Skill biased technological change across the development spectrum

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1 Introduction

A central feature of economic development is the changing nature of the production process of goods and services. An accepted view of economic progress would state that as countries become richer, production and trade patterns change with a higher share of domestic value added being generated through more technologically sophisticated processes – both within agriculture, services and industries as well as due to a shift away from agriculture. During this process, most countries witnessed a marked increase in the diversity of available goods and services for consumption and notably a shift in demand toward skilled workers. Little by little, occupations which require intensively manual skills give way to occupations requiring more cognitive skills. Central to this process is the finding that supply of highly-skilled labor has increased, while their employment and wage shares have also increased. In other words, demand for highly-skill labor has exceeded that of supply.

The most common explanations for these developments have been, in one hand globalization and trade, and in the other skill-biased technological change, the latter affecting new and more sophisticated industries such as information and communication technologies (see Autor, Katz, & Krueger, 1998; Kelly, 2007). Economic effects will increase their magninute in the medium- and long-term and can have large implications on labor earnings and the distribution of global income inequality. Consider that even the most conservative education and population projections suggest a dramatic increase in the global supply of educated labor in the coming decades. With some confidence it can be sayed that 4 out of every 5 new entrants into the global pool of *educated* labor will come from middle-income countries. Some of these countries are experiencing large demographic transitions. High-income countries' contribution to the global supply of educated labor will decrease, as a matter of fact. Trying to argue against this tectonic shift in the global economy is to neglect the enormous progress made by low- and middle-income countries in providing basic health and education to billions of people around the globe. Nevertheless, if we posses some minimum level of certainty about education and population trends in the decades to come, uncertainty is the norm about the pace at which technology is created and adopted, let alone on how technological change will affect labor incomes.

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The literature on the *pervasive* skill-biased technological change can be traced back to Berman, Bound, & Machin, (1998) which provide a general framework to address this question in a supply and demand equilibrium setting. In their paper it was shown that demand for less-skilled workers in high-income countries plummeted in the 1980s. In open economies, they argue, skill-biased technical change is augmenting the supply of labor by releasing less-skilled labor. Since most industries increased the proportion of skilled workers despite generally rising or stable relative wages, the authors argue in favor of skill-biased technological change. Some evidence suggest a similar effect in low and middle-income countries.

Since then, important efforts have been made to quantify the impact of both trade and technological change on the demand for skills. For instance, positive relations have been found between demand for skills and research and development expenditures, innovation or other technology proxy variables. Alternative explanations for these upgrading of skills have been attributed to globalisation via foreign trade (Paul & Siegel, 2001), including outsourcing (Geishecker, 2006; Minondo & Rubert, 2006); and organisational change (Caroli & Reenen, 2001). There are few studies that jointly address labor force upskilling in low-, middle-, and high-income countries. Due to the nature of the question, the majority of studies provide evidence on the process of upskilling in a particular country or a narrow set of countries relying extensive on survey or census microdata. In these cases, efforts are devoted to the analysis of the between- and within-industry changes in employment and wages shares. Typically, within-industry changes are associated with skill-biased technological change, while between-industry changes are associated with foreign trade intensity and composition. Kang & Hong (2002) for instance, investigates the demand for skills in the Republic of Korea and finds that employment and wages shares changes can be largely explained by whithin industry shifts, especially in the manufacturing sector. Kelly (2007) examines changes in industry skill scores for Australia notably finding that effects can differ in time. In the more recent period, the author finds that changes in economy wide skill level were dominated by within-industry changes in occupational composition.

This paper contributes to this branch of the literature by providing additional evidence on changes in employment and wages shares for a variety of countries across the development spectrum. These changes are decomposed into between and within-industry components by type of worker, using occupation and education classifications. This paper also provides statistical evidence about the effect of economic complexity on changes in employment and wage shares. The paper is organized as follows. Section 2 shows upskilling patterns across the four dimensions: education, occupation, industry, and per capita income calculated using global collection of household suveys. Section 3 test empirically the relevance of trade and technology on upskilling in the using two-points in time for a sub sample of countries with available data. Conclusions and limitations of this paper are presented in the last section.

2 Upskillilng in Developed and Developing Countries

2.1 Data

It is not easy to construct a reliable cross-country data by industry or occupation due to limited availability of informantion and geographically-inconsistent industry and/or occupation classification systems. This paper relies on the International Income Distribution Database (I2D2 version 5), which is a global compilation of household surveys maintained by the World Bank[1]. Data was collected from I2D2's demographic (age, gender, relationship to household head), education (years of schooling), labor (occupation, employment status, industry), and welfare modules (per capita income and/or consumption). The cross-country analysis presented on Section 2.2 uses a sample of 130 household surveys with nearly 12 million observations that represent the global income distribution for the year 2007[2]. Section 3 uses a smaller sample of countries. Household suveys for 72 countries were selected if there was at at least two comparable surveys with at least 4 years apart between them.

With respect to household surveys there are important data caveats that must be recognized beforehand, some of which are already covered in the literature[3] while others might well be considered as anecdotal. Specific to this paper include the following. First, while wages are present in the database, the inconsistent process of collecting labor income across countries make comparisons challenging. For this reason, wages can proxied by the per worker welfare aggregate (income/consumption) which is collected with more comparable methods. The per capita welfare measure varies by country depending on data availability, but consumption was always preferred over income. Second, the welfare aggregate aggregate only includes imputations or corrections made by the Statistical Offices and already available in the original household survey, the most important include household rent and agricultural incomes. Second, I2D2 – as any other source of harmonized household survey data, is predispose to human errors and hence is constantly under revision. A series of data validations were performed before including any survey in the analysis. Third, the welfare aggregate in I2D2 is originally reported in local currency units (LCUs) and the author was responsible for transforming LCUs into PPP$. Anecdotically, it is practically impossible to replicate the official \$1.25/day World Bank poverty estimate using household

[1] An earlier version of the data is describes in Montenegro & Hirn (2009)

[2] This database has been usually linked to the LINKAGE (van der Mensbrugghe, 2011) macro computational general equilibrium (CGE) model using the Global Income Distribution Dynamics (GIDD) framework (see Bussolo, De Hoyos, & Medvedev (2010), for a recent application (Devarajan, Go, Maliszewska, Osorio-Rodarte, & Timmer, 2015)).

[3] For instance, Beegle, De Weerdt, Friedman, & Gibson (2012) document the large implications of small variations in survey desing for household consumption measurement. Devarajan (2013) highlights the technical weak capacity to collect statistics in Africa alongside the political aspects behind generating them. Deaton & Dupriez, (2011) discuss implications for global poverty measurement using PPP exchange rates vis-à-vis household consumption measurements.

surveys. In order to cope with this inconsistency, the author is forced to scale each country's income distribution to match the World Bank poverty estimate. Whenever this scaling was not marginal the survey was not considered for the analysis. Certainly, a great effort is being done to make a global microdatabase consistent and, to the extent of possible, publicly available. The task is enourmous and few institutions have the scope and capacity to provide this type of public goods[4].

Demographic projections used in this paper come from the Shared Socio-Economic Pathways database (version 1.0)[5], which is assembled with contributions from the Unitated Nations (UN) Population Statistical Division, The Organization for Economic Cooperation and Development (OECD), and the International Institute for Applies Systems Analysis (IIASA). Complementary macro economic data, mainly used in Section 3.2, was obtained from the World Bank Open Data Platform[6], the Penn World Tables (version 8.1)[7], and the Observatory of Economic Complexity[8].

2.2 Changes in employment structure by industry and income level

Labor is divided into four categories according to occupation and educational attainment[9]. This paper differentiates workers in terms of occupation, as white-collar workers and blue-collar workers[10], and by educational attainment, as skilled and unskilled workers[11]. Table 1 below presents the contribution to the global pool of labor for each group: white-collar high-skill (WCHS), white-collar low-skill (WCLS), blue-collar high-skill (BCHS) and blue-collar low-skill (BCLS). The weighted global pool of workers in our sample is equal to 1,260 millions. More than half of the global pool are blue-collar unskilled workers majoritarily living in middle income countries. White-collar high skilled labor accounts for 18 percent of the global pool, among them, 45 percent live in high-income countries. Table 2 below disaggregates labor categories by industry. In general terms, labor is equally dispersed among industries, wih the marked exception of blue-collar low-skilled

[4] There are other databases varying in regional, time coverage, quality, and scope of harmonization. For instance, the Luxembourg Income Study, the SEDLAC database

[5] https://secure.iiasa.ac.at/web-apps/ene/SspDb/dsd?Action=htmlpage&page=about

[6] http://data.worldbank.org using Azevedo, (2014) Stata modeule WBOPENDATA

[7] http://www.rug.nl/research/ggdc/data/pwt/pwt-8.1

[8] https://atlas.media.mit.edu/en/

[9] This resembles the labor classification presented by Kang & Hong (2002) for the case of South Korea.

[10] Using I2D2 occupation variable, white-collar workers include: 1) Senior officials, 2) Professionals, and 3) Technicians; and blue-collar workers include: 4) Clerks, 5) Service and market sales workers, 6) Skilled agricultural, 7) Craft workers, 8) Machine operators, 9) Elementary occupations, 10) Armed forces, and 99) Other occupations.

[11] In this paper, we define loosely skilled workers as those with at least 9 years of schooling.

workers; as a matter of fact, 1 in every 4 workers from the global pool belong to this category.

Table 1 Contribution to total labor by income group

Income Group	**BCLS**	**BCHS**	**WCLS**	**WCHS**	**Total**
Low	5.6	0.7	0.2	0.4	6.9
Lower-Middle	22.1	6.5	1.4	3.7	33.8
Upper-Middle	21.4	7.9	3.6	5.9	38.8
High	2.8	9.0	0.5	8.2	20.6
N/A	0.4	0.0	0.0	0.0	0.0
Total	52.4	24.2	5.6	18.2	100.0

Table 2 Contribution to total labor by industry

Industry	**BCLS**	**BCHS**	**WCLS**	**WCHS**	**Total**
Agriculture	25.0	3.6	0.3	0.3	29.2
Mining	0.7	0.3	0.1	0.1	1.2
Manufacturing	6.2	4.7	0.9	2.3	14.1
Public utilities	0.4	0.5	0.1	0.3	1.4
Construction	6.0	2.0	0.3	0.7	9.0
Commerce	5.1	4.1	1.9	2.8	13.9
Transport & commun.	2.9	2.1	0.4	0.9	6.2
Finance & Business	0.6	1.5	0.1	2.7	4.9
Personal Services	2.2	3.7	0.8	5.7	12.4
Others	3.4	1.5	0.7	2.1	7.7
N/A	0.0	0.2	0.0	0.3	0.0
Total	52.4	24.2	5.6	18.2	100.0

Figure 1 below shows the total wage bill disaggregated by type of worker and countries' income level. Skilled labor accounts for 43 percent of the total wage bill in low-income countries, and as expected, this share increases as per capita income rises, reaching a total of 82 percent in high-income countries. The orders of magnitude are important. Consider that more than 100 million white-collar high-skill workers residing in high-income countries (out of 260 million total workers) contribute to 40 percent of the total wage-bill in this group of countries. In contrast, 5 million white-collar high-skill workers, out of a total of 87 million in low-income countries, contribute to 20 percent of their respective total wage bill.

Figure 1 Wage bill Shares by type of worker and countries' income level

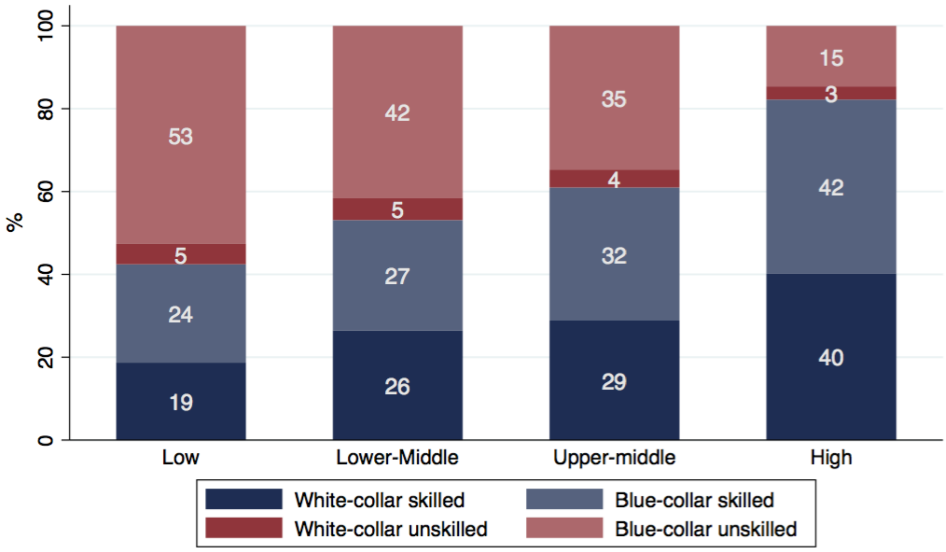


Figure 2 Wage gap and labor shares for low, middle, and high-income countries

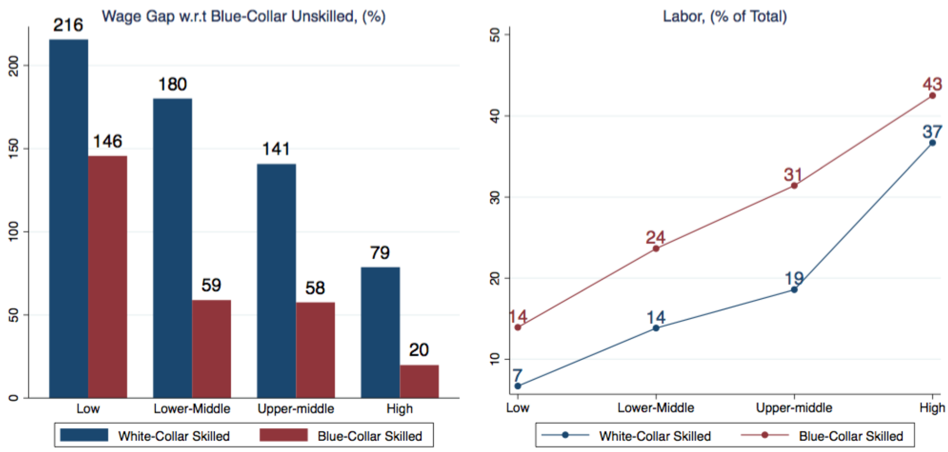


Figure 1 Wage bill Shares by type of worker and countries' income level

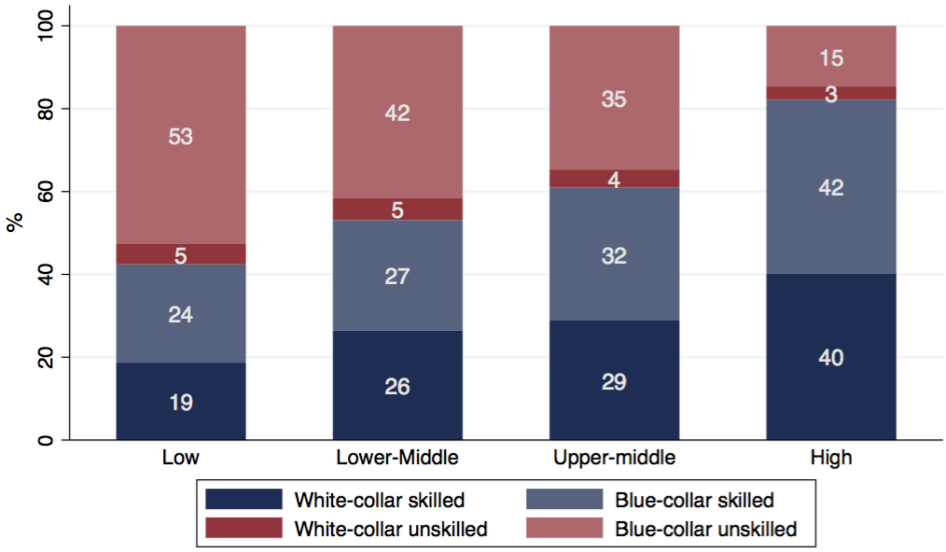


Figure 2 depicts the process of global upskilling across the income per capita spectrum. Bars on the left-pane show the average wage gap (%) of skilled labor with respect to unskilled blue-collar workers for low, lower-middle, upper-middle, and high-income countries. In contrast, lines on the right-pane show blue-collars' labor shares as a percentage of total labor. By combining these two figures it can be seen that, as income per capita increases, relative wages for blue-collars decline and their contribution to total labor rises. Consistent with supply and demand, higher relative wages for skilled workers observed in low-income countries can be explained by the relative scarcity of skilled labor. In low income countries, the average white-collar skilled worker earns 216% more than the blue-collar unskilled, but white-collar skilled only represents, on average, 7% of total labor. As skilled labor becomes more abundant in countries with higher per capita incomes, blue-collars' relative wages start to decline with respect to unskilled labor. The wage gap is reduced to 79% while the white-collar skilled labor participation rises to 37% of total labor.

Figure 3 Wage gap and labor shares by industry

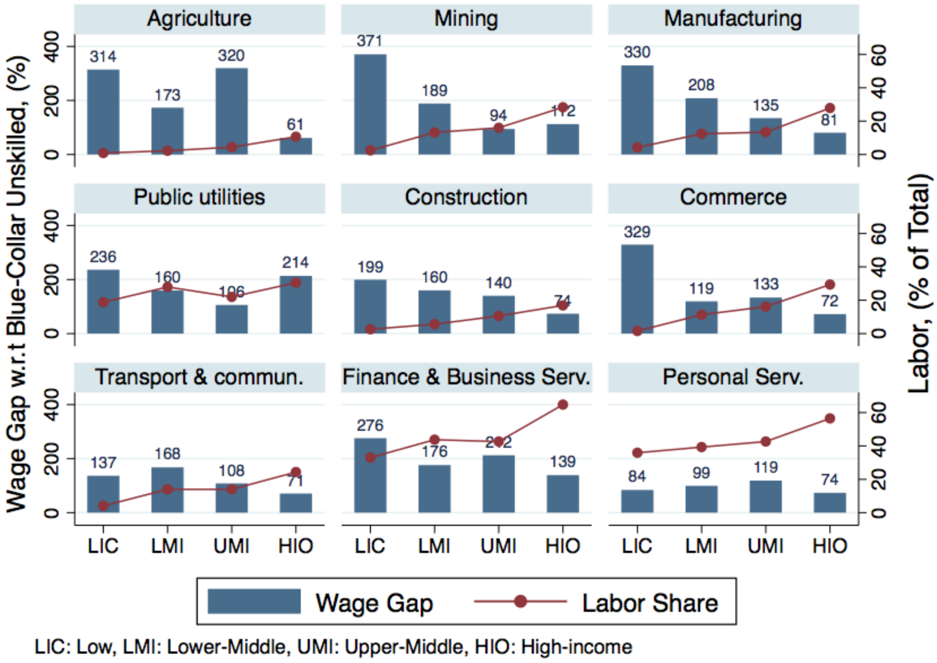


Figure 3 above shows the average wage gap and labor participaton for white-collar high-skill workers with respect to the blue-collar unskilled at the industry level. It can be seen that industries that are considered, generally speaking, to be more technologically sophisticated have a more marked negative relationship between wage-gap and the labor share of white-collar skill labor. The effect is more pronounced in mining, manufacturing, construction, commerce, and finance and business-oriented services. Agriculture, public utilities, and personal services do not show, on average, this negative pattern.

3 Empirical Investigation

3.1 Within and between-industry decomposition[12]

Berman et al., (1998) argued that the causes of skill upgrading can be analyzed by between and within industries' shifts. Increases in international trade would work primarily by shifting the derived demand for labor between industries from those intensive in low-skill labor to those intensive in high-skill labor. On the other hand, biased technological change would shift the skill composition of labor demand within industries. They proposed a general method that decomposes an overall shift within the economy into within-industry and between-industry shifts. This method enables us to study the factors behind changes in employment and wage shares for low- and high-skill workers.

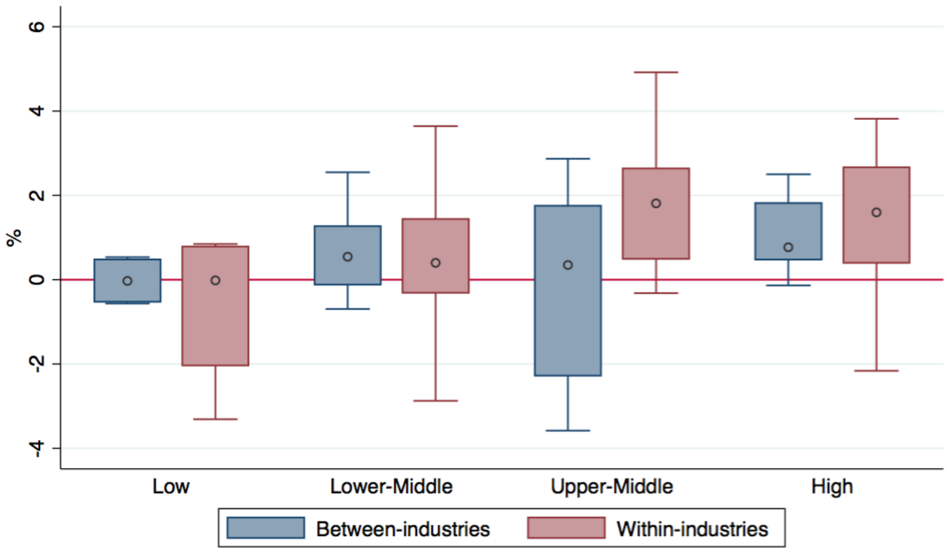
[12] This section is based on Kang & Hong, (2002)

The aforementioned decomposition method is based on the premise that the variance can be divided into the expectation of conditional variance and variance of conditional expectation. Let then be $P_n = E_n/E$ be an aggregate proportion of white-collar high-skill labor, $P_{n,i} = E_{n,i}/E$ be the proportion of white-collar high-skill labor in industry i, $S_i = E_i/E$ be the employment share of industry i. The overall change in employment shares of white-collar high-skill labor can be decomposed into within and between industries shifts as follows:

$$\Delta P_n = \sum_{i=1}^{n} \Delta S_i \overline{P_n} + \sum_{i=1}^{n} \Delta P_{n,i} \overline{S_\iota}$$

The first term on the right reports a change in the aggregate proportion of white-collar high-skill workers attributable to shifts in employment shares between industries with different proportions of white-collar high-skill workers. The second term represents a change in the aggregate proportion attributable to changes in the proportion of white-collar high-skill workers within each industry. We performed this decomposition for the subsample of countries with available data as mentioned in Section 2. Figure 4 below aggregates these results by income group. The figure shows that as income rises, the within-industry component of the changes in employment grows in absolute terms and with respect to the effect attributable to movements between industries. These findings are consistent with the idea that the within-industry effect is larger in high-income countries. A similar trajectory is observed by decomposing wage bill changes into its between and within components.

Figure 4 Decomposition of the changes in the share of white-collar high-skill workers across countries



3.2 Multivariate analysis

In the previous section, it was shown that upskilling in middle and high-income countries can be explained by whithin industries shifts. This section investigates further the statistical relationship regarding the between and within-shift components across countries. It is expected that the between-industry component of the change in employment shares of white-collar high-skill workers will be more important in low-income countries and that this effect is mostly influenced by trade. The within component, in the other hand, will be more pronounce in high-income countries and will be due to skill-biased technological change. The effect of the capital output ratio on both components is expected to be important, and will be used as control. More specifically, we regress the left and right-hand sides of the decomposition equation agains trade and technology variables using the following specifications:

$$L_c = \beta_{L,0} + \beta_{L,1}\Delta(Trade_c / Y_c) + \beta_{L,2}(K_c / Y_c) + \varepsilon_{L,c}$$

$$R_c = \beta_{R,0} + \beta_{R,1}(ECI_c) + \beta_{R,2}(K_c / Y_c) + \varepsilon_{R,c}$$

where i indexes countries; L_c denotes the between-industry component of the change in employment of white-collar high-skill workers, R_c denotes the within-industry change; $Trade_c$, K_c and Y_c denote trade, capital and value added, respectively. We use ECI_c, the economic complexity index as the preferred method to address skill-biased technological change (see Hausmann et al., 2013)[13].

In our regression specification, capital-skill complementarities imply positive β_2. The constant term can be interpreted as changes common to all countries, and the sum of constant and disturbance as the specific for each country. The Economic Complexity Index (ECI) reflects country-specific factors which may lead to biased technological change. Table 3 below shows the estimation results. The most important finding is that ECI is positive and statistically significant in all specifications that deal with the within-industry component, while it remains negative and not statistically different than zero in all specifications related with the between-industry components. Trade to output ratio is statistically significant in all specifications that deal with the between-industry component. This effect should be interpreted together with the large and significant constant term. In other words, there is a large between-industry component that gets diluted as the trade to output ratio rises. As expected, the between-industry component would be then larger in low-income countries, where the trade to output ratios are smaller and will be reduced in importance as these countries gets richer and with higher trade to output ratios. Capital-output ratios are statistically significant in the

[13] ECI has the advantage of not being mathematically derived from any income or GDP aggregate, nevertheless it is strongly correlated with a country's income level. ECI is constructed using basic assumptions about the complexity of countries and the complexity of products. These assumptions are applied to global trade patterns of revealed comparative advantage in exports.

between-industry component, but not statistically significant on the within-industry specification. This nonetheless needs further investigation. More importantly is the fact that as economies get more complex, the within-industry effect dominates. This statistical relationship has been taken as evidence of skill-biased technological change. Much deeper investigation is still needed. The fact that an economy is gaining in complexity necessarily implies that a new set of economic activities have been created, we are still placing them within old boundaries.

Table 3 Regression Results

(A) Dependent Variable: Between-Industry Component

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ECI						-0.3	-0.17	-0.13	0.184
ln(Trade/Y)			-1.330*	-1.678*	-1.747*				-1.43
Y Growth	0.075	0.371*		0.107	0.414*		0.082	0.232	0.371
Δ(K/Y)		0.176*			0.160**			0.121*	0.117*
Income Level									
D UMI			-2.83			-1.29			
D LMI			-4.55			-2.75			
D HIO			-2.89			-0.91			
Constant	0.678	-0.55	9.728*	7.816*	6.854*	2.234	0.424	-0.13	5.383
R-squared	0.003	0.118	0.207	0.073	0.196	0.126	0.013	0.097	0.165

(A) Dependent Variable:Within-Industry Component

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ECI						1.246*	1.622*	1.952**	1.971**
ln(Trade/Y)			1.581*	1.478*	1.575				-0.09
Y Growth	0.069	0.009		0.041	-0.03		0.530*	0.645*	0.653*
Δ(K/Y)		-0.05			-0.04			-0.02	-0.02
Income Level									
D UMI			-0.45			-0.95			
D LMI			1.947			0.973			
D HIO			0.367			-1.99			
Constant	1.756**	1.894	-5.24	-4.53	-4.78	2.463	-0.56	-1.33	-1.00
R-squared	0.002	0.012	0.148	0.059	0.065	0.171	0.131	0.195	0.195

Notes: 1. Equation were calculated using OLS with robust standard errors
2. Asteriks denotes statistical significance at 5, 1, and 0.1 percent levels

4 Conclusions and Limitations

This study has provided some cross-country evidence about the magnitude of within-industry effects on changes in employment shares. First, this paper finds that observed wage gap across countries can largely be explained by the relative scarcity of highly-skilled versus low-skilled labor. As a result, in low-income countries, skilled-labor contribution to the total wage bill is higher, as a percentage of total, than in middle-, and high-income countries. It has also been shown that this pattern not only holds across the income per capita dimension, but also is very persistent across industries. As expected, the wage-gap and skill scarcity relationship holds in industries that are mostly affected by trade or by technological change, and its quite limited in more protected industries. Our results suggest that skill-biased technological change is predominantly affecting middle- and high-income countries. Statistical evidence support the notion that the effect of skill-biased technological change gets stronger as economies increase it's complexity and advance throughout the development spectrum.

There are several lines of work that can improve this paper. First, a macro theoretical model can be tested in light with its findings including additional proxy variables for technological change as well as other instruments that can help mitigate endogeneity problems (mostly related with the capital and trade to output ratios). Second, heterogeneity present in the microdata can be exploited further, for instance using alternative decomposition methods. It might be desirable to quantify medium to long-term effects on global inequality by linking macro and micro models. A much deper look into the emerging evidence that indicate deviations from skill-biased technological change in middle-income countries. It has been documented, for instance, that during the last decade, the majority of countries in Latin America faced a strong decline in inequality caused by a relative strong growth in labor earnings at the bottom of each countries income distribution.

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