Is that where you work or what you do? Understanding job polarization in Brazil

by

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Abstract

Although relatively well documented and accepted in the US and Europe, the notion of labour market polarization is not so clear in the developing world. In this study, I aim to answer two questions: (i) Are the patterns of employment and wage polarization seen in the industrialized countries also found in Brazil? And (ii) has the occupational structure—what you do—gained importance over the sectoral structure—where you work—in explaining the dynamics of the labour market. By applying standardized and reproducible aggregations of occupations by task content, I found strong evidence of employment polarization but not of wage polarization. Moreover, this study corroborates the idea that the occupational structure is a key driving force behind the determination of employment and wage dynamics, although further investigation is required to understand the relationship between job polarization and the wage distribution. This study also contributes to the literature by adjusting the classification of occupations (CBO) and activities (CNAE) to make the categories compatible before and after the 2002 changes. Thus, I preserved all the National Household Survey Sample's (PNAD-IBGE) valid responses between 1981 and 2013.

Keywords: Polarization; Brazilian labor market; wage distribution; occupation; industries; skills

To my family, for loving me unconditionally.

"It is not so very important for a person to learn facts. For that he does not really need a college. He can learn them from books. The value of an education in a liberal arts college is not the learning of many facts, but the training of the mind to think something that cannot be learned from textbooks."

— Albert Einstein, quoted in Frank (1947), p.214.

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Chapter 1

Introduction

As the process of economic development is typically uneven, we normally observe significant differences in the rate of growth across sectors. In other words, a more traditional explanation for the patterns of employment and wages could be given by the performance of the industries. A fast-growing sector would tend to offer more and better-paid jobs whereas stagnating activities would close job positions and be less competitive in the job market. Nevertheless, although sometimes correlated, output growth is not fully translated into changes in either employment or wages. Clearly, there are other factors causing these changes beyond the industry structure.

With this background in mind, this study tests the hypothesis of polarization in the Brazilian labour market by studying the changes in employment shares and wage distribution. Moreover, I examine whether the occupations are gaining importance in determining the labour market dynamics or not.

This study follows Acemoglu and Autor (2011) closely in the description and analysis of labour market polarization, since the authors provide a comprehensive and reproducible framework. I use the Brazilian National Household Sample Survey (PNAD) for the period between 1981 and 2013, preserving all valid observations by making the changes in the classifications of occupations and economic activities compatible before and after the changes implemented in 2002. In this way, this study provides a unified framework for understanding the phenomenon of polarization in the Brazilian labour market.

Chapter 2

Literature Review

2.1 Polarization in the United States and Europe

The literature on labor market polarization started in the United States in response to the limitation of the theory of returns to education and skill-biased technological change (SBTC) to explain the developments in the U.S. labor market after the 1990s decade.

As first developed by Tinbergen (1974, 1975) and Freeman (1975), the SBTC framework relates technology with returns to skills. The idea is that some technological changes, like the computer revolution in the 1970s, could favor more-skilled labor by increasing both its relative demand and wages, as compared to less-skilled labor. The reason would be that the new technology could increase more-skilled labor productivity, whereas the less-skilled workers could not take the same advantage of that[1]. But as the returns to skills increase, and given that skills and education are closely related, the incentives for acquiring education increase, raising the supply of skills. That constitutes the so-called 'race between education and technology', since an oversupply of skills can potentially offset the enlarged returns to skills. Moreover, as Goldin and Katz (2008) show, this simple framework with labor supply and demand for two different levels of skills —measured as educational attainment —suffices to explain the wage structure of most of the twentieth century.

However, since the 1990s decade, the US labor market changed in a way that not only the wage inequality between the highest end and the middle of the skill distribution increased in the US, but also the disparity in the earnings between the middle and the lowest end

[1]Not all technological change is skill-biased. The industrial revolution of the late seventieth and early eightieth centuries increased the relative demand and earnings of lower-skilled labor.

of the skill distribution decreased. What became to be understood is that the relationship between technology and skills complementarity is not one-to-one. The widespread usage of computers since the 1970s not only increased the productivity of high-skilled workers, but also allowed for the automation of certain tasks, i.e. directed substituting for certain types of labor. The key point of the "routinization" hypothesis is that there are specific types of tasks, consisting of a known sequence of actions, that could be translated into a code and performed by a machine. Thus, these 'routine' tasks could potentially be automated. On the other hand, Polanyi-like tasks, that involve tacit knowledge and cannot be codified by an algorithm, would necessarily win the race against technology.

In their seminal work on job polarization, Autor, Levy and Murnane (2003)—henceforth ALM—explain the hollowing out of the occupation distribution in industrial countries as caused by a non-neutral technical change, compounded by offshoring, that mined the demand in jobs involving routine tasks. The authors use an intricate combination of the Dictionary of Occupational Titles (DOT) and the Census Occupation Codes (COC) to classify each occupation according to its task requirements. The goal of ALM is to understand how computerization altered job content and human skill demands since 1960s. The authors decompose the variation in the task requirements of jobs into an 'extensive' (across occupations) and an 'intensive' (within occupations) margins. The use of the DOT instead of its successor, the Department of Labor's O*NET is based on the fact that the former provides a time series information on the skill requirement for detailed occupations economy-wide, which the latter does not. Using these COC-DOT aggregations, ALM select five variables that fit best their skill constructs.

1. non-routine cognitive tasks: DCP (Direction, Control, and Planning) and GED-MATH (General Educational Development - Mathematics);
2. routine cognitive tasks: STS (Set limits, Tolerances, or Standards);
3. routine manual tasks: FINGDEX (Finger Dexterity);
4. non-routine manual tasks: EYEHAND (Eye-Hand-Foot coordination);

Analyzing the Census IPUMS one percent extracts for 1960, 1970, 1980 and 1990, and to CPS Merged Outgoing Rotation Group (MORG) files for 1980, 1990 and 1998, using all observations on non-institutionalized, employed workers, ages 18 – 64, ALM successfully show an increase in the relative demand—measured by employment share—in occupations

requiring non-routine, either cognitive or manual, tasks. This side of the phenomenon is dubbed by Acemoglu and Autor (2011) the 'job polarization'.

Extending ALM, Autor, Katz and Kearney (2006)—henceforth AKK—show that a model of computerization in which (i) routine tasks present in most middle-wage jobs are substituted by computers, (ii) non-routine cognitive tasks of high-wage occupations are strongly complementary to computers and (iii) non-routine manual tasks of low-wage jobs are neither substituted by nor complementary to computers is able to explain not only the 'job polarization' mentioned before but also the 'wage polarization', i.e. the respective pass-though of the employment share changes into changes in the wages. In fact, what later studies show is that the above list of task-content of occupations is also a decreasing ordering of skill-content—educational attainment—and mean occupational wages. Therefore, whatever the ranking of skills is, the phenomenon of hollowing out of changes in the employment shares and in relative wages increase is apparent.

In "Skills, Tasks and Technologies: Implications for Employment and Earnings", a chapter of the fourth volume of the Handbook of Labor Economics (2011), Daron Acemoglu and David Autor unify the previous literature and produce a detailed data analysis in a rather comprehensive and reproducible fashion. The authors propose an enhancement of the skill-biased technological change framework (SBTC), labeled "the canonical model", so that it could suitably encompass some key empirical facts observed in industrialized countries, in particular the non-monotonic changes in the distribution of employment and earnings across occupations of various skill levels during different decades. To prepare the ground for the 'task-based model', Acemoglu and Autor (2011) provide an overview of the labor market in the U.S. and European Union economies in 48 pages of detailed work that covers the period of 1963 to 2008. The authors use a combination of data sources that includes March CPS, May/ORG CPS, Census and the ACS. The labor market is narrowed to the non-military, non-agricultural employees (not institutionalized or self-employed), aged 16-64 years, who worked 35-plus hours per week and 40-plus weeks in the reference year. We present in detail some of their empirical work, which we used as guidelines for this project.

Acemoglu and Autor (2011)'s data analysis begins by showing the facts that first motivated the studies on SBTC: the sharp increase in the skill-premium—or college/high-school log weekly wage ratio—and the simultaneously decrease in the relative supply college-educated over high-school graduated workers after 1982 in the U.S. At this point, the

authors show that the SBTC view on the patterns of the skill premium may not consider the whole picture, since the data show a convexification of the returns on education. For future reference, the educational groups used by Acemoglu and Autor (2011) are:

- HSD: High school dropout;
- HSG: High school graduate;
- SMC: Some college;
- CLG: College graduate;
- GTC: Greater than college.

The changes in the overall wage inequality are initially addressed by plotting graphs of the evolution 10th, 50th and 90th percentiles of the distribution of the log of weekly wages of full-time, full-year workers, normalized to zero in the start of 1963. The picture clearly shows a rapid increase in the 90th percentile during the 1980s with a moderate approximation of the 10th percentile from the median in the 1990s.

Ranking 318 Census IPUMS occupations by their 1980 mean wage, Acemoglu and Autor (2011) show the broader picture of job polarization by plotting their changes in employment shares across time. As expected, the patterns of a significant increase in the relative demand for both low-skilled worker and high-skilled workers appear again. Additionally, the authors show large evidence that a similar phenomenon is observed in most EU economies and cite studies that show job polarization in Japan too.

More interestingly, Acemoglu and Autor (2011) show that the change in employment shares can be also seen across the occupational structure, beyond the task-content definition. Using 10 categories of occupations that dialogues with previous literature on task-content discussed before, the authors illustrate which group of occupations are referred to by low, middle or high-skilled jobs. Their occupational groups and task correspondences are as follows:

1. Non-routine cognitive tasks: managerial, professional and technical occupations;
2. Routine cognitive tasks: sales, clerical and administrative support occupations;
3. Routine manual tasks: production, craft, repair, and operative occupations; and
4. Non-routine manual tasks: service occupations.

Acemoglu and Autor (2011)'s Figure 12 shows that it is exactly the middle-skilled occupations (routine cognitive and routine manual) that have experienced a significant reduction

in their shares of employment in the last few decades. On the other hand, both the highly educated and highly paid occupations (non-routine cognitive cluster) and the services occupations that experienced an increase in their shares.

The crucial point is that the highly sophisticated aggregation in terms of task measures used by ALM and AKK, among others, although useful to examine intensive changes (within occupations), is not essential to understand the extensive changes (across occupations). Using a group of three task categories—non-routine cognitive, routine and non-routine manual—Acemoglu and Autor (2011) verify that their 'heuristic characterization' of the occupational task content is a robust one. Luckily for us, the results are positive, since this approach provides more transparency and reproducibility to the studies on polarization.

Although highly intuitive that the increase might somehow reflect the overall economic performance of some sectors of the economy, Acemoglu and Autor (2011) subsequently show that the job polarization phenomenon is beyond that. Using a standard shift-share decomposition at the level of the 10 occupational categories presented before and 11 consistent non-farm sectors divided analogously, the study finds that, after 1979, the cross-industry shifts were more than offset by the within-industry decrease in the employment shares. The results are shown in Table 6.

Finally, Acemoglu and Autor (2011) show that occupation became the main determinant of wages, outweighing the importance of educational level in the last few decades. The authors use Census and ACS data from 1959 through 2007 to separately estimate a set of cross-sectional OLS regressions of log full-time, full-year weekly wages on a quartic in potential experience and four sets of control variables:

- years of completed schooling;
- 5 education dummy variables (as above);
- 10 occupation dummy variables (as above);
- 11 industry dummy variables (as used in the shift-share decomposition).

The partial R-squared value (net of the experience quartic) of each set of regressors in each year are plotted in Figure 17, which shows that the explanatory power of the 11 industry dummies on wages is significantly low throughout the period, whereas the explanatory power of education and occupation on wages is always higher and even greater after 1979. Moreover, the explanatory power of the 10 occupation dummies rises sharply

after 1999. To reinforce the robustness of using the occupation clusters instead of the task measures, Acemoglu and Autor (2011) repeat the calculations for the same occupation and education dummies and also for two different groups of task measures. Opportunely, partial R^2 values of both task measures groups are quite close to the explanatory power of the occupation dummies.

As a last comment, the authors mention that the marginal explanatory power of the offshorability measure is very low in the regressions made, which is in line which the previous literature. In other words, although intuitively relevant, the available data could not this part of the supposed effect of offshoring on the wage polarization.

Regarding the European labor market, Acemoglu and Autor (2011) use data from Goos et al. (2009) to show that there was an overall decrease of the middle-paid jobs share in total employment, compensated by increases in either low-paid and/or high-paid jobs in every EU economy between 1993 and 2006. Additionally, the authors use Eurostat data for ten economies between 1992 and 2008 to analyze the changes in employment shares of eight occupational groups somewhat related to the ten groups used for the study US data. The trends showed are very similar to the ones seen in the US, namely a continued increase in the employment shares of Managers, Professionals and Technicians associated with decreases in the employment shares of Operators, Assemblers and Craft workers.

Closely related to the initial studies on job polarization, in particular ALM, Spitz-Oener (2006) provides evidence of significant changes in the occupational structure of employment between 1979 and 1998/1999. Studying a unique dataset that allowed the author to analyze the task requirement of each occupation, Spitz-Oener (2006) corroborates the findings of ALM for the United States, nameley that there has been a major advance in the requirement of complex skills within occupations across time, magnifying analytical and interactive non-routine tasks in detriment of both cognitive and manual routine activities.

2.2 Job polarization in Latin America and Brazil

Perhaps due to the complexity and DOT-specificness of the inaugural research on job polarization and therefore due to the lack of compatible data, we find few investigations of the phenomenon in developing countries.

Medina and Posso (2010) build computer-used related tasks intensities to analyze the changes in occupation employment shares in Colombia, Mexico and Brazil between 1984 and 2009. The paper is mainly focused on Colombian data, for which the relationships between task-requirements and educational attainment by occupation are established and then extrapolated to the other two countries. The authors detect a U-shape dynamics in the changes of employment shares and wages across occupations, analogous to the patterns seen in the U.S. and Europe, following the reported plunge in computer prices and widespread usage of computer-related technologies in Colombia. Similar developments are reported to be found in the Mexican labor market, although somewhat less convincing, but not in the Brazilian case[2]. The main difference as compared to the findings in the US, for instance, is that the very low end of the employment and wages distributions on either skill or mean wages percentiles of the occupations actually loses terrain in Colombia and Mexico, where the gains start to appear somewhere between the 5th and the 15th percentiles.

Bulla (2014) applies a combination of Goos et al. (2009) —in the use of occupation mean wages as a proxy of the skill content of a job —and Acemoglu and Autor (2011) —in the aggregation of the occupations, with a few extensions —to analize household data in Brazil, Mexico and Colombia from 2002 to 2012. The paper finds sharp evidence that employment declined for some middle-skilled occupations but rose mildly for both low-skilled and high-skilled occupations. The patterns for wages, however, were in different directions. While earnings grew for low-skilled jobs, they drop for high-skilled occupations.

Analyzing only Brazilian data, for two periods of time —1987 and 2011 —Hermeto (2013) tests the hypothesis of polarization in terms of an increase in the demand for skills. The study uses two distinct classifications of the occupations: one based on their technological content[3] and another based on the complexity of the tasks implemented (following the DOT in a rather heuristic way, in the same fashion but not exactly matching the groups constructed by Acemoglu and Autor (2011). The test is conducted by running separate cross-section OLS regressions of the log of monthly wages on several controls and the occupation dummies, with mixed and inconclusive results.

[2]The period covered by the Mexican data studied was from 1990 to 2000. For Brazil, the authors uses the same household survey as we used in this project, but only for the period between 1991 and 2001, before the reclassification in the occupation categories.

[3]Using the aggregations constructed by Rodrigues (2006).

The work perhaps more closely related to ours is Flori (2007). The author uses the same dataset, restricted to the metropolitan areas and for only two periods in time: 1984 and 2001. The occupation groups, however, are not exactly the same as in Acemoglu and Autor (2011). The paper finds strong evidence of an increase in the demand for high-skilled workers, measured by the increase in the employment shares of Managers, Professionals and Technicians occupations. Nevertheless, perhaps because of the different occupation groups used, the author finds that Services occupations are the main losers both in terms of employment shares and wages. In summary, Flori (2007) concluded that there is no evidence of polarization, as found in the US and European labor markets.

With respect to earnings differentials in Brazil, Gonzaga et al. (2006) provides evidence that the trade liberalization implemented in Brazil from 1988 to 1995 is associated with decreases in the employment shares and relative prices of skill-intensive sectors. The paper also finds an overall increase in the relative share of skilled labor in total employment together with a decline in the skill premium, in the same direction but smaller than the fall predicted by the change in the patterns of trade, à la Stolper-Samuelson. The period covered by the paper was between 1988 and 2001, using PNAD household surveys, although the author focus on the earning differentials until 1995, as they reflect more directly the trade liberalization.

Using one aspect of the trade liberalization, namely the removal of the barriers to trade in the computer technology sector, Funchal and Soares Junior (2013) shows that the widespread availability of computer for affordable prices positively affected the demand for non-routine tasks, as opposed to routine tasks, specially in sectors and industries more intensive in computer usage.

Finally, Lemos (2009) applies panel data techniques to monthly household data from 1984 to 2004 to demonstrate that the minimum wage —as determined by the Ministry of Labor and Employment (MTE) —compressed the wage distribution in Brazil. The effect is felt more intensively in the lower part of the wage distribution, where the spillovers are considerable.

Chapter 3

Data

This study uses the annual Brazilian National Household Sample Survey (PNAD), implemented by the Brazilian Institute of Geography and Statistics (IBGE). PNAD surveys are based on a multi-stage probability sampling that draws around 150,000 households in each annual sample. This produces a micro dataset of about 350,000 observations (persons) in each year surveyed. The questions investigate general characteristics of the population, like education, labor and income, among others. IBGE provides the sample weight, or expansion factors, of each observation, which equals the reciprocal of the probability of selecting the respective household.

PNAD microdata is available for year 1976 onwards but, unfortunately, some of the variables suffered critical changes throughout the years. These variables include the classifications of both the occupations and the industries categories, which changed significantly in 1981 and in the 2000s decade. For that reason, we opted to use the data covering the period of 1981 to 2013[1]. Still, a great deal of the work in this study was dedicated to harmonize occupation and the industry categories. In 2002, PNAD started to adopt the "Brazilian Classification of Occupations" (CBO-Domiciliar) for the labor occupations and the "National Classification of Economic Activities" (CNAE-Domiciliar) for the industries.

The CBO-Domiciliar increased the occupation categories from 381 to 511 values. The goal of the reclassification was to follow the ISCO-88 (International Standard Classification of Occupations). The change is certainly positive for international comparisons, but had

[1]The survey was not realized in 1991, 1994, 2000 and 2010. We used Data Zoom package, developed by the Department of Economics at PUC-Rio, with some modifications and corrections to convert PNAD microdata to Stata software.

the cost of jeopardizing the compatibility with previous data. Official documentation on the restructuring process provides a code to translate the new classification—more disaggregated—back to the old classification. Since our goal was to analyze the occupational changes in detail, having all our data following the old, restricted classification was not desirable, so we used that information to adjust the old categories into the new classification. All the studies cited in our literature review drop the observations for occupation categories that are not perfectly compatible in the two classifications. We opted to keep all valid observation, whenever possible. Yet, although worthy, the process involved a certain amount of discretion, as some occupations were redivided in two or more categories under the new system, so it was a sensitive task to select which one would be the best fit for each one of the old categories. Overall, our goal was not to cause large disruptions in 2002 in the time series for the employment shares of the ten groups of occupations that will be used in this study. In Figure 3.1 we show the employment shares for these aggregations after the alterations. As can be seen, for almost all categories, the changes observed from 2001 to 2002 are not so distinct from the overall trend before and later. The only important exception is protective services, since occupations that used to be under the label "Undefined" received a more precise definition since 2002. Furthermore, Figure 3.1 also shows some awkward roughness in other points in time that are apparently due to PNAD's weight changes. For that reason, we use three-year moving averages whenever possible in the estimations of the next chapter.

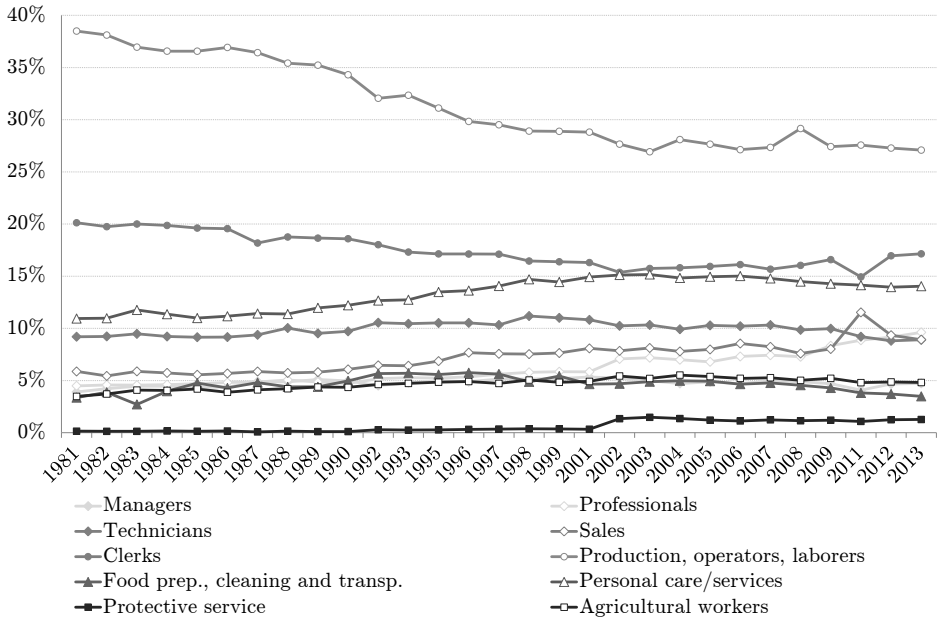

Figure 3.1: Employment shares of full-time formal workers by occupation category

Regarding the industries, CNAE-Domiciliar increased the number of activities classified since 2002 from 166 to 211. But in this case we opt to simply aggregate the values into the 12 desired groups separately. The groups selected were the same for which we have GDP data, as detailed below. Figure 3.2 plots the employment shares for full-time formally employed workers by these 12 groups of economic activity.

To study the changes in employment and income by industry and by occupation, we selected a subset of the larger data according to the following criteria:

(i) people aged 14 to 66 years old: the starting working age in Brazil is usually defined as 15 years old and 65 years is the minimum age for public-financed retirement[2];

(ii) worked at least 36 hours a week, which is the limit for a full-time job in the banking sector;

(iii) were formally employed: private sector employees whose employment contract was registered with the Ministry of Labor or public sector employees—whose contracts do not comply to the same rules, but can also be considered as long-term contracts.

[2]We increased both limits to avoid discarding observation that are qualitatively similar to the precise values. In Brazil, 15 years is the average age a person has when graduating from primary school, while some people graduate with 14 years old. For the upper bound, since the reference month is September, it is possible that the person had just turned 65 at that month, but fully worked until then.

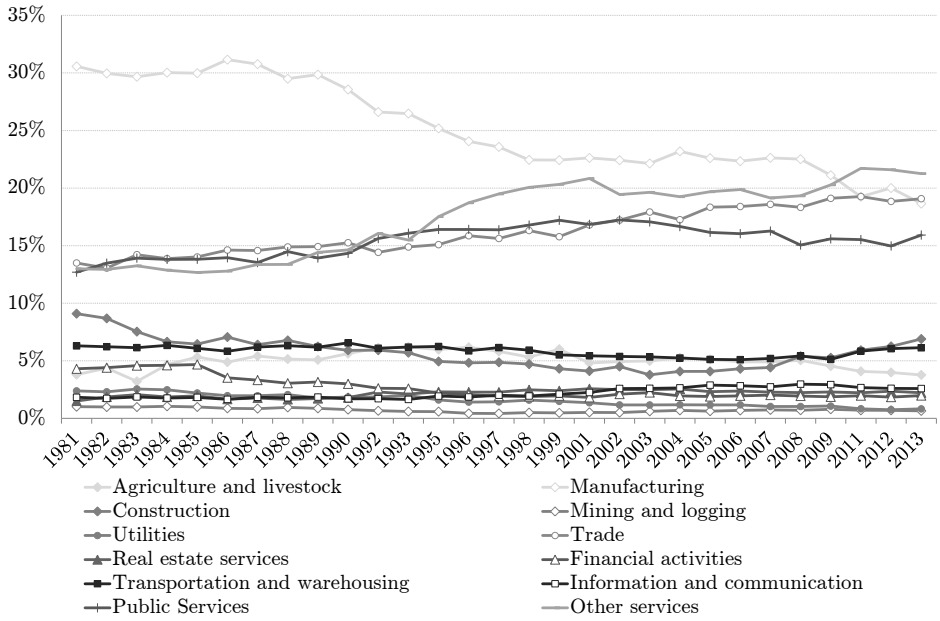

Figure 3.2: Employment shares of full-time formal workers by industry category

This group is the equivalent of full-time full-year workers in Acemoglu and Autor (2011). Note that we discarded military, but we kept agricultural workers, since their representativity is significant. In our case, we call this group "full-time formal employees", or FTFE. Those workers represent, on average 40% of the total working force and 25% of the population aged from 14 to 66 years old, that we call "potential economically active population", or PEAP.

Our variable for wages is actually captured under a broader question: "what was the income from your main labor occupation in the reference month?". It means that it could potentially encompass monetary compensation benefits, which became significantly important in some categories of occupation since 2000s decade. In practice, however, it may not be so representative of this kind of earnings, since the reference month of PNAD is always September whereas most of the financial sector bonuses, for instance, are paid between December and February in Brazil. We keep the variable in monthly basis, since the weekly working hours report seems to be less reliable. The real values are calculated using a deflator based on the National Consumer Price Index (INPC), with year base of 2012. The deflator is the geometric mean of the prices index from August to September of each year, so that it is centered in the beginning of the month, when, in general, the wages are paid.

The series are available online, at the Ipeadata website. As a last note, we point out that we have in our sample from 10% to 20% of the observations with reported wages below the official minimum wage. Since we are using survey data, this difference can eventually be due to underreporting. Or there are some other unknown factors responsible for the discrepancies. In any case, we opted to keep the information as it is.

Additionally to the microdata drew from PNAD, we also used the Gross Domestic Product (GDP)—measured as value added at basic prices—for 12 groups of industries. The data is provided by IBGE under the National Accounts System. The only modification we made was in the values between 1981 and 1994, for which the 12 groups considered did not add to 100 percent since there used to be a 13th group in that period that referred to the financial intermediary services[3]. We simply normalized the values of participation in the GDP to sum to 100% in each year. Figure 3.3 plots these participation shares across time, as a percent of GDP.

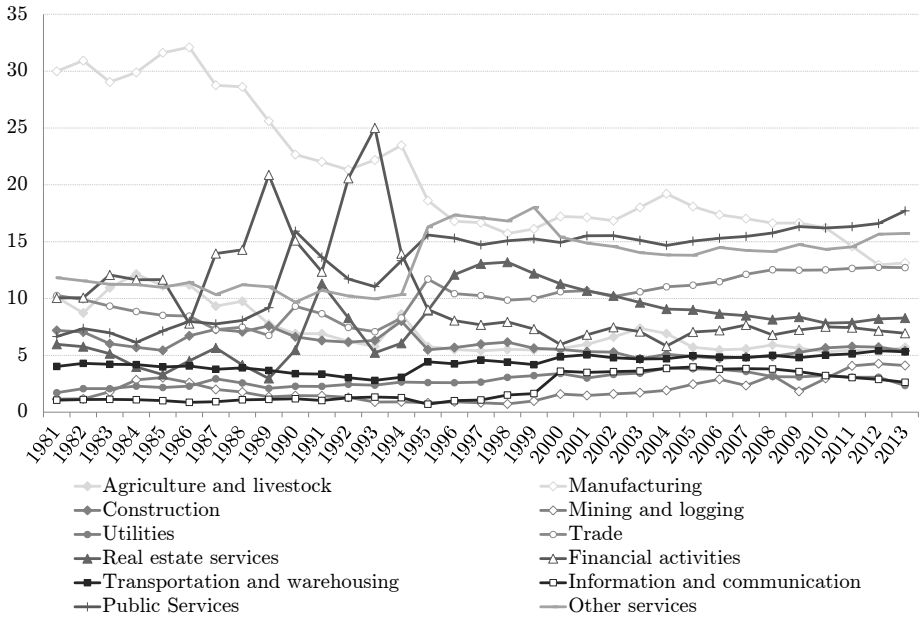

Figure 3.3: Participation shares of the industry groups (% of GDP)

The education groups were created based on the variable of completed years of schooling. Given that in 2013, only 50% of Brazilian population 15+ years old had completed

[3]This category used to compute the inflation-related transactions during Brazilian hyperinflationary period, which lost relevance since 1995 with the price stabilization.

primary/elementary school or less—8.5% of the total being illiterate—, our educational groups needed to consider also this level of schooling[4]. Figure 3.4 plots the employment shares of full-time formal workers by education group, as described below:

- illiterate (ILL): informed that they could not read nor write;
- less than secondary school (LSS): literate and has 10 or less years of schooling;
- secondary school graduate (SSG): literate and has exactly 11 years of schooling;
- college incomplete (SMC): literate and has from 12 to 15 years of schooling;
- college graduate (CLG): literate and has exactly 16 years of schooling;
- greater than college (GTC): literate and has 17 or more years of schooling.

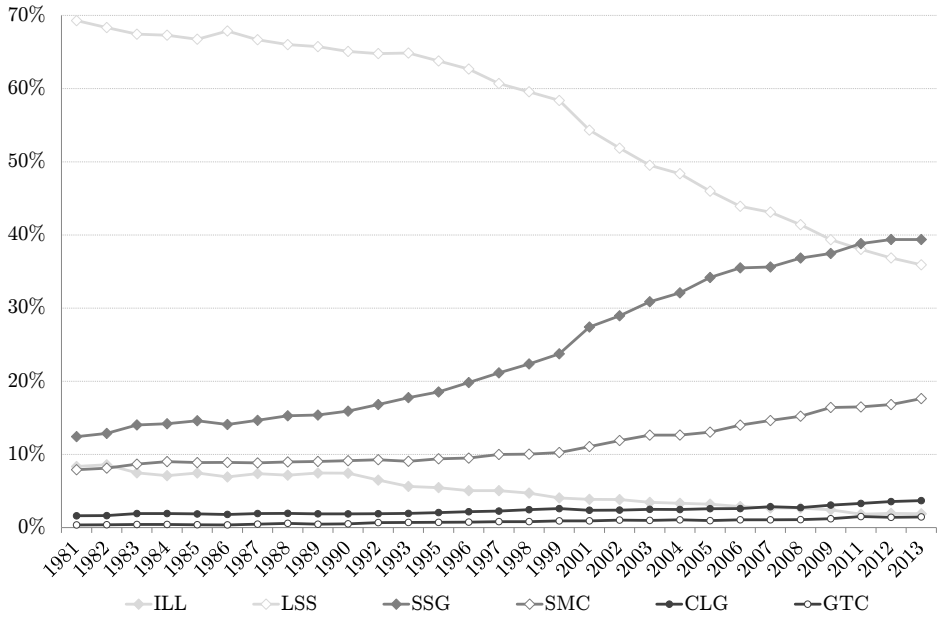

Figure 3.4: Employment shares of full-time formal workers by education group

[4]In 1971, the compulsory education was extended from four to 8 years of schooling. The initial age of school changed from 7 to 6 years old in 2010, extending elementary school to 9 years. In Brazil, compulsory education means only that the government is forced to provide free education within that range of schooling, with no legal penalty for not being at school. A new law promulgated in 2009, extending the compulsory schooling from 4 to 17 years old, but the educational system has until 2016 to make this change fully operational.

Chapter 4

Analysis and results

4.1 Historical background

During the period covered by this study, the Brazilian economy experienced important shifts in its sectoral composition. Trade liberalization initiated in the late 1980s and intensified during the 1990s as a significant relaxation of governmental protectionism in the industrial sector reduced its share of GDP from 40% to 25% from 1981 to 2013, since many firms could not face the ever-growing competition in the international markets that followed. The agricultural sector continued to lose ground during this period, dropping its participation from 10.1% to 5.7%. Therefore, the main driver of economic growth was the services sector, whose GDP share increased from 50% to 69%. On average, real GDP grew 2.7% per year during this period, while the services sectors grew 3.0%, the industrial sector 2.0% and agricultural sector 3.2% annually. Perhaps not surprisingly, the sector participation in full-time formal employment mirrored these developments. Figure 4.1 shows the trajectories of sector participation in the GDP and in full-time formal employment (FTFE).

Another important feature of this period concerns the wage distribution. The two 'lost decades' of low economic growth in Latin America caused an overall decline in the wages, to a certain extent intensified by the hyperinflationary environment that lasted until 1994. The mean wage just started to recover in the early 2000s as economic growth accelerated. Additionally, the Brazilian government engaged in a solid policy of income transfers to the lowest stratum of population, which involved a continued increase in the minimum wage, determined nationally by the Ministry of Labour and Employment (MTE). In 1981, the minimum wage was 28% of the mean wage of our FTFE sample while by 2013

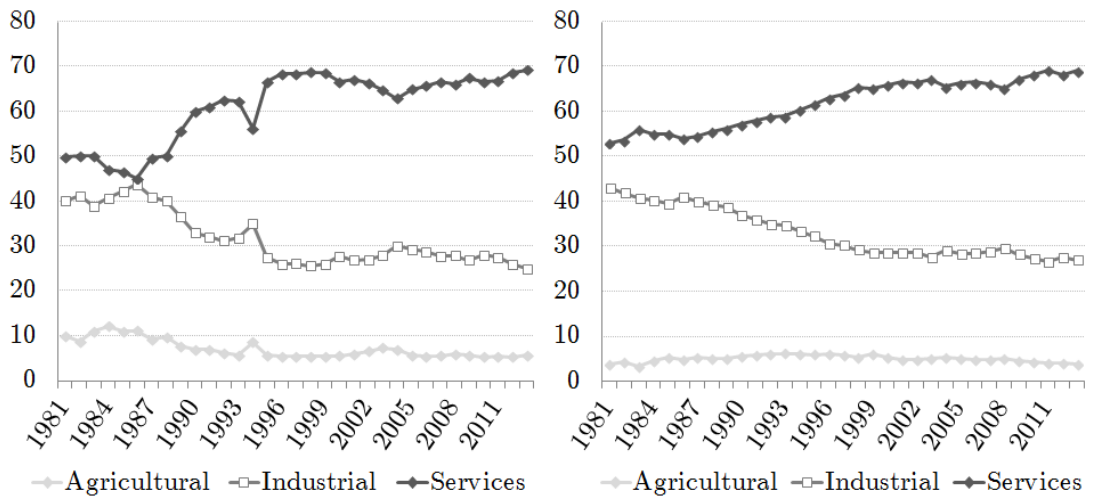

Figure 4.1: Sector participation in the GDP (left panel) and in full-time formal employment (right panel)

it reached 41% of the mean wage. In fact, the minimum wage doubled in that period, while the mean wage of our sample increased only 13%, in real terms[1]. Parallelly, the unemployment rate fell persistently from 2004, from 12.3% to 5.4% in 2013—12-month average in December 2003 and 2013—, while the FTFE participation rates increased from 23% to 31% of the working-age population (PEAP), in the same period. Arguably, the increasing labour market tightness contributed to spread the exceptional minimum wage hikes across the lowest parts of the wage distribution. Figure 4.2 plots the cumulative growth of the 10th, 50th and 90th percentiles and the mean of the wage distributions of full-time formal employees across time, together with the minimum wage. This plot is comparable to Acemoglu and Autor (2011)'s Figure 8, which shows almost inverted trajectories.

4.2 Job polarization

Using the ten occupation groups described above, we can directly analyze whether Brazil experienced the job polarization as seen in the industrialized countries. In order to facilitate this comparison, we partially reproduce Figure 12 of Acemoglu and Autor (2011) using Brazilian data in Figure 4.3, which plots the percentage point change in employment shares by occupation group[2]. The plot shows some evidence of polarization, although there are a

[1] All the wage values are deflated to September 2012, as described in the Data chapter.

[2] Acemoglu and Autor (2011) plots the percent change in level, which does not add much to the analysis of Brazilian data in this period, since all occupation groups presented growth in their employment levels.

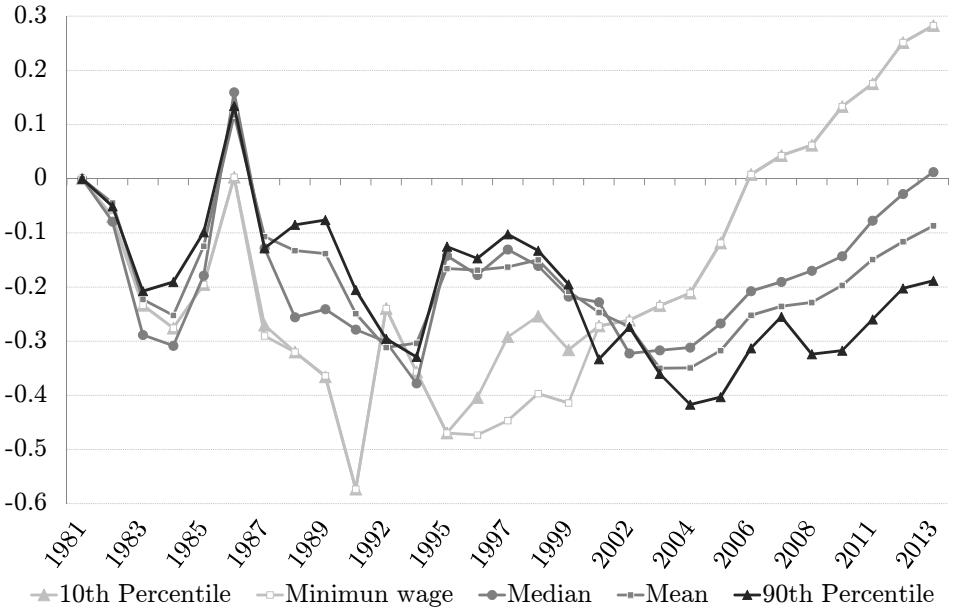

Figure 4.2: Cumulative log change in real wages at 90th, 50th and 10th percentiles, the mean and the minimum wage

few outliers. Within the non-manual cognitive aggregation, for instance, the changes in the employment shares of managers and technicians are relatively much less significant than the ones seen in the U.S. during the 1980s and 1990s, and even become negative afterwards. Considering the "middle skill" jobs, the changes are all in the same direction, although the decline in the production/operators/labourers group is more noticeable, partially because we added two of their groups in one. Regarding the service occupations, the increases are less eye catching, with the exception of food preparation, cleaning and transportation in the 1990s.

To capture the patterns of job polarization more clearly and using the aggregation of occupation categories by task requirement as proposed by Acemoglu and Autor (2011), we plot the percentage point changes in employment shares by task content clusters. As Figure 4.4 shows more clearly, the Brazilian labour market experienced job polarization as seen in industrialized countries, with a pronounced shift of the employment shares from routine to non-routine occupations.

The main question now is whether this change in the employment shares is driven by the sectoral shifts discussed before or if it is part of a broader phenomenon encompassing

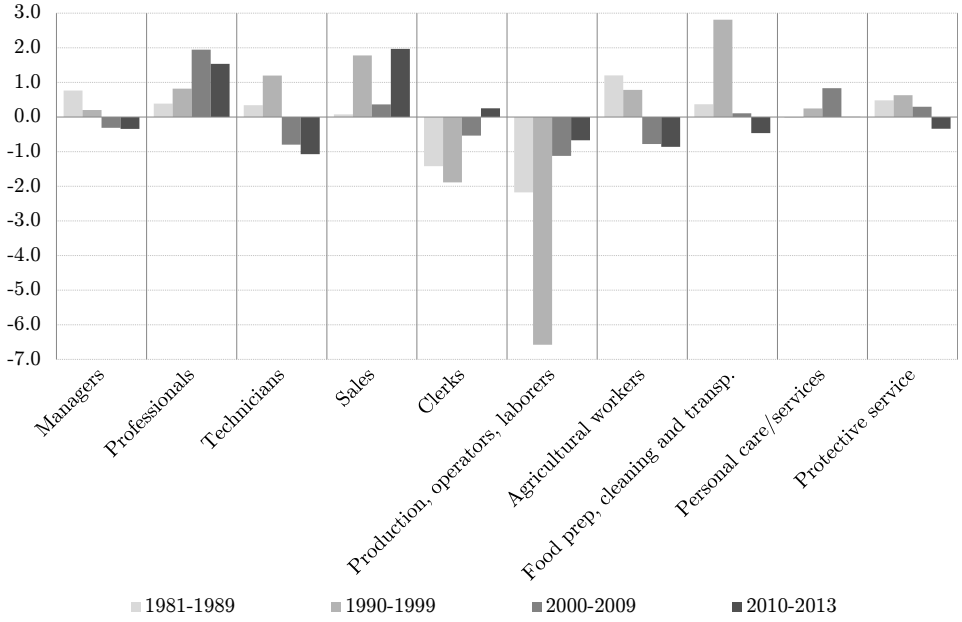

Figure 4.3: Change in the employment shares by occupation (percentage points)

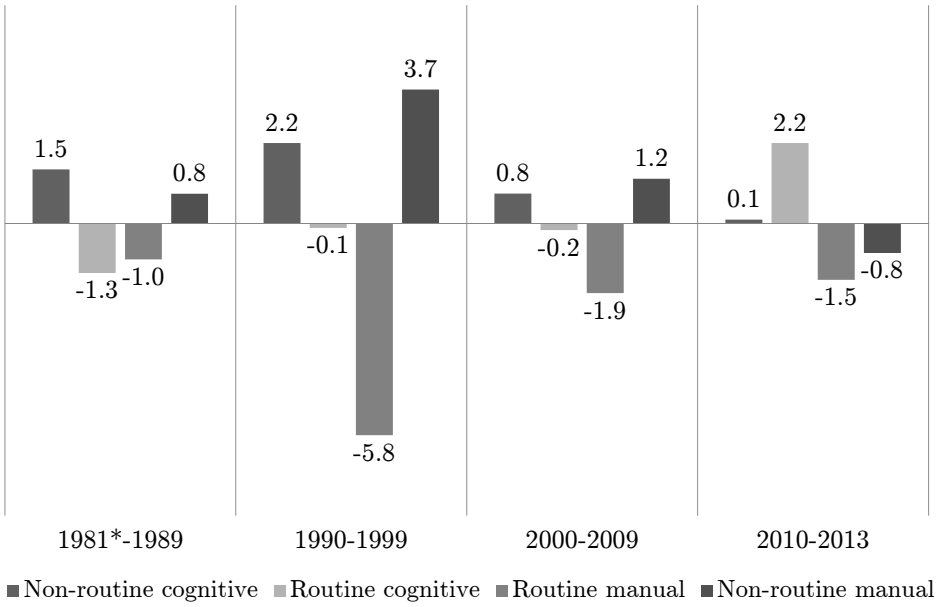

Figure 4.4: Change in employment shares by the task content of the occupations (percentage points)

all industries. To answer this question I perform a conventional decomposition of the employment changes within and between the industries, considering the relative importance of each occupation category. Let $OccSh_i$ be the employment share of each of the four i occupation groups presented in Figure 4.4, $IndSh_j$ represent the employment share of each of the twelve j industry categories presented in chapter 3, Δ before a variable represent the percent point change between two periods and a bar over the variable represent the average value of two points in time. To construct each block of Table 4.1 we perform the following calculation:

$$\Delta OccSh_i = \sum_j \Delta IndSh_j \cdot \overline{OccSh}_{i,j} + \sum_j \Delta OccSh_{i,j} \cdot \overline{IndSh}_j$$

The left-hand side represents the total change in employment share of each occupation and is shown in the first line of each block. The first term on the right represents the changes "between" industries, i.e. keeping constant the within-industry occupational structure, and is shown in the second line. The last term represents the changes in employment shares "within" industries, i.e. holding the employment shares of each industry constant, and is shown in the third line of each block.

Table 4.1—comparable to Acemoglu and Autor (2011)'s Table 6—shows that the occupational component is not only the main determinant of job polarization, but it even offsets industry growth in some cases. For the routine cognitive group, for example, although the growth in the sectoral employment shares would result in increases in the occupation employment shares in the 1990s and in the 2000s—by 0.4pp and 1.39pp, respectively—the decline in the usage of routine cognitive occupations within industries resulted in net decreases in their participation in employment in these periods. Even in the most recent period, between 2010 and 2013, when GDP growth decelerated due to the international crisis, occupational changes within industries continue to override the employment changes across industries in determining the overall occupational changes in employment shares. The only significant exception, however, happened in the 1990s when the employment shares changes in two of the four groups—routine manual and non-routine manual—were caused by changes across industries. This point is far from being irrelevant, since those are the largest changes in employment shares among all the periods and occupation groups reported.

Table 4.1: Decomposition of the changes in employment shares of each task-based occupation category between and within industries (percentage points)

	Changes by Decade			
	1981*-1989	1990-1999	2000-2009	2010-2013
Professional, Managerial, and Technical Occs (Non-Routine Cognitive)				
Total Δ	1.49	2.22	0.83	0.11
Industry Δ	0.08	1.15	-0.16	-0.17
Occupation Δ	1.42	1.07	1.02	0.28
Clerical, Administrative, and Sales Occs (Routine Cognitive)				
Total Δ	-1.36	-0.10	-0.18	2.23
Industry Δ	-0.14	0.40	1.39	0.33
Occupation Δ	-1.22	-0.50	-1.57	1.89
Production, Craft, Repair and Operative Occs (Routine Manual)				
Total Δ	-0.95	-5.81	-1.90	-1.53
Industry Δ	-0.17	-5.31	-0.68	-1.05
Occupation Δ	-0.78	-0.49	-1.23	-0.47
Service Occupations (Non-Routine Manual)				
Total Δ	0.82	3.70	1.25	-0.81
Industry Δ	0.23	3.77	-0.56	0.89
Occupation Δ	0.59	-0.08	1.78	-1.70

Source: PNAD-IBGE. Elaborated by the author.

4.3 Wage polarization

As one would expect by looking at the cumulative change in the percentiles of the wage distributions across time in Figure 4.2, we cannot find exactly the same patterns of wage polarization in Brazil as seen in the industrialized economies. Nevertheless, given the growing importance of the occupational structure in employment changes, I propose investigating the relative significance of occupations in determining wages, as compared to the industry and the educational level of the worker. For that, I reproduce Figure 17 of Acemoglu and Autor (2011), which plots the partial R-squared value (net of controls) of four sets of different regressors in each period[3]. We calculate each point of Figure 4.5 in three steps: (i) by regressing a worker's wage on a set of controls—gender, race, dummy for metropolitan area and quartic of potential experience—; (ii) by regressing each of the variables of interest on the same set of controls; and (iii) by regressing the residual of the first regression on the residuals of the second set of regressions and capturing the R^2 value of that regression. The four sets of variables of interest are the same as in Acemoglu and Autor (2011).

The results are not significantly different from the ones found with U.S. data, especially with respect to the strikingly low explanatory power of the industry dummies throughout the entire period. Nevertheless, unlike Acemoglu and Autor (2011), we do not find a continued increase in the explanatory power of the education and occupation variables after 1979. Moreover, we see a somewhat parallel decline in their explanatory power on wages during the 1980s followed by a recovery in the 1990s. After 1999, however, we observe a decline in the explanatory power of both education-related variables, whereas the occupation dummies kept their explanatory power at the same level.

The relationship between wages and occupations can be seen more clearly in Figure 4.6, which plots the log of the mean wages by task content clusters and the position statistics of the wage distribution presented previously. What we see in general, but especially after 1999, is the growth in the mean wages of non-routine cognitive and routine cognitive jobs remained in between the 90th percentile and the overall mean, while the routine manual and non-routine manual growth followed the growth in the 10th percentile more closely. This pattern alone would suggest that the key threshold in the Brazilian wage distribution is not

[3] Acemoglu and Autor (2011)'s Figure 17, however, covers the longer period from 1959 to 2007.

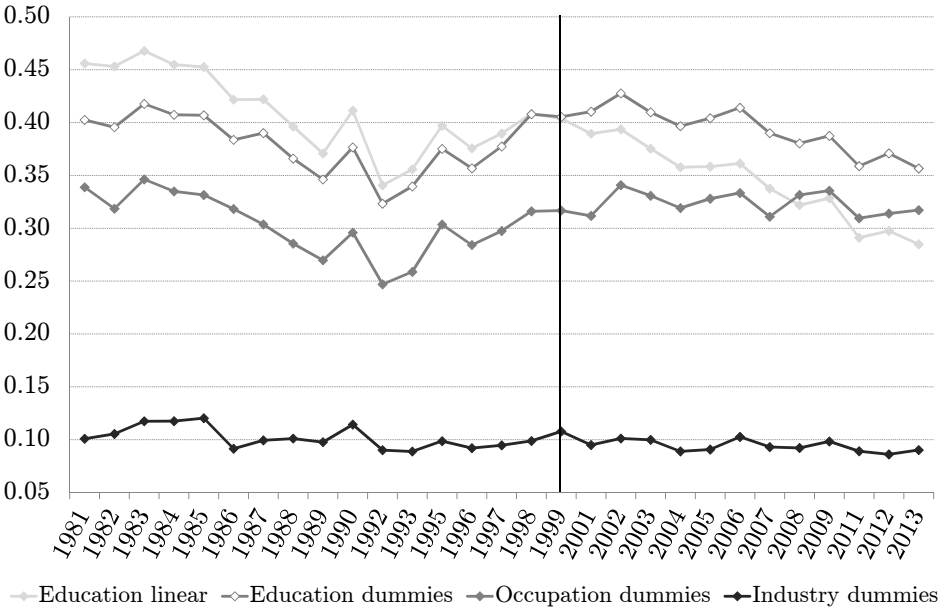

Figure 4.5: Partial R-squared by group of explanatory variables

routine/non-routine tasks, but manual/cognitive tasks. In levels, however, the mean wage of both routine clusters remain very close throughout the whole period, although non-routine manual wages are closer to routine wages than non-routine cognitive wages.

Putting together the shifts in the employment shares and the changes in the patterns of the wages by occupation categories, we gain a better understanding of the factors affecting the wage distribution. Between 1981 and 2013, the employment share of non-routine manual jobs—the low-end of the wage distribution—increased from 15% to 20% while the employment share of non-routine cognitive jobs—the high-end of the wage distribution—rose from 18% to 23%. Meanwhile, the routine manual employment share fell from 42% to 31% and the routine cognitive share fluctuated around 25%. Roughly, these developments mean that the threshold for low-skilled occupations is now around the 20th percentile while the threshold for the high-skilled occupations lies close to the 77th percentile.

Looking at Figure 4.7, one can more easily see a flattening of the wage distribution during the period studied. If there is any convexification, it would be restricted to the high end of the wage distribution, in which the high-skilled workers could be exponentially benefiting from technological change. But even in this case, we do not observe increases

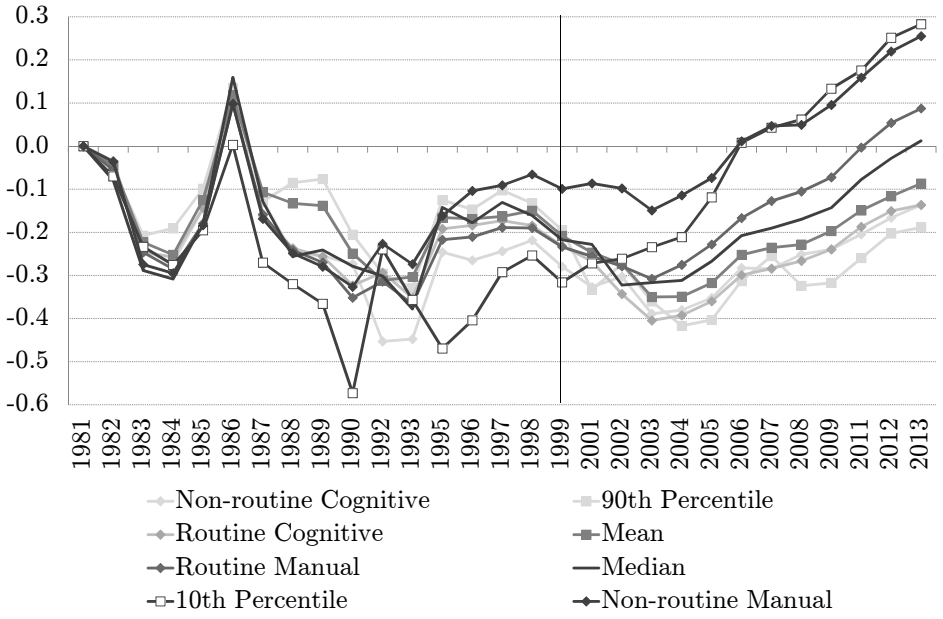

Figure 4.6: Cumulative change in real wages by occupation

in the wage level for high-skill workers, as seen in industrialized countries. For the low end of the distribution, one cannot say much in terms of the effects on earnings caused by technological change, since they are clearly directly affected by the increases in the minimum wage. For the middle-skilled workers, we see a mixed pattern, with the wages of less-skilled workers somehow following the ones paid for low-skill workers whereas the distribution of wages closer to the upper threshold shows some signs of convexification.

For comparison, in Figure 4.8 we plot the growth in the mean wages by educational group. We see that the performance of the illiterate workers was a bit below the growth in the 10th percentile and workers with less than secondary school completed had mean wages growth above the mean growth. The trajectory of the growth in the wages of secondary school graduate workers was similar to the minimum wage growth, although with much lower level of cumulative growth in the period. The trajectories of workers with some college or above followed distinct patterns; workers with degrees higher than college performed significantly better than the other two groups of workers.

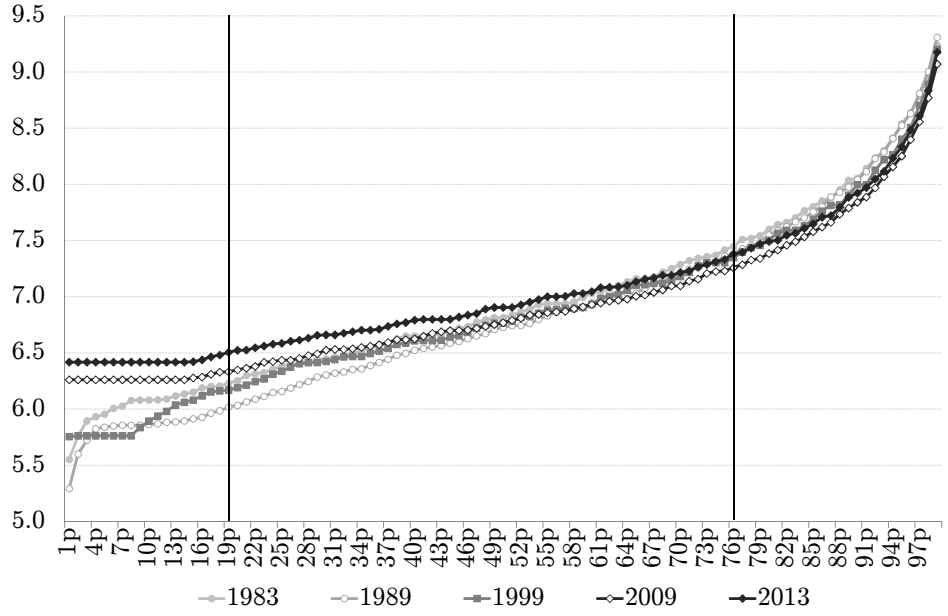

Figure 4.7: Wage distribution (log monthly real wage)

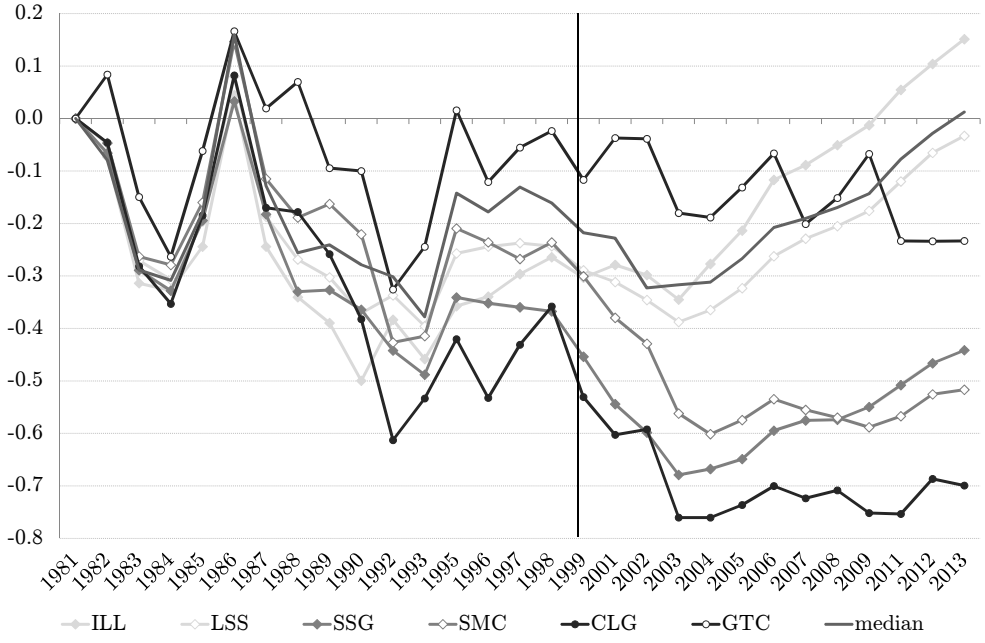

Figure 4.8: Cumulative change in real wages by educational attainment

Chapter 5

Conclusions

Following the most recent literature on labour market polarization closely, I found strong evidence of increased polarization in the patterns of employment, both within and across Brazilian industries. The same cannot be said about the dynamics of the wages, for which the changes in the distribution over percentiles shows more likely a pattern of flattening than 'convexification'. Nevertheless, this study corroborates the idea that occupational structure plays a key role in labour market dynamics, both in industrialized and developing countries. The shifts in the employment shares and wages proved to be more closely related to the nature of the job—what you do—than to the industry—where you work.

As related literature shows, the sharp fall in the prices and the widespread usage of computers in Latin America since the 1990s increased the demand for non-routine tasks and decreased the demand for routine tasks. The analysis of this project supports the hypothesis that the technological change experienced by the industrialized economies since the 1970s affected the labour market in developing countries in a similar way. Unlike there, however, the new technologies and their uneven impact on labour demand apparently did not cause an exponential increase in wage inequality, at least in Brazil.

To the extent that the Brazilian labour market experienced unique transformations in the period studied, like the unprecedented advance in the minimum wage, plunge in the unemployment rate and rise in labour-force participation, the divergence between the employment and wage developments suggests that other factors beyond the task-based framework may have played a bigger role. In particular, it is possible that the fall in the relative supply of unskilled labour and the still relatively higher cost of replacing workers in tasks of low complexity, low-skill labour might have remained cheaper than machines.

Similarly, the increasing gains in labour productivity experienced by high-skill labour in developed countries might have been conditional on a higher level of skills than we see in Brazil—albeit increasing, both quantity and quality of educational attainment in Brazil remain significantly below the values reached by industrialized economies. Further analysis may investigate the effect of the changes in the educational level of the workforce within and across occupations to gain a better understanding of how the changes in technologies and in the supply of skills might be affecting labour productivity and wage structure in Brazil.

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Appendix A

Descriptive statistics

Table A.1: Working force and educational attainment shares

	1981*	1989	1999	2009	2013
Working force (% PEAP)	60.9	64.5	64.5	67.5	66.6
Full-time formal employees (% PEAP)	23.5	25.8	22.3	27.9	30.7
Full-time formal employees (% working force)	37.8	39.4	33.7	40.8	45.8
Education (% PEAP)					
ILL	20.6	17.0	11.7	7.7	6.3
LSS	67.1	66.8	66.3	54.5	50.6
SSG	7.1	9.5	14.0	24.6	27.6
SMC	4.2	5.3	6.1	10.4	11.9
CLG	0.8	1.0	1.4	2.0	2.5
GTC	0.2	0.3	0.5	0.7	1.0
Education (% FTFE)					
ILL	8.1	7.3	4.6	2.6	1.9
LSS	68.4	66.1	59.5	41.2	36.9
SSG	13.1	15.1	22.4	36.7	39.2
SMC	8.2	9.0	10.1	15.5	17.0
CLG	1.7	1.9	2.4	2.9	3.5
GTC	0.4	0.5	0.9	1.1	1.5

Source: PNAD-IBGE. PEAP stands for Potentially Economically Active Population, i.e. people between 15 and 65 years old. FTFE stands for full-time formal employees.
All values are 3-year backward-looking averages, except for 1981*, which is the average of the values of 1981, 1982 and 1983.

Table A.2: Employment and GDP shares by industry

	1981*	1989	1999	2009	2013
Industry shares in total employment					
Agriculture and livestock	26.8	22.7	22.1	16.2	13.6
Industrial sectors	25.6	24.4	20.6	23.1	23.1
Manufacturing	15.0	15.9	12.1	14.6	13.1
Construction	8.9	6.9	7.3	7.4	9.0
Mining and logging	0.7	0.8	0.3	0.4	0.4
Utilities	1.0	0.9	0.8	0.7	0.5
Services sectors	47.6	52.9	57.3	60.7	63.3
Trade	13.0	14.8	16.8	18.0	18.1
Real estate services	1.1	1.3	1.2	1.4	1.5
Financial activities	2.2	2.1	1.1	1.3	1.4
Transportation and warehousing	4.2	4.2	4.3	4.5	5.2
Information and communication	1.2	1.5	1.7	2.8	2.6
Public services and govern.	7.7	9.2	8.9	9.7	10.5
Other services	18.2	19.9	23.3	23.0	24.0
Industry shares in full-time formal employment					
Agriculture and livestock	3.8	5.2	5.7	4.8	3.9
Industrial sectors	41.9	39.3	29.4	28.9	27.2
Manufacturing	30.1	30.0	22.8	22.1	19.3
Construction	8.4	6.5	4.6	5.0	6.4
Mining and logging	1.0	0.9	0.5	0.8	0.7
Utilities	2.4	1.9	1.5	1.0	0.8
Services sectors	54.29	55.46	64.86	66.26	68.90
Trade	13.6	14.8	15.9	18.7	19.1
Real estate services	1.8	1.7	2.4	2.3	2.3
Financial activities	4.4	3.2	1.9	1.9	1.9
Transportation and warehousing	6.2	6.2	5.9	5.3	6.0
Information and communication	1.8	1.8	2.0	2.9	2.6
Public services and govern.	13.4	14.0	16.8	15.6	15.5
Other services	13.1	13.7	20.0	19.6	21.5
Industry shares in the value-added GDP					
Agriculture and livestock	9.93	8.94	5.46	5.70	5.49
Industrial sectors	40.1	39.2	25.9	27.5	26.2
Manufacturing	29.99	27.66	16.17	16.77	13.56
Construction	6.76	7.32	5.92	5.01	5.63
Mining and logging	1.37	1.71	0.85	2.47	4.15
Utilities	1.95	2.53	2.97	3.27	2.83
Services sectors	50.01	51.84	68.62	66.78	68.33
Trade	9.83	7.17	10.03	12.38	12.70
Real estate services	5.63	4.26	12.81	8.34	8.12
Financial activities	10.73	16.37	7.64	7.24	7.18
Transportation and warehousing	4.18	3.78	4.39	4.87	5.28
Information and communication	1.10	1.05	1.41	3.73	2.86
Public services and govern.	7.00	8.34	15.02	15.86	16.88
Other services	11.54	10.86	17.32	14.37	15.31

Source: PNAD-IBGE.

Table A.3: Employment shares by occupation

	1981*	1989	1999	2009	2013
Occupation shares in total employment					
Non-routine cognitive	14.21	17.05	17.47	20.20	20.98
Managers	4.31	5.49	5.24	5.16	4.96
Professionals	3.46	4.14	4.86	7.35	9.03
Technicians	6.44	7.42	7.37	7.69	6.99
Routine cognitive	17.17	18.46	18.98	18.94	20.32
Sales	7.85	8.66	11.01	9.63	10.30
Clerks	9.33	9.79	7.97	9.32	10.02
Routine manual	54.51	48.99	46.47	40.42	38.61
Production, operators, laborers	28.19	27.07	24.64	24.42	25.14
Agricultural workers	26.32	21.92	21.83	16.01	13.47
Non-routine manual	14.11	15.51	17.09	20.43	20.10
Food prep., cleaning and transp.	11.90	12.75	13.84	14.84	14.27
Personal care/services	0.57	0.76	1.22	2.97	3.19
Protective services	1.64	2.01	2.03	2.62	2.64
Occupation shares in full-time formal employment					
Non-routine cognitive	18.03	19.52	21.74	22.57	22.69
Managers	4.19	4.95	5.16	4.84	4.50
Professionals	4.54	4.93	5.75	7.69	9.22
Technicians	9.30	9.64	10.84	10.04	8.97
Routine cognitive	25.68	24.33	24.22	24.05	26.27
Sales	5.73	5.80	7.58	7.94	9.91
Clerks	19.95	18.53	16.65	16.11	16.36
Routine manual	41.18	40.20	34.41	32.51	30.97
Production, operators, laborers	37.85	35.68	29.10	27.98	27.31
Agricultural workers	3.32	4.52	5.31	4.53	3.67
Non-routine manual	15.11	15.94	19.63	20.86	20.06
Food prep., cleaning and transp.	11.22	11.59	14.40	14.51	14.04
Personal care/services	0.14	0.11	0.36	1.19	1.20
Protective services	3.76	4.24	4.87	5.16	4.82

Source: PNAD-IBGE.

Table A.4: Employment shares by occupation in each industry (a)

	1981*	1989	1999	2009	2013
Agriculture and livestock					
Non-routine cognitive	7.16	7.44	7.47	4.99	5.17
Managers	5.49	5.47	6.07	3.78	3.69
Professionals	0.23	0.43	0.19	0.37	0.53
Technicians	1.44	1.53	1.21	0.84	0.94
Routine cognitive	1.80	1.94	1.18	1.37	1.01
Sales	0.05	0.12	0.02	0.07	0.07
Clerks	1.75	1.82	1.16	1.30	0.94
Routine manual	89.55	88.43	90.15	91.38	92.23
Production, operators, laborers	7.17	8.37	3.42	3.83	4.66
Agricultural workers	82.38	80.06	86.73	87.55	87.57
Non-routine manual	1.49	2.20	1.20	2.26	1.60
Food prep., cleaning and transp.	0.90	1.25	0.83	1.71	1.05
Personal care/services	0.00	0.00	0.00	0.02	0.00
Protective services	0.59	0.95	0.37	0.53	0.55
Manufacturing					
Non-routine cognitive	12.84	13.94	13.89	16.59	17.99
Managers	2.79	2.75	3.72	3.99	4.53
Professionals	2.98	3.41	3.14	3.42	3.95
Technicians	7.07	7.78	7.03	9.19	9.51
Routine cognitive	16.22	16.62	16.51	12.63	13.63
Sales	1.73	1.71	3.18	2.03	2.03
Clerks	14.49	14.92	13.33	10.61	11.60
Routine manual	65.73	63.75	64.81	65.05	63.36
Production, operators, laborers	65.49	63.17	64.18	64.13	62.60
Agricultural workers	0.24	0.58	0.63	0.92	0.76
Non-routine manual	5.21	5.69	4.79	5.72	5.02
Food prep., cleaning and transp.	3.39	3.63	3.16	4.38	3.78
Personal care/services	0.00	0.00	0.01	0.09	0.03
Protective services	1.82	2.06	1.62	1.25	1.21
Construction					
Non-routine cognitive	6.36	7.78	8.90	11.41	8.64
Managers	0.84	1.40	1.26	1.50	1.16
Professionals	2.56	3.25	3.99	4.09	3.27
Technicians	2.96	3.13	3.66	5.82	4.21
Routine cognitive	8.29	10.70	7.40	6.32	4.69
Sales	0.02	0.07	0.08	0.28	0.26
Clerks	8.27	10.63	7.32	6.04	4.43
Routine manual	81.42	77.14	80.42	78.32	83.81
Production, operators, laborers	81.38	76.95	80.15	78.09	83.71
Agricultural workers	0.04	0.19	0.26	0.23	0.10
Non-routine manual	3.93	4.38	3.28	3.95	2.86
Food prep., cleaning and transp.	1.42	1.48	1.53	2.37	1.69
Personal care/services	0.00	0.00	0.00	0.02	0.00
Protective services	2.51	2.90	1.75	1.56	1.17

Source: PNAD-IBGE.

Table A.5: Employment shares by occupation in each industry (b)

	1981*	1989	1999	2009	2013
Mining and logging					
Non-routine cognitive	12.68	16.87	17.03	25.93	29.24
Managers	1.78	3.79	1.95	4.60	4.87
Professionals	3.05	4.40	7.05	7.03	8.32
Technicians	7.85	8.67	8.04	14.30	16.05
Routine cognitive	15.73	13.48	13.38	7.11	7.59
Sales	0.23	0.00	0.92	0.13	0.22
Clerks	15.51	13.48	12.46	6.98	7.37
Routine manual	64.38	62.35	65.58	59.76	57.08
Production, operators, laborers	63.32	61.87	64.92	59.64	56.99
Agricultural workers	1.06	0.47	0.66	0.12	0.09
Non-routine manual	7.21	7.30	4.00	7.20	6.10
Food prep., cleaning and transp.	3.04	3.78	2.00	5.37	3.42
Personal care/services	0.00	0.00	0.00	0.00	0.00
Protective services	4.17	3.53	2.00	1.83	2.68
Utilities					
Non-routine cognitive	16.88	22.61	23.59	21.47	25.42
Managers	2.33	4.32	4.19	2.94	3.73
Professionals	7.56	8.72	8.18	6.58	7.90
Technicians	6.98	9.57	11.22	11.95	13.78
Routine cognitive	20.74	24.00	17.47	12.98	12.98
Sales	0.03	0.15	0.30	0.30	0.71
Clerks	20.71	23.85	17.17	12.68	12.26
Routine manual	37.53	39.36	34.26	31.50	28.92
Production, operators, laborers	37.46	39.20	34.21	31.24	28.32
Agricultural workers	0.07	0.15	0.05	0.25	0.60
Non-routine manual	24.86	14.04	24.67	34.05	23.68
Food prep., cleaning and transp.	22.76	12.43	22.96	32.91	30.87
Personal care/services	0.00	0.00	0.00	0.00	0.02
Protective services	2.09	1.61	1.72	1.14	1.80
Trade					
Non-routine cognitive	11.52	13.03	13.36	13.65	11.12
Managers	6.72	7.84	7.97	6.56	5.51
Professionals	0.92	0.97	1.00	1.61	1.48
Technicians	3.89	4.22	4.38	5.48	4.13
Routine cognitive	60.41	57.39	59.84	58.24	65.48
Sales	37.32	34.40	39.36	37.34	47.62
Clerks	23.09	22.99	20.48	20.90	17.86
Routine manual	23.73	24.45	22.65	20.89	16.01
Production, operators, laborers	23.70	24.31	22.56	20.85	15.97
Agricultural workers	0.03	0.14	0.09	0.05	0.04
Non-routine manual	4.34	5.13	4.15	7.21	7.39
Food prep., cleaning and transp.	2.35	2.92	2.47	5.83	6.29
Personal care/services	0.00	0.00	0.01	0.05	0.04
Protective services	1.99	2.20	1.67	1.33	1.06

Source: PNAD-IBGE.

Table A.6: Employment shares by occupation in each industry (c)

	1981*	1989	1999	2009	2013
Real estate services					
Non-routine cognitive	6.2	6.1	5.8	6.5	7.2
Managers	1.8	2.1	1.6	1.6	1.7
Professionals	0.5	0.4	0.7	1.4	1.2
Technicians	3.8	3.5	3.5	3.5	4.3
Routine cognitive	14.6	15.3	11.5	10.0	14.0
Sales	0.0	0.0	0.2	0.4	0.4
Clerks	14.6	15.3	11.3	9.6	13.5
Routine manual	2.5	2.6	3.5	2.5	1.6
Production, operators, laborers	2.5	2.6	3.4	2.5	1.6
Agricultural workers	0.0	0.1	0.1	0.0	0.0
Non-routine manual	76.8	76.0	79.2	81.1	77.2
Food prep., cleaning and transp.	54.6	53.8	49.3	41.9	42.1
Personal care/services	0.0	0.0	0.0	0.3	0.1
Protective services	22.2	22.2	29.9	38.9	34.9
Financial activities					
Non-routine cognitive	22.2	31.7	40.3	46.5	43.9
Managers	11.6	19.0	21.0	22.1	24.2
Professionals	4.5	5.6	7.9	10.0	10.3
Technicians	6.1	7.2	11.5	14.4	9.4
Routine cognitive	71.5	60.4	54.8	47.8	52.1
Sales	0.2	0.2	1.4	2.4	1.7
Clerks	71.3	60.2	53.4	45.3	50.3
Routine manual	1.9	2.8	1.0	1.6	0.6
Production, operators, laborers	1.9	2.7	1.0	1.6	0.6
Agricultural workers	0.0	0.0	0.0	0.0	0.0
Non-routine manual	4.5	5.0	3.9	4.1	3.4
Food prep., cleaning and transp.	2.8	2.8	2.4	2.5	2.2
Personal care/services	0.0	0.0	0.0	0.1	0.1
Protective services	1.6	2.2	1.5	1.5	1.1
Transportation and warehousing					
Non-routine cognitive	11.4	11.8	10.7	9.6	8.6
Managers	2.1	3.0	2.2	3.0	2.7
Professionals	1.7	1.6	1.1	1.8	1.7
Technicians	7.6	7.2	7.4	4.8	4.3
Routine cognitive	20.6	19.2	19.0	17.6	14.7
Sales	0.3	0.4	0.7	0.8	0.5
Clerks	20.3	18.8	18.3	16.8	14.2
Routine manual	53.6	53.6	54.3	55.6	64.5
Production, operators, laborers	53.5	53.5	54.3	55.3	64.5
Agricultural workers	0.1	0.0	0.0	0.2	0.1
Non-routine manual	14.4	15.4	16.0	17.3	12.1
Food prep., cleaning and transp.	12.2	12.5	14.2	14.2	9.9
Personal care/services	0.0	0.0	0.0	0.0	0.2
Protective services	2.2	2.9	1.8	3.0	2.0

Source: PNAD-IBGE.

Table A.7: Employment shares by occupation in each industry (d)

	1981*	1989	1999	2009	2013
Information and communication					
Non-routine cognitive	39.7	40.7	39.8	49.2	53.6
Managers	4.0	6.6	5.1	7.7	7.6
Professionals	11.7	12.3	10.9	18.9	22.7
Technicians	24.0	21.8	23.8	22.5	23.3
Routine cognitive	26.6	26.8	29.8	34.0	31.3
Sales	0.8	1.1	5.3	3.5	3.5
Clerks	25.8	25.8	24.5	30.5	27.7
Routine manual	16.8	17.3	18.0	7.5	7.4
Production, operators, laborers	16.4	16.9	17.8	7.4	7.4
Agricultural workers	0.4	0.4	0.2	0.0	0.1
Non-routine manual	16.9	15.2	12.5	9.4	7.7
Food prep., cleaning and transp.	12.2	9.5	7.7	6.7	5.0
Personal care/services	0.1	0.0	0.3	0.2	0.3
Protective services	4.6	5.7	4.5	2.4	2.3
Public services and government					
Non-routine cognitive	44.6	45.8	53.6	52.8	54.1
Managers	7.5	7.4	8.3	6.3	5.1
Professionals	12.9	13.9	16.7	24.4	29.8
Technicians	24.2	24.5	28.6	22.1	19.2
Routine cognitive	22.2	17.5	15.8	16.6	17.6
Sales	0.1	0.1	0.2	0.2	0.1
Clerks	22.1	17.4	15.6	16.4	17.4
Routine manual	14.0	14.1	9.9	6.9	6.2
Production, operators, laborers	13.8	13.6	9.7	6.7	6.1
Agricultural workers	0.2	0.4	0.3	0.2	0.1
Non-routine manual	19.2	22.7	20.6	23.8	22.1
Food prep., cleaning and transp.	12.0	15.0	12.3	13.1	12.7
Personal care/services	0.1	0.1	0.2	1.8	1.5
Protective services	7.1	7.6	8.1	8.9	7.9
Other services					
Non-routine cognitive	21.3	21.4	19.2	19.9	21.5
Managers	2.5	3.6	2.5	3.0	2.9
Professionals	6.4	6.3	6.3	8.2	10.7
Technicians	12.4	11.5	10.4	8.7	7.9
Routine cognitive	23.1	23.0	22.5	21.3	22.8
Sales	0.6	0.9	1.8	1.4	1.0
Clerks	22.5	22.1	20.7	19.9	21.8
Routine manual	5.6	5.6	5.0	4.1	4.7
Production, operators, laborers	5.1	5.1	4.4	4.0	4.6
Agricultural workers	0.4	0.5	0.6	0.1	0.1
Non-routine manual	50.1	50.1	53.3	54.7	51.0
Food prep., cleaning and transp.	41.7	40.6	42.8	40.2	37.2
Personal care/services	1.0	0.7	1.6	4.4	4.3
Protective services	7.4	8.7	9.0	10.1	9.5

Source: PNAD-IBGE.

Table A.8: Mean wages as percentages of the overall mean wage in each period

	1981*	1989	1999	2009	2013
Overall measures					
90th percentile	201.0	206.4	206.6	185.3	181.4
Median	58.2	55.4	60.4	63.4	65.5
10th percentile	27.9	23.3	25.2	38.2	40.3
Minimum wage	27.9	23.2	22.1	38.2	40.3
Mean	100.0	100.0	100.0	100.0	100.0
Educational attainment					
Illiterate (ILL)	56.6	52.2	52.2	63.0	64.8
Less than secondary school (LSS)	84.2	81.5	78.2	78.6	79.0
Secondary school graduate (SSG)	143.4	136.8	117.7	94.3	91.4
Some college (SMC)	267.8	285.0	245.5	172.7	157.6
College graduate (CLG)	544.9	556.7	423.1	302.1	270.3
Greater than college (GTC)	482.7	552.2	499.5	441.6	354.6
Industry groups					
Agriculture and livestock	59.0	56.3	55.9	73.6	77.8
Industrial sectors	106.4	111.7	106.6	103.1	102.1
Manufacturing	110.6	113.1	107.0	102.6	101.5
Construction	83.9	87.5	92.5	96.4	97.0
Mining and logging	136.2	166.5	142.7	155.0	156.8
Utilities	134.0	173.3	142.1	118.6	119.9
Services sectors	98.9	97.6	102.2	100.9	100.6
Trade	82.7	84.1	90.8	87.2	86.1
Real estate services	68.2	58.9	75.9	76.0	78.2
Financial activities	214.9	265.6	267.1	181.8	176.6
Transportation and warehousing	118.9	122.6	123.6	113.6	110.9
Information and communication	131.0	132.7	137.7	123.8	122.3
Public services and govern.	111.3	107.8	123.2	132.2	131.2
Other services	75.4	75.7	83.2	85.6	88.6
Occupation groups					
Non-routine cognitive	204.7	205.6	191.0	179.9	173.4
Managers	299.3	282.3	249.0	221.6	219.4
Professionals	334.4	339.7	290.8	240.5	218.3
Technicians	135.7	135.2	134.6	130.3	121.7
Routine cognitive	103.9	102.8	101.3	90.2	88.4
Sales	70.6	73.4	80.6	81.7	81.7
Clerks	116.0	114.2	112.4	94.8	92.7
Routine manual	87.0	86.3	84.8	89.5	91.4
Production, operators, laborers	90.6	91.8	92.3	92.9	94.0
Agricultural workers	54.7	52.8	53.3	70.9	74.5
Non-routine manual	58.3	57.5	64.2	71.0	72.5
Food prep., cleaning and transp.	51.9	50.9	57.0	64.8	66.9
Personal care/services	89.7	93.7	76.2	79.9	79.0
Protective services	81.3	79.1	90.0	89.2	89.7

Source: PNAD-IBGE and Ministry of Labor and Employment (MTE) for minimum wage.

Appendix B

Stata code for the wage regressions

wage_regressions.do* - Printed on 08/04/2015 19:39:45

```
foreach y in 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1992 1993 1995 1996 1997 1998 1999 2001 2002 2003 2004 2005 2006 2007 2008 2009 2011 2012 2013 {

** Effect of controls on wages **;
regress lwage white metropol female potexp potexp2 potexp3 potexp4 fpotexp fpotexp2 fpotexp3 fpotexp4 [pw=PNAD_weight] if year==`y'
predict o_`y', resid

/***** linear education *****/
** Effect of controls on the variables of interest **;
regress schooling white metropol female potexp potexp2 potexp3 potexp4 fpotexp fpotexp2 fpotexp3 fpotexp4 [pw=PNAD_weight] if year==`y'
predict i_edl_`y', resid
** Partial r-squared **;
regress o_`y' i_edl_`y' [pw=PNAD_weight] if year==`y'
gen r2_edl_`y' = e(r2)
format %12.0g r2_edl_*
drop i_edl_`y'

/***** education dummies *****/
foreach int in LSS SSG COI COG GTC {
regress `int' white metropol female potexp potexp2 potexp3 potexp4 fpotexp fpotexp2 fpotexp3 fpotexp4 [pw=PNAD_weight] if year==`y'
predict i_edd_`int'_`y', resid
}
** Partial r-squared **;
regress o_`y' i_edd_LSS_`y' i_edd_SSG_`y' i_edd_COI_`y' i_edd_COG_`y' i_edd_GTC_`y' [pw=PNAD_weight] if year==`y'
gen r2_edd_`y' = e(r2)
format %12.0g r2_edd_*
drop i_edd_*

/***** occupation dummies *****/
foreach int in managers professionals technicians sales clerks productionetc foodcleantrans persocare protective {
regress `int' white metropol female potexp potexp2 potexp3 potexp4 fpotexp fpotexp2 fpotexp3 fpotexp4 [pw=PNAD_weight] if year==`y'
predict i_occ_`int'_`y', resid
}
** Partial r-squared **;
regress o_`y' i_occ_managers_`y' i_occ_professionals_`y' i_occ_technicians_`y' i_occ_sales_`y' i_occ_clerks_`y' i_occ_productionetc_`y' i_occ_foodcleantrans_`y' i_occ_persocare_`y' i_occ_protective_`y' [pw=PNAD_weight] if year==`y'
gen r2_occ_`y' = e(r2)
format %12.0g r2_occ_*
drop i_occ_*

/***** industry dummies *****/
foreach int in indextmin indmanuf indconst indutilities servtrade servtrans servinfo servfin servothers servrealest servgovern {
regress `int' white metropol female potexp potexp2 potexp3 potexp4 fpotexp fpotexp2 fpotexp3 fpotexp4 [pw=PNAD_weight] if year==`y'
predict i_ind_`int'_`y', resid
}
** Partial r-squared **;
regress o_`y' i_ind_indextmin_`y' i_ind_indmanuf_`y' i_ind_indconst_`y' i_ind_indutilities_`y' i_ind_servtrade_`y' i_ind_servtrans_`y' i_ind_servinfo_`y' i_ind_servfin_`y' i_ind_servothers_`y' i_ind_servrealest_`y' i_ind_servgovern_`y' [pw=PNAD_weight] if year==`y'
gen r2_ind_`y' = e(r2)
format %12.0g r2_ind_*
drop o_`y' i_ind_*
}
```

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