample of countries, these resources do not necessarily trickle down to more innovation in the business sector if these segments of the economy do not forge healthy linkages. To the best of our knowledge, however, there is unfortunately not a measure available for a large number of countries that could be used to directly gauge the extent of these interactions.

Another relatively low magnitude and insignificant effect was detected for $GOVERN_j$, although this variable comes close to being statistically significant at the 15% level. This result suggests that the issue of what constitutes "good" governance for innovation is a bit more complicated than what first meets the eye. For example, a strict enforcement of property rights, especially in the intellectual domain, is favorable for "new to the world" innovations, but might actually slow down the diffusion of knowledge. Hence, $GOVERN_j$ probably represents a mixed bag of effects that together add up to only a weakly positive coefficient in the estimate. Finally, POP_j has a very limited impact, so that size of the country by itself does not really matter for the innovativeness of firms.

A glance at the random part of the model reveals that after the country-level predictors have been included, standard deviation and particularly the Chi-square statistics of the random effect for the intercept decrease, which confirms that a relevant part of the unexplained variance across countries has been accounted for. But this residual remains fairly significant, so there is still considerable unobserved diversity across countries.[17] Some of these differences could be very difficult to ever measure properly, including expectations about technology, the economy and society at large; the extent of trust, honesty or "social" capital; whether there is "innovative culture" and other cultural differences.[18] Furthermore, cognitive differences between respondents in different countries could drive the measurement errors of the micro variables, which collapse into the residuals too. For example, what is sufficiently "new", "major" or "successful" to qualify for a positive answer about innovation in the survey might have been perceived differently by respondents with diverse cultural background, so those from cultures more "modest" in assessing their achievements reported less spectacular results. All that a researcher can do about this, given the imperfect data in hand, is to properly account for these unobserved (or unobservable) differences in the multilevel framework.

Since estimates of a multilevel model that properly relaxes the independence assumption have not been presented in the literature on this topic so far, for a comparison we report in the third column of Table 4 the results of what would be the conventional specification of the model. If the random effects, in other words the unobserved differences across countries, are correlated both to $INNPDT_{ij}$ and the incumbent predictors, the conventional model generates spurious correlations. A brief look at the results confirms that, indeed, this is the case. Standard errors estimated by the conventional model are in most cases at least three times lower than those obtained from the multilevel estimate, therefore substantially increasing the statistical significance of the coefficients, some of which were not even significant at the conventional levels before. Even though the main outcome has remained qualitatively similar, it is easy to imagine that in other studies a bias of this magnitude can easily

[17] Adding more country-level predictors could reduce the residual, but given the relatively low number of countries in the sample, further extending of the model would unfortunately prevent us from estimating robust standard errors. As already discussed above, other relevant country-level predictors tend to be highly correlated to the incumbent variables, causing problems of multicollinearity if inserted into the model. Hence, these attempts run into limitations of the data.

[18] An invaluable source of information about these cultural traits is the so-called World Value Survey, but this data has not been collected for 12 out of the 32 countries in the sample, and there is no credible way to estimate the missing figures, so we are not able to use this insight here.

lead to misleading conclusions.[19]

As anticipated above, the last column in Table 4 presents the "best" model that was generated by the backward stepwise selection procedure.[20] Since statistically insignificant variables do not contribute much to the predictive power of the model, and since there is a relatively low number of countries in the sample, reducing the number of coefficients helps us improve accuracy and efficiency of the estimate. But a comparison with the intercept-as-outcome model reveals that the results are generally robust to this procedure.

Because there are only statistically significant coefficients, this specification is particularly suitable for deriving predictions of the model. Table 5 shows the predicted probabilities of firms to innovate. Horizontally, we increase the extent of the firm's technological capabilities given by the vector $TECH_{ij} \in (R\&D_{ij}, PROF_{ij}, ISO_{ij}, WWW_{ij}$ and $SKILL_{ij})$, for which there is the min($TECH_{ij}$) category of firms with zero scores on these variables, a typical firm with mean($TECH_{ij}$) scores and the max($TECH_{ij}$) category of firms with extensive technological capabilities.[21] Vertically, there are various specifications of the country where the firm operates given by the vector of relevant framework conditions $FRAME_j \in (GAP_j, LITERA_j, TAX_j, POLITY_j$ and $INFLAT_j)$. Everything else, including $SIZE_{ij}$, AGE_{ij}, SEC_{ik}, GP_{il} and u_j, is held constant at average.

19 Lederman (2010) claims to perform a "multilevel" analysis, although the random effects are not accounted for, so the estimated model is not multilevel (or hierarchical) in econometric terms. Similarly Almeida and Fernandes (2008) did not account for these effects, even though the hierarchical nature of the data clearly called for doing so.

20 At the beginning of this procedure, we estimate the full model, eliminate the least statistically significant predictor, re-estimate the reduced model, and then stepwise repeat this exercise until the model includes only (at least at the 10% level) significant predictors.

21 For the max($TECH_{ij}$) category the top value of $PROF_{ij}$ was truncated at 50% of employment, because a higher share is not viable in most sectors covered by the database.

Table 5: Predicted probabilities of $INNPDT_{ij}$ based on the backward stepwise selection estimate (in %)

		$TECH_{ij}$ Min	Mean	Max
$FRAME_j$	Armenia	44.5	59.8	85.8
	Mean	28.5	42.5	75.0
	Morocco	11.2	19.0	48.7
GAP_j	+1 st. dev.	34.9	49.9	80.2
$LITERA_j$		32.6	47.3	78.5
TAX_j		23.4	36.2	69.7
$POLITY_j$		37.8	53.0	82.1
$INFLAT_j$		26.2	39.8	72.8
GAP_j	-1 st. dev.	22.8	35.5	69.1
$LITERA_j$		24.7	37.9	71.2
TAX_j		34.2	49.1	79.7
$POLITY_j$		20.7	32.7	66.3
$INFLAT_j$		30.9	45.3	77.1

Note: All else is held constant at average; $TECH_{ij} \in$ ($R\&D_{ij}$, $PROF_{ij}$, ISO_{ij}, WWW_{ij} and $SKILL_{ij}$); $FRAME_j \in$ (GAP_j, $LITERA_j$, TAX_j, $POLITY_j$ and $INFLAT_j$).

At this point, the interpretation of these figures should be clear. Firm-level technological capabilities are essential. All else equal to average, the estimated probability to innovate is 28.5% for a firm with the minimum technological capabilities, but 75.0% for the most capable firm. But there is more to this story, because the national environment has powerful effects, too. An otherwise average firm located in Armenia, which offers the most favorable combination of framework conditions, is predicted to have a 59.8% probability to innovate, whereas a firm with the same characteristics located in Morocco, which has the most adverse environment, is estimated to have only a 19.0% chance of success. Hence, only because of the national framework conditions the latter firm is about three times less likely to innovate. More detailed calculations of one standard deviation shifts in the individual $FRAME_j$ variables further demonstrate how much the potential for imitation given by GAP_j is important to take into account in the analysis of new-to-the-firm innovations but at the same time that the other national factors that condition the exploitation of this potential make a similar (or even more) dramatic difference; especially if one considers their joint effect.

It should be stressed, furthermore, that the results do not suffer from a serious problem of multicollinearity, neither among the firm- nor country-level predictors. Among the firm-level predictors the correlation coefficient never exceeds 0.40, which confirms that these variables capture distinct characteristics of firms. A brief look at correlations between the country-level predictors reveals that the main potential problem constitutes the modest correlation between the $GOVERN_j$ variable and (correlation coefficients in brackets) GAP_j (-0.60), $PUBRD_j$ (0.55) and $POLITY_j$ (0.53) and the correlation between the GAP_j and $LITERA_j$ variables (-0.56). But a closer examination of the estimates with this in mind reveals that the results are not driven by these correlations. After all, this should be obvious from the "best" model, from which the worst trouble maker $GOVERN_j$ has been eliminated.

So far we have not looked at the diagnostic measure of multilevel models called the index of dispersion. Although logit multilevel models do not have a separate term for the level-1 error, we can calculate a level-1 error variance scaling factor that measures the extent to which the observed errors follow a theoretical binomial error distribution (Luke 2004, pg. 57). If the index of dispersion equals 1, there is a perfect fit between the observed errors and the theoretical assumptions. A significant over- or under-dispersion indicates model misspecification, the presence of outliers or the exclusion of an important level in the model. Less than 5% dispersion is usually seen as satisfactory. Since the index is very close to unity, from this technical point of view the results do not suffer from a major problem. A more detailed look at the estimated residuals for the intercept confirms this conclusion because there is not a major outlier with u_{0j} more than two standard deviations from the mean and their distribution follows a normal probability curve.

In addition, the robustness of the results have been tested for the composition of the sample regarding the exclusion of countries with estimated data for the $PUBRD_j$ variable, the exclusion of GP_{il}=2 countries, the exclusion of national samples with less than 200 observations and the inclusion of firms in the industry only. But these limited samples do not allow estimating robust standard errors, so the results are strictly speaking not comparable to the full sample and hence not reported here, although they are available from the author upon request. Nevertheless, the main outcome of these estimates is that the results of GAP_j, TAX_j and $POLITY_j$ remain remarkably stable across the board and $PUBRD_j$ and POP_j are never statistically significant at conventional levels, whereas the coefficients of $LITERA_j$, $GOVERN_j$ and $INFLAT_j$ are somewhat sensitive. All in all, however, the results are not qualitatively different from those based on the full sample.

Overall, the results show that national framework conditions have a substantial effect on the odds of firms to innovate, 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 the odds materialize in their joint effects. Arguably the innovative performance of the economy is not about the achievements of firms on the one side and the government on the other, but essentially about what they are capable of accomplishing together.

6. Conclusions

All too often innovation policy in developing countries remains locked in the science-centered perspective on innovation. A growing number of governments even mimic the elusive policies of the frontier countries by setting bold targets of R&D expenditures per GDP (Gaillard, 2008), which usually imply reshuffling a noticeable amount of public resources in this direction because firms seldom invest large amounts into R&D in developing countries. But the results of this paper indicate that goals like these might turn out to be futile for achieving innovation-based growth, because in developing countries there does not seem to be a direct connection between the extent of public research infrastructure and the propensity of firms to innovate. A much more productive concern for many of these governments could well be how to better leverage the existing amount of resources in this domain rather than how to channel more public spending down the same route.

A need for a broad approach to innovation policy is firmly supported by the results, because generic conditions given by the extent of basic education, (dis)incentives to innovate rooted in the tax system, the way the political system is organized and macroeconomic stability turn out to be fairly relevant. In particular, the results call for improving our understanding of the relationship between democracy and innovation, which emerged from the analysis as one of the key connections, but which has arguably not received the attention that it deserves in the recent innovation literature, even though this was a major topic in Schumpeter's work (Schumpeter, 1943). Another result that needs to be flagged is that a democratic political system seems to matter more than what tends to be generally perceived as "good" governance, at least in terms of Kaufmann et al. (2009), which feeds into the controversy about governance issues in the global economy (Cimoli et al., 2009). More research certainly needs to be done on the complex interplay between governance, democracy and innovation.

Yet, there remains considerable heterogeneity among countries that we have not been able to pin down. Many of these unobserved conditions, which could be expectations, social traits or cultural differences, are very hard (or even impossible) to measure. Even though robust regularities have been detected, there is obviously a limit on how much we can explain by quantitative modeling. Admittedly, the rest needs to be illuminated by more detailed qualitative research that can dive much deeper into the particular context. Furthermore, as already noted, this unexplained variance is also likely to reflect measurement error. Despite the best efforts of those who develop the data, both firm- and country-level indicators need to be understood as rough proxies of the phenomena in question. Hence, there is good reason to be modest. Accepting the fact that there is considerable uncertainty involved, that the "unknown" element is always likely to be an inherent part of the picture and that, therefore, surprises are inevitable, might well be the best point of departure for designing innovation policies.

Nevertheless, the main purpose of this paper has been to highlight multilevel modeling as a promising method for future research on the contextual nature of innovation. Although there are many relevant hypotheses that are within any of the levels of analysis, there is a host of issues that require considering the relations between them. Arguably, this "unit of analysis" problem might be elegantly resolved, at least in empirical research, by explicit multilevel modeling of innovation that would use micro data to study the interaction between firms and their surroundings such as sectoral, regional and national innovation systems.

Although we have constrained ourselves to the "intercept-as-outcome" multilevel model in this paper, there is a variety of specifications that in principle could be estimated. A straightforward extension would be to consider cross-level interaction terms between the firm- and country-level predictors, which could not be done here due to the limits of the data. Another possible avenue for further research 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. All that matters is access to suitable data.

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