Skills, jobs and earnings in Latin America: A task-based approach

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Abstract

In this paper we study the employment patterns in both high-skilled and low-skilled jobs in urban labor markets in Brazil, Mexico and Colombia. By considering a task-based approach, we analyze where in the distribution of skills and for what type of occupations, employment has grown in the last decade. We also test if the employment patterns can be explained by the routinization hypothesis. Our results suggest that employment fell strongly for some middle-skilled occupations such as secretaries, machinery operators and handicrafts and increased mildly for both low-skilled and high-skilled occupations. According to the decomposition results, changes in the share of employment for some routine cognitive occupations are fully explained by changes within industries. However, changes in routine manual jobs are mainly due to changes between industries.

Key words: Job polarization, Technical change, Wage inequality
Journal of Economic Literature Classification: E24, J24, J31

1 Introduction

Recent theoretical developments have proposed models where the rapid adoption of computer technologies changes the tasks performed by the workers at their jobs. The tasks-based approach presented by Autor et. al., (ALM) in 2003 argues that technological change results in a substitution of routine tasks by computer and other machines.[1] According to this framework, as the price of computer capital falls, the demand for workers that perform routine activities decreases, and the demand for workers that perform nonroutine activities rises. The nonroutine cognitive and interactive tasks are complementary to the technology; the routine tasks are substitutes while the nonroutine manual tasks are not directly affected by technical change. The main implication of this model is that employment and wages can growth in different part of the distribution of skills and not only in the upper part as the Skill-Biased Technological Change (SBTC) predicts.

The polarization of employment has been widely documented in advanced economies. Empirical evidence for the US is provided by Autor et. al., (2003, 2006, 2009), and Lemieux

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[1] A tasks is "routine" if it can be accomplished by machines following explicit programmed rules.

(2008); for the case of UK and Germany evidence is provided by Goos and Manning (2007), and Spitz-Oener (2006) and Dustmann et. al., (2009), and for fourteen European OECD countries is provided by Goos et.al., (2009). Since employment and wages have grown in the tails of the distribution of skills, there is a direct implication in the wage inequality which increases in the majority of these countries. Theoretically, there are at least three explanations for job polarization. The routinization hypothesis, the effect of the globalization (offshoring), and the increasing demand for services in advance economies (Goos et.al., 2009). For Latin American economies there have not been studied this phenomenon.

The main contribution of this paper is to provide empirical evidence of the job polarization in urban labor markets in Brazil, Mexico and Colombia as well as to test the routinization hypothesis. That is, we study to what extent employment has growth in the tails of the distribution of skills and to what extent such growth can be explained by the effect of technical change on labor demand. We use for the first time detailed data on occupations from the household surveys in the case of Brazil (PNAD), Mexico (ENEU and ENOE) and Colombia (ECH and GEIH). In particular, we classify the information of occupation at the main job according to the International Standard Classification of Occupations (ISCO) for both countries (each country has its own national classification of occupations).

Our empirical strategy relies in two steps. First, we group occupations into six broad categories of routine and nonroutine jobs according to the Acemoglus (2011) framework. That is nonroutine analytic, nonroutine interactive, routine manual, nonroutine manual, and we split into two categories the routine cognitive jobs. Then we study the changes in employment sharing and wages. Second, we perform a decomposition exercise of the changes in employment at each routine and non-routine occupation between and within industries. This is so relevant because changes in employment could be more a result of changes in industry toward sectors that uses more abstract and manual occupations than a result of the technical change that affects all industries. So the within component by industry allows us to test the routinization hypothesis directly.

The paper is structure as follows. In section 2 we present the literature review of job polarization. Section 3 describes the empirical strategy and it comments the main issues in the measuring of skill content of jobs. The data is explained in section 4. In section 5 we present the empirical results. Finally, section 6 concludes.

2 Literature review

In this section we describe the two main theoretical contributions recently proposed and then the empirical evidence. On the one hand, Autor et. al., in 2003 develop a theoretical framework where the rapid adoption of computer technologies changes the tasks performed by workers at their jobs. In the model, computer capital both replaces workers in performing cognitive and manual tasks (that can be accomplished by following explicit rules), and complements workers in performing non-routine problem-solving and complex communication tasks. The model predicts how demand for workplace tasks responds to an economy-wide decline in the price of computer capital. So the industries and occupations that are initially intensive in labor input of routine tasks would make relatively larger investments in computer capital as its price declines. They find for the US that within industries, occupations and educational groups, computerization is associated with reduced labor input of routine manual and routine cognitive tasks and with increased labor input of non-routine cognitive tasks.

A more general theoretical framework is given by Acemolgu et. al., (2011). They propose a general task-based model that explains central empirical facts observed in the last two decades in most of the developed countries for which the "canonical" model could not account for.[2] Empirical evidence of the SBTC before Acemoglu's contribution was based on models as the suggested by Katz and Murphy (1992).[3] In the Acemoglu's framework, the assignment of skill to tasks is endogenous and technical change may involve the substitution of machines for certain tasks previously performed by labor. The model treats skills (embodied in labor), technologies (embodied in capital) and trade or offshoring as offering competing inputs for accomplishing various tasks. Thus, which input (labor, capital or foreign supply via trade) is applied in equilibrium to accomplish which tasks depends in a rich but intuitive manner on cost and comparative advantage.[4]

According to Acemoglu et. al (2011), the canonical model is a special case of this more general task-based model, and hence the model generates similar responses to changes in relative supplies and factor augmenting technical change. Nevertheless there are also richer implications because of the endogenously changing allocation of skills to tasks. Notably, while factor-augmenting technical progress always increases all wages in the canonical model, it can reduce the wages of certain groups in this more general model. In addition, other forms of technical change, in particular the introduction of new technologies replacing workers in certain tasks, have richer but intuitive effects on the earnings distribution and employment patterns.[5]

Empirically, the polarization of employment has been widely documented in advanced economies. Evidence for the US can be found Autor et. al., (2003, 2006, 2009), and Lemieux (2008); for the UK and Germany can be found in Goos and Manning (2007), and Spitz-Oener (2006) and Dustmann et. al., (2009); and for fourteen European OECD countries can be found in Goos et.al., (2009). The general conclusion is that for most of the developed countries there has been a polarization of employment which in turn is explained by the routinization hypothesis. To our knowledge, the polarization hypothesis has not been tested yet in Latin

[2]That is, the significant decline in real wages of low skill workers, the non-monotone changes in wages at different parts of the earnings distribution during different decades, the broad-bases increases in employment in high skill and low skill occupations relative to middle skilled occupations, the rapid diffusion of new technologies that directly substitute capital for labor in tasks previously performed by moderately skilled workers, and the expanding offshoring of opportunities, enabled by technology.

[3]The canonical model operationalizes the supply and demand for skills by assuming two distinct skill groups that perform two different and imperfectly substitutable tasks or produce two imperfectly substitutable goods. The technology is assumed to take a factor augmenting form, which, by complementing either high or low skill workers, can generated skill bias shifts. That is, the model treats technology as exogenous and assumes that technical change is by its nature skill biased.

[4]The equilibrium allocation of skill to tasks is determined in a continuum of tasks by two thresholds, IL and IH, such that all tasks below the lower threshold IL are performed by low skill workers, all tasks above the higher threshold IH are performed by high skill workers, and all intermediate tasks are performed by medium skill workers.

[5]They model the introduction of new technologies that directly substitute for tasks previously performed by workers of various skill levels. The same ideas can also be easily applied to the process of outsourcing and offshoring. Since some tasks are far more suitable to offshoring than others, it is natural to model offshoring as a technology that potentially displaces domestic workers of various skill levels performing certain tasks, thereby altering their wages by increasing their effective supply and causing a shift in the mapping between skill and tasks.

America.[6]

3 Empirical Strategy

3.1 Routine and Nonroutine jobs

The measure of the job complexity is one of the key issues in the empirical work in the job polarization field. Such measure allows us to construct the distribution of skills from a classification of occupations in the household surveys. Here we comment two of the main strategies used in literature. In the seminal paper, ALM (2003) use the Dictionary of Occupational tittles (DOT) to measure the skill content of occupations. They reduce DOT variables to a relevant subset using both textual definitions of DOT as well as means of DOT evaluations from the Handbook of Analyzing Jobs. Then they transform the DOT measures into percentile values corresponding to their rank in the 1960 distribution of tasks input and study their trends.

The DOT measures have however several drawbacks. In particular, as Acemoglu et al., (2011) highlights, the DOT and its successor the Occupational Informational Network (O*NET) contain numerous potential tasks scales, and it is rarely obvious which measure (if any) best represents a given tasks construct. In this paper we follow to Goos et.al., (2009) and we use the wage at the initial year (in 26 occupations) as a proxy of skill content of a job. In order to classify jobs between routine and non-routine occupations and since we do not have any type of measure as DOT for the countries in our sample, we follow the Acemoglus (2012) proposal. We also split the routine cognitive jobs into two categories since there are jobs more likely to be replaced by technological advances. The main drawback of the paper is that we can only study the changes in the demand for skills in the extensive margin.

3.2 Routine and Nonroutine jobs

We use the occupational data from household surveys to classify jobs into the six broad categories. So non-routine analytical occupations are composed by professionals and technicians; non-routine interactive occupations are related to managers; routine cognitive 1 are secretaries, stenographers, cashiers, and telephone switchboard operators; routine cognitive 2 are other clerks and sales; routine manual jobs are production craft, repair and operators; non-routine manual occupations are protective service, food preparation, cleaning services and personal care. In table 1 we present more information about occupations.

In order to test if the changes in total employment of non-routine and routine occupations are due to the effect of technical change (and are not the result of the changes in the composition of industry toward sector that use more abstract or manual occupations), we decompose these changes by each type of occupation between and within industries. We follow Acemoglu and Autor (2011) and we perform a standard shift-share decomposition of the change in the overall share of employment in occupation j over time interval t, as in equation (1)

[6] From the demand side, the literature for the region deals with the effect on skill premia of both technical change and globalization (trade reforms and Foreign Direct Investment) only in the 1990s. See Harrison and Hanson (1999), Feenstra and Hanson (1997), Montes-Rojas (2006), and Acosta and Montes-Rojas (2008).

$$\Delta E_{jt} = \sum_k \Delta E_{kt}\lambda_{jk} + \sum_j \Delta\lambda_{jkt}E_k \tag{1}$$

$$\equiv \Delta E_t^B + \Delta E_t^W \tag{2}$$

The change in the overall share of employment ΔE_{jt} can be decompose into the part attributable to changes in industry composition ΔE_t^B, and into the part attributable to the within-industry shifts ΔE_t^W. The change in industry k's employment share during time interval t is given by $\Delta E_{kt} = E_{kt1} - E_{kt0}$. The average employment share of industry k over the sample interval is given by $E_k = (E_{kt1} + E_{kt0})/2$. The change in occupation j's share of industry k employment during time interval t is given by $\Delta\lambda_{jkt} = \lambda_{jkt1} - \lambda_{jkt0}$. The occupation j's average share of industry k employment during that time is $\lambda_{jk} = (\lambda_{jkt1} + \lambda_{jkt0})/2$.

4 Data

The empirical analysis is based on employment and wage data from household surveys. We use for Brazil the Pesquisa Nacional por Amostra de Domicilios (PNAD) from 2001 to 2009. For Mexico we use the Encuesta Nacional de Empleo Urbano (ENEU) from 2001 to 2004 and Encuesta Nacional de Empleo (ENOE) thereafter. For Colombia we use the Encuesta Continua de Hogares (ECH) from 2002 to 2006 and Gran Encuesta Integrada de Hogares (GEIH) thereafter. The information of economic activities is classified according to the International Standard Industrial Classification ISIC (Rev. 3 to two digits). Jobs in each national classification of occupations are classified first into 26 occupations according to the International Standard Classification of Occupations ISCO. We only consider urban wage-earners workers who are between 18 and 65 years old. We keep urban areas that can be observed all period. We rule out workers who do not report earnings as well as those who work in agriculture and mining sector. The data comes from the second quarter of each year. In table 2 we present the sample size for each country.

5 Empirical Results

5.1 Job Polarization

In figure 1 we present the changes in the employment share by skill percentile.[7] Occupations are ranked according to their median wage in 2002. The circle size represents the occupation weight on total employment in 2002. According to figure, most of the changes in employment have taken place both in the low-skilled and middle-skilled occupations. In particular, while jobs in the bottom of the skill distribution increased their share in total employment, middle-skill jobs shrank their weight. Only for Colombia, high-skilled occupations had a larger increasing in employment share. The figure also shows the smoothed changes estimates from a locally weighted regression. Despite differences across countries, the u shape evidences job polarization in the last decade.

[7]The skill distribution is built from 83 occupations for Brazil and Mexico, and from 57 occupations for Colombia

In order to analyze better such changes in employment we cluster occupations into 26 categories comparable across countries. Table 3 shows occupations ranked according to their skill level. Despite jobs are not in the same position in the skill distribution for the three countries, there is a strong consistency of jobs among high-skilled, middle-skilled and low-skilled occupations. In the top of the distribution we find for example physicists, mathematicians, life science professionals, health professionals, and executive managers. In the middle-skill occupations we find clerks in general, machine operators and precision and handicraft jobs. Services in general and street salesperson are jobs in the bottom of the skill distribution. The distribution of occupations by skill level is in line with empirical evidence for developed countries.

In figure 2 and figure 3 we present the changes in employment and the changes in the median wage for the 26 occupations. It is clear that there are important changes in employment share in the middle-skilled occupations. In particular, secretaries, stenographers, machine operators and precision handicraft decreased their share in total employment. The employment changes at lower part of the skill distribution (service jobs) are in general stronger that changes at the upper part (professionals). Employment changes in middle-skill distribution have motivated a lot of research in developed countries. Up until now, no empirical evidence for developing countries has been provided to know to what extent job polarization have occurred, and what are the explanations for such employment changes in the skill distribution.

One drawback of the literature on job polarization is that it does not study further the wage changes by occupations. Researchers focus mainly on changes in employment. It is assumed a positive relationship between employment and wages. So employment drops in the middle-skilled occupations are consistent with falls in wages by such jobs. In other words, they assume that labor demand is the driven force in explaining changes in wages. Thus, if employment and wages rise at bottom and at top of the skill distribution wage inequality increases. Nevertheless, if labor demand is not the leading force, wages can also decrease and inequality not necessarily rise in a job polarization scenario. Next we discuss the results for the three developing countries considered.

The third panel in figure 3 shows the changes in median wage by skill level. Wages increases for the low-skilled occupations (particularly for Brazil and Colombia) and fall for high-skilled occupations. In the middle-skill jobs, telephone switchboard operators had an important decrease in wages. As a general picture we have on the one hand, employment and wages rise in the bottom of the distribution of skills, and on the other hand, employment rises and wages fall in the top of the skill distribution. Then, the direct implication is that wage inequality fall for all countries during the period. It seems to be that there is a strong positive effect of labor demand for low-skilled jobs. The result at the top of the distribution is interesting. It would suggest some evidence in favor of over-education, but more research is needed.

5.2 Explaining employment patterns

One of the leading explanations for job polarization is the routinization hypothesis. It suggests that certain tasks performed by workers can be substituted for computer capital or other applied technological advances. The more likely jobs to be affected would be jobs with routine tasks. In order to study to what extent the routinization hypothesis would explain the changes in employment we classify occupations into routine and nonroutine jobs according to table 1.

In table 4 we present the changes in employment sharing by routine-nonroutine occupations. The most important result here is the fall in sharing of routine cognitive 1 and routine manual jobs. These drops are huge in the case of Mexico and Colombia than in the case of Brazil. Such changes are our first target. So we are interested in knowing where such changes come from. The decreased in routine jobs could be explained either by routinization hypothesis or by changes in industry composition as a result for example of the international trade. To test the hypothesis we decompose changes in employment by using equation 1. If the technical change is the main factor in explaining changes in the middle-skilled occupations, the within industry component should be negative and greater than the between industry component.

The results from the decomposition are presented in table 5. The changes in routine cognitive occupations within industries are negative and explained comprehensively the decreasing employment share for all countries. The changes in routine manual occupations within industries are negative as routinization hypothesis stated but smaller than the changes between industries. As a result, the decreasing share of routine manual occupations is explained more by industry shifts in these countries than by a technical change in labor market. The change in industry composition in turn, would be explained either by higher international competition that depresses employment in manufacture sector or by strong demand toward sector that use more abstract and nonroutine manual occupations or by both.

6 Conclusion

In this paper we study the employment changes along skill distribution in urban labor markets of Brazil, Mexico and Colombia. We found that employment fell strongly for some middle-skilled occupations (Secretaries, machinery operators and handicrafts) and increased mildly for both low-skilled and high-skilled occupations (nonroutine analytic jobs). One surprising result is that wages grew in the bottom of the skill distribution but fall steadily for high-skilled occupations. It would be explained why wage inequality drop in the last decade. Evidence for the drop in inequality in the region is provided by Gasparini et. al., 2011, and Lopez-Calva et. al., 2010.

Results from the decomposition of the routine-nonroutine employment shifts, suggest that the fall in the share of routine cognitive 1 (Secretaries, stenographers, cashiers) is fully explained by routinization hypothesis. However, the effect of technical change on routine manual jobs was lower that the effect of the changes in industry composition in Mexico and Colombia. More research is needed to know to what extent the changes in industry composition are for example due to international trade. In particular, the role of others emerging economies as China that competes directly with them in manufactured goods.

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Table 1. Routine and Nonroutine occupations

Acemoglu and Autor (2011)	Occupation	
Nonroutine cognitive	Nonroutine analytic	03.Physics, mathematical, engineering professionals
		04.Physics, mathematical, engineering associate professionals
		05.Life science and health professionals
		06.Life science and health associate professionals
		07.Economist, accountants
		08.Lawyers
		09.Writers, artists and sportsmen
		10.Education workers
		11.Other proffesionals
		12.Other associate professionals
	Nonroutine interactive	01.Executive managers
		02.Other managers
Routine cognitive	Routine cognitive 1	13.Secretaries, stenographers, typists
		14.Cashiers, tellers and the similar
		15.Telephone switchboard operators
	Routine cognitive 2	16.Other clerks
		21.Sales
		22.Street salesperson
Routine manual	Routine manual	17.Machinery operators
		18.Precision, handicraft, and related workers
Nonroutine manual	Nonroutine manual	19.Drivers
		20.Building workers
		23.Cooks, bartenders, porters
		24.Protective services workers
		26.Other services
		27.Other

Table 2. Sample size

Brazil		**Mexico**		**Colombia**	
year	size	year	size	year	size
2002	76.002	2002	69.618	2002	15.935
2009	90.303	2010	45.490	2010	17.400

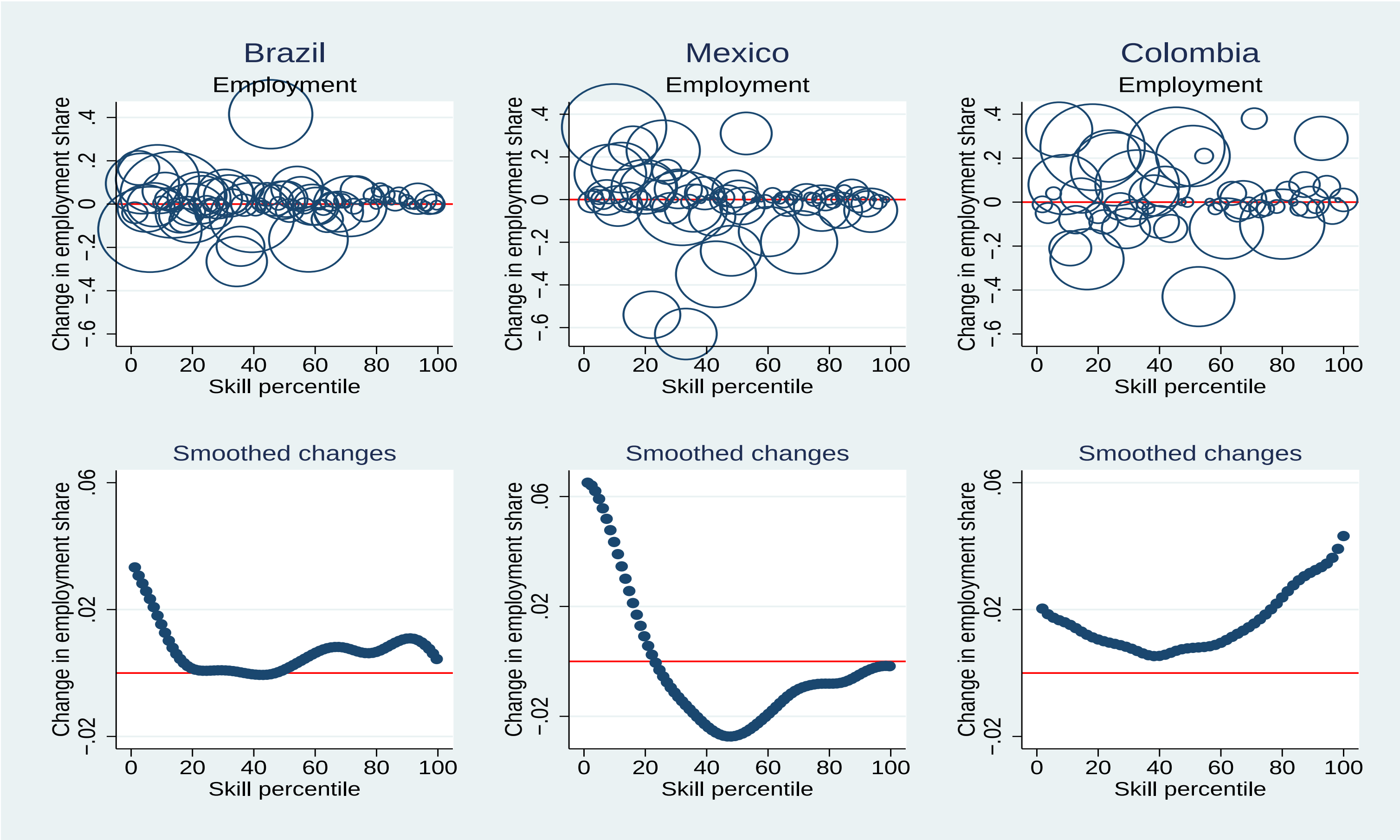

Figure 1. Changes in employment share by skill percentile. 83 occupations

Table 3. Occupations by skill level

Brazil	Mexico	Colombia
03.Physical, mathematical, eng	01.Executive managers	08.Lawyers
05.Life science and health pro	03.Physical, mathematical, eng	01.Executive managers
07.Economist, accountants	05.Life science and health pro	05.Life science and health pro
08.Lawyers	10.Education workers	03.Physical, mathematical, eng
01.Executive managers	08.Lawyers	07.Economist, accountants
24.Protective services workers	11.Other proffesionals	10.Education workers
10.Education workers	07.Economist, accountants	11.Other proffesionals
11.Other proffesionals	09.Writers, artists and sports	02.Other managers
12.Other associate professiona	02.Other managers	09.Writers, artists and sports
09.Writers, artists and sports	12.Other associate professiona	04.Physics, mathematics, engin
04.Physics, mathematics, engin	06.Life science and health ass	06.Life science and health ass
06.Life science and health ass	04.Physics, mathematics, engin	15.Telephone switchboard opera
02.Other managers	15.Telephone switchboard opera	13.Secretaries, stenographers,
16.Other clerks	13.Secretaries, stenographers,	14.Cashiers, tellers and the s
15.Telephone switchboard opera	16.Other clerks	12.Other associate professiona
19.Drivers	19.Drivers	16.Other clerks
13.Secretaries, stenographers,	14.Cashiers, tellers and the s	17.Machinery operators
14.Cashiers, tellers and the s	20.Building workers	26.Other services
18.Precision, handicraft, and	17.Machinery operators	21.Sales
17.Machinery operators	21.Sales	24.Protective services workers
21.Sales	18.Precision, handicraft, and	18.Precision, handicraft, and
26.Other services	24.Protective services workers	19.Drivers
23.Cooks, bartenders, porter	27.Other	23.Cooks, bartenders, porter
27.Other	26.Other services	27.Other
20.Building workers	23.Cooks, bartenders, porter	20.Building workers
22.Street salesperson	22.Street salesperson	22.Street salesperson

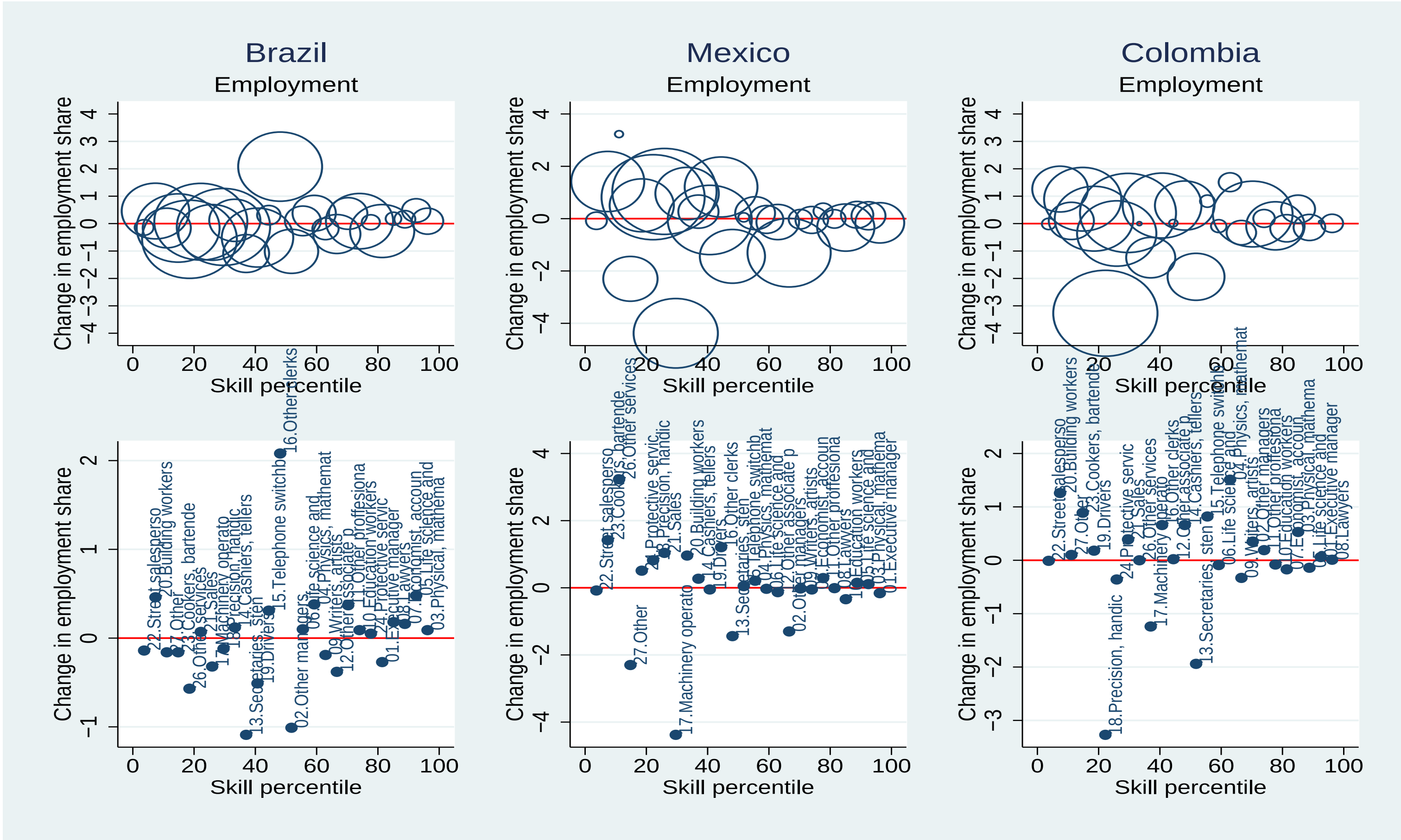

Figure 2. Changes in employment share by skill percentile. 25 occupations

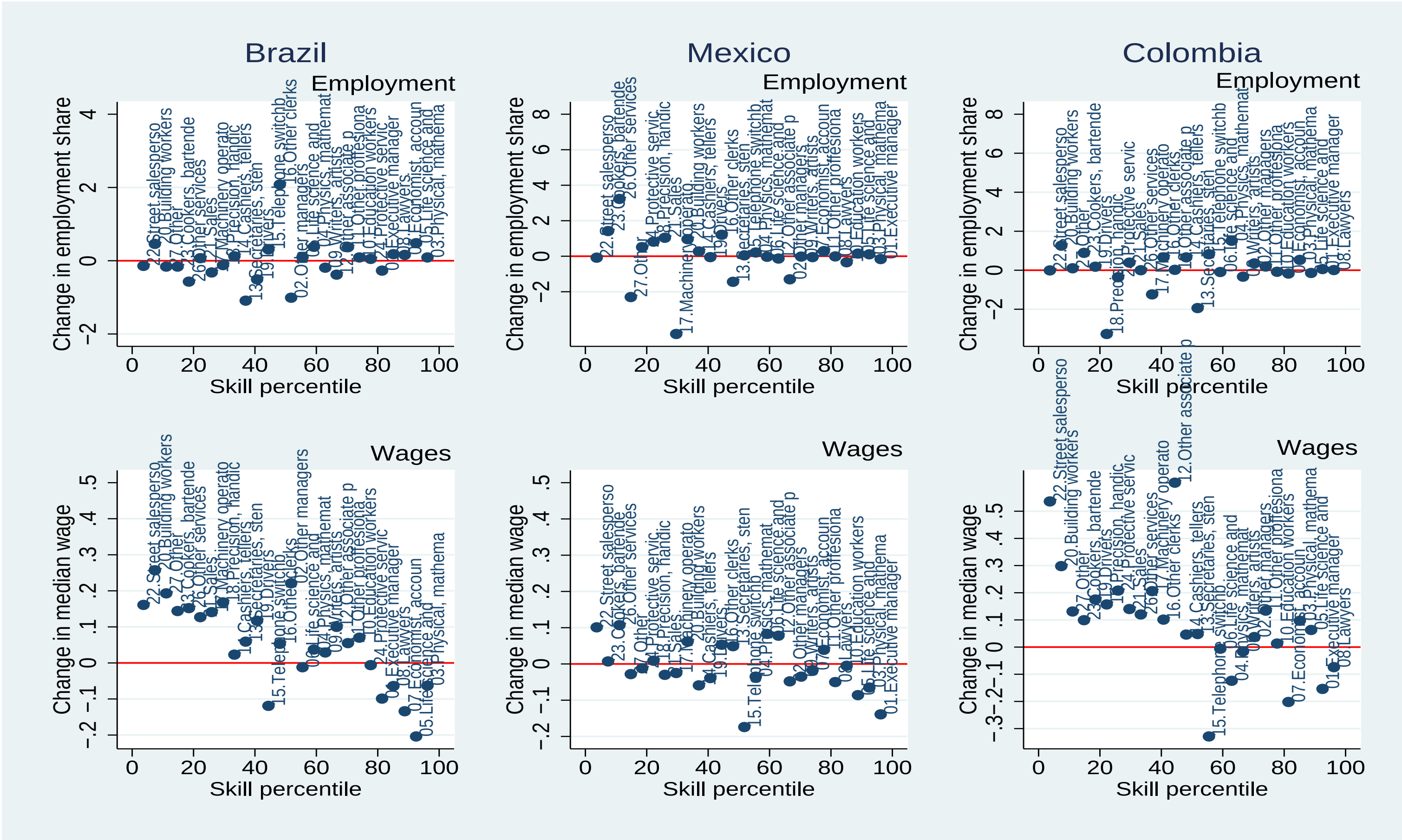

Figure 3. Changes in employment share and in median wages by skill percentile.

Table 4. Employment sharing by routine and nonroutine occupations

Occupation	Brazil 2002	2009	Δ	Mexico 2002	2010	Δ	Colombia 2002	2010	Δ
Nonroutine analytic	20.1	21.0	0.9	17.2	17.4	0.2	15.1	15.6	0.5
Nonroutine interactive	8.0	6.8	-1.2	10.6	8.9	-1.7	8.1	8.7	0.6
Routine cognitive 1	6.4	5.6	-0.8	7.4	6.2	-1.2	9.9	9.4	-0.5
Routine cognitive 2	18.8	20.9	2.1	19.1	20.9	1.7	20.6	21.8	1.2
Routine manual	15.0	14.6	-0.4	20.1	18.5	-1.6	17.0	12.9	-4.0
Nonroutine manual	31.7	31.1	-0.6	25.6	28.1	2.6	29.4	31.6	2.2

Table 5. Decomposition of the changes in employment 2002-2010

Occupation	Brazil B	W	Total	Mexico B	W	Total	Colombia B	W	Total
Non routine analytic	-0.52	1.43	0.91	-0.33	0.53	0.20	-0.04	0.45	0.41
Non routine interactive	-0.04	-1.21	-1.25	-0.26	-1.42	-1.69	0.15	0.47	0.63
Routine cognitive 1	0.09	-0.90	-0.81	0.10	-1.33	-1.23	0.49	-0.96	-0.47
Routine cognitive 2	0.75	1.44	2.19	0.77	0.94	1.71	-0.13	1.34	1.12
Routine manual	-0.38	-0.06	-0.44	-2.26	0.70	-1.57	-2.30	-1.75	-4.04
Non routine manual	0.10	-0.70	-0.60	1.98	0.59	2.58	1.83	0.44	2.27