UNIVERSIDADE FEDERAL DO RIO DE JANEIRO
INSTITUTO DE ECONOMIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ECONOMIA

FILIPE DA SILVA

TECHNOLOGICAL CHANGE AND POLARIZATION OF THE BRAZILIAN LABOR MARKET

Rio de Janeiro
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Dissertação de Mestrado submetida ao Programa de Pós-Graduação em Economia da Indústria e Tecnologia, Instituto de Economia, Universidade Federal do Rio de Janeiro, como requisito parcial à obtenção do título de Mestre em Economia.

Advisor: José Eduardo Cassiolato

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À Mauriceia Ribeiro da Silva, a melhor mãe do mundo!

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ABSTRACT

Da Silva, Filipe. **technological change and polarization of the Brazilian labor market**. 2021. 89 f. Dissertação (Mestrado em Economia) - PPGE, Instituto de Economia, Universidade Federal do Rio de Janeiro, Rio de Janeiro, 2021.

Technology has been causing several changes across and within economies, and by doing so it has been mainly impacting the composition of labor markets. In this sense, this master's thesis intends to discuss the technological shock on the labor market brought about by innovations and further developments on automation technologies, as well as information and communication technologies (ICTs). We point out the replacement of routine tasks as the technological paradigm of the past few years and developments in ICTs as the technological directions. As a consequence of these technological advancements, developed countries have been reporting the polarization of their labor markets. In these economies, this phenomenon has been associated with wage polarization and, in the Brazilian context, we also associate it with the raise of job precariousness. For this matter, we adopt the so-called modern theory of technological unemployment to analyze the Brazilian labor market structural changes in the past 30 years. We explore this theme using a large empirical data source from the Brazilian Institute of Geography and Statistics (IBGE) for 1991, 2000, and 2010. As methodological means: first, it was used the Routine task intensity (RTI) index to capture routine occupations across Minimal Comparable Areas (MCA); second, a 2sls model was constructed in order to identify, if any, polarization patterns through the relationship between routine and service jobs. It was found a clear pattern of polarization in the Brazilian labor market.

Keywords: Skill-Biased Technological Change, Job Polarization, Innovation, Technological Unemployment.

ABSTRACT

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O progresso tecnológico vem impactando mercados de trabalho ao redor do mundo. Neste sentido, esta dissertação de mestrado pretende discutir e mensurar o choque tecnológico que o mercado de trabalho brasileiro sofreu nos últimos 30 anos. Advogamos que este efeito vem sendo provocado por inovações, desenvolvimentos em tecnologias de automação e avanços em tecnologias de informação e comunicação (TIC). Nesse sentido, apontamos para a substituição de tarefas rotineiras como o paradigma tecnológico de interesse e para os desenvolvimentos nas TICs, por exemplo, como avanços em direções tecnológicas. Na literatura, relacionam a evolução desse impacto tecnológico com a polarização dos mercados de trabalho. Esse fenômeno, encontrado sobretudo em economias maduras, está associado a outros eventos como a desigualdade salarial e, no contexto brasileiro de economia em desenvolvimento, nós o associamos ao aumento da precarização. Para analisar tais mudanças estruturais nos últimos 30 anos, se utilizou como fonte de dados os censos do Instituto Brasileiro de Geografia e Estatística (IBGE) para os anos de 1991, 2000 e 2010. Primeiro, nossa estratégia empírica utiliza como base o Routine Task Intensity (RTI) index para determinar a participação de ocupações chamadas rotineiras entre Áreas Mínimas Comparáveis (AMC). Em um segundo momento, a participação dos empregos rotineiros em AMC foi utilizada para alimentar um modelo econométrico de dois estágios (2sls model) que visou analisar a relação entre empregos rotineiros e o crescimento dos empregos classificados como serviços. Como consequência desse exercício empírico, foi encontrado nesse trabalho um forte indicativo da polarização do mercado de trabalho brasileiro.

Keywords: Mundança Tecnológica, Skill-biased Technological Change, Desemprego Tecnológico, Inovação.

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1 INTRODUCTION

The literature on technological change and unemployment has been approached by new ideas that have been causing the renewing of this well-known trade-off. The emergence of a micro approach into this theory has opened a new theoretical stream which in this work we will be addressing as modern theory of technological change. There has been a consensus that the canonical model could not have explained the labor market dynamics of the past few years, i. e., the skill-biased technological change (SBTC) model has been surpassed by a micro-oriented task approach. The recent years of economic growth have been characterized by the rise of automation and digitization, where robots and fully automated factories are a reality rather than a trend. Innovations on both supply and demand sides of the world economy have been changing paradigms and technological directions. At the very core of this debate, there has been a consensus that the labor market has been, and will continue to be, the most affected by technical innovations.

This work goes in the same direction by recognizing technological progress as the main driver of labor market structural changes, although we acknowledge that demand shifts, and offshoring forces also have contributed to this impact. Having said that, we point out automation, robotization, and computerization as the technological developments that carried and are carrying these transformations out. Looking ahead, we expect that Artificial Intelligence (AI) and the industry 4.0 technological kit will become the main forces to impact in the labor force. Currently, the technological pace already achieved by these technologies has increased productivity and efficiency measures across the globe. Nevertheless, there also have been emerging concerns regarding mass unemployment risk, i. e., technological change capable of accelerating job obsolescence. From a developing country perspective, all these innovations and technical progress raise concerns about a consequent rise of job precariousness and income inequality.

As mentioned before, the literature on technological impacts has evolved over recent years. Autor et al. (2003) argued that the binary approach stated by the literature on the subject — educated vs less-educated workers — already in the 2000s was not capable of providing a good explanation for the real-world-phenomena. They declared that was necessary to look at occupations' tasks content in order to improve the approach. Acemoglu and Autor (2011) have documented this fact by presenting a technological unemployment theory, contrasting earlier approaches with new-born ones. They called "canonical model" early approaches to the technological trade-off debate and called "modern theory", the canonical theory improved by contemporaneous contributions. Mainly, the introduction of task content analyses into canonical models. The canonical SBTC model is characterized by its aggregated level of analysis, where the assumption of technological replacement is the same regardless of the tasks performed by workers. This model's more simplistic perspective assumes technology as complementary for more educated workers but sees it as a substitutive force for less-educated ones. As we have seen, this aggregative approach has less explanatory power coping with real-world phenomena. On the other hand, the incrementation of micro-analysis on the canonical model has raised its explanatory power when facing those same phenomena. The modern theory has been capable of explaining the past labor market mutations using its disaggregated point of view. Among noteworthy upgrades in the canonical model, we highlight the role played by the introduction of the task content analyses and the hypothesis of routine replacement. These contributions have enriched the canonical theory and brought about more reality to the technological unemployment debate.

Over the years, technological change has been recognized by its correlation with a number of changes in the economic environment. Remarkable authors such as

Schumpeter (1942) and Solow (1957) have indicated that technological progress, in a broad sense, is responsible for the economy's dynamic. Reviewing the literature, we find that technological progress has been pointed out for driving changes in structures, rates and growth. [1]. In addition, it has also been correlated with income inequality, wage inequality and technological unemployment, although the literature lacks tools to adequately prove some of these relations according to Weller (2017), Frey and Osborne (2013), David and Dorn (2013) among others. These correlations are especially important for developing countries. That said, technological change has again been gaining importance due to its strong relationship with the labor force and the phenomena it has been bringing to the economy in the digital era. Modern theory has proven capable of addressing some of these problems. Although we recognize the mentioned trade-off as controversial and embedded into complexity, it only means that further research is needed. The current technological change wave, i. e., the digital economy has proven to be capable of shaping the entire society when a new paradigm or a new technological trajectory emerges.

Inspired by David and Dorn (2013), in this work, we adopt their methodological approach to analyze the Brazilian labor market. We argue that Brazilian society requires such an approach because the early identification of the job polarization phenomenon could prevent the deepening of already complex structural problems. The current technological change wave, sometimes identified as the digital economy, has proven capable of shaping the entire society when a new paradigm or a new technological trajectory emerges. We point out that technical progress and innovation have been dictating which occupations, skills, and tasks will be extinct. This is causing many consequences on the job market, such as wage polarization, job precariousness, and aggravating income inequality. Due to its reverberation, we justify the search for pieces of evidence of it as well as the early detection of these

[1]For a historical perspective of structural change models see Syrquin (1988). For rates and growth see Syrquin (2007), Justman and Teubal (1991).

impacts on the Brazilian job market by using the modern theory of technological unemployment.

Having said that, the general goal of this work is to investigate compositional changes in the Brazilian labor market in the past 30 years, i. e., we ask mainly *how* and not *if* automation, computerization, and robotization changed the occupational composition of the Brazilian labor market in the past 30 years through the use of IBGE censuses' microdata. On the grounds of this, we hypothesize that it will be found that ICT and automation have been causing the polarization of the Brazilian job market. We believe that occurred in the past 30 years a substantial growth of low- and high-skilled occupations at expense of middle-skilled workers in the Brazilian labor market due to the impact of these technologies. This work will also be an important contribution to the Brazilian debate on job polarization once it uses a different approach in comparison to the existing Brazilian literature. The remainder of this work is organized as follows: In the second chapter, we discuss the trajectory of both canonical and modern technological change theory. The third chapter presents the labor market polarization debate. In the fourth chapter, we present the methodological approach as well as the empirical results. Finally, in the fifth chapter, we conclude.

2 TECHNOLOGICAL CHANGE AND UNEMPLOYMENT: CANONICAL AND MODERN THEORY

The emergence of the contradictory debate between technological change and the labor force seems to reappear every pre-industrial revolution. We have seen the same debate in previous stages of the microelectronics revolution in the 1980s. Nowadays, it again is the subject of much scientific work given the emergence of the so-called fourth industrial revolution, i. e., industry 4.0 Schwab (2017). Events like these have triggered past development on the debate of technological change and unemployment. Historically, the debate between employment and technology has been approached by different narratives such as innovation-employment nexus, productivity, and growth debate. Summarizing, this debate is a pool of several others, and its direct effects are as important as its indirect effects (compensation mechanisms). In this chapter, we present the trajectory of both canonical and modern theories of technological unemployment.

2.1 Technological Change and Unemployment: Canonical Theory

2.1.1 Canonical Theory Trajectory

2.1.1.1 Classical contributions: Ricardo and Marx

By taking a historical perspective, we start by the first contributions to the technological unemployment debate, which dates the 1800s. The first industrial revolution caused a huge social and structural impact in this period. As well documented in the literature, many occupations suffered machinery replacement provoked by technological change. By the time, economic theorists and scientists sought to comprehend whether technological unemployment should be seen as a short term or long-term phenomenon. The recognition of the technological unemployment impact as a short-term phenomenon was one of the well-known hypotheses raised by the period; this conclusion was mainly derived from Say's law. The ones arguing in favor of this point of view believed that the supply side was capable of creating its demand, thus technological unemployment could not last long.

David Ricardo (1821. p 287) on his book "On the Principles of Political Economy and Taxation" described as follows the relationship between jobs and technology: "the opinion entertained by the laboring class, that the employment of machinery is frequently detrimental to their interests, is not founded on prejudice and error, but is conformable to the correct principles of political economy." Although this perspective can be considered inflexible, it reflects how human beings were facing and seen the introduction of machinery into society.

Therefore, technological unemployment as a temporary phenomenon was the natural conclusion extracted from this period. It was assumed that the production growth was associated with the reduction of the general level of unemployment; the second conclusion that was made by the time laid on the well-known wages' dynamic. The argumentation behind this conclusion postulated that wages instead of the demand for goods were the determinant of employment level; thus, if wages were set too high by the market, it would result in unemployment. Hence, wages were determined by the circulating capital or "wages fund." On the other hand, according to Woirol (1996), in the same period, a second "major theoretical argument approached to argue that technological change could lead to a lasting rise in the aggregate level of unemployment."

By the same period, Marx was creating his so-called theory of compensation. This theory can also be understood as the theory of technological counter-effects. It explains the economic mechanisms responsible for generating consumption, which hence acts as reverting job losses. The first compensation effect reported in Marx's theory regards the number of the workforce needed to construct the same machinery responsible for replacing the labor force. The second compensation effect is delivered by the rise of productivity; this one reduces prices and hence generates a higher consumption level. The third effect is produced by the rise of capitalist expenditures, whose revenue has increased in this process of technological change. Other developments of this period for the trade-off technological change-unemployment were given by Malthus and Sismondi, Mill and Marx.

> (a) That there may be a lack of markets for the increased output, (b) that there may be a lack of capital to employ released labor, (c) that the rise in purchasing power from technological change hypothesized by the Say's Law compensation theory would not occur, and (d) that technological change led to a constantly decreasing ratio circulating to fixed capital. (Woirol (1996), p, 19)

2.1.1.2 Neoclassical contributions

Subsequently, in the marginalist theory's emergence period, those in favor of this theory also adopted a compensation approach to explaining the relationship between unemployment and wages. According to the marginalists, when machines replace labor force, its price (wages) starts to fall. Consequently, it makes workers more attractive to firms' owners; in other words, labor oversupply makes wages to fall. Although this was another relevant contribution to the technological change debate, this theory was not developed to explain the technological unemployment phenomenon. The marginalist theory was created as an economic mechanism for reaching the economic full-employment status. Therefore, in this perspective, the solution for unemployment problems is described as a matter of time once the free market is necessary and sufficient to guarantee the full-employment through its self-adjusting mechanism.

> Technological innovation can simply lead to temporal labor destruction. The possible mismatch is not due to the lack of job opportunities, squeezed by technical progress, but by the lack of a downward equilibrating salary, able to match the reduced demand for labor. By analyzing the series of subsequent effects, the relative capital depreciation induced by technological progress results in a lower interest rate, thereby fueling the investment activity. [...] The interest rate clears the market for capital. On the labor market, wages play the equivalent equilibrating role that interest rates play in the capital market. Calvino and Virgillito (2018)

2.1.1.3 The empirical literature contributions

Although the theories developed until here were useful for technological unemployment matters, the proper debate of technological unemployment dates to the last years of the 1920s and the beginning of the 1930s. Its emergence was mainly determined by the publication of the first sound data on productivity measures in the United States. According to Woirol (1996), the data disclosed by the Bureau of labour statistics (BLS)[1] showed a 59 per cent rise in productivity in industrial employment from 1919 to 1925. Another important event that contributed to its emergence was the onset of the 1927 recession.

The result of the combination of these data findings with the recession of 1927 arose a widespread popular concern about technological change and unemployment. The revolution in production processes like Fordism can depict what was happening in this period; the factories now use the well-known massive production system of Henry Ford. In agriculture, the impact was at most delivered by the transition between traditional agriculture to the intensive one. Contemporary journals and

[1] See Woirol (1996) chapter 2 p. 23 for more information about the data

articles were explicitly saying that the bulk of unemployed workers was a technological change outcome. As reported by Woirol (1996), despite the good numbers presented by the manufacturing sector, the net effect was negative. According to him, between 1910 and 1920, an increase of 3,500,000 jobs was reported in the US. Among them, 3.000.000 of whom were absorbed in manufacturing, transportation, and mining. However, since 1919 these industries started to present a worker surplus of 1.2000.000.

As the reader already may have noticed, this work uses and therefore lay on key arguments, phenomena, and theories. In this sense, we need to clarify some of those before continuing our explanation. Starting with the concept of technological unemployment, we follow the Oxford Dictionary of Economics' definition in this study.

> "Unemployment due to technical progress. This applies to particular types of workers whose skill is made redundant because of changes in methods of production, usually by substituting machines for their services. Technical progress does not necessarily lead to a rise in overall unemployment". (Black et al. (2012): p. 405).

Until now, we have explained how the period general thought comprehended that technological change would positively impact the short-run unemployment level, but the long-run impact would be quite the opposite. In this sense, in the long-run technological change should act as labor-augmenting. However, the vast amount of literature produced at this point was derived from data trends showing the persistence of technological unemployment even in the long run. The truth is, at the beginning of the debate, renowned economists were watching from outside. However, when it became a massive societal discussion, professional economists started to get involved in technological unemployment matters. By the time mentioned, economists were differing in opinion on two topics. The first one was about the data used in several publications, they were arguing that the data used lacked sectors responsible for the absorption of the unemployed workers. On the other side, those defending the second topic argued that technological unemployment was starting to impact the labor market.

In fact, for several years, a great effort had been devoted to the study of technological change using limited databases. The database used in all those studies only covered railways, mining, manufacturing, and agriculture sectors. In this sense, it is easier to understand why to attribute to the absence of sectors the difficulties of employment absorption. Nonetheless, the intent of invalidating the database was also discarded because it was impossible to empirically prove the argument. The ones in favor of the long-run technological unemployment hypothesis decided to follow the data trend by saying it was just the beginning of the technological change impact. Interestingly though, technological change remained a lively discussion despite the emergence of the great recession.

Even after the great recession took place as the main subject of the period, some relevant authors continued to contribute to the technological unemployment debate. John Maynard Keynes, whose work is recognized as a remedy for recession times, has written about technological unemployment in the 1930s. Keynes' perspective can be considered more pessimistic in comparison with its peers. He described the phenomenon as a disease and said that they would see technology causing a drastic decrease in weekly worked hours and massive societal transformations in the course of his generation. It is possible to say that Keynes was more visionary than other authors by predicting some future consequences of technological change.

> "This means unemployment due to our discovery of means of economising the use of labor outrunning the pace at which we can find new uses for labor. But this is only a temporary phase of maladjustment. All this means in the long run that mankind is solving its economic problem" (Keynes, 1036, p. 325)

Although Keynes was right about job loss predictions and the difficulties human beings would face, the proposed timing he said these transformations would happen was not so accurate. Over the years, there has been occurring job losses and we have seen that professions such as telephone operators, designers, spinners, among others, do not exist anymore. As we spoke before, these professionals have suffered an unemployment far different from the common ones presented in macroeconomic monthly surveys. Therefore, this is the kind of unemployment that forces job seekers to reskill themselves to find a place in the labor market. That said, it means an individual seeking for a job that may not exist anymore due to technological progress intensity.

2.1.1.4 Schumpeterian contributions

Another author that also explained this process and brought about a new economic perspective was Schumpeter. Furthermore, the author postulated that we should consider innovation and technological progress as the economy engines. According to him, the economy's dynamic is dictated by the disruptive force that innovation exerts on equilibrium status, i. e., innovation causes economic disequilibrium. Freeman et al. (1995) says that Schumpeter's perspective states that "new technologies can give rise to major waves of investment and employment in new industries and services which, in turn, stimulate expansion throughout the economy". In the same context, the author also postulates that "revolutionary new technology can create the basis for a virtuous circle of growth in which investment is high, labour productivity grows fast but output grows even faster"[2]. Schumpeter's work was capable of revolutionizing the economic theory by challenging neoclassical's hypothesis of equilibrium and its competition model. In this sense, technological unemployment is an endogenous phenomenon that emerges from the enterprise's business models.

[2] In this sense we can see similarities between the Kaldorian and Schumpeterian cycle of growth. See Cabral et al. (2019) for a Kaldorian model explanation

The neoclassical theory's contribution to this debate is mainly based on a self-adjusting process or price-salary mechanism that emerges as soon as an innovation or technological progress hits the market. When innovations raise workers' productivity, meaning they make the labor force cheaper to firms' owners, they generate an aggregate effect on the economy. Workers' better productivity level, according to this perspective, will automatically reflect in higher levels of economic growth, consumption, and wages. For them, this process is direct and straightforward. The Neoclassical approach sees innovation's impact on employment rates through its theory based upon the representative firm's idea. This idea is built upon the existence of perfect information, given technology, and a generic production function capable of suiting every single firm on the market. On the other side, the Schumpeterian perspective interprets this phenomenon as complex (therefore not straightforward) and impossible to discern *ex-ante*.

According to Cassiolato et al. (2003), "the main argument sustaining this notion is that innovations (as knowledge) cannot be seen as isolated events; and that technical change is the result of an interactive process, which both determines and is determined by the institutional environment and which depends on both: radical and incremental innovations; technical, organizational and institutional innovations." In this sense, neither the innovation generation nor its impact in the economy is a simple process as postulated by the neoclassical theory. The net effect of innovations depend on several conditions such as the kind of innovation, if the new product is going to entirely and only replace the old ones, spillovers, among other factors.

> "At the outset, it is important to dispel the frequent confusion between the sustaining/disruptive and incremental/breakthrough distinctions. Incremental and breakthrough refer to technological process, and qualify the innovation with respect to the prior state of the art: an incremental innovation marks a small step forward (typically the improvement of a feature or characteristic of a technological paradigm), whereas a breakthrough innovation involves a significant technological jump (akin to a change of technological paradigm)". De Streel and Larouche (2015)

The Schumpeterian school of thought sees in the sought-for extraordinary profits what makes enterprises incessantly try new methods to innovate; consequently, this process generates obsolescence and unemployment. As defined by Schumpeter in his remarkable work, innovation has as a characteristic of something new added to the company's routine. In this sense, it can be a product, a process, or a new organizational strategy. Although we have a distinct and more modern economy than Schumpeter's days economy, the innovative process's importance is no different; meaning enterprises still compete for extraordinary profits through innovations. All over this work, we will be referring to innovation as technological innovations.

The Schumpeterian strand explained technological innovation's emergence through concepts such as paradigms, trajectories, and technical directions. In the present study, we are going to restrict these concepts in technological ones. These concepts are fundamental to understanding how technology has been impacting the economy, and mainly, how technological unemployment occurs. For the first concept, technological paradigms, we are going to use Giovanni Dosi's definition, where:

> "We shall define a 'technological paradigm' as a 'model' and a 'pattern' of solution of selected technological problems, based on selected principles derived from natural sciences and on selected material technologies. First of all, the similarities relate to the mechanism and procedures of 'science', on the one hand, and those of technology on the other". Dosi (1984)

A successful technological paradigm implies a combination of knowledge updates and feedbacks. In this sense, the success of a paradigm comes: 1) from past technological achievements that are still relevant today 2) by searching for breakthroughs on those same paradigms. In a broader sense, scientific breakthroughs occur upon evolution in technological paradigms. As aforementioned, the second Schumpeterian concept, technological trajectories, comes from technological approaches to a paradigm. A paradigm trajectory is a technological choice used to move ahead into a dilemma. In this way, a technological trajectory would be an activity of technical progress that moves along techno-economic trade-offs. In sum, technological choices or approaches used in paradigms determine whether or not technology will be labor-saving.

There is still the third Schumpeterian concept called technological directions which is found within a technological trajectory notion; technological directions provide dynamics to technological progress. In this sense, technological progress and innovations are solutions that emerge from scientific developments or as a consequence of going forward in a technological direction. It is also important to highlight that the emergence of these difficulties—technological directions are used to solve these difficulties—can be motivated either by technological or economic reasons. It is from shifts in the techno-economic trade-off that technical progress occurs. Furthermore, the selection of a technological paradigm, and the subsequent technological trajectory choice, is influenced by the economic and social environment. Additionally, Schumpeter also attributes to demand a prominent role in selecting these concepts. According to Dosi (1984), social and economic environment act "first selecting the 'direction of the mutation' (i.e., selecting the technological paradigm) and then selecting among mutations in a more Darwinian fashion".

In general, the Schumpeterian school of thought has been interpreting technological change as an opposite force to employment generation. However, it is also important to highlight that although Schumpeter pointed out job losses and obsolescence of skills as a consequence of technological innovations, innovation does not only behave as labor-saving. The literature on the subject tends to consider that process innovation mainly has a negative impact on jobs while product innovation mostly leads to job creation. However, in Schumpeterian models, technological progress is responsible for job obsolescence. Postel-Vinay (2002) summed up the dynamic proposed in these models by saying that "faster technological change is accompanied by faster obsolescence of skills and technologies, hence, more intense labor turnover and higher frictional unemployment." The dynamic proposed by Schumpeter is well explained by Calvino and Virgillito (2018).

> In particular, it is built on the concepts of clustered innovation, product life cycle, imitation, and diffusion: the interplay of these elements determines the emergence of cycles or waves where periods of growth, due to the launch and diffusion of new products, alternate with periods of market saturation. Unemployment arises as a result of technological innovation, whose diffusion takes considerable time and affects different sectors asymmetrically. Calvino and Virgillito (2018)

Despite being easy to interpret product and process innovation as exerting opposite forces on employment generation, the discussion goes more in-depth. The truth is, the empirical evidence has been suggesting that different kinds of innovations have different impacts across sectors.

The simplified distinction between introducing new goods and introducing a new production method is barely a matter of perspective. Furthermore, it is a Schumpeterian view, and we may think of it as an almost didactic perspective. The computer manufacturing can be seen either as product innovation or process innovation. An average person may use a computer for entertainment; in this sense, this person will see it as simple product innovation. However, on the other side, an industrial or an entrepreneur will be using the same computer to create new possibilities and methods for its production system. Using Dosi (1984)'s words, "in practice, product innovation of one sector are often process innovation for other sectors which are using them. The distinction nonetheless is theoretically fruitful". Thinking of product innovation and the compensation effect it should play in this simplistic interpretation, new products should not exclusively replace obsolete ones. Having said that, when a product innovation acts only cannibalizing an obsolete product, the result is an ambiguous net effect.

Kohler et al. (2013) has extracted the same conclusion of its research. This result was acquired from their empirical model, where they used an impressive sample of roughly five thousand firms. In Schumpeter's perspective, innovation plays a fundamental role in determining economic growth although it also brings about negative externalities such as obsolescence of technologies and skills. Schumpeter called this phenomenon "creative destruction." In certain ways, by using this term, he tried to alert us about some technological risks that could also lead to unemployment. According to Boianovsky and Trautwein (2010), Schumpeter has considered this kind of unemployment by far the most dangerous and vital.

In this way, creative destruction is a recurrent phenomenon in the Schumpeterian economy, i. e. in an economy characterized by dynamic competition.

> The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets, ... (This process] incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism. (Schumpeter (2013), p.83)

The so-called third industrial revolution triggered out the development of some significant contributions to the technological unemployment debate. We can say that before the third industrial revolution, this debate possessed a macro biased analytical framework, i.e., the analysis was made at an aggregated level. The theoretical contributions to the debate of the 1980s started a micro revolution into this theoretical framework. Despite Schumpeter's and several other authors' contributions, the truth is: the analytical framework used on technological change and labor market dilemmas at the beginning of the 1980s could not properly explain what information and communication technologies (ICT) were about to cause. The mid-1980s period is recognized by significant technological and structural change; Freeman's words well explain this transformation.

> "A vital characteristic of this third type of technical change is that it must have pervasive effects throughout the economy, i.e., it must lead not only to the emergence of a new range of products and services in its own right, but it must also affect every other branch of the economy by changing the input cost structure and conditions of production and distribution throughout the system". Freeman (1987)

The historical perspective we intend to bring until here showed that the early stages of the technological unemployment debate could be summarized by the short and long-run impact discussion. Some authors argued that technology would be labor-augmenting in the long-run. On the other side, the Schumpeterian stream argued in favor of a more profound labor-saving impact in the long-run, characterized by the irreversibility of firms' technological choice. In this work, we assume both hypotheses as radical. Although well-aligned with the firm's technological choice narrative, it is important to highlight the neo-Schumpeterian point of view. For them, technology completely shifts the firm's production function rather than just equilibrating the factor substitution mechanism through relative price dynamics. What is interesting, though, is Ricardo's early understanding of labor market structural changes. According to him, a new job may not match the old job's skills or location requirements.

In sum, our interpretation of the technological progress impact on the labor market goes in the same direction as Mortensen and Pissarides (1998). We assume that what determines the destruction or creation of jobs is the technologies' state of the art. Therefore, it is impossible to assume a general behavior for technological progress's long-run impact. Although the evolution until here was significant in explaining the process of obsolescence of jobs and technologies delivered by the accumulation of knowledge and technological innovations, it was far from describing the real impact that technological progress was having by the date.

2.2 Technological Change and Unemployment: Canonical Model

In order to contextualize the appearance of this model, we must draw the reader's attention to the ICT emergence, the consequent world globalization process, and the trade liberalization occurring by the time. This process, as well described by Freeman, raised the attention of several economists around the world and it was responsible for the reappearance of the technological unemployment debate. ICTs were recognized as a pervasive and "general-purpose" technology, which was biased increasing the demand for skilled labor. The revolution in communication systems, for example, caused the obsolescence of a large number of clerical jobs. According to Freeman et al. (1995)'s words in the 1990s, "information and communication technology has had tremendous global impact, arguably ushering in a new, postindustrial era. ICT both destroys and creates jobs, while lowering costs, countering inflation, and raising competitiveness". Furthermore, the authors also said that ICT's impacts were far beyond the traditional "closed economy" framework used in classical, neo-classical or Schumpeterian economic thinking.

The internet emergence caused an intensification of trade and a decrease in administrative costs. Summing up, the third industrial revolution was responsible for starting a huge and significant wave of process innovation. Following Ciarli et al. (2018)'s assumption about the impact of process innovation, in this work, we understand process innovation as having the only objective of reducing production costs. Besides that, we assume, although recognizing this is an open debate, that process innovation has a conflictual relationship with job creation. Having said, we mainly interpret and consider process innovation as exerting a labor-saving force on the labor market. The following phrase, extracted from Linden et al. (2011), describes how the technological impact on jobs was perceived by the time: "globalization skeptics argue that the benefits of globalization, such as lower consumer prices, are outweighed by job losses, lower earnings for U.S. workers, and a potential loss of technology to foreign rivals."

As aforementioned, technological innovations of this period not only revolutionized the market with new products but also with huge process innovation. In this time, the demand side was impacted by personal computers and technologies that were making life easier, this positively affected consumption. There was a rising demand for small electronic goods, like cell phones and chips, whose production uses tiny components with extremely tight tolerances in fit and quality. This demand aggravated the labor replacement impact because this kind of precision can only be reached by robots. On the other hand, the supply side suffered huge cost decreases due to the introduction of these same robots and machines. Besides the ICT impact, we also highlight the strong revolution in transportation methods. Consequently, the world became globalized, and the enterprises' administrative framework was more centralized due to technology. As a result, enterprises began to lay-off workers in occupations intensively impacted by computerization.

As underlined by Szapiro et al. (2016) "the increasing liberalisation of trade and financial markets and the important developments in transport and communication technologies have brought profound changes in the organisation of production and innovation activities across nations and localities." This entire process disentangled the emergence of several global value chains (GVC)[3] and strengthening of many others. As reported by Szapiro et al. (2016), countries—mainly the poor or the ones in development—were forced to jump into[4] this new production system in order to get a share or to keep advancing its developing process. It is also interesting to highlight that this phenomenon, and the trade liberalization, helped to raise inequalities across countries. Countries characterized by late industrialization

[3]According to Lee et al. (2018) value chain refers to the series of value-creating activities that transform raw or intermediate materials into finished products

[4]See Vargas (2001) to empirical studies on local productive systems in developing countries and the emergence of competitive pressures from the globalization of production markets.

were mainly capable of inserting them-self in through (and due to) using low-paid labor. Regarding it, Lee et al. (2018) says that "while joining GVC appears to be necessary for learning, the risk in being stuck in low value-added activities without making progress toward higher tier in the value chains exists, consequently causing the economy to fall into the so-called middle-income trap."

This intense global transformation generated significant labor structural changes mainly caused by the computerization replacement effect and the world's factories' decentralization. Early stages of substantial technological changes like this usually trigger societal fear; it has concerned policymakers and economists at least since the 18Th century. This fear is a consequence of radical changes on trajectories and technological directions that could result, as we have been seen, in huge waves of replacement effects. Usually this fear has been triggered by labor-saving technologies that according to Freeman and Soete (1990) overshadow the development of new products and new services.

In a seminal work relating the structuralism and Freeman's ideas, Lastres and Cassiolato (2017) underlined that "already before the 1990s, both Freeman and Furtado anticipated these social negative results, connecting them with the international division of labour that was unravelling based on the concentration of knowledge-intensive activities in the most developed countries and the predominance of less-strategic activities in peripheral countries and regions". In this sense, both authors were alerting the consequences of significant structural changes delivered by technology. According to Freeman et al. (1995), to assess the employment creation and destruction effects of ICT we have to bear in mind both direct and indirect effects. The latter are the consequences elsewhere of technology penetration but the former results in job creation in producing and delivering those new products and services.

The first contributions to the debate of technological change unemployment had not enough power to explain the technological impact that the third industrial revolution's technologies were having in society in the 1980s. Namely computers, cellphones, robots, etc. This happened due to the macro perspective of the models used to interpret the structural transformations occurring by the time. Namely classical, neoclassical, and Schumpeterian models. By reason of this limited perspective, these models could not help predict consequences and further structural impacts on the labor market. In this sense, these models could not provide support in policymakers' decisions or alleviate societal expectations about technology.

The traditional model's transformation into what we call "the canonical model" was not originated through job losses' statistics as happened in the 1930s. The literature depicts that it was derived from salary measures. In the 1980s, developed countries, mainly the U.S., suffered wage inequality rise, and the appearance of this phenomenon was associated with computer emergence and the microelectronic revolution. Researchers started to notice not only a broader gap in wages but also that technology was playing different roles depending on skill levels. In general, it was observed that highly skilled workers were experiencing wage appreciation while only some of the less-skilled workers were having the same wages' appreciation.

The reasonable explanation created for the occurring process assumed that more skilled workers were working with computers and not being replaced by them, i. e., it was presumed that technology was behaving as a complementary force to human capital. This finding brought about the hypothesis that earnings' inequality was derived from technological change. Some authors also noticed that this historical evidence could be viewed as the increased earnings gap between college graduate and high school degree workers. On the other side, Freeman et al. (1995) was arguing that "manufacturing employment in the OECD economies has grown most in high-wage, high-technology, science-based sectors which use skilled labor". The authors highlighted that there was a concern with the declining demand for unskilled workers. They also pointed out the necessity of reskilling workers and to boost education for the most affected by these transformations. In this sense, Freeman et al. (1995) were anticipating labor market structural changes in early stages of the canonical model's appearance and proposing how to alleviate these structural changes.

The canonical model literature could also be recognized by the terms wage premium and college premium—the relative value of college workers' wages versus high schools'. As we said, this finding was pointing out to an increasing trend in demand for specific skills and consequently to a different pattern of return to skills. The literature concluded that a technological phenomenon was causing a shift in demand in the labor market and the reason was technological biased disruptions. Cassiolato et al. (2003) also explained the same process but from a slightly different perspective.

> "In that has come to be known as the "knowledge Era", the economy is relying on knowledge-based activities much more than ever before. There are at least three, interrelated, main arguments for this: (i) the proportion of labor that handles tangible goods has become smaller that the proportion engaged in the production, distribution and processing of knowledge; (ii) the share of codified knowledge and information in the value of many product and services is significantly increasing; (iii) knowledge-intensive actives are rapidly growing". Cassiolato et al. (2003)

Labor market structural changes are a mix of distinct effects. According to Morrison Paul and Siegel (2001), it happens because "this hypothesis remains that the value of education is enhanced by technological change because greater knowledge or skill enables firms to implement new technologies more effectively." This phenomenon in most of the specialized literature was accused of stems from the rapid technological change or the increase in international trade outsourcing.

After a while, the term skill-biased technological change (SBTC) was coined in the literature and, as we said, it was first noticed due to the rise of wage disparities. Besides the features we have spoken of, the model states that there is imperfect substitution between workers with different skill levels. Although the literature explains SBTC as a supply-side phenomenon, it also addresses some demand-side changes such as the rise of products' consumption that technology caused a price impacted. SBTC created a massive supply of unskilled-intense goods and raised the demand for skilled workers. As a result, the relative wage of less-skilled workers fell in developed countries. Berman et al. (1998) showed that in OECD countries between the years 1979 and 1992 unemployment rate reached 9.9 percent and unskilled workers represented most of this number. The same authors studying twelve developed countries found within-sectors shifts away from unskilled labor. It was also found that SBTC impacted the same industries in different countries. Yet, the authors noticed that electrical machinery, machinery (including computer), and printing industries showed the most remarkable skill upgrading.

In this work we use the idea of canonical model stated by Acemoglu and Autor (2011).

> A central organizing framework of the voluminous recent literature studying changes in the returns to skills and the evolution of earnings inequality is what we refer to as the canonical model, which elegantly and powerfully operationalizes the supply and demand for skills by assuming two distinct skill groups that perform two different and imperfectly substitutable tasks or produce two imperfectly substitutable goods. Acemoglu and Autor (2011)

The canonical model's central assumption says that technological progress has created a higher demand for or complemented high-skilled workers while replacing middle-skilled ones. In that time, technological developments enabled ICT to perform a subset of tasks; it also allowed offshoring emergence. As a consequence, middle-skilled workers that were previously performing these tasks started to experience a considerable change in the returns of certain types of skills.

2.2.1 SBTC: Canonical Model Mathematical Representation

The traditional model found in Berman et al. (1998) and Acemoglu and Autor (2011) divided the labor market into two skill groups, high-skilled and low-skilled workers. In general, SBTC models assume skilled-workers as having college degrees and low-skilled workers as having high school degrees. It is also important to highlight that there is no distinction between skills and tasks. As technology behaves as factor-augmenting, technological change increases the productivity of both low and high-skilled workers.

Usually, SBTC models adopt two assumptions, as we have found in Card and DiNardo (2002): (1) relative demand has risen for groups that are more likely to use computers; (2) relative demand has risen for more highly paid workers. Also important, the traditional mathematical representation of SBTC models has been given through functions of constant elasticity of substitution (CES). This kind of production function is useful in explaining factors changes to achieve the same amount of goods production. In this case, we present an equation with two production factors, high-skilled and low-skilled workers. Below we have the representation of the low-skilled labor supply as well as the supply of high-skilled workers.

$$L = \int_{i \in \beta} l_i di \quad \text{and} \quad H = \int_{i \in \chi} h_i di \tag{2.1}$$

The equation above uses an integral structure to represent the total labor supply of both production factors; in this regard, L stands for the total labor supply of low-skilled in the market, and H represents the total supply of high-skilled. The letter l and h represent the unit of low and high-skilled workers, respectively. As we spoke before, SBTC models employ a constant elasticity of substitution function to represent both technological choices and industries' structure. In the next equation, we present the full representation of our production function[5].

$$Y = [\gamma(A_L L)^{\frac{\sigma-1}{\sigma}} \quad + \quad (1-\gamma)(A_H H)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{2.2}$$

Where Y is the total production of our economy, γ and $(1-\gamma)$ are the distribution parameters, A_L and A_H are factor-augmenting technology terms. The parameter σ can assume any value into the interval $[0, \infty]$, and it represents the elasticity of substitution between high skill and low skill labor. The elasticity of substitution between high and low skill workers performs an essential role in supporting effects interpretations given different technological changes in the market.

As proposed by Acemoglu and Autor (2011), we interpret high and low-skilled workers as gross substitutes when the elasticity of substitution $\sigma > 1$, and gross complements when $\sigma < 1$. As well-known and well-established in the economic literature, constant elasticity functions can assume three different forms depending on the values of the parameter σ. In the first case, when $\sigma \longrightarrow 0$, high and low-skilled workers take the Leontief form where technology does not allow factors substitution. It means the output, Y, will be produced by using a fixed combination of L and H, the factor combination must respect the initially established proportion. In the second case, when $\sigma \longrightarrow \infty$, it behaves as a function of perfect substitution between factors. In this case, technology allows output generation by using high or low-skilled workers, the cheaper production factor will be chosen. In the third

[5]See Card and DiNardo (2002) for the logarithmic form of the CES function applied to an SBTC model

case, when $\sigma \longrightarrow 1$, it becomes the well-known Cobb-Douglas function where the parameters $(\frac{\sigma-1}{\sigma})$ will determine the production factors combination.

By revising SBCT literature, we have found other representations of the CES function. Bellow, we present its simplified version where the distribution values were suppressed. This simplified version has the same explanatory power of the function bellow.

$$Y = [(A_L L)^{\frac{\sigma-1}{\sigma}} \quad + \quad (A_H H)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{2.3}$$

Technology in this model has a factor-augmenting characteristic. In this sense, technology can enhance both high or low-skilled workers. Besides, the labor markets are considered competitive, meaning their marginal product value gives low skill and the high skill unit wage. We can obtain this value by differentiating our main equation concerning L and H. Bellow, we have the representation of the high-skilled workers' wages (ω_H).

$$\omega_H = \frac{\partial Y}{\partial H} = A_H^{\frac{\sigma-1}{\sigma}} [A_L^{\frac{\sigma-1}{\sigma}} (H/L)^{-\frac{\sigma-1}{\sigma}} \quad + \quad A_H^{\frac{\sigma-1}{\sigma}}]^{\frac{1}{\sigma-1}} \tag{2.4}$$

After differentiating, the wage unit (W_i) of the high-skilled workers can be found as follows:

$$W_i = \omega_H h_i \tag{2.5}$$

Below, we have the wages and low-skilled workers unit wages (ω_L).

$$\omega_L = \frac{\partial Y}{\partial L} = A_L^{\frac{\sigma-1}{\sigma}} [A_L^{\frac{\sigma-1}{\sigma}} \quad + \quad A_H^{\frac{\sigma-1}{\sigma}} (H/L)^{\frac{\sigma-1}{\sigma}}]^{\frac{1}{\sigma-1}} \tag{2.6}$$

After differentiating, the low-skilled workers wage unit (W_i) can be found as follows:

$$W_i = \omega_L l_i \tag{2.7}$$

Additionally, the model has the following characteristics: 1) it presents two sectors and two goods 2) the produced goods are considered imperfect substitutes, and both sectors employ high- and low-skilled workers 3) an increase in the relative supply of high-skilled workers also increases the demand for low-skill workers' services what pushes up their wages unit. In this sense, in the canonical model, technology increases both wage units.

Summing up, the most relevant case for us happens when technological progress impacts low-skilled workers. An increase in A_L will make low-skilled workers more productive and, in this sense, will cause an excessive supply of this kind of skills. By assuming that the substitution elasticity between H and L is lesser than 1, sectors cannot replace skills, i. e., it is impossible to produce only by using L or H. In this case, the excessive supply of low skills in the market makes its relative wage value smaller than the high skill. Although this model lacks skill replacing technologies, it was an important step to explain technological change impacts on the labor market, wages, and therefore enrich labor analyses.

2.3 Technological Change and Unemployment: Modern Theory

The canonical model was not accurate enough to explain the recent technological impact of technologies such as automation and robotization, and their relation with phenomena such as job polarization and wage polarization as spoke by Goos and Manning (2007)[6]. This fact was also documented by Autor et al. (2006), Autor et al. (2008) and David and Dorn (2013). The lack of a disaggregated analysis makes impossible for this theory to explain phenomena coming from micro-disruptions in the job market. On the other hand, the newest theory is characterized by a strong and disaggregated empirical analysis based on the task content incrementation. This new approach provides a more precise discrimination of which occupation has been suffering technological replacement.

2.3.1 The Modern Theory of Technological Unemployment

The literature on technological impacts on the labor market has evolved over recent years. Acemoglu and Autor (2011) documented this fact and presented the theory of technological unemployment in two parts, the canonical and modern theory. The newest theory can explain processes that have been occurring because of its occupational approach and task content analysis. The canonical model was firmly accepted and capable of explaining significant labor market transformations; nonetheless, technology has evolved through time, causing its obsolescence. In sum, the literature was calling for a more detailed point of view of the contemporary labor market transformations. Following Acemoglu and Autor (2011) and Van Reenen

[6]There is little doubt that technology has a powerful impact on the labor market. Nevertheless, the dominant current view about the nature of its impact, the hypothesis of skill-biased technical change, is only a partial truth and cannot explain all of the important changes in the labor market such as job polarization

(2011), we point out to some canonical model's limitations:
1) it fails in explaining why low skill wages were relatively declining when facing technological progress while the model treated technology as factor augmenting.
2) it fails in explaining the emergence and the fast pace of replacing technologies impacting even high-skilled workers.
3) it has no explanation for the emergence of offshoring[7] opportunities where foreign labor was allowed to compete due to technological developments against local industries.
4) it treats technology as an exogenous process when it should be considered an entrepreneurs' environmental choice.
5) broad-based increases in employment in high skill and low skill occupations relative to middle-skilled occupations (i.e., job 'polarization').

The modern theory can better explain how technology has been affecting the labor market by constructing the hypotheses of the existence of the easiest codification of determined tasks. Furthermore, this vision takes into account the engineering point of view to build and explain the phenomena called job polarization and wage polarization. In this section, we try to join the literature on SBTC first construct by Acemoglu and Autor (2011) and Saint-Paul (2008) with the routine-replacing technical change (RRTC) framework developed by David and Dorn (2013), Goos et al. (2014) and Van Reenen (2011). Following Goos and Manning (2007), we agree that "the routinization hypothesis provides a plausible explanation for why the demand for middling jobs has fallen and why we see the process of job polarization."

To adequately comprehend this literature is essential to bear in mind the distinction between the concepts of tasks and skills. In this work, we assume tasks as activities that an occupation demands. Additionally, skills are the workers' endow-

[7]For the literature in offshoring impact on labor markets see Autor, Dorn and Hanson (2011), Autor, Dorn and Hanson (2016), and Author (2018).

ment, and it could be the outcome of education or specific knowledge, i. e., human capital. Workers use their endowment to perform different tasks. Notwithstanding, some tasks are easily performed and other tasks can only be performed with specific knowledge—which is one of the reasons for wage disparities.

The tasks requirement and the respective endowment required to perform these tasks are dictated by technical progress effect and pace. Once again, this is one of the main processes tied to causing wage inequality. When technological progress outran some task requirements using TICs, robots or computers, the expected endowment used to perform these occupations also changes. Meaning technology has been changing occupations' requirements through time. In this sense, technology can raise, diminish or completely change occupations' endowment demands. Having said that, we argue that the polarization phenomenon has as one of its main causes workers' incapability to improve their endowments. Consequently, it causes obsolescence of occupations due to massive task replacement or, in other cases, it generates reskilling difficulties that result in structural changes.

The modern theory has been dealing with job polarization, and it has been doing so by using the task content approach; through its use, many authors have found polarized growth of employment and wages in developed countries. To understand this approach and the job polarization phenomenon, it is necessary first to simplify workers' tasks into three categories. The occupation's task content is the key explanatory factor for job polarization processes. Following David and Dorn (2013), tasks performed on the job market by workers are classified as abstract, manual, and routine. It must be said that each occupation has a combination of manual, abstract, and routine tasks, which means there is not purely occupation. Following Acemoglu and Autor (2011), we conceptualize these three tasks as follows:

Abstracts tasks are the ones that intensely demand problem-solving, intuition, persuasion, and creativity. Usually, these tasks are related to occupations such as programmers, engineers, lawyers, doctors, scientists, managers, among others. In general, these occupations demand highly educated workers; additionally, they present a small routine content. On the other hand, manual tasks could also present some routine content; in this sense, it is essential to divide manual tasks from routine ones. The pure manual tasks require situational adaptability, visual and language recognition, and in-person interactions. These occupations typically demand a low degree of education; as examples, we have occupations such as drivers, cookers, operators, transportation services, storage, among others.

Table 2.1: The impact of computerization on each category according to Autor et al. (2003)

	Routine Tasks	Effect of ICT
	Analytic and interactive tasks	
Examples	Record-keeping Calculation Repetitive customer service (bank teller)	Forming/testing hypotheses Medical diagnosis Legal writing Persuading/selling Managing
Computer impact	Substantial substitution	Strong complementarities
Examples	Picking or sorting Repetitive assembly	Janitoral services Truck driving
Computer impact	Substantial substitution	Limited opportunities for substitution or complementarity

In the literature, routine tasks are defined as repetitive-manual tasks and are mainly assigned as physical. According to Autor et al. (2003), "computer technology substitutes for workers in performing routine tasks that can be readily described with programmed rules, while complementing workers in executing non-routine tasks demanding flexibility, creativity, generalized problem-solving capabilities, and complex communications." Typically, industrial unskilled and semiskilled jobs are the ones that mostly perform this kind of task. As examples of routine occupations, we can point out operators, assemblers, and clerical jobs. Until the third industrial revolution, it was complicated from an engineering point of view to machines to perform such tasks, but nowadays, it is relatively easy to develop computers, code lines, and machines with enough capacity to perform these tasks.

The well-accepted hypothesis of computer technologies' impact on routine jobs comes from its price dynamic, meaning the technologies' falling price. The following studies adopted this hypothesis Autor et al. (2003), David and Dorn (2013), Katz et al. (1999) and Autor et al. (2006). Summing up, due to the falling prices of computer capital, the two mechanisms of technological impact — substitution and complementarity — elevated the relative demand for non-routine tasks. It reflects the famous Moore's Law. According to Flamm (2003), it states that today's computational speed and capability will increase two-fold every two years, and we will pay less for it as a consequence of the productivity gains. According to the World Economic Forum (2016)[8], "the cost of advanced technologies is plummeting". Consider just one example: a top-of-the-range drone cost $100,000 in 2007; in 2015, a model with similar specifications could be bought for $500. A top-of-the-range smartphone in 2007 cost $499; a model with similar specifications cost $10 in 2015). The negative relationship between technologies' evolution and prices, as well the impact technological directions that strongly impact the labor market are a consequence of innovations.

2.3.2 Innovation in the Modern Theory context

In this theory, as in the former theory, innovation can deferentially effect the labor market causing both skills and tasks to change. Gagliardi (2014) discovered evidence of a negative relationship between innovation and employment using patents

[8]http://reports.weforum.org/digital-transformation/onward-and-upward-the-transformative-power-of-technology/

Table 2.2: Task Description according to Van Reenen (2011)

Task Type	Task Description	Examples of Occupations	Effect of ICT	Education Levels
Routine Manual	Rules based repetitive procedural	Assembly line workers	Direct substitution	Low
Routine Non-Manual	Rules based repetitive procedural	Clerical Book-keepers	Direct substitution	Middle
Non-Routine Non-Manual	Abstract problem solving(analytic) Mental flexibility	Managers Doctors Lawyers Scientists	Strongly complementary	High
Manual	Environmental adaptability interpersonal adaptability	Janitors Security guards Walters Drivers	Broadly neutral	Low

as a proxy for innovation; furthermore, the author also found a more significant effect on middle-skilled workers. This assumption is also based on contributions of the literature of skill-biased technological change where the routinized tasks are being replaced by technological innovation like automation. In this literature, innovation shows a different impact depending on which kind of tasks each worker performs. It means innovation for some of those workers could be complementary, and for some, a replacement.

The effect innovation and technical progress exert on the labor market depend on the intensity of job-creation – also introduced as countervailing effects—, and by intensity, we mean in which tier of technological intensity the job is created. About that, Moretti (2010) found a job-creation of 1-2 in the non-tradable sector studying the US labor market when one job was created in the tradable sector. However, what is impressive in this study is the increase in the multiplier when the job-creation occurs in the high-tech sectors; the author found a multiplier of six in the non-tradable sector. In this sense, certain innovations could cause a positive impact on job-creation.

At the same time, product innovation is capable of changing job market structures when it does not carry redundancies in the new product production. For example, a radical innovation or a new business field delivered by R&D could lead to a completely different structure of employment and usage of technology. In this sense, an entirely new production process would be created, demanding new personal, machinery, technology, so forth. As implicit said before, innovation first impacts the job market as a job-creating technology; this happens because it generates new fields, processes, products, and administrative novelty in order to develop the new product or prototype.

Even when it does carry production redundancies, it first acts as labor-augmenting, and after that, it acts as a job-destroying technology, replacing or erasing old processes, preferences, and products. Ciarli et al. (2018) found evidence of job market structural change investigating the relationship between R&D and employment on the UK local labor market; the impact was found mainly in places that presented a higher initial level of routinized jobs. Nonetheless, it is essential to highlight that this relationship in the literature has a different dynamic depending on the analysis level.

In sum, besides displaying the same impacts of pure technological progress, innovation brings to the analysis of a complex component. Redundancies, process innovation, and product innovation are phenomena embedded in complexity and the resulting impact on the labor market is determined by: 1) the nature of innovation itself 2) the kind of job that will be created during the product development process 3) in which employment tier or sector (abstract jobs, tradable sector, etc) the new job will be created.

2.3.3 Modern Theory Mathematical Representation

This model is mainly based on the contributions of David and Dorn (2013), and as in the canonical model, it is typically represented by constant elasticity of substitution (CES). This new model presents a two-sector simplified economy $(j = g, s)$ where g represents the production of "goods" and s represents the service production. These outcomes are produced by using four production factors, this a differential in comparison to canonical model that only used two production factors. The manual factor is represented by L_m, routine factor is represented by L_r, the abstract factor is represented by L_a, and K represents the capital. These tasks are performed by two types of workers, the high-skilled and low-skilled ones $(i = H, U)$. Here, the idea is to think about the "service" sector as a supplier of low-skill in-person services such as gardening, hair-cutting, and food service. On the other hand, the high-tech services, such as the more technological and skill demanding sector, are supplied by the goods sector. The sector of goods involves the rest of the economic activities: manufacturing industries and skilled service industries such as banking, or higher education.

The first sector, responsible for the production of goods, combines routine and abstract labor and computer capital. Generally, its products require a higher level of skills. Our equation is presented in efficiency units and uses the following technology:

$$Y_g = L_a^{1-\beta}[(\alpha_r L_r)^\mu \quad + \quad (\alpha_k K)^\mu]^{\frac{\beta}{\mu}} \tag{2.8}$$

In this model $\beta, \mu \in (0, 1)$, the elasticity of substitution between abstract labor and total routine task input is always 1. Further, the elasticity of substitution between routine labor and computer capital is represented by $\sigma_r = \frac{1}{(1-\mu)}$. We assume the later as greater than 1 to represent technological change impacts on this specific task. In this sense, we assume that K acts as a complement to abstract labor and as a relative substitute for routine labor as already explained in our theoretical developments.

Additionally, we assume that the service sector uses only manual workers to produce its outcome. As can be seen below, the following equation represents the demand of this sector for manual workers, and it is also represented in efficiency units as L_m:

$$Y_s = \alpha_s L_m \tag{2.9}$$

Where $\alpha_s > 0$ is the efficiency parameter of the equation. Further, we will normalize α_s to 1 in the rest of this work in order to use α_r as a relative efficiency term. In the model, the supply of high-skilled H and low-skilled U workers is given by a continuum of mass one, meaning we do not work with discrete units. Additionally, we assume that the supply of high-skilled workers inelastically reacts to demand shifts in the goods sector. Moreover, low-skilled workers are responsible for supplying either manual and routine labor. Another essential assumption here concerns the skills that a low-skilled worker uses when performing a distinct task. At performing manual tasks, low-skilled workers have homogeneous skills though they have heterogeneous skills at performing routine tasks.

It is also relevant to explain that workers of type U can only supply inelastically to tasks offering the highest income level. Besides that, these workers can only supply routine tasks if the earnings on this kind of task are higher than in manual tasks. These assumptions reveal a self-selection mechanism that also helps to explain wages behavior in the proposed economy.

The following equation gives the computer capital production function:

$$K = Y_k(t)e^{\delta t}/\theta \tag{2.10}$$

Where $Y_k(t)$ is the amount of final consumption good assign to the production of K, $\delta > 0$ is a positive constant that represents the productivity rising rate, i. e., it represents technological progress in our economy. $\theta = e^{\delta t}$ is a efficiency parameter. Additionally, we assume that computer capital fully depreciates between periods; this is built on the idea that computer capital generates flow services to continually pay its rental price.

In the first period, one unit of Y can be used to produce one efficiency unit of computer capital: $1 = e^{\delta}/\Theta$. In our economy, we postulate that competition is capable of making the price of computer capital (per efficiency unit) equal to the marginal and average cost. As time advances, this price tends to fall as the following equation reflects:

$$p_k(t) = \frac{Y_k}{K} = \theta e^{-\theta t} \tag{2.11}$$

After defining our economy's supply side, we can close the model by building the demand side as follows:

$$u = (c_s^{\rho} + c_g^{\rho})^{\frac{1}{\rho}} \tag{2.12}$$

Where $\rho < 1$. The substitution elasticity between goods and services is given by $\sigma_c = 1/(1-\rho)$. All workers/consumers of our economy have identical CES utility functions. The economic behavior of our agents is to optimize profits and utility taking prices and wages as given. Also important to highlight that the assumption of long-run zero profits is guaranteed by constant returns to scale.

The main conclusion extracted from this model concerns the elasticity of substitution in production between computer capital and routine labor, and the consumption's elasticity of substitution between goods and services. If the first is higher than the second, the continuously falling price of automating routine tasks will keep its impact on wages, which means it will continue to cause manual tasks' wages to exceed the routine's ones. Because routine task-intensive occupations, such as clerical and repetitive production jobs, are typically found in the middle of the occupational skill distribution, we say that the labor market "polarizes."

3 JOB POLARIZATION

Before going deep in explaining the job polarization phenomenon, it is essential to explain in a macro perspective how it occurs in society. Initially, technological change or certain types of innovation lead to unemployment, although, as we already said, in the long run, we should be worried about the structural changes in the labor market. Due to that, it is necessary to understand the process through which these structural changes occur. Koch et al. (2019) says "that the skill-biased technical change (SBTC) hypothesis predicts that if innovation increases the demand for skilled labor and skills are slow to adjust, the oversupply of unskilled labor and the low supply of skilled labor may trigger employment polarization." In this sense, SBTC delivers job polarization both through innovations or sheer technological progress.

In order to explain the job polarization phenomenon, we start by presenting two countervailing impact approaches (labor market structural changes) found in the literature that deals with technological unemployment. Following Calvino and Virgillito (2018), we present two macro phenomenon perspectives, the Classical-Neoclassical, and the Keynesian-Schumpeterian mechanism.

The first approach, the Classical-Neoclassical countervailing mechanism, can be disentangled in four types of counter-effect: 1) new machines 2) decrease in prices 3) wage dynamic 4) new investments. Understanding that technological change leads to more intensive use of capital replacing workers, the first effect represents a labor shit from the machine-using sector to the machine-producing sector. The second one is purely the demand effect caused by prices dynamic. Increases in productivity are one of the natural impacts of technologies, and it direct induces to reduction in production costs.

Due to the classical-neoclassical premise of competitive markets, the lower prices automatically generate higher demand countervailing the first displacement impact on employment. The third mechanism also acts through the neoclassical premise of competitive markets; the labor market self-adjusting mechanism leads automatically to unemployment reduction once excessive labor supply appears in the economy (called wage dynamic). The accumulation of extra-profits causes the fourth impact due to economical price flotation. This leads to investments in physical capital, creating an expansion of productive capacity and hence labor demand.

The second approach, the Keynesian-Schumpeterian countervailing mechanism, can be described in the following two effects: an increase in incomes and new products. The first mechanism depends on workers' appropriability of productivity gains displayed by technology. Having it in place, according to the Keynesian theory, it leads to a higher level of demand that hence sparks employment to raise. The new product's impact, on the other hand, can be more complex. Although the introduction of new branches and products can stimulate consumption and consequently create jobs, to obtain a positive net effect, new products should not only act replacing old ones (causing product obsolescence). But a positive net impact can be obtained when new products fill unmet demands.

Finally, but not least, product innovation's ambitiousness can come up when a new product acts as process innovation. In this sense, Calvino and Virgillito (2018) postulates that "the structural change from agriculture to manufacturing, and from the latter to services, is a clear example of the spread of technical change across sectors". In sum, it means that technology can emerge as product innovation for one sector, but it can be labor displacing in another sector. Having said that, technology is continually acting as labor-saving and labor augmenting, and its net effect is everything less deterministic. Furthermore, Calvino and Virgillito (2018) also explains a series of relevant facts that can be responsible for undermining these effects.

The job market's polarization is an important theme because it represents a simultaneous growth of low-skilled and high-skilled jobs over middle-skill jobs. In other words, it also can be represented as the relative growth of high wage and low wage occupations. As we have said before, the literature usually adopts the term skilled workers for those who have a college degree, and the term unskilled workers is a synonym for those having a high school degree. In this sense, following Ciarli et al. (2018), we see that middle-wage or middle-skilled workers are becoming refugees on the labor market's service tier. Hence, this process is triggering a structural change towards sectors low-skill and with low education requirements.

In the literature, this phenomenon was first noted by Acemoglu (1999) and is highly associated with developed countries. That said, the polarization of the labor market has been found in the US labor market and some European countries. Among the authors that have empirically found job polarization we can cite: Autor et al. (2006), Autor et al. (2008), David and Dorn (2013), Goos and Manning (2007), Goos et al. (2009) Spitz-Oener (2006), Dustmann et al. (2009), Michaels et al. (2014). It has been possible to see in these countries a twist of tails as can seen in the figure 3.1.

The figure 3.1 is a representation of the US labor market as well as the Brazilian labor market and it displays a clear job polarization pattern. Meaning the middle-skill jobs are losing field to service jobs through technologies' impact. These technologies are significantly impacting workers performing repetitive tasks. We will be calling these occupations as "routine occupations". Routine occupations perform well-understood procedures which makes them susceptible to codi-

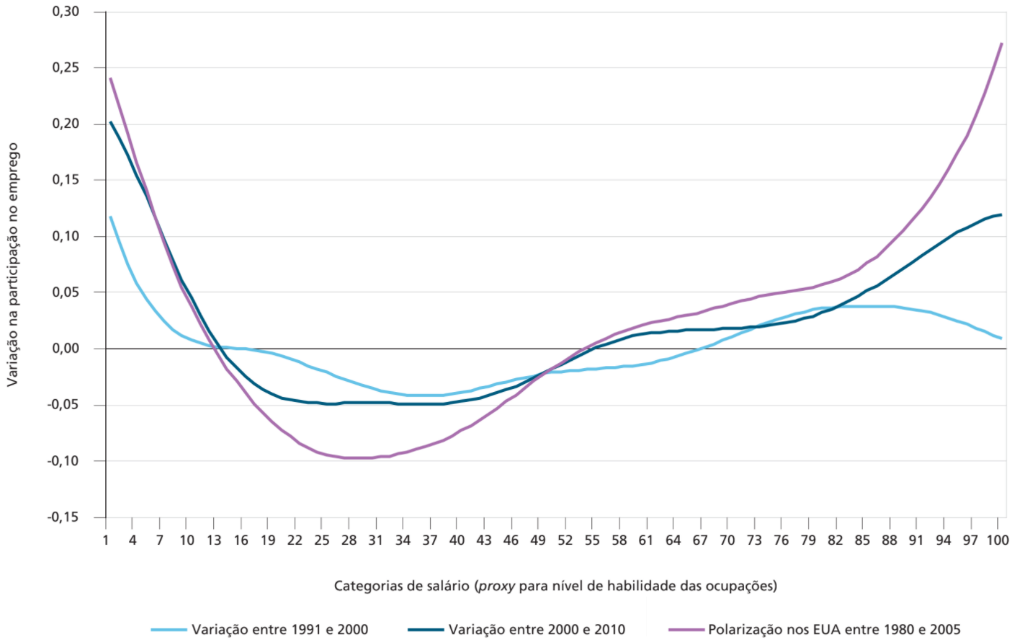

Figure 3.1: Skill Distribution of the US Labor Market extracted from Machado (2017)

fication by computers, clerical administrative and industrial jobs are examples of these occupations. Acemoglu and Autor (2011) says that "tasks that primarily involve organizing, storing, retrieving, and manipulating information most common in middle-skilled administrative, clerical and production tasks are increasingly codified in computer software and performed by machines."

The figure displays the relation between employment share and the distribution of skill ranked by occupational mean wage. The middle-wage workers have been experiencing a decrease in their participation in both US and Brazilian labor according to Machado (2017). Despite less accentuated trend between 1991 and 2000, it is possible to see a clear pattern of polarization in the 2000/2010 time period. Though our empirical exercise corroborates a polarization pattern in the Brazilian economy, we found a less clear polarization trend between the years 2000 and 2010.

Following Autor et al. (2003), David and Dorn (2013) and many other authors, we agreed that this pattern of structural change is correlated with the productivity growth that has been causing a decline in prices of information and communication technologies. In this way, the declining prices of technology are inversely correlated with the routine occupations' share in local labor markets. For those who perform abstract tasks, computer technologies, and automation impact enhancing their skills and wages. Those occupations are located on the right side of chart 3.1. Service occupations, on the other hand, are considered hard to replace due to dexterity and lack of routine, these are located on the chart's left side. Consequently, the lowest part of chart 3.1 represents the technological footprint of routine occupations.

The declining price of technologies is accelerating the technological change pace and the susceptibility of routine occupations to technological replacement. Therefore, this behaves keeps it a skill-biased phenomenon. The argument behind this literature says that a local labor market with a higher routine occupation share has a higher probability of presenting a growth of service jobs — or non-college workers share. This process is also known as rolling out of middle-skill occupations. An excellent example of this technological impact is the robots' usage on manufacturing production plants, the automotive industry is pioneering on this. Its production process is characterized by assembling lines with strong repetitive tasks presence. To reinforce our argument on this relation, we cite Chiacchio et al. (2018)'s work where it was found strong evidence of the robots' impact reducing the demand for workers in EU countries.

Reviewing past literature, we can see that these changes in structures are not a new phenomenon to society. Outlining the past-present history of industrial revolutions and the migration phenomena caused by it, we will see what Campa (2018) saw. For him, "A first migration was observed from agriculture to manufacturing, a visible phenomenon because it also led to massive migration from rural to urban areas. A second migration of the labor force, less visible but equally significant, occurred from the manufacturing sector to the services sector. Historically, a structural change like the one we have been testifying is not uncommon.

Although the evolution of ICT has received much attention due to its direct effect on the labor market, it also has some indirect effects. Experts also have seen that job polarization is driven by new possibilities raised by technology. David and Dorn (2013) point out to three other potential explanations for the rise of service employment:

> (i) growing offshoring (rather than automation) of job tasks, which displaces low skill workers into non-offshorable service occupations; (ii) rising income at the top of the wage distribution, which stimulates demand for in-person services among wealthy households (an income effect, as in Clark 1957); and (iii) rising returns to skill, which spur college-educated workers to increase labor supply and substitute market for home-based production of household services (Manning 2004; Ngai and Pissarides 2008; and Mazzolari and Ragusa 2013).

The authors draw our attention to focus that offshoring, enabled by technology, allows the replacement of local workers by foreign workers. Technology, since the third industrial revolution, has been causing a decentralization trend on production. The break-through delivered by the third industrial revolution mainly impacted transport and communication technologies, and these are the main responsible for global value chain expansion. Knowing this, we can say that offshoring is a process where a shift of output occurs from the home country to another country. Therefore, the connection here comes out of the hypothesis that the offshoring has also been impacting the labor market through routine tasks.

The higher consumption power of agents with higher wages was also pointed out by David and Dorn (2013) as a job polarization force. Notwithstanding, this relation can be characterized as a multi collinear relationship between wages and polarization, i. e., job polarization causes as much wage polarization as wage polarization causes job polarization. That said, job polarization in developed countries has shown a pattern of wage polarization. The latter follows the same rule of job polarization because middle-wage jobs are being replaced by technology. In this way, the high-skilled and low-skilled jobs are respectively the high-waged and low-waged jobs, and the middle-skilled jobs are the middle-waged jobs. This structural change is also called for the disappearance of the white-collar and blue-collar jobs.

We believe that wage polarization could be worsening the income distribution in developing countries that already have an unequal income distribution; it could mean a worsening of the entire social structure. For example, Weller (2017) highlights that historically "it is true that in some sectors and/or regions the introduction of new technologies caused strong job losses that generated massive increases in poverty." The income problem is another reason to verify whether this phenomenon has been impacting the Brazilian economy. On the other hand, Nickell and Bell (1995) pointed out that through time Germany experienced very little increase in wage inequality. Looking at Germany society, we argue that its educational system causes this evidence, meaning the human capital of unskilled workers has been enhanced, making technological replacement smaller.

Consequently, the composition change caused by job polarization worsens wage inequality, income inequality, and even causes jobs precariousness. To summarize our point, in the phenomenon of polarization, most of the workers employed in routine occupations are having problems moving up to occupations more technologically demanding, meaning workers are having problems with reskilling. Because of this labor market evidence, polarization has been causing problems like income inequality and wage polarization. These two are responsible for inequality in a broader sense, and in the long-run, it can result in profound social changes. Ciarli et al. (2018) says that "without proper retraining programs, these workers characteristics are likely to be path-dependent: workers will have a low probability to move to better occupations: there more so the more the gap between their skills and those demanded by R&D related occupations widens." Due to the replacement effect and the reskilling difficulties caused by the technical change, the middle-skills jobs have been forced to compete in the low-skill category.

The job market's polarization could also be represented as a raise in the low skill jobs or a raise in the non-college service occupations. There is an essential difference between non-college occupations and service occupations; the non-college occupations are not the same as the entire service sector. David and Dorn (2013) defines non-college occupations as jobs that involve assisting or caring for others and generally with no more than a high school degree.

These occupations are janitors, baby sisters, gardeners, cleaners, home health aides, recreation occupations, security guards, food workers, hairdressers, and beauticians. As a result of the skills valuation, there is a higher supply of college occupations, which impacts creates polarization as well. For the US labor market David and Dorn (2013) documented a contrast of the raise of non-college workers, they found a "declining employment in all similarly low-educated occupation groups, which include production and craft occupations, operative and assembler occupations, and transportation, construction, mechanical, mining, and farm occupations".

As we have said all over this work, the literature on job polarization draws attention to technological progress as the main force responsible for raising the productivity and wages of abstract and manual jobs. However, even our data do not cover theses transformations; a fascinating fact is that recent technological achievements are making even the manual tasks susceptible to replacement. Meaning that even the non-routinized occupations by reason of technological change pace have been automated thanks to the industry 4.0's technologies. Drivers and couriers classified as manual jobs, and hence with the lowest probabilities to be automated, nowadays, are beginning to be affected by technology. This was the thought introduced by Autor et al. (2003) back in 2003.

Currently, driverless cars, delivery robots, and AI are examples of the technological pace we have been facing. Besides that, we have seen changes in occupations' activities as technology evolves; this is happening because technology is changing the occupation's technological requirements, reaffirming our idea of the workers' hard adaptability — but this is not a new phenomenon in society. Goos and Manning (2007) documented that papers were showing job polarization patterns since the 90s, but the first article to name it was the article of Autor et al. (2003).

Underdeveloped countries more susceptible to feel technological impacts. On average, these countries have lower levels of schooling and barriers to find qualified professionals, which could lead to a structural worsening of problems well-known to these countries. Therefore, it is vital to highlight that our main concern about the labor market's polarization is its impact on social structures. With this in mind, and knowing that Brazilian production specialization in middle technological intensity goods that are mainly characterized by low-complexity, we stress the relevance to do a descriptive analysis of its labor market. The outcome of this work could be relevant to help policy-makers to cope with upcoming social changes in Brazilian society.

3.1 Literature

This literature review aims to gather relevant academic work on job polarization themes to reinforce our work's relevance and its contribution. In this sense, we will reference scientific productions studying the relationship between technological change and labor market structural change, as well as SBTC models. The following academic works were chosen due to the report of important consequences to society and its literature relevance. Finally, but not least, we will specifically be seeking to highlight social problems derived from the introduction of computers and automated technologies, namely wage and income inequality, among other effects of technology penetration.

First, it is crucial to say that the shift towards the service sector that is the motive of our concern does not involve high technology services. Instead, we express concern about the movement towards low educated service occupations. David and Dorn (2013) named these as service occupations, i. e., a low-education group that provides personal care services. Additionally, Acemoglu and Restrepo (2017) pointed out to sectorial impact on occupations caused by technology. The authors highlighted that automation mostly impacts industries such as automobile manufacturing, electronics, metal products, chemicals, pharmaceuticals, plastic, food, glass, and ceramics.

Acemoglu (1999) studying the evolution of relative earnings in the US found evidence that high-school graduates were earning 30% less than the graduates. Simultaneously, it was found a strong, and early, evidence of wage inequality, as well as a composition change in the North American labor market. Acemoglu (1999) then raised the hypothesis of technological impact in middle jobs. In his words, ""middling" jobs open both to skilled and unskilled workers may be replaced by high-quality (capital) jobs." For the author, a composition change led to wage differences and higher unemployment rates for skilled and unskilled workers. This work's mathematical contribution was marvelous, although we believe that a greater weight to technological impact would enhance its explanatory power.

In pioneering work about computerization's effects on the labor market, Autor et al. (2003) decided to use the Routine Task Intensity (RTI) approach to see how computerization alters skill demands through time. Some authors recognize this work as the one where the term job polarization was coined. Autor et al. (2003) studied the United States' occupational task composition of the Dictionary of Occupational Titles from 1960 to 1998. Their work was mainly based on two assumptions about the adoption of computers in production, namely: (1) it substitutes workers executing cognitive and manual tasks that can be performed by following explicit rules; and (2) it complements workers executing non-routine problem-solving and complex communications tasks.

They found that the falling prices of computers play a significant role in routinized occupations' extinctions. The main finding of this work was the reducing routine labor input caused by computerization; it was found within industries, occupations, and education groups. Using a similar classification we have adopted in this work, they found that the routine manual and routine cognitive tasks were the most impacted. Additionally, as we also assume in this work, they found that computerization increased non-routine cognitive tasks' labor input. In this sense, computerization was proved to cause a compositional change in occupations requirements. Their model was capable of explaining 60% of the total shift. These findings reinforce our concerns.

In relevant research, Autor et al. (2006)'s aim was to measure and understand how a decline in computing power leads to a labor market polarization. In order to do so, they classified occupations in manual, routine, and abstract. This work used a three-level task classification instead of a five-level classification, the latter is more commonly found in studies using the modern theory. The authors found that the "growth in the demand for skills combined with a slowdown in the growth of the relative supply of college workers helps explain US wage changes."

They also argued that part of this phenomenon could be explained by skill-biased technical change (SBTC). Additionally, they demonstrate that employment growth differed sharply in the 1990s versus the 1980s. According to Autor et al. (2006), the US experienced a more accentuated growth of employment in jobs at the bottom and upper part in comparison to the middle part of the skill distribution. Leading to a job polarization pattern in the US labor market. Therefore, they showed that computerization behaves as a complement for non-routine cognitive tasks, substitute for routine tasks, and it has little impact on non-routine manual tasks.

In a well-recognized work, Goos and Manning (2007) (following Autor et al. (2003)) were pioneers in the study of labor market polarization for the UK labor market. They sought evidence of the polarization phenomenon in the UK and found that since 1975 there have been signals of it. The authors also argued that there had been a growing increase in participation of the highest-wage and lowest-wage occupations and women's participation in the labor market. They found that the pattern of employment changes in Britain over the period 1975–1999 does show job polarization. The objective of this work was to seek pieces of evidence of a higher demand for skills instead of an approach to service occupations.

Although not having written about job polarization, Moretti (2010) on his work explained some labor market compositional trends. He presented a study about job creation and its multipliers that reveals changes in the US job composition. According to the evidence found, new employment in a tradable sector, characterized by more skilled workers, has a multiplier effect of 2.5. He also highlighted that each additional job created in the manufacturing sector creates 1.6 jobs in the nontradable sector (services). This study was developed to analyze compositional changes in jobs across US cities and demonstrate, though not explicitly, a signal of polarization. All in all, outlining some limitations, we point out that it lacks endogenous labor demand changes that we solve through technological impact.

On the other side, Van Reenen (2011) 's article reinforces our polarization argument by explicitly talking about it when studying the US and UK labor market. According to him, since the 1990s, these two countries have been experiencing a shrinking in the middle of three parts of the job market. The author's justification for this phenomenon lies in computerization, i. e., information and communication technologies as being complementary to more skill-intensity tasks and substitutes for routine ones. In the author's words, the labor market changes are happening "due to technology-related increases in the demand for skilled workers outstripping the growth of their supply." Again overlapping arguments, the author pointed out that technology impacts the most clerk occupations and they treat technological impact as endogenous.

Fernández-Macías (2012) examining 15 countries in a two-digit occupation level, tried to test the hypothesis of a single labor market structural pattern to European countries. In the end, it was found a plurality of results and a recognition that the polarization hypothesis delivered by technology can not be denied. This work grabbed our attention due to two factors: first, it used a different methodological approach, and second, the author has attributed others causes to polarization than technological change.

It was found that the structural change of Continental Europe can be considered job polarization, but the Scandinavia follows a structural upgrading pattern. On the other hand, Southern Europe has followed an expansion of middling jobs, which is the opposite of job polarization. According to the author, this plurality of effects is caused by distinct forces on the labor market, such as Law changes, institutions' choices, regulation, and European economic integration. Among all fifteen countries, "four countries (or six being generous) fitted more or less the polarization pattern, four countries fitted an unambiguously upgrading pattern and a final group of four countries showed an upgrading pattern."

David and Dorn (2013)'s work is one of the bases of this study. This article has provided us with a rich mathematical and theoretical framework capable of explaining labor market modern phenomena. By studying the US, the authors identified strong evidence on job polarization from 1980 to 2005. It is interesting to notice that the falling prices of computer technologies have been causing polarization, but it also has been changing consumer preferences. Additionally, they argue that technical progress for abstract occupations comes as a complementary force; consequently, enhancing wages and demand for these occupations. They found a clear pattern of polarization and changes in relative wages.

An interesting contribution of this work was the identification that routinized occupations had wage gains given task aggregation. That is, automation has been increasing the abstract content in routine occupations as technological change happens. The authors' mathematical and empirical models were capable of corroborating the following hypotheses: 1) Local labor markets specialized in routine tasks occupations deferentially adopted information technologies. 2) those same labor markets experienced earnings growth at the tails of the skills distribution. 3) The authors also found that commuting zones specialized in routine jobs are more likely to face a shrinking routine occupation. Hence, those workers involved in routine tasks have been given place to services occupations.

In influential work, Michaels et al. (2014) tested if information and communication technologies were delivering polarization in labor markets of the United States, Japan, and nine European countries from 1980 to 2004. Therefore, they sought shreds of evidence of increasing demand for the highly educated at the expense of middle-educated workers. For them, "industries and countries that had faster growth in ICT also experienced an increase in demand for college-educated workers, relative to workers with intermediate levels of education, with no clear effect on the least educated."

They found that industries faster-adopting information and communication technologies were increasing their demand for more educated workers leading to a polarization pattern. The author called ICT-biased polarization the pattern found in those industries shifting demand from middle-educated workers to highly educated workers. Furthermore, they also detected evidence that trade openness was associated with job polarization. Despite the job polarization finding, they have not used an in-depth routine approach to determine ICT's impact. Their results were the most found through studying the relationship between education levels and ICT impact. We believe their work lacked a better explanation for these technologies' structural impact in comparison to other studies reported in this work. The authors also tested the RD hypothesis and found a positive impact of it on job polarization for those countries.

In a well-known work, Goos et al. (2014) tested the hypothesis of routine biased technological change (RBTC) and offshoring biased technological change. As well as Michaels et al. (2014), they found that RBTC is much more important in explaining labor market polarization than offshoring. Their results were found seeking for job polarization in 16 Western European countries. Additionally, their data covered the 1993–2010 period. The authors advocate that "within each industry there is a shift away from routine occupations leading to within-industry job polarization. Nevertheless, RBTC also leads to significant between-industry shifts in the structure of employment".

In this work, the authors used individual-level harmonized data of the European Union Labor Force Survey (ELFS) for the period of 17 years, 1993–2010.

Their data covered the following 16 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, and the United Kingdom. It was found that the Western Europe labor structure has been facing a rising of employment shares for high-paid professionals, managers, as well as low-paid personal service workers. On the other side, the region has been experiencing a falling of employment shares in manufacturing and routine office workers. In sum, the region presented a clear pattern of job polarization.

As technology develops, the job polarization trend seems to persist due to the replacement impact technology has on routine tasks. Acemoglu and Restrepo (2017) studying the US through commuting zones approach found a negative relationship between robot adoption and computer-assisted technologies in job creation. At the same time, it was also detected a significant impact on wage reductions delivered from adopting these technologies. According to the authors, it happened due to industrial robot usage between 1990 and 2007. The results were found by regressing employment and wage changes on robot adoption exposure in each commuting zone. As a result, the authors' estimation showed that "one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 percent".

Autor and Salomons (2018) also studying the technological impact on the labor market, found evidence of the effect of automation in the period from 1970 to 2007. The changes in employment shares were found using data from 28 industries in 18 OECD countries. According to the authors, automation technologies generated an increase of employment across industries due to countervailing responses to technological change: own-industry output effects; cross-industry input-output effects; between-industry shifts; and final demand effects. This countervailing mechanism creates new job vacancies in other industries resulting in a shift in favor of non-routine occupations. Raj and Seamans (2018), also studying the technological impact on employment, reported that automation and robotics might have accounted for about one-tenth of the US gross domestic product (GDP) increase between 1993 and 2007. However, on the other hand, it was found a negative impact on the number of jobs created.

Graetz and Michaels (2017) studying developed economies found evidence of the rolling out of middle-skill jobs, i. e., job polarization. They got this result when looking for explanations for low post-recession employment growth. The authors pointed out to technological unemployment as the leading cause of the low growth pattern across countries. Seventy-one recessions were examined across 17 developed countries from 1970-2011. The authors also suggested that middle-skill jobs, which usually involve routinized tasks, are most affected by technological displacement force.

Bárány and Siegel (2018) studying the US from 1960 until 2007 confirmed polarization patterns. The author argued that contrary to the literature, job polarization of the US labor market was started in the 1950s. Due to the novelty of the emergence of polarization even before the creation of ICTs technologies, the authors proposed a structural explanation of the phenomenon. According to the authors, "as long as the goods produced by the different sectors are complements, a change in relative productivities increases labor demand in the relatively slow growing sectors." Hence, they argue that wages in these sectors characterized by slow growth have to increase in order to attract workers.

Ciarli et al. (2018) comparing commuting zones in UK, identified a structural change in its labor market. The authors' goal was to seek for the impact of RD investments on routinized jobs. It was found that there was no job multiplier derived from RD investments. A major structural change across commuting zones was detected, though. Revealing strong labor market structural change, the authors estimated that for each high-level job created, the number of self-employment jobs, especially in the service sector, would create up to six jobs.

We believe it is also important to mention the literature on automation probabilities. This literature also lay on the routine tasks hypothesis in order to explain the automation technologies' impact in the coming years. Frey and Osborne (2013) found that 47% of the US and 57% of jobs on average in the OECD countries will be replaced by automation technologies. Pajarinen et al. (2014) pointed out to 35.7% in Finland and for Germany Brzeski and Burk (2015) estimated it to be 59%. Bowles (2014)[1] estimated that in Europe, the aggregated variation is going to range from 45% up to over 60%. Ramaswamy et al. (2018) shows that the risk of automation is about 55% in Uzbekistan, 85% in Ethiopia, 77% in China, and 69% in India. Most of the works about automation probability, such as those we have mentioned above, rely on Frey and Osborne's probabilities of automation. According to the authors, entire occupations are at risk due to the increasing capabilities of automation technologies.

Arntz et al. (2016) used a totally different methodological approach by estimating the probabilities of tasks extinction rather than entire occupations being wiped out. Although significant differences were found in the automation risk estimation, the numbers pointed to upcoming substantial structural changes. The authors found that for the 21 countries of the Organization for Economic Cooperation and Development (OECD), there exist, on average, 9% of jobs at risk of automation. Albuquerque et al. (2019) estimating the probability of automation for the Brazilian labor market did not find results contrary to the studies mentioned above. According to the authors, Brazil presented 24,970,587 jobs at risk of automation. Moreover, the projections made in this work showed that by 2026 Brazil

[1]Bowles, J. (2014), The Computerization of European Jobs, Bruegel, Brussels

would have 30 million unemployed workers due to automation.

3.1.1 Brazilian Literature

Although the job polarization pattern is well established and commonly observed among developed countries, there is still an open debate about the phenomenon in the Brazilian economy. The Brazilian literature on the job polarization of the past few years not only studied shits in occupier demand, we could also found literature on task requirements.

Bressan and Hermeto (2009) studied the impact of technologies on the Brazilian labor market. The authors were looking for pieces of evidence of polarization as well as unequal impacts of polarization over men and women. Based on panel data for the years 1983 and 2003, the study found an increasing demand for occupations that require a higher level of technology, i. e., occupations classified as non-routine. The study relied on IBGE's PNAD (Pesquisa Nacional por Amostra de Domicílios) data and the authors did a harmonization between the PNAD and the United States Dictionary of Occupational Titles (DOT). They noticed that occurred a reduction in the wage gap between women and men in occupations with higher technological requirements, i. e., non-routine and non-manual occupations. The authors concluded that the technological requirements contributed more to the fall of the wage gap between men and women than pure technological progress.

Riva (2016) found evidence of polarization on the Brazilian labor market through the relationship between computer prices and changes in task requirements. According to the author, labor market inputs have shifted towards non-routine manual activities in place of routine activities between the years 1988 and 1997. The study explored the impact of computer-specific industrial policy on the task requirements using matched employer-employee longitudinal data. To perform the empirical exercise, the author used data of the Labor's Annual Social Information Reports (RAIS, in Portuguese) and measures of occupational task intensity based on the Brazilian Occupational Classification (CBO, in Portuguese Classificação Brasileira de Ocupações). An exogenous shock was applied in prices to identify the effects of computerization on work earnings and labor inputs. As a result, it was found job polarization evidence in task requirements. Despite using an interesting empirical approach, this study used only a 10-years-period to identify structural change.

Studying the way in which automation and globalization play out in 21 developing countries in Africa, Latin America, and Asia, Maloney and Molina (2016) found evidence of job polarization in Brazil and Mexico. Those two countries are characterized by a strong industrial jobs presence, and according to the authors they should be affected by the ongoing automation and off-shoring impact on middle-skilled "routine" tasks. It was found that both Mexico and Brazil displayed that the operator's category has grown relatively less after the 2000s, meaning a discrete but significant sign of polarization. It was used the Integrated Public Use Microdata Series (IPUMS) developed by the Minnesota Population Center, which harmonizes census micro-data from around the world as the data source. The occupational exercise was based on the OCCISCO variable which records the person's primary occupation, these occupations were harmonized with the 1988's International Standard Classification of Occupations (ISCO). As a result, the authors worked with job 11 categories.

Machado (2017) found evidences of job polarization for the Brazilian labor market. The authors used the same data and time period of this work, i. e., IBGE censuses data for the years 1991, 2000, and 2010. They observed that the employment in the commerce and services sector increased and that there had been a reduction of employment in occupations located in the industry and agriculture.

During the 1991-2000 period, the Brazilian labor market showed a slower polarization trend in comparison with the 2000-2010 time period. We found the opposite relation in this study.

Almeida et al. (2018) investigated how the provision of internet services changed the demand for skills in the Brazilian economy. Furthermore, they studied the impact of labor regulations on the firms' demands for skills, i. e., how the adoption of technology by enterprises interact with regulatory changes. The authors argued that labor institutions are aimed at protecting workers, but by doing so, they usually increase labor costs and favor the adoption of computer-related technologies by enterprises. It was found that digital technology adoption shifted the demand for skills toward increased use of non-routine and cognitive tasks. Interestingly, the authors also observed that labor market regulations disproportionately benefit skilled workers. This work used spatial data at the level of municipalities as well as spatial data for labor inspections as a representative of regulatory changes. This work used the Brazilian RAIS (Relação Anual de Informações Sociais) database, as well as the Brazilian Classification of Occupations (CBO) and the U.S. Department of Labor's Occupational Information Network (O*NET) in the occupational and task approach. The study was performed in the 1999-2006 period. Besides, tasks were classified in cognitive, manual, non-routine, and routine.

Almeida et al. (2018)'s "findings suggest that technology-intensive industries located in cities with earlier access to the internet reduce their relative reliance on manual and routine tasks, thereby shifting the skill composition of industries and cities toward cognitive and non-routine tasks". The objective of this work was not the study of polarization, nonetheless, they found evidence of changes in the composition of the labor market through internet adoption and regulatory changes. Although relying on good empirical and spatial data, we believe this work could have used a better proxy for penetration of ICTs, such as robots and computers.

Herdeiro et al. (2019) used Acemoglu and Autor (2011)'s "canonical model" framework to analyze the relationship between the skill-biased technological change and the evolution of relative supply and wages for three distinct groups in Brazil between 1981 and 2015. The authors used IBGE's PNAD (Pesquisa Nacional por Amostra de Domicílios) as data source. Among the findings, the authors observed a slowdown in the relative demand for intermediate workers over the period. Furthermore, the groups of unskilled and intermediate workers were found significantly substitutes for each other. Having said, they found a wage polarization trend and significant pattern of polarization.

As we said at the beginning of this section, the polarization debate is still open in the Brazilian economy. Usually, and this is a shred of evidence found in developed countries, the polarization of the labor market and the wage polarization are simultaneously found. Nonetheless, the Brazilian economy has not clearly displayed this relationship. This work comes to contribute to the empirical literature on the subject, though it does not provide answers to wage polarization. Summing up, this work uses a different approach in comparison to the ones reported in this literature review. For example, we do not study the trends in high-skilled jobs, instead, we focus on the relationship between routine jobs and service jobs. The data, otherwise, is commonly used during empirical approaches.

4 METHODOLOGY

4.1 Data

First of all, we have been dealing with a high-quality data-set, meaning we have millions of observations. We also have spatial data at municipality level to perform a robust empirical analysis. These data, whose source is the IBGE (Brazilian Institute of Geography and Statistics), are the Brazilian censuses. The Brazilian census has been carried out every ten years, and a massive number of households in the Brazilian territory are visited ever since it started. As an example, the 2010 census sampled 6.2 million households and a total of 20.6 million individuals.

Our priority was to perform a strong empirical analysis that could capture structural changes in the Brazilian job market. Having said, we chose the IBGE's censuses as dataset due to its sample amplitude and informal market coverage; the latter is crucial in order to capture service jobs in the Brazilian context. Because of the informal market coverage and comprehending structural changes take long to happen, we decided to use data covering a broad period at expense of other data options available. Each of the following empirical exercises proceeds in two stages due to the instrumental variable methodological approach.

Our data-set covers the 1991, 2000, and 2010 censuses. This period, approximately thirty years, was chosen in order to better capture the polarization's structural effects in the Brazilian labor market, if any. This time range is also contemporaneous to significant technological transformation in our society, such as the ICTs revolution. Researchers always desire the most timely and accurate database to work with; it is no different in our case. The chosen period is the most recent possible given the availability of the IBGE's censuses during the writing process.

Furthermore, it is worth saying that in the literature on labor market polarization, the first evidence of polarization in developed countries appeared even before the 1970s. In this sense, bearing in mind that technological related structural changes take more time to occur in developing economies, we believe our data poses a good potential of the phenomenon's identification. Our sample of workers comprises the economically active population (EAP), meaning workers' age range from 10 to 65 years old. Moreover, the census only captures the occupational data of workers employed at the week in which it was collected. Table 4.1 resumes some of our data features. For the service occupations used as proxy for polarization see the appendix in this work and the online appendix.

Table 4.1: Data Features

Year	Occup obs	Net Occup Obs	Occupation's Codes	Male	Female	MCA Count
1991	17.047.012	6.165.191	381	3.191.911	1.391.678	3800
2000	20.274.496	6.804.072	511	4.911.513	2.871.386	3800
2010	20.635.499	8.409.729	438	5.405.570	3.745.537	3800

Our occupational sample has approximately 22 million observations; although this a substantial number, we have been relying on the occupation's share as the main variable of interest. Even amounting less, these are responsible for 263.529 observations across 3800 minimal comparable areas (MCA). What we have been calling "share observations" is the participation of routine and service jobs by MCA and year.

In this work, the MCA methodology was applied to avoid spatial problems within the data-set. To be more specific, thousands of municipalities were changed, created, merged or erased during the analytical period. Due to that, we have used Ehrl (2017)'s methodology to find minimal comparable areas all over the chosen period.

The methodology is presented as follows: first, the one that the spectator has been reading, we talk about the database features; second, we present the routine task intensity (RTI) index; third, the classification of occupations; fourth, the empirical model; and, fifth, the instrumental variable approach.

4.2 Methodology

It should be said, first, that the chosen methodological approach of this work follows the work of David and Dorn (2013), Autor et al. (2003), and Autor et al. (2008). We decided to split up this methodology into stages for better organization and explanation. First we use the Routine Task Intensity index to estimate the participation of routine occupations across MCAs through the RTI index; Second, the results of the first step will be feed in an econometric model that, based on large literature, will allow us to input causality between technological change and labor market structural changes; third, we show our instrumental variable approach. Our central hypothesis says: there has been occurring a polarization of the Brazilian labor market in the past years.

4.2.1 Routine Task Intensity (RTI) Index

The RTI index has been widely used due to its non-discretionary character regarding occupational assessments. The method was developed to evaluate the level of routinization across sectors, occupations, or places. Basically, the index shows how much of the tasks performed by a worker are repetitive. The workers that mostly perform routine tasks could be considered routine occupations and are more susceptible to technological impacts. In this sense, due to the RTI index, we could estimate and classify the share of routine occupations across MCAs used in this work. There are different versions of RTI index in the literature: 1) the Autor et al. (2003)'s version is based on the Dictionary of Occupational Titles (DOT) of the United States 2) Arntz et al. (2016)'s version was developed for the OECD countries [1] 3) The Luxembourg Income Study Database (LIS)'s version, which we will be using in this document, is based on 23 countries — which includes Brazil's censuses compatibility. Basically, they differ in the task requirement of each occupation, i. e., the same occupation could be assigned as performing different tasks depending on the chosen version. There is also the classification used by Frey and Osborne (2017), the authors use a classification based on the O'NET. However, this work does not use a task approach.

Summing it up, the RTI index's purpose is to verify how abstract, routinized, or manual a single occupation can be. After the index's calculation, we can perform sectoral and spatial analysis through aggregations. In this work, we used the Luxemburg Income Study (LIS) RTI dataset [2] developed by Mahutga et al. (2018) to several countries, which is compatible with the Brazilian household censuses at

[1] Although recognized as a task approach, this version was not developed for job polarization studies.

[2] According to Mahutga et al. (2018) "To produce these data, we recoded 23 country-specific occupational schemes (74 LIS country-years) to the two-digit ISCO-88 scheme. When combined with the handful of LIS countries already reporting their occupations in ISCO-88, we produce individual level RTI and OFFS scores for 38 LIS countries and 160 LIS country-years".

two-digit occupational classification. In order to use the LIS dataset, we converted, as can be seen on the online appendix, the occupational observations of the Brazilian censuses into the two-digit code used by LIS.[3] The data-set was developed to be compatible with CBO-Domiciliar used both in 2000 and 2010 censuses. The 1991 census and its harmonization with the CBO-Domiciliar pattern were made available by the IBGE[4]. The LIS' RTI data-set was built on the ISCO-88 code, due to that is possible to apply our methodology. In short, the methodology consists of measuring the content of routinized tasks in each occupation, which, in turn, would be a better proxy than considering an entire occupation as routine. The RTI index is calculated as follows:

$$RTI_k = ln(T_k^R) - ln(T_k^M) - ln(T_k^A) \tag{4.1}$$

Where $ln(T_k^R)$ represents routine tasks content, $ln(T_k^M)$ manual tasks content and $ln(T_k^A)$ the abstract tasks present in each occupation. As can be seen, RTI positive values represent greater routine tasks content within an occupation. After figuring out these values, we approach the values made available by the LIS database as terciles. Therefore, we consider the occupations located in the highest tercile as routine occupations. Consequently, these are the most likely to be replaced via technological progress over the years.

4.2.2 Econometric Model

Recent work on polarization, AI, and robotics impacts on the labor market have been using commuting zones or travel to work areas (TTWA) as a spatial

[3]To access the data see http://www.lisdatacenter.org/resources/other-databases/
[4]See the online appendix: https://drive.google.com/drive/folders/1UzgvFjAa5Mvpr0Bcbw5MCsqWyDvvn53L?usp=

unit of analysis. Unfortunately, we do not have such a framework for the Brazilian economy, and we will be addressing this problem by using MCA as a proxy for local labor markets. The unit of analysis in our model is the participation of routine occupations across MCA.

The model's main input is the share of routine jobs across MCA which is extracted through the RTI index. Previous work on job polarization subject have divided jobs into five categories: non-routine/cognitive, routine/cognitive, routine/-manual, non-routine/manual and non-routine/interactive. On the other hand, in this work, we decided to follow Autor et al. (2003), Autor et al. (2006), Autor et al. (2008) and Goos et al. (2014) categorizing jobs into three categories: abstract, manual, and routine. The latter being the main one of our interest. In this sense, the use of the RTI will help us to determine which occupation is routine, manual, or abstract. Usually, routine jobs are the ones that mostly perform repetitive tasks, abstract jobs are the ones that mostly perform cognitive thinking tasks, and manual jobs normally combine the skills mentioned above but rely the most on dexterity.

Following the leading hypothesis on this work, our model describes that a higher participation of routine occupations at a given point in time would be correlated with significant shift towards non-college jobs' participation (service jobs) in a second point in time. Having said that, the MCA with higher routine content should present growth and hence a shift toward the participation of service occupations.

$$\Delta SNC_{\text{2010-1991}} = \delta + \beta RSH_{1991} + \varepsilon_i \tag{4.2}$$

where $\Delta SNC_{\text{2010-1991}}$ represents the growth of service occupations across MCA between the period 1991-2010. RSH_{1991} represents the participation of routine occupations across MCA in the year 1991, according to our theoretical approach, MCAs presenting a high share of routine occupations should display an accentuated growth of service jobs. β represents our coefficient of interest, therefore being a proxy for the impact of a high share of routine jobs in the service jobs' growth. ε_i represents the variation not explained by the econometric model. In this model, the coefficient's signal is crucial to verify our hypothesis. A negative signal would represent evidence of the Brazilian job market's polarization once the share of service occupations in 2010 is greater than in 1991.

4.2.3 Instrumental Variable Approach

As the reader might have noticed, the above-described model has only one explanatory variable. Following several works aforementioned, we argue that the share of routine jobs across MCA is a good proxy for job polarization identification. To prove that what we are capturing is not a result of endogeneity, we propose using an instrumental variable. In this sense, a 2sls model (two-stage least squares) will be made. The first stage of the 2sls model consists of estimating the explanatory variable by using the instrumental variable approach. In the second stage, we will estimate a simple OLS model, but this time using the instrumented variable we found in the first stage. We argue that industrial jobs can be seen as routine jobs; due to that, we point out industrial jobs' historical participation as a good instrument for the routine share across MCA. In this regard, our instrument is directly correlated with the participation of routine jobs in 1991, but only indirectly related to our dependent variable.

$$RSH_{1991} = SHEI_{1970} + \varepsilon \tag{4.3}$$

Where SHEI_{1970} is the historical participation of industrial jobs across states,

ε represents the error or the variation that our model could not explain, and RSH_{1991} represents the participation of routine jobs across MCA in the year 1991.

4.3 Results

In our first regression, figure 4.1, we estimated the co-variation between the routine content across MCA in 1991 and the service sector's growth between 1991 and 2010. We had 3601 observations and almost thirty years of structural change period to check for this estimation. It is essential to say that these 3601 observations are composed of millions of occupations computed across municipalities. In this light, the chosen instrument follows the instrumental variable literature's recommendations[5].

All over this section, the first column will always present the results of the first stage of the 2sls model, while the second column will be displaying the second stage's results, i. e., our predicted parameter. As can be seen, our model is well fitted at a 99 percent confidence interval meaning the exhibited results are statistically significant. Furthermore, as aforementioned, our main parameter's signal is what matters the most in this analysis. A positive signal would represent evidence of the Brazilian job market's polarization once the share of service occupations in 2010 is greater than in 1991. The 0.976 coefficient describes that a higher routine content across MCA is positively related to service jobs growth in the 1991-2010 period. Therefore, the model points out that 1 unit increase in the participation of routine jobs across MCA at the year of 1991 is correlated with a 0.976 increase of the participation of service jobs between 1991 and 2010. Summing up, the first results extracted from the data presented in this work lead to the developed countries' findings.[6]

[5]The econometric results have shown it as a strong instrument

[6]About the R2: "Whether a negative R2 should be reported or simply suppressed is a matter of taste. At any rate, the R2 really has no statistical meaning in the context of 2SLS/IV." For

	(1) IV-First Stage	(2) 2SLS
share_routine_91	0.392***	0.976***
	(0.0195)	(0.0600)
Constant	-0.0820***	-0.175***
	(0.00439)	(0.00981)
Observations	3601	3601
R-squared	0.0976	.
F-statistic	405.7	

Standard errors in parentheses
Robust standard errors.
Dependent variable in (1) is x1 (Predictor x1). Dependent variable in (2) is y (Outcome 1).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4.1: Third Regression (1991 versus 2010)

For the next regression, we decided to explore the data in a slightly different way. We approached the data with a distinct criterion in order to identify job polarization trends, if any. In this sense, only MCA located in the top tercile of 1991's routine share was selected resulting in 1227 observations. According to the theoretical framework, these should present an accentuated growth of service jobs during the first regression's chosen period. Although the displayed results refuted the accentuated growth hypothesis, we have got an exciting finding. Our main parameter, $share\_routine\_91$, has shown a decreasing trend as the routine content across MCA rises. This could mean that in the first regression we were capturing some noise across MCA. As mentioned before, usually this methodology is applied in TTWA or commuting zones, the decreasing trend shows a problem into our spatial unit, though we still have evidence of polarization. The instrumented parameter's significance increase is another relevant fact displayed in figure 4.2.

As stated in our mathematical model, the falling prices of technology have

more information see https://www.stata.com/support/faqs/statistics/two-stage-least-squares/

	(1) IV-First Stage	(2) 2SLS
share_routine_91	0.0857**	0.762***
	(0.0265)	(0.196)
Constant	-0.00169	-0.185***
	(0.00767)	(0.0530)
Observations	1227	1227
R-squared	0.00894	.
F-statistic	10.43	

Standard errors in parentheses
Robust standard errors.
Dependent variable in (1) is x1 (Predictor x1). Dependent variable in (2) is y (Outcome 1).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4.2: Second Regression (Limited to 1227 Observations)

been driven a relative rise of labor replacing technologies. According to the Statista database, the global sales volume of industrial robots tripled over the past decade. In 2018, the worldwide total shipments reached about 400,000 units and the automotive sector is driving a large part of theses sales. In the automotive sector worldwide, the penetration of industrial robots exceeds 2,000 installations per 10,000 employees. See figure 4.3.

Most empirical works covering job polarization subjects have also been carried out with an interaction between the routine share coefficient and computer penetration. Therefore, these models associate job polarization processes with the falling prices of computer technologies, i. e., the relative cost of choosing computers instead of human force. In 2005 the average price of computers, excluded tablets, was 951 US dollars while the same indicator has shown that the average computer price reached 414 US dollars in 2015.[7]. Unfortunately, we could not find a computer

[7]This indicator includes desktop PCs, notebooks, and netbooks. For more information, see https://www.statista.com/statistics/203774/average-selling-price-of-pcs-exclusive-tablets-worldwide/

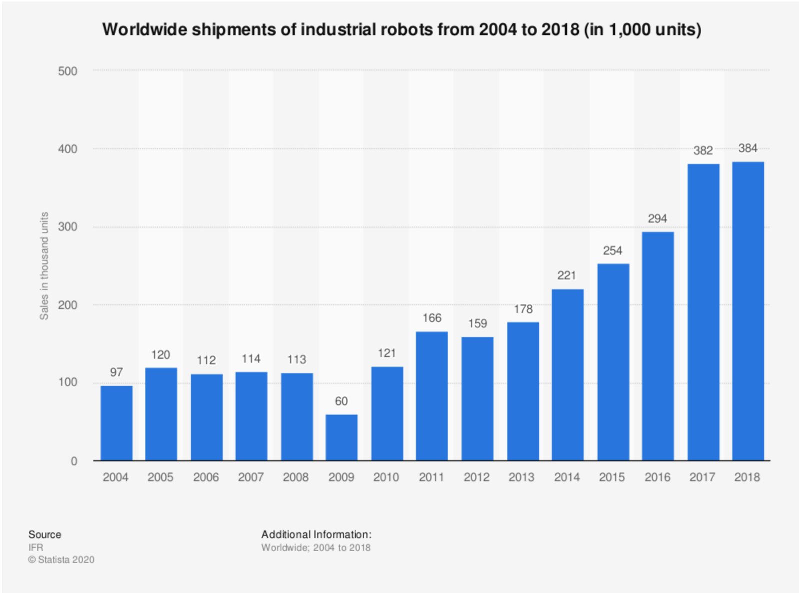

Figure 4.3: Robots Shipments

penetration index for the Brazilian economy available for the analyzed period[8]. As an alternative, we thought of industrial robots' penetration as a good replacement proxy for labor market structural changes. According to Statista database, the average cost of industrial robots worldwide declined steadily over the past decade, from about $46,000$ US dollars in 2010 to $27,000$ US dollars in 2017. According to Statista's recent forecast, related costs are expected to decrease to $10,856$ dollars by 2025. See figure 4.4.

Unfortunately, and once again, the Brazilian data covering technologies are still evolving; therefore, we could not find robots penetration suitable data for the chosen period. Having said that, the available data could not provide a large enough period for structural change identification to play the interaction coefficient. Moreover, a different database could not be chosen because it could not capture the informal sector as needed. Independently, the data is showing that there has been

[8]To access data for computer penetration see http://data.cetic.br/cetic/explore

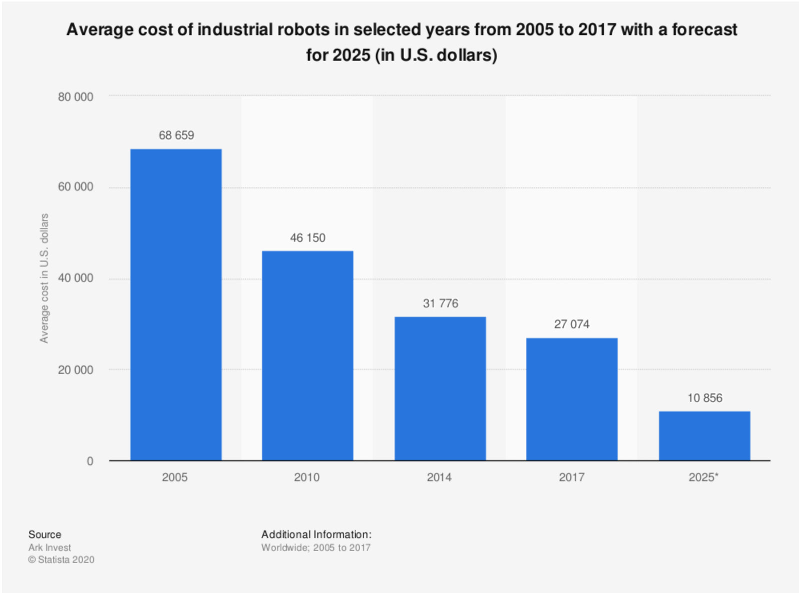

Figure 4.4: Robots Prices from 2005 to 2017

occurring rise in industrial robot sales in Brazil in the past few years. In 2017 the number of units amounted to 996 robots, and Statista forecasted this number to increase by approximately four percent by 2021, reaching 1,036 units. See figure 4.5.

As our last effort in order to identify, if any, a different data trend, we undertake the following empirical analysis using data for the years of 2000 and 2010. In this regard, we hypothesize that we could find in the figure 4.6 a stronger result or at least a smaller coefficient since ICT penetration is more substantial in developing countries as by the 2000s.

The regression presented in figure 4.6 uses an even larger MCA sample; it used 3799. Besides that, in the second column, our estimated parameter gained significance throughout the use of the instrumental variable approach. In this intent, besides evaluating a different period, we decided to test if the MCA with a higher share of routine occupations in 2000 is correlated with service jobs growth between

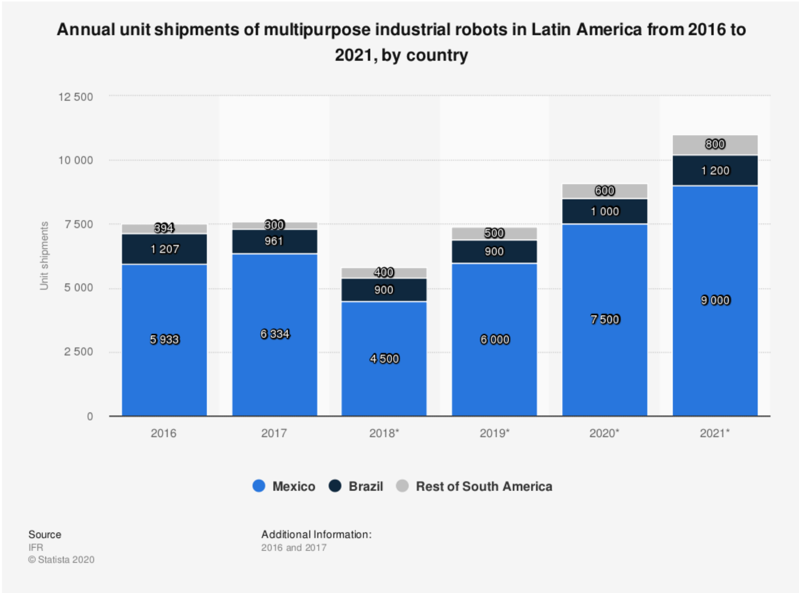

Figure 4.5: Estimated Annual Shipments of Multipurpose Industrial Robots

	(1) IV-First Stage	(2) 2SLS
share_routine_00	0.0194	0.110***
	(0.0142)	(0.0325)
Constant	-0.0419***	-0.0563***
	(0.00312)	(0.00573)
Observations	3799	3799
R-squared	0.000451	.
F-statistic	1.860	

Standard errors in parentheses
Robust standard errors.
Dependent variable in (1) is x1 (Predictor x1). Dependent variable in (2) is y (Outcome 1).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4.6: Second Regression (2000 versus 2010)

the years of 2000 and 2010. Additionally, the same instrument was used. Our data trends still suggest that the Brazilian job market has suffered job polarization. Interestingly, though, our main parameter (*share_routine_*00) has shown a falling trend. The 0.11 value could be interpreted as a slow trend to polarization of the

Brazilian job market.

5 CONCLUSION

We conclude by highlighting that this study's findings can be understood as promising and useful because it provides policy-makers with valuable Brazilian labor market insights (a polarization pattern, lack of data on technological penetration, the necessity of reskilling today's routine workers, among other findings). First of all, the work performed here is valuable because it contributes to the empirical literature on the polarization of labor markets. The fact it was made about a developing country is a plus once this debate is still open in these countries. Moreover, the methodology applied here differs from most of the reported literature on Brazilian labor market polarization. In this sense, it is important to say that throughout this empirical exercise, which is detailed in the online appendix [1], we had the opportunity to rely on the IBGE's censuses sound data, millions of observations geographical identified, and a robust econometric model.

As we have stated, the knowledge era and the impact of ICTs on the labor market directly result from developments in paradigms and technological directions. Following this thread, firstly, we understood routine task replacement as the labor market paradigm of the past few years. Secondly, we see robotization and computerization as the primary technological choices approaching this paradigm problem, i. e., these are the so-called technological directions. As we were looking for structural changes, the short-term impact of this process was not in the focal point of the analysis. Due to that, we focused our theoretical framework on the long-run impact of the employment-innovation nexus and the employment-technological change trade-off on the labor market. Summing up, the long-run countervailing impact of developments on both paradigms and technological direction was our main objective

[1] For more information, see the online appendix: https://drive.google.com/drive/folders/1UzgvFjAa5Mvpr0Bcbw5M

in this study.

To do that, it was crucial to distance our theoretical and empirical approaches from the canonical models of technological change. Before the micro influence, skill-biased technological models were only considering two labor market tiers and two labor market effects delivered by technology. In the first tier, representing more educated workers, a productivity enhancement was assumed due to technology penetration while in the second, characterized by less-educated workers, it was expected a replacement effect. The modern theory came up with a different idea, they presented three (sometimes five) tiers where the technological impact is not determined by the workers' educational level but by the tasks they have been performing. In this scenario, for example, workers performing manual tasks, who are likely to end up being less educated ones, have been assigned with totally different effects. In the canonical model, it was stated that technology was replacing those workers while the modern theory has attributed it with productivity enhancements when facing technological impact[2]

In brief, we believe the polarization of the job market phenomenon should be studied because it could precede or be a sign of more complex phenomena in developing countries contexts. In the literature, polarization and wage inequality have been pointed out as associated phenomena. Notwithstanding, the rise of service jobs at the expense of industrial jobs on the Latin American background can potentially represent an income inequality worsening in the long-run and rise in job market informality once service jobs are synonym of informality for developing countries. These consequences could make the already complex Latin American structure we have been facing worse off through inequalities accentuation. As we have said, our general goal was to investigate compositional changes in the Brazilian labor market

[2]We could point out several examples but to have an idea every machine developed to assisting manual tasks, such as gardening machines, can be cited.

in the past 30 years. With this in mind, it is possible to say this task was successfully accomplished when we look at the empirical work performed. With regard to the raised hypothesis of polarization of the Brazilian job market induced by ICT and automation penetration, the basic findings we have here are consistent with research showing polarization patterns. Having said, this work join the works of Riva (2016), Maloney and Molina (2016), Machado (2017), Almeida et al. (2018) among others finding polarization patterns for the Brazilian labor market.

Despite that, it is also important to draw the readers' attention to some weak spots of this empirical work.

1) First of all, the lack of reliable data on the penetration of ICT for the Brazilian economy covering a significant period for structural change identification; this data would have made our empirical exercise stronger due to the use of an interaction variable.

2) Secondly, and this one has been highlighted by several authors when judging the task approach, the routine task index (RTI) used in this work was developed based on European occupations. In this sense, even tasks performed by occupations sharing the same title may vary across countries (for example, due to technology) what could diminish our model's accuracy.

3) Thirdly, the use of commuting zones as spatial unity instead of MCAs would have allowed for a lot better structural change phenomenon capture. However, the development of it requires far more time than it is been given for a master's thesis completion.

All things considered, the outcomes of this research are leading us to the following conclusions:

1) a fourth sector, the agricultural one, still plays a significant role in the Brazilian employment composition, and it has generated the possibility of both routine and service jobs to grow. The countries where job polarization was found showed a more homogeneous and mature composition on the labor market.

2) we also consider, though a not so strong effect on it, that abstract jobs due to GVCs and innovation dynamics of the past years may also have been contributing to this result. In this sense, we advocate that innovation and knowledge jobs are not headquartered in developing countries. Furthermore, industrial participation in the Brazilian GDP has been diminishing. The tier representing abstract jobs has likely been shrinking what contributes to the acquired results.

3) The offshoring hypothesis should also be tested in further research because it could represent an impact on this relationship once we experienced the so-called China effect.

4) Likewise, it is essential to point out that the regulatory framework can, at a certain level, determine the impact of these technologies on the labor market, i. e., it can limit or even mitigate the impact of technology as shown by Almeida et al. (2018). By regulatory framework, we mean: employment protection legislation, access to finance, the strength of collective bargaining, and minimum wage settings.

Once we have found a polarization pattern in our data, future investigations are necessary to validate the kinds of conclusions that can be drawn from this study. We do not have yet a computer, industrial robot, or another kind of technological penetration data that could have provided us with a reasonable period to capture structural changes. This situation will finally happen with the 2020 Brazilian census launching, for now, we did what was possible to advance on the subject. Still, we consider that this work can be a valuable source of knowledge for policy-markers.

In this sense, a future and deeper exercise is needed, and it might achieve further results by investigating the relationship between technology, labor market structural changes, wages polarization, and offshoring.

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APPENDIX A

Online Appendix:

https://drive.google.com/drive/folders/1UzgvFjAa5Mvpr0Bcbw5MCsqWyDvvn53L?usp=sharing

Table A.1: Service Occupations

Lis Code	Occupation Name
33	Teaching Associate Professionals
51	Personal And Protective Services Workers
52	Models, Salespersons And Demonstrators
61	Market-Oriented Skilled Agricultural And Fishery Workers
71	Extraction And Building Trades Workers
83	Drivers And Mobile-Plant Operators
91	Sales And Services Elementary Occupations

Table A.2: Service Occupations

Lis Code	Occupation Name	RTI Score
73	Precision, Handicraft, Printing And Related Trades Workers	1.742398
82	Machine Operators And Assemblers	0.6191809
72	Metal, Machinery And Related Trades Workers	0.5826445
93	Labourers In Mining, Construction, Manufacturing And Transport	0.5742638
74	Other Craft And Related Trades Workers	1.382539
81	Stationary-Plant And Related Operators	0.445601
42	Customer Services Clerks	1.555783
41	Office Clerks	2.410058

Grupos de ocupaciones BID	Correspondencia en Acemoglu y Autor (2011)	Tipo de tareas
• Gerentes y directivos	Gerentes y directivos	Tareas cognitivas no rutinarias
• Especialistas en operaciones financieras y negocios • Especialistas en ciencias matemáticas y computación • Especialistas en ciencias biológicas • Especialistas en ciencias sociales • Trabajadores sociales y similares • Abogados y similares • Especialistas de la educación • Bibliotecarios • Artistas y atletas • Técnicos de medios y comunicación • Profesionales de la salud	Profesionales	
• Técnicos en ciencias biológicas • Técnicos en ciencias físicas • Técnicos en ciencias sociales • Técnicos de la salud • Pilotos y controladores aéreos	Técnicos	
• Vendedores	Vendedores	Tareas cognitivas rutinarias
• Apoyo administrativo	Apoyo administrativo	
• Personal en la construcción • Personal en la industria extractiva • Instalación y reparación de equipo	Trabajadores en la producción de bienes	Tareas manuales rutinarias
• Operadores de maquinaria • Conductores de vehículos automotores	Operarios de maquinaria	
• Personal en servicios de seguridad	Personal en servicios de seguridad	Tareas manuales no rutinarias
• Limpieza y mantenimiento • Preparadores de alimentos	Preparadores de alimentos y limpieza y mantenimiento	
• Cuidado de terceros • Atención a clientes	Cuidado de terceros	

Figure A.1: IADB occupational classification