The coming wave of educated workers:
Size and impact on global inequality[1]

INCOMPLETE DRAFT

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Abstract

Distributional change is a complex phenomenon and there are many forces at work. This paper focuses on those forces that are more directly related to supply and demand trends in labor markets. On the supply side it considers: demographic shifts, improvement in education achievements and policies related to labor supply (such as increasing access to education, enabling inter-sectoral mobility, etc.); and, on the demand side: technological change, sectoral pattern of growth, and trade (globalization). The intergenerational improvement in education will increase the supply of skilled workers. By the time these young cohorts reach the labor market, there would be important consequences on skill wage premia, sector mobility and income distribution. For understanding these outcomes in the long run a general equilibrium setup is much needed.

JEL Classification: D31, J11, J31, E24

KEY WORDS: Global Inequality, Education, Demographic trends, Structural change

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Summary

1 Introduction: setting the stage

As 2015, the end-point date for the Millennium Development Goals, is approaching an important debate has started on whether a new set of goals and specific targets will be established and what these will look like. It may take some time to settle this debate but it is clear that, among the post-2015 goals, poverty reduction will still figure in prominently. In this context, the World Bank, in a reiteration of its mandate of ending poverty, has announced not only new poverty goals, but also a specific 'inequality' goal in terms of shared prosperity (see Basu, 2013).

Understanding the dynamics of inequality (within and between countries), the central objective of this paper, has thus been gaining a more central stage, as inclusive growth is now a goal in itself, and as the viability of the future global poverty target will depend on it. Globally, further reductions of the between country component of inequality will be possible only if more and more of the poorest countries will reach and maintain sustained growth rates. But this will help in achieving the twin targets only if the within country inequality component will also decrease or, at least, will not increase. In other words, prosperity will have to be truly shared. This paper contributes to the understanding of distributional change by providing a quantitative analysis of the recent patterns of the skill premium and of the forthcoming wave of skilled workers from developing countries on growth, inequality and poverty.

Distributional change is a complex phenomenon and there are many forces at work. This paper focuses on those forces that are more directly related to supply and demand trends in labor markets. On the supply side it considers: demographic shifts, improvement in education achievements and policies related to labor supply (such as increasing access to education, enabling inter-sectoral mobility, etc); and, on the demand side: technological change, sectoral pattern of growth, and trade (globalization).

The continued increase in the intergenerational gap in education (i.e. the fact that younger cohorts have quite higher proportions of educated individuals than older cohorts) and the reduction of the inter-gender one (thanks to the improvements in education) mean that a strong rise in supply of skilled individuals is coming. Even if educational policies and attainments were not to increase anymore in the future, this rise will be irreversibly brought about by aging. As the population ages younger, better-educated cohorts enter the workforce and older, less educated ones leave. This causes the average schooling of the working age population to increase. Importantly, this shock will not be uniform across countries. The higher level of education is only one part of the forthcoming wave; the other is the size of the younger cohorts relative to the older ones. Depending of what will happen on the demand side, the education and gender earnings premia will likely decrease with profound consequences for: (i) international trade patterns; (ii) global and local economic growth; (iii) inequality within countries; and (iv) inequality across countries (see, for examples on these issues, K. Edwards and A. Hertel-Fernandez, 2010; D. Blanchflower and R. Freeman, 1999; R. Shimer, 2001; R. Freeman, 2008). The forthcoming changes could be comparable to what Freeman (2007) called the “great doubling” when referring to the entry of about 1.5 billion workers (from China, India, and the former Soviet bloc) in the global labor market in the 1990s.

This paper uses and extends a modeling framework that includes the above features and that has been developed at the World Bank: the Global Income Distribution Dynamic (GIDD) modeling tool. The GIDD is first global microsimulation tool which combines a consistent set of price and volume changes from a global computable general equilibrium (CGE) model with microdata at the household level for the whole world. The GIDD should not be considered a forecasting tool: its objective is not to produce statistically efficient estimates of the future global income distribution, but to build alternative scenarios which are consistent with economic theory and initial observed values.

In order to construct ‘reasonable’ scenarios for the evolution of inequality and poverty – and in particular on the inequality impacts of demographic and educational changes – this paper has to rely upon a methodology that has three main features:

(a) it accounts for both the supply (education) as well as the demand (technology) sides, i.e. it has to be a general equilibrium approach;
(b) it incorporates both the dynamics effects at the aggregate or sectoral levels but has enough micro detail to capture changes in distribution of personal incomes at the household level;
(c) it has to be global in nature to make inferences on the prospects of inequality both within and across countries;

This essay makes several contributions to the prevailing literature on scenarios for the evolution of poverty and inequality. First, it takes into account demographical changes by different level of education attainment using a unique dataset that combines harmonized household surveys for approximately 130 countries. Second, it incorporates the effect of changes in wage skill premia and labor sector mobility on income inequality.

The remainder of this paper is organized as follows: Section 2 provides describes the observed pattern of global inequality in the last decades and explains how the education wave may impact inequality through labor market. Section 3 introduces the methodology used in the projections based on LINKAGE and GIDD framework. Section 4 describes the data and provides some descriptive statistics. Section 5 presents the empirical results and some robustness check. The last section concludes the paper.

2 Reshaping the World: global inequality and labor force composition

If we compare the path of inequality across the world since 1950 there were critical changes between or within countries and the outcome may depend on the concept of inequality adopted.[2] Milanovic (2013) suggests three concepts of global inequality: 1) Inequality across countries based on GDP per capita or average household income, without population-weighting; 2) Inequality across countries based on GDP per capita or average household income population-weighted; 3) Global inequality individual-based.

The first two concepts refer to inequality between countries, which is one of the components of global inequality based on individuals. From 1950 to 2000s there was a remarkable difference with respect to the pattern of inequality according to these different concepts. Inequality between countries population-unweight (concept 1) increased, while inequality between countries population-weight (concept 2) decreased. However, in the last decade (after 2000s) both concepts converged on the trends of a dramatic reduction on inequality (see Milanovic, 2013).

By taking into account the average income (population-weighted or not) we are considering only the between country component of global income distribution. The within country component of inequality is also critical and do not necessarily have a similar pattern. It is possible that a given low income country catch up those with higher income and at the same time it rises inequality among their own residents. Therefore, among these concepts of global inequality, the individual based (concept 3) is the only one that takes into account the between and within inequality across nations.[3] However, it requires a large amount of micro data (at household or individual level) allowing for international comparison.[4]

There are at least two important remarks that come from comparing these different concepts of global inequality: First, individual-based inequality is larger than if concepts 1 or 2 are taken into account;[5] Second, there was also a decreasing trend between 2000 and 2010 (see Milanovic, 2013 and Lakner and Milanovic, 2013) at individual level, but there was only a slight reduction if compared to the pattern using concepts 1 and 2.[6]

What can we expect for the next decades? In addition to the data constraint, in a forward looking perspective we also need to deal with "uncertainty". A reasonable approach is to

[2] Also, the source of information.
[3] The within component is part of the twin targets of the World Bank.
[4] A large effort has been done and the quantity (and quality) of the data has substantially improved.
[5] This is evidence that inequality within countries also matter for global inequality measures.
[6] This may suggest that within country component of inequality may have increased in this period. For example, the share of income hold by the top 1% in the USA rose dramatically (see Alvaredo et. al., 2013).

combine the enormous improvement on household surveys with a model that is consistent with economic theory in order to generate comparable scenarios that allows us to learn with potential outcomes. In this paper we argue that a critical channel to take into consideration is through changes in skilled labor supply driven by the combination of demographic changes and education attainment.

Developing countries have been growing faster than rich ones for long time.[7] In addition, their weight in the global economy has been increasing in terms of many different metrics: population, international trade, GDP, savings and investment. Due to the fact poor and populous countries have grown fast, global inequality has decreased, even if inequality within many countries has increased. What does the growing importance of developing countries as suppliers of skilled workers means for global inequality?

As the population ages younger, better-educated, cohorts enter the workforce and older, less educated, ones leave. This intergenerational education gap is one part of the education transition; the other is the size of the younger cohorts relative to the older ones. The average schooling of the working age population tends to increase (even without any additional education effort).

In sub-Saharan Africa, for example, some countries have experienced both an increase in the average years of education for the young, as well as larger pool of young workers. In Benin, for example, the difference in the average number of years of education for 25-29 years as compared to 60-64 year olds was in 1980 about 0.03 years (0.51 years-0.48 years). By 2010, this difference rose to 1.5. (The direction and magnitude of these differences are robust to wider cohort definitions.) Furthermore, the population ratio of 25-29 years old to 60-64 year old rose to 2.6 from 0.6 percent, during the same period. Indeed, this trend is followed by other countries such as Rwanda, Gambia, and Kenya. Most of the gains in rising educational attainment in Africa, however, are in primary and secondary education. There has been little movement in increasing the rates of tertiary education and beyond (with the exception of a few countries, like Gabon).

Since the 1980's, for most Latin American countries, the average number of years of education has been rising. In Bolivia, for example, the difference in the average number of years of education between young and old cohorts was 3.5 years. By 2005, this difference rose to over 5 years. That is, younger generations were acquiring 5 more years of education than their older counterparts. This trend is followed by Brazil, Mexico, Chile, among a few (albeit, with slight dips following 2000), and these increases are evident both in average years of schooling as well as in tertiary schooling. In Bolivia, the difference in the average number of years of tertiary education between young and old was close to zero but the difference rose to about a quarter of a year by 2005. In contrast with sub-Saharan Africa, in LAC the ratio of young to old cohorts is remaining constant or, for the majority of country, slightly declining. Therefore, while

[7] Insert references.

subsequent working age populations are becoming increasingly educated, their volume is not increasing.

Because China and India have been the drivers of declining global inequality as well as contributors to the global labor force, a pressing question is whether future generations will be able to supply enough skilled workers. In China, the overall rate of educational attainment has not been rising and neither has the supply of young workers. Some express concern that an increasingly inefficient Chinese labor force would need to be re-educated in order to remain competitive in the coming decades. India educational attainment has been rising, while the dependency ratio has stabilized. However, the rise in educational attainment has not been as remarkable as we might have expected. The difference-in-difference in the average number of years of education has risen by one year (the difference being 1.7 in 1980 to 3.0 in 2005 with a small increase in tertiary education, which pales in comparison to even some LAC countries.

In contrast to the developing world, OECD and transition countries are on a downward trend in terms of educational attainment. Younger generations are acquiring fewer average years of education than their elders. As Freeman (2005) discusses, the US' share of world enrollments in higher education has fallen from 29 percent in 1970 to 12 percent in 2006. Therefore, this education transition (or education wave) will not be uniform across countries and developing countries will play the leading role in this process. For this reason, it is necessary to add education by gender and age cohorts as demographic dimensions in forecasting [see Lutz, Goujon and Dobhammer-Reither (1999) and Lutz and Goujon (2001)].

Table 1 illustrates the demographic transition in a simple exercise. Let us separate the population of a given country in four groups according to their age (young/old) and years of schooling (unskilled/skilled) used as a proxy for level of skill. Let us assume working age populations from 15 to 65, where young are defined as workers from 15 to 39, while old are defined as workers from 40 to 64. Also, let us assume that this population is divided between 50% of young versus 50% of old people.[8] We observe that everything else constant, the young cohort in 2010 will replace the older one by 2030 and as a result the overall working age population gets more skilled.

Table 1: Global demographic transition (example)

Year 2010			
	skills		
	Skilled	Unskilled	Total
Young	60%	40%	100%
Old	30%	70%	100%
Total	45%	55%	100%

Year 2030			
	skills		
	Skilled	Unskilled	Total
Young	60%	40%	100%
Old	60%	40%	100%
Total	60%	40%	100%

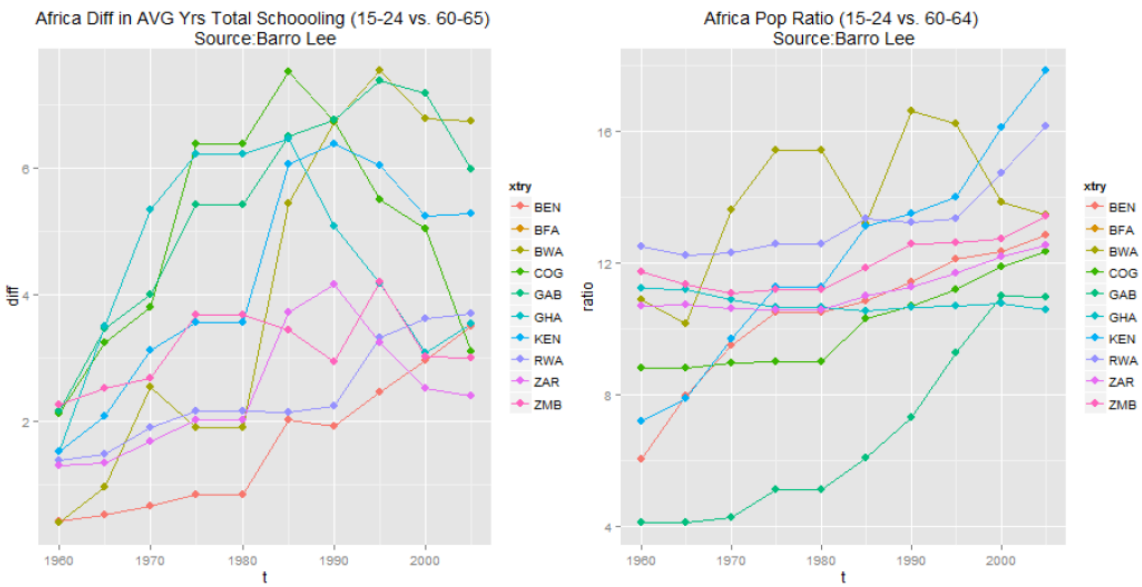
Source: Authors' elaboration

[8] Table 1 shows the share of skilled/unskilled workers according to each age group and the total.

Is this story consistent with the pattern recently observed in developing countries?

Figure 1 shows the educational transition in Sub-Saharan Africa. It is remarkable that the difference between the average years of schooling between a young cohort (15-24 years old) versus an old cohort (60-65 years old) has increased dramatically for the majority of countries. This means that the new generation that reaches the labor market is more educated that the older cohort that has been replaced in the labor force, which changes the composition of the labor force, as suggested in Table 1. This is also consistent with other regions (e.g. Latin America and Caribbean).

Figure 1: Education transition in Sub-Saharan Africa



Source: Authors' elaboration

It is well known that there is a strong (positive) correlation between level of education (measured by years of schooling) and income per capita. Richer countries also have a population with more years of schooling. Although this might be a common pattern resulted from the improvement of access to the education system, countries around the world are in different stages. For example, high income countries reached a condition where the level of education of their population in working age is as high as the new cohorts. At the same time, the fertility rate in developing countries is larger than in high income. Therefore, in the coming years the share developing countries on the global population will be larger and this new generation that are growing up will be more educated than the previous one.

We can expand the previous example (see Table 1) and decompose the global population in two groups of countries (developing and high income). The share of population from developing and emerging markets was approximately 86% in 2010. By 2030 they will represent about 88% of total population[9]. Let us keep these proportions and assume that the young cohort represents 50% of the working age population versus 50% of the old cohort. If we keep the share of skilled/unskilled workers constant in high income countries, the changes in the global labor force composition will be driven by the transition in developing countries.

Table 2: Global demographic transition decomposed in two groups of countries (example)

Year 2010 – Developing (86%)			
	skills		
	Skilled	Unskilled	Total
Young	55%	45%	100%
Old	20%	80%	100%
Total	37.5%	62.5%	100%

Year 2010 – High Income (14%)			
	skills		
	Skilled	Unskilled	Total
Young	90%	10%	100%
Old	90%	10%	100%
Total	90%	10%	100%

Year 2010 – Total (100%)			
	skills		
	Skilled	Unskilled	Total
Young	60%	40%	100%
Old	30%	70%	100%
Total	45%	55%	100%

Year 2030 – Developing (88%)			
	skills		
	Skilled	Unskilled	Total
Young	55%	45%	100%
Old	55%	45%	100%
Total	55%	45%	100%

Year 2030 – High Income (12%)			
	skills		
	Skilled	Unskilled	Total
Young	90%	10%	100%
Old	90%	10%	100%
Total	90%	10%	100%

Year 2030 – Total (100%)			
	skills		
	Skilled	Unskilled	Total
Young	60%	40%	100%
Old	60%	40%	100%
Total	60%	40%	100%

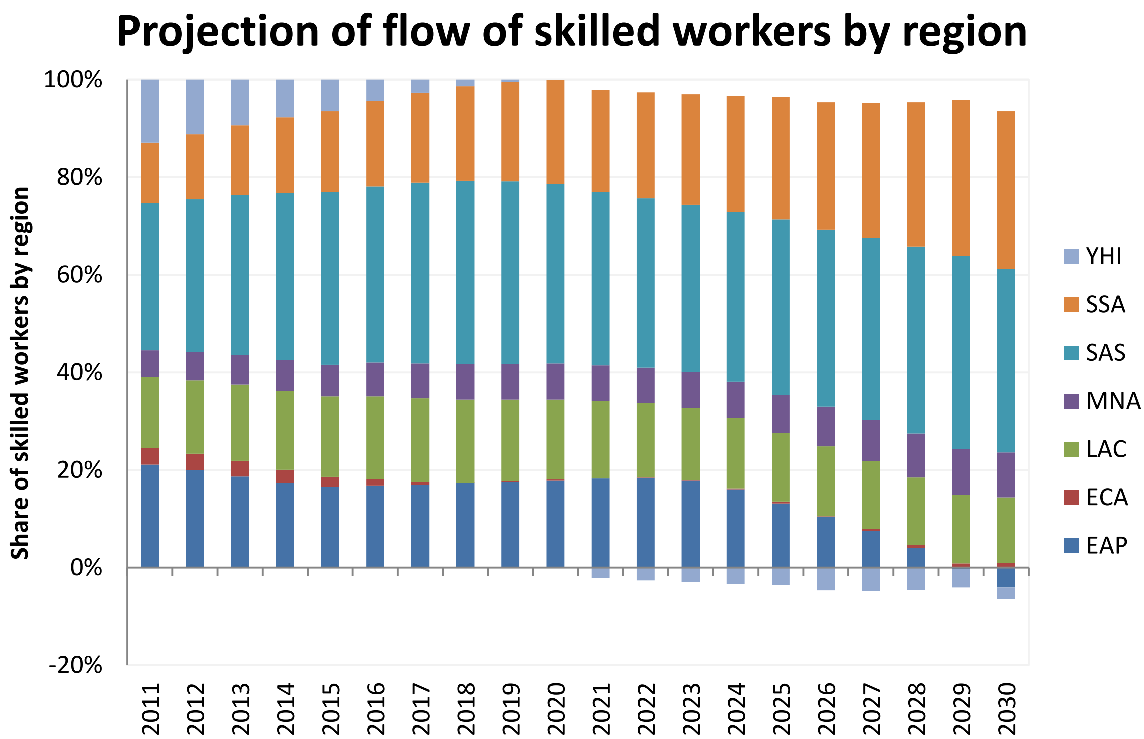
Source: Authors' elaboration

This hypothetical exercise in Table 2 emphasizes an important trend with respect to the labor market in the coming decades: **most of the changes in the global working age composition due to education attainment will come from the developing world.[10]** If we use a threshold of 9 years of schooling, the number of skilled workers will rise approximately 5% in high income OECD countries between 2010 and 2030, while it increases about 34% in developing countries in the same period (see Figure 2).

[9] According to the UN-WPP projections for 2030 (medium scenario). Division of the Department of Economic and Social Affairs of the United Nations Secretariat (2013). World Population Prospects: The 2012 Revision. New York: United Nations.

[10] For further details on the projection of population by gender, age cohort and education attainment; see the demographic pyramids (Figure 12) on the Appendix (A1).

Figure 2: Share of the projected flow of skilled and workers (by region)



Source: GIDD projections
Note: YHI: High Income countries, SSA: Sub-Saharan Africa; SAS: South Asia;

What does the increase of skilled labor supply driven by developing countries mean for inequality? Following the discussion on section 2, we should consider three channels: a) The effect of this process in inequality within countries; b) The effect on inequality between countries; c) The effect on global inequality.

To begin with, keeping everything else constant, an increase in the entrance of educated people in the labor market may reduce the wage skill premia.[11] The difference of wages between skill levels (and sectors of employment) of workers is remarkable particularly in developing countries. Even ex-post, skill and sector wage premia (and their changes) account for large amount of total inequality (changes). Therefore, an expected outcome from these changes in the labor supply is that it may shrink the wage gap and diminish labor income inequality. In this regard, it is important to highlight that labor income is the main source of income for the majority of population around the world.

The change in wage premia, the sector reallocation and the changes in the size of each worker's cohort (by sector and level of skill) are the main drivers used by GIDD to explain inequality dynamics. On the one hand, an increase in the entrance of educated people in the labor market may reduce the wage skill premia within a sector (e.g. the wage gap between skilled and

[11] An important discussion in the literature regarding wage skill premia refers to technological skill bias.

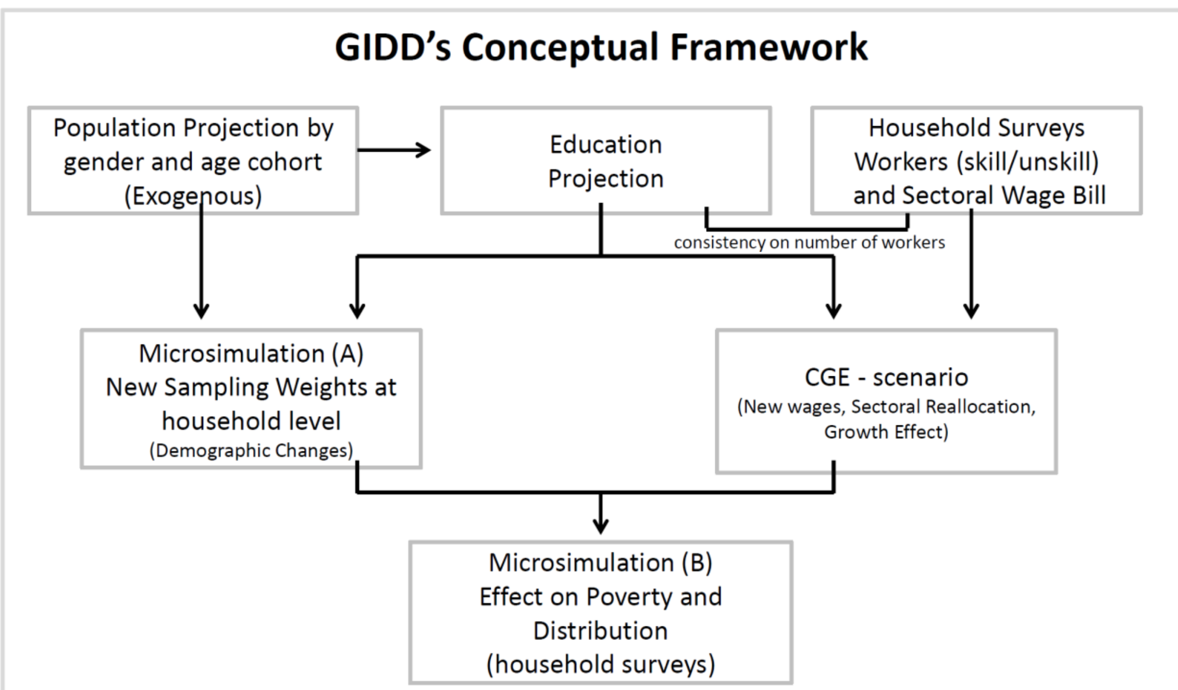
unskilled workers in agriculture will shrink). On the other hand, the demand towards more intensive skilled sectors will motivate workers' migration between sectors (e.g. from agriculture to non-agriculture activities). In addition, the education wave will increase the share of people among the skilled workers.

In order to capture the effect of this labor supply shock on relative prices between sectors and level of skill in a forward looking perspective, it is necessary to put together the demand and the supply side in a general equilibrium setting, for which the well-established empirical tool is the Computable General Equilibrium (CGE) model (see Bourguignon et. al., 2008). Then it is necessary micro data (e.g. household surveys) in order to transmit this shock at the micro level (e.g. individual or household levels). The following section provides details about the framework used in GIDD model to analyze macro shocks on a micro approach.

3 Model background (GIDD and LINKAGE)

The Global Income Distribution Dynamic (GIDD) is the first global microsimulation tool which combines a consistent set of price and volume changes from a global computable general equilibrium (CGE) setup with household surveys at the global level (see Bussolo et. al. 2010).

Figure 3: GIDD framework



Source: Author's elaboration based on Bussolo et. al. 2010

The GIDD projection is composed by five main steps (see **Error! Reference source not found.**):

a) First, we generate a projection of population by gender, age cohort and education attainment by interacting the UN-WPP projection with detailed information on years of schooling that are available on the household surveys (see Bussolo et. al., 2014a). This projection incorporates the fact that every year there is a new cohort of younger workers that replace an older cohort in the working age population[12]. This population projection plays two different roles in GIDD model. Firstly, it is used to generate an exogenous shock of skilled relative to unskilled labor supply to project CGE's scenarios (see c). Secondly, the demographic composition projection is also used for re-sampling the household surveys (see d);
b) Second, we build a new data set on sectoral wage bill split by years of schooling as proxy for different level of skilled workers (see Cruz et. al., 2014). There are two main advantages of this definition for skilled workers[13]: i) The initial volume of workers is consistent with what can be observed in household surveys; ii) It allows incorporating projections of growth in the number of skilled and unskilled workers. This data is used to split the share of value added by skilled and unskilled workers in a given sector. This procedure aims to guarantee the consistency for the initial condition of the wage skill premia for each sector between the input-output matrix data and the household surveys[14].
c) Third, we use the population projection and the sectoral wage bill as inputs to run the LINKAGE[15] model and project CGE's scenarios. The outcome will provide the volumes (labor units[16]) and the new set of wage-price for each group of workers (skilled versus unskilled) by different sectors (agriculture versus non-agriculture) relative to unskilled workers in agriculture, which is used as a *numéraire*.
d) Fourth, the household surveys are reweighted using a non-parametric procedure based on the population projection.[17] This method attributes more weight for individuals that become more representative in the new projected population, keeping constant the household structure. As an example, if the population projection for a given country shows that the share of female individuals between 30 and 35 years old with more than 9 years of schooling increases from 2010 to 2030, the re-weighting procedure will incorporate this change.
e) Finally, the LINKAGE results combined with the re-weighed sample are used for running the GIDD microsimulation. We do so by transmitting the shocks from CGEs' scenarios to

[12] We call this process as a pipeline effect.
[13] A definition of skilled workers based on occupation results from the interaction of the supply of workers of different level of skills and the demand for a given position, such as management.
[14] In Cruz et. al., 2014 we provide further details on the comparison between the sectoral wage bill generated by household surveys and the input-output matrix provided by the Global Trade Analysis Project (GTAP).
[15] LINKAGE model is a global dynamic computable general equilibrium (CGE) model maintained by the World Bank to support global trade policy analysis. For further details on LINKAGE methodology, see Van Der Mensbrugghe (2011).
16 In the current version of LINKAGE/GIDD model the actual (absolute) number of workers has been used as labor unit. The initial volume in the model was generated from household surveys. For further details, see Cruz et. al. 2014.
[17] See further details in appendix.

the reweighted household surveys and analyze their impact on poverty and income distribution.

There are four main outcomes from LINKAGE used in GIDD: i) changes in the number of workers between sectors, which means how many workers moved from to the shrinking sector (e.g. agriculture) to the expending sector (e.g. non-agriculture); ii) changes in relative average wage-prices with respect to sector and level of labor skill; iii) aggregated shocks (e.g. GDP per capita growth, consumption per capita growth); iv) relative prices of food with respect to non-food goods.

Therefore, there are two main channels through which aggregated shocks from LINKAGE global CGE model affects within-country income distribution in GIDD: a) Factor returns (W): GIDD accounts for changes in the wage skill and sector premia; b) Quantity (L): GIDD allows for labor mobility between sectors. Whereby, (W) and (L) are equilibrium level of wages and number of workers, consistent with supply and demand given by LINKAGE model.

Due to the fact the shocks transmitted at the household level are homogeneous within each group of workers according to the level of skill and sector, **without the sector mobility component, inequality within the 4 groups of workers (agri, nonagri | skilled, unskilled) remains constant**. Therefore, a straightforward questions is how much of inequality is attributed to the between sector-skill level component, which is captured by the model? Indeed, the urban-rural gap in living standard still seems to explain an important component of inequality. Young [2013] used the Demographic and Health Surveys for 65 countries and found that the urban-rural gap accounts for 40% of mean country inequality and much of its cross-countries variation. If we decompose a generalized inequality index as a function of (α), such that α= 0, we have:

$$GE(\alpha) = \frac{1}{\alpha(\alpha-1)}\left[\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i}{\bar{y}}\right)^{\alpha} - 1\right] \quad (4)$$

$$GE(\alpha) = \underbrace{\sum_{k=1}^{m}\left(\frac{\bar{y_k}^{\alpha}}{\bar{y}}\right)\left(\frac{n_k}{n}\right)^{1-\alpha} GE(\alpha)_i}_{\text{Within Inequality}} + \overbrace{\frac{1}{(\alpha^2-\alpha)}\left[\sum_{k=1}^{m}\frac{n_k}{n}\left(\frac{\bar{y_k}^{\alpha}}{\bar{y}}\right) - 1\right]}^{\text{Between Inequality}} \quad (5)$$

If we assume $\alpha = 0$m then:

$$GE(_0) = \underbrace{\frac{n_k}{n}GE_0^k}_{\text{Within}} + \overbrace{\frac{n_k}{n} ln\left(\frac{\bar{y}}{\bar{y}_k}\right)}^{\text{Between}} \quad (6)$$

The main component captured by GIDD that brings important implications to within country is relative changes between groups of workers (agri, nonagri | skilled, unskilled).[18]

4 Data and descriptive statistics

The GIDD dataset is derived from household surveys (HS) harmonized and available on the International Income Distribution Database[19] (I2D2). It provides a cross section of surveys using 2007 as a baseline.[20] 12.5 million individuals are sample in 128 countries. The household level data covers 85% of GDP and 90.3% of global population[21] (see Table 3). Furthermore, the coverage of GIDD with respect to household surveys is large for most of the regions, both in terms of population and GDP.

Table 3: Coverage of the dataset (at household level)

World Bank Region	GIDD				
	GDP PPP$ (billions)	GDP PPP$ (%)	Population (millions)	Population (%)	Observations
World	53,064	84.8	5,976	90.3	12,532,755
Developing Countries	21,213	91.8	4,987	92.8	7,301,369
EAP	8,766	96.1	1,819	94.7	1,122,317
ECA	1,951	85.0	206	78.3	340,873
LAC	4,546	99.8	536	97.6	2,260,235
MNA	870	44.7	198	63.7	748,036
SAS	3,721	99.9	1,542	100.0	1,105,989
SSA	1,360	91.6	686	86.9	1,723,919
High Income	31,851	80.7	989	79.8	5,231,386

Source: Author's elaboration based on I2D2

From these surveys we first extract information on individuals' age, employment status, sector of activity, years of schooling and wage to project the population growth by school attainment (Bussolo et. al., 2014a) and the sectoral wage bill database (Cruz et. al., 2014). These pieces of

[18] **Error! Reference source not found.** There is a negative correlation between level of GDP per capita and the hare of the between component of Theil-inequality (results are available under request).

[19] The I2D2 resulted from a World Bank project aiming to collate, harmonize and make accessible comparable information from household surveys held by the World Bank, for poverty, inequality, education, demographics, and labor market analysis. For further details on I2D2, see Montenegro and Maximilian (2008).

[20] For each country it was chosen the closest survey of 2007 to be consistent with the database used in the LINKAGE model. From this dataset we derived the GIDD Sectoral Wage Bill database (Cruz et. al., 2014) and the GIDD Population Projection by school attainment (Bussolo et. al., 2014a).

[21] If Japan and Switzerland are included with aggregated information generated from household surveys, using the Luxemburg Income Study dataset, the GDP coverage increases to approximately 93%.

information are provided to LINKAGE model in order to establish consistency between the skill definition and volume of workers between the CGE model and the microsimulation.

The definition of skilled workers is based on years of schooling (the threshold is above 9 years of schooling). This definition allows incorporating changes in labor supply resulted from education attainment, which is more appropriate for policy analysis, by assuming a direct channel between education and level of skill. One of the issues to deal with this approach is the discretionarity regarding a comparable global threshold of school attainment to define labor skill. Let alone the difference in terms of quality of education among different countries.

Table 4: Share of workers by region, sector of activity and skill level

Regions	AGRI (%)		NAGRI (%)		Number of (paid) workers (million)		
	Skill	Unskill	Skill	Unskill	Skill	Unskill	Total
EAP	3.50	34.02	27.48	35.00	554.6	333.1	887.7
ECA	5.30	9.39	67.11	18.21	48.0	8.3	56.3
LAC	1.46	11.39	44.96	42.18	183.8	27.1	210.9
MNA	1.85	10.17	45.67	42.30	40.7	5.6	46.3
SAS	5.23	34.49	23.69	36.59	278.8	183.7	462.5
SSA	4.46	37.50	22.73	35.30	98.3	71.0	169.3
High Income	2.05	1.22	84.10	12.63	405.8	13.7	419.6
Total (number)	3.48	25.05	39.89	31.59	1,610.0	642.5	2,252.5

Source: Author's elaboration based on GIDD-dataset

Table 5: Average wage and skill premia by region (US$ of 2007)

Regions	AGRI		NAGRI		Skill premia		
	Skill	Unskill	Skill	Unskill	Skill	Unskill	Total
EAP	95	70	231	116	1.35	1.65	3.28
ECA	177	129	288	195	1.37	1.51	2.22
LAC	480	221	583	300	2.17	1.36	2.64
MNA	93	80	169	121	1.16	1.51	2.11
SAS	81	57	109	66	1.42	1.15	1.90
SSA	141	53	212	102	2.67	1.94	4.01
High Income	2,014	1,285	2,506	1,462	1.57	1.14	1.95
Total (number)	594	374	787	448	1.59	1.20	2.11

Source: Author's elaboration based on GIDD-dataset

Note: the list of countries used in the descriptive statistics is in section ( ) of the appendix.

Table 4 shows the share of workers by sector (agriculture and non-agriculture) and skill level for 2007. It is noticeable that the share of skilled workers is much larger in high income countries and ECA region. If we take three regions (EAP, SAS and SSA) together they had approximately 96% of the people living below poverty line[22] in 2008. In all of these regions more than 34% of the paid workers are unskilled and work in agriculture.

Some important channels through which changes in the composition of labor supply (due to demographic transition and increasing in education attainment) can affect income inequality in the long run is through how the movements of workers between these cells (agri, nagri | skilled, unskilled) may affect labor income distribution. This outcome is expected as far as we observe wage premia regarding to education and sectoral mobility. First, it shows that there is a remarkable difference between average wages of workers (conditioned on their level of skill) between regions23. An average unskilled worker in non-agriculture in high income countries has a wage that is significantly larger than an average skilled worker in a non-high income economy24. In addition, it is noticeable that there is a wage skill premia for both sectors25 and a sectoral wage premia for both levels of skills.

5 Empirical Results

This section presents the empirical results from LINKAGE's scenario and the GIDD's microsimulation. The LINKAGE model is a global, multi-region, multi-sector, dynamic applied general equilibrium model. Therefore, its scenarios provide many outcomes of interest. In this section we focus on the outcomes related to the shocks transmitted to the households through GIDD (e.g. GDP and consumption growth, changes in relative wages and workers' sectoral reallocation.)

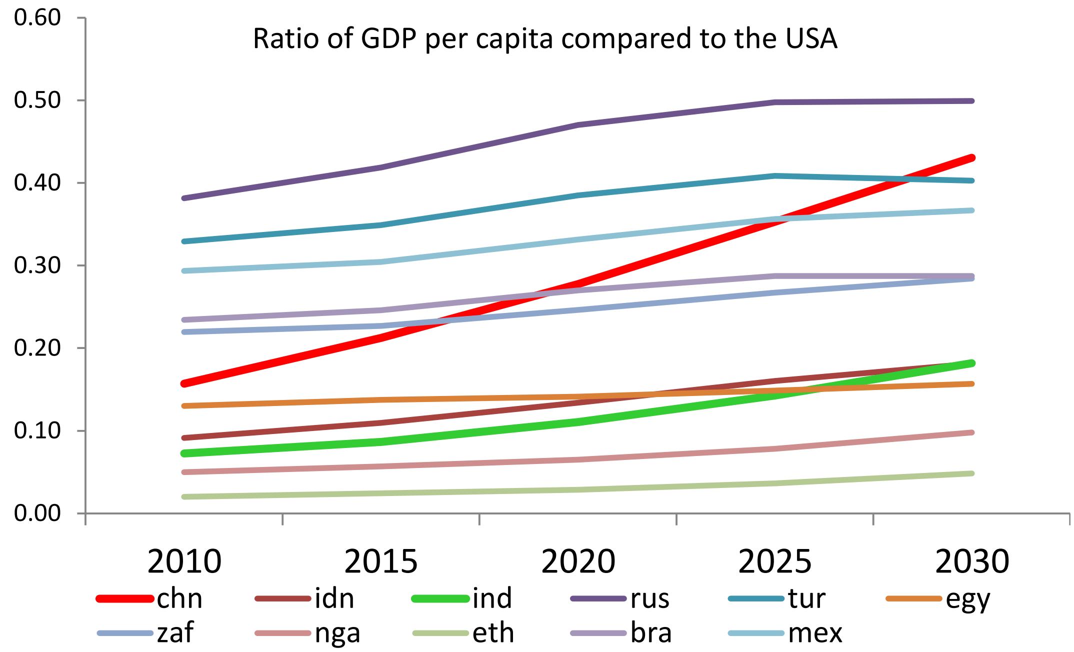
5.1 LINKAGE: the baseline scenario

To begin with, we can emphasize two important results with respect to global income distribution projection for 2030. First, there is a trend of convergence in the GDP per capita between major emerging countries and the USA (see

Figure 4). The fact that we observe a convergence trend regarding income per capita means that the between (countries) component of global inequality will decrease. Indeed, this has been a critical determinant of reduction on inequality observed in the last decades.

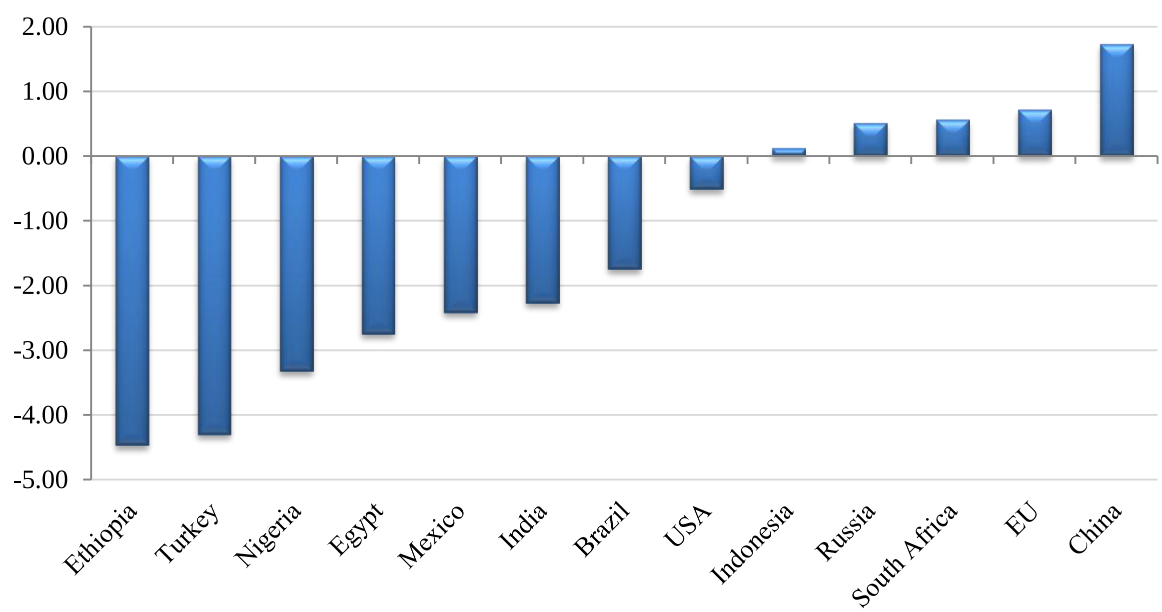
[22] According to POVCALNET 2008.
[23] This heterogeneity is also large within regions and within countries. These differences are representative for the between component of global income inequality.
[24] This is not under PPP.
[25] The wages for skilled workers in agriculture are higher than the wages for unskilled workers in the same sector. The same happens in non-agriculture activities.

Figure 4: Growth and Convergence (2010-2030)



Source: Author's elaboration based on LINKAGE projections

Figure 5: Change in Wage Skill Premia (% difference 2030-2011)



Source: Author's elaboration based on LINKAGE projections

The wage skill premia in the agricultural sector shrinks for most of the countries, but not for Indonesia, Russia, South Africa, European Union[26] and China (see Figure 5). However, for some countries like China, the fact that there is an increase on the wage skill premia may result in an increase of inequality within the country.

Table 6: Projected share of workers by region, sector of activity and skill level (2030)

Regions	AGRI (%)		NAGRI (%)		Number of (paid) workers		
	Skill	Unskill	Skill	Unskill	Skill	Unskill	Total
EAP	3.36	30.20	29.76	36.68	587.9	296.9	884.7
ECA	4.90	8.94	68.31	17.85	49.7	8.0	57.6
LAC	1.60	9.62	50.13	38.66	261.4	33.0	294.4
MNA	1.48	7.23	52.48	38.81	72.3	6.9	79.2
SAS	4.88	32.28	27.26	35.58	331.3	195.9	527.3
SSA	4.07	33.67	24.26	38.01	230.1	139.5	369.5
High Income	2.00	0.96	86.75	10.30	425.4	13.0	438.3
Total (number)	3.32	22.83	41.70	32.16	1,958.0	693.1	2,651.1

Source: Author's elaboration based on GIDD-dataset

Table 6 shows the projection for paid workers by sector and level of skill for 2030 and Table 7 shows the variation in the sectoral and skilled level composition by region, based on LINKAGE's scenario and GIDD's simulation. The most remarkable changes are related to decreasing in the unskilled workers in agriculture vis-à-vis an increasing of the share of skilled workers in non-agriculture activities.

Table 7: Changes in the share of workers by region, sector of activity and skill level (2030)

Regions	AGRI (%)		NAGRI (%)		growth rate (paid workers)		
	Skill	Unskill	Skill	Unskill	Skill	Unskill	Total
EAP	-0.14	-3.82	2.28	1.68	1.06	0.89	1.00
ECA	-0.40	-0.45	1.21	-0.36	1.03	0.97	1.02
LAC	0.14	-1.78	5.16	-3.52	1.42	1.22	1.40
MNA	-0.37	-2.94	6.81	-3.50	1.78	1.24	1.71
SAS	-0.35	-2.21	3.57	-1.01	1.19	1.07	1.14
SSA	-0.39	-3.83	1.52	2.70	2.34	1.96	2.18
High Income	-0.05	-0.26	2.65	-2.33	1.05	0.94	1.04
Total (number)	-0.16	-2.22	1.81	0.57	1.22	1.08	1.18

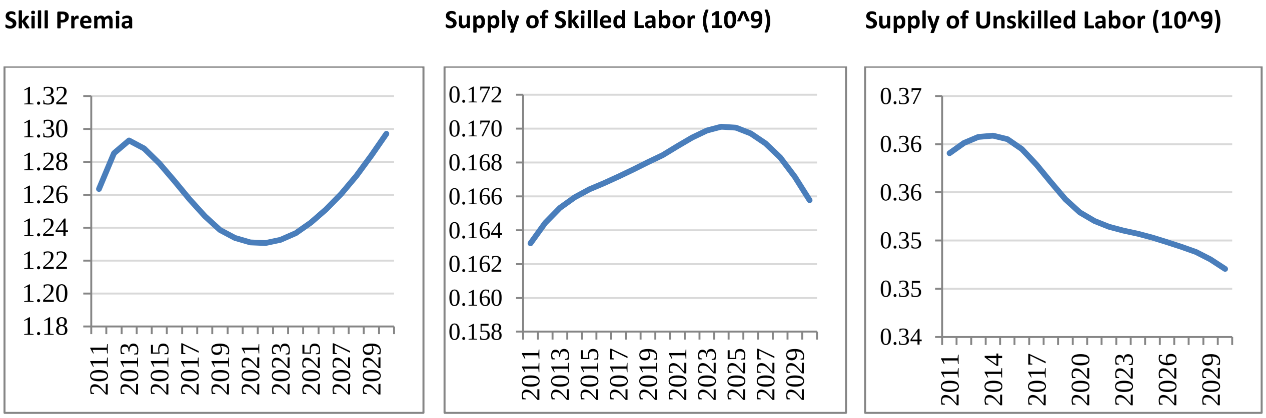
Source: Author's elaboration based on GIDD-dataset

Due to the importance of China (in terms of population and economy sizes) it is worth to investigate further the reasons why the wage skill premia goes up in China.

[26] Add further details on the estimation for European Union.

Figure 6 shows a non-linear trend in the skill premia for China between 2011 and 2030, switching from a jump in the first coming years, followed by a reduction between 2013 and 2020 and a new increasing trend after 2023. This is consistent with the fact that the supply of unskilled workers goes in the same direction of skilled (in increases) in the first two years of the projection and the supply of skilled workers decrease after 2023.

Figure 6: Supply and Wage Skill premia in China



Source: Author's elaboration based on LINKAGE projections

In addition to the supply side (number of skilled/unskilled workers), it is also important to understand the demand behavior with respect to the labor market for different sectors in order to disentangle the effect on the average wage skill premia. In the context of a general equilibrium setup this is critical because an increasing in the relative supply of skilled workers should be follow by raising the demand for this workers in sectors with higher skill intensity (e.g. services against agriculture).[27] In case there is not enough expansion of demand for skilled workers, the wage skill premia can be remarkable smaller. We show in appendix (section A2) that the ratio of skilled by unskilled workers in services is much larger than in agriculture and the share of consumption on services has increased in most of the regions.

5.2 GIDD results: The effect on global income distribution

Using the LINKAGE baseline scenario we can project the effect of the "education wave" on the global income distribution. In section 3 we describe the main mechanism through which shocks from CGE are transmitted at the household level. According to the baseline scenario, the world will become more equal (see Table 8). The (individual-based) Gini index reduces from 0.75 in 2007 to 0.68 in 2030.

[27] Even though the extensive literature using firm level data has been showing that firms are very heterogeneous even within a narrow definition of sector, there is a large evidence that on average firms with

Using the Theil index it is possible to decompose inequality between and within countries.[28] The reduction in inequality is mostly driven by the component between countries, which are mainly explained by differences in economic growth. Also, the ratio between the income per capita of those on the 75th percentile of the distribution and those in the 25th percentile reduces from 5.87 to 5.57. Regarding poverty headcount, results suggest that the share of poor individuals living below the poverty line (1.25 daily international dollars under PPP) goes down from about 22% in 2007 to XX% in 2030.

Table 8: Effect of education wave on global inequality

Global Inequality	global		change
	2007	2030	(2030-2007)
Gini index (%)	0.75	0.68	-0.07
GE(1) (Theil-T) (%)	1.31	1.09	-0.22
Between - GE(1) (Theil) (%)	0.94	0.69	-0.25
Within - GE(1) (Theil) (%)	0.37	0.40	0.03
P75P25	5.87	5.57	-0.30
MEAN	388.56	668.69	280.13
Coefficient of Variation	3.52	3.56	0.04

Source: Author's elaboration based on Linkage and GIDD projections

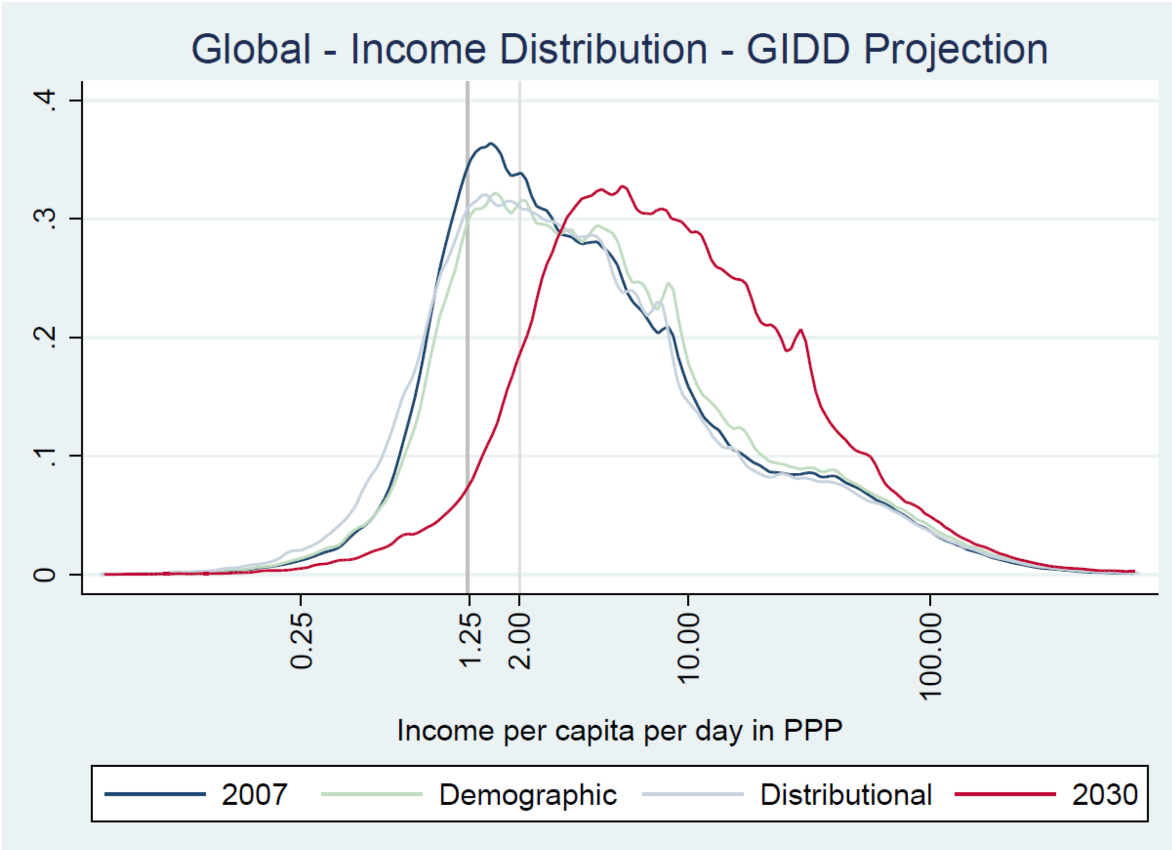
Figure 7 shows the expected effect on global income distribution decomposed by demographic effect, changes in relative wages effect (distributional) and growth effect. If we compare global income distribution in 2007 with the projection for 2030, we observe that the base seems slightly wider, the hump in the right hand side seems to disappear, and the slope of the kernel density function in 2030 is not as steeper as in 2007when it crosses the poverty line (1.25 daily international dollar under PPP). A potential consequence is that the share of population living below poverty line (headcount) becomes less sensitive to economic growth shocks with neutral distribution[29].

The demographic effect refers to changes in the distribution related to the reweighting the household sample. Individuals those become more representative in the projected population for 2030, according to their age-cohort, gender and school attainment have their weight increased in the projection for 2030. This procedure itself has a distributional effect. A second channel of changes comes from changes in relative wages and sectoral migration (e.g. workers moving from agriculture to non-agriculture sectors). Finally, the difference between demographic and relative wage changes comes from economic growth, which is not necessarily neutral with respect to global income distribution due to the between effect.

[28] The Theil index allows for inequality decomposition between and within countries.

[29] If you move the distributions keeping the same shape, (e.g. a given economic growth with homogenous effect on household income per capita) the share of people out of poverty would be smaller under the 2030's distribution.

Figure 7: Projection of Global Income Distribution (2007-2030)

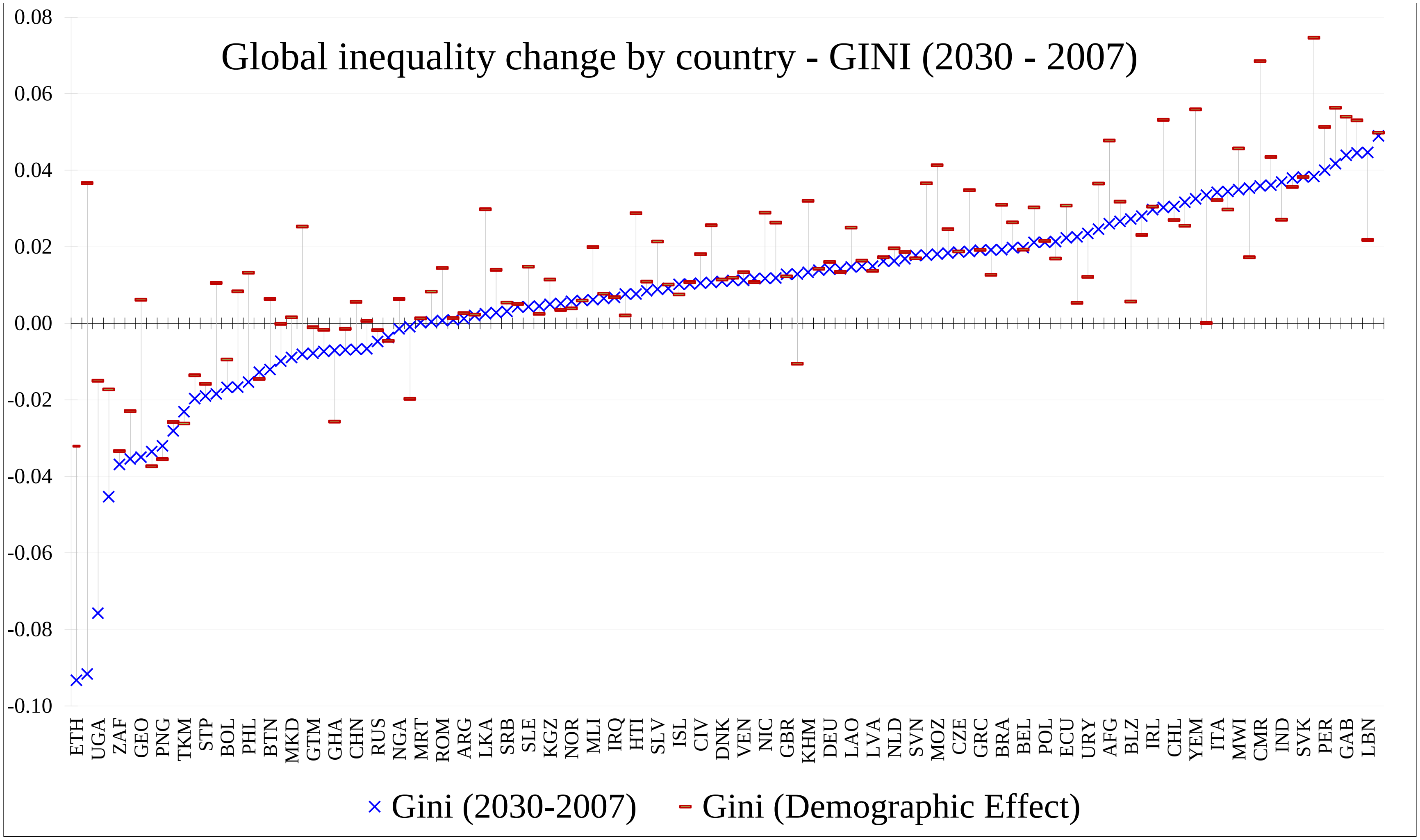


Source: Author's elaboration based on Linkage and GIDD projections

Figure 5 provides an aggregate picture of global income distribution, but it is not informative to understand the effect in individual countries. A high economic growth in populous countries like India and China can have important implication on reducing global income inequality through the between countries' component, but do not necessarily result in more equality within these countries.

In this regard, an advantage of the GIDD framework is the large coverage in terms of data (about 130 countries) allows incorporating demographic, labor reallocation and relative price shocks for individual countries at the household-level. While the poverty target of the World Bank group is at the global level, the goals on shared prosperity are related to inequality within countries. Figure 8 shows the projection for the changes in the Gini index from 2007 to 2030 by country. We observe that inequality increases in a large amount of nations. In addition, in some cases like in India, the demographic effect goes towards different directions.

Figure 8: Global inequality changes by country



Source: Author's elaboration based on GIDD projections.

5.3 What are the channel driving the results?

Section 3 shows that there are three important channels through which shocks transmitted at the household-level may affect inequality: a) demographical changes; b) relative wage; c) sectoral reallocation; d) growth. The last one affects global income inequality through the between country component, but not within country.

The demographic changes play a critical role in this process. On the one hand, the demographic projections are used as a labor supply shock of skilled workers in the CGE model. On the other hand, it is used for reweighting household surveys in order to provide a structure consistent with projected demographic structure with respect to gender and age. Therefore, there are two channels through which demographic changes act in GIDD's framework, which requires a careful procedure for avoiding double effect of a single shock. Also, due to the fact the shocks are not applied simultaneously in the microsimulation, it is feasible to decompose them.

First, what is called "demographic effect" in the previous sub-section refers to changes in income distribution resulted from reweighting the household surveys, keeping everything else constant. This procedure captures the fact that in those countries with demographic transition in place: 1) The share of working age population will likely be larger; 2) The share of skilled workers will be larger. By taking these factors into account the reweight procedure affects income distribution because it increases the weight of skilled working age population. By doing so, it may change the sectoral composition of workers based on their demographic characteristics (gender, age and schooling). (see Bussolo et. al., 2007)

Therefore, when the CGE's shocks on sectoral number of workers (agriculture and non-agriculture) are transmitted to the household level, the reallocation takes into consideration the reweighting process. Therefore, the number of workers in each sector matches the CGE's scenario. Although these changes take place simultaneously, in the GIDD framework they are accommodated in a sequentially, which allows to decompose the effect that comes from each process.

Due to the fact that households are wage (price) takers in the microsimulation, the LAVs regarding relative wages and growth should have no effect on income distribution within workers' cohort (skilled, unskilled | agriculture, non-agriculture). Yet, sectoral workers reallocation and the reweight procedure generate important changes within groups.

Table 9 illustrates the variation in the Gini coefficient within workers' cohort comparing different sequences of the microsimulation with the initial condition. First of all, the reallocation of unskilled workers from sector A to sector N impacts the distribution within both cohorts (UA and UN). The first column shows the variation in Gini within cohort when unskilled workers in agriculture that were reallocated to non-agriculture are excluded from the sample. Therefore, using initial weights (2007) without those workers that were reallocated affect inequality only in the UA group. Column (2) shows the variation in Gini within cohorts keeping the same sample used in column (1), the same weights (2007) but the new income per capita in 2030, after the relative wage's and economic growth shock. It is noticeable the effect observed in column (2) is similar to column (1). The changes in both columns are driven by the exclusion of workers that are reallocated from agriculture to non-agriculture. Column (3) keeps the income per capita (2030) assigned after the relative wage and GDP growth shocks and reallocates the unskilled workers (excluded in columns 1 and 2) from agriculture to non-agriculture. We observe that inequality changes only to the UN cohort, if compared with columns (1) and (2). Column (4) shows the Gini by cohort using the same sample of column (2) and the new weight (after reweighting). Column (5) shows the Gini by cohort using the same sample of column (3) and the new weight (after reweighting).

Table 9: Variation of Gini within group of workers (skilled, unskilled | agriculture, non-agriculture)

	China					India				
Groups	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
UA	0.5%	0.5%	0.5%	0.4%	0.4%	-1.0%	-1.0%	-1.0%	-5.1%	-5.1%
UN			-0.2%	-1.3%	-1.9%			-0.6%	-5.5%	-5.1%
SA				4.3%	4.3%				-9.5%	-9.5%
SN				0.1%	0.1%				-0.9%	-0.9%
	Brazil					Nigeria				
Groups	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
UA	1.1%	1.1%	1.1%	4.0%	4.0%	3.2%	3.2%	3.2%	4.3%	4.3%
UN			-0.5%	-2.5%	-2.9%			-0.6%	-1.5%	-1.8%
SA				-3.8%	-3.8%				0.5%	0.5%
SN				-5.1%	-5.1%				-3.0%	-3.0%
	Mexico					Indonesia				
Groups	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
UA	-0.4%	-0.4%	-0.4%	-16.8%	-16.8%	0.9%	0.9%	0.9%	-0.9%	-0.9%
UN			0.1%	-4.9%	-4.8%			-0.1%	-2.0%	-1.9%
SA				-8.7%	-8.7%				-8.9%	-8.9%
SN				-4.6%	-4.6%				-1.7%	-1.7%
	Russia					Ethiopia				
Groups	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
UA				0.0%	0.0%	0.0%	0.0%	0.0%	-4.1%	-4.1%
UN	5.2%	5.2%	5.2%	7.9%	7.9%			0.0%	2.6%	2.6%
SA			-0.2%	1.6%	1.1%				32.0%	32.0%
SN				0.6%	0.6%				8.6%	8.6%
	Egypt									
Groups	(1)	(2)	(3)	(4)	(5)					
UA	0.0%	0.0%	0.0%	5.8%	5.8%					
UN			0.0%	6.7%	6.7%					
SA				-10.1%	-10.1%					
SN				-4.4%	-4.4%					

Source: Author's elaboration based on GIDD projections

Note: UA: unskilled workers in agriculture; UN: unskilled workers in non-agriculture; SA; skilled workers in agriculture, SN: skilled workers in non-agriculture

These exercises in Table 9 show that there are some important changes on inequality within workers cohort due to reweighting the household surveys. In the case of India, for example, it has important implications for inequality within skilled workers in Agriculture.

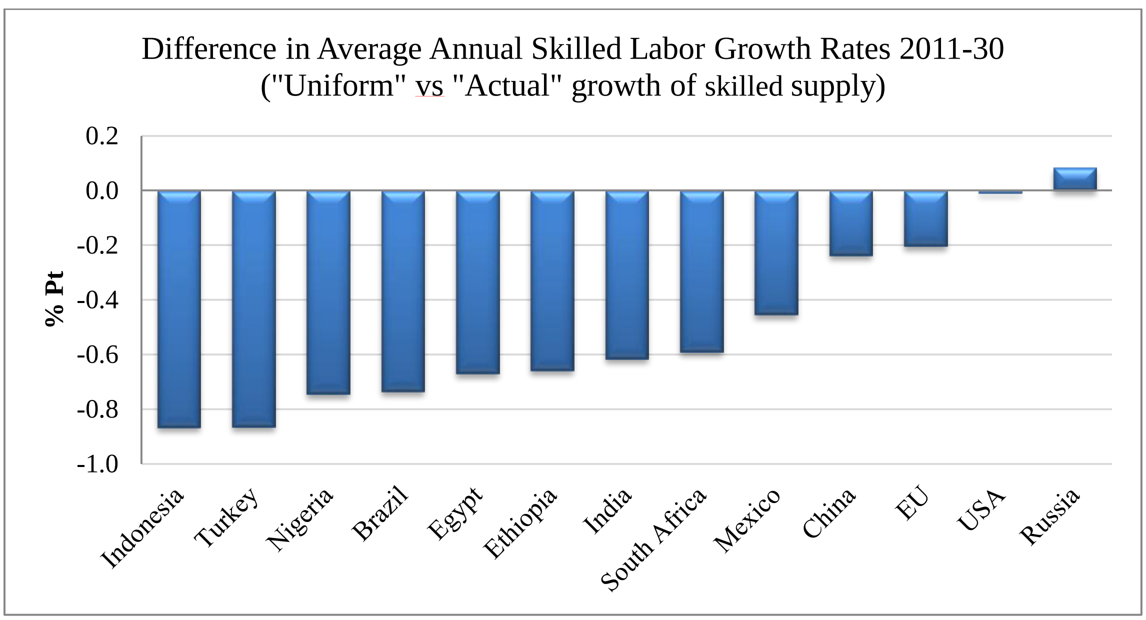
5.4 Robustness check

A critical feature of our baseline scenario is that the education wave will generate an increase in the supply of skilled workers relative to unskilled ones and this process will be driven by demographic transition taking into account higher level of education attainment of younger generations in developing and emerging countries. As a counterfactual, we run an alternative scenario where we assume that the growth rates of skilled /unskilled workers are the same. Therefore, there are no changes in the relative supply of workers.

In this case, the supply shock is (mostly) eliminated. Note that the total working age population (skilled + unskilled) grows at the same rate in this alternative scenario. All other exogenous variables are the same as in the previous scenario. Figure 9 shows that the annual growth rate of skilled workers is smaller in the alternative scenario, except for Russia, where the share of skilled workers is smaller in the younger cohorts. Also, Figure 10 shows that the economic growth is smaller and

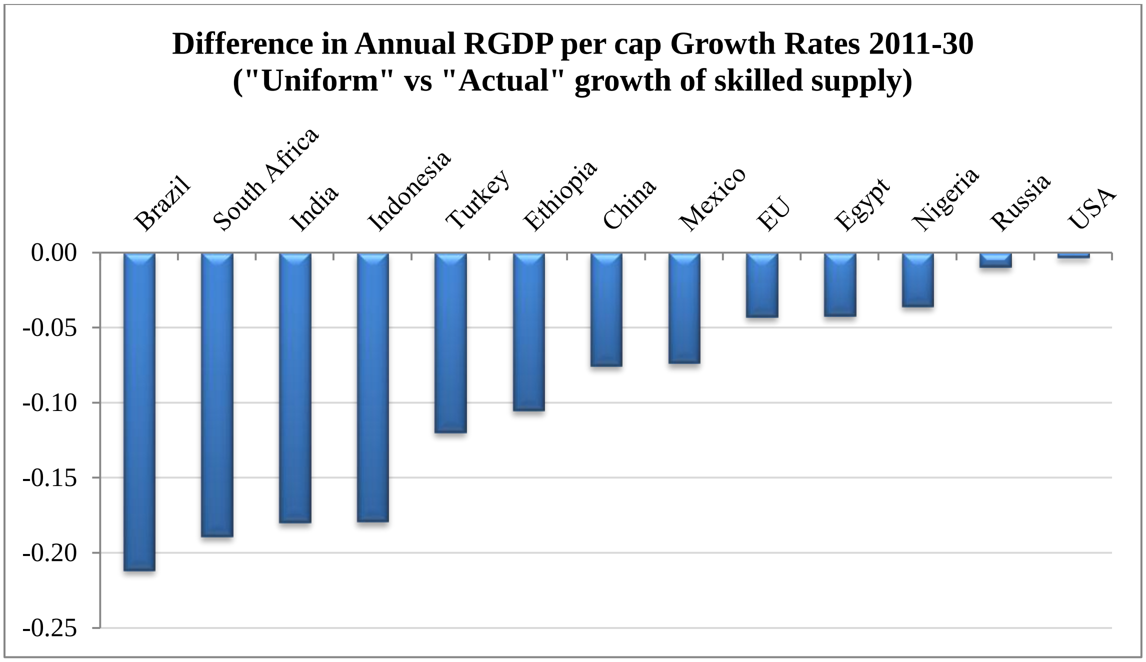
Figure 11 shows that the wage premia is higher, in the second scenario (keeping the share of skilled workers constant).

Figure 9: Difference in average annual skilled labor growth rates



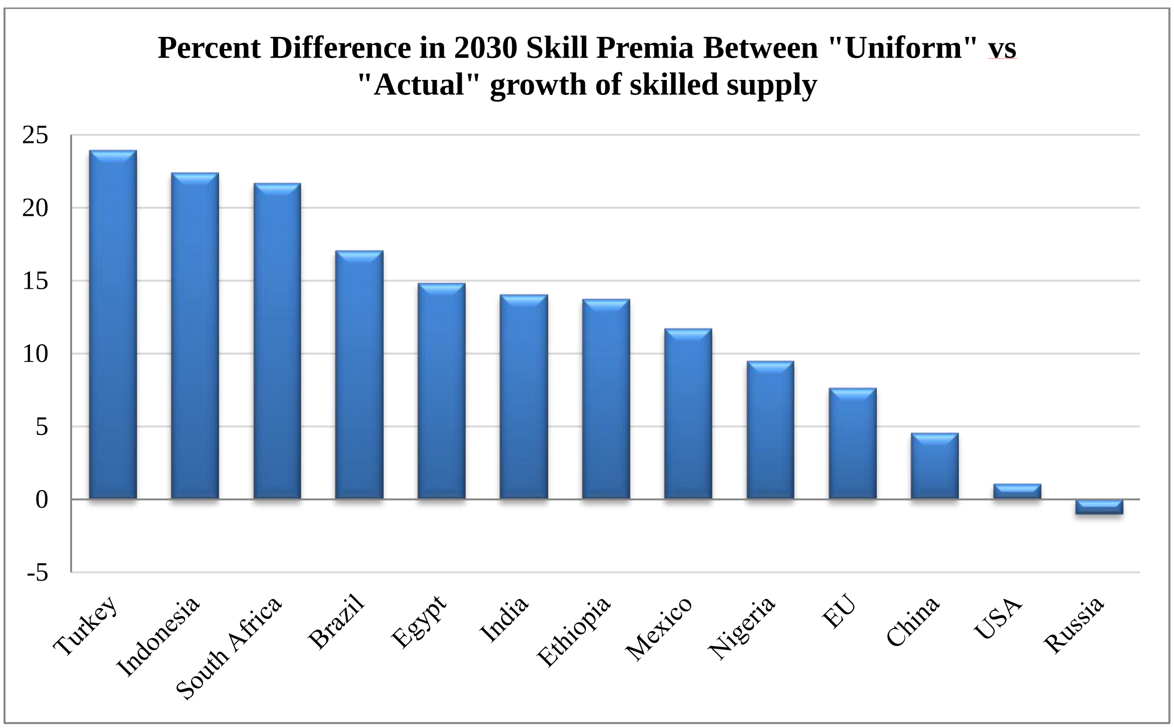
Source: LINKAGE projections.

Figure 10: Difference in annual GDP per capita growth rates



Source: LINKAGE projections.

Figure 11: Difference in skill premia



Source: LINKAGE projections.

Differences in the two scenarios depend on: the parameterization of the model and in particular on the elasticity of substitution in production amongst factors (skilled unskilled and capital); and the parameterization of the saving function (how responsive it is to demographic shifts); Exogenous trends of the productivity shifters; closure of the current accounts; And these are only the caveats for the CGE model.

Differences in the two scenarios depend on: Assuming no cohort effect; assuming (for the moment) no demand shifts due to price changes (more important in the short run); Individual versus household level microsimulation (inter-household inequality).

6 Conclusion

This paper analyzed, in an ex-ante fashion, the effects of the education wave of skilled workers from developing countries. First, we show that most of the variation in the skilled global working age population will be driven by developing economies. The two most important reasons in this process are related to demographic transition and education attainment, a combination of increasing the share of working age population and having younger cohorts more educated than the older ones, which is not prevalent in high income countries.

Second, the paper shows that global inequality will likely decrease. The result is mainly driven by a convergence of income per capita between countries, where the demographic transition and the education wave play an important role.

References

Alvaredo, F., A. B. Atkinson, T. Piketty, and E. Saez (2013). The top 1 percent in international and historical perspective. Technical report, National Bureau of Economic Research.

Blanchflower, D. and Freeman, R. (1999) Preparing Youth for the 21st Century: The Transition from Education to the Labour Market. Proceedings of the Washington D.C.

Bussolo, M., Cruz, M. and Osório-Rodarte, I. (2014) GIDD Sectoral Wage Bill Database by Education Attainment. In: 17th GTAP Conference.

Bussolo, M. Rafael E. De Hoyos, Medvedev, D. and Mensbrugghe D.. Global Growth and Distribution: Are China and India Reshaping the World? The World Bank Policy Research Working Paper, n. 4392, November 2007.

Lakner, C. and B. Milanovic (2013). Global income distribution: from the fall of the berlin wall to the great recession. World Bank Policy Research Working Paper (6719).

Bourguignon, F., Bussolo, M. and Da Silva, L.P. The impact of macroeconomic policies on poverty and income distribution: macro-micro evaluation techniques and tools. World Bank-free PDF, 2008.

Bussolo, M., De Hoyos R. and Medvedev D. Economic growth and income distribution: linking macroeconomic models with household survey data at the global level. International Journal of Microsimulation, pages 92-103, 2010.

Milanovic, B. (2013). Global income inequality in numbers: in history and now. Global Policy 4 (2), 198-208.

Ravallionm M. (2014) How Long Will It Take to Lift One Billion People Out of Poverty? The World Bank Policy Research Working Paper, n. 6325.

Richard B. Freeman (2007). "Labor Market Institutions Around the World," NBER Working Papers 13242, National Bureau of Economic Research, Inc.

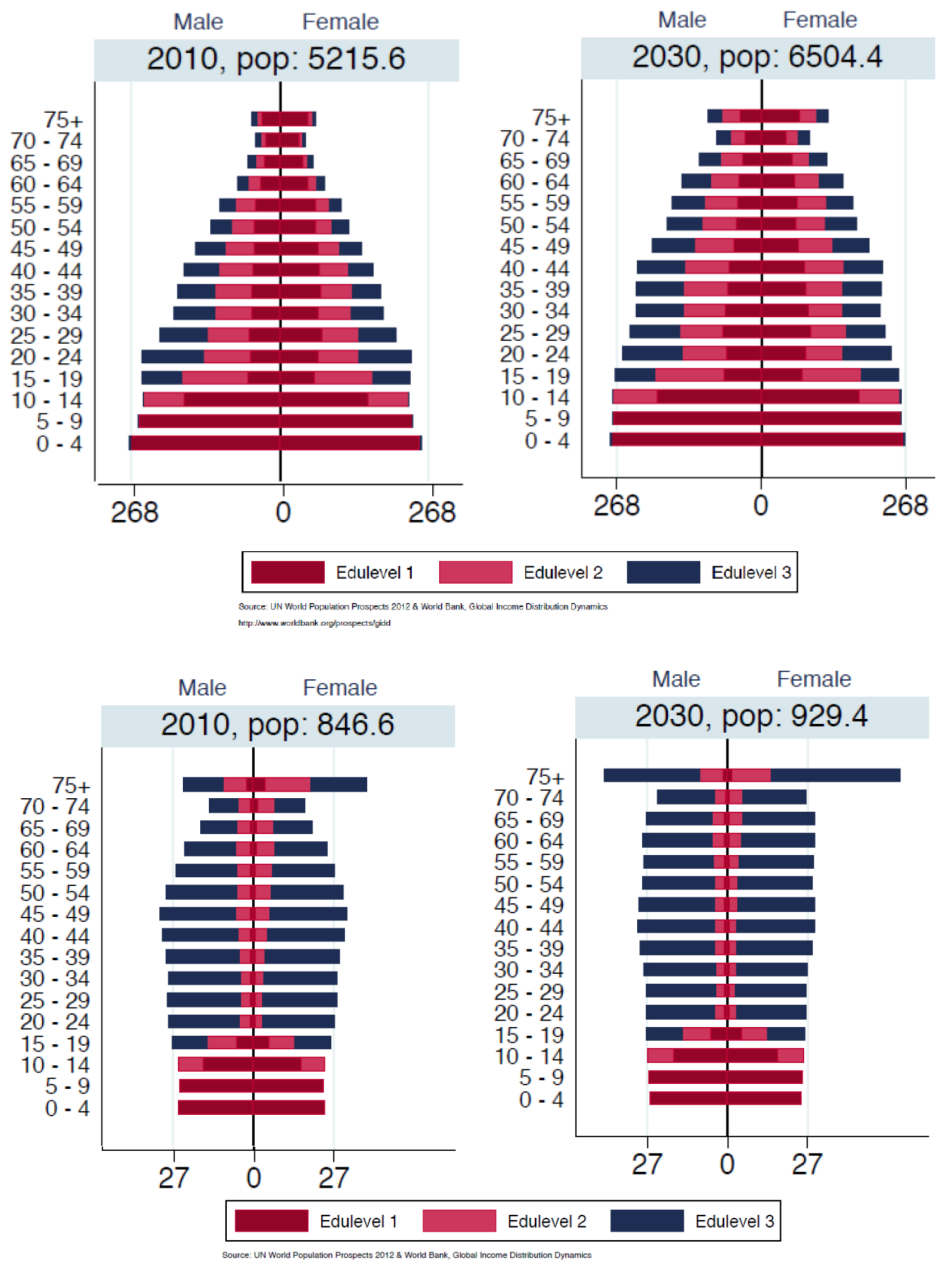
Van Der Mensbrugghe, D. Linkage Technical Reference Document, version 7.1. Development Prospects Group, The World Bank., Washington-DC, 2011.

Young, A. Inequality, the urban-rural gap, and migration*. The Quarterly Journal of Economics, 128(4):1727{1785, 2013.

Appendix

A1- Demographic projections by age, gender and education

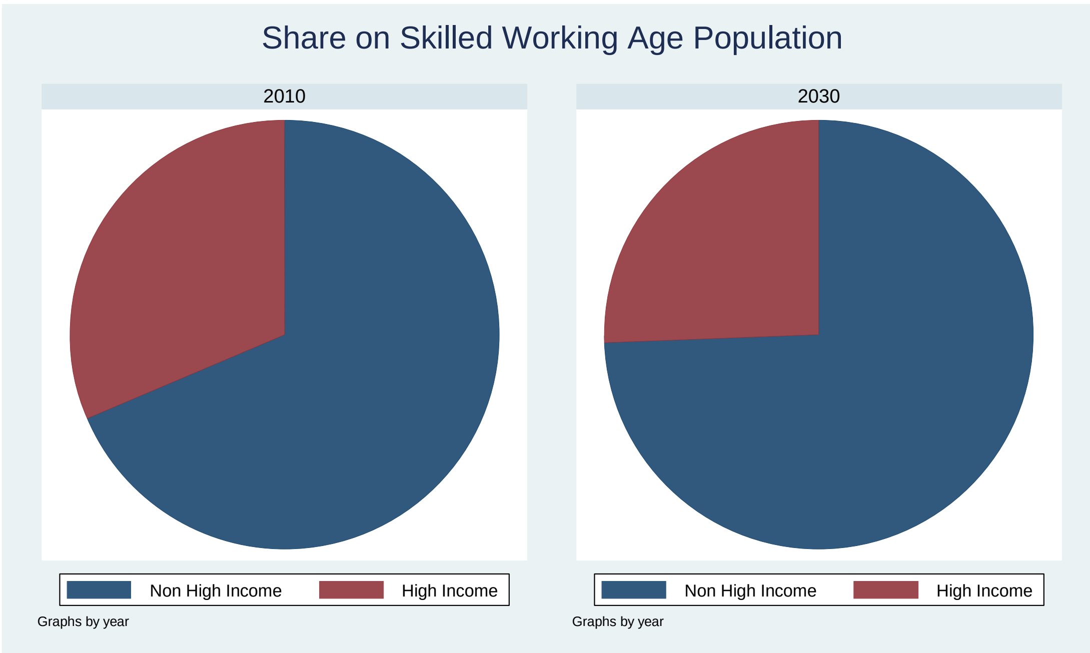
Figure 12: Demographic pyramid (2010-2030)



Source: GIDD projections

This growth of 17.6% of global population will come most from developing and emerging economies. These countries will also become the main provider of the variation in skilled workers. While most of the high income countries have already most of their adult population with more than 9 years of schooling, many developing countries will see a significant increase in the number of more educated people in the coming years.

Figure 13: Share of skilled workers (2010-2030)



Source: GIDD projections

The share in participation provides an idea of a scenario used as counterfactual, where the share of skilled and unskilled workers is kept constant.

A2- The GIDD model

This appendix is an extension of Bussolo et. al. (2010) which explains the original methodology in GIDD. In this paper we extended the GIDD model by incorporating new household surveys and using and adjusting the initial condition for number of workers and wage skill premia between the CGE model and the microsimulation. We provide a summary of the framework emphasizing the main changes.

There are four main outcomes from LINKAGE used in GIDD: i) changes in the number of workers between sectors, which means how many workers moved from to the shrinking sector (e.g. agriculture) to the expending sector (e.g. non-agriculture); ii) changes in relative average wage-prices with respect to sector and level of labor skill; iii) aggregated shocks (e.g. GDP per capita growth, consumption per capita growth); iv) relative prices of food with respect to non-food goods.

Therefore, there are two main channels through which macro shocks from LINKAGE global CGE model affects within-country income distribution in GIDD: a) Factor returns (W): GIDD accounts for changes in the wage skill and sector premia; b) Quantity (L): GIDD allows for labor mobility between sectors. Whereby, (W) and (L) are equilibrium level of wages and number of workers, consistent with supply and demand given by LINKAGE model.

A) Adjusting the initial condition of the CGE and the Household survey

B) Sectoral Mobility and Economic Growth for CGE Model

Our population projection provides the number of skilled and unskilled workers for the coming years. The CGE model projects scenarios that incorporate mobility of workers between sectors. An important linkage aggregate variable (LAVs) is the growth rate of workers according to different skills by sector. First, we translate this relative growth rate in number of workers. For example, let us assume a given country has 100 workers (10% skilled workers in agriculture, 40% unskilled workers in agriculture, 10% skilled workers in non-agriculture and 40% skilled workers in non-agriculture) in 2010. Therefore, in the initial condition, there are 20 skilled workers and 80 unskilled.

Also, let us assume that the population projection indicates that by 2030 there will be 120 workers and 30 of them are skilled, which means that 25% of the working age population will be composed by skilled workers and 75% will be unskilled. The CGE model provides a scenario that projects how these workers will be split among different sectors, which involves component of labor supply, but also demand for labor. Let us assume that the composition projected for 2030 is the following: 10% skilled workers in agriculture, 25% unskilled workers in agriculture, 15% skilled workers in non-agriculture and 50% skilled workers in non-agriculture. Indeed we receive this LAV from CGE as being the growth rate of skilled and unskilled workers by sector. Based on this information we can project the number of unskilled workers in agriculture, which moved from 40 (in 2010) to 30 (in 2030), a reduction by 25%. The number of unskilled workers in non-agriculture would increase from 40 (in 2010) to 60 (in 2030), a growth of 50%. The number of skilled workers increases from 20 (in 2010) to 30 (in 2030), a growth of 50%.

The information on the initial condition of how workers are split in different sectors in LINKAGE model comes from the household surveys used in the microsimulation. Therefore, the question that arises is how do we move workers between sectors and which wages we do assign to these workers? First of all, when we re-weight the household surveys in order to take into account the changes in the population structure for 2030, there is also a change in workers' sectoral distribution that comes with this exercise.

For example, an individual with given observable characteristics (e.g. age, gender and school achievement) working in non-agriculture sector may become more representative in the projected population for 2030. Therefore, we check the difference between the number of individuals by level of skill, allocated in each sector after re-weighting the survey and the projection that comes from the CGE model, which determines the number of workers that should be reallocated between sectors.

The household survey will likely provide a large amount of workers that could be moved from the shrinking sector (e.g. agriculture) to the expanding sector (e.g. non-agriculture). One option that can be considered is to move these workers randomly. The GIDD employs a methodology based on the Propensity Score (PS) of migration. First, it estimates a set of parameters of conditional probability function of being a worker in the expanding sector. Second, it ranks the workers in the shrinking sector (agriculture) according to their propensity score and assigning migrant status to workers with the highest score until the number of workers in each sector matches the projections from the CGE model. In the current version of GIDD, this procedure is implemented at individual level[30]. The propensity of an individual j works in the expanding (non-agricultural) sector is given by the following probit estimation:

(1) Pr(NAj=1) = P(Xj, Zj)

Where Xj and Zj are vectors of personal and household characteristic[31]. Based on this estimation, a propensity score is assigned to the workers in shrinking sectors according to their observable characteristics. Once we move workers from the shrinking to the expanding sector their wages are adjusted in order to incorporate the sector wage premia. The first step in this process is estimating a Mincer equation for workers in shirking (A) and expanding (NA) sectors:

(2) Ln(Y)j,s = XjBs + Ej,s Where s=(A, NA)

We assign new wages based on migrants' observable (Xj) and unobservable characteristics captured by the residual Ej,s .

C) How does the final income is assigned?

After we reallocate workers between sectors, the final step in the GIDD microsimulation is to adjust wages by skill and sector, as well the average income/consumption according to the outcomes from CGE model.

Another set of linkage aggregate variable (LAVs) from CGE are the wage premia by sector. As previously explained, the LINKAGE model has an initial condition of number of workers and skill wage premia that is consistent with the household surveys. The LINKAGE model will provide scenarios for the skill wage

[30] The previous version of GIDD applied this method at the household level (see Bussolo, et. al. 2010).
[31] In the current version of GIDD the following variables are being used in the probit estimation:

premia by sector. The average wage of unskilled workers in agriculture is kept as a numéraire ($y_{1,1}$) and the wage premia regarding sector and skill is determined with respect to this difference.

Equation (3) shows the initial condition for the wage premia:

$$(3)\ \mathrm{g_{s,l}} = \frac{\mathrm{y_{s,t}}}{\mathrm{y_{1,1}}} - 1$$

Where $y_{1,1}$ is the average wage for unskilled workers in agricultural sector, and $y_{s,l}$ is the average wage by sector (s) and skill (l). For example, if a skilled worker has an average wage of \$ 150, while the average wage for unskilled workers is \$ 100, the wage skill premium in agriculture would be 1.5. The CGE's scenario provides three sets of wage premium relative to the numéraire ($y_{1,1}$). The changes in wage applied in GIDD takes into account the growth rate of skill premia (see eq. 4).

$$(4)\ \hat{\mathrm{g}}'_{\mathrm{s,l}} = g'_{\mathrm{s,l}} \frac{\hat{g}_{s,l}}{g_{\mathrm{s,l}}}$$

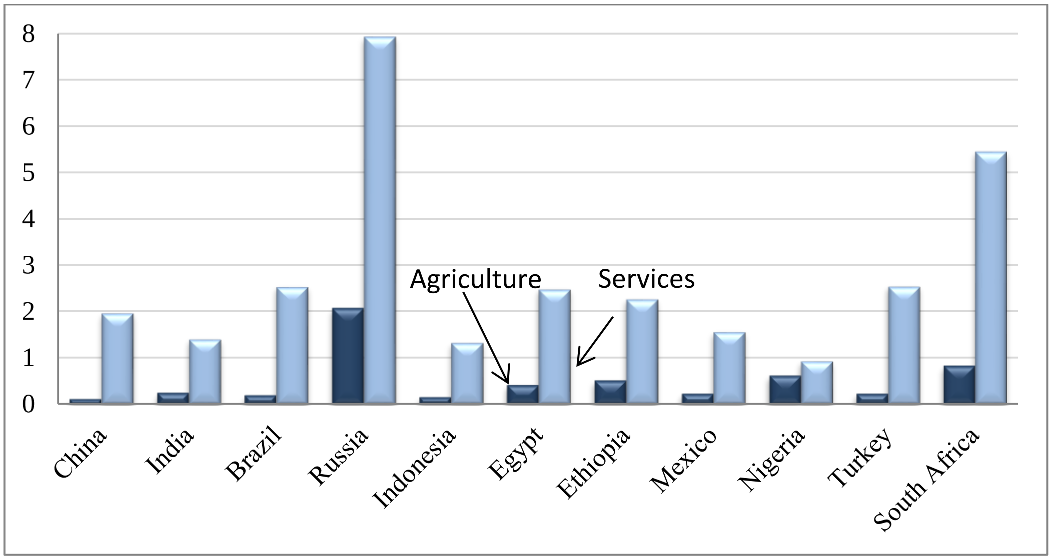
Where $\hat{\mathrm{g}}'_{\mathrm{s,l}}$ is the ratio between the predicted of wage premia ($\hat{g}_{s,l}$) by the initial premia ($g_{\mathrm{s,l}}$). This procedure generates an important re-distribution effect regarding new relative (wage) prices, which affects income income distribution through labor income.

The last step in the microsimulation refers to the transmission of aggregated growth. We do so by applying the gdp per capita growth (or the consumption per capita growth) in the income previously assigned to workers through sectoral reallocation and changes in relative wages (wage premia).

$$(5)\ \mathrm{Y}' = \mathrm{Y}' \frac{\hat{Y}}{Y}$$

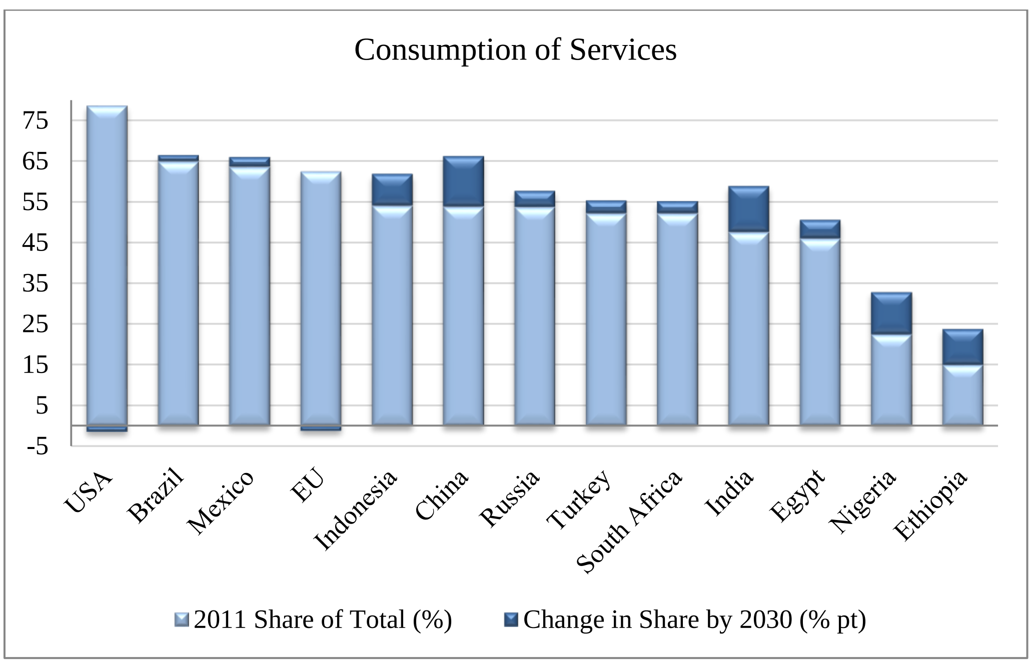
A3- Demand and supply of skilled versus unskilled workers by sector

Figure 14: Ratio of Skilled to unskilled Workers



Source: GIDD projections

Figure 15: Consumption of Services



Source: LINKAGE projections