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Mind the skills gap! Regional and industry patterns in emerging economies

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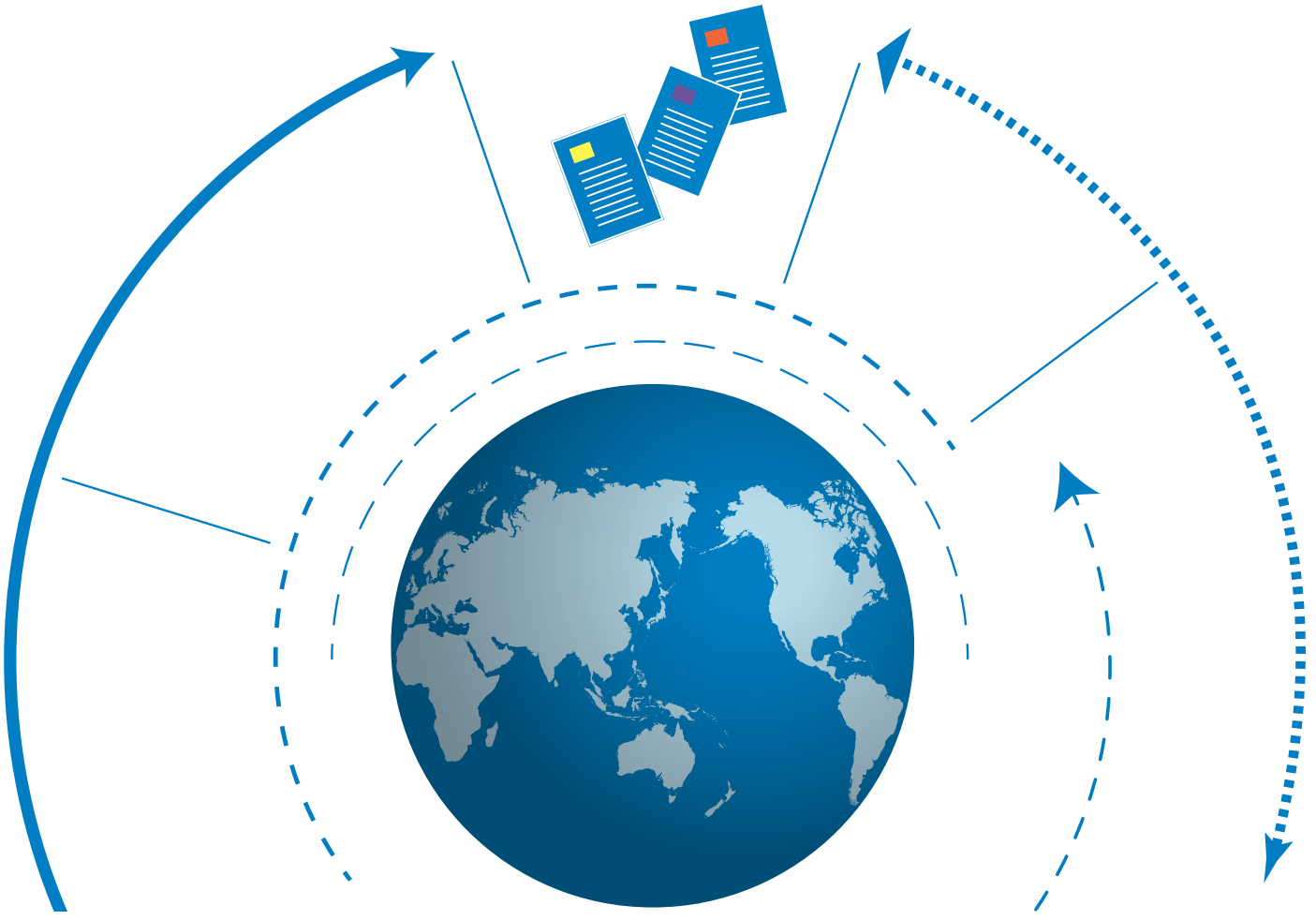

OECD DEVELOPMENT CENTRE

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PREFACE

The middle-income trap, whereby GDP growth slows down once a country approaches an intermediate level of development, is particularly persistent in Latin America. Although average per capita income in the region was relatively high in the mid-20th century, most Latin American countries have been unable to reduce significantly the income gap with advanced economies and reach high income status. The few regional exceptions are Chile, Uruguay and a few Caribbean countries. In all, trends that contrast with certain European and Asian countries, much more effective in joining the high-income group during the last half of the 20th century.

Education, skills and innovation are key areas to enable more Latin American countries to escape the middle-income trap and strengthen the region's emerging middle class. Improvements to the stock and quality of education and skills, together with a stable macroeconomic context and an innovation-friendly environment, determine countries' capacity to direct their growth models towards higher value-added activities. Investment in human capital drives long-term economic growth and is an essential part of any inclusive-growth strategy. It is therefore necessary to improve equality of opportunity and social mobility by limiting the effect of people's socio-economic background and informal employment on their access to high-quality education at all levels.

The *Latin American Economic Outlook 2015: Education, Skills and Innovation for Development*, elaborated in association with ECLAC and CAF, showed that Latin America is the region with the widest gap between skills supply and demand, which adds to a high labour informality. This paper makes a contribution to this debate providing in-depth analysis of the skills gap by emerging regions.. The analysis goes one step beyond and identifies the relevance of the skill gap by sectors, while controlling for firm and country characteristics. The results highlight the critical level of the skill gap in particular regions and sectors, particularly in advanced manufacturing, which in turn signal the important barriers to productive diversification in the emerging world.

In addition to contributing to the Development Centre's work on Latin America and its flagship report, the paper is useful for the OECD *Skills Strategy* and for country analysis, such as the OECD *Multi-Dimensional Country Reviews* and the OECD *Better Policies* series.

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January 2016

RÉSUMÉ

La plupart des économies émergentes se caractérisent par des niveaux de productivité faibles. Même si la croissance économique a été robuste dans la plupart des pays émergents au cours des deux dernières décennies, elle a généralement été fondée sur l'accumulation des facteurs, avec une contribution marginale de la productivité. Alors que la littérature économique montre le capital humain et les compétences comme des composantes clés de la productivité, les difficultés des entreprises à trouver les compétences adéquates mettent un frein au développement. Ce document cherche à identifier où cet écart de compétences est le plus dominant, notamment parmi les régions émergentes et les secteurs. Pour ce faire, il élabore une analyse empirique à partir de deux spécifications basées sur des variables dépendantes limitées. Les résultats montrent l'Amérique latine comme la région émergente où les entreprises ont le plus de difficultés à trouver les compétences adéquates, bien avant l'Asie émergente et l'Europe, mais aussi l'Afrique sub-saharienne. Au niveau des secteurs, deux types d'industries manufacturières de pointe (machines et véhicules à moteur) sont particulièrement touchés par cette problématique. Les recommandations politiques reposent sur la nécessité de résoudre l'inadéquation entre offre de compétences des systèmes éducatifs et besoins de l'économie.

Classification JEL: J24, O4.

Mots-clés: compétences, productivité, entreprises.

ABSTRACT

Most emerging economies are characterised 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 the greatest problems derived from the lack of adequate skills, well ahead of emerging Asia and Europe, but also of 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.

JEL Classification: J24, O4.

Keywords: skills gap, productivity, firm survey data.

I. INTRODUCTION

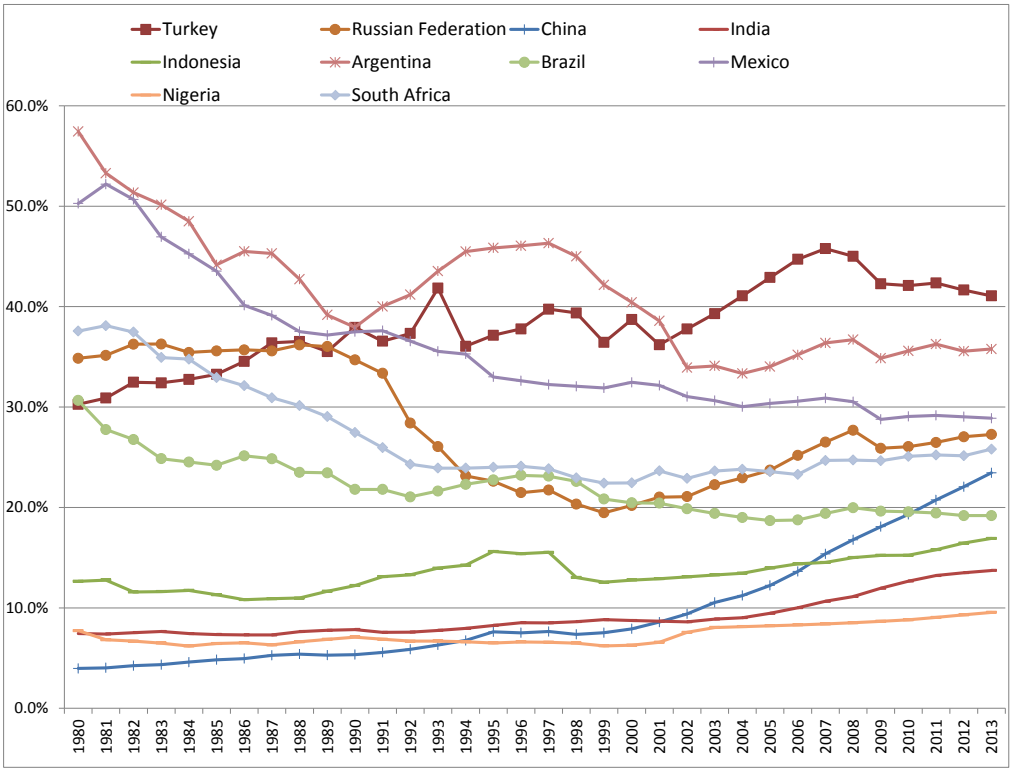
Economic competitiveness and productivity growth depend critically on human capital (Barro, 1991; Mankiw, Romer and Weil, 1992; Benhabib and Spiegel, 1994). Among its various components, the issue of skills is gaining increasing relevance, at least among policy makers (e.g. World Economic Forum, 2015).

Raising productivity is at the top of the agenda among developed economies, but this should also be the case 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 advanced economies,[1] with some notable exemptions in East Asia after the crisis (China, India and Indonesia; OECD, 2014). This divergence is especially evident in the big Latin American economies (Daude and Fernandez-Arias, 2010), and is at odds with conventional theories of technological catch-up (Solow, 1956; Grossman and Helpman, 1991; Romer, 1986, 1990). This evolution helps to explain a popular empirical theory among development economists, the "middle-income trap", where economies register a long-lasting slowdown at mid-levels of output per capita. Most frequently, the incidence of the middle-income trap is traced to the difficulty of adjusting the economy to the sources of growth that become more important after reaching middle-income levels (Eichengreen, Park and Shin, 2011; Aiyar et al., 2013; Felipe, Abdon and Kumar, 2012).

The malfunctioning of the labour market, specifically the mismatch between the education system and the productive sector is evident in the formal economy in most regions and sectors, and adds to the high levels of informality. According to the last round of the World Bank *Entreprise Surveys*, around 2010, 20.9% of firms identify an inadequately educated workforce as a major constraint. This figure ranges between 35.9% in Latin America (also with significant variations among countries), and 13.6% in East Europe and Central Asia (Figure 2). The variation is evident across industries. Two advanced manufacturing industries (machinery and motor vehicles) are particularly affected by this relative scarcity of adequately trained workers worldwide (Figure 3).

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.*

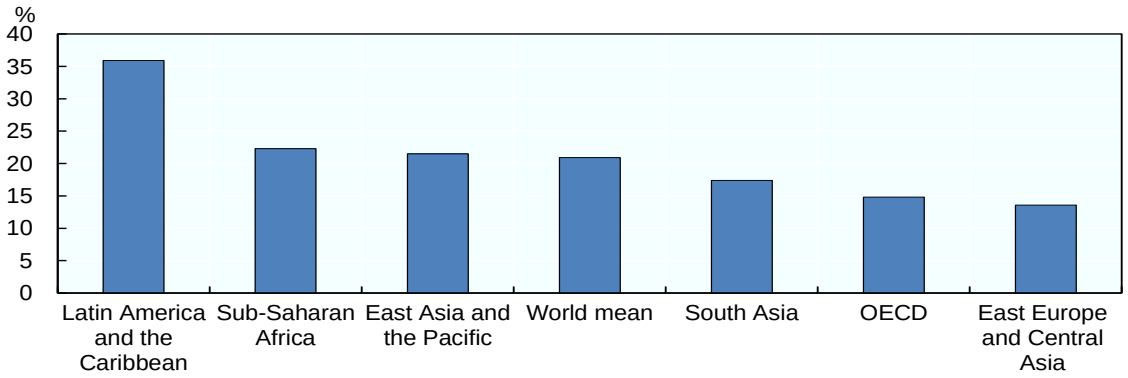
Figure 1. **Labour productivity in selected emerging economies (as percentage of US level; PPP adjusted)**



Note: GDP per person employed (1990 International dollars).
Source: Own elaboration, based on The Conference Board *Total Economy Database.*

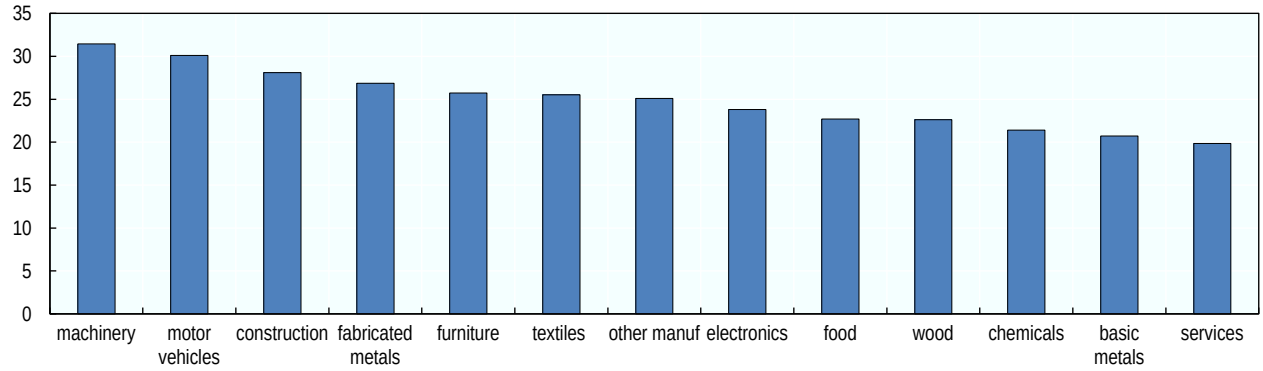
This paper aims to single out the regional and sector patterns in skill gaps, focusing on all emerging regions. In order to do so, we adopt an eclectic approach to skills, without distinguishing between types of skills due to data limitations (we will refer to this in the literature review). Given that 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 (see Jutting and De Laiglesia, 2009 for emerging economies, and Bosch, Melguizo and Pages, 2013 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 (2015a), *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 (2015a), *Enterprise Surveys Database*.

The paper is organised 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 studies which address its consequences (e.g. low productivity, high unemployment). The data and methodology are 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 for individual regions, which allows a deeper analysis 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 gaps have been abundant in developed economies (see Cappelli (2014) for the US and Adalet McGowan and Andrews (2015) for OECD countries using the *Survey of Adult Skills* PIIAC). 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.

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-skilled 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, there are fewer examples of empirical attempts to estimate skill gaps in emerging or developing economies. Among them, Lyon et al. (2012) use 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 firms' performance.

The incidence of skills gaps over firms' 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 gaps 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. Similarly, Alaimo et al. (2015) address the issue of skills gaps and policy responses in the same region, in a broader framework to create better jobs. Bartlett (2013) also identifies sizeable skills gap for a subset of European and geographically and economically close countries, particularly for medium levels

of skills, which signals the inefficacy of vocational and formal education degrees in these countries. Among country studies, Mehrotra et al. (2013) offers an evaluation of skills gaps in India, an example of 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, although key for policy action, arises when the analysis gets deeper into the type of skills. For instance, 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. These are precisely the skills on which the education sector focuses.

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, or even non-existent, 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, which surveys formal, non-agricultural, private firms. The dataset covers questions related to country characteristics that have a potential impact on firms' performance, such as infrastructure, access to finance and informality, among others. These perceptions of the business environment are complemented with other variables focused on firms' 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 or territories the only survey available dates back to 2010 and for some of them there is another survey available for 2006 (15 economies 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. However, to our knowledge, it represents the only source with the desired degree of regional coverage.[2]

Table 1 shows the main characteristics of our sample. We use a final sample of 38 428 panel observations (firm-year), from surveys undertaken between 2006 and 2011. Our data covers the following emerging regions: Africa, East Asia and Pacific, Europe and Central Asia, Latin America and Caribbean and South Asia.[3] The sample has an unintentional relatively large

2 Another usual source of information is the *Talent Shortage Survey* conducted by ManPower, which analyses, 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 ten years (2006-15), it only has limited country coverage, and it also leaves the informal sector out of the analysis. There are an increasing number of efforts, but only with a regional coverage. Among them, see the aforementioned Alaimo et al. (2015) for original country surveys in selected Latin American countries.

3 We excluded the available observations for firms located in the Middle-East and North Africa, as they comprised only around 200 observations, which questions their representativeness. In all, the sample includes the following countries and territories economies by region: in Africa, Angola, Botswana, Burkina Faso, Burundi, Cameroon, Democratic Republic of the Congo, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Côte d'Ivoire, Kenya, Madagascar, Mali, Mauritania, Mauritius, Mozambique, Namibia, Nigeria,

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)**

Number of firms: 34 428

Obstacle	Absence (1)	12 297	Sector	Basic metals	700
	Minor (2)	8 147		Chemicals	7 559
	Moderate (3)	8 599		Construction	89
	Major (4)	6 454		Electronics	399
	Very severe (5)	2 931		Fabricated metals	3 141
Regions	Africa	7 892		Food	8 542
	East Asia Pacific	4 465		Furniture	2 087
	Europe and Central Asia	7 533		Machinery	2 843
	Latin America and the Caribbean	14 206		Motor vehicles	601
	South Asia	4 332		Other manufacturing	1 255
Size	Small (5-19 workers)	14 946		Services	499
	Medium (20-99 workers)	13 876		Textiles	9,255
	Large (+100 workers)	9 606		Wood	1 458

We proxy the skills gap based on answers to the question "*Is an inadequately educated workforce no obstacle, a minor obstacle, a moderate obstacle, a major obstacle, or a very severe obstacle to the current operations of this establishment?*".[4] It is an ordinal categorical variable, with responses ranging 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 they are a very severe obstacle.[5] In all, higher values of the dependent variable are symptomatic of an unsatisfied demand for skills that becomes a constraint for business operations. Table 1 also shows the main features of our dependent variable.

Rwanda, Senegal, South Africa, Swaziland, Tanzania, Uganda, Zambia and Zimbabwe. In East Asia-Pacific, China (People's Republic of), Indonesia, Philippines, Viet Nam. In Europe and Central Asia, Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Former Yugoslav Republic of Macedonia, Georgia, Hungary, Kazakhstan, "Kosovo", Kyrgyzstan, Latvia, Lithuania, Moldova, Mongolia, Montenegro, Poland, Romania, Russia, Serbia, Slovak Republic, Slovenia, Tajikistan, Turkey, Ukraine and Uzbekistan. In Latin America and the Caribbean, Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Trinidad and Tobago, Uruguay and Venezuela. In South Asia, Afghanistan, Bangladesh, Lao PDR, Nepal, Pakistan and Sri Lanka.

4 This question is coded as L30b in the World Bank *Enterprise Survey Database*.

5 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.

Latin American and European and Central Asian firms declare facing greater obstacles to firms' performance, according to a first descriptive analysis of the behaviours of the dependent variable across regions. In particular, 34% of surveyed firms from Latin America and the Caribbean are either in the "major" or "very severe" categories. In contrast, 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 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.

We use a fairly conventional set of control variables in development economics regressions. We proxy the development stage of the country by per capita GDP in USD adjusted for purchasing power parity, using the World Bank *World Development Indicators*. 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 region and industry of the firm. 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. East Asia and Pacific and the sector of Other Manufacturing are the reference groups for each type of categorical variable.

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 variable 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[6] 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 generalised 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

6 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.

sample the middle category, representative of "moderate obstacle". In all, we arrive to a new dependent variable with two levels, which we can estimate through a standard logit.[7]

The second estimation method is a generalised 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 the exploitation of all the information included in the original dependent variable, as there is no need to collapse it; thus, the generalised 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 has five ordinal levels, the generalised 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 generalised 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).[8] 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.

7 After losing these observations, our new sample consists of 29 771 observations.
8 In Table 2, the level of the dependent variable that is analysed is specified in the column "dependent variable level".

IV. RESULTS

Table 2 shows the results for the above-mentioned specifications, i.e. the logit with the collapsed values of the dependent variable and the generalised 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.[9]

Starting with the standard logit on the collapsed dependent variable, the positive and significant coefficient for per capita income (*lgdp*) suggests that the difficulties for a firm to find the talent it needs are greater in richer economies. Given that our sample only includes developing economies, this result places middle-income economies with more difficulties for satisfying their demand for skills. This is compatible with the "middle-income trap" hypothesis.

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, since all the regional dummies turn out positive and significant in this specification. 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 than that of a firm located in East Asia-Pacific. For a firm operating in Europe and Central Asia, this same odds ratio *vis-à-vis* East Asia-Pacific is 9 times, while for Africa and South Asia they are 3.9 and 4.3, respectively.

With regard 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 a lack of adequate skills. In all, these results identify a greater skills gap in advanced manufacturing industries.

The results on the generalised ordered logit estimation tend to ratify all previous results for regions and sectors (see second block in Table 2). The variables for Latin America, Europe and Central Asia, Africa and South Asia are positive and significant for all levels of the dependent

9 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.

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. For the other regions, the same probability is 11 times in Africa and South Asia, and 33 times in Europe and Central Asia.

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

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			

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
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			
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			

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
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		

Note: Significant coefficients at 95% are represented in bold letters.

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) category. For Machinery, this odds ratio is 1.7. The rest of the industries fall short of a clear pattern on their 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 generalised 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 (third block in Table 2). 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 a 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 each 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 generalised ordered logit, as it leads to a problem of quasi separation of data.[10] 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.

This estimation largely confirms, once again, the effects previously identified with regard to advanced manufacturing (Table 3). For 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

10 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).

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 samples

REGIONAL SAMPLES									
Generalized Logit		AFR				ECA			
Parameter	dependent vble. Level	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio
Intercept	2	-0.4	2.41	0.12		-0.5	0.70	0.40	
	3	**-1.6**	27.75	<.0001		-0.5	0.69	0.41	
	4	**-1.8**	25.60	<.0001		-0.8	1.90	0.17	
	5	**-1.9**	16.26	<.0001		-0.8	1.25	0.26	
lgdp	2	0.0	0.48	0.49	0.98	-0.1	1.25	0.26	0.93
	3	**0.1**	5.24	0.02	1.09	0.0	0.26	0.61	0.97
	4	0.1	4.01	0.05	1.09	0.0	0.04	0.84	1.01
	5	0.0	0.11	0.74	1.02	-0.1	0.99	0.32	0.93
skill_intens	2	0.0	0.20	0.66	1.02	0.0	0.03	0.86	0.99
	3	**0.1**	6.58	0.01	1.10	-0.1	3.22	0.07	0.92
	4	0.1	3.54	0.06	1.08	0.0	0.30	0.59	0.98
	5	**0.1**	4.96	0.03	1.10	0.0	0.53	0.47	0.97
FOOD	2	-0.1	0.22	0.64	0.93	**0.7**	14.42	0.00	2.02
	3	-0.1	0.71	0.40	0.86	**0.4**	5.11	0.02	1.46
	4	**-0.4**	5.18	0.02	0.65	0.2	0.93	0.34	1.17
	5	**-0.6**	5.99	0.01	0.55	0.3	1.91	0.17	1.34
TEXTILE	2	-0.2	2.40	0.12	0.79	**0.8**	16.67	<.0001	2.20
	3	-0.3	2.24	0.13	0.76	**0.6**	12.48	0.00	1.86
	4	**-0.5**	5.79	0.02	0.63	**0.6**	12.11	0.00	1.80
	5	**-0.7**	8.41	0.00	0.48	**0.9**	18.07	<.0001	2.50
WOOD	2	0.0	0.05	0.83	1.04	0.1	0.31	0.58	1.14
	3	0.2	0.77	0.38	1.21	0.1	0.16	0.69	1.09
	4	**0.5**	5.79	0.02	1.68	-0.3	1.84	0.18	0.74
	5	-0.4	1.44	0.23	0.67	0.1	0.05	0.83	1.06
CHEMICAL	2	-0.2	0.88	0.35	0.86	**0.5**	8.19	0.00	1.72
	3	0.1	0.07	0.78	1.05	0.3	2.12	0.15	1.29
	4	-0.3	2.77	0.10	0.71	0.0	0.00	0.98	1.00
	5	-0.4	2.30	0.13	0.67	0.2	1.08	0.30	1.26
BASIC METALS	2	0.2	0.60	0.44	1.23	0.7	3.83	0.05	2.05
	3	0.3	1.04	0.31	1.36	0.5	2.55	0.11	1.73
	4	0.3	0.88	0.35	1.34	0.4	1.34	0.25	1.49
	5	0.1	0.04	0.85	1.09	0.5	1.68	0.20	1.73
FABRICATED METALS	2	0.0	0.02	0.89	0.98	**0.7**	10.92	0.00	1.96
	3	0.1	0.48	0.49	1.15	**0.5**	6.13	0.01	1.58
	4	-0.3	1.82	0.18	0.75	0.3	2.44	0.12	1.33
	5	-0.2	0.48	0.49	0.83	0.4	3.28	0.07	1.53
MACHINERY	2	-0.1	0.07	0.79	0.95	**0.7**	11.95	0.00	2.02
	3	-0.3	0.96	0.33	0.78	**0.7**	16.84	<.0001	2.11
	4	-0.1	0.23	0.63	0.88	**0.6**	13.33	0.00	1.91
	5	-0.5	2.02	0.16	0.58	**1.0**	19.59	<.0001	2.68
ELECTRONICS	2	0.0	0.00	0.97	1.03	0.6	3.98	0.05	1.80
	3	0.8	2.09	0.15	2.32	0.3	1.02	0.31	1.33
	4	-0.8	0.59	0.44	0.44	0.4	2.72	0.10	1.54
	5	-0.2	0.03	0.86	0.83	0.6	3.47	0.06	1.84
AUTO	2	0.2	0.47	0.50	1.25	**1.3**	13.52	0.00	3.56
	3	0.2	0.20	0.66	1.19	0.5	1.49	0.22	1.57
	4	0.0	0.00	0.98	1.01	**0.7**	4.65	0.03	2.08
	5	-0.5	0.50	0.48	0.63	0.6	1.78	0.18	1.81
FURNITURE	2	0.0	0.04	0.84	1.03	0.2	0.34	0.56	1.17
	3	-0.1	0.17	0.68	0.92	0.1	0.20	0.66	1.11
	4	-0.3	1.55	0.21	0.78	**0.5**	5.59	0.02	1.67
	5	-0.1	0.28	0.59	0.87	**0.6**	5.25	0.02	1.87
CONSTRUCTION	2	-0.1	0.02	0.90	0.90	**1.5**	12.51	0.00	4.55
	3	**1.4**	4.23	0.04	3.94	0.2	0.12	0.73	1.21
	4	**1.5**	5.01	0.03	4.46	0.6	1.63	0.20	1.80
	5	0.4	0.10	0.76	1.42	0.4	0.49	0.48	1.54
SERVICES	2	0.3	0.41	0.52	1.29	**0.6**	5.30	0.02	1.85
	3	0.4	0.81	0.37	1.47	0.4	3.19	0.07	1.56
	4	-0.4	0.49	0.48	0.67	0.0	0.01	0.93	1.02
	5	0.5	0.67	0.41	1.57	0.1	0.03	0.87	1.06
Observations		7892				7435			

Table 3. (cont.)

REGIONAL SAMPLES									
Generalized Logit		LAC				SAR			
Parameter	dependent vble. Level	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio	Estimate	Chi-Sq	Pr>ChiSq	Odds ratio
Intercept	2	**-2.7**	23.63	<.0001		**5.4**	47.17	<.0001	
	3	**-2.3**	20.99	<.0001		**8.1**	89.68	<.0001	
	4	**-3.4**	40.66	<.0001		**4.0**	14.46	0.00	
	5	**-4.2**	37.39	<.0001		-0.2	0.02	0.88	
lgdp	2	**0.3**	22.19	<.0001	1.32	**-0.8**	54.39	<.0001	0.46
	3	**0.3**	28.74	<.0001	1.33	**-1.2**	108.76	<.0001	0.30
	4	**0.4**	47.31	<.0001	1.47	**-0.7**	23.34	<.0001	0.51
	5	**0.4**	29.87	<.0001	1.49	-0.3	1.68	0.19	0.76
skill_intens	2	0.1	3.68	0.06	1.06	**-0.1**	5.23	0.02	0.90
	3	**0.1**	15.97	<.0001	1.11	**-0.2**	8.19	0.00	0.86
	4	**0.1**	8.17	0.00	1.08	-0.1	1.41	0.24	0.93
	5	0.0	0.92	0.34	1.04	-0.4	2.87	0.09	0.70
FOOD	2	0.0	0.06	0.81	1.05	0.3	1.47	0.23	1.30
	3	0.0	0.07	0.80	1.04	0.4	3.44	0.06	1.56
	4	0.0	0.08	0.78	0.95	-0.3	1.32	0.25	0.72
	5	-0.3	1.58	0.21	0.76	-0.2	0.16	0.69	0.81
TEXTILE	2	0.0	0.03	0.85	1.04	**0.4**	4.11	0.04	1.53
	3	0.0	0.00	0.99	1.00	**0.9**	15.14	0.00	2.46
	4	0.0	0.00	0.98	1.00	**0.6**	5.41	0.02	1.84
	5	0.0	0.03	0.87	1.04	0.8	2.66	0.10	2.25
WOOD	2	0.0	0.01	0.91	1.03	-0.1	0.04	0.84	0.94
	3	-0.3	1.49	0.22	0.76	0.5	3.06	0.08	1.67
	4	-0.1	0.12	0.72	0.92	-0.5	1.43	0.23	0.63
	5	-0.6	3.38	0.07	0.56	-0.3	0.15	0.70	0.77
CHEMICAL	2	0.0	0.01	0.91	0.98	0.2	1.01	0.31	1.25
	3	-0.1	0.22	0.64	0.92	**0.7**	8.87	0.00	2.04
	4	-0.2	0.79	0.37	0.86	-0.1	0.20	0.66	0.88
	5	**-0.5**	4.60	0.03	0.63	-0.1	0.03	0.86	0.91
BASIC METALS	2	-0.1	0.18	0.67	0.88	-0.1	0.11	0.74	0.91
	3	0.0	0.01	0.91	1.03	0.1	0.07	0.79	1.09
	4	0.1	0.11	0.73	1.10	-0.4	1.26	0.26	0.66
	5	-0.4	1.25	0.26	0.66	-0.5	0.54	0.46	0.60
FABRICATED METALS	2	0.0	0.05	0.83	1.05	-0.2	0.33	0.56	0.83
	3	0.2	0.74	0.39	1.17	0.2	0.53	0.47	1.27
	4	0.3	2.54	0.11	1.35	-0.5	1.19	0.28	0.63
	5	0.0	0.01	0.92	1.02	0.1	0.01	0.94	1.05
MACHINERY	2	0.3	1.45	0.23	1.29	0.6	3.95	0.05	1.76
	3	0.0	0.06	0.81	1.05	**1.2**	17.36	<.0001	3.38
	4	0.4	3.56	0.06	1.44	0.6	2.91	0.09	1.81
	5	**0.5**	4.70	0.03	1.66	-0.3	0.12	0.73	0.77
ELECTRONICS	2	**0.9**	4.75	0.03	2.37	0.3	0.20	0.66	1.39
	3	0.4	1.29	0.26	1.54	0.7	0.79	0.38	1.94
	4	0.1	0.03	0.86	1.08	0.3	0.13	0.72	1.38
	5	0.0	0.00	0.96	0.98	1.1	0.88	0.35	3.13
AUTO	2	0.1	0.06	0.81	1.09	-0.3	0.61	0.44	0.72
	3	0.5	2.39	0.12	1.62	0.7	3.36	0.07	2.00
	4	**1.1**	13.52	0.00	3.06	0.0	0.01	0.94	1.04
	5	**1.6**	23.70	<.0001	5.03	0.4	0.21	0.65	1.42
FURNITURE	2	0.2	0.77	0.38	1.23	0.0	0.01	0.93	0.98
	3	0.2	1.18	0.28	1.25	0.0	0.00	0.95	1.02
	4	0.2	1.06	0.30	1.25	-0.1	0.09	0.76	0.90
	5	**0.7**	7.26	0.01	1.97	-0.1	0.04	0.84	0.88
CONSTRUCTION	2	9.4	0.02	0.89	>999.999	-0.4	0.08	0.77	0.70
	3	10.1	0.02	0.88	>999.999	0.0	0.00	0.98	0.97
	4	9.1	0.02	0.89	>999.999	-10.6	0.00	0.96	<0.001
	5	9.1	0.02	0.89	>999.999	-10.3	0.00	0.98	<0.001
SERVICES	2	0.4	0.98	0.32	1.53	0.3	1.17	0.28	1.36
	3	0.3	0.63	0.43	1.37	0.6	3.61	0.06	1.78
	4	0.3	0.70	0.40	1.40	-0.7	2.42	0.12	0.50
	5	0.4	0.52	0.47	1.42	-1.2	1.09	0.30	0.31
Observations		14206				4332			

Note: Significant coefficients at 95% are represented in bold letters.

Looking at regional patterns, our results show that Europe and Central Asia show the larger number of industries with skills gaps, as shown by number of positive and significant industry coefficients, while in Latin America they are severe but concentrated in advanced manufacturing sectors like Machinery or Motor Vehicles. This situation in Europe and Central Asia could be symptomatic of labour markets with deficits 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 South Asia, industries characteristic of standardised technology (Textiles) and Machinery are found to be 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

Most emerging economies are characterised by lagging levels of productivity. The theoretical and empirical literature states 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 paper addresses empirically the skills gap in emerging regions, and shows that this barrier is especially evident in Latin America, the region where firms have the greatest problems derived from a lack of adequate skills. Latin America is well ahead of emerging Asia and Europe, but also of sub-Saharan Africa. In our preferred estimation, the analysis shows that Latin American firms are 3 times more likely than South Asian firms and 13 times more likely than Asian-Pacific 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. Unfortunately, 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 not only of inequality and low inclusion, but also of tamed productivity and high informality levels among workers and among firms.

However, the robustness of the results confirm the need for an urgent policy respond. 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 and covering informal businesses.

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