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ARE SOCIAL SKILLS HELPING WOMEN IN THE BRAZILIAN LABOR MARKET?

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We document an increase in the likelihood of women working in a good job (those with higher wages) in the Brazilian high-skilled labor market in the period of 1994-2017. We highlight the importance of social skills in explaining why the growing demand for high-skilled workers has not been equal across gender. To do so, we built a novel Brazilian Classification of Occupations (CBO) rating based on skill content compatible with the O*NET task index. Our results show a positive relationship between social skills and the female share of occupations, which suggests that women have been choosing professions intensive in this skill. We also provide results consistent with neuroscience literature, which has reported that women have a comparative advantage in performing tasks that require social skills. Finally, we find that the relevance of such skills in determining wages is higher for women than men in recent years.

KEYWORDS: Social skills, High-skilled labor market, Wage differentials.

1. INTRODUCTION

The job market has changed rapidly in recent years in response to technological changes. A vast international literature has documented a rising demand for high-skilled labor and a fall in demand for workers performing routine tasks. The main findings compose the *job polarization* literature, which indicates a rise in demand for manual tasks as well (Autor et al. (2006); Spitz-Oener (2006); Goos and Manning (2007); Acemoglu and Autor (2011); Autor and Dorn (2013); Goos et al. (2014); Ikenaga and Kambayashi (2016)). However, few studies look at gender differences in this context.

In this paper, we show that the growing demand for high-skilled workers has not been equal across gender in Brazil. The likelihood of women with a college-degree working in a *good job* increased between 1994 and 2017, while the probability for men fell in the same period. By *good jobs* we mean those occupations in which the median wage is in the top 20th percentile in the previous year. Our findings are primarily based on the increase in the number of women earning high wages. Given the well-known rise in the female labor supply in recent years – due to the massive incorporation of women in the labor market –, we argue that the explanation for such an increase is demand driven. In fact, we are able to rule out alternative explanations for this phenomenon. In the appendix, we show that both the rise in women's labor supply and the possible shifting in demographic and spatial characteristics of individuals do not account for all the gender differences in the high-skill labor market.

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To explore the potential drivers of the increase in the likelihood of women choosing *good jobs*, we follow the theoretical model presented by Cortes et al. (2018). The model suggests two channels for the phenomenon. The first one refers to decreasing gender discrimination in the high-skill labor market. The second is about the rising demand for specific female labor in this market (what they call *Female Bias*). The hypothesis is that women have been more in demand because they are best at social skills tasks – since they have a comparative advantage in jobs that require them. Also, the returns of these tasks have recently increased in the labor market. This would explain why the probability of women working in better paid jobs has increased as well.

The women's comparative advantage hypothesis has been confirmed by empirical evidence. In fact, psychology and neuroscience literature indicates a natural ability of women performing social tasks. There are sex developmental differences in brain structure and function that lead women to be more empathetic and better at interacting with others (Chapman et al., 2010). The ability to understand what others are thinking and feeling enables women to better manage and organize work teams and collective intelligence (Woolley et al., 2010).

Prominent literature in economics has explored the growing importance of social skills in the labor market. In this context, social skills are associated with leadership, communication, and interpersonal skills. In the workplace, interacting with other people and understanding the overall environment has become more valuable because it increases team productivity. Several studies have presented evidence for the increasing social skills demand by showing that they are a strong predictor of employment and wages for young adults. The increasing value of social skills in the labor market has been explained by the difficulty of computers in replacing human interactions (Borghans et al., 2008; McCann et al., 2015; Kambourov et al., 2014; Autor, 2015; Deming, 2017). Also, it has been identified as one of the determinants of the closing gender-wage gap (Black and Spitz-Oner, 2010; Bacolod and Blum, 2010; Borghans et al., 2014).

We investigate the hypothesis of Female Bias in the Brazilian labor market. The central assumption of our work is that the appreciation of social skills has benefited women because they have a comparative advantage in these skills. We contribute to the literature by providing a classification of Brazilian occupations according to their task content. This classification is based on the O*NET[1] task index. Using the O*NET index, for each occupation we constructed measures of social, cognitive, routine, and manual task content. We followed the assumption that task content is similar across countries for similar occupations. We matched the skill intensity content of occupation with the Annual Report on Social Information (RAIS[2]) database to investigate whether the women's comparative advantage hypothesis holds in the Brazilian labor market. To do so, we aim to determine whether: (i) women self-select into intensive social occupations; and (ii) the returns of social skills are higher for women than men.

Our results show a positive relationship between the magnitude of the social skills content of a given occupation and share of women in such a job. Because such a share is negatively correlated with other tasks such as cognitive, routine, and manual, our findings suggest that women choose jobs that are intensive in social skills. We also provide results consistent with neuroscience literature, which show that women have a comparative advantage in performing tasks that require social skills. Finally, we found that the relevance of such skills in determining wages is higher for women than men.

Besides this introduction, this paper is organized into five other sections. In the next one, we discuss the literature on the growing importance of social skills and the women's comparative advantage in such skills. In the third section, we show evidence of the different gender trends

[1]US Department of Labor's Occupational Information Network database (O*NET).
[2]Relação Anual de Informações Sociais - RAIS.

in the high-skilled labor market and discuss how it fits the findings reported in the international literature. In section four, we present the data, detail the construction of the classification of Brazilian occupations based on skill content compatible with the O*NET, and show some descriptive statistics of the Brazilian high-skilled labor market. We present the empirical strategy to investigate the two questions stated above and its results in section five. Section six summarizes and concludes our study.

2. RELATED LITERATURE

Our paper relates to the literature on skills and job polarization in the labor market, which gained prominence with Autor et al. (2003). According to a vast body of research,[3] the declining price of computers has lowered the demand for workers who execute routine tasks, while the employment and earnings have increased for low- and high-ability workers who perform manual tasks and cognitive, respectively.

More recent literature has explored the fast-expanding set of tasks performed by computers. Over time, they began to replace some cognitive tasks as well. The idea is that in the implementation of the IT Revolution, cognitive tasks were a key component of the capital investment phase given that they were essential to build and maintain the new capital. So its demand increased rapidly. However, with the maturity of this investment, the demand for cognitive tasks began to narrow as computers also started to replace some human interactions (Beaudry et al., 2016). In the recent past, automation using explicit rules or manually written computer algorithms were limited to areas where there was explicit knowledge to codify. Now, machine learning (ML) and artificial intelligence (AI) are replacing even high-skilled labor.

> Recent rapid progress in ML has been largely driven by an approach called deep learning and has made it possible for machines to match or surpass humans in certain types of tasks, especially those involving image and speech recognition, natural language processing, and predictive analytics. (Brynjolfsson et al., 2018, p. 1)

Related to this phenomenon, Deming (2017) reports that science, technology, engineering, and mathematics (STEM) employment and earnings have been decreasing in the United States. The paper also documents the growing importance of the other cognitive occupations that require interpersonal interactions, such as managers, nurses, teachers, lawyers, economists, and others. In this context, social skills have gained relevance as some human interactions are still difficult to automate, increasing their relative value over other skills in the labor market (Autor, 2015). The ability to listen and read, and instantly react or make a decision are still challenges for computers. In addition, the ability to "read between the lines" and to feel the best time to interfere or make a decision are exclusively human characteristics.

Besides having the advantage of being difficult to be replaced by computers, social skills have gained value in the market as they increase productivity of firms. According to Deming (2017), team productivity increases when some people have social ability, since it reduces coordination costs and allows workers to specialize in their best tasks, increasing overall productivity. For the United States labor market, the authors show that high-paying jobs have increasingly required social skills because of their ability to help raise the productivity of other factors, including cognitive labor.

Several studies have explored the growing importance of the ability to interact with or handle interactions with other people. Most of them explore adolescent social skills from high school surveys and match them with adult labor market outcomes. With this methodology, Borghans

[3]See Autor et al. (2006); Spitz-Oener (2006); Goos and Manning (2007); Acemoglu and Autor (2011); Autor and Dorn (2013); Goos et al. (2014); Ikenaga and Kambayashi (2016).

et al. (2014) report that employment and earnings grew in occupations requiring "people skills" in Britain, Germany, and the United States. Others construct models to capture social skills returns in the labor market. In the model of Kambourov et al. (2014), workers differ from each other by the level of "relationship skills." Those with higher levels are associated with higher earnings and a stable marriage. In the multi sector model of McCann et al. (2015), there are productivity gains from specialization and team production, but it requires communication and coordination between team members, which makes social skill more valuable, since it raises the productivity of cognitive workers. The complementarity between cognitive and social skills is also highlighted by Weinberger (2014), who also links the pre labor skills to adult outcomes.

The rise in the demand for social skills has also been related to closing of the gender wage gap: the increase in earnings in occupations that require social skills have benefited women more intensively than men (Bacolod and Blum, 2010; Borghans et al., 2014; Black and Spitz-Oner, 2010). The fundamental hypothesis is grounded in the psychology and neuroscience literature, which has found that women are better at engaging in interactions with other people and caring for others (Gilligan, 1993). Studies such as Woolley et al. (2010) argue that the presence of women on teams/groups increases what they call *collective intelligence*, which is not affected by its member's cognitive level (individual intelligence), but by the social sensitivity of the group. The reports also indicate women's advantage in decoding nonverbal communication (Hall, 1978).

Other authors argue that the sex difference in social abilities is related to the intrauterine development of brain structure and function. For Chapman et al. (2010), females have, on average, a stronger drive to empathize than males, which involves a better understanding of what others are thinking and feeling, and, therefore, a better aptitude for interacting in the social world. Those traits are defined, according to the authors, by the level of fetal testosterone. In the same line, Baron-Coen et al. (2005) shows that women are stronger at empathizing, while men are better at systemizing, which implies that women are better in predicting and responding to agents' behavior.

In the context of analyzing gender-specific effects of technological changes, Cortes et al. (2018) finds that women may have benefited from the increased demand for social skills. They present a simple equilibrium model of the high-skilled labor market, considering the traditional neoclassical framework of labor demand and supply. In addition, Cortes et al. (2018) use estimations of labor demand for social skills obtained by the specific attributes required in job advertisements (whose database was made available by Atalay et al. (2020)) to construct "the change in the importance of social skills of each occupation (i.e., change in demand for social skill)." They found a positive relation with the increase in female share in a given occupation, which corroborates their theoretical model's predictions.

3. EVIDENCE FROM THE BRAZILIAN HIGH-SKILLED LABOR MARKET

This section presents evidence that movements in the high-skilled labor market have not been equal across genders. In particular, we show that there has been an increase in women's employment in *good jobs* and a decrease in the likelihood that a college-educated male is employed in a high-wage/cognitive occupation. The Brazilian labor market is characterized by a clear separation between high- and low-skilled driven occupations, which implies that some *good jobs* are only available for more educated workers. For this reason, we focus on the high-skilled labor market.

We consider high-skilled workers those who have at least a college degree in terms of educational attainment. Good jobs are defined as occupations whose median wage is in the highest 20th percentile of the 1994 occupational wage distribution. Both definitions follow what was

TABLE I

HIGH-SKILLED OCCUPATIONAL AND EMPLOYMENT STATUS - 1994-2017

High-Skilled Workers		1994	2017	Difference Total	Difference %
Total	Number	681,912	2,897,600	2,215,688	324.9
	Good jobs (%)	43.9	39.9	−4.0	−9.1
	Others (%)	56.1	60.1	4.0	7.1
Women	Number	264,013	1,508,231	1,244,218	471.3
	Good jobs (%)	24.5	33.2	8.7	35.7
	Others (%)	75.5	66.8	−8.7	−11.6
Men	Number	417,899	1,389,369	971,470	232.5
	Good jobs (%)	56.1	47.1	−9.0	−16.0
	Others (%)	43.9	52.9	9.0	20.5

Note: Elaborated by the author from RAIS data, 18-65 year-old employees from private sector with at least college degree. Employment categorized by ranking in occupational wage distribution of 1994. Good jobs are defined as those in the top 20th wage percentile of the 1994 wages distribution.

adopted by Cortes et al. (2018). Our analysis uses microdata from the RAIS database for 1994 to 2017, provided by the Ministry of Labor and Social Security (data is detailed in Section 4).

The number of high-skilled workers increased by nearly 2 million between 1994 and 2017, more than half of women (1.2 million). Despite the substantial increase in the high-skilled labor supply, the probability that a high-skilled worker was employed in a high-paying occupation (*good job*) dropped over the same period from 43.9% to 39.9%. This decrease, however, hides divergent trends across genders. Table I presents high-skilled occupational employment and shows the key statistics motivating our analysis. In 1994, the probability of a woman working in a *good job* was 24.5% and increased to 33.2% in 2017. By contrast, the portion of high-skilled men working in *good jobs* was about 56.1% in 1994 and it dropped to 47.1%. This evidence is particularly striking given the massive increase of women's participation (women's labor supply) in the high-skilled labor market.

The divergent gender trends in the probability of working in *good jobs* implies that there is a rise in the female share of employment in these jobs. Figure 1 shows the increased relative sorting of women into *good jobs*. Each circle represents a 4-digit occupation (CBO) and its size indicates the occupation's share of aggregate employment in 1994. Along the horizontal axis, occupations are ranked by their place in the 1994 wage per hour distribution.[4] On the vertical axis is the 1994-2017 change in the female share of high-skilled employment[5] by occupation. Although the proportion of women has increased in all occupations, the proportion of women in higher-paying jobs increased significantly between 1994-2017. The positive association has an estimated coefficient that is significant at 1% level.

The results suggest the changing occupational choices of men and women may have played an important role in explaining the increase in female share employment in *good jobs*. In the Appendix A, we perform a decomposition exercise to show that the rising movement of the

[4]Occupation's wage per hour is calculated by the median wage per hour of the workers from each 4-digit occupation.

[5]For visual clarity, Figure 1 excludes seven occupations where the change in women's share of high-skilled employment increased by more than 40 percentage points and five occupations where the change fell more than 40 percentage points. The fitted regression line is based on all occupations, and its coefficient is significant at the 1% level.

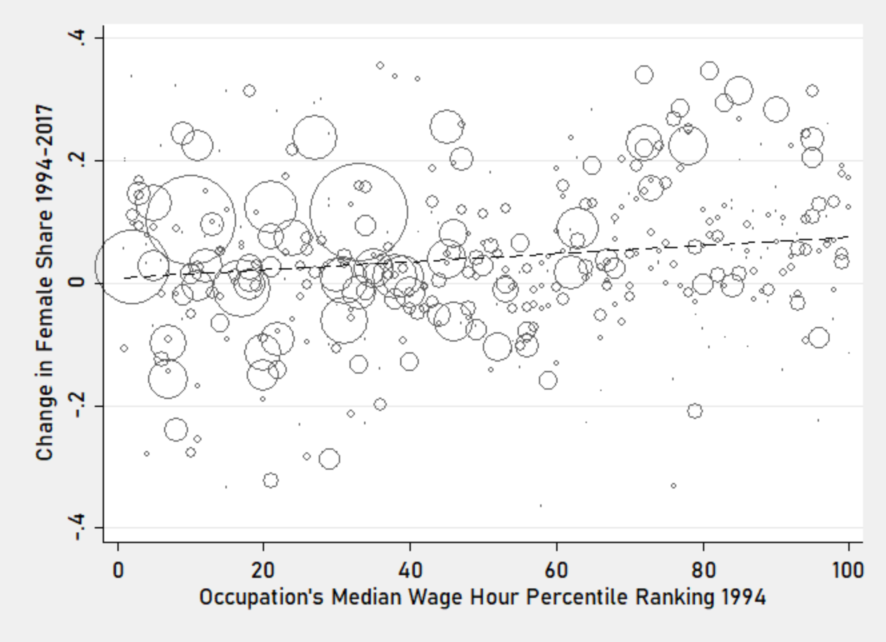

FIGURE 1.—Change in female employment share among college graduates and occupational wage ranking. Source: Elaborated by the author from RAIS data. Notes: The figure plots log changes in employment shares and occupational median wage per hour by 1994 occupational skill percentile rank using a locally weighted smoothing regression. Skill percentiles are measured as the employment-weighted percentile rank of an occupation's median log wage in RAIS dataset. Each circle represents a 4-digit occupation (CBO) and its size indicates the occupation's share of aggregate employment in 1994. Consistent occupation codes (CBO codes) for 1994 and 2017 were used using method described in subsection 4.1. The positive association has an estimated coefficient significant at the 1% level (0.001106 – a rise by one percentile in the CBO's ranking correlates with a 0.1 increase in the change of the share of women, on average).

female share of high-skilled employment is not entirely explained by the increase in the population of college-educated women.

3.1. *Interpreting the Changes of Women's Share of Good Jobs*

The data shows that high-skilled women have progressively sorted into *good jobs* over time, whereas high-skilled men have increasingly sorted into other occupations. In order to rationalize the possible mechanisms that explain these changes, we use the model proposed by Cortes et al. (2018). The main equation of the model shows that the difference between the changes in men and women's share of good jobs can be attributed to two factors: changes in comparative advantages and changes in discrimination.

The labor market equilibrium equation of Cortes et al. (2018) is:

$$\Delta a^*_{Mt} - \Delta a^*_{Ft} = \underbrace{\Delta\left(\frac{Z^G_{Ft}}{Z^G_{Mt}}\right) - \Delta\left(\frac{Z^O_{Ft}}{Z^O_{Mt}}\right)}_{\text{Change in Relative Productivity}} + \underbrace{\Delta\left(1+\tau^O_t\right) - \Delta\left(1+\tau^G_t\right)}_{\text{Change in Discrimination}}, \tag{1}$$

where $\Delta a^*_{Mt} - \Delta a^*_{Ft}$ denote the differential change in women choosing *good jobs* between men and women. The term a^*_{gt} is the ability of the marginal worker of gender g who self-select into good jobs at time t. Note that Δa_{gt} is the change across time in the ability of the marginal worker of gender g who self-select into good jobs. Also, note that the lower the ability of the marginal worker is, the greater the share of workers of that gender participating in the good-job sector is. Therefore, if $\Delta a^*_{Mt} - \Delta a^*_{Ft}$ is positive, this means that women are entering the good-job sector at a faster pace than men.

The LHS of (1) can be divided into the two components of the RHS of the equation. The productivity of high-skilled workers is gender-specific so that Z^i_{Mt} stands for male and Z^i_{Ft} for female, with $i = G,O$, where G refers to *good jobs* and O refers to other jobs. Hence, the first term of RHS of equation (1) express the change in the relative productivity of women with respect to men in both markets. Lastly, $(1+\tau^G_t)$ is the discriminatory component against high-skilled women in *good jobs*, which may differ from that in other occupations, $(1+\tau^O_t)$, thus $\Delta(1+\tau^O_t) - \Delta(1+\tau^G_t)$ denote the differential change in discrimination between both markets.

For Cortes et al. (2018), equation (1) gives two channels for raising women's employment in good jobs. The first one is related to the greater increase in the demand for female labor relative to males, which they call *Female Bias*. The growing demand for women $(\Delta(Z^G_{Ft}) > \Delta(Z^G_{Mt}))$ implies $\Delta(Z^G_{Ft}/Z^G_{Mt}) > \Delta(Z^O_{Ft}/Z^O_{Mt})$, when one assumes the demand for other jobs is constant. The second channel is the fall in discrimination in *good jobs* relative to other occupations $\Delta(1+\tau^O_t) > \Delta(1+\tau^G_t)$.

To explore the hypothesis of *Female Bias*, this analysis rests on two claims. The first is based on psychology and neuroscience empirical research that shows women have comparative advantage in social skills. Studies such as Gilligan (1993); Hall (1978); Chapman et al. (2010); Baron-Coen et al. (2005) have documented that women are better at performing interactions with other people and care more about others. Stoet and Geary (2021) show that student aspirations vary across gender. The study finds that male adolescent aspirations are more toward thing-oriented occupations, while women adolescent aspirations are more people-oriented. Cuevas et al. (2021) also show gender differences in preferences.

The second claim is that the value of social skills has increased in the Brazilian labor market recently. Deming (2017), and Weinberger (2014) documented this fact for the United States, and Borghans et al. (2014) do the same for Britain and Germany. The assumption about the growing importance of social skills takes into account the difficulty of technology replacing the interaction between humans. The ability to lead, coordinate, and motivate people is more important nowadays than ever. Moreover, having empathy for others, interpreting what someone else might be thinking or feeling can help reduce conflicts and promote a healthy, thriving workplace. The spread of preset rules to perform many tasks has increased the efficiency of the labor market. Still, the coordination of this new kind of work is what improves efficiency.

According to the model of Deming (2017), social skills reduce the transaction cost of combining tasks within a team in the output production and, consequently, raise productivity. Thus, the demand for occupations with a high level of social skills intensity increases in the labor market. The main difficulty in investigating it empirically in Brazil is the absence of an adolescent survey about youth skills such as the National Longitudinal Survey of Youth (NLSY79) in the United States to match with adult outcomes or job advertisement indexes as provided by Atalay et al. (2020). Without such information, the estimation of shifts in demand for social skills becomes hard to perform.

It is reasonable to assume that the second claim is true for Brazil as technology advances have similar impacts around the world. The time it takes to replace some workers with machines will vary from one country to another, but in more extended periods, it tends to converge.

Internal rules could make this transition harder to enact in some countries.[6] Even so, most job replacements by computers/machines have been widespread in the last two decades such as bank tellers, online sales, the process of operating systems in enterprises, etc. The impacts of those changes tend to be similar to all countries.

By assuming that both claims are true, we are able to relate the second channel of the rise in women's employment in a *good job* (i.e., *Female Bias*) to the observed movements in the occupational skill requirements. First, we analyze if social skills are correlated with a higher female share in occupations. Second, we investigate if there was an increase in demand for social skills since 2000 and whether it has attracted more women for occupations where the demand has increased. Finally, we examine whether social skills are, in fact, a comparative advantage for women – and consequently whether they have helped raise women's wages.

4. DATA

We use labor market data from the RAIS database for 1994 and 2017, made available by the Ministry of Labor and Social Security. RAIS is an administrative database that compiles all formal employment information of Brazil. All private and public companies have to provide information to the government about active employment contracts. They provide information regarding hiring, terminations, contracted hours, salaries, and employee characteristics such as age, education level, gender, among others.

RAIS is a mandatory formal labor market census annually requiring Brazilian companies to report information about their employees on a regular basis. It covers almost all of the formal sector.[7] Its downside is the restriction to the formal sector, ignoring workers in the informal sector. So the results of this paper are restricted to the formal sector and it is silent about the informal sector dynamics.

Our analysis focus on full time (more than 36 hours per week), full-year (more than 12 months in the same job), 18-65 year-old employees working in the private sector. We exclude individuals who work in the armed forces or farming, forestry, fishing occupations. We do so for international comparability of results, because most of the major studies in the field exclude these occupations from the sample. We used the nominal wage of each year to obtain real wages adjusted by the consumer price index (INPC[8]). We constructed real wages per hour using the number of hours hired. We also used variables of gender, age, educational attainment, and time at work.

Even though we are working with real wages per hour, we excluded part-time workers to prevent these from being a source of wage bias. We also excluded workers from the public sector because of the public-sector wage premium, which can also be a source of bias. The downside of ignoring the public sector is that we may underestimate women's probability of working in a good job because the female share is higher in the public sector. We consider the possible bias may have greater effects than the underestimation of the college-educated female population.

Our approach follows Autor et al. (2003) and assumes that the labor market clears when workers are matched to jobs that require the skills they have. For instance, a worker employed as an engineer has skills for math (cognitive) while a carpenter has skills for manual tasks. We

[6]One example is the case of bus ticket collectors in Brazil. Some municipalities, such as Novo Hamburgo (Rio Grande do Sul state), for instance, prohibit the replacement of bus ticket collectors by ticket validation machines by law.

[7]The RAIS information is not precise for the public sector.

[8]Índice Nacional de Preços ao Consumidor.

worked with CBO, which has two versions. The first one dated back to 1994 and remained until the 2000s. Another version of CBO was launched in 2002 and is still valid today. For our proposal, we made both versions compatible with each other with a procedure described in Appendix B.

4.1. *Measuring task content of Brazilian occupations (CBO)*

Our second challenge was to build a measure of the occupation's task content for CBO. The seminal work of Autor et al. (2003) classifies the task content of occupation using the U.S. Department of Labor's Dictionary of Occupational Titles (DOT). The five measures of tasks (nonroutine analytic, nonroutine interactive, routine cognitive, routine manual, and non-routine manual) are defined aggregating five variables of DOT in the corresponding 3-digits of U.S. census occupation classifications (SOC). *Nonroutine analytic* corresponds to "GED Math (MATH)"; *Nonroutine interactive* corresponds to "Direction, Control, Planning (DCP)"; *Routine cognitive* corresponds to "Set Limits, Tolerances, or Standards (STS)"; *Routine manual* corresponds to "Finger Dexterity (FINGDEX)"; and *Nonroutine manual* corresponds to "Eye Hand Foot Coordination (EYEHAND)."

Autor et al. (2006) used DOT as well, but collapsing the original five task measures into three task aggregations: abstract, routine and manual tasks. *Abstract* corresponds to the simple average of two DOT variables: "MATH" and "DCP." *Routine* corresponds to the simple average of "STS" and "FINGDEX." Finally, *Manual* corresponds to the DOT variable "EYEHAND." Autor and Dorn (2013) used the same measures.

Subsequent literature adopted the successor of DOT, the Occupational Information Network (O*NET). O*NET is a survey that questions a random sample of U.S. workers in each occupation about many issues concerning their abilities, skills, knowledge, work context, and work activities. The questions are rated on the ordinal scale. The O*NET survey began in 1998 and is updated frequently.

There is no such survey for the Brazilian labor market. So the way we captured the task content of CBO was to translate the O*NET scales to the international classification ISCO2008 and then translate to CBO. Our implicit assumptions are that the CBO's task content is similar to SOC's task content.

We map the O*NET-SOC occupational classification scheme to ISCO-08 coding following the step-by-step crosswalk provided by Hardy et al. (2018). Once we were able to collapse by mean O*NET scales in the ISCO-08 occupations, we used the same R text-mining tool as when we made the compatibility of CBO1994 - CBO2002 to extract the CBO2002 corresponding to the ISCO1988 related to O*NET-SOC.

O*NET task measures used in this paper (translated to CBO) are composite measures of O*NET Abilities, Skills, Knowledge, and Work Context level, using level and context scales. The O*NET database records hundreds of different measures of skills, but it is not possible to use all of them simultaneously because the estimations would not be precise due to multicollinearity (Bacolod and Blum, 2010).

We closely followed Deming (2017) and Cortes et al. (2018) to define *Social Skill Intensity*. It is given by the average of four O*NET measures from module "Social Skill": i) Skill of Social Perceptiveness (2.B.1.a); ii) Skill of Coordination (2.B.1.b); iii) Skill of Persuasion (2.B.1.c); and iv) Skill of Negotiation (2.B.1.d). The first measure is related to the skill of paying attention to others and having some degree of developed emotional intelligence. It is obtained through the statement: "being aware of other's reactions and understanding why they react as they do." The coordination measure captures the ability to quickly adapt to the action of others and is obtained by questioning whether the worker is used to "adjusting actions in relation to other's actions" when performing its job.

The persuasion measure is about the ability to make someone do or believe something by giving them good reasons to do so. The survey statement about this item is: “persuading others to change their minds or behavior.” Finally, the negotiation measure extracts the capability to reduce the differences between team workers and “to put them on the same page” by the statement about: “bringing others together and trying to reconcile differences,”

We combine the definitions from Deming (2017) and from Autor et al. (2003) to have our measure of *Cognitive Task Intensity*, averaging six measures of O*NET: i) Ability of Mathematical Reasoning (1.A.1.c.1); ii) Skill of Mathematics (2.A.1.e); iii) Knowledge of Mathematics (2.C.4.a); iv) Skill of Management of Financial Resources (2.B.5.b); v) Skill of Management of Material Resources (2.B.5.c); and vi) Skill of Management of Personnel Resources (2.B.5.d).

The three first measures account for the mathematical development required for a job. At high levels, workers are required to know advanced calculus (as engineers, statisticians, physicists, etc.), while at low levels, they have to know only the basics in math, such as arithmetic. The math ability is a measure that takes into account not only the mathematical knowledge itself but also the occupation requirement of mathematical reasoning and the capacity to solve math logic problems. For the knowledge module, the statement is: “whether the occupation requires knowledge of mathematics.” For the ability and skills modulus, the questions are “the extent to which an occupation requires mathematical reasoning” and “whether the occupation requires using mathematics to solve problems.”

The other three measures refer to the skills of managing in general, like managing money, material, and people. They are obtained by the following questions about the importance of “determining how the money will be spent to get the work done and accounting for these expenditures”;“obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do specific work”; and “motivating, developing, and directing people as they work, identifying the best people for the job.”

Routine Task Intensity is given by the average of two measures, as in Deming (2017): i) Work Context of Degree of Automation (4.C.3.b.2); and ii) Work context of Importance of Repeating Same Tasks (4.C.3.b.7). They refer to the measure of “how automated is the job” and “how important is repeating the same physical or mental activities over and over, without stopping of performing this job?”

Finally, *Manual Task Intensity* is given by the average of two measures as in Cortes et al. (2018): Ability of Multilimb Coordination (1.A.2.b.2); and ii) Ability of Speed of Limb Movement (1.A.2.c.3). They capture the motor aptitudes of body, in the sense of coordination of the limbs (“the ability to coordinate two or more limbs - for example, two arms, two legs, or one leg and one arm – while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.”), and quick response with and moving them (“the ability to quickly move the arms and legs.”).

We used level scales for most task intensity items, which go from 0 to 7, but the work context variables are scaled from 0 to 5. For this reason, we standardized each O*NET measure to have zero mean and standard deviation one, similar to what most of the literature chose to do.[9]

Our task indexes are defined by a combination of two or more O*NET measures, depending on the index. For *Cognitive Task Intensity*, for example, we used six O*NET measures, while for *Manual Task Intensity*, we used only two. So, once we obtained each of the indexes (Social, Cognitive, Routine, and Manual), we standardized each of them to have mean zero and standard deviation one. We do so to have comparable indexes. Each of them is evaluated now by its standard deviation to the mean.

[9]See Acemoglu and Autor (2011) for details.

Most of the literature uses task information registered at a specific point of time, as it was the same for each occupation over time. As in Cortes et al. (2018), we analyze the change in the task content of the occupations over time by using different versions of the O*NET database. The task content difference between two or more years is viewed as a change in the demand for a specific task measure over time.

We present the top and bottom ten occupations with the highest and lowest level of of each index in 2000 and 2017 in the Appendix C. The occupational task indexes are available in Sulzbach (2020).

4.2. *Descriptive Statistics*

Using the matched dataset, which incorporates RAIS data by CBO2002 and the task content of each occupation obtained through O*NET, we show the descriptive statistics of the high-skilled labor market in Brazil. Table II shows the main characteristics of individuals. When we look to total workers with college-degrees, we see an increase in the percentage of women between 1994 and 2017. On average, the workers were slightly older in 1994 (37.7 years old) than in 2017 (37.3 years old). The average age of women is lower in this market and has grown between the periods analyzed, unlike men. The nominal wage earned by workers is still lower for women, but the difference shrunk over time. In the following estimations, we use real wages. The number of formal workers by region is quite steady over time, with more than half of them located in the southeast region of Brazil.

Focusing on our variables of interest, Table II indicates that cognitive tasks are more required in general than social skills. However, there is a difference between genders. For men, cognitive is more relevant in both years, having reduced relevance between 1994 and 2017. For women, on the other hand, both cognitive and social requirements have increased over the years, but social media is most required in both years. Occupations in high-skilled markets little require routine tasks. When the sample refers only to female workers, the routine became less required over time, contrary to that of men. Manual is the least required task for college-educated workers, with a negative index for all in both years.

5. EMPIRICAL STRATEGY AND RESULTS

In this section, we present the empirical strategy to investigate the model predictions in Brazil and its results. We first investigate the correlation between social skills and the occupation share of women. We then evaluate the hypothesis of social skills helping increase women's earnings through time, contributing to the female comparative advantage.

5.1. *Social skills and women's occupational share*

To address the first analysis, i.e., whether social skills are correlated with a higher female share in occupations, we regress the level of female share of employment within each 4-digit level occupation, controlling for other tasks:

$$\phi_j = \alpha + \lambda_1 \theta_{sj} + \lambda_2 \theta_{cj} + \lambda_3 \theta_{rj} + \lambda_4 \theta_{mj} + \varepsilon_j \tag{2}$$

where ϕ_j denotes the share of women in each occupation in each year, α is a constant, $\theta_k j$ with $k \in (s, c, r, m)$ represents occupational mean task content where s denotes social skills, c denotes cognitive, r denotes routine, and m denotes manual. As usual, ε_j is the error term of the equation. We perform a weighted least squares to maximize the efficiency of parameter estimation, since data does not guarantee that each point provides equally precise information

TABLE II

DESCRIPTIVE STATISTICS - 1994-2017 – HIGH-SKILLED WORKERS (COLLEGE-DEGREE)

Variable (mean)		Total 1994	Total 2017	Women 1994	Women 2017	Men 1994	Men 2017
Age (years)		37.7	37.3	35.7	36.6	39.0	38.1
Women (%)		0.39	0.52				
Wage (R$)		1,629	6,383	1,050	4,928	1,994	7,962
Experience (months)		102.3	74.0	90.4	69.4	109.8	79.1
Hours worked (hours)		41.9	42.5	41.8	42.4	42.1	42.6
Region	South (%)	0.15	0.17	0.15	0.17	0.14	0.17
	Southeast (%)	0.54	0.54	0.53	0.52	0.54	0.55
	North (%)	0.02	0.03	0.02	0.03	0.02	0.03
	Northeast (%)	0.10	0.11	0.11	0.13	0.09	0.10
	Central-West (%)	0.05	0.07	0.05	0.07	0.05	0.06
Indexes	Social (sd)	0.60	0.59	0.56	0.62	0.63	0.54
	Cognitive (sd)	0.72	0.65	0.42	0.55	0.91	0.76
	Routine (sd)	0.11	0.15	0.23	0.16	0.04	0.13
	Manual (sd)	–0.88	–0.81	–0.92	–0.89	–0.86	–0.73
Number of workers (thsnd.)		682	2,897	264	1,508	418	1,389

Note: Elaborated by the author from RAIS data, 18-65 year old employees from private sector with at least college degree.

about the deterministic part of the total process variation – i.e. the standard deviation of the error term is not constant. We estimate Equation 2 for both years, 1994 and 2017.

The results are in the first column of Table III. Occupations that require more social skills have a larger share of women among the workers. In 1994, one deviation from the mean in the social index increases the occupational share of women to 8.4 percentage points, which is significant at a 1% level. The results remain when we control for the other tasks, as shown by column 2 of Table III. In this case, the coefficient is nearly 7.2 percentage points and still significant at a 1% level. On the other hand, cognitive and manual occupational requirements reduce women's participation. The coefficient's signs are in accordance with the findings of Cortes et al. (2018) for the American labor market.

The same exercise was performed with 2017 data. The percentage of tasks in an occupation that require social skills increases the female share by 10.8 percentage points, which is statistically significant. Controlling for the content of other tasks of an occupation, the social skill coefficient indicates that women share increased by 8.1 percentage points and is still significant at a 1% level. In 2017, cognitive and manual tasks remained negatively correlated with female share of occupations, and routine skill continues to be statistically insignificant.

5.2. *Wage Evidence*

The final step in our investigation is to test the hypothesis of social skills helping increase women's earnings through time, contributing to the female comparative advantage. We perform a two-stage estimation. In the first one, we estimate gender-specific wage premium of each occupation in each year by quantile regression. Then, we estimate the impact of social skills on the wage premium.

In the first step, we estimate gender-specific wage premium for each 4-digit occupation by regressing log hourly real wages in 18-65 year-old individual workers in the private market

TABLE III

IMPORTANCE OF OCCUPATIONAL TASKS IN THE FEMALE SHARE OF HIGH-SKILLED EMPLOYMENT

	1994 (1)	1994 (2)	2017 (3)	2017 (4)
Social	0.08***	0.07***	0.11***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
Cognitive		–0.09***		–0.10***
		(0.02)		(0.02)
Routine		–0.02		–0.01
		(0.01)		(0.01)
Manual		–0.10***		–0.14***
		(0.02)		(0.01)
Constant	0.27***	0.28***	0.30***	0.32***
	(0.01)	(0.01)	(0.01)	(0.01)
Obs.	412	412	425	425
R^2	0.07	0.22	0.11	0.35

Note: Standard errors in parentheses. (*) $p < 0.10$, (**) $p < 0.05$, (***) $p < 0.01$. The dependent variable is the female share of occupational employment. The regression is performed by weighted least squares.

on age (five groups[10]), education (five categories[11]), tenure, and tenure squared by quantile regression. The regressions are run for each gender, year (1994 and 2017) and occupation. The coefficients of the constant are taken as the gender-specific occupational wage premium.The formal equation to be estimated is:

$$\ln(w_i) = \alpha + X_i\beta + \varepsilon_i \tag{3}$$

where $\ln(w_i)$ denotes log hourly real wages, α is the constant vector, which gives us the estimation of wage premium, X_i is the vector of all individual characteristics as age, education, tenure and tenure squared, β denotes the coefficient vector of X_i, and ε_i is the error term.

We are interested in analyzing the relationship between the wages using the conditional median function, so we perform a semiparametric estimation to capture the outliers of regression with more robustness. The variance-covariance matrix of the estimators (VCE) is estimated by bootstrap.[12] For proper convergence, we excluded occupations with less than ten registered workers.

Once we had the gender-specific wage premium of each occupation, we analyzed the impact of social skill on it in the second step. We regressed the wage premium of each gender and each year on social skills controlling for other tasks.

$$\Omega_j = \rho + W_j\delta + \varepsilon_j \tag{4}$$

where Ω_j represents gender-specific wage premium of occupation j, ρ denotes the constant, W is a vector of explanatory variables, which includes social skills, cognitive, routine and manual

[10]Consider age1=under 25 years old; age2=between 25-35 years old; age3=between 35-45 years old; age4=between 45-55 years old and age5=above 55 years old.

[11]Consider educ1 = illiterate; educ2 = incomplete elementary school; educ3 = complete elementary school; educ4 = high school; educ5= college degree or more.

[12]Booststrap repetitions = 30.

tasks, occupational female share, and interaction of social and cognitive tasks, and ε_j is the error term of the equation. We performed weighted least squares to maximize the efficiency of parameter estimation.

Table IV presents the main results of the regression for women. The first two columns consider only the relation between social skill intensity and women's wages. Occupations with a social index one standard deviation above the mean had a 0.376 higher wage premium (in log) in 1994 and 0.148 in 2017 with 1% level of confidence.

When we control for other task measures and female share of each occupation (Model 2), the contribution of social skills to the women's wage fall to 0.137 and 0.131 for years 1994 and 2017, respectively. In this case, R-squared is higher. The key result is the steadiness of social skill contribution to wages between 1994 and 2017. In the same period, cognitive skills have become relatively less important since 1994, with a 1% level of confidence, from 0.225 to 0.157. Also, the inclusion of the female share in the regression shows occupations with a strong female presence tend to pay lower wages. The negative impact of female share, however, has become less relevant over the years, as it has gone from -0.844 to -0.409. Even in the high-skilled labor market, there is a tendency of women concentrating on lower-paying occupations, but the effect of this concentration in earnings is narrowing.

The literature has also documented that social skills raise the productivity of cognitive workers (McCann et al., 2015; Weinberger, 2014; Deming, 2017). Controlling for the interaction between social and cognitive skills, the contribution of social skills remains similar to Model 2, with similar coefficients and stable trend. The cognitive index is still losing importance, and the interaction between social and cognitive skills helps to increase women's wages in both years.

In contrast with their effect on the female labor market, social skills seem to have lost their impact on wages over time for men. Its coefficient was 0.267 in 1994, considering Model 2, while in 2017, it was not statistically different from zero. Even for men's earnings, the higher female share in an occupation has negative effects. That is, men working in occupations that are female-dominated earn lower wages than those working in occupations with a lower concentration of women. In 1994, occupations that are dominated by women paid 1.28 lower wages. The negative effect fell to 0.49 in 2017. When we control for the interaction between social and cognitive skills, the declining importance of social skills on men's wage premium prevails, the drop in cognitive is even more significant, and the combination of social and cognitive skills gains relevance in determining men's wages.

Social skills do seem to be a comparative advantage for women in the high-skilled job market. Its relevance in determining wages remained the same between 1994 and 2017 for women, while it fell for men. Besides, social increases cognitive skills returns, so that individuals with the combination of both tasks have higher salaries. This is true not only for women, whose impact of the combination has doubled between the years analyzed but also for men, whose effect has gone from negative to positive.

6. CONCLUSIONS

The increasing demand for high-skilled workers in recent years is well known. In this paper, we provide evidence of gender-specific divergent trends in the likelihood of a high-skilled individual working in a *good job*. The rising probability of women working in a good job contrasts with the declining probability of college-educated men. We show that such a difference is not fully explained by the increase of women's supply labor in the high-skilled market (college-educated) neither by demographic and spatial characteristics.

Our main assumption follows the empirical evidence reported in the international literature on the growing demand – and thus its importance – for social skills in the labor market. Taking

TABLE IV

FEMALE OCCUPATIONAL WAGE PREMIUM – HIGH-SKILLED LABOR MARKET

	Model 1		Model 2		Model 3	
	1994	2017	1994	2017	1994	2017
Social	0.38***	0.15***	0.14*	0.13***	0.14*	0.14***
	(0.07)	(0.03)	(0.08)	(0.04)	(0.08)	(0.04)
Cognitive			0.23***	0.16***	0.22***	0.15***
			(0.07)	(0.03)	(0.07)	(0.04)
Routine			–0.11**	0.02	–0.11	0.03
			(0.05)	(0.02)	(0.05)	(0.02)
Manual			–0.09	0.05*	–0.09**	0.06
			(0.06)	(0.03)	(0.06)	(0.03)
Female Share			–0.84***	–0.41***	–0.84	–0.40*
			(0.18)	(0.09)	(0.18)	(0.09)
Social×Cognitive					0.01***	0.03***
					(0.05)	(0.03)
Obs.	223	330	223	330	223	330
R^2	0.12	0.07	0.30	0.27	0.29	0.26

Note: Standard errors in parentheses. (*) $p < 0.10$, (**) $p < 0.05$, (***) $p < 0.01$. The dependent variable is the gender-specific wage premium of occupation. The regression is performed by weighted least squares.

TABLE V

MALE OCCUPATIONAL WAGE PREMIUM – HIGH-SKILLED LABOR MARKET

	Model 1		Model 2		Model 3	
	1994	2017	1994	2017	1994	2017
Social	0.38***	0.15***	0.27***	0.06	0.18**	0.06
	(0.06)	(0.03)	(0.07)	(0.04)	(0.08)	(0.04)
Cognitive			0.20***	0.17***	0.28***	0.16***
			(0.07)	(0.04)	(0.07)	(0.04)
Routine			0.08	–0.02	0.08	0.00
			(0.05)	(0.02)	(0.05)	(0.02)
Manual			–0.21***	–0.04	–0.25	–0.04
			(0.06)	(0.03)	(0.06)	(0.02)
Female Share			–1.28***	–0.49***	–1.15***	–0.43
			(0.20)	(0.09)	(0.21)	(0.08)
Social×Cognitive					–0.06***	0.03***
					(0.05)	(0.02)
Obs.	320	396	320	396	320	396
R^2	0.10	0.07	0.47	0.25	0.36	0.26

Note: Standard errors in parentheses. (*) $p < 0.10$, (**) $p < 0.05$, (***) $p < 0.01$. The dependent variable is the gender-specific wage premium of occupation. The regression is performed by weighted least squares

this evidence as valid for Brazil, we investigate the role of social skills in the rising demand for women in this market. We contribute to the literature on labor economics by building a measure of task content of the Brazilian classification of occupations (CBO), including the measure of the CBO's social skill index. To do so, we assume that occupational task content is similar across countries, and match the CBO's task intensity with the RAIS database.

We show that there is a positive relation between social skills and the female share of occupations, which suggests that women self-select into professions intensive in this kind of skill. We also provide results consistent with neuroscience literature, which documents that women have a comparative advantage in performing tasks that require social skills. The relevance of such skills in determining wages is higher for women than men (in 2017). Social skills also raise cognitive returns in both cases. We also contribute to the literature by showing evidence about the relation between social skills and women's share in occupations and their wages. Promising research can derive from this first step, especially considering the Brazilian labor market.

APPENDIX A: EVIDENCE FROM THE BRAZILIAN HIGH-SKILLED LABOR MARKET: DECOMPOSITION EXERCISES

In this section, we present two decomposition exercises. The first one investigates the hypothesis of the trend difference in the probability of working in a good job is related to the demographic characteristics of men and women in the high-skilled labor market. We do so by running the Oaxaca-Blinder decomposition technique. In the second one, we present a decomposition of a rising movement of the female share of high-skilled employment into two components: (i) the rise of college-educated women population; and (ii) occupational choice of men and women.

A.1. *Oaxaca-Blinder Decomposition*

In this subsection we adapt the Oaxaca-Blinder decomposition technique (Oaxaca, 1973; Blinder, 1973) to the framework of our interest in investigating some evidence of the high-skilled market. We process the decomposition for all individuals (men and women). The probability of working in a *good job* is observed in two periods: 1994 ($s_i = 0$) or 2017 ($s_i = 1$). It is a function of individuals characteristics, which formally can be written as:

$$\begin{aligned} \pi_i^s &= X_i\beta_1 + \varepsilon_{1i}, \text{ if } s_i = 1 \\ \pi_i^s &= X_i\beta_0 + \varepsilon_{0i}, \text{ if } s_i = 0 \end{aligned} \tag{5}$$

where π_i^s represents the probability of working in a *good job* in year $s \in \{1,0\}$ and X_i is the vector composed of individual characteristics. Moreover, we have that $E[\varepsilon_{1i}|X_i, si] = E[\varepsilon_{0i}|X_i, si] = 0$.

The difference in the probability between 1994 and 2017 is given by:

$$E[\pi_i^s|si = 1] - E[\pi_i^s|si = 0] = (E[Xi|si = 1] - E[Xi|si = 0])\beta_0 + E[Xi|si = 1](\beta_1 - \beta_0) \tag{6}$$

The first term on the right side of Equation (6) $(((E[Xi|si = 1] - E[Xi|si = 0])\beta_0)$ represents the difference in wage due to observable characteristics of individuals in both sectors, which is known as *explained component of the gap*. The second term $(E[Xi|si = 1](\beta_1 - \beta_0))$ refers to characteristics we do not observe, such as the abilities of workers, for example. We obtain these unobserved components through the difference of coefficients obtained in each sector applied to the characteristics of individuals who compose the formal market. This last component is called *unexplained term of the decomposition*.

As one can see in the Table A.I, demography and spacial characteristics (*explained component*) do not account for a large part of the difference in the probability of a high-skilled employee (total) working in a *good job*. Variables such as age[13] and region of residence contribute only 9.8% to the decrease observed between 1994 and 2017. We see a similar pattern

[13]We only use age as a demographic variable because information of race or physical disability are not available before 2003. We did not use place of birth, as Cortes (2016) did, because there were few variations among individuals.

TABLE A.I

DECOMPOSITION OF THE CHANGE IN THE PROBABILITY OF WORKING IN A "GOOD JOB"

	Total		Women		Men	
	p.p	%	p.p	%	p.p	%
Difference	−3.9900*** (0.0006)	100.00	8.7300*** (0.0009)	100.00	−9.0000*** (0.0008)	100.00
Unexplained	−3.6000*** (0.0006)	90.20	8.2600*** (0.0009)	94.60	−8.3600*** (0.0008)	92.90
Explained	−0.3900*** (0.0001)	9.80	0.4700*** (0.0002)	5.40	−0.6400*** (0.0001)	7.10
age	−0.3700*** (0.0001)	9.20	0.4500*** (0.0001)	5.20	−0.6600*** (0.0001)	7.30
south	−0.1000*** (0.0000)	2.50	−0.1100*** (0.0000)	−1.20	−0.0500*** (0.0000)	0.60
north	0.0200*** (0.0000)	−0.60	0.0400*** (0.0000)	0.40	0.0000* (0.0000)	0.00
northeast	−0.0600*** (0.0000)	1.50	−0.0500*** (0.0000)	−0.50	−0.0200*** (0.0000)	0.20
central-west	0.1200*** (0.0000)	−2.90	0.1400*** (0.0000)	1.60	0.0900*** (0.0000)	−1.00

Note: Standard errors in parentheses. (*) $p < 0.10$, (**) $p < 0.05$ (***), $p < 0.01$. We only use age as a demographic variable because information of race or physical disability are not available before 2003. We also did not use place of birth, as Cortes (2016) did, because there were few variations among individuals.

for men (7.1%). In the case of women, for whom the probability difference increased, the explained part has even less importance (5.4%). Aging helped high-skilled women to increase the probability of working in a *good job* (5.2%), while this variable contributed to reducing the gap for the case of men and total.

Our results indicate that compositional changes in demographics and regions are insufficient to explain the divergent trend in probability of working in *good jobs*, which seems to be due predominantly to changes in the propensity to work in them, conditional on observable characteristics.

A.2. *A decomposition of the movement of women in high-skilled labor market*

The massive increase in the number of college-educated women over the past years seems to be the most critical driver of the rising female share of high-skilled employment in a *good job*. However, is that the only reason for the increasing movement? What is its importance on the overall advance of female share in *good jobs*?

As shown by Cortes et al. (2018), the female share of high-skilled employment in *good jobs* can be decomposed as:

$$\sigma_t = \frac{F_t^{good}}{F_t^{good} + M_t^{good}} = \frac{\overline{F_t} * \pi_t^F}{\overline{F_t} * \pi_t^F + \overline{M_t} * \pi_t^M} \tag{7}$$

where F_t^{good} is number of women in a *good job* (median wage in top 20%) in time t, M_t^{good} is number of men in a *good job* in time t, $\overline{F_t}$ is the total number of high-skilled (college-educated) women, $\pi_t^F \equiv \frac{F_t^{good}}{\overline{F_t}}$ is the fraction of high-skilled women employed in a *good job*. By similarity, $\pi_t^M \equiv \frac{M_t^{good}}{\overline{M_t}}$ is the same for men.

TABLE A.II

HIGH-SKILLED FEMALE SHARE OF EMPLOYMENT AND COUNTERFACTUAL EXERCISE

	Observed				Counterfactual	
	1994	2017	Variation p.p	%	2017*	2017**
Population vs Occupational Choice					Population	Occupation
Top 20% (%)	21.6	43.3	21.7	100.6	32.1	30.8

Note: Elaborated by the author from the RAIS data, 18-65 year-old employees from private sector with at least college degree. The counterfactual 2017* considers the effect of the rise in the female high-skilled (college-educated) population. It is built holding π_t^F and π_t^M at levels of 1994, allowing only the number of high-skilled men and women to vary. The counterfactual 2017** considers the women's occupational choice for higher-paying jobs. It is built keeping the high-skilled population at the level of 1994, allowing only the fractions π_t^F and π_t^M to vary.

Table A.II shows the counterfactual exercises. Among all high-skilled workers, the probability of women working in a *good job* rose from 21.6% to 43.3%. The 21.7 percentage point increase is explained by a component due to high-skilled population growth (mainly women) and another element due to changes between occupations (increasing the proportion of women in top decile wage per hour occupations). The column entitled 2017* considers the effect of the rise in the female high-skilled (college-educated) population. In this case, the counterfactual is built holding π_t^F and π_t^M at 1994 levels, allowing only the number of high-skilled men and women to vary. The increase in the female high-skilled population has an important role. If only this component had happened, the probability of women working in *good jobs* would be 32.1%, explaining about 48.4% of the rise. Thus, the women's effort to be better educated did impact the female share of *good jobs*.

The column entitled 2017**, on the other hand, considers the women's occupational choice; that is, it takes into account the rise of female choice for higher-paying occupations. To construct that, we kept the high-skilled population at the 1994 level, allowing only the fractions π_t^F and π_t^M to vary. If only women's migration to *good jobs* had happened (without a rise in the level of college-educated women), the proportion of women in these occupations would be 30.8%, accounting for 42.3% of the increase. In sum, the population and the occupational choice effects played a similar role.

The results are similar to what Cortes et al. (2018) found for the United States, where the population's contribution was 36.1%. Occupational choice had a bit larger effect there (49.2%). In both cases, the evidence shows there are other important aspects beyond the rise in the female share of the college-educated population. The change in the men and women's occupational choice equilibrium is something that we have to look at properly.

APPENDIX B: 1994-2017 CBO COMPATIBILITY

Our first challenge was to make occupations from 1994 and 2017 compatible. To do so, we use the official crosswalk available on the Special Secretary of Social Security and Labor's website. There were missing correspondents to the occupations with final code 90 in the 5-digits of the 1994 classification (from now CBO1994), which referred to the "other occupations," whose share in total employment was not negligible.

A solution we found was to use the crosswalk between CBO1994 and International Standard Classification of Occupation (ISCO) from 1988 (henceforth ISCO88), provided by Concla-IBGE.[14] We then constructed a text-mining tool, ran in R, to extract the CBO2002 correspon-

[14]Available in https://concla.ibge.gov.br/images/concla/documentacao/ibgexcbo94.xls

dent of the ISCO1988 related to the specific missing CBO1994 from the PDF files. To solve the problem of a large number of CBO2002 correspondents to each ISCO1988, we used the Stringsim function from R to compare the text-similarity of the occupation's definition with the JW method. We combine this specific rule with our subjective analysis to determine the approximated correspondent.

There were additional occupations CBO1994 without a correspondent in CBO2002, beyond those just mentioned (5-digit ended with 90). We deleted the CBO1994 with initial 2-codes equal to 99 because their registration identified "undefined occupations." Also, we excluded the CBO1994 not referenced in the CBO1994 book and the registrations in newer occupations with too few workers (occupations did not exist in recent years nor in 1994).

Finally, we discarded the information about occupations that no longer need to declare information to RAIS[15] such as directors without employment relationship (for which FGTS[16] is not collected), legislators, domestic workers, interns, autonomous and cooperative workers. For comparison purposes, we also aggregate some CBO2002 that were counted as a single occupation in 1994. As an example, we aggregated all of the occupations referred to as directors. The list of occupations we had to deal with in this situation and the exclusions cited above is presented in the next table.

APPENDIX C: TOP AND BOTTOM TEN OCCUPATIONS OF EACH TASK

Table C.I reports the top and bottom ten occupations with the highest and lower level of Social Skills Intensity, respectively, in 2000 and 2017. Occupations of the top in 1994 are dominated by management positions (directors and managers), lawyers, social workers, and others (even economists). The picture of the top 10 occupations in social skills did not change too much until 2017. On the bottom are the occupations that involve working with natural resources such as stones, ores, ceramics, and others when we look to the index in 2000. In 2017, occupations with more manual tasks were ranked at the bottom, like laundry and leather tanning workers.

Table C.II shows the same to Cognitive Tasks Intensity. Engineers, directors, and managers were the principal occupations in the top 10 highest levels of Cognitive Skills. In 2017, engineers were more predominant in the top 10, including statisticians and some managers. On the other hand, models, laundry workers and gold miners and salt operators are on the bottom in both years. The list in 2000 also includes, for example, funeral service workers and stonemasons. Meanwhile, workers in building management services, in telemarketing and leather tanning are the list in 2017.

Concerning Routine Skills Intensity, occupations on Top 10 in 2000 were machine and equipment operators, ore processing, and leather tanning, as we can see in Table C.III. In 2017, equipment operator occupations were predominant, and cashiers and ticket agents were added to the list. Occupations involving schools counselors, lawyers, and veterinarians were the ones with less routine content in 2000.

Table C.IV reports the top and bottom ten occupations according to the Manual Skills Intensity. Occupations on the top were dominated by police, firefighters, security guards, athletes, and physical education professionals in 2000, while carpenters, prospectors, iron and metal workers ranked on the top ten occupations in 2017. At the bottom of routine content intensity

[15]The 2011 RAIS manual made the declaration not mandatory for some occupations.

[16]FGTS is the Portuguese acronym for "Guaranteed Fund for Length of Service," an obligatory social insurance fund, which is composed of the saving of 8% of a worker's earnings monthly to support them in case of specific eventualities, such as long-term sickness or resignation.

TABLE B.I

GROUPING OF OCCUPATIONS (CBO2002)

GROUP	CBO2002
Group I	1210 1221 1222 1223 1224 1225 1226 1227 1231 1232 1233 1234 1236 1237 1238 1311 1312 1313 1313
Group II	1412 1413
Group III	1424 1427
Group IV	2030 2011 3253
Group V	2141 2629
Group VI	2143 2021 2122
Group VII	2145 2222 2211
Group VIII	2212 3012 3201
Group IX	2221 2034 2140
Group X	2233 5193
Group XI	2311 3311
Group XII	2313 3312 3321
Group XIII	2331 3313
Group XIV	2332 3322
Group XV	2344 2033
Group XVI	2347 2514
Group XVII	2394 3331 3341
Group XVIII	2512 2525
Group XIX	2521 2526
Group XX	2612 4231
Group XXI	2613 3712
Group XXII	2628 3761
Group XXIII	3003 3001
Group XXIV	3116 3191 7610
Group XXV	3133 3135
Group XXVI	3141 3142
Group XXVII	3182 3186
Group XXVIII	3183 3187
Group XXIX	3184 3192
Group XXX	3211 3212
Group XXXI	3225 3226
Group XXXII	3412 3413
Group XXXIII	3523 2012
Group XXXIV	3532 2532
Group XXXV	5132 2711 5136
Group XXXVI	5134 5135
Group XXXVII	5163 5102
Group XXXVIII	5173 5103 5153
Group XXXIX	7251 7255
Group XL	7411 7401
Group XLI	7421 9152
Group XLII	7601 7605
Group XLII	7614 7654
Group XLIV	7621 7620
Group XLV	7641 7640
Group XLVI	7734 7735
Group XLVII	7817 7813
Group XVIII	7841 7801
Group XLIX	8112 8131
Group L	8117 3114
Group LI	8417 3250
Group LII	8421 8486
Group LIII	9109 9102
Group LIV	9113 3144
Group LV	9501 9502 9503
Group LVI	9511 9513

were archivists, lawyers, insurance, stock, and financial assets brokers, notaries, chemicals, accountants, among others in both years.

TABLE B.II

OCCUPATIONS THAT DID NOT EXIST IN 1994 OR HAD FEW EMPLOYEES IN 2017 OR HAD NO REFERENCE IN THE CBO2002 BOOK

CBO 2002	**Description**
1130	Dirigentes de Povos Indígenas, de Quilombolas e Caiçaras
1141	Dirigentes de Partidos Políticos
1142	Dirigentes e Administradores de Entidades Patronais e dos Trabalhadores e de Outros Interesses Socieconômicos
1143	Dirigentes e Administradores de Entidades Religiosas
1144	Dirigentes e Administradores de Organizações da Sociedade Civil Sem Fins Lucrativos
2263	Profissionais das Terapias Criativas, Equoterápicas e Naturológicas
2514	Filósofos
2527	Sem referência
3519	Sem referência
5121	Trabalhadores dos Serviços Domésticos em Geral
5167	Astrólogos e Numerólogos
5168	Esotéricos e Paranormais
5198	Profissionais do Sexo
7911	Artesãos

TABLE B.III

OCCUPATIONS THAT WERE NOT REFERENCED IN CBO1994 BOOK

CBO 1994		
2337	19930	28704
2425	19940	28720
5390	19950	28736
7420	20496	32784
7640	20512	32800
11090	20528	32816
16290	20544	32832
16400	24592	59975
16416	24608	59980
16432	24624	83405
16448	24640	92185
19390	28688	

TABLE C.I

TOP AND BOTTOM 10 OCCUPATIONS IN THE SOCIAL SKILL INTENSITY DISTRIBUTION - 2000 AND 2017

Social Skills Intensity 2000		**Social Skills Intensity 2017**	
Top 10 **CBO 2002 - Descrição**	**Bottom 10** **CBO 2002 - Descrição**	**Top 10** **CBO 2002 - Descrição**	**Bottom 10** **CBO 2002 - Descrição**
Diretores Gerais	Trabalhadores de Beneficiamento de Pedras Ornamentais	Tabeliães e Registradores	Lavadores e Passadores de Roupa, à Mão
Advogados	Ceramistas (Preparação e Fabricação)	Assistentes Sociais e Economistas Domésticos	Supervisores da Indústria Têxtil
Gerentes de Suprimentos e Afins	Trabalhadores da Fabricação de Cerâmica Estrutural para Construção	Ministros de Culto, Missionários, Teólogos e Profissionais Assemelhados	Trabalhadores da Preparação do Curtimento de Couros e Peles
Gerente de Pesquisa e Desenvolvimento	Trabalhadores de Beneficiamento de Minérios	Advogados	Trabalhadores do Curtimento de Couros e Peles
Gerentes de Tecnologia da Informação	Afiadores e Polidores de Metais	Gerentes de Suprimentos e Afins	Supervisores na Indústria do Curtimento
Assistentes Sociais e Economistas Domésticos	Trabalhadores de Estruturas de Alvenaria	Gerentes de Comercialização, Marketing e Comunicação	Operadores de Usinagem Convencional de Madeira
Economistas	Trabalhadores na Operação de Máquinas de Concreto Usinado	Gerentes de Operações de Serviços em Instituição de Intermediação Financeira	Trabalhadores de Tecelagem Manual, Tricô, Crochê, Rendas e Afins
Gerentes de Produção e Operações em Empresa da Indústria Extrativa, de Transformação e de Serviços de Utilidade Pública	Operadores de Instalações e Equipamentos de Fabricação de Materiais de Construção	Gerentes de Recursos Humanos e de Relações do Trabalho	Trabalhadores de Moldagem de Metais e de Ligas Metálicas
Gerentes de Operações de Serviços em Empresa de Transporte, de Comunicação e de Logística	Operadores na Preparação de Massas para Abrasivo, Vidro, Cerâmica, Porcelana e Materiais de Construção	Gerentes de Operações Comerciais e de Assistência Técnica	Trabalhadores nos Serviços de Administração de Edifícios
Arquitetos e Urbanistas	Operadores de Equipamentos de Fabricação e Beneficiamento de Cristais, Vidros, Cerâmicas, Porcelanas, Fibras de Vidro, Abrasivos e Afins	Diretores Gerais	Trabalhadores da Preparação de Artefatos de Tecidos, Couros e Tapeçaria

TABLE C.II

TOP AND BOTTOM 10 OCCUPATIONS IN THE COGNITIVE SKILL DISTRIBUTION - 2000 AND 2017

Cognitive Skills 2000		**Cognitive Skills 2017**	
Top 10 **CBO 2002 - Descrição**	**Bottom 10** **CBO 2002 - Descrição**	**Top 10** **CBO 2002 - Descrição**	**Bottom 10** **CBO 2002 - Descrição**
Engenheiros Químicos e Afins	Modelos	Engenheiros Civis e Afins	Modelos
Diretores Gerais	Filólogos,Tradutores, Intérpretes e Afins	Engenheiros Químicos e Afins	Trabalhadores nos Serviços de Administração de Edifícios
Gerentes de Tecnologia da Informação	Alimentadores de Linhas de Produção	Engenheiros de Minas e Afins	Lavadores e Passadores de Roupa, à Mão
Gerentes de Pesquisa e Desenvolvimento e Afins	Lavadores e Passadores de Roupa, à Mão	Engenheiros Metalurgistas de Materiais e Afins	Trabalhadores da Preparação do Curtimento de Couros e Peles
Engenheiros Civis e Afins	Trabalhadores Auxiliares dos Serviços Funerários	Pesquisadores de Engenharia e Tecnologia	Supervisores na Indústria do Curtimento
Economistas	Trabalhadores Operacionais de Conservação de Vias Permanentes (Exceto Trilhos)	Engenheiros Mecânicos e Afins	Supervisores da Indústria Têxtil
Engenheiros Eletricistas, Eletrônicos e Afins	Trabalhadores dos Serviços Funerários	Profissionais de Estatística	Trabalhadores do Curtimento de Couros e Peles
Gerentes de Operações de Serviços em Empresa de Transporte, de Comunicação e de Logística (Armazenagem e Distribuição)	Garimpeiros e Operadores de Salinas	Gerentes Administrativos, Financeiros, de Riscos e Afins	Operadores de Telemarketing
Engenheiros Mecânicos e Afins	Trabalhadores de Beneficiamento de Pedras Ornamentais	Engenheiros de Produção, Qualidade, Segurança e Afins	Vendedores em Domicílio
Gerentes de Suprimentos e Afins	Trabalhadores na Operação de Máquinas de Terraplenagem e Fundações	Gerentes de Produção e Operações em Empresa da Indústria Extrativa, de Transformação e de Serviços de Utilidade Pública	Trabalhadores de Tecelagem Manual, Tricô, Crochê, Rendas e Afins

TABLE C.III

TOP AND BOTTOM 10 OCCUPATIONS IN THE ROUTINE SKILL DISTRIBUTION - 2000 AND 2017

Routine Skills 2000		**Routine Skills 2017**	
Top 10 **CBO 2002 - Descrição**	**Bottom 10** **CBO 2002 - Descrição**	**Top 10** **CBO 2002 - Descrição**	**Bottom 10** **CBO 2002 - Descrição**
Trabalhadores na Operação de Máquinas de Concreto Usinado	Ministros de Culto, Missionários, Teólogos e Profissionais Assemelhados	Engenheiros Agrimensores e Engenheiros Cartógrafos	Modelos
Trabalhadores de Beneficiamento de Minérios	Advogados	Farmacêuticos	Tabeliães e Registradores
Preparadores e Operadores de Máquinas-Ferramenta Convencionais	Programadores, Avaliadores e Orientadores de Ensino	Operadores Polivalentes de Equipamentos em Indústrias Químicas, Petroquímicas e Afins	Professores de Nível Superior na Educação Infantil
Ajustadores Mecânicos Polivalentes	Veterinários e Zootecnistas	Supervisores de Produção em Indústrias Químicas, Petroquímicas e Afins	Ministros de Culto, Missionários, Teólogos e Profissionais Assemelhados
Operadores de Instalações e Equipamentos de Fabricação de Materiais de Construção	Gerentes de Produção e Operações em Empresa da Indústria Extrativa, de Transformação e de Serviços de Utilidade Pública	Operadores de Equipamentos de Destilação, Evaporação e Reação	Trabalhadores Polivalentes da Confecção de Artefatos de Tecidos e Couros
Operadores de Máquinas de Fabricar Papel e Papelão	Corretores de Imóveis	Operadores de Equipamentos de Coqueificação	Supervisores na Confecção de Calçados
Preparadores de Pasta para Fabricação de Papel	Trabalhadores dos Serviços Funerários	Operadores de Máquinas à Vapor e Utilidades	Trabalhadores Artesanais da Confecção de Calçados e Artefatos de Couros e Peles
Trabalhadores de Forjamento de Metais	Geólogos, Oceanógrafos, Geofísicos e Afins	Operadores de Equipamentos de Filtragem e Separação	Trabalhadores de Acabamento de Calçados
Trabalhadores do Curtimento de Couros e Peles	Técnicos de Vendas Especializadas	Operadores de Equipamentos de Moagem e Mistura de Materiais (Tratamentos Químicos e Afins)	Trabalhadores da Preparação da Confecção de Calçados
Trabalhadores da Preparação do Curtimento de Couros e Peles	Supervisores de Vendas e de Prestação de Serviços	Caixas e Bilheteiros (Exceto Caixa de Banco)	Trabalhadores da Classificação de Fibras Têxteis e Lavagem de Lã

TABLE C.IV

TOP AND BOTTOM 10 OCCUPATIONS IN THE MANUAL SKILL DISTRIBUTION - 2000 AND 2017

Manual Skills 2000		**Manual Skills 2017**	
Top 10 **CBO 2002 - Descrição**	**Bottom 10** **CBO 2002 - Descrição**	**Top 10** **CBO 2002 - Descrição**	**Bottom 10** **CBO 2002 - Descrição**
Trabalhadores Subaquáticos	Arquivistas e Museólogos	Trabalhadores Auxiliares dos Serviços Funerários	Tabeliães e Registradores
Trabalhadores nos Serviços de Administração de Edifícios	Ministros de Culto, Missionários, Teólogos e Profissionais Assemelhados	Garimpeiros e Operadores de Salinas	Gerentes de Recursos Humanos e de Relações do Trabalho
Policiais, Guardas- Civis Municipais e Agentes de Trânsito	Tabeliães e Registradores	Carpinteiros Navais	Contadores e Afins
Encanadores e Instaladores de Tubulações	Advogados	Carpinteiros de Carrocerias e Carretas	Profissionais de Estatística
Trançadores e Laceiros de Cabos de Aço	Corretores de Seguros	Trabalhadores na Operação de Máquinas de Terraplenagem e Fundações	Corretores de Valores, Ativos Financeiros, Mercadorias e Derivativos
Árbitros Desportivos	Técnicos de Seguros e Afins	Trabalhadores Aquaviários	Vendedores em Domicílio
Profissionais da Educação Física	Leiloeiros e Avaliadores	Trabalhadores de Traçagem e Montagem de Estruturas Metálicas e de Compósitos	Operadores de Telemarketing
Atletas Profissionais	Farmacêuticos	Forneiros Metalúrgicos (Segunda Fusão e Reaquecimento)	Representantes Comerciais Autônomos
Bombeiros e Salva-Vidas	Químicos	Trabalhadores de Trefilação e Estiramento de Metais Puros e Ligas Metálicas	Psicólogos e Psicanalistas
Vigilantes e Guardas de Segurança	Professores na Área de Formação Pedagógica do Ensino Superior	Operadores de Fornos de Primeira Fusão e Aciaria	Profissionais da Escrita

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