Mind the Skills Gap! Regional and Industry Estimates in Emerging Economies

Ángel Melguizo (OECD Development Centre)
José Ramón Perea (OECD Development Centre)

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Abstract

Most emerging economies are characterized by lagging levels of productivity. While economic growth has been robust in much of the emerging world during the last two decades, it has generally been grounded on factor accumulation, with marginal contributions from productivity. With the economic literature pointing to human capital and skills as a key conduit of productivity, the inability of firms to find the skills they need appears as a key brake on development. This paper aims to identify the dimensions where this skill gap is more prevalent, particularly across emerging regions and industries. We devise an empirical analysis that uses two alternative specifications based on limited dependent variable analysis. The results place Latin America as the emerging region where firms have greatest problems derived from the lack of adequate skills, well ahead from emerging Asia and Europe, but also from Sub-Saharan Africa. In terms of sectors, two advanced manufacturing industries (machinery and motor vehicles) are particularly affected by this relative scarcity of adequately trained workers. Policy recommendations hinge on the need to solve the mismatch between the provision of skills by educational systems and the needs of the economy.

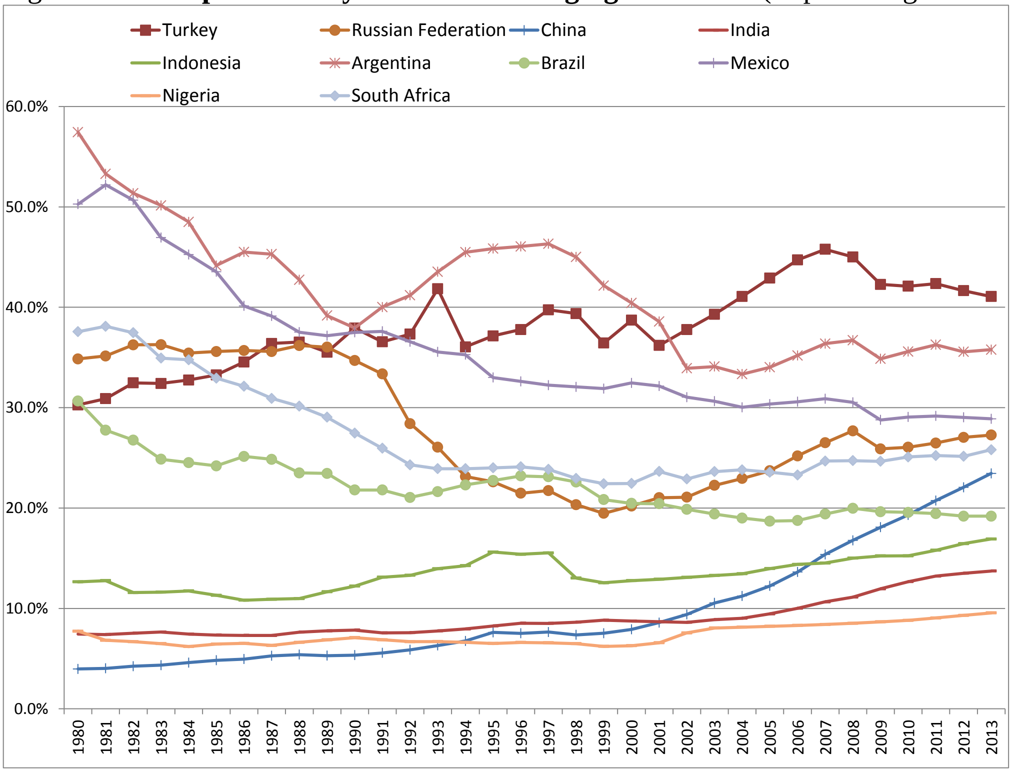
Keywords: skills gap, productivity, firm survey data.
JEL codes: J24, O4

I. Introduction

Economic competitiveness and productivity growth depend critically on human capital. Early studies (Mankiw et al., 1992; Benhabib and Spiegel, 1994) showed a strong and positive causal effect of human capital over economic growth. Yet, more recent contributions have at times called into question the relationship between human capital and growth. As Pritchet (2001) remarks, several factors may complicate the task of finding a positive relationship between both variables, from the quality of education to low demand of skills by private firms. In all, a sound diagnostics of more subtle aspects of skills (i.e., levels, quality and demand) are becoming more relevant, particularly among policy-makers (World Economic Forum, 2015).

Raising productivity is at the top of the agenda among developed economies, but should be as well among emerging regions. As **Figure 1** shows, there is a generalised lack of convergence in productivity levels in key emerging countries to the levels of the United States[1], with some notable exemptions after the East Asian crisis in countries like China, India and Indonesia (OECD, 2014). This divergence is especially evident in the big Latin American economies, and is at odds with conventional theories of technological catch-up[2]. This evolution helps to explain a popular empirical theory among development economists, the 'middle-income trap', where economies are more prone to experience secular slowdowns in growth at mid-levels of output per capita (Eichengreen et al., 2011; Felipe et al., 2012).

Figure 1. **Labor productivity in selected emerging economies** (as percentage of US level; PPP adjusted)



Source: Author's calculations, based on The Conference Board *Total Economy Database.*
Note: GDP per person employed (1990 $ GK)

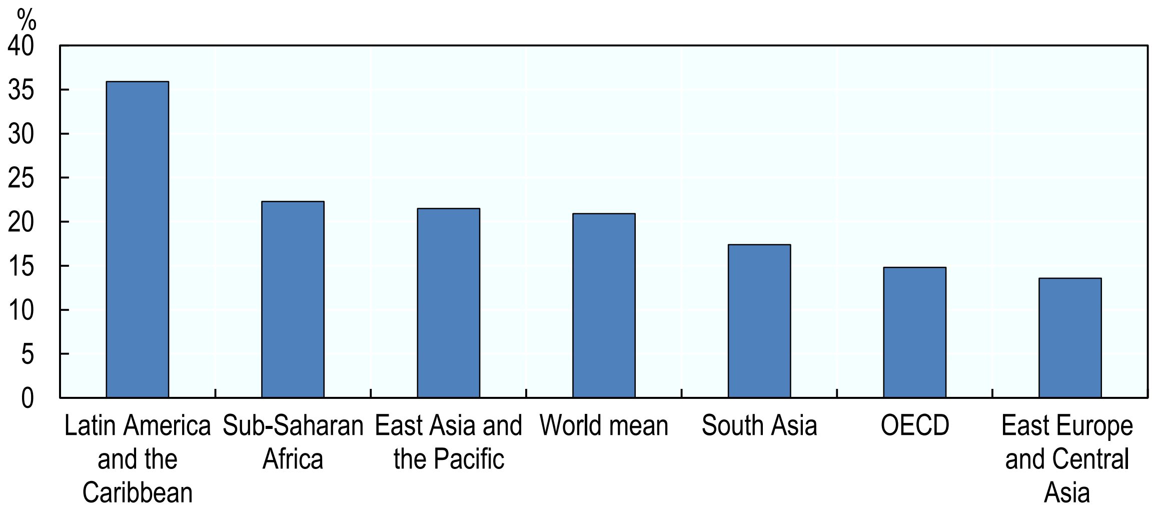
The malfunctioning of the labour market, or more precisely the mismatch between the education system and the productive sector is evident in the formal economy, as illustrated by the responses of formal firms on the barriers to their activity in the World Bank *Entreprises Survey*. Therefore, it adds to the high levels of informality, and it is not confined to it (see for instance Levy, 2008 for Mexico). According to the last round of this survey, referred around 2010, 20.9 percent of firms identify an inadequately educated workforce as a major constraint. This figure ranges between 35.9 per cent in Latin America (also with significant variations among countries), and 13.6 percent in East Europe and Central Asia (**Figure 2**). The variation is evident across industries. Two advanced manufacturing industries (machinery and motor

[1] The choice of the US as the reference for productivity levels is standard in the literature. In our case, it is also justified by the fact that the US shows a relatively low level of skill gap, according to the Manpower *Talent Shortage Survey*.
[2] See De la Fuente (1997) for a review of the literature.

vehicles) are particularly affected by this relative scarcity of adequately trained workers worldwide (**Figure 3**).

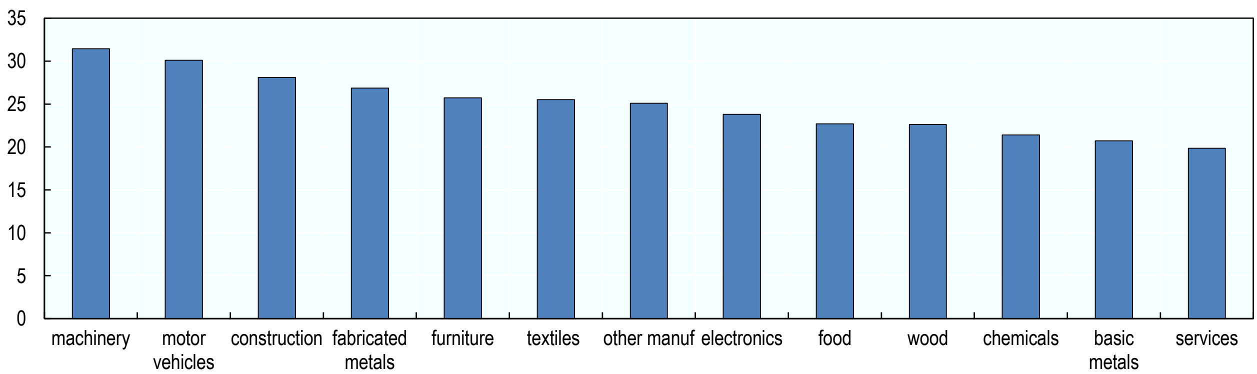
This paper aims to single out the regional and sector patterns in skill gaps, focusing on the main emerging regions. In order to do so, we adopt an eclectic approach to skills, without distinguishing, due to data limitations, between types of skills (we will refer to this in the literature review). Given that our database only covers the formal economy, we will miss a substantial part of the story behind the dismal evolution of productivity levels in emerging economies, where informality is pervasive (Jutting and De Laiglesia, 2009, and Bosch, Melguizo and Pages, 20103 for Latin America). Nevertheless, we believe we are filling a gap in the literature on this matter in emerging economies, with key policy implications in terms of productive development policies.

Figure 2. **Firms finding major or very severe performance obstacles derived from skills by region** (% of surveyed firms, *circa* 2010)



Source: World Bank. Enterprise Surveys Database.

Figure 3. **Firms finding major or very severe performance obstacles derived from skills by sector** (% of surveyed firms, *circa* 2010)



Source: World Bank. Enterprise Surveys Database.

The paper is organized as follows. Section II provides a concise overview of the literature on skills gaps. We concentrate on empirical papers who quantify its size and underlying factors, not covering the papers which address its consequences (e.g. low productivity, high unemployment). The data and methodology is explained in Section III. In particular, we refer to alternative data sources and describe ours. Section IV shows our main results, for the whole set of emerging regions (Africa, East Asia and Pacific, Europe and Central Asia, Latin America and Caribbean, and South Asia), and by these individual regions, which allows to get deeper at the industry level. Section V concludes, presenting some key policy recommendations. The references close the paper.

II. Brief literature review

Studies on the existence of skills gap have been abundant in developed economies (Cappelli, 2014). Their emergence not only responds to the greater availability of firm surveys covering business perceptions of skills shortages; it is also grounded on theoretical reasons that have depicted a more complicated scenario for satisfying a demand for skills that has grown in size and complexity. Here, technological progress has fostered an increase in the relative demand for skilled workers, both because of the complementarity between skilled workers and new technologies, but also because the relative demand for low-skill workers decreases as technological innovations are taking over routine tasks that they previously carried out (Acemoglu and Zilibotti, 2001; Autor, Katz and Krueger, 1998).

Similarly, *globalisation* has been advanced as another driver of the demand for skills. Trade and capital liberalisation have strengthened the role of skills as a source of economic competitiveness (Lall, 2000). This same liberalisation process has facilitated new business structures (e.g., global value chains) that generate additional demand for a wide array of skills, from technical knowledge of the digital world to “soft skills” such as agile thinking, interpersonal communication or the ability to operate in multicultural, geographically dispersed environments (Oxford Economics, 2012).

While the previous factors apply equally to advanced and emerging economies, we find fewer examples of empirical attempts to estimate skill gaps in emerging or developing economies. An example is the review provided in Lyon et al. (2012). The study relies also on the World Bank *Enterprise Surveys* to evaluate the factors associated with the skills deficit in a sample of 25 low and middle-income countries. The study finds that the skills deficit is not “extremely relevant” to the majority of firms. In most cases, skills gaps are rated as a minor obstacle when compared to other factors that can affect firm performance.

The incidence of skill gaps over firm performance is more evident in studies with a specific regional or country focus. An example of the former is Schwalje (2011), which evaluates the incidence of skills gap in Latin America and the Caribbean. The overall conclusion points to the idea that Latin American education systems have not been able to create the skills needed for facilitating development and productive diversification in the region. Bartlett (2013) identifies as well sizeable skill gaps for a subset of European Neighbourhood Policy Countries, particularly for medium levels of skills, which signals the inefficacy of vocational and general high school degrees in these countries. Among country studies, Mehrotra et al. (2013) offers an evaluation of skill gaps in India. In this way, the study exemplifies the extent to which countries that combine a large pool of individuals suitable for employment and a policy effort to increase educational coverage are also exposed to significant mismatches between supply and demand of skills.

A more complex question arises when the analysis gets deeper into the type of skills. Some authors (see Cunningham and Villasenor, 2014) argue that the skill mismatch may stem from differences between perceptions of educators and employers. Based on a sample of 28 studies in the US and UK, and emerging economies worldwide, they show a consistent demand by employers for socio-emotional (ethics, punctuality and honesty) and high-order cognitive skills (notably oral communication), rather than the basic cognitive or technical ones. For instance, Kern et al. (2013) highlight the positive correlation of wage earnings with traits like agreeableness or conscientiousness. In a similar fashion, Heckman et al. (2006)

shows the importance that motivation and self-esteem have over labor market outcomes. Despite this evidence, the education sector largely focuses on cognitive and technical skills.

All things considered, we find little references that offer a comparative analysis of the existence of skill mismatches across economic regions and industries, which in turn motivate the current study.

III. Data and methodology

Data on the demand and supply of skills is scarce in developing economies. In addition, the main existing data sources show various limitations that introduce difficulties for international and historical comparisons.

In this paper we rely on data extracted from the *Enterprise Survey* database. Created by the World Bank, it includes surveys to formal, non-agricultural, private firms. The dataset covers questions related to country characteristics that have a potential impact over firm performance, such as infrastructure, access to finance and informality, among others. These perceptions on the business environment are complemented with other variables focused on firm characteristics and performance (e.g. size, growth). Therefore, it provides comprehensive and international data about different aspects related to the workforce in a firm, including the difficulties to find workers with the adequate skills. While this database allows for international comparisons, within the region as well as with other developed and developing regions, it has some limitations. First, for many countries the only survey available dates back to 2010 and for some of them there is another survey available for 2006 (15 countries were surveyed). Therefore it is not possible to conduct an historical analysis of the evolution of the lack of skills. And secondly, the firms that are surveyed belong to the formal sector, thus leaving aside a large part of the economy and omitting significant elements of the supply and demand for skills in the region. Another relevant source of information is the *Talent Shorgtage Survey* conducted by ManPower, which analyzes, among others, the difficulties faced by employers to find the skills they need and the job posts which they find more difficult to fill. While this report covers a much longer period of 10 years (2006-2015), it only has a limited country coverage (e.g. eight Latin American countries in the 2015 report) and it also leaves the informal sector out of the analysis.

Table 1 shows the main characteristics of our sample[3]. We reach a final sample of 38,428 panel observations (firm-year), from surveys undertaken between 2006 and 2011. Our data covers the following

[3] The countries included, by region and year of survey are: in Africa, Angola (2006 and 2010) Botswana (2006 and 2010), Burkina Faso (2009), Burundi (2006), Cameroon (2009), Democratic Republic of Congo (2006 and 2010), Ethiopia (2010), Gambia (2006), Ghana (2007), Guinea (2006), Guinea Bissau (2006), Ivory Coast (2009), Kenya (2007 and 2010), Madagascar (2009), Mali (2007 and 2010), Mauritania (2006), Mauritius (2009), Mozambique (2007), Namibia (2006), Nigeria (2007), Rwanda (2006), Senegal (2007), South Africa (2007), Swaziland (2006), Tanzania (2006 and 2010), Uganda (2006 and 2010), Zambia (2007) and Zimbabwe (2010); in East Asia Pacific, China (2010), Indonesia (2009), Philippines (2009) and Vietnam (2009); in Europe and Central Asia, Albania (2007), Armenia (2009), Azerbaijan (2009 and 2010), Belarus (2008 and 2010), Bosnia and Herzegovina (2009), Bulgaria (2007 and 2009), Croatia (2007), Czech Republic (2009), Estonia (2009), Macedonia (2009), Georgia (2008 and 2010), Hungary (2009), Kazakhstan (2009 and 2010), Kosovo (2009), Kyrgyz Republic (2009 and 2010), Latvia (2009), Lithuania (2009), Moldova (2009), Mongolia (2009), Montenegro (2009), Poland (2009), Romania (2009), Russia (2009 and 2010), Serbia (2009), Slovak Republic (2009), Slovenia (2009), Tajikistan (2008), Turkey (2008), Ukraine (2008), Uzbekistan (2008). In Latin America and the Caribbean, Argentina (2006 and 2010), Bolivia (2006 and 2010), Brazil (2009), Chile (2006 and 2010), Colombia (2006 and 2010), Costa Rica (2010), Dominican Republic (2010), Ecuador (2010), El Salvador (2006 and 2010), Guatemala (2006 and 2010), Honduras (2006 and 2010), Jamaica (2010), Mexico (2006 and 2010), Nicaragua (2006 and 2010), Panama (2006 and 2010), Paraguay (2006 and 2010), Peru (2006 and 2010), Trinidad and Tobago (2010), Uruguay (2006 and 2010), Venezuela (2010).

emerging regions: Africa, East Asia and Pacific, Europe and Central Asia, Latin America and Caribbean and South Asia[4]. Thus, it has a relatively large proportion of firms located in Latin America (37% of observations), as well as firms operating in food, chemicals or textile industries.

Table 1. **Database. Main descriptive statistics** (number of firms)

N	38,428	
obstacle	Absence (1)	12,297
	Minor (2)	8,147
	Moderate (3)	8,599
	Major (4)	6,454
	very severe (5)	2,931
Regions	Africa	7,892
	East Asia Pacific	4,465
	Europe and Central Asia	7,533
	Latin America and Caribbean	14,206
	South Asia	4,332
size	small (5-19 workers)	14,946
	medium (20-99 workers)	13,876
	large (+100 workers)	9,606
sector	basic metals	700
	chemicals	7,559
	construction	89
	electronics	399
	fabricated metals	3,141
	food	8,542
	furniture	2,087
	Machinery	2,843
	motor vehicles	601
	other manufacturing	1,255
	Services	499
	Textiles	9,255
	Wood	1,458

Table 1 also shows as well the main features of our dependent variable. It is an ordinal categorical variable, based on the answers to the question *"Is an inadequately educated workforce no obstacle, a minor*

In South Asia, Afghanistan (2008), Bangladesh (2007 and 2010), Lao PDR (2010), Nepal (2009 and 2010), Pakistan (2007) and Sri Lanka(2010).

[4] We excluded the available observations for firms located in Middle-East and North Africa, as they added up only around 200 observations, which questions its representativeness.

obstacle, a moderate obstacle, a major obstacle, or a very severe obstacle to the current operations of this establishment?"[5] The survey classifies the responses from 0 to 4, with 0 implying that the skills of the workforce are no obstacle to firm performance, while a value of 4 indicates that it is a very severe obstacle[6]. In all, higher values of the dependent variable are symptomatic of an unsatisfied demand for skills that become a constraint for business operations.

A first descriptive analysis of the behaviours of the dependent variable across regions and industries provide the following results. Firms in Africa and East Asia-Pacific declare facing fewer obstacles to their performance as a result of a poorly trained workforce. About half of the observations for these regions are in the "no obstacle" response category. In contrast, 34% of the observations form Latin America and the Caribbean are either on the "major" or "very severe" categories. After Latin America, Europe and Central Asia is the second region facing greater obstacles on firm performance. In terms of industries, Motor Vehicles and Machinery register the most pressing problems in satisfying their demand for skills. In these industries, about a third of firms surveyed declare major or very severe obstacles.

Our set of control variables are fairly conventional in development economics regressions, starting with the development stage of the country, proxied by per capita GDP in USD adjusted for purchasing power parity (PPP)[7]. In order to control for the heterogeneity in the demand for skills across productive processes, we include a variable on the skill intensity of the firm. We follow a method advanced by previous studies (e.g., Alfaro and Charlton, 2007), which measures skill intensity as the ratio of workers involved in non-production tasks over those in production tasks. In addition, we include two types of *dummy* variables, accounting for the regional and industry of the firm. In constructing these series, we use East Asia and Pacific and the sector of Other Manufacturing as reference groups for each type of categorical variable. Finally, we include the interaction term between our variable on skill intensity and the regional dummies, with the purpose of testing the existence of non-linear effects on the effect of skill intensity across the various regions.

Having a categorical ordered dependent variable favours the adoption of an ordered logit as the estimation method. The most basic estimation approach for this type of dependent variables is the model of proportional odds. This approach assumes that the estimated coefficients are the same across the different levels of the dependent variable. This assumption, also known as of "proportional odds" or "parallel lines" might be difficult to satisfy, particularly in the presence of multiple categories of the dependent variable.

Our sample indeed fails the test[8] for equality of coefficients across different levels of the dependent variable, an outcome that leads us to the two methods we employ in our analysis, a 'collapsed' approach and a generalized ordered logit. First, we 'collapse' the different values of the dependent variable into two categories, indicative of low and high obstacles. For the category of low obstacle we consider values of the dependent variable of 0 and 1 ('no obstacle' and 'minor obstacle'), while the high obstacle category brings together values of 3 and 4 ('major' and 'very severe' obstacle, respectively). With the purpose of differentiating more clearly between these new levels, we eliminate from the sample the middle category, representative of 'moderate obstacle'[9]. In all, we arrive to a new dependent variable with two levels, which we can estimate through a standard logit.

[5] This question is coded as L30b in the World Bank *Enterprise Survey Database*.

[6] The variable also includes entries with values for "do not know" or "does not apply". We eliminate these observations from our sample to maintain the ordinal coherence of the dependent variable.

[7] Data for this variable is extracted from the World Bank *World Development Indicators*.

[8] We perform a score test whose null hypothesis is the equality of coefficients across cutting points of the dependent variable, and included in the SAS Logistic procedure.

[9] The elimination of the middle category in the "collapsed" version of our sample results in a loss of 8,599 observations.

The second estimation method is a generalized ordered logit (Fu, 1998; Maddala 1983). This method relaxes the "proportional odds" assumption of the ordered logit, therefore allowing for the coefficients of explanatory variables to change between levels of the dependent variable without the need for restructuring the data (Liu and Koirala, 2012). In so doing, it allows to exploit all the information included in the original dependent variable, as there is no need for collapsing it; thus, the generalized ordered logit is a more adequate option than other limited dependent variable methods (e.g., multinomial logit) that ignore the categorical order of the dependent variable (Williams, 2010). For a case where the dependent variable hasfive ordinal levels, the generalized logit model can be written as follows

$$P(Y_i > j) = g(X\beta_j) = \frac{\exp(\alpha_j + X_i\beta_j)}{1 + \{\exp(\alpha_j + X_i\beta_j)\}} \qquad j = 1, .., 4$$

$$\begin{gathered} P(Y_i = 1) = 1 - g(X_i\beta_1) \\ P(Y_i = 2) = g(X_i\beta_1) - g(X_i\beta_2) \\ P(Y_i = 3) = g(X_i\beta_2) - g(X_i\beta_3) \\ P(Y_i = 4) = g(X_i\beta_3) - g(X_i\beta_4) \\ P(Y_i = 5) = g(X_i\beta_4) \end{gathered}$$

In the above fashion, the generalized logit becomes a set of four binary logit regressions, with the 'no obstacle' category (level 1) being contrasted bilaterally with each of the other categories (level 2 to 5)[10]. This exercise allows not only to identify whether the previous results of the standard logit are maintained across the entire range of the dependent variable values, but also whether there are sizeable changes in significance and odds ratios between its various levels.

IV. Results

Table 2 shows the results for the abovementioned especifications, i.e., the logit with the collapsed values of the dependent variable and the generalized ordered logit. For each of the explanatory variables, a positive coefficient is associated with greater probability of the firm to encounter performance obstacles as a result of an inadequately trained workforce[11].

Table 2: **Main results. Full sample**

[10] In Table 2, the level of the dependent variable that is analysed is specified in the column "dependent variable level".

[11] We perform these estimations with the statistical software SAS. Throughout these estimations, we include the option "descending", by which a positive coefficient is related to higher values of the dependent variable.

BASELINE MODEL										INTERACTION MODEL		
	Collapsed Logit				Generalized Logit					Collapsed Logit		
Parameter	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	dependent vble. Level	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	Estimate	Chi-Sq	Pr>ChiSq
Intercept	-3.3	238.7	<.001		2	-1.1	27.5	<.001		-3.3	235.62	<.001
					3	-1.8	65.5	<.001				
					4	-3.2	160.3	<.001				
					5	-5.2	184.0	<.001				
lgdp	0.1	8.9	0.003	1.07	2	0.0	4.3	0.04	1.05	0.07	8.91	0.002
					3	0.0	2.7	0.10	1.04			
					4	0.1	11.3	0.001	1.10			
					5	0.1	4.2	0.04	1.08			
skill_intens	0.0	1.9	0.172	1.02	2	0.0	0.3	0.61	1.01	0.06	1.01	0.32
					3	0.0	5.5	0.02	1.03			
					4	0.0	2.0	0.16	1.02			
					5	0.0	0.1	0.80	0.99			
AFR	1.4	303.3	<.001	3.94	2	0.0	0.8	0.39	0.96	1.35	253.47	<.001
					3	0.3	25.1	<.001	1.38			
					4	1.1	163.2	<.001	3.06			
					5	2.4	130.9	<.001	10.95			
ECA	2.3	905.5	<.001	9.5	2	0.0	0.0	0.862	0.99	2.29	804.58	<.001
					3	0.9	217.5	<.001	2.43			
					4	1.9	522.6	<.001	6.64			
					5	3.5	294.0	<.001	32.93			
LAC	2.6	1313.6	<.001	13.39	2	0.4	69.6	<.001	1.48	2.6	1126.79	<.001
					3	1.6	905.6	<.001	5.12			
					4	2.5	1021.9	<.001	12.29			
					5	3.8	359.3	<.001	45.56			
SAR	1.5	308.6	<.001	4.37	2	0.5	64.9	<.001	1.62	1.57	284.23	<.001
					3	1.3	352.0	<.001	3.49			
					4	1.5	267.3	<.001	4.65			
					5	2.4	120.8	<.001	11.13			
FOOD	-0.2	5.7	0.017	0.83	2	0.2	4.6	0.03	1.20	-0.19	6.34	0.01
					3	0.1	1.5	0.21	1.11			
					4	-0.1	1.1	0.30	0.91			
					5	-0.2	2.0	0.16	0.84			
TEXTILE	0.1	1.4	0.231	1.1	2	0.1	2.8	0.09	1.16	0.08	1.11	0.29
					3	0.2	4.5	0.03	1.20			
					4	0.1	1.6	0.21	1.12			
					5	0.2	2.9	0.09	1.23			
WOOD	-0.1	0.3	0.608	0.95	2	0.0	0.0	0.93	1.01	-0.06	0.36	0.55
					3	0.0	0.1	0.73	1.04			
					4	0.1	0.2	0.64	1.06			
					5	-0.3	2.5	0.11	0.77			
CHEMICAL	-0.2	6.7	0.01	0.82	2	0.1	1.0	0.31	1.09	-0.21	7.2	0.01
					3	0.1	1.3	0.26	1.10			
					4	-0.1	2.0	0.16	0.88			
					5	-0.2	3.8	0.05	0.78			
BASIC METALS	0.0	0.0	0.883	0.98	2	0.1	0.8	0.37	1.12	-0.03	0.05	0.82
					3	0.1	0.3	0.57	1.08			
					4	0.1	0.2	0.68	1.06			
					5	-0.1	0.4	0.53	0.88			

Table 2 (cont.)

	BASELINE MODEL									INTERACTION MODEL		
	Collapsed Logit				Generalized Logit					Collapsed Logit		
Parameter	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	dependent vble. Level	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	Estimate	Chi-Sq	Pr>ChiSq
FABRICATED METALS	0.1	0.5	0.465	1.06	2	0.2	3.9	0.05	1.21	0.06	0.43	0.51
					3	0.3	7.7	0.01	1.30			
					4	0.2	2.5	0.12	1.17			
					5	0.1	0.5	0.48	1.10			
MACHINERY	0.3	10.4	0.001	1.32	2	0.4	12.9	<.001	1.42	0.27	9.63	0.002
					3	0.3	11.1	0.001	1.39			
					4	0.4	12.9	<.001	1.45			
					5	0.5	16.2	<.001	1.71			
ELECTRONICS	0.0	0.0	0.969	0.99	2	0.5	8.4	0.004	1.57	-0.01	0.0029	0.96
					3	0.2	1.6	0.20	1.24			
					4	0.1	0.5	0.46	1.15			
					5	0.2	1.0	0.31	1.27			
AUTO	0.5	14.8	<.001	1.63	2	0.3	5.8	0.02	1.41	0.48	14.21	0.002
					3	0.4	6.7	0.01	1.47			
					4	0.5	11.7	0.001	1.71			
					5	1.0	26.2	<.001	2.63			
FURNITURE	0.2	3.0	0.085	1.17	2	0.2	3.0	0.08	1.19	0.15	2.82	0.09
					3	0.1	0.8	0.36	1.10			
					4	0.1	1.0	0.32	1.12			
					5	0.4	9.2	0.002	1.53			
CONSTRUCTION	0.2	0.5	0.503	1.2	2	0.7	5.1	0.02	2.04	0.17	0.4	0.53
					3	0.7	4.3	0.04	1.96			
					4	0.6	2.9	0.09	1.79			
					5	0.3	0.4	0.51	1.35			
SERVICES	-0.3	4.1	0.044	0.75	2	0.2	2.6	0.10	1.27	-0.26	3.45	0.06
					3	0.3	3.1	0.08	1.29			
					4	-0.2	1.0	0.32	0.84			
					5	-0.2	0.7	0.41	0.83			
skill_intens*AFR										0.06	0.71	0.4
skill_intens*ECA										-0.09	1.83	0.18
skill_intens*LAC										-0.02	0.11	0.74
skill_intens*SAR										-0.2	5.07	0.02
Observations	29771				38330					29771		
Regional dummies	Yes				Yes					Yes		
Sector dummies	Yes				Yes					Yes		

The standard logit on the collapsed dependent variable yields the following results. First, the positive and significant coefficient for *lgdp* suggests that the difficulties for a firm to find the talent it needs are greater in richer countries. Given that our sample only includes developing countries, this result places middle income countries with more difficulties for satisfying their demand for skills. This is compatible with the 'middle-income trap' hypothesis. Second, all the regional dummies turn out positive and significant in this specification. Therefore, firms operating in emerging regions other than East Asia-Pacific (our reference group in the creation of regional dummies) are more likely to encounter performance obstacles. Specifically, Latin American firms show the greatest problems, followed by Europe and Central Asia. The results in terms of odds ratios suggest that these regional differences are far from negligible. For instance, the probability that a Latin American firm is placed on the high obstacle category is 13 times greater to that of a firm located in East Asia Pacific. For a firm operating in Europe and Central Asia, this same odds ratio vis-a-vis East Asia-Pacific is 9 times, while for Africa and South Asia they are 3.9 and 4.3, respectively.

With regards to the results for the industry dummies, Machinery and Motor Vehicles stand out for having a positive and significant coefficient. In terms of odds ratios, the probability that a firm in the Machinery sector finds itself in the high obstacle category is 1.3 times that of a firm in Other Manufacturing, the reference group for the industry dummies. This same odds ratio reaches 1.6 in the case of Motor Vehicles, the highest among the industry variables. In contrast, Food, Chemicals and Services enter the specification with negative and significant coefficients, i.e., they are less likely to face performance problems derived from lack of adequate skills. In all, these results identify a greater skill gap in advanced manufacturing industries.

The results on the generalized ordered logit estimation tend to ratify our previous results. With regards to the regional dummies, the variable for Latin America is positive and significant for all levels of the dependent variable, with an odds ratio that increases significantly as we move from lower to higher levels of the dependent variable. In this way, the probability for a Latin American firm to face very high performance obstacles reaches 45 times that of a Latin American firm facing no obstacles. Lower, but still sizeable odds ratios are found for other categories[12]. A relatively similar pecking order of categories is found for the other regional categories, albeit at lower odds ratios.

Moving to the results on the sector variables, once again Machinery and Motor Vehicles stand out as the sectors with greater performance trouble derived from the absence of adequate skills on their workforce. Both cases show positive and significant coefficients and odds ratios that ascend with the level of the dependent variable. For instance, a firm in the Motor Vehicles category is 2.6 times more likely to be in the 'very severe obstacle' category (level 5) than in the 'no obstacle' (level 1). For Machinery, this odds ratio is 1.7. The rest of the industries fall short of a clear pattern on its relation with the dependent variable, with coefficients that are significant only at one level of obstacles: furniture, for instance, maintains a positive sign and statistical significance only for the 'very severe obstacle'. Other sectors, like Fabricated Metals or Construction, register coefficients that are positive and significant only for comparisons involving low levels of the dependent variable. Finally, those sectors that registered negative and significant coefficients in the logit estimation with collapsed levels of the dependent variable (Chemical, Services) lose their statistical significance in the generalized ordered logit.

Another specification included in table 2 considers a set of interaction terms between each of the regional dummies and the variable on skill-intensity of the firm. Given that in our previous estimations, the variable on skill intensity does not turn out significant, the inclusion of this new variable aims to disentangle potential effects of skill intensity in specific regions. This specification confirms our previous results on the regional and skill intensity variables. With regards to the interaction terms, only the one involving South Asia is significant, with negative sign. In all, the results on interaction terms yield no indication that the likelihood of facing performance obstacles derived from poorly trained workforce increases with the skill requirements of the firm.

Estimation over regional subsamples

A complementary inquiry we aim to pursue is disentangling possible interaction effects between our sector and regional variables. In principle, this goal could be carried through a model with interaction terms between both types of variables. This approach, however, would yield a total of 64 binary variables (4 for regions, 12 for industries and 48 interaction terms). The large number of dummies renders the model unfit for estimation through the generalized ordered logit, as it leads to a problem of quasi separation of data[13]. To circumvent it, we break our sample into regional subsamples, which in turn allows us to disregard the use of interaction terms. Applying this criterion over regional subsamples helps to discriminate further the propensity of performance obstacles across sectors and regions.

The results of this final estimation are included in **Table 3**, from which we can highlight the following. First, the effects previously identified with regards to advanced manufacturing are largely endorsed. For

[12] Odds ratios are 5.1 and 12.3 times for levels 3 and 4 of the dependent variable, respectively.

[13] Separation of data occurs when the outcome variable separates a predictor variable or a combination of predictor variables completely. In this case, the Maximum Likelihood estimator does not exist. See on this matter Albert and Anderson (1984).

Machinery, these effects are present in Europe and Central Asia, Latin America and South Asia; all of them with positive and significant coefficients, as well as the largest odds ratios. In the case of Motor Vehicles, significant effects are found for Europe and Central Asia and Latin America. In addition, positive and significant estimates for at least two levels of the dependent variable are only found for Fabricated Metals and Electronics in Europe and Central Asia, and Textiles in South Asia. For Textiles in particular, the positive and significant result in South Asia contrasts with negative and significant coefficients in Africa.

Table 3: **Main results. Regional subsamples**

REGIONAL SAMPLES																									
Generalized Logit		AFR						ECA						LAC						SAR					
Parameter	dependent vble. Level	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	95% confidence limits		Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	95% confidence limits		Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	95% confidence limits		Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	95% confidence limits	
Intercept	2	-0.4	2.41	0.12				-0.5	0.70	0.40				-2.7	23.63	<.0001				5.4	47.17	<.0001			
	3	-1.6	27.75	<.0001				-0.5	0.69	0.41				-2.3	20.99	<.0001				8.1	89.68	<.0001			
	4	-1.8	25.60	<.0001				-0.8	1.90	0.17				-3.4	40.66	<.0001				4.0	14.46	0.00			
	5	-1.9	16.26	<.0001				-0.8	1.25	0.26				-4.2	37.39	<.0001				-0.2	0.02	0.88			
lgdp	2	0.0	0.48	0.49	0.98	0.92	1.04	-0.1	1.25	0.26	0.93	0.83	1.05	0.3	22.19	<.0001	1.32	1.18	1.49	-0.8	54.39	<.0001	0.46	0.37	0.56
	3	0.1	5.24	0.02	1.09	1.01	1.17	0.0	0.26	0.61	0.97	0.86	1.09	0.3	28.74	<.0001	1.33	1.20	1.47	-1.2	108.76	<.0001	0.30	0.24	0.38
	4	0.1	4.01	0.05	1.09	1.00	1.18	0.0	0.04	0.84	1.01	0.90	1.14	0.4	47.31	<.0001	1.47	1.32	1.64	-0.7	23.34	<.0001	0.51	0.38	0.67
	5	0.0	0.11	0.74	1.02	0.91	1.15	-0.1	0.99	0.32	0.93	0.81	1.07	0.4	29.87	<.0001	1.49	1.29	1.72	-0.3	1.68	0.19	0.76	0.50	1.15
skill_intens	2	0.0	0.20	0.66	1.02	0.93	1.11	0.0	0.03	0.86	0.99	0.93	1.06	0.1	3.68	0.06	1.06	1.00	1.12	-0.1	5.23	0.02	0.90	0.81	0.98
	3	0.1	6.58	0.01	1.10	1.02	1.19	-0.1	3.22	0.07	0.92	0.84	1.01	0.1	15.97	<.0001	1.11	1.05	1.16	-0.2	8.19	0.00	0.86	0.78	0.95
	4	0.1	3.54	0.06	1.08	1.00	1.18	0.0	0.30	0.59	0.98	0.92	1.05	0.1	8.17	0.00	1.08	1.02	1.14	-0.1	1.41	0.24	0.93	0.82	1.05
	5	0.1	4.96	0.03	1.10	1.01	1.19	0.0	0.53	0.47	0.97	0.88	1.06	0.0	0.92	0.34	1.04	0.97	1.11	-0.4	2.87	0.09	0.70	0.46	1.06
FOOD	2	-0.1	0.22	0.64	0.93	0.69	1.26	0.7	14.42	0.00	2.02	1.41	2.91	0.0	0.06	0.81	1.05	0.72	1.52	0.3	1.47	0.23	1.30	0.85	2.00
	3	-0.1	0.71	0.40	0.86	0.61	1.22	0.4	5.11	0.02	1.46	1.05	2.03	0.0	0.07	0.80	1.04	0.75	1.45	0.4	3.44	0.06	1.56	0.98	2.50
	4	-0.4	5.18	0.02	0.65	0.45	0.94	0.2	0.93	0.34	1.17	0.85	1.62	0.0	0.08	0.78	0.95	0.68	1.34	-0.3	1.32	0.25	0.72	0.41	1.26
	5	-0.6	5.99	0.01	0.55	0.34	0.89	0.3	1.91	0.17	1.34	0.88	2.04	-0.3	1.58	0.21	0.76	0.50	1.16	-0.2	0.16	0.69	0.81	0.29	2.30
TEXTILE	2	-0.2	2.40	0.12	0.79	0.58	1.07	0.8	16.67	<.0001	2.20	1.51	3.22	0.0	0.03	0.85	1.04	0.72	1.50	0.4	4.11	0.04	1.53	1.01	2.32
	3	-0.3	2.24	0.13	0.76	0.54	1.09	0.6	12.48	0.00	1.86	1.32	2.62	0.0	0.00	0.99	1.00	0.72	1.39	0.9	15.14	0.00	2.46	1.56	3.86
	4	-0.5	5.79	0.02	0.63	0.44	0.92	0.6	12.11	0.00	1.80	1.29	2.52	0.0	0.00	0.98	1.00	0.71	1.40	0.6	5.41	0.02	1.84	1.10	3.08
	5	-0.7	8.41	0.00	0.48	0.29	0.79	0.9	18.07	<.0001	2.50	1.64	3.82	0.0	0.03	0.87	1.04	0.68	1.58	0.8	2.66	0.10	2.25	0.85	5.93
WOOD	2	0.0	0.05	0.83	1.04	0.72	1.52	0.1	0.31	0.58	1.14	0.72	1.82	0.0	0.01	0.91	1.03	0.64	1.66	-0.1	0.04	0.84	0.94	0.55	1.64
	3	0.2	0.77	0.38	1.21	0.79	1.85	0.1	0.16	0.69	1.09	0.72	1.66	-0.3	1.49	0.22	0.76	0.49	1.18	0.5	3.06	0.08	1.67	0.94	2.96
	4	0.5	5.79	0.02	1.68	1.10	2.58	-0.3	1.84	0.18	0.74	0.48	1.14	-0.1	0.12	0.72	0.92	0.59	1.45	-0.5	1.43	0.23	0.63	0.30	1.34
	5	-0.4	1.44	0.23	0.67	0.35	1.28	0.1	0.05	0.83	1.06	0.62	1.80	-0.6	3.38	0.07	0.56	0.31	1.04	-0.3	0.15	0.70	0.77	0.21	2.85
CHEMICAL	2	-0.2	0.88	0.35	0.86	0.62	1.19	0.5	8.19	0.00	1.72	1.19	2.50	0.0	0.01	0.91	0.98	0.68	1.42	0.2	1.01	0.31	1.25	0.81	1.93
	3	0.1	0.07	0.78	1.05	0.73	1.52	0.3	2.12	0.15	1.29	0.92	1.80	-0.1	0.22	0.64	0.92	0.67	1.28	0.7	8.87	0.00	2.04	1.28	3.26
	4	-0.3	2.77	0.10	0.71	0.48	1.06	0.0	0.00	0.98	1.00	0.71	1.39	-0.2	0.79	0.37	0.86	0.61	1.21	-0.1	0.20	0.66	0.88	0.51	1.54
	5	-0.4	2.30	0.13	0.67	0.40	1.13	0.2	1.08	0.30	1.26	0.82	1.93	-0.5	4.60	0.03	0.63	0.41	0.96	-0.1	0.03	0.86	0.91	0.32	2.60
BASIC METALS	2	0.2	0.60	0.44	1.23	0.73	2.08	0.7	3.83	0.05	2.05	1.00	4.19	-0.1	0.18	0.67	0.88	0.48	1.60	-0.1	0.11	0.74	0.91	0.53	1.57
	3	0.3	1.04	0.31	1.36	0.76	2.44	0.5	2.55	0.11	1.73	0.88	3.39	0.0	0.01	0.91	1.03	0.61	1.73	0.1	0.07	0.79	1.09	0.60	1.96
	4	0.3	0.88	0.35	1.34	0.73	2.48	0.4	1.34	0.25	1.49	0.76	2.93	0.1	0.11	0.73	1.10	0.64	1.87	-0.4	1.26	0.26	0.66	0.32	1.37
	5	0.1	0.04	0.85	1.09	0.47	2.50	0.5	1.68	0.20	1.73	0.75	3.97	-0.4	1.25	0.26	0.66	0.32	1.37	-0.5	0.54	0.46	0.60	0.15	2.36

REGIONAL SAMPLES														
Generalized Logit		AFR						ECA						
Parameter	dependent vble. Level	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	95% confidence		Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	95% confidence	
FABRICATED METALS	2	0.0	0.02	0.89	0.98	0.70	1.37	0.7	10.92	0.00	1.96	1.31	2.91
	3	0.1	0.48	0.49	1.15	0.78	1.68	0.5	6.13	0.01	1.58	1.10	2.27
	4	-0.3	1.82	0.18	0.75	0.49	1.14	0.3	2.44	0.12	1.33	0.93	1.90
	5	-0.2	0.48	0.49	0.83	0.48	1.42	0.4	3.28	0.07	1.53	0.97	2.41
MACHINERY	2	-0.1	0.07	0.79	0.95	0.62	1.45	0.7	11.95	0.00	2.02	1.36	3.00
	3	-0.3	0.96	0.33	0.78	0.47	1.29	0.7	16.84	<.0001	2.11	1.48	3.00
	4	-0.1	0.23	0.63	0.88	0.52	1.48	0.6	13.33	0.00	1.91	1.35	2.70
	5	-0.5	2.02	0.16	0.58	0.27	1.23	1.0	19.59	<.0001	2.68	1.73	4.14
ELECTRONICS	2	0.0	0.00	0.97	1.03	0.29	3.62	0.6	3.98	0.05	1.80	1.01	3.19
	3	0.8	2.09	0.15	2.32	0.74	7.23	0.3	1.02	0.31	1.33	0.77	2.30
	4	-0.8	0.59	0.44	0.44	0.05	3.64	0.4	2.72	0.10	1.54	0.92	2.58
	5	-0.2	0.03	0.86	0.83	0.10	7.06	0.6	3.47	0.06	1.84	0.97	3.48
AUTO	2	0.2	0.47	0.50	1.25	0.66	2.40	1.3	13.52	0.00	3.56	1.81	7.00
	3	0.2	0.20	0.66	1.19	0.56	2.52	0.5	1.49	0.22	1.57	0.76	3.26
	4	0.0	0.00	0.98	1.01	0.44	2.31	0.7	4.65	0.03	2.08	1.07	4.04
	5	-0.5	0.50	0.48	0.63	0.18	2.25	0.6	1.78	0.18	1.81	0.76	4.31
FURNITURE	2	0.0	0.04	0.84	1.03	0.75	1.43	0.2	0.34	0.56	1.17	0.69	1.97
	3	-0.1	0.17	0.68	0.92	0.64	1.34	0.1	0.20	0.66	1.11	0.70	1.78
	4	-0.3	1.55	0.21	0.78	0.52	1.16	0.5	5.59	0.02	1.67	1.09	2.55
	5	-0.1	0.28	0.59	0.87	0.52	1.45	0.6	5.25	0.02	1.87	1.10	3.20
CONSTRUCTION	2	-0.1	0.02	0.90	0.90	0.16	5.01	1.5	12.51	0.00	4.55	1.97	10.52
	3	1.4	4.23	0.04	3.94	1.07	14.55	0.2	0.12	0.73	1.21	0.43	3.41
	4	1.5	5.01	0.03	4.46	1.20	16.55	0.6	1.63	0.20	1.80	0.73	4.46
	5	0.4	0.10	0.76	1.42	0.15	13.29	0.4	0.49	0.48	1.54	0.46	5.15
SERVICES	2	0.3	0.41	0.52	1.29	0.60	2.77	0.6	5.30	0.02	1.85	1.10	3.13
	3	0.4	0.81	0.37	1.47	0.64	3.40	0.4	3.19	0.07	1.56	0.96	2.53
	4	-0.4	0.49	0.48	0.67	0.21	2.07	0.0	0.01	0.93	1.02	0.61	1.71
	5	0.5	0.67	0.41	1.57	0.53	4.64	0.1	0.03	0.87	1.06	0.54	2.06
Observations		7892						7435					

REGIONAL SAMPLES													
Generalized Logit		LAC						SAR					
Parameter	dependent vble. Level	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	95% confidence limits		Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	95% confidence limits	
FABRICATED METALS	2	0.0	0.05	0.83	1.05	0.70	1.57	-0.2	0.33	0.56	0.83	0.45	1.55
	3	0.2	0.74	0.39	1.17	0.82	1.67	0.2	0.53	0.47	1.27	0.67	2.40
	4	0.3	2.54	0.11	1.35	0.93	1.95	-0.5	1.19	0.28	0.63	0.27	1.45
	5	0.0	0.01	0.92	1.02	0.65	1.62	0.1	0.01	0.94	1.05	0.27	4.18
MACHINERY	2	0.3	1.45	0.23	1.29	0.85	1.95	0.6	3.95	0.05	1.76	1.01	3.08
	3	0.0	0.06	0.81	1.05	0.72	1.52	1.2	17.36	<.0001	3.38	1.91	5.99
	4	0.4	3.56	0.06	1.44	0.99	2.11	0.6	2.91	0.09	1.81	0.92	3.57
	5	0.5	4.70	0.03	1.66	1.05	2.62	-0.3	0.12	0.73	0.77	0.17	3.42
ELECTRONICS	2	0.9	4.75	0.03	2.37	1.09	5.14	0.3	0.20	0.66	1.39	0.33	5.91
	3	0.4	1.29	0.26	1.54	0.73	3.27	0.7	0.79	0.38	1.94	0.45	8.42
	4	0.1	0.03	0.86	1.08	0.48	2.44	0.3	0.13	0.72	1.38	0.24	8.12
	5	0.0	0.00	0.96	0.98	0.35	2.70	1.1	0.88	0.35	3.13	0.29	33.89
AUTO	2	0.1	0.06	0.81	1.09	0.53	2.26	-0.3	0.61	0.44	0.72	0.32	1.63
	3	0.5	2.39	0.12	1.62	0.88	3.00	0.7	3.36	0.07	2.00	0.95	4.18
	4	1.1	13.52	0.00	3.06	1.69	5.55	0.0	0.01	0.94	1.04	0.41	2.66
	5	1.6	23.70	<.0001	5.03	2.63	9.65	0.4	0.21	0.65	1.42	0.31	6.52
FURNITURE	2	0.2	0.77	0.38	1.23	0.78	1.94	0.0	0.01	0.93	0.98	0.58	1.66
	3	0.2	1.18	0.28	1.25	0.84	1.88	0.0	0.00	0.95	1.02	0.57	1.84
	4	0.2	1.06	0.30	1.25	0.82	1.91	-0.1	0.09	0.76	0.90	0.46	1.77
	5	0.7	7.26	0.01	1.97	1.20	3.22	-0.1	0.04	0.84	0.88	0.25	3.07
CONSTRUCTION	2	9.4	0.02	0.89	>999.999	<0.001	>999.999	-0.4	0.08	0.77	0.70	0.06	8.05
	3	10.1	0.02	0.88	>999.999	<0.001	>999.999	0.0	0.00	0.98	0.97	0.08	11.55
	4	9.1	0.02	0.89	>999.999	<0.001	>999.999	-10.6	0.00	0.96	<0.001	<0.001	>999.999
	5	9.1	0.02	0.89	>999.999	<0.001	>999.999	-10.3	0.00	0.98	<0.001	<0.001	>999.999
SERVICES	2	0.4	0.98	0.32	1.53	0.66	3.53	0.3	1.17	0.28	1.36	0.78	2.38
	3	0.3	0.63	0.43	1.37	0.63	2.94	0.6	3.61	0.06	1.78	0.98	3.21
	4	0.3	0.70	0.40	1.40	0.63	3.11	-0.7	2.42	0.12	0.50	0.21	1.20
	5	0.4	0.52	0.47	1.42	0.55	3.69	-1.2	1.09	0.30	0.31	0.04	2.80
Observations		14206						4332					

Looking at regional patterns, our results show that Europe and Central Asia comprise the largest number of positive and significant industry coefficients. This situation could be symptomatic of labour markets with deficit in a large set of skills, both technical and soft; or specifically in skills that are a general requisite for many industries, from those more associated to skills and technology to more traditional ones (e.g., textiles, furniture, services). In addition, Latin America appears also as a region with an important skills gap, but one that is clearly concentrated in advanced manufacturing sectors like Machinery or Motor Vehicles. A situation slightly different to the one we find in South Asia, where an industry characteristic of standardized technology (Textiles) and Machinery are found as the industries more prone to face obstacles from poorly trained workers. Finally, Africa stands out for being the region where some industries reach negative and significant coefficients. This is particularly the case of Food and Textiles, where the likelihood of confronting major or very severe performance obstacles is about half the odds of facing no obstacles. For this region, only construction firms seem negatively affected by inadequately trained workers.

V. Conclusions and policy implications (in progress)

Most emerging economies are characterized by lagging levels of productivity. This paper shows empirically that, at least part of this story is related to human capital, broadly understood. Formal firms in emerging regions display significant levels of skill gaps, namely a mismatch between the demand of the productive sector and the supply of the education system.

This is specially the case Latin America, which emerges as the emerging region where firms have greatest problems derived from the lack of adequate skills, well ahead from emerging Asia and Europe, but also from Sub-Saharan Africa. The analysis in this publication shows that Latin American firms are 3 times more likely than South Asian firms and 13 times more likely than Pacific-Asian firms to face serious operational problems due to a shortage of human capital.

In terms of sectors, two advanced manufacturing industries (machinery and motor vehicles) are particularly affected by this relative scarcity of adequately trained workers. The challenge for those sectors is particularly steep, because they tend to be more sophisticated sectors, with greater connectivity and complexity. They could therefore support the region’s structural change and transformation towards a knowledge-intensive and technology-intensive development model.

This assessment is not without limitations. We do not have information on the type of skills demanded, and not provided by education institutions. There is a growing consensus on the relevance of socio-emotional and high-order cognitive skills rather than the basic cognitive or technical ones. Sadly, we cannot test this hypothesis on an international level. And, probably more relevant, the available databases only cover the formal sector, omitting a key cause of not only of inequality and low inclusion, but also tamed productivity and, high informality levels among workers and among firms.

However, the robust empirical results we show should be understood for an even more urgent call precisely for this reason. Labour mismatch is also evident in the formal economy in emerging regions. Therefore, education policies should be significantly revised, including vocational education and training. A more active participation and co-ordination with the private sector is very important, since it can offer guidance on current and future business demands and provide training directly in the workplace. Rigorous evaluation mechanisms should be implemented, to identify what works better for the firm, but also for the worker (wage, stability). Finally, more data, as usual, is needed, especially on the demand for skills, covering informal businesses.

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