

Are Automation and Trade Polarizing Developing Country Labor Markets, Too?

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Abstract

The automation and out-sourcing of routine, codifiable tasks are seen as driving polarization in labor markets in high-income countries. This paper first offers several explanations for why developing countries might show differing dynamics, at least for the present. Census data then confirms this, showing on average no evidence of polarization in developing countries. However, incipient

polarization in a few countries as well as major drives to automate in some large, labor intensive producers suggests this may not remain the case. This raises concerns first about the impact on equity within those countries, but second the possibility that the traditional flying geese pattern”—whereby low skilled jobs are progressively off-shored to poorer and poorer countries—may be short circuited.

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1 Introduction

This paper asks whether we should expect to find the sharp polarization of labor markets found in high-income countries to emerge in the developing world, and then employs global census data to see whether we do.

For the United States, Katz et al. (2006); Autor (2010); Autor and Dorn (2013) document expanding job opportunities in both high-skill, high-wage occupations and low-skill, low-wage occupations, coupled with contracting opportunities in middle-wage, middle-skill white collar and blue-collar jobs. In particular, job opportunities are declining in middle-skill white collar clerical, administrative and sales occupations and in middle-skill, blue-collar production, craft and operative occupations. This especially hits the earnings and labor force participation rates of workers without college education and particularly men. Goos et al. (2014) document that this phenomenon has appeared in each of 16 European countries from 1993 to 2006: middle wage occupations decline as a share of employment in all 16 countries with an unweighted average of 8 percentage points while high wage and low wage occupations increased in the vast majority. Beaudry et al. (2013) show that the collapse of middle level paying jobs has now spread to the high-skill labor market. Even growth optimists, such as Brynjolfsson and McAfee (2014) predict major shifts in the composition of labor and the need for compensatory social policies to offset the resulting inequality.

From the prevalence of polarization across the advanced countries, Autor concludes that a common set of forces are at work. Of these, a leading explanation is the ongoing automation and off-shoring of middle-skilled “routine” tasks that were formerly performed by workers with moderate education. Routine tasks as described by Autor et al. (2003) are sufficiently defined that they can be carried out by a computer executing a program or alternatively, by a comparatively less-educated worker in a developing country who carries out the task with minimal discretion. These would include book keeping, clerical work and repetitive production tasks. Acemoglu and Autor (2011) offer a model where technological progress

does not necessarily raise earnings in all sectors as in the standard models, but where machines substitute for tasks previously performed by labor leading to polarization and real earnings falls. Generally, the literature has emphasized such technological change over trade forces. Michaels et al. (2014), for instance, find for 11 advanced countries that industries with high ICT growth shifted demand from middle to highly educated workers. Autor argues that the general wisdom by the end of the 1990s was that trade flows were simply too small to explain the vast changes in skill demands and wage structures and Acemoglu and Autor (2011) suggest this empirically as well. David et al. (2013) for instance, specifically measure the impact of the rise of China and find that, while not negligible, it accounts for only 25% of the fall in manufacturing employment in the United States. However, recent work (Autor et al., 2016) suggests that the impact of China on US manufacturing may well have been larger than previously thought.

The demise of labor at the hands of automation hence again emerges as a preoccupation in the United States and Europe, much as Autor (2015) and Acemoglu and Restrepo (2015) note it was for luminaries such as Keynes, Heilbroner and Leontieff in earlier eras, and the US government in the 1960s. They offer a more optimistic view. Automation indeed displaces existing tasks, but then there is another type of technological change enabling the creation of new, more complex versions of existing tasks, in which labor has a comparative advantage. Initially, these tasks will go to higher skilled workers, but over the medium term, they will be standardized and passed to less skilled workers. In their model, the displacement effects of automation auto-correct and the distribution of income remains stable over time. Indeed, Autor (2015) argues in *Why Are There Still So Many Jobs? The History and Future of Workplace Automation* that journalists and even expert commentators tend to overstate the extent of machine substitution for human labor and ignore the strong complementarities between automation and labor that increase productivity, raise earnings, and augment demand for labor” and that over the longer term, polarization is unlikely to continue. Over the short to medium term, however, we are left with a disturbing set of empirical regularities.

2 Should We Expect to See Polarization in Developing Countries as Well?

Clearly the question is vitally relevant to developing countries as well. However, the way in which automation and globalization play out in emerging economies may differ from their advanced counterparts:

Differing initial occupational distributions: Potential polarization dynamics are layered on very different initial occupational structures and positions in the demographic transition. Most mechanically, in many developing countries, the sector of middle income workers engaged in codified tasks is small in the first place- in Ghana, for instance, 90% of the workforce is informal and engaged in low skilled services and artisanal production (see, for example Falco et al. (2015) and this is representative of many low-income countries. Hence, we would expect to see little in the way of displacement of these types of jobs. In addition, many developing countries still have large shares of the labor force in agriculture and fisheries and are experiencing manifold forces pushing them toward urbanization.

The net impact of off-shored jobs: Off-shored jobs from advanced countries are precisely moving to developing countries and hence we would expect to see a complementary expansion of the middle- a “de-polarization” of the wage distribution in at least some host countries. That said, to the degree that newer arrivals to off-shoring, such as China or Vietnam, compete with established destinations such as Mexico, the net effect of diversion vs. increased total off-shoring is unclear. Hanson and Robertson (2008) find that for Hungary, Malaysia, Mexico, Pakistan, the Philippines, Poland, Romania, Sri Lanka, Thailand, and Turkey, China’s impact has been negative, but relatively small. Lederman et al. (2009) finds similarly modest effects for Latin America. Hence, the diversion effects, to date, seem muted

and we may find overall, that trade generates the reverse of, or at least milder, polarization effects.

Removal of barriers to entry: New technologies may also give new leverage to citizens to break down existing barriers to entry and efficiency growth (think Uber), facilitate information flows on markets and opportunities, potential products, inputs, and production technologies to make possible entire new industries: Travel agents, finance, tourism, international marketing of local products etc.

The impact of ICT: The impact of technological progress in LDCs is also not clear. Michaels et al. (2014) identify a strong correlation of ICT adoption and polarization. However, as Eden and Gaggl (2015) argue, ICT related capital stocks are lower in LDCs as they probably should be given the lower capital-labor ratios, the higher cost of ICT capital, and the structure of their economies. Hence the displacement effects on jobs directly affected by ICT adoption may be lower.

Automation related productivity growth in small open economies: The employment impact of technological progress in larger countries depends on the relative product elasticity- if the fall in price arising from the labor savings more than proportionately increases demand, we will see an expansion of employment. Since, more open developing countries are often assumed to be price takers, we should therefore see any domestic innovations in productivity rewarded massively with huge expansion in employment. Rodrik (2015) argues, however, that both the fall in prices arising from the global adoption of technology as well as opening up to trade and the preexistence of far better producers have offset this effect. In fact, with the exception of some Asian countries, he argues that LDCs may be suffering a kind of premature de-industrialization where their nascent industrialization has been truncated earlier in their development than has been historically the case.

More limited feasibility of automation?: The degree to which automation is adopted depends heavily on a country's technological absorptive capacity, the skill of the workforce, ability to mobilize resources for large capital investments, capacity for maintenance, and attention to tolerances which may make it less easy to substitute away from labor in many poorer countries.

Skills for emerging complementary tasks?: To the degree the automation does occur, the likelihood of developing the kinds of upgraded jobs to complement the automation would seem lower in countries with weak educational bases in the first place. Or put differently, if a country had to raise workforce cognitive and non cognitive skills to be attractive to MNC assembly operations, this task would seem more challenging as the offered jobs are the upgraded complements to assembly operations.

The first set of estimates of the combination of these effects is modestly pessimistic. Broadly following Goos et al. (2014), WorldBank (2016), using labor force surveys argues that middle skilled occupations intensive in routine cognitive and manual skills have decreased across the developing world as well, with the exception of China, Ethiopia, Argentina and Nicaragua.

3 Data

We pursue the approach of Autor (2010) of tracking job categories across time for 21 developing countries in Africa, Latin America and Asia. We use the Integrated Public Use Microdata Series (IPUMS) developed by the Minnesota Population Center which harmonizes census micro-data from around the world. The project has collected the world's largest archive of publicly available census samples. The data are coded and documented consistently across countries and over time to facilitate comparative research.¹

¹See <https://international.ipums.org/international/>.

We use *OCCISCO* variable which records the person’s primary occupation² coded according to the major categories in the International Standard Classification of Occupations (ISCO) scheme for 1988 and have 11 categories: *Legislators, Senior Officials and Managers; Professionals; Technicians and Associated Professionals; Clerks, Skilled Agricultural and Fishery Workers; Crafts and Related Trades Workers; Plant and Machine Operators and Assemblers; Service Workers and Shop and Market Sales; Elementary Occupations; Armed Forces* and *other occupations and no identified occupations*. Table 1 lays out the categories we include in more detail.

Autor (2010) and Autor and Dorn (2013) map these 3-digit categories into a distinct set of skill sets listed in figure 1 to better capture “routine” tasks. Hence, in the original ISCO categorization, operators of machines in manufacturing appear in “Plant and Machine Operators, and Assemblers” (category 8) but manufacturing workers who do not operate machinery appear in “elementary occupations” (category 9). Both may be more routine than, for instance, food preparation or personal care, also found in category 9, which require potentially less skill, but which are also less easy to automate. As we are working with numerous countries with varying degrees of disaggregation and sometimes inconsistent or ambiguous categorizations across time that have been standardized by the census categories, we work directly with those. As we show, for the United States, this does not change the conclusions appreciably.

The available census data for developing countries for which we can follow employment in a substantive way before and after 1990 are limited, but not unrepresentative. From Latin America we have Brazil, the Dominican Republic, Ecuador, El Salvador, Mexico, Nicaragua, Panama, and Peru, most of which have had a manufacturing tradition. From Asia we have India, Indonesia, Vietnam, and Fiji. From the Middle East: Arab Republic of Egypt, Mo-

²For someone with more than one job, the primary occupation is typically the one in which the person had spent the most time or earned the most money.

rocco and West Bank and Gaza. From Africa: Ghana, Liberia, Malawi, Mali, South Africa, and Zambia. Other countries are available, but may have limited time series. For instance, China and Germany are represented in the IPUMS but their series end at the 1990s and hence we exclude them.

The number of Advanced Countries (AC) and Developing Countries (DC) which we use to pool in regression analysis is greater:

AC includes Austria, Canada, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Switzerland, United Kingdom and United States.

DC includes Argentina, Armenia, Belarus, Bolivia, Brazil, Burkina Faso, Cambodia, Cameroon, Chile, China, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Fiji, Ghana, Guinea, Haiti, Hungary, India, Indonesia, the Islamic Republic of Iran, Iraq, Jamaica, Jordan, Kenya, Kyrgyz Republic, Liberia, Malawi, Malaysia, Mali, Mexico, Mongolia, Morocco, Mozambique, Nicaragua, Nigeria, Pakistan, Panama, Paraguay, Peru, Philippines, Puerto Rico, Romania, Rwanda, Senegal, Sierra Leone, Slovenia, South Africa, South Sudan, St. Lucia, Sudan, Tanzania, Thailand, Turkey, Uganda, Uruguay, Venezuela, Vietnam, West Bank and Gaza, Vietnam and Zambia.

4 Results

To ensure that categorization differences are not affecting our results, Figure 1 presents Autor's (2015) graph for the United States and Figure 2 replicates it using our data and categories which are available for all our sample. The results are consistent. Operators and assemblers, and crafts and related show a decline across the last decade compared to the elementary occupations and the more skilled categories. Figure 2 also documents the same

for France. These two countries support the findings of the existing literature.

The graphs from the developing world (Figures 2-8), however, are far less clear. First, the operators and assemblers category rarely shows a decline. Indonesia perhaps shows the most convincing case over the last decade.³ For most of the sample, however, the operators and assemblers category is expanding in absolute terms and generally in relative terms. Vietnam serves as perhaps the archetypal off-shoring destination that hosts Samsung, Intel and others. Here we see that operators and assemblers have increased relative to every category with the exception of professionals. India, up to 2004, tells a similar story. Operators and assemblers show some of the highest growth rates and increasing over time while, again, elementary occupations show an absolute decline. These two important cases do not appear to show much evidence of polarization with the data available. Ecuador, Egypt, El Salvador, Ghana, Malawi, Mali, Morocco, Nicaragua, Peru, and South Africa, all suggest broadly similar patterns.

Mexico and Brazil similarly show absolute gains in these categories, both quite rapidly up to 2000. However, growth has slowed over the 2000s and *relative growth* indeed does suggest potential polarization. The literature cited above argues for only modest impact of the emergence of China and India on Latin America. Further, the rise in global trade largely driven by outsourcing occurred in the "long 90's," 1988 to the early 2000s, the period of greatest expansion of the operators category in these countries. It may be that these countries have been more integrated in the automation wave than others. Panama shows a broadly similar pattern. Liberia over 1974 to 2008 shows positive absolute but relative falls as well although the brutal civil war there complicates inference.

Overall, the category of crafts and related follows the broad tendencies in operators and assemblers in Brazil, Egypt, India, Indonesia, Liberia, Malawi, Mali, Mexico, Panama, South

³The West Bank and Gaza, the only available economy not shown, exhibits a reduction, but then it does in virtually all categories and the the fall in elementary occupations is far greater.

Africa, Zambia and perhaps Morocco. In Mexico, for example, the evolution is almost identical. This may reflect that, while not routine tasks, nonetheless electrical and electronic trades workers, metal machinery, and building workers are inputs into industries that are. That said, we might expect that automating plants would require these skills as much as traditional.

Finally, Figure 8 aggregates across our broader sample of countries and plots the average growth rate by sector post-1990 relative to pre-1900. It is clear that the patterns are very different between the two samples. In the advanced countries, both skilled agricultural and operators show absolute declines while more advanced and elementary tasks increase. In the developing countries, operators, professionals and elementary occupations grow at approximately the same rate.

These graphical findings are confirmed by regression analysis with the broader panel of countries. Specifically, we estimate the equation:

$$L_{it}^c = \beta_1 I[t \geq 2000 \wedge AC]_{it} + \beta_2 I[t \geq 2000 \wedge DC]_{it} + \gamma_i + \varepsilon_{it} \quad (1)$$

where L_{it}^c is the log-level (or the share) of each of the major categories in the International Standard Classification of Occupations (ISCO) scheme for country i in year t and c represent the job category. $I[.]$ is a dummy variable equal to one if $[.]$ condition is satisfied, 0 otherwise; γ_i captures individual country fixed effects. The time dummies capture differential changes by job category after the break point between advanced (DC) and developing country (LDC) groups relative to the pre-breakpoint period. We two way cluster for standard errors by country and year level as suggested by Bertrand et al. (2004).

Table 2 presents the results for the log of absolute employment as the dependent variable and table 3, the share of employment. Preliminary regressions allowing the break point to change from 1995-2005 suggest 2001 as having the most explanatory power (R^2), very close

to the break point discussed by Autor and this informs the definition of the dummies above.

The presence of country fixed effects means that the dummies are measuring the average of country log level changes in employment (shares) by group relative to their pre-2000 levels and not relative to some third category. These broadly approximate the growth rate of the second period relative to the first. We first notice little difference between the two groups in legislators or professionals and only modestly faster growth of technicians in developing countries. Second, both clerks and service workers show growth rates roughly three times higher in the developing countries. Third, skilled agricultural and fishery workers show insignificant change in developing countries, but a substantial fall in advanced countries suggesting a more rapid emptying out of the rural areas there. Fourth, among the key categories of the craft and operators categories, we find insignificant growth/decline among the advanced countries broadly consistent with Autor, while developing countries continue strong growth equal to any other sector except technicians. Elementary occupations maintain a similar level of growth as well, despite, somewhat in contrast with Autor's findings, stagnation in advanced countries. In sum, in the advanced countries, we do see stagnation in the categories associated with the displacement of codifiable tasks in the "center" of the occupational distribution, but in developing countries, job growth is broadly similar across categories with the exception of skilled agricultural and forestry sectors, consistent with expected demographic shifts across the development process.

Table 3 showing employment shares confirms this difference in the polarization process. For the advanced countries, craft workers show a 3.6 lp fall, and operators an 4.5 lp fall (although statistically insignificant) while legislators grew 2.9 lp, professionals 4.4 lp, and technicians 6.3 lp. Again, elementary occupations do not show strong growth weakening the conclusion of polarization. But the point estimates suggest a loss of the codifiable type job class. This is not replicated for the developing countries. Professionals, technicians and service workers shows significant gains 1.4, 2.3, 5.6 lp respectively. This is virtually entirely

offset by the fall in skilled agriculture and fishery workers show which show a 11.4 lp fall, again, expected structural change. Crafts, operators and elementary occupations show much smaller point estimates and are never significant reflecting the conflicting tendencies revealed in the graphical analysis. Again, however, there is no evidence of polarization.

5 Looking Forward: Latent Polarization, Grounded Geese?

The results above suggest that overall, we are not seeing the polarization found in the advanced countries. Yet. Indonesia shows an absolute fall in the operators category while technicians and service and elementary occupations rise. Both Mexico and Brazil show relatively slow growth of the operators category which, while not showing the absolute hollowing out found in the United States, is consistent with polarization.

Further, press accounts suggest the emergence of the same automation dynamic in important follower countries. In China, there are signs that robotization is proceeding rapidly. Perhaps the most pessimistic observer, Martin Ford, argues that from 1995-2002 roughly 15% or 16 million of the manufacturing workforce has been displaced by automation and some iconic firms, like Foxconn, intend to have their million-worker factories 70% automated by 2018. Guangzhou, the provincial capital of Guangdong Province in the heart of China's manufacturing zone, aims to have 80% of its firms automated by 2020. The International Federation of Robotics predicts that China will have more installed robots than any other country by 2017. Part of this may reflect the dramatic fall in robot prices. The payback period for a welding robot in the Chinese automotive industry, for instance, dropped from 5.3 years to 1.7 years between 2010 and 2015, and by 2017 is forecast to shrink to just 1.3 years.

In addition, both the Chinese and Korean governments now subsidize the introduction of robots. The reasons vary. The Korean government is re-shoring to ensure adequate industrial capacity at home. China seeks both to raise the quality of its exports as an effort to brand Chinese products and this is easier with robots than the slower process of upgrading the workforce. In addition, it seeks a share of a rapidly expanding robotics market.⁴⁵

This raises two concerns related to internal and international equity. As in the advanced countries, we may not yet see the new more complex labor tasks described by Acemoglu and Restrepo (2015) emerging as automation proceeds. While China has complemented automation with investment in training for more complex jobs, recent college graduates report having problems finding employment and 43% consider themselves over-educated for their positions, much as Beaudry et al. (2013) suggest is happening in the United States.⁶

Perhaps the largest concern is that as automation eliminates routine manufacturing type jobs, we may see a short circuiting of the traditional forces generating the “flying geese” pattern where stages of the value chain are passed down from advancing to lagging coun-

⁴See Financial Times, April 28, 2016.

⁵“According to the International Federation of Robotics, an association of academic and business robotics organizations, China bought approximately 56,000 of the 227,000 industrial robots purchased worldwide in 2014 – a 54 percent increase on 2013. And in all likelihood, China is just getting started. Late last month, the government of Guangdong Province, the heart of China’s manufacturing behemoth, announced a three-year program to subsidize the purchase of robots at nearly 2,000 of the provinces – and thus, the world’s – largest manufacturers. Guangzhou, the provincial capital, aims to have 80 percent of its factories automated by 2020. China’s central government, always keen to avoid the disgruntlement of its working class, has made efforts of its own. It has committed to expanding vocational education so China’s low skill workers will not be left behind in an automated economy.” See <http://www.bloombergtimes.com/articles/2015-04-09/robots-leave-behind-chinese-workers>.

⁶“That might not be a problem if the Chinese economy were generating plenty of higher-skill jobs for more educated workers. The solution, then, would simply be to offer more training and education to displaced blue-collar workers. The reality, however, is that China has struggled to create enough white-collar jobs for its soaring population of college graduates. In mid-2013, the Chinese government revealed that only about half of the country’s current crop of college graduates had been able to find jobs, while more than 20 percent of the previous years graduates remained unemployed. According to one analysis, fully 43 percent of Chinese workers already consider themselves to be over educated for their current positions. As software automation and artificial intelligence increasingly affect knowledge-based occupations, especially at the entry level, it may well become even more difficult for the Chinese economy to absorb workers who seek to climb the skills ladder”. See <http://www.nytimes.com/2015/06/11/opinion/chinas-troubling-robot-revolution.html>.

tries. Even if Chinese workers, building on the learning by doing of the workforce over the last 20 years, are able to move into complementary higher paying jobs, where will automation leave the follower countries with very unskilled labor that in the past might have expected to inherit the routine jobs that China is now shedding, but which are now in fact, disappearing altogether? Vietnam, which has benefited from redirection of off-shoring as China's wages have risen, also has seen substantial automation of, for instance, the textile industry over the last decade.⁷ The worry, then, is that there remains a large global population with relatively weak cognitive and non-cognitive skills who will not be writing code and programming robot routines anytime soon, but who will not inherit unskilled jobs either.

6 Conclusion

This paper has used census data to explore to what degree findings of polarization in the advanced world can be found in the developing world. We first offer several reasons why we might not expect to see the same tendencies found in the advanced world, or at least not yet. It is also possible that between being destinations for off-shoring, and the fact that new technologies may enable LDC citizens to overcome myriad structural and political economy obstacles that form barriers to creating better jobs, the net impact might be expected to be positive in the medium term. We then confirm previous findings of polarization graphically for the US and France. However, we do not find strong evidence for polarization in LDCs. The key category- plant and machine operators and assemblers, does not show absolute or relative decrease in most developing countries across the last decades. Regression analysis supports the graphical findings that on average, we do not find evidence of polarization in LDCs.

This does not imply much about the future. We find that Indonesia, Brazil and Mexico do show relative decline in the operators category which could suggest potential polarizing

⁷John Luke Gallup *End of Development? The Peril of Automation for Vietnam*. 2015.

forces. Also of concern is that the moves toward robotization in China and other manufacturing centers that could exacerbate internal inequality and short circuit the pattern of progressive handing down of routine manufacturing tasks to follower countries. Hence it may be the non-appearance of the Vietnam pattern of expanding assembly and operators in Africa, for example, that will be the important story.

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Figures and Tables

Table 1: ISCO categories and mainly subdivisions

ISCO categories	ISCO code	Subdivision
Managers	11	Chief executives, senior officials and legislators
	12	Administrative and commercial managers
	13	Production and specialised services managers
	14	Hospitality, retail and other services managers
Professionals	21	Science and engineering professionals
	22	Health professionals
	23	Teaching professionals
	24	Business and administration professionals
	25	Information and communications technology professionals
	26	Legal, social and cultural professionals
Technicians and associate professionals	31	Science and engineering associate professionals
	32	Health associate professionals
	33	Business and administration associate professionals
	34	Legal, social, cultural and related associate professionals
	35	Information and communications technicians
Clerical support workers	41	General and keyboard clerks
	42	Customer services clerks
	43	Numerical and material recording clerks
	44	Other clerical support workers
Service and sales workers	51	Personal service workers
	52	Sales workers
	53	Personal care workers
	54	Protective services workers
Skilled agricultural, forestry and fishery workers	61	Market-oriented skilled agricultural workers
	62	Market-oriented skilled forestry, fishery and hunting workers
	63	Subsistence farmers, fishers, hunters and gatherers
Craft and related trades workers	71	Building and related trades workers, excluding electricians
	72	Metal, machinery and related trades workers
	73	Handicraft and printing workers
	74	Electrical and electronic trades workers
	75	Food processing, wood working, garment and other craft
Plant and machine operators, and assemblers	81	Stationary plant and machine operators
	82	Assemblers
	83	Drivers and mobile plant operators
Elementary occupations	91	Cleaners and helpers
	92	Agricultural, forestry and fishery labourers
	93	Labourers in mining, construction, manufacturing and transport
	94	Food preparation assistants
	95	Street and related sales and service workers
	96	Refuse workers and other elementary workers

Table 2: Testing changes in log of employment after 2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Elementary occupations	Service workers and market sales	Skilled agricultural and fishery	Clerks	Crafts and related	Operators and assemblers	Technicians	Professionals	Legislators and Managers
<i>Year</i> ≥ 2000*AC	0.266 (0.257)	0.326*** (0.0667)	-0.449*** (0.141)	0.188** (0.0852)	0.0613 (0.141)	-0.0430 (0.269)	1.051*** (0.186)	0.666*** (0.0996)	0.706*** (0.124)
<i>Year</i> ≥ 2000*DC	0.686*** (0.151)	0.967*** (0.133)	-0.0138 (0.0755)	0.608*** (0.135)	0.498*** (0.0968)	0.704*** (0.173)	1.316*** (0.233)	0.777*** (0.133)	0.692*** (0.166)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210	210	210	209	210	208	203	210	210
R-squared	0.891	0.945	0.977	0.957	0.965	0.937	0.884	0.946	0.944

Two way robust-clustering standard errors to year and country level

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: Regression of log employment on dummy for post-1990 period by sector with country fixed effects. Advanced country (AC) and Developing country (DC) samples as defined in text. IPUMS data.

Table 3: Testing changes in share of employment after 2000

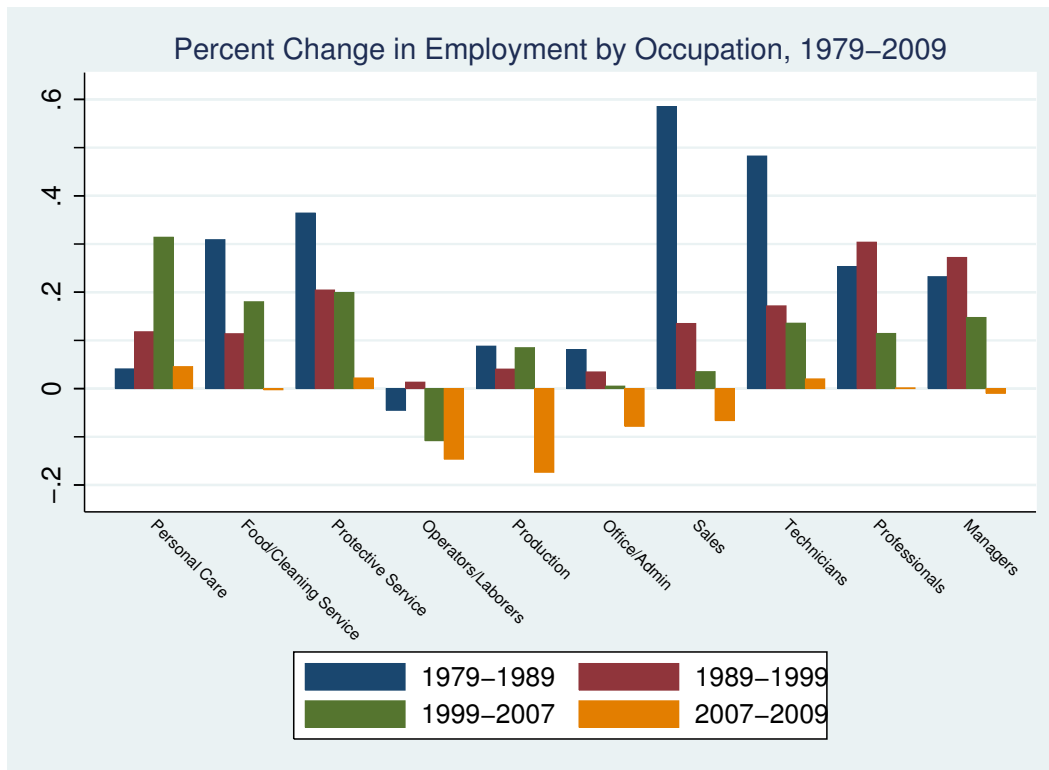
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Elementary occupations	Service workers and market sales	Skilled agricultural and fishery	Clerks	Crafts and related	Operators and assemblers	Technicians	Professionals	Legislators and Managers
<i>Year</i> ≥ 2000*AC	-0.682 (1.852)	0.862*** (0.267)	-4.786*** (1.354)	-1.006 (0.669)	-3.596** (1.585)	-4.537 (3.447)	6.318*** (0.851)	4.441*** (0.825)	2.869*** (0.536)
<i>Year</i> ≥ 2000*DC	1.169 (1.072)	5.161*** (0.996)	-11.39*** (2.489)	0.887 (0.540)	-0.672 (0.528)	0.617 (0.838)	2.305*** (0.490)	1.421*** (0.361)	0.465 (0.334)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210	210	210	209	210	208	203	210	210
R-squared	0.774	0.719	0.935	0.915	0.816	0.683	0.794	0.866	0.816

Two way robust-clustering standard errors to year and country level

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: Regression of employment share on dummy for post-1990 period by sector with country fixed effects. Advanced country (AC) and Developing country (DC) samples as defined in text. IPUMS data.

Figure 1



Source: (Autor, 2010).

Figure 2: Changes in Employment by Occupation: Advanced Countries

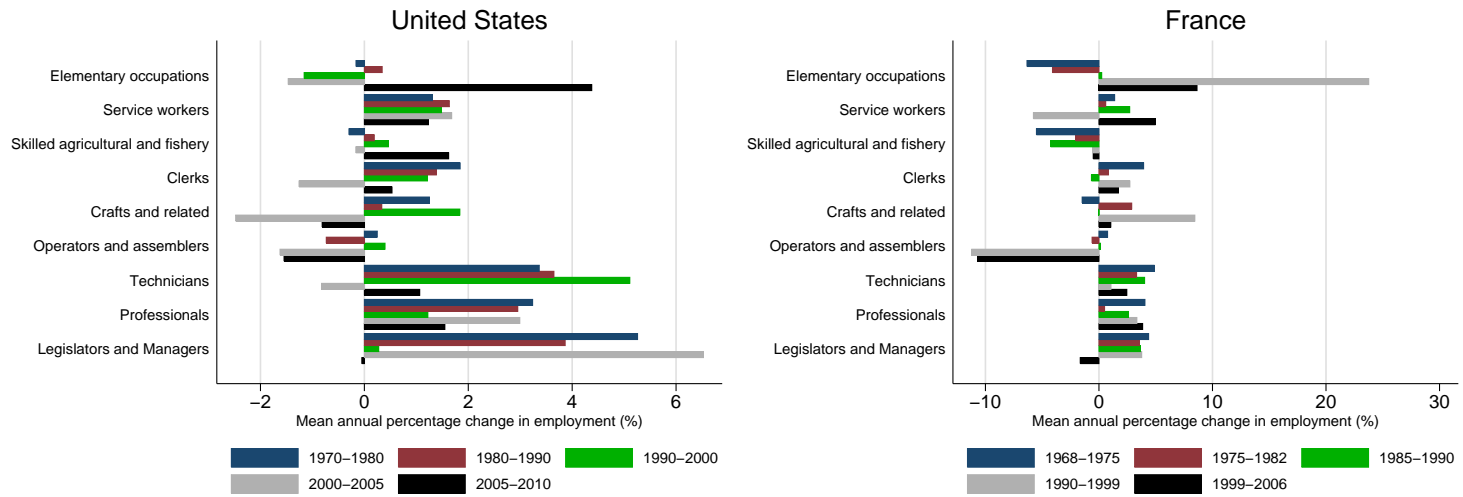


Figure 3: Changes in Employment by Occupation: Developing Countries

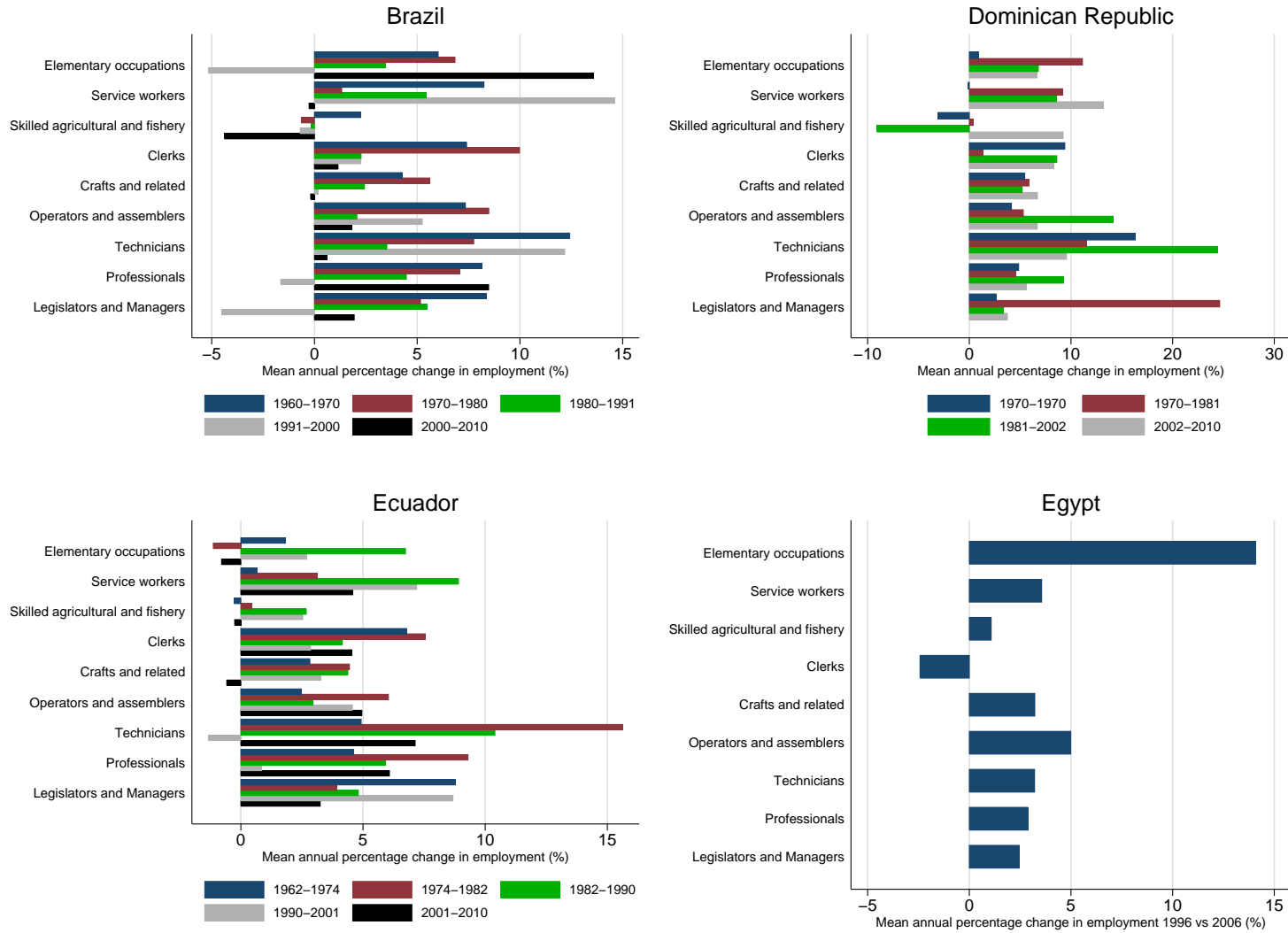


Figure 4: Changes in Employment by Occupation: Developing Countries

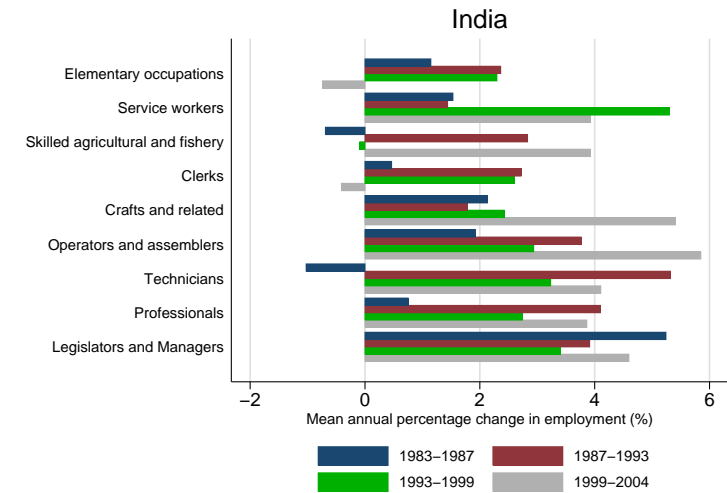
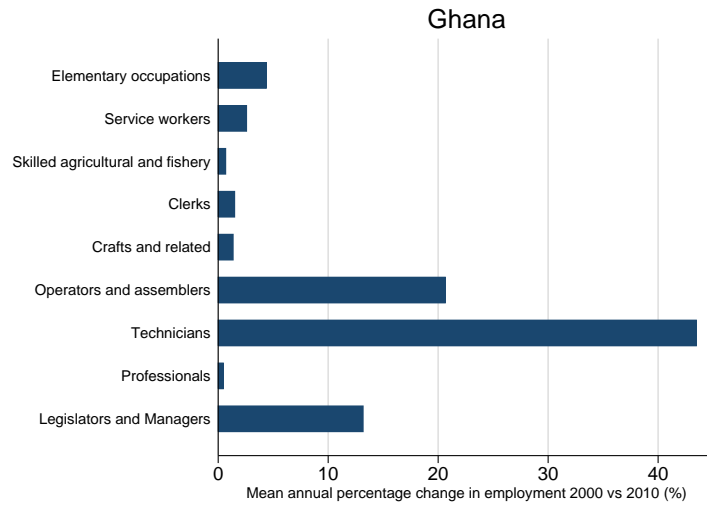
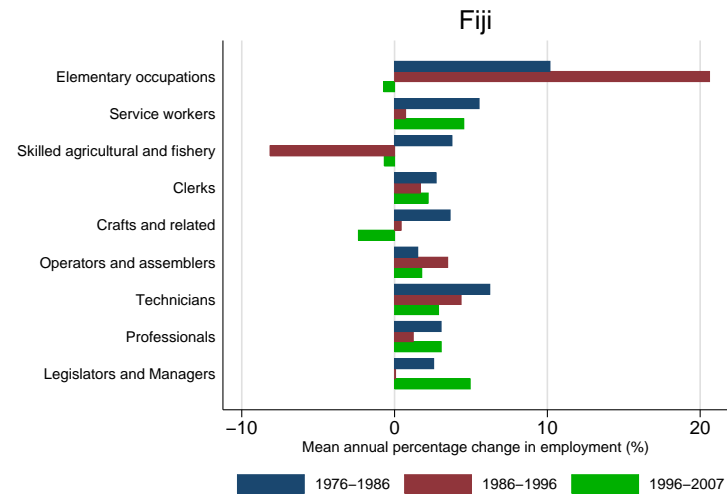
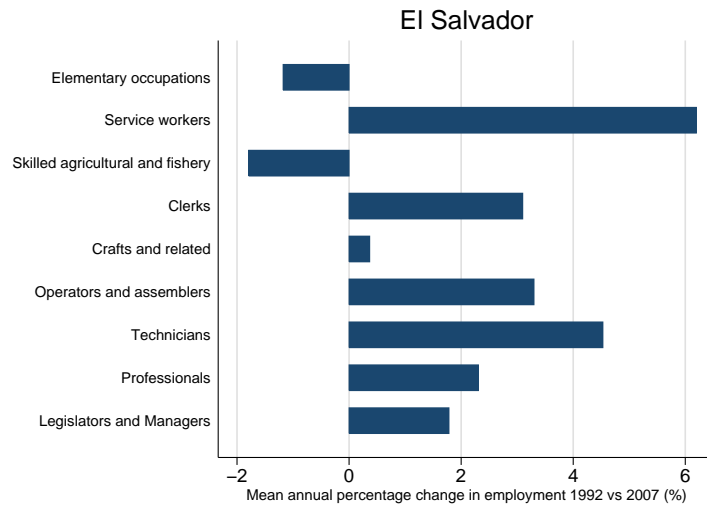


Figure 5: Changes in Employment by Occupation: Developing Countries

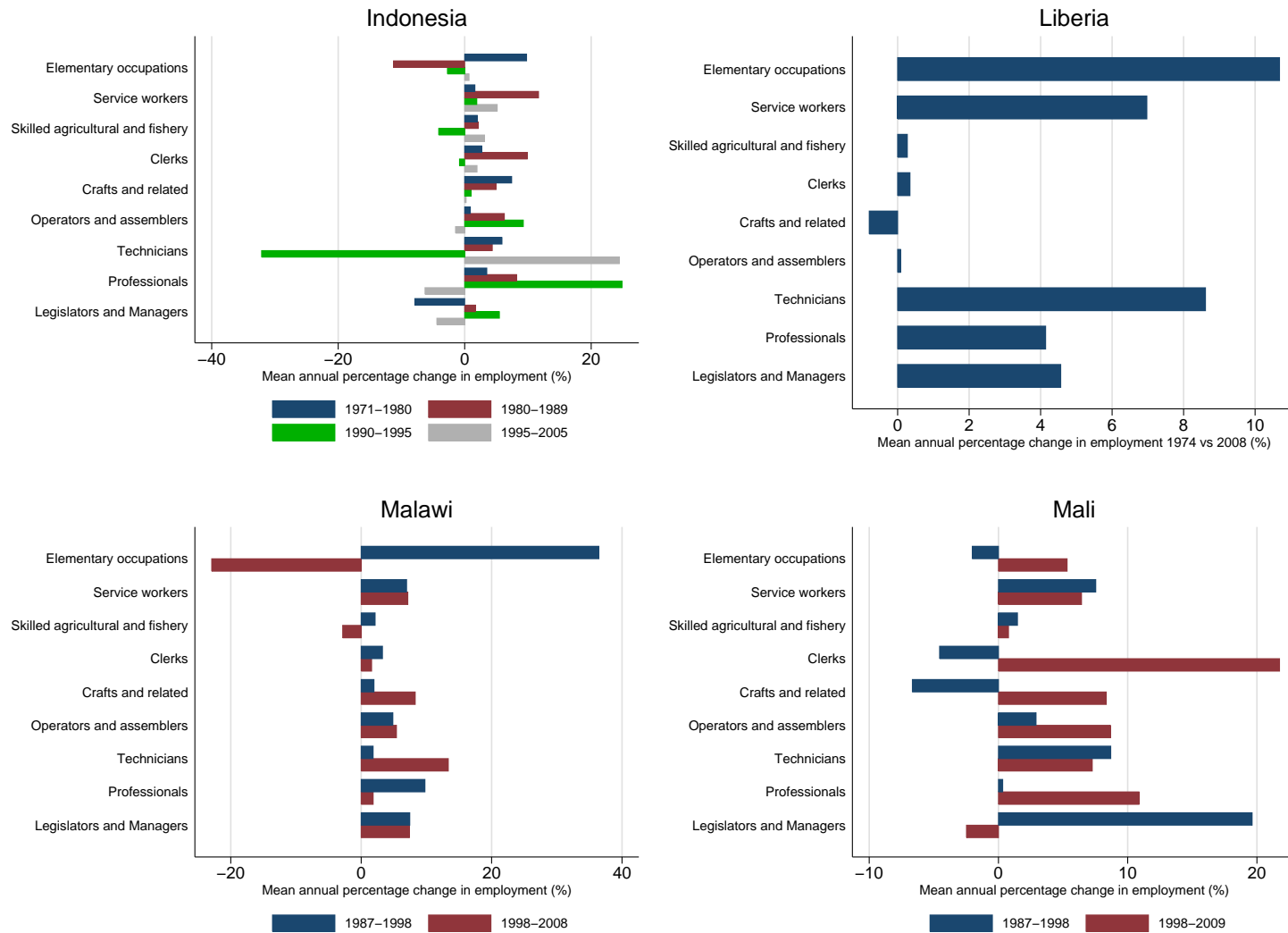


Figure 6: Changes in Employment by Occupation: Developing Countries

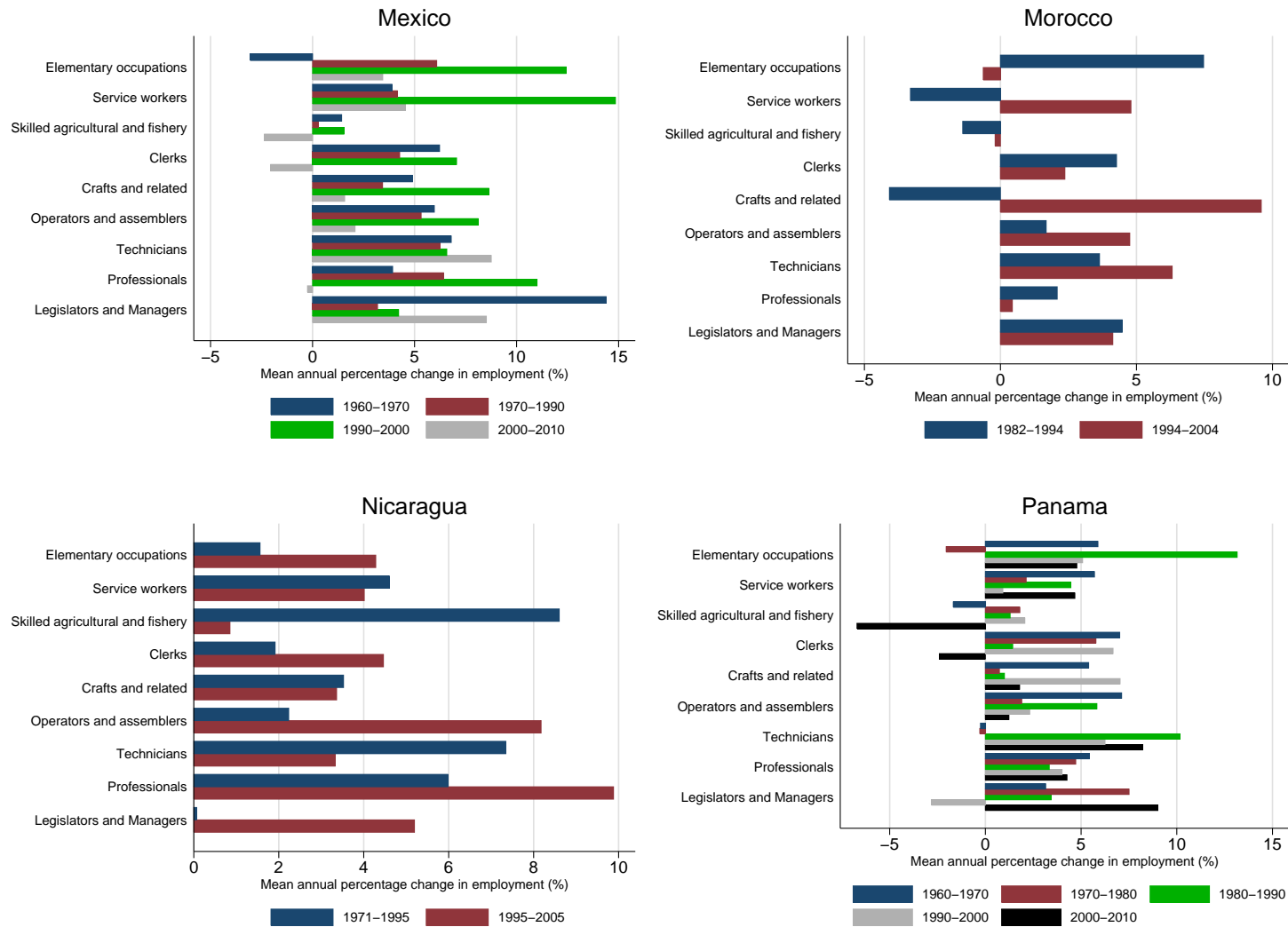


Figure 7: Changes in Employment by Occupation: LDCs

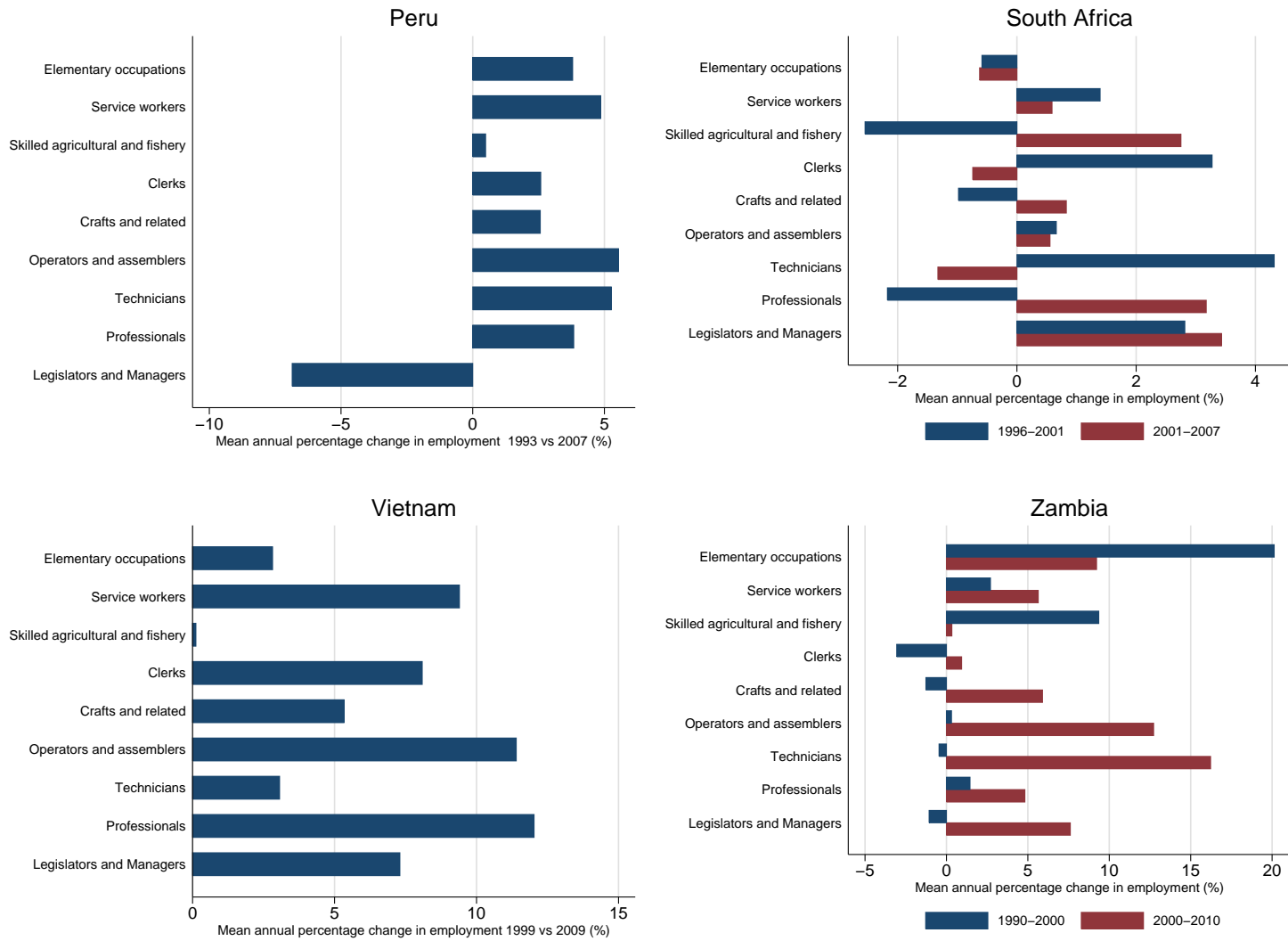


Figure 8: Employment by Occupation, 1979-2012

