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IS THE BRAZILIAN LABOUR MARKET REGRESSING? AN EMPIRICAL AND THEORETICAL ANALYSIS OF UNEMPLOYMENT BETWEEN 2012 AND 2021

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Dissertação apresentada ao Programa de Pós-graduação em Economia do Centro de Desenvolvimento e Planejamento Regional, como requisito parcial à obtenção do título de Mestre em Economia.

Orientador: Prof. Dra. Mariangela Furlan Antigo
Coorientador: Prof. Dr Juan Pablo Gama Torres

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Depois, o incentivo à universidade pública foi fundamental: de uma adolescente crescida em um uma bolha nos diversos "Brasis" que marcam o nosso país, entrar na universidade pública foi fundamental para realçar a importância (marcada em casa) das políticas públicas, de um país menos desigual, com menores taxas de pobreza e com melhores prospecções futuras. O lado crítico, que já fazia parte da minha personalidade, foi aflorado por um ambiente instigante, que me fez entender que só podemos mudar, criticar e melhorar aquilo que estudamos a fundo e com base nas evidências científicas. Diante disso, meu segundo agradecimento não é específico à uma pessoa, mas à universidade pública de qualidade e que instiga o pensamento próprio. A UFMG me fez abrir caminhos para o meu próprio pensamento, abriu alas e contribuiu para o meu repertório. Diante de tempos difíceis, agradeço às instituições, principalmente às instituições educacionais públicas, porque a resistência e a educação, na minha opinião, são fundamentais para mudar o rumo de um país. Um Brasil menos desigual, na minha concepção de mundo, só é possível por instituições que resistem como a UFMG.

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Encerro com Clarice Lispector: "um dos indiretos modos de entender é achar bonito. Do lugar onde estou de pé, a vida é muito bonita. Entender é um modo de olhar. Porque entender, aliás, é uma atitude. O que a gente não entende, se resolve com amor."

Abstract

The main objective of this dissertation was to analyse unemployment, as well as to analyse the labour market dynamic considering socio-economic classification of occupations, through 2012 and 2021 in Brazil. Based on the "Continuous PNAD" interviews (the PNAD-C), carried by IBGE, it was possible to create a panel following the individuals and their dynamic within the labour market in more than one trimester. Three methods were employed: a multinomial logit model, survival analysis and a theoretical model. Mainly, the mean time in unemployment in Brazil increased during the analysed period. Worse still, results highlight that workers are entering unemployment and remaining in that position, thus indicating immobility within this state. Moreover, this immobility was also observed within other labour market states, as results for the multinomial logit model have shown higher probabilities of remaining in the same labour market state as of the first interview. The duration analysis has indicated that educational attainments might be intrinsically related to the ranking in socio-economic occupations: lower (higher) educational attainments result in higher chances of exiting unemployment and finding a lower (higher) socio-economic occupation. The outputs obtained in the parametric model indicate that being a woman, having lower educational attainments, not being in the position of head of the household and living in the North and Northeast regions of Brazil results in lower risks of finding a job. Finally, regarding the macroeconomic scenario, the probabilities of being unemployed and finding employment have been much lower from 2016 onward. Finally, results from the parameterized model have shown that firms are less likely to hire long-term unemployed individuals. Worse still, women and individuals with lower educational attainments suffer the most from the scarring effect. Those with lower educational attainments and in long-term unemployment not only face the stigma effect of finding a job, but they might be facing monetary hardships that also affect other aspects in life and well-being.

Key words: unemployment; duration; educational attainment; occupations; labour market;

Resumo

O objetivo principal desta dissertação foi analisar o desemprego, bem como analisar a dinâmica do mercado de trabalho considerando a classificação socioeconômica das ocupações entre 2012 e 2021 no Brasil. A partir das entrevistas da PNAD Contínua (PNAD-C), realizadas pelo IBGE, foi possível criar um painel acompanhando os indivíduos e sua dinâmica no mercado de trabalho em mais de um trimestre. Três métodos foram empregados: um modelo logit multinomial, análise de sobrevivência e um modelo teórico. No geral, o tempo médio de desemprego no Brasil aumentou durante o período analisado. Além disso, os resultados destacam que os trabalhadores estão entrando no desemprego e permanecendo nessa posição, indicando, assim, imobilidade dentro desse estado. Além disso, essa imobilidade também foi observada em outros estados do mercado de trabalho, pois os resultados do modelo logit multinomial apresentaram maiores probabilidades de permanecer no mesmo estado do mercado de trabalho a partir da primeira entrevista. A análise de duração indicou que os níveis de escolaridade podem estar intrinsecamente relacionados com a classificação nas ocupações socioeconômicas: níveis educacionais mais baixos (mais altos) resultam em maiores chances de sair do desemprego e encontrar uma ocupação socioeconômica mais baixa (mais alta). Os resultados obtidos no modelo paramétrico indicam que ser mulher, ter menor escolaridade, não ocupar o cargo de chefe da família e residir nas regiões Norte e Nordeste do Brasil resultam em menores riscos de encontrar emprego. Por fim, em relação ao cenário macroeconômico, as probabilidades de estar desempregado e encontrar emprego foram muito menores a partir de 2016. Finalmente, os resultados do modelo parametrizado mostraram que as empresas são menos propensas a contratar desempregados de longa duração. Pior ainda, as mulheres e os indivíduos com menor escolaridade sofrem mais com o efeito cicatriz. Aqueles com níveis educacionais mais baixos e desempregados de longa duração não apenas enfrentam o estigma de encontrar um emprego, mas também podem enfrentar dificuldades monetárias que também afetam outros aspectos da vida e do bem-estar.

Palavras-chave: desemprego; duração; níveis educacionais; ocupações; mercado de trabalho;

List of Figures

Summary

1 Introduction

A widely applied indicator in economics is the unemployment rate, as mismatches in supply and demand in the job market are invariably related to economic cycles. While recessions are marked by high rates of unemployment, good economic scenarios usually result in low rates of unemployment. In Brazil, the first decade of the 2000s was marked by low rates of unemployment due to the expansion of the economy and the implementation of social policies. During this period, there was a significant increase in the size of the formal labour market and in real income, and reductions in inequality and poverty levels. In 2014, Brazil's unemployment rate reached 6.6%, its minimum level in almost twenty years.This positive scenario led to the strong belief that in the following decade the Brazilian economy and, especially, the labour market indicators would continue to improve and that high rates of unemployment and extreme poverty would soon be regarded as part of the past. However, this proved not to be the case. By 2015, the Brazilian unemployment rate started increasing again. Reis (2019) called attention to the upward trend in unemployment since 2015, showing that in 2014 the unemployment rate was around 7%, and that by 2017 it had reached over 13%. To make matters worse, the Covid-19 pandemic has caused an even greater disruption to the Brazilian labour market, as it has dramatically increased unemployment rates. According to the IBGE (2021) (Brazilian Institute of Geography and Statistics), in the first trimester of 2021 the unemployment rate reached 14.7%, indicating that 14.8 million Brazilians are currently unemployed and suffering the consequences.

The sharp increase in the number of those unemployed has aggravated existing inequalities. Firstly, it causes a decrease in families' income, thus negatively imparting other social indicators, such as extreme poverty. According to Nassif-Pires (2021), the number of individuals expected to be (living) in poverty by the end of 2021 is 61.1 million, which represents 28% of the Brazilian population. Also, according to ILO (2021) the rise in the unemployment rate negatively impacts inequalities within the labour market. Groups that were previously more vulnerable (i.e.: women, youngsters and informal workers) were the ones that suffered the most the economic downturn.

Furthermore, workers who experience periods of unemployment during the recession can also have a long-term impact on future employment trajectories as a result of the "scarring effect" (ILO (2021)). The "scarring effect" or "stigma effect" is defined as the negative long-term effect that unemployment has on future employment trajectories. Firms are less likely to hire an unemployed worker (or a worker who has been unemployed), as they regard unemployment as a negative signal due to possible lower productivity rates (see Nickell (1979), Clark et al. (1979), Heckman and Borjas (1980), Vishwanath (1989), Blanchard and Diamond (1994), Acemoglu (1995)). Therefore, and according to ILO (2021), even after the improvement of the economic scenario, these effects may

persist in the labour market.

There may be serious consequences for unemployed individuals in the labour market. As there is a preference to employ persons who have experienced shorter periods of unemployment, those who have experienced longer periods of unemployment may take longer in transitioning from unemployment to employment. Hence, the unemployment exit rate is a decreasing function of duration (see Clark et al. (1979); Heckman and Borjas (1980); Jackman and Layard (1991)). Also, if workers go through long periods of unemployment, they might lose abilities and skills. Therefore, duration in unemployment can also result in human capital loss (Acemoglu (1995)).

Therefore, the unemployment rate is an insufficient parameter for shedding light on various dynamic relations within the labour market (ILO (2019a)). It is of utmost importance to analyse duration of unemployment and transitions from unemployment to employment (and vice-versa), especially regarding long-term unemployment. Blanchard and Diamond (1994), for example, have shown that there is a preference to employ persons who have experienced shorter periods of unemployment. Thus, the unemployment exit rate is a decreasing function of duration, indicating that the longer the duration of unemployment, the more difficult it becomes to transition from unemployment to employment (see Clark et al. (1979), Heckman and Borjas (1980), Jackman and Layard (1991), Acemoglu (1995), Biewen and Steffes (2010), Cockx and Picchio (2013), Van Belle et al. (2017)).

As this was an old issue resurfacing, there are few new studies covering unemployment and job search theory in Brazil nowadays. Given this circumstances, this dissertation aims to analyse the recent unemployment phenomenon in Brazil. The individual traits, the macroeconomic scenario and household aspects were considered, as they differently affect the duration of unemployment and the possibilities among labour market states. Furthermore, a microeconomic theoretical model of job search considering unemployment was developed in light of the Brazilian labour market features to assess long-term unemployment and its behaviour in the country. It is important to highlight, that to my knowledge there is no previous researches for the latter topic. Thus, it can be seen as a new tool for assessing long-term unemployment in Brazil and for developing public policies related to the topic.

Besides this introductory section, the dissertation is organized as follows: section 2 reviews the theoretical and empirical literature on unemployment, duration of unemployment and transitions within the labour market status. The following section (3) will present the different methodological approaches that were used in the thesis. Results were shown in section (4) and were followed by the theoretical model in section (5). Finally, section (6) concludes and discusses the implications of unemployment and its possible public policies.

2 Literature Review

2.1 Theoretical Review

In light of imperfect information, the job search theory's simplest model describes the behaviour of search for employment by an unemployed person who dedicates all of his efforts looking for a job. Albeit being oversimplified, the model is essential in understanding the dynamics of search and the unemployment spells. Therefore, the following basic model stems from Cahuc et al. (2014). In this model, the intensity of search is the same for all individuals and everyone has access to unemployment insurance benefits. Furthermore, once an individual is employed, one cannot look for another job. The key aspect is that the job-seeker does not know the exact wage of each job.

It is further assumed that the agent, the one looking for a job, is risk-neutral and disutility of work is not taken into account. Given that a job offer is represented by a constant real wage w, the instantaneous utility function of the individual is, therefore, w. Also, we suppose that a waged worker loses his or her job on a short interval of time at the rate qdt. In addition, the real instantaneous rate of interest is constant and exogenously given by r; then, therefore, the discount factor is given by $\frac{1}{(1+rdt)}$. The discounted expected utility of an employed person with wage w is equal to the discounted sum of the flow of income wdt and the discounted expected future income. The latter is given by the sum of the probability of the expected utility of continued employment, $(1-qdt)V_e$, and the complementary probability of the discounted expected utility of an unemployed individual, $(qdt)V_u$. This can be seen below:

$$V_e \frac{1}{(1+rdt)}[wdt + (1-qdt)V_e + qdtV_u] \tag{1}$$

it's important to highlight that V_e is the expected utility of an employed individual and V_u is the expected utility of an unemployed individual. Also, rearranging, the following expression will show that the expected flow of income will be equal to wage and an average income:

$$rV_e = w + q(V_u - V_e) \tag{2}$$

Equation 2 stems from the possibility of a change in the employee's status (either being unemployed or employed). Based on this, the discounted expected utility of an employee receiving a wage w (denoted by $V_e(w)$) is given by:

$$V_e(w) - V_u = \frac{w - rV_u}{r+q} \tag{3}$$

It is an increasing linear function of the wage offered. Also, the expected flow of income decreases with the discounted expected utility of an unemployed person. Thus, the optimal job

search strategy is either to keep looking for employment if the job-seeker does not receive any offer or to accept a wage offer if $V_e(w) > V_u$. The latter is based on the second relation, once an individual only accepts wage w if it is superior to a threshold x, known as reservation wage and denoted by the real instantaneous rate of interest multiplied by the discounted expected utility of an unemployed person.

Also, the arrival rate of job offers, given by λ, which is constant and exogenous represents the difficulties that arise from the job-seekers' search for employment. The costs related to the search for a job are given by a scalar, $c > 0$ and the gains associated with the search (such as unemployment benefits) are given by the scalar $b > 0$. Therefore, the net instantaneous income from the job search is represented by $z = (b - c)$. Hence, while the discounted utility expected upon receiving an offer of employment is expressed in the following manner:

$$V_\lambda = \int_0^x V_u \, dH(w) + \int_x^\infty V_e(w) \, dH(w) \tag{4}$$

in which the function $H(.)$ is the cumulative distribution of the possible wages, the discounted expected utility for an individual that continues on the job search is in the stationary state:

$$V_u = \frac{1}{1 + rdt}[zdt + \lambda dtV + (1 - \lambda dt)V_u] \tag{5}$$

Rearranging terms and multiplying both sides of 5 by $1 + rdt$ yields the job-seeker's discounted expected utility:

$$rV_u = z + \int_x^\infty [V_e(w) - V_u] \, dH(w) \tag{6}$$

It is possible to implicitly depict the reservation wage as a function of the parameters of the model. This is observable through the equation below.

$$x = z + \frac{\lambda}{r + q} \int_x^\infty (w - x) \, dH(w) \tag{7}$$

From this equation, the reservation wage has only one optimal value and it maximizes the intertemporal utility of a job-seeker. Moreover, the exit rate from unemployment derives from knowing the reservation wage and is given by $[1 - H(x)]$. Accordingly, the average duration of unemployment is thus equal to:

$$T_u = \frac{1}{\lambda[1 - H(x)]} \tag{8}$$

From this equation it is perceptible that the average duration of unemployment is an increasing function of the reservation wage. In addition, if the probability of a job-seeker getting a job is one out of ten, then this person will remain unemployed for ten weeks on average.

In order to analyse the comparative statics of the basic model, 7 can be re-written defining the reservation wage as it follows:

$$\phi(x, z, r, \lambda, q) = 0 \text{ and, therefore, } \phi(x, z, r, \lambda, q) = x - z - \frac{\lambda}{r+q}\int_x^{\infty}(w-x)\,dH(w) \quad (9)$$

Equation 8 sheds light in the direction of the variations in the reservation wage as a function of the parameters of the model:

$$\frac{\partial x}{z} > 0, \frac{\partial x}{\lambda} > 0, \frac{\partial x}{r} < 0 \; and \; \frac{\partial x}{q} < 0 \quad (10)$$

Based on 10 and 8 it is possible to deduce the comparative statics of the average duration of unemployment: $\frac{\partial T_U}{z} > 0$, $\frac{\partial T_U}{r} < 0$ $\frac{\partial T_U}{q} < 0$. These relations show that an increase in the net income from looking for work results in an increase in the duration of unemployment, given that a job-seeker with higher compensation will demand higher wages. Also, an increase in r is closely related to a person with a lower reservation wage, which reverberates in a decrease in the length of unemployment. Finally, an increase of the job loss rate indicates that the current demands of job-seekers diminish and, thus, decreases the average duration of unemployment. However, relation 7 has shown that an increase of the arrival rate of wage offers causes job-seekers to increase their reservation wage and, therefore, increases the average duration of unemployment. In this sense, Cahuc et al. (2014) highlighted that the direction of consequent change in the average duration of unemployment and in the exit rate from unemployment is unknown.

As search theory progressed, many assumptions of the basic model were relaxed. This abandonment of assumptions, aimed to better approach the reality of the search process. Based on economic theory, prior unemployment has a behavioural effect, as it may alter individual preferences and constraints in the future. These relationships produce true state dependence and explain that the greater the number of previous spells of unemployment and the longer their duration, the more likely an individual will be unemployed (Heckman and Borjas (1980)).

Heckman and Borjas (1980) developed a continuous-time model of heterogeneity which identifies four types of structural dependence, namely "Markovian", "occurrence dependence", "duration dependence" and "lagged duration dependence". On the first type of state dependence, the probability of becoming unemployed (or remaining in this position) differs between an employed worker and an unemployed worker. “Occurrence dependence” is when the number of previous spells of unemployment influences the worker’s probability of becoming or remaining unemployed. “Duration dependence”, which is the third type of state dependence, is when the length of the duration of unemployment influences the probability of remaining unemployed. Finally, “lagged duration dependence” is when the length of previous unemployment spells influences the probabilities of becoming or remaining unemployed.

In the Markovian dependence, an employed worker at time t is constantly on the risk of becoming unemployed and the instantaneous rate of entering unemployment from employment is $a_{12} = (-a_{11})$. The distribution of time to unemployment, F_{12} can be seen below:

$$F_{12}(y_{12}) = 1 - exp(-a_{12}t_{12}) \tag{11}$$

The density function is, therefore,

$$f_{12}(t_{12}) = a_{12}exp(-a_{12}t_{12}) \tag{12}$$

$$E(t_{12}) = \frac{1}{a_{12}} \tag{13}$$

Thus, this exponential function is both independent of the time of employment (the length of time in a spell does not influence the rate of transition) and of the time period in which the event happens (preceding spells do not affect the transition function).

In order to capture "occurrence dependence", Heckman and Borjas (1980) have modified the "waiting time" in the distribution function of time to unemployment (11). In this manner, they have indexed the instantaneous probability of transiting to employment from a current state of unemployment by the number of spells of employment up to the current spell. Also, they have adjusted the transition rate from one state to another to include the number of previous spells of unemployment and the number of previous spells of employment.

Also, Heckman and Borjas (1980) determined "lagged duration dependence" by the nature of the statistical dependence of the exit times of employment and unemployment spells. This type of dependence allows to see how previous spells of unemployment have influenced subsequent unemployment spells.

Finally, in order to analyse "duration dependence", the authors have used the concept of the hazard function, which is "the conditional density of exit time from a state given the amount of time spent in the state in the current spell" (Heckman and Borjas, page 254, 1980). There is a "duration dependence" if the hazard function depends on the length of time in the current spell. There is a negative duration dependence if

$$\frac{\partial h_{ij}(t_{ij})}{\partial t_{ij}} < 0 \; i, j = 1, 2, i \neq j \tag{14}$$

Equation 14 implies that the longer the worker is unemployed, the longer he/she will remain in this state given that there is a decrease in the probability of leaving unemployment. A positive

duration dependence, however, occurs when the inequality is reversed. As it was stated in Cahuc et al. (2014), a decrease in the reservation wages results in a positive duration dependence.

Nickell (1979) was interested in understanding which were the causes of the enormous variation in the duration of spells of unemployment: while some individuals presented only weeks of unemployment, others presented years of unemployment. He analysed the unemployment for males in Britain using data from the General Household Survey in 1972. The author estimated the conditional probabilities of an individual leaving unemployment and then used those probabilities to understand the expected durations of unemployment. Results have shown different probabilities of leaving unemployment over the duration of an unemployment spell. Also, and in accordance with Heckman and Borjas (1980), he has found negative duration dependence, as the probability of transitioning from unemployment to employment decreases considerably after six months.

Clark et al. (1979) highlighted that brief spells of unemployment or "normal turnover", only represents a small part of measured unemployment. In fact, most of the measured unemployment is associated with long-term unemployment (longer unemployment spells). This is due to the difference between the mean expected duration of completed spells of unemployment and expected unemployment duration. Therefore, the higher frequency of unemployment among unemployed workers with shorter spells of unemployment and the apparent brevity of completed spells of unemployment does not imply that most unemployed workers will quickly transition to employment.

In the same line, Abraham et al. (2016) have created a matched employer-employee dataset for American workers between 2003 and 2010 using the CPS and individuals' labour force status, in order to analyse unemployment in the United States. Results have shown that long-term unemployed workers experienced worse employment conditions when compared to short-term unemployed. Furthermore, long-term unemployed workers present higher earning losses conditional on being employed than short-term unemployed.

Also, workers who have experienced long-term unemployment suffer a depreciation in their skills (loss of human capital). Based on this fact, Acemoglu (1995) developed a model in which unemployed workers can choose how much of their skills set to maintain given an incurred cost, in order to understand just how skill loss influences the labour market and to assess the formulation of long-term unemployment policy.

The model, therefore, endogenizes the loss of skills during unemployment and two equilibria are possible: no-skill equilibrium and skill-loss equilibrium. On the former equilibrium, the length of time the worker is unemployed does not affect hiring decisions. Hence, there is no discrimination and unemployed workers choose not to lose their skills, and are, therefore, hired. The second equilibrium shows duration dependence, for the long-term unemployed who have lower exit

probabilities than the short-term unemployed. Long-term unemployed workers anticipate workplace discrimination and choose not to maintain their skills and not to incur the necessary cost to maintaining their skills, to obtain employment in the 'skilled' sector. As a result, the long-term unemployed are discriminated against in the 'skilled' sector and are not hired. The resulting skill-loss equilibrium results in higher steady-stead unemployment and lower welfare, which may indicate the need for public policy (if one doesn't already exist).

Clark et al. (1979) have indicated that part of the observed joblessness can be explained by prolonged periods of inability or unwillingness to locate employment. On this matter, Coles and Smith (1998) developed a model of marketplace matching, known as stock-flow model, in order to understand the type of matching behaviour between unemployed workers and vacancies in the English labour market, between 1987 and 1995. Results emphasize changes in search behaviour: over time, unemployed workers may have fewer vacancies to apply to or become discouraged and reduce their search intensity. Furthermore, there was a strong correlation between the exit probabilities of unemployed workers for less than two weeks with the stock of vacancies.

Biewen and Steffes (2010) also highlighted the importance of analysing long-term unemployment, as the loss of human capital and stigmatization of those unemployed workers may result in inactivity. On this topic, Flinn and Heckman (1983) have shown that transitioning from unemployment to employment is behaviourally distinct than transitioning from being out of the labour force to employment. The exit rate from unemployment to employment is higher than the exit rate from being out of the labour force to employment. Using data from the National Longitudinal Survey of Young Men, they tested if the classifications unemployed and out of the labour force were behaviourally meaningless distinctions and rejected this hypothesis.

Mainly, authors have emphasized the negative duration dependence associated with unemployment: the longer a person remains unemployed, the more likely this person is to remain in this state. There is a decrease in the probability of leaving unemployment. Furthermore, the number of previous spells may also influence this probability. As a consequence, long-term unemployed workers experience worse re-employment conditions and, thus, lower exit probabilities than short-term unemployed workers.

Hence, there's a stigma associated with unemployed workers that has been widely explored within the scenario of imperfect information and signalling theory. The duration of unemployment and, especially, the duration of long-term unemployment have a negative effect, known as the "stigma effect", on the probability of obtaining a job (see Clark et al. (1979); Heckman and Borjas (1980); Vishwanath (1989); Blanchard and Diamond (1994); Acemoglu (1995)).

Within the scope of screening models, Vishwanath (1989) developed a job search model

incorporating the "stigma" effect of unemployment. In this model, an unemployed individual seeks employment. This search might result either in a match with a firm or in a decision to keep looking for another position in the labour market. There is only a match if the test (or interview) applied by the firm has a positive outcome. The optimal result of this model shows that an individual's probability of finding employment decreases the longer he/she remains unemployed. Thus, the duration of unemployment of an individual is a signal of the lower productivity (of that individual) for the firms and can lead to some form of discrimination in the hiring process.

Applying a different method, Blanchard and Diamond (1994) also analysed how the duration of unemployment affects the employability of individuals and how wages are determined in the labour market. To observe the employer's preference in hiring, a ranking model is associated with the matching process of job creation and destruction. Since vacancies may have more than one application, firms rank applicants according to the duration of unemployment. Results have shown that there is a preference in employing persons who have experienced shorter periods of unemployment. Therefore, the unemployment exit rate is a decreasing function of duration. While there are some advances in the theoretical approach, the model only considers duration of unemployment when firms rank, and this is a rather simplistic view of reality. For example, real firms would also consider observed heterogeneity (i.e.: race and gender) in the hiring process.

Accordingly, Lockwood (1991) developed another screening model, in which firms imperfectly test (or interview) job applicants in order to obtain information about their prospective employees. If this strategy is employed by the firms, the higher the worker's productivity, the faster he/she would exit unemployment. Therefore, when the length of the unemployment spell is long, employers consider it as a signal of lower productivity. In agreement with Vishwanath (1989), in the model's equilibrium, firms prefer not to hire workers with high unemployment durations.

As the business cycle affects the dynamics of the labour market, it also influences the duration of unemployment. Lockwood (1991) has found that the length of the unemployment spell is affected by demand and supply, being longer when there is a negative demand shock. Kroft et al. (2013) have also found that duration dependence is stronger when the labour market is tight, indicating that employers use the length of unemployment to capture worker's unobserved productivity.

Ljungqvist and Sargent (1998) also considered skill loss when developing a human capital model to analyse high rates of long-term unemployment in welfare states from the 80s onwards. The search model considered that workers' skills depreciate over their unemployment spells (skills lost at layoffs) and unemployment benefits are determined by workers' past earnings. Duration dependence and heterogeneity are determinants on the probability of leaving unemployment (Ljungqvist and Sargent (1998)). Results have shown differences between tranquil times and turbulent times in the

depreciation of skills during spells of unemployment. While during tranquil economic times the skill lost is slow and does not influence the amount of long-term unemployment, turbulent times results in instantaneous loss of skills at layoffs.

Likewise, Biewen and Steffes (2010) employed a random-effect probit model to analyse the existence of stigma effects considering labour market cycles for the German labour market between 1991 and 2004. Results have indicated stigma effects: past unemployment increases current unemployment risk. They found a strong correlation between the stigma effect and the state of the labour market, indicating that the stigma effect is higher when the unemployment rate is low than when the unemployment rate is high.

Recently, audit studies have been used to understand the relation between job search outcomes and the duration dependence of unemployment. Mainly, they have shown that long-term unemployment is viewed as a negative signal by employers, as individuals with longer unemployment spells received fewer call-backs than job applicants with identical traits, but shorter unemployment spells.

Kroft et al. (2013) analysed, through a field experiment, how the employers' behaviour affected the adverse effect of long-term unemployment in 100 U.S cities. The authors have sent fictitious resumes to real job postings (medium/low skill jobs) between 2011 and 2012, varying the length of the unemployment spell between 0 (employed) and 36 months. Results have shown duration dependence, given the decrease in the call-back rate for long unemployment spells.

In Sweden, Eriksson and Rooth (2014) conducted a field experiment in the Swedish labour market in 2007, including high skill and medium/low skill occupations. As in Kroft et al. (2013), they have found a negative duration dependence of unemployment and, partly, this was explained by employers' reluctance to hire long-term unemployed. When the length of the duration of unemployment was longer than nine months for medium/low skill jobs, employers regarded it as a negative signal, showing the existence of stigma effects for long-term unemployment for medium/low skill jobs. However, this negative effect for long-term unemployment spells is not found for highly educated workers. Differently from what Heckman and Borjas (1980) predicted in their continuous-time model of heterogeneity, Eriksson and Rooth (2014) haven't found "lagged duration dependence" to be an important factor in the employers' hiring decision in Sweden.

Van Belle et al. (2017) have proposed a vignette experiment in which human resource professionals make fictitious hiring decisions related to job candidates with different durations of unemployment, in order to understand employee's reluctance to hire long-term unemployed workers (thus, employee's hiring decisions) in Belgium in 2017. Those workers were assessed based on four theoretical explanations for the unemployment scarring effect, namely signalling theory (information

as a signal), skill loss (costs of maintaining skills while unemployed), queuing theory (employers rank job candidates by the observed traits) and rational herding (employers follow the behaviour of other employers when contracting employees) and, then, a multiple mediation model was estimated. Results have demonstrated that as the duration of unemployment increases, the chances of being invited for an interview decreases, thus indicating a long-term unemployment scarring effect related to employer's preferences on hiring. Employers see long-term unemployment as a signal of lower intellectual and lower motivation, and they also attribute it to lower productivity. The perceived skill loss and queuing based on perceived trainability had a small mediating role on the results.

To understand how unemployment duration, age and interim job status affected call-back rates to job applications, Farber et al. (2019) fielded a resume audit study, in 2017, in eight American cities. Among those cities, half had low unemployment rates and the other half had high unemployment rates to capture how regional and unemployment rate differences influence job search outcomes. They have designed a mechanism that randomly assigned real job advertisements with fictitious women with a similar education (college graduates from a non-elite public university or college). Also, applications were limited to collar office positions, which were either classified as a high skill job or as a low skill job. Results have shown that applicants who were unemployed for 52 weeks had call-back rates that were 2.5% lower than those with shorter unemployment spells (24 weeks of unemployment). They also have found that there's a negative effect of holding an interim job when applying to a high-skilled position. Finally, the authors did a multivariate analysis to understand the probabilities of a call-back considering the same traits applied in the univariate analysis. In the same line, results have shown that the call-back probability for those individuals unemployed for 52 weeks were 20% smaller than those with shorter periods of unemployment.

From the theoretical review it is possible to say that the duration of the unemployment negatively influences the probability of an individual transitioning from unemployment to employment. Moreover, firms view the duration of unemployment of a worker as a signal of lower productivity, resulting in the "stigma effect". Therefore, firms may use information on unemployment to discriminate against workers in the hiring process. According to the review, this can be even worse for long-term unemployed individuals. The heterogeneity amongst workers may also influence the probability of leaving unemployment: different traits may result in different duration of unemployment and in faster/slower transitions within the labour force status.

Regarding individual traits, older individuals tend to remain longer in unemployment than younger individuals (Nickell (1979); Clark and Summers (2007)). Clark and Summers (2007) have shown that white unemployed youngsters present lower unemployment duration than nonwhite unemployed youngsters, indicating substantial differences regarding race. The same study also suggests that youth's unemployment is affected by the labour market condition, highlighting the need

to analyse the macroeconomic scenario. When it comes to household factors, Nickell (1979) has shown that being married increases the duration of unemployment. Also, an increase in the number of children in the household, increases the duration of unemployment. Finally, Eriksson and Rooth (2014) have shown that there are differences in unemployment spells for different schooling levels: highly educated workers do not face the stigma effect for long-term unemployment in Sweden.

2.2 Brazilian Empirical Review

There are substantial differences in the duration of unemployment, within a specific period, amongst Brazil's various regions. In the analysis of Bivar (1993), Menezes-Filho and Picchetti (2000), Antigo and Machado (2006) and Andrade (2004), we can notice that the average duration of unemployment differs according to the period and the metropolitan area or region in analysis in Brazil. For the metropolitan area of São Paulo, using the PME (Monthly Employment Survey), Bivar (1993) has shown that the average unemployment duration, between 1983 and 1990, was 6.2 months and Menezes-Filho and Picchetti (2000) has found that the average duration of unemployment was 6.64 months in 1997. Antigo and Machado (2006), for instance, have found that the average duration of unemployment in the metropolitan area of Belo Horizonte was 3.69 months between 1997 and 2001. Finally, Andrade (2004) has estimated that the average duration of unemployment was 22 months between 1997 and 2003 in the metropolitan region of Salvador. Those results indicate that, even for similar periods, there are substantial regional differences in the duration of unemployment in Brazil.

Accordingly, Ferrari and Brasil (2015) analysed if there were regional disparities amongst unemployment rates in all twenty seven Brazilian federal units using microdata from PNAD between 1992 and 2012. In order to do that, they tested if there were unit roots in the panel. They have estimated a fixed-effect autoregressive model to observe if the unemployment rate in the federal units converged to a national equilibrium or to a specific equilibrium for each region. Results have shown that each Brazilian State presents a specific natural unemployment rate, indicating different equilibriums. Therefore, regions differently affect unemployment, suggesting attentive analysis for each Brazilian region.

More recently, Oliveira and Carvalho (2016) analysed regional labour market differences in Brazil through an equilibrium job search model where firms may differ in terms of labour productivity (continuous productivity dispersion). They have used data from the 2009 PME (Monthly Employment Survey) to estimate the parameters of the theoretical models. In this model, two forms of wage determination were tested and the authors have found that bilateral bargaining was more suitable for the Brazilian labour market. Based on the estimation of frictional parameters and on the bilateral bargaining, they were able to recover the unobserved productivity distribution associated

with the observed wage distribution. Results have shown regional inequalities on unemployment rates and on search frictions. It's interesting to highlight that the results indicate that part of regional unemployment rate inequality can be explained by the arrival rate of job offers while employed (search frictions). Metropolitan areas in the South or Southeast regions had higher arrival rate of job offers while employed and higher arrival rate of job offers while unemployed than metropolitan areas in the Northeast.

Those studies indicate substantial differences among regions, indicating that unemployment and its duration may differently impact each region. As Brazil is an extremely heterogeneous country, regional discrepancies shall be included in the analysis. Furthermore, it seems pertinent to analyse how the Brazilian economic literature defines the relation between individual traits and the duration of unemployment or unemployment transition. Different characteristics may result in longer or shorter transition periods from unemployment to employment. For example, in general, women's duration of unemployment is longer than men's duration of unemployment (Barros et al. (1997); Andrade (2004); Antigo and Machado (2006); Reis and Aguas (2014)).Therefore, women are less likely to transition from unemployment to employment.

Different ages affect the duration of unemployment differently. According to Barros et al. (1997) and Antigo and Machado (2006), young people tend to have higher unemployment rates than adults. However, the probability of leaving unemployment decreases with age (Barros et al. (1997)). Andrade (2004) have shown that youngsters experience shorter durations of unemployment because they usually have informal, and therefore unstable, jobs in the labour market. Reis (2019) found that when unemployment rates are low, the probability of young people transitioning from unemployment to employment is higher. This probability disappears when unemployment rates are high.

In a more specific study, Reis (2015) analysed youth's unemployment duration in Brazil between the entrance in the economically active population and the first job. In order to estimate duration models, he used data from the PME for the six largest metropolitan areas between 2006 and 2012. Three groups were compared: youngsters between 15 and 24 years old that have never worked; youngsters in the same age that have worked before; and individuals between 25 and 60 years old who have had obtained a job before. Results have shown that youngsters that never have worked presented a higher probability of remaining unemployed. This result is even worse for jobs in the formal labour market and for a full-time job.

Regarding race, Andrade (2004) has found that the average duration of unemployment for black people was higher than for white people in the metropolitan area of Salvador between 1997 and 2003. According to the authors, this situation reflects discrimination against black people in the labour market. Conversely, Arruda et al. (2017) have shown that there is a lower probability

of black workers facing long-term unemployment in the South and Southeast regions of Brazil in 2013, due to the fact that such workers have lower reservation wages. In addition, Reis and Aguas (2014) have shown that the probability of transitioning from unemployment to an informal job was 10% higher for black workers than for white workers. They have also shown that black workers tend to transition more to vulnerable jobs that were not secured by social security. Although those results might be different in different periods, they do indicate that black workers tend to be more vulnerable to unemployment than white individuals.

When analysing educational attainment, the relation between the unemployment rate and education has an inverted U-shape. Barros et al. (1997) have demonstrated that unemployment rates increase from 0 to 7 years of study and then decrease. The duration of unemployment, however, increases as educational levels increase (Barros et al. (1997); Menezes-Filho and Picchetti (2000); Andrade (2004); Antigo and Machado (2006); Reis (2019)). This can be related, according to Menezes-Filho and Picchetti (2000), with higher reservation wages, given that higher educational levels are usually associated with higher wages. Reis (2019) has found that the macroeconomic scenario affects the differences in probabilities between educational groups. When the labour market condition is negative, the differences between persons with higher education and those with lower education decreases. This might result from a decrease in job opportunities to those with lower educational levels or a behavioural change in individuals with higher educational levels. This change in the behaviour would be the willingness to accept job offers that highly educated individuals wouldn't accept in a good economic scenario of the labour market.

When it comes to the position in the household, the expected household chiefs' unemployment duration is lower than other household members (Menezes-Filho and Picchetti (2000); Andrade (2004); Monte et al. (2009); Arruda et al. (2017);). In addition, Barros et al. (1997) have demonstrated that unemployment rates are higher for individuals in the position of son/daughter in the household. Also, Oliveira et al. (2009) have shown that household chiefs present lower unemployment and inactivity rates than persons in the position of son/daughter in the household. Also, an increase in the number of children in the household increases the probability of unemployment and inactivity for women, while this probability decreases for men.

Scherer et al. (2017) have analysed the household chiefs' unemployment duration for the six biggest metropolitan areas using the PME (Monthly Employment Survey). Results have shown that the household chiefs' unemployment duration is longer in Salvador and Rio de Janeiro. Moreover, the probabilities of finding employment are higher in the metropolitan areas of Belo Horizonte and Porto Alegre. Regarding individual traits, they have shown that male household chiefs present higher chances of finding a job than women household chiefs in the six biggest metropolitan areas in Brazil. Furthermore, the household chiefs' unemployment duration increases as educational levels increase.

The macroeconomic scenario might positively or negatively affect the unemployment duration (Menezes-Filho and Picchetti (2000); Antigo and Machado (2006); Nunes et al. (2016); Reis (2019)). Antigo and Machado (2006) have found that in a biennium with economic crisis the probability of obtaining a job was smaller than in the biennium with a positive economic scenario. In a recent study, Reis (2019) used the Continuous PNAD to analyse the probability of transitioning from unemployment to employment in different Brazilian labour market scenarios between 2012 and 2017. The probability of remaining unemployed after one year was 56.1% and after two years this probability was 33.2% in the analysed period. This indicates that survival in unemployment tends to be long. While 2012 and 2013 were marked by low unemployment rates within a positive economic scenario, in 2016 and 2017 unemployment rates were comparatively higher, as the economic background had worsened. Results have shown that the probability of remaining unemployed after searching for a job for one year was 10.4% higher in 2016 than in 2012 (52.8% in 2012 and 63.2% in 2016).

In a different analysis, Nunes et al. (2016) observed transitions between employment and unemployment throughout economic cycles. Based on the PME, they have analysed the six biggest metropolitan areas in Brazil during two periods: between 1983 and 2001 and between 2002 and 2013. The authors have analysed aggregate probabilities of job admissions and the variation on the probabilities of job lay-offs throughout time. Results have shown that 75% of the cyclical variations of unemployment in the metropolitan areas were due to fluctuations on the job admission's probabilities between 1983 and 2001. This number increased to 80% between 2004 and 2013. Therefore, they have found that the unemployment rate behaviour depends more on the job admission rate.

The economic scenario also influences transitions from unemployment to formal jobs. According to Reis (2019), between 2016 and 2017 (negative economic scenario) the probability of transitioning from unemployment to a formal job was 12.3%, while between 2012 and 2013 (positive economic scenario) the probability of transitioning from unemployment to a formal job was 20.6%. It is the same when analysing transitions from employment to informal jobs, but the difference isn't as significant as it is for transitioning to formal employment. Finally, Reis (2019) has shown that the probabilities of transitioning from unemployment to better quality employment are lower when unemployment rates are higher. The decrease in the probabilities of transitioning from unemployment to low quality jobs are smaller than the decrease in the probabilities of transitioning from unemployment to better quality jobs in a bad economic scenario. Therefore, low-quality jobs are easier to attain than high-quality jobs (associated with higher wages) in a negative economic scenario.

Santolin and Antigo (2020) have shown, through a productivity shock in the economy, the

relation between wage flexibility, real wages and long-term unemployment. The authors have created a pseudo-painel using the PNAD data between 2001 and 2015 for six metropolitan areas of Brazil, namely São Paulo, Rio de Janeiro, Belo Horizonte, Salvador, Recife and Porto Alegre. It is important to highlight that the analysis was done for the formal labour market. Firstly, the authors have found that in the presence of short run unemployment (productivity shocks), the flexibility in the worker's real wages was small. Also, the results suggested that white individuals, those aged between 35 and 49 years old and those with higher schooling levels presented higher wage-unemployment elasticities. Therefore, the unemployment rate's impact was higher on the wage of individuals with those traits in economic fluctuations. Results have shown that, on average, males, white individuals and those with higher schooling levels (more than nine years of study) presented higher wage rates and lower unemployment rates. Oppositely, women, non-white and those with lower schooling levels (zero to four years of study) presented lower wage rates and higher unemployment rates between 2001 and 2015. As for long-term unemployment, the authors haven't found any evidence on the influence of individual traits on the duration of this state.

Many authors have also studied how unemployment affects re-employment wages. For instance, Monte et al. (2009) analysed which variables influenced the recently occupied person's wage considering the time of the job search when this individual was unemployed. The authors have used the 2000 PME (Monthly Employment Survey) to compare the wage of those who were employed with the wage of those who were unemployed and obtained a job in the six biggest metropolitan areas. Also, they have used quantile regressions to verify how the duration of unemployment influenced their income. Results have shown that workers who were unemployed and obtained a job received, on average, 30% less than those who were never unemployed. This clearly indicates a penalty for individuals who were unemployed for a period of time. In accordance, they have found that each additional month in unemployment resulted in a decrease of approximately 3% on the future wage. Therefore, the higher the duration of unemployment, the lower the wage in a future job. This effect is worse between those with higher schooling levels and those in the top quantiles of the conditional income distribution. As an example, an additional month in unemployment for those in the 0.9 quantile produced a 3.6% difference on the wage in comparison to those employed. Meanwhile, an additional month in unemployment for those in the 0.1 quantile resulted in a 1.4% difference on the wage in comparison to those employed.

Accordingly, Reis (2021) used the Continuous PNAD data to analyse how transitions from employment to unemployment affected re-employment earnings in Brazil over the Brazilian business cycle between 2012 and 2017. A difference-in-difference model and a propensity score matching model were applied and results have shown that transitioning from employment to unemployment during a negative economic scenario yielded a decrease between 10% and 15% in re-employment

earnings. According to Reis (2021) this loss may be due to the re-employment in the informal economy vis-à-vis the prior employment in the formal economy. Also, workers who have become unemployed in a negative job market scenario tend to be unemployed for a longer period than those who have become unemployed in a positive economic scenario.

Within the labour force status dynamics, it is also important to analyse two possible transitions: those individuals who become discouraged and those who become inactive. On this matter, Aguas et al. (2014) analysed the behaviour of discouraged individuals (those that are not working or searching for a job, but are willing to work) and their dynamic in the labour force status. They have tested if discouraged persons have a similar transition behaviour to unemployed persons or if their behaviour is similar to inactive individuals. In order to do that, the authors used data from PME between 2003 and 2008 for the six largest metropolitan areas in Brazil. Results have shown that discouraged and inactive work-seekers are behaviourally different when considering the labour market dynamics and its transitions. According to the authors, the willingness to work of discouraged individuals implies an increase in the probability of transitioning to employment in the future.

The worst scenario when analysing the dynamics in the labour force status is associated with inactivity, because persons outside the labour force may not only lose human capital, but also lose labour income. In this line, Oliveira et al. (2009) analysed how different socioeconomic traits influenced the probabilities of unemployment and inactivity for male and females in Brazil. They have used the 2004 PNAD (National Household Sample) to estimate a multinomial logit of the associated probabilities of unemployment and of those out of the labour force in the Brazilian metropolitan areas. Results have shown that there was an inverse relation between schooling levels and inactivity rates: those with higher schooling levels had a higher opportunity cost for being outside of the labour force. Furthermore, women (especially black women) presented higher inactivity rates than men.

Barbosa (2019) has shown, using the Continuous PNAD, that the increase of inactive and unemployed workers since 2015 in Brazil yielded an increase in the share of individuals without labour income, contributing to the increment of income inequality. Moreover, Reis and Aguas (2014) have shown, using the PME, that between 2006 and 2013 individuals with longer unemployment spells were more likely to transition from unemployment to inactivity. Amongst those who were unemployed for less than a year, 31.5% transitioned to inactivity. This rate raised to 40%, considering individuals facing unemployment for over two years.

In conclusion, Bacciotti and Marçal (2020) have done a backcalculation exercise of the unemployment rate time-series using the Continuous PNAD. Therefore, they have reconstructed the unemployment rate using the PNAD since 1976 and estimated the missing values of the unemploy-

ment rate of the Continuous PNAD with unobserved component models represented in time-space using the Kalman filter. The obtained time-series, which goes from 1976 to 2016, indicated that the unemployment rate has reached its peak in 2016. The authors highlighted that even in other recessive economic periods, throughout the analysed period, the unemployment rate has not been as high as in 2016. This highlights the importance of analysing unemployment in Brazil. Moreover, it seems pertinent to analyse the duration of unemployment and transitions from unemployment to employment (and vice-versa).

As it was possible to see in the Brazilian Empirical review, it is important to consider individual, household and macroeconomic factors when analysing the duration of unemployment. Those traits might differently impact unemployment and its duration. Furthermore, albeit few studies focusing on the Brazilian unemployment recent, this is a matter of great importance, as unemployment may result in serious consequences for individuals in this situation and for society.

3 Methodology

BRAZILIAN DATA

The so called "Continuous PNAD" (henceforth, the PNAD-C), carried by IBGE (Brazilian Institute of Geography and Statistics), provides continuous information concerning demographic and educational features of the Brazilian labour market. Geographically, it covers Brazil and its macro-regions, federal units, and metropolitan areas. Hence, to better comprehend unemployment and its dynamic in Brazil , this survey, between the years 2012 and 2021, was analysed. Furthermore, as literature shows that the labour market differently affect youth and adults, this analysis focuses on adults aged between 30 and 64 years old.

The sample is characterized by repeated cross section data that enables the following of a cohort overtime, and the interviews adhere to a 1-2(5) rotating scheme. Each household is interviewed five times throughout five trimesters, being interviewed for one month and then leaving the sample in the following two months. As this rotation scheme is repeated five times, it is possible to create a panel tracing the individual. This can be seen in the table below.

Table 1: Rotating scheme of the Continuous PNAD

	PANEL																										
Month/Yr	**A1**	**B1**	**C1**	**D1**	**E1**	**F1**	**G1**	**H1**	**I1**	**J1**	**K1**	**L1**	**M1**	**N1**	**O1**	**A2**	**B2**	**C2**	**D2**	**E2**	**F2**	**G2**	**H2**	**I2**	**J2**	**K2**	**L2**	**M2**
Jan./2018	5			4			3			2			1															
Feb./2018		5			4			3			2			1														
Mar./2018			5			4			3			2			1													
Apr./2018				5			4			3			2			1												
May/2018					5			4			3			2			1											
Jun./2018						5			4			3			2			1										
Jul./2018							5			4			3			2			1									
Aug./2018								5			4			3			2			1								
Sep./2018									5			4			3			2			1							
Oct./2018										5			4			3			2			1						
Nov./2018											5			4			3			2			1					
Dec./2018												5			4			3			2			1				
Jan./2019													5			4			3			2			1			
Feb./2019														5			4			3			2			1		
Mar./2019															5			4			3			2			1	
Apr./2019																5			4			3			2			1

Source: Own elaboration based on the PNAD-C.

In this table, it's possible to see that there are 15 groups in the rotating scheme and, in each month, there are five groups (A1, D1, G1, J1 and M1) in different interviews. As an example, the group M1 had its first interview in January 2018 and its last (fifth) interview in January 2019. The households in M1 were replaced by the households in M2 in April 2019, being, therefore, this group's first interview.

Given that IBGE does not provide the individual identification, we employed a similar

methodology to Ribas and Soares (2008) track the individual and, thus, create a panel for the Continuous PNAD. We have used individuals' date of birth (day, month, and year), sex, UF (federation unit), UPA (primary sampling unit), stratum, household number and panel number, as those traits are the same throughout time, to match cross-section data from the interviews. This panel was developed in a study group from PEDES at CEDEPLAR. It results from the effort of Ana Maria Hermeto, Mariangela Furlan Antigo and me.

Table 2 compares the panel size and the first interview to shed light on the created panel. As panel data involves repeated observations, it is possible to have partial response in the interviews, meaning that survey respondents do not continue to provide responses in the following interviews or may miss one or more interviews but return later. Hence, this partial response, also known as sample attrition, results in missing data. As individuals in deprived situations may be more likely to drop out of the panel sample, this missing data may lead to attrition bias (sample may be unrepresentative) (Cameron and Trivedi (2005)). Therefore, it is expected that the use of panel data for certain types of economic analysis may impart in a slightly optimistic outlook, when compared to cross-section analysis.

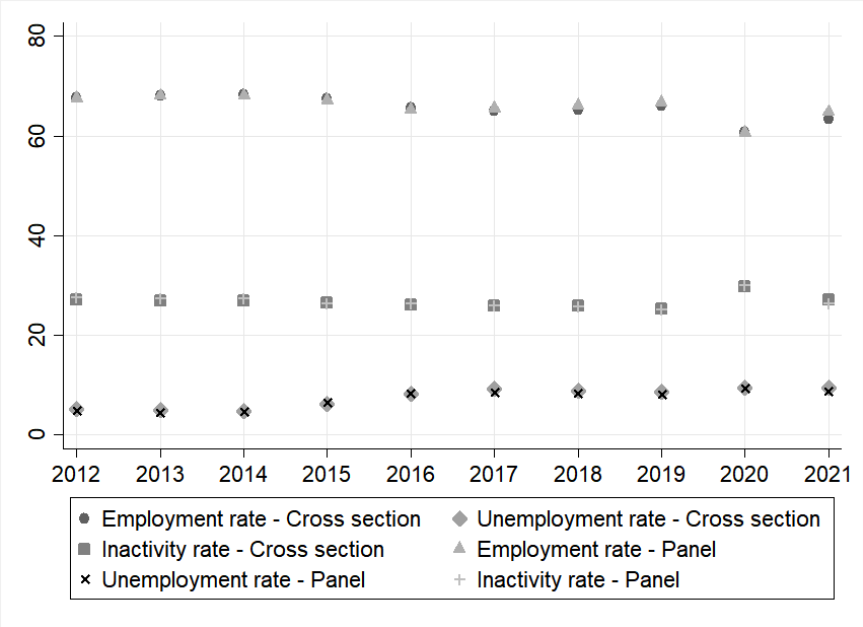
Table 2: Comparison between the panel size and the first interview

	Interview	Number of obs.	Panel size	Data loss	Panel only with adults (30 to 64 years old)
	1st	4174244			
Panel following the	1st and 2nd	3193774	76.511	23.489	2.008.983
	1st, 2nd and 3rd	2833589	67.883	32.117	1.780.449
	1st, 2nd, 3rd and 4th	2560487	61.340	38.660	1.607.691
	1st, 2nd, 3rd, 4th and 5th	2338383	56.019	43.981	1.467.502

Source: Own elaboration based on the PNAD-C.

Considering that between the first and the second interview there is 23.48% of missing data in the panel, it is feasible to analyse its potential selection bias by graphically comparing indicators in the cross-section data with the panel data from the PNAD-C (figure 1). If both present the same trend in the graphical analysis, this could indicate that the panel is not adding much bias to the sample. Referred in the graph below, three indicators related to the labour market have been used to check for potential bias: the employment rate, the unemployment rate, and the inactivity rate. In agreement with the previous discussion, the panel data is slightly optimistic when compared to the cross-section data, but both types of data analysis follow the same trend. Hence, this graphical analysis leads to the conclusion that the panel is not adding considerable bias to the data and, thus, will not lead to erroneous conclusions.

Figure 1: Indicators in the cross-section and panel data, 2012-2021, Brazil.



Source: Own elaboration based on the PNAD-C, 2012-2021.

Some further methodological aspects shall be considered before proceeding to employed methods and results. In the analysis, an occupational classification hierarchy (OCH) was used based on Jorge et al. (2016) and on the 2002 Brazilian Classification of Occupations (CBO). The table below contains the job's occupational group and the associated classification[1]. In this framework, occupations are organised within a hierarchical structure according to the function performed in the CBO and groups are aggregated by competence level and similarity in performed activities. Thus, occupations are aggregated by similar cognitive skills required for that job, that is, by the complexity of the performed tasks. Therefore, the socio-economic classification considers the position in the job, as a proxy for different forms of insertion in production based on performed tasks, and occupation, which accounts for hierarchy in production and the kind of work performed in a job. Despite its limitations, individuals' occupations are usually a good approximation of their social position in the labour market and, thus, in the social structure (JANNUZZI (2000)).

Hence, classifying and aggregating occupational information allows for a better understanding of the social disparities inherent in the Brazilian labour market. Moreover, one may associate higher (lower) levels of the OCH with better (worse) types of employment, for those in lower class occupations have substantially less control over changes, especially regarding employment conditions. Therefore, the OCH may enlighten the chasm between occupations in Brazil.

[1]It is important to highlight that all occupations within domestic services were not included in this analysis, for being a different analysis than the rest of the Brazilian labour market.

Table 3: Occupational Classification Hierarchy based on the CBO.

Main job's occupational group based on the CBO	Occupational Classification Hierarchy (OCH)
Directors and managers	High
Science professionals and intellectuals	
Mid-level technicians and professionals	Medium
Clerical support workers	
Services and sales workers	Low
Skilled agricultural, forestry, hunter and fishery workers	
Skilled workers, laborers and craftsmen in construction, mechanical arts and other crafts	
Plant and machine operators and assemblers	
Elementary occupations	

Source: Own elaboration based on the PNAD-C.

SURVIVAL ANALYSIS

Duration and transition analysis are also known as survival analysis. To analyse the duration of unemployment and unemployment transitions, we will follow Cameron and Trivedi (2005).

It is important to highlight that the unemployment duration variable presents two types of censoring. As we consider the elapsed time until the transition from unemployment to employment, the exact time of the spell is unknown resulting in left-censoring. Also, given that the sample follows a rotating scheme, the individual remains in the same declared state in his/her last interview during the two months out of the sample. This indicates, thereby, the presence of interval-censoring, that is, the spell is observed in an interval form.

Given that the duration of unemployment is measured as an interval, the unemployment duration is a discrete random variable, denoted T. According to Cameron and Trivedi (2005), the hazard function is the instantaneous probability of leaving a state conditional on survival time, as it can be seen below:

$$\lambda(t) = \lim_{\triangle(t)\to 0} \frac{Pr[T \leq T < t + \triangle(t) | T \geq t}{\triangle(t)}$$

$$\lambda(t) = \frac{f(t)}{S(t)}$$

Thus, the discrete-time hazard function is:

$$\lambda_j = Pr[T = t_j | T \geq t_j]$$

$$\lambda_j = \frac{f(t_j)}{S(t_j-)}$$

where $t_j, j = 1, 2, ...$ is the discrete time and $S(a_)) = \lim_{t\to a-} S(t_j)$.

Based on the hazard function, it is possible to recursively get the discrete-time survivor function:

$$S(t) = Pr[T \geq t]\xi$$

$$S(t) = \prod_{j \mid t_j \leq t} (1 - \lambda_j)$$

In which, $S(t)$ is a decreasing step function. Finally, the discrete-time cumulative hazard is seen below:

$$\Lambda(t) = \sum_{j \mid t_j \leq t} \lambda_j$$

And, therefore, the discrete probability that the unemployment spell ends at t_j is ${}_jS(t_j)$.

NONPARAMETRIC MODELS

Mostly, non-parametric models are used to describe the analysed database. The Kaplan-Meier estimator considers information from all of the observations available by incorporating survival to any point in time as a series of intervals defined by a rank ordering of the survival times. This estimator, also known as product limit estimator of the survival function is given by:

$$\wedge S(t) = \prod_{j \mid t_j \leq t} (1 - \wedge\lambda_j) = \prod_{j \mid t_j \leq t} (\frac{r_j - d_j}{r_j})$$

Then, $\wedge S(t)$ is the number of spells in the sample of unemployment duration greater than t and divided by the sample size. Also, d_j is the number of spells ending at time t_j and r_j is the number of spells at risk at time $t_(j-)$.

If the sample is heterogeneous, survival curves and their risk functions may lead to wrong conclusions. When heterogeneity is not controlled, the risk functions appear to decline, even when there isn't any decline for any individual in the sample. A way to reduce the effect of heterogeneity is to estimate survival functions on residuals from regression models; alternatively, it is possible to estimate and plot reference survival functions after adjusting models of Cox regression. Therefore, nonparametric analysis can be used to decide between parametric models.

PARAMETRIC AND SEMI-PARAMETRIC REGRESSION MODELS

In parametric regression models, the underlying distribution of the outcome is specified in terms of unknown parameters. The exponential, the Weibull, the log-logistic, the lognormal and the gamma are examples of distributions that are commonly used for survival time. Therefore, in parametric survival models, time is assumed to follow some distribution and specifying any one of the probability density function, survival function, or hazard function allows the other two functions to be determined (Kleinbaum and Klein (2010)).

Among these models there are two different types of assumptions: the accelerated failure time (AFT) and the proportional hazards (PH). In the first, the assumption is applicable for a comparison of survival times, meaning that the effect of covariates is multiplicative (proportional) with respect to survival time. In the latter, the assumption is applicable for a comparison of hazards, that is, the effect of covariates is multiplicative with respect to the hazard (Kleinbaum and Klein (2010)). While the Exponential and Weibull accommodate both types of assumption, the Log-normal, Log-logistic and Gamma are AFT models. Finally, the Generalized Weibull is a PH model.

The following table, in accordance with Cameron and Trivedi (2005), shows the standard parametric models and their hazard function.

Table 4: Standard parametric models and their hazard function

Parametric model	Hazard function	Survivor function
Exponential	γ	$exp(-\gamma t)$
Weibull	$\gamma\alpha t^{\alpha-1}$	$exp(-\gamma t^{\alpha})$
Generalized Weibull	$\gamma\alpha t^{\alpha-1}S(t)^{-\mu}$	$[1-\mu\gamma t^{\alpha}]^{1/\mu}$
Log-normal	$\frac{exp(-(ln\ t\ -\ \mu)^2/2\sigma^2)}{t\sigma\sqrt{2\Pi}[1-\Phi((ln\ t-\mu)\sigma)]}$	$1-\Phi((ln\ t\ -\ \mu)/\sigma)$
Log-logistic	$\alpha\gamma^{\alpha}t^{\alpha-1}/[(1+(\gamma t)^{\alpha})]$	$1/[1+(\gamma t)^{\alpha}]$
Gamma	$\frac{\gamma(\gamma t)^{\alpha-1}exp[-(\gamma t)]}{\Gamma(\alpha)[1-I(\alpha,\gamma t)]}$	$1-I(\alpha,\gamma t)$

All the parameters are restricted to be positive.

Source: Own elaboration based Cameron and Trivedi (2005)

It is important to emphasize, as stated in Cameron and Trivedi (2005), that due to the memoryless property of the exponential, the exponential distribution has a constant hazard rate. Also, the Weibull hazard function reduces to the exponential if $\alpha = 1$, it is monotonically increasing if $\alpha > 1$and monotonically decreasing if $\alpha < 1$. In addition, the Generalized Weibull allows a more flexible shape of the hazard function. Finally, the log-normal and the log-logistic for >1first increases with t and then decreases with t.

There is also the Cox proportional hazards model, a semi-parametric model as the hazard function is unspecified. This arises from the Cox likelihood, in which the baseline hazard cancels out in each term and, as a consequence, does not influence in the estimation of the regression parameters (Kleinbaum and Klein (2010)).

The hazard in the Cox model is given by the product of the baseline hazard function and the exponential expression to the sum of the p explanatory X variables, as it can be seen below:

$$h(t,x) = h_0(t))e^{\sum_{i=1}^{p}\beta_i x_i}$$

It is important to highlight that the baseline hazard is a function of time, but the explanatory variables are time-independent (whose value for a given subject does not change over time).

EXTENDEND COX MODEL

In the extended Cox model is possible to use both time-independent and time-dependent variables. The extension allows to incorporate product terms of some function of time and time-independent variable (Kleinbaum and Klein (2010)). The extended Cox model is shown as it follows:

$$h(t, X(t)) = h_0(t))exp\left[\sum_{i=1}^{p_1} \beta_i x_i + \sum_{i=1}^{p_2} \delta_j x_j(t)\right]$$

where, $h_0(t)$, is the baseline hazard function multiplied by an exponential function containing time-independent and time-dependent explanatory variables. In this model, when analysing the duration of unemployment, it was taken into consideration individual, household and macroeconomic factors. The individual factors are related to sex, race, age, education attainment. Regional aspects such as living in a metropolitan area, an urban area and the region were also considered. Furthermore, the household factor is the position in the household. Thus, between 2012 and 2020, temporal dummies were used to indirectly capture the macroeconomic behaviour of the period.

MULTINOMIAL LOGIT MODEL

According to Greene (2003) and Cameron and Trivedi (2005), the Multinomial Logit Model takes part in a variety of models known as qualitative response models, in which the dependent variable represents a discrete choice. As an example, whether being employed or unemployed is a qualitative decision, which in order to be modelled should be transformed into a binary code. In this sense, multinomial models are an extension of models for binary choice, considering that these models are used when there are several possible outcomes. The general approach, in consonance with Greene (2003), is:

$$Prob(event\ j\ occurs) = Prob\,(Y = j) = F\,[relevant\ effects,\ parameters]$$

Accordingly, as the labour force status is represented by more than two outcomes, a multinomial logit model, based on Wooldridge (2006), Heij et al. (2004) and Greene (2003), could be employed. For the purpose of this thesis, the labour force status is represented by a categorical variable (j). Within this variable, men and women (sex is considered separately as they present meaningful disparities in the labour market) can be allocated amongst six options (j) that have no natural ordering and are mutually exclusive:

1. Unemployed

2. Outside the labour force - Inactive
3. Discouraged
4. Employed - high OCH
5. Employed - medium OCH
6. Employed - low OCH

Cameron and Trivedi (2005) have highlighted that if one jth alternative is observed, then it will be equal to one, meanwhile the remaining options will be equal to zero. In this sense, "the multinomial density for one observation can then be conveniently written as" (Cameron and Trivedi, page 496, 2005):

$$f(y) = p_1^{y_1} \times ... \times p_m^{y_m} = \prod_{j=1}^{m} p_j^{y_j}$$

In light of the theoretical literature, the explanatory variables will be the same considered in the duration models. This enables comparing the models and seeing how they complement each other. As PNAD-C panel is used, the explanatory variables were controlled by the first interview, while the dependent variables were considered using the second interview. This method allows observing how the traits in the previous period influences on the preceding period. Therefore, controlling by the first interview permits to analyse if there is a path dependence associated with unemployment.

To this extent, it is assumed that the chosen labour market status (u_i^j) is the maximal by the individual "i" when deciding on "j"; and that x' are the explanatory variables. In this sense, $u_i^j = x'i$. Therefore, the multinomial model for labour market status is given, in agreement with Greene (2003), by:

$$Pr(Y_i = j) = \frac{e^{\beta_j x_j}}{1 + \sum_{k=1}^{j} e^{\beta_k x_i}} \; if \; j = 0, 1, 2, 3, ..., J, \beta_0 = 0$$

In order to withdraw an indeterminacy in the model, still in accordance with Greene (2003), it was taken into consideration, that given that the probabilities sum to one, $\beta_0 = 0$. Considering that all error terms are independent and identically distributed, for the reference category (employed persons) , the multinomial logit becomes:

$$Pr(x_i = j|x_i) = \frac{e^{\beta_j x_j}}{1 + \sum_{k=1}^{j} e^{\beta_k x_i}} \; if \; j = 0, 1, 2, 3, ..., J, \beta_0 = 0$$

Given the dependent variable and its "j" categories, the main goal is to compare categories simultaneously. In this specific case, for instance, the comparison will happen between $j = 2$, which represents unemployed individuals, and the reference category, that is $j = 1$, representing people employed in high OCH.

The estimation of the parameters is given by maximum likelihood. Hence, the log-likelihood of the multinomial model is a generalization of the logit model according to Greene (2003). The author defined that if, in one hand, an individual i chooses the alternative j, $d_{ij} = 1$ and on the other hand, $d_{ij} = 0$ if one does not choose alternative j. This will follow for all the $J - 1$ possible outcomes. Thus, the log-likelihood is given by:

$$lnL = \sum_{i=1}^{n} \sum_{j=0}^{J} d_{ij} ln\ Prob\ (Y_i = j)$$

Moreover, in this model, "all the parameters together determine the marginal effect of xi on the probability to choose the jth alternative" (Heij et al., page 495, 2004). In addition, it is also possible to compute the log-odds ratios of the model, which will provide the odds ratio for each category (that is, it is independent of the other choices in the model).

4 Results

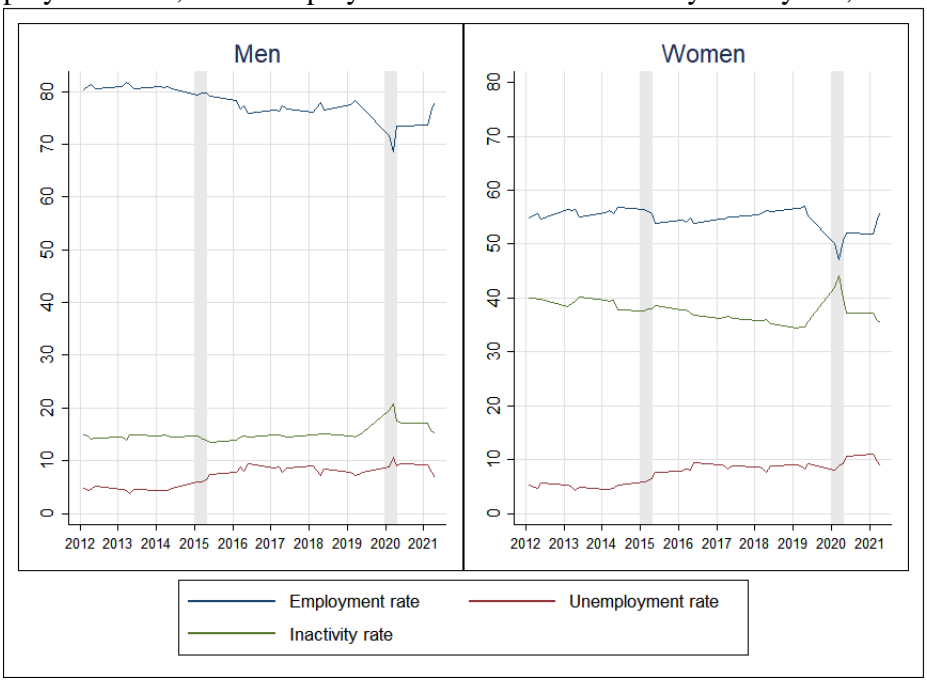
4.1 Descriptive analysis

Figure 2 presents the employment rate, the unemployment rate and the inactivity rate by sex between 2012 and 2021 for the Brazilian labour market. Evidently, women and men present different trends in the labour market, with women being in a much more vulnerable situation than men. While men's employment rate throughout the years is approximately 75%, women's employment rate throughout the years is approximately 55%. To make matters worse, women's inactivity rate (around 40%) has been much higher than that for men (around 15%) during the analysed period. Distinctively, the pandemic crisis was marked by a sharp increase in the inactivity rate, mainly for women. Accordingly, Costa et al. (2021) highlight that, although the risks of transitioning to inactivity increased in the pandemic, they were especially higher for women, black and youngsters.

Moreover, there was a stark decrease in the employment rate for both sexes, followed by an increase in the unemployment rate. Regarding unemployment, the same trend can be seen: the unemployment rate for women is slightly higher than for men throughout the period. Since the 2015 economic crisis, the Brazilian labour market has been suffering from a decrease in the employment

rate, and an increase in the unemployment rate, worth noting women being disproportionately affected. It's interesting to highlight that throughout the following years unemployment rates have not only remained above their 2015 pre-crisis levels, but indeed increased considerably. To add to the economic woes, the COVID-19 pandemic caused an even greater disruption: the unemployment rate reached its historical peak in 2020, surging to nearly 12% for men and 15.5% for women. Those results are accurate with ILO (2022), evidencing that groups that were previously in a more vulnerable situation in the labour market have experienced higher losses, especially regarding employment. Thus, the differences for women and men highlight the need to analyse the labour market by sex (also in agreement with Barros et al. (1997); Andrade (2004); Antigo and Machado (2006); Reis and Aguas (2014)).

Figure 2: Employment rate, the unemployment rate and the inactivity rate by sex, Brazil, 2012-2021.

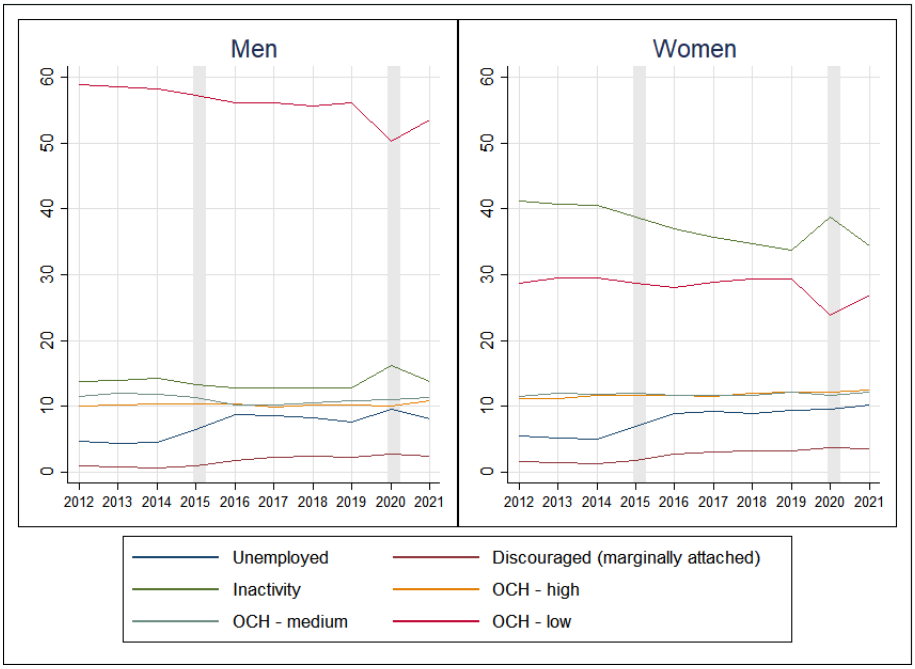


Source: Own elaboration based on the PNAD-C, 2012-2021.

As Figure 3 suggests, the employment situation deteriorated considerably during the last years, especially with the pandemic, and an increase in the unemployment and inactivity. Thus, it seems indeed pertinent to understand in which type of occupation workers were employed during the analysed period. Figure 3 shows the Brazilian labour market by sex, considering the occupational classification hierarchy (OCH). Broadly speaking, around 60% of males were employed in lower socio-economic ranked occupations (low OCH), followed by approximately 12% of those in medium socio-economic occupations (medium OCH), and only 8% in higher socio-economic occupations (high OCH). The very same tendency of higher rates of women employed in lower OCH (approximately 28%), followed by medium OCH (12%) and lower OCH (11%) can be observed in

the figure. There is a sharp decrease in the rate of lower OCH, independently of the sex, between 2019 and 2020. This pattern reflects employment changes in 2020 that were particularly acute for people in the lower OCH, an occupational group hit particularly hard at the onset of the pandemic. Although some people were able to work at home (those in the higher OCH category or medium OCH category), lower occupational groups (lower OCH) were generally unable to work from home. As a result, they were either working and facing the risks of the disease (these groups have less control over employment changes), or they came across unemployment or inactivity.

Figure 3: Brazilian labour market considering the occupational classification hierarchy (OCH) by sex, Brazil, 2012-2021.



Source: Own elaboration based on the PNAD-C, 2012-2021.

Looking at a broader array of economic indicators sheds even more light on the differences within the labour market: different educational attainments yield different participation percentages in the labour market status. The following tables present the percentage of individuals, assorted by educational attainment, in each labour market status.

Table 5: Participation in the labour market status by educational attainment for men, Brazil, 2012-2021

	No formal education/ Incomplete primary education	Primary education/ Incomplete secondary education	Secondary education (complete)	Incomplete higher education	Higher education	Total
Unemployed 2nd interview	33,06	20,7	33,57	6,38	6,29	100
Discouraged 2nd interview	58,2	18,16	20,13	1,73	1,77	100
Inactive 2nd interview	52,07	16,12	20,02	6,73	5,06	100
OCH - high 2nd interview	7,01	5,72	19,05	7,6	60,62	100
OCH - medium 2nd interview	7,56	9,63	45,17	15,73	21,91	100
OCH - low 2nd interview	47,65	19,54	27,6	2,44	2,78	100

Source: Own elaboration based on the PNAD-C.

Table 6: Participation in the labour market status by educational attainment for women, Brazil, 2012-2021

	No formal education/ Incomplete primary education	Primary education/ Incomplete secondary education	Secondary education (complete)	Incomplete higher education	Higher education	Total
Unemployed 2nd interview	19,47	17,68	42,76	8,33	11,75	100
Discouraged 2nd interview	45,19	18,91	29,88	2,49	3,53	100
Inactive 2nd interview	49,05	16,4	23,77	4,44	6,35	100
OCH - high 2nd interview	1,88	2,11	13	6,81	76,2	100
OCH - medium 2nd interview	2,71	5,7	47,62	16,26	27,7	100
OCH - low 2nd interview	34,29	18,51	37,56	4,11	5,53	100

Source: Own elaboration based on the PNAD-C.

Among those unemployed, inactive and in lower socio-economic occupations, most individuals have no formal education/incomplete primary education and primary education (complete)/incomplete secondary education. Oppositely, when analysing higher socio-economic occupations, it is straightforward the preponderance of those with higher education. Finally, most of the workers in medium socio-economic occupations have a completed secondary education, followed by higher education and incomplete higher education. Therefore, results are twofold: those with lower educational attainments are mostly to be found in lower socio-economic occupations, unemployment

or inactivity and the majority of those with higher educational attainment are encountered in higher socio-economic occupations or in middle socio-economic occupations. Moreover, the analysis is very similar for men and women, but it is interesting to emphasise that when analysing the distribution for higher socio-economic occupations for women, the difference among education attainments is more pronounced than men.

Given this scenario, figure 4 displays the employment rate by educational attainments and sex. It is worth noting that, whilst the chasm between men and women is persistent, this gap decreases for higher educational attainments, such as higher education and incomplete higher education. Another interesting aspect is that those with higher educational attainments present higher employment rates than those with lower educational attainments. This stark contrast indicates precisely that unemployment rates are higher among those with lower educational levels, as demonstrated by Figure 5 below. Individuals in this situation usually encounter difficulties in finding better jobs due to the need of higher educational attainments and, accordingly, face a twofold increase in insecurity in the labour market.

Considering the macroeconomic scenario, both recessions in 2015 and 2020 have caused a decrease in the employment rate for all educational attainments. This effect is to a greater extent very clear for 2020, where the employment rate diminished markedly for everyone. Although these rates improved in the following year, the employment rate remained below the pre-pandemic levels. This negative cyclical condition accounting for a worse employment rate is also found by Menezes-Filho and Picchetti (2000); Antigo and Machado (2006); Nunes et al. (2016); Reis (2019).

Figure 4: Employment rate by educational attainment and sex, Brazil, 2012-2021.

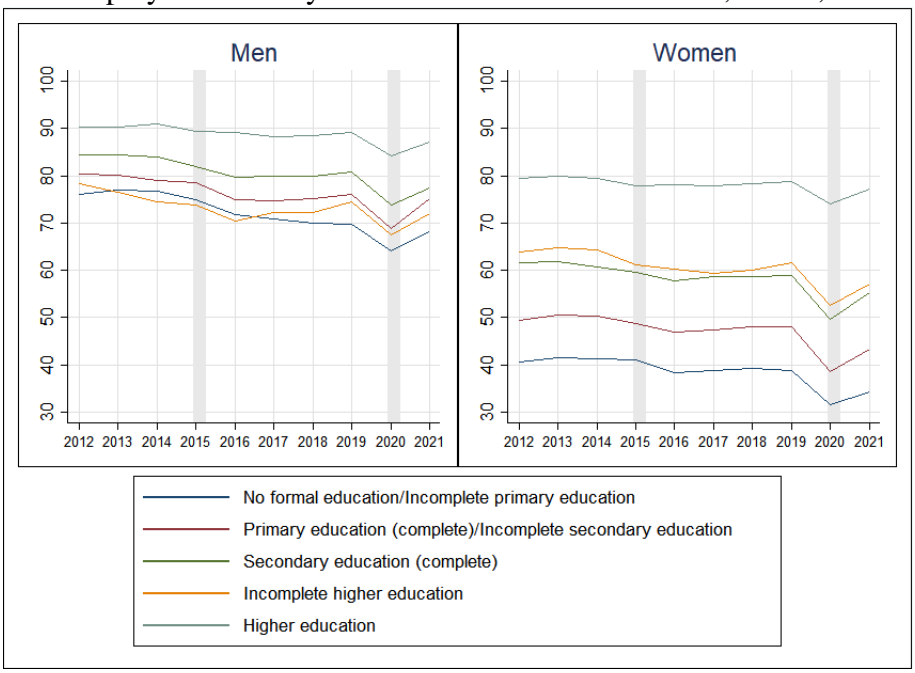
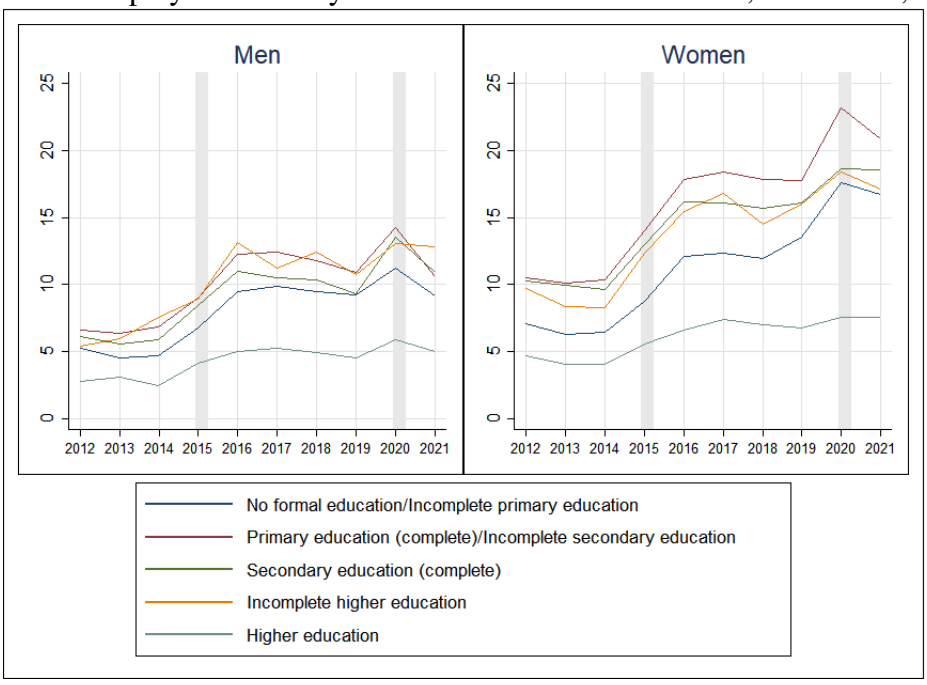


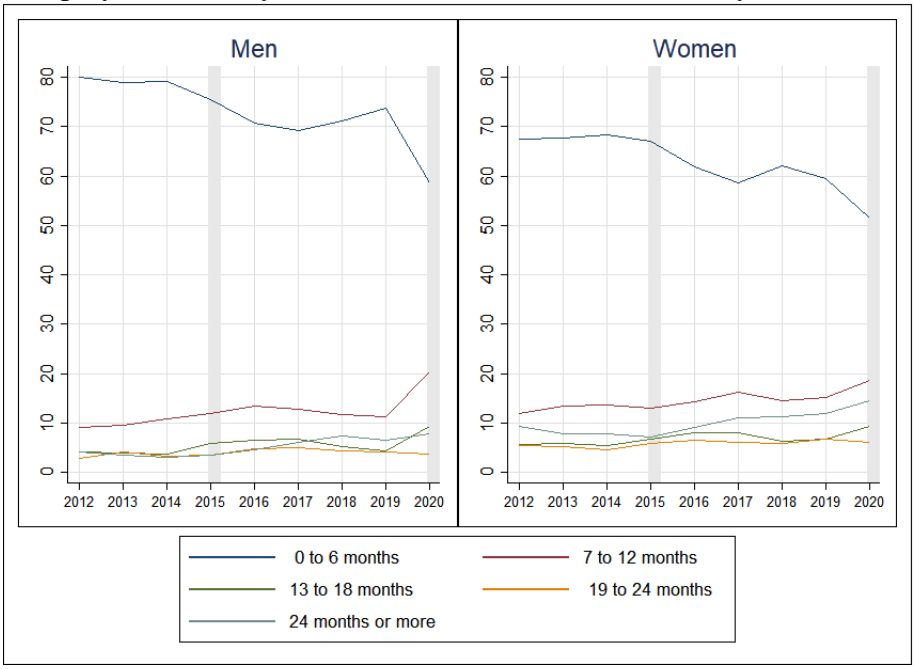
Figure 5: Unemployment rate by educational attainment and sex, 2012-2021, Brazil.



Source: Own elaboration based on the PNAD-C, 2012-2021.

Finally, Figure 6 displays the unemployment rate by time of unemployment in months. While the unemployment rate for those unemployed between 0 to 6 months represents the highest share of those in unemployment, with both crises the rate for short-term unemployment (0 to 6 months) decreases considerably. This, however, does not imply a positive scenario, for the considerable increase in those groups of individuals unemployed for a longer period, such as those unemployed between 7 to 12 months, 13 to 18 months and those unemployed for 24 months or longer. This increase in unemployment time is one visible sign of the breakdown of the Brazilian labour market. Especially, the increase in the share of long-term unemployed (people who were jobless for 24 months or longer) highlights the urgent need for further analysis of this group, noting the longer one remains unemployed, the harder to leave this condition (in consonance with Clark et al. (1979); Heckman and Borjas (1980); Jackman and Layard (1991); Acemoglu (1995); Biewen and Steffes (2010); Cockx and Picchio (2013); Van Belle et al. (2017)). Aggravating matters, ILO (2021) indicates that workers who experience unemployment during the recession could suffer from the "scarring" effect, meaning that unemployment could affect future employment trajectories.

Figure 6: Unemployment rate by time (in months) in this condition by sex, 2012-2021, Brazil.



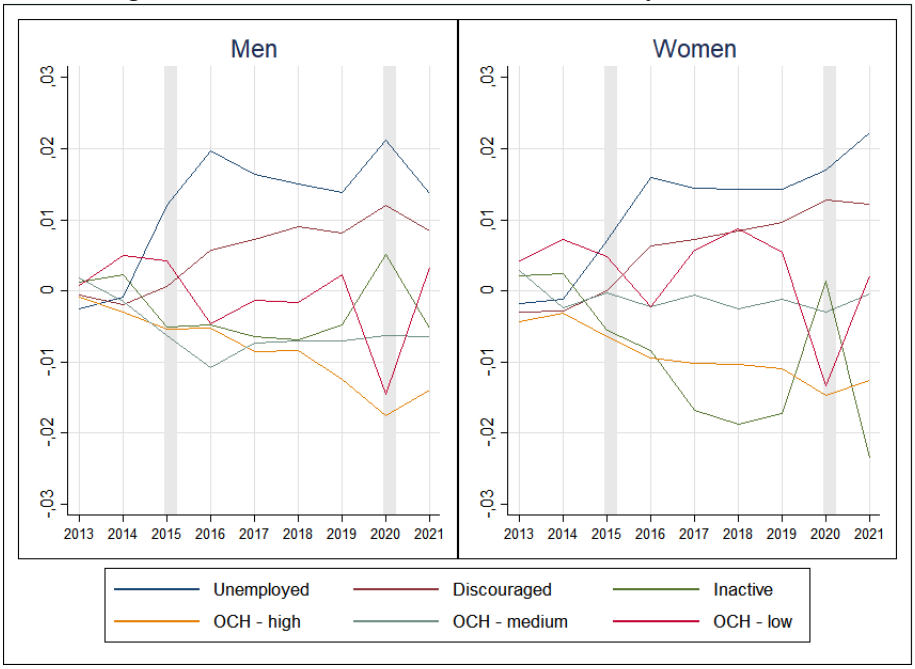
Source: Own elaboration based on the PNAD-C, 2012-2021.

4.2 Multinomial Logit Model

Corroborating findings in the descriptive analysis, Figure 7 presents the marginal effects for each possible labour market state in the second interview, considering the economic scenario (the baseline category is 2012) for both sexes.

Since the economic crisis in 2015, the probabilities of being unemployed and discouraged have increased considerably, while the probability of being in a higher socio-economic occupation (high OCH) has decreased, independently of the sex. This scenario yielded more inequality, due to an increase in the share of individuals without labour income (Barbosa (2019)). Moreover, the decrease in higher OCH and an increase in lower OCH during the years between crises indicate, thus, worse employment opportunities in the labour market, accordingly presenting higher vulnerabilities and being more susceptible to economic fluctuations. Specifically, either in the aftermath of the first economic crisis (2016) and in the Covid-19 pandemic in 2020, men and women in lower OCH have been extremely affected, as their range in probabilities decreased significantly.

Figure 7: Marginal effects for the economic scenario by sex, Brazil, 2012-2021.



Source: Own elaboration based on the PNAD-C, 2012-2021.

It is interesting to observe how the economic scenario differently affects inactivity. Despite the economic crisis in 2015, between 2014 and 2019 the probabilities of being inactive were decreasing vis à vis the probability of being inactive in 2012. This scenario, however, changed drastically with the event of the covid-19 for both sexes. According to Costa et al. (2021), there was an increase in the proportion of women who transitioned from employment to inactivity during

the pandemic. Moreover, one can see from the figure that the probabilities of being inactive also increased considerably for men.

Considering how the economic scenario affects labour market states, it seems rather pertinent seek for path dependence between previous states in the labour market and the current one. Thereby, the table below presents the marginal effects for each possible labour market state in the second interview, taking into consideration the previous state in the labour market (labour market state in the first interview) for both sexes. It is important to note that the baseline category is "OCH - high in the first interview", as this would be the best category/state in which one could be in the labour market.

Table 7: Marginal effects for each labour market state by sex, Brazil, 2012-2021

	Unemployed 2nd interview - Men	Unemployed 2nd interview - Women	Discouraged 2nd interview - Men	Discouraged 2nd interview - Women	Inactive 2nd interview - Men	Inactive 2nd interview - Women	OCH - high 2nd interview - Men	OCH - high 2nd interview - Women	OCH - medium 2nd interview - Men	OCH - medium 2nd interview - Women	OCH - low 2nd interview - Men	OCH - low 2nd interview - Women
Unemployed 1st interview	0,398	0,389	0,027	0,035	0,079	0,210	-0,493	-0,513	-0,051	-0,051	0,040	-0,071
Discouraged 1st interview	0,142	0,115	0,165	0,206	0,192	0,371	-0,507	-0,529	-0,062	-0,074	0,070	-0,088
Inactive 1st interview	0,041	0,024	0,018	0,015	0,655	0,718	-0,505	-0,532	-0,068	-0,073	-0,142	-0,151
OCH - medium 1st interview	-0,002	-0,003	-0,001	-0,001	-0,004	-0,025	-0,449	-0,481	0,476	0,577	-0,021	-0,067
OCH - low 1st interview	0,006	0,003	0,003	0,003	0,000	-0,001	-0,482	-0,495	-0,047	-0,046	0,519	0,536

Source: Own elaboration based on the PNAD-C.

Thus, table 7 provides an accurate result of state dependence in the Brazilian labour market: there is a higher probability of remaining in the same labour market state as of the first interview, possibly indicating immobility between states for both sexes. By way of illustration, results emphasise that, for example, the probability for men and women of remaining unemployed in the second interview is on average 39.8% higher for those who were unemployed in the first interview. Accordingly, Heckman and Borjas (1980) highlight that prior unemployment yield true state dependence.

In addition, the probability of being unemployed in the second interview is, respectively, 14.2% higher for men and 11,5% for women who were marginally attached to the labour market (discouraged) in the first interview. These probabilities of being unemployed in the second interview are lower, when analysing inactivity and occupational socio-economic classification. Especially, one might notice that, on average, the probability of being unemployed in the second interview is -0.2%

lower for men placed in a medium socio-economic ranked occupation in the first interview and -0,3% for women placed in a medium socio-economic ranked occupation in the first interview. Therefore, the higher the socio-economic classification, the lower the probabilities of being in unemployment, inactivity, discouragement or in lower OCHs, regardless of the sex. This bestows lower chances of being exposed to vulnerable situations in the labour market which, in turn, results in better quality of life and well-being.

4.3 Unemployment duration: survival analysis

The survival data analysis of the following tables and figures have been estimated using the non-parametric Kaplan-Meier estimator. For a general description of unemployment duration, this method is very insightful. The hazard function is the instantaneous probability of leaving unemployment conditional on survival time. Thus, it is important to highlight that the probability of leaving unemployment was initially based on the probability of transitioning to employment (finding a job).

The table below shows the survival probability for unemployment duration and the exit rate for some selected months between 2012 and 2021 in Brazil. After one month in unemployment, the exit rate of unemployment was 2%, suggesting that meagre 2% of the unemployed individuals found a job. After 48 months, or 2 years, the exit rate reached 9%, which is still a paltry rate. The survivor function for long-term unemployment is 0.5782, indicating that the probability of remaining unemployed is very high. Hence, this portrays a serious problem in the Brazilian labour market, as workers are entering unemployment and remaining in that position. This potentially indicates immobility within states in the labour market, corroborating previous findings of this work.

Table 8: Survivor function and number of exits from unemployment, Brazil, 2012-2021

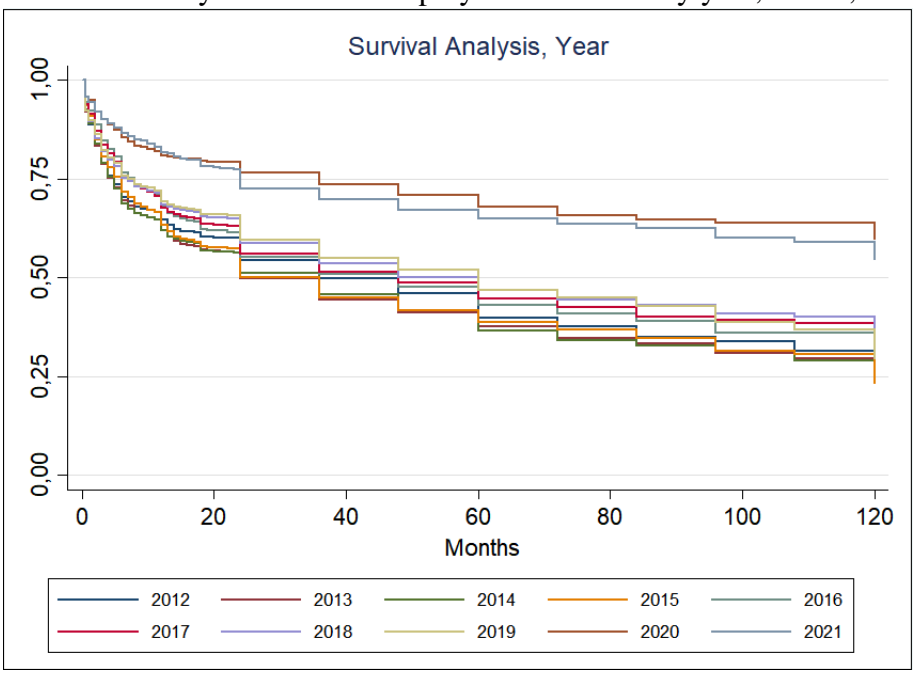
Time (in months)	Total number of unemployed	Exit rate from unemployment	Survivor Function	Std. Error	95% Confidence interval	
0,5	61225	0,0661	0,9339	0,001	0,9319	0,9358
1	52574	0,0265	0,9091	0,0012	0,9068	0,9114
2	49417	0,0476	0,8659	0,0014	0,8631	0,8686
4	39036	0,0283	0,806	0,0017	0,8027	0,8093
6	33673	0,0402	0,7546	0,0019	0,7509	0,7584
12	24503	0,0381	0,6836	0,0022	0,6793	0,6878
18	17864	0,0191	0,6432	0,0024	0,6386	0,6478
24	15874	0,0934	0,5782	0,0026	0,5731	0,5833
36	9338	0,0821	0,5307	0,0029	0,525	0,5364
48	5697	0,0602	0,499	0,0032	0,4925	0,505
60	3915	0,0840	0,4569	0,0037	0,4496	0,464

Source: Own elaboration based on the PNAD-C.

It is worth noting that the mean time in unemployment is 48 months (4 years). This calls for the urgent need of public policies and better understanding of the Brazilian labour market, bearing in mind that the unemployment exit rate is a decreasing function of duration (see Clark et al. (1979); Heckman and Borjas (1980); Jackman and Layard (1991)). Furthermore, this shows that, on average, people who enter unemployment tend to be in long-term unemployment (those unemployed for 24 months or longer). This is a relevant issue, as firms usually view this as a sign of lower productivity and human capital loss, and thus become less likely to hire a worker with that status (Nickell (1979), Clark et al. (1979), Heckman and Borjas (1980), Vishwanath (1989), Blanchard and Diamond (1994), Acemoglu (1995)).

Analysing beyond those average results is relevant given that the individual traits, the macroeconomic scenario and transitioning to different types of occupation might differently impact on the average time of unemployment. The following figure shows the survival analysis of the duration of unemployment by each studied year. The y axis shows the value of the survival function, and the x axis shows the period in months. Therefore, the figure shows the probability of remaining unemployed in each period and the Kaplan-Meier estimate is a step function with discontinuities or jumps at the observed "death times" from unemployment. As different macroeconomic scenarios differently impact unemployment, it may also differently impact duration of unemployment. The figure interestingly displays that with the Covid-19 crisis the duration of unemployment increased considerably. Although in 2021 duration of unemployment decreased in comparison to 2020, for both years the number of months spent in that condition is much higher, when compared to other years. Apart from those two years, 2018 and 2019 deliver the higher survivor functions. This leads one to concur that the labour market was previously facing challenges that were aggravated with the sanitary crisis. On the one hand, from the individual perspective, long periods of unemployment may result in loss of well-being and, within the worse utmost scenario, in social exclusion. On the other, from the macroeconomic perspective, high rates of long-term unemployed persons may result in higher poverty rates and lower economic growth.

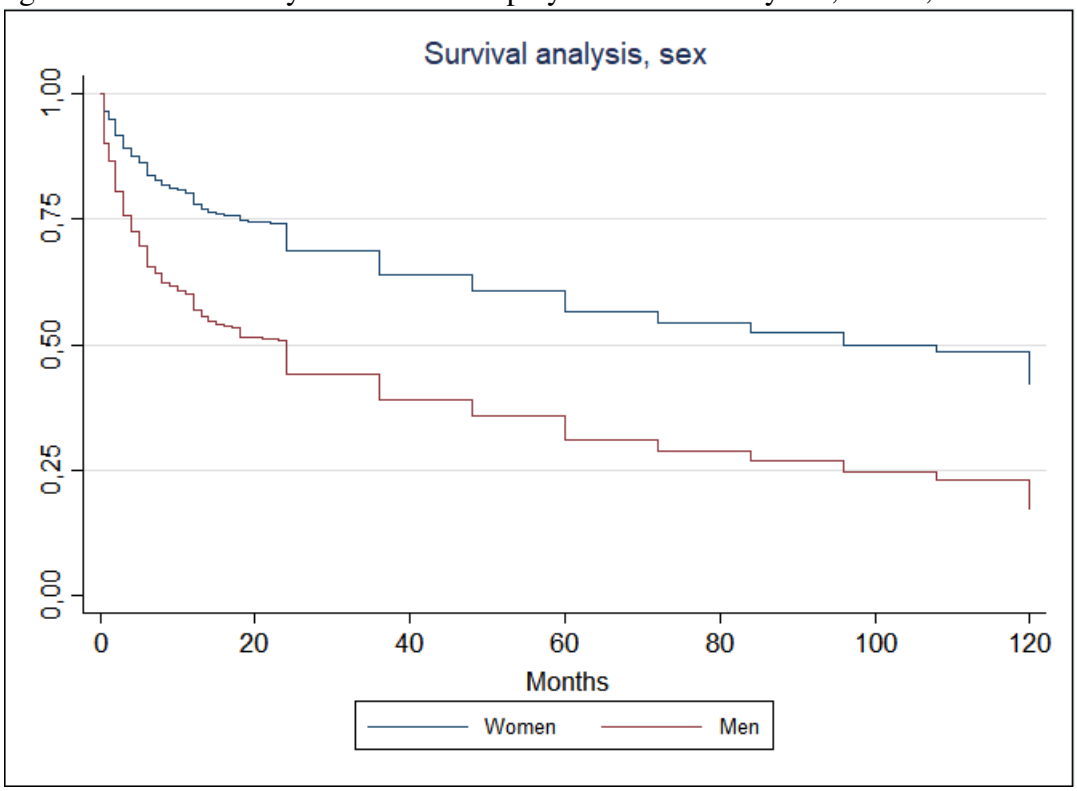
Figure 8: Survival analysis for the unemployment duration by year, Brazil, 2012-2021.



Source: Own elaboration based on the PNAD-C, 2012-2021.

When analysing by sex, it is noticeable from Figure 9 that women present higher chances of surviving unemployment than men and, therefore, they are less likely to transition from unemployment to employment. While the average duration of unemployment for women is 96 months, men stay, on average, 24 months in unemployment. Barros et al. (1997); Andrade (2004); Antigo and Machado (2006); Reis and Aguas (2014) also found that women's duration of unemployment is longer than men's duration of unemployment.

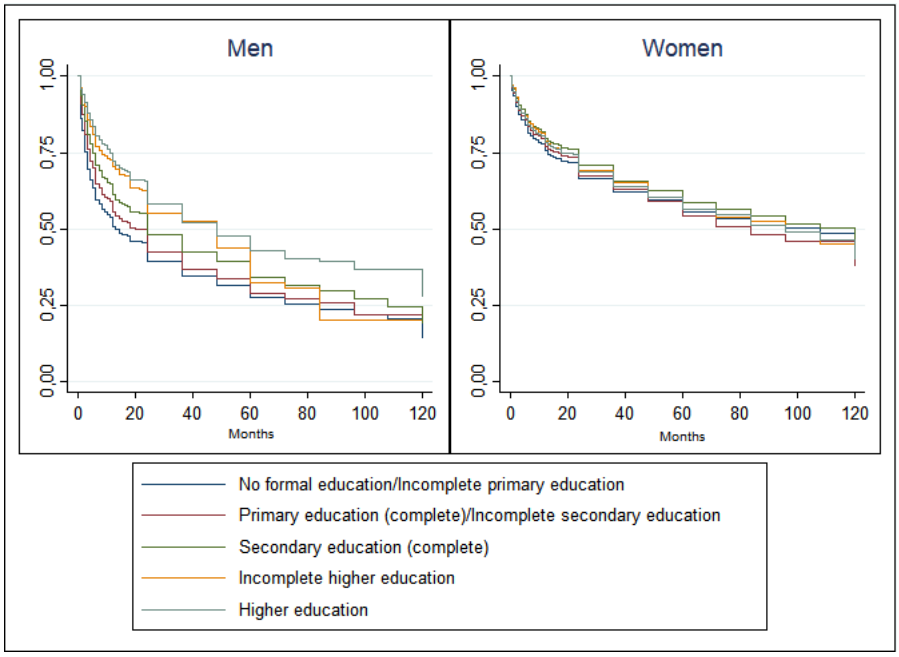
Figure 9: Survival analysis for the unemployment duration by sex, Brazil, 2012-2021.



Source: Own elaboration based on the PNAD-C, 2012-2021.

Figure 10 displays the duration of unemployment by different educational attainments and sex. Firstly, women present higher risks than men of surviving unemployment for all educational attainment levels. Although, the effect for women is not as prominent as for men, for both sexes people with lower educational attainments present a lower duration of unemployment, indicating that those groups transition from unemployment to employment faster than people with higher educational attainments. Those with higher educational attainments have higher reservation wages, inducing the possibility of screening through better jobs and better wages which, in turn, may result in longer periods of unemployment.

Figure 10: Survival analysis for the unemployment duration by sex and educational attainment, Brazil, 2012-2021.



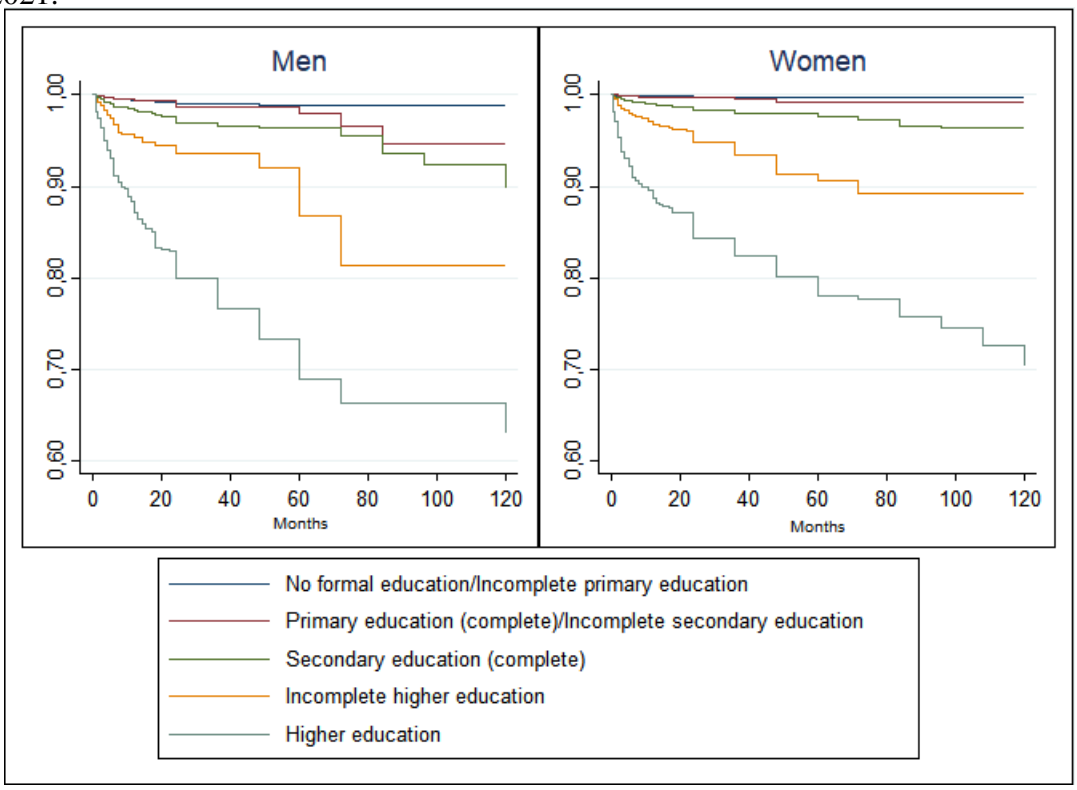
Source: Own elaboration based on the PNAD-C, 2012-2021.

To analyse the premise that transitioning from unemployment to different types of occupation result in a different outcome than the one observed in figure 10, the following figures present the survival analysis for the unemployment duration considering the probability of leaving unemployment to different occupations grouped accordingly in the occupational classification hierarchy (OCH). Three different figures were obtained: one for transitioning to occupations in the higher OCH, one for transitioning to occupations in the medium OCH and, finally, one for transitioning to occupations in the lower OCH. As it was previously discussed, it is possible to associate the OCH levels with different employment's quality.

Figure 11 shows the survival analysis considering the probability of leaving unemployment to higher socio-economic ranked occupations by sex and educational attainments. Those with higher educational attainments present lower survival functions in unemployment than those with lower educational attainments, when considering transitions to higher socio-economic ranked occupations. This means that, as one might realise, those with higher education and those with incomplete higher education are more likely to find a higher socio-economic ranked occupation. Worth noting, conversely, that, those with no formal education/incomplete primary education are most likely not to find a job of this kind, remaining in unemployment (their risk function remains practically unchanged through the studied period). Following this very same trend, women with complete primary education and incomplete secondary education also tend not to find a high OCH occupation

and, consequently, they will remain in unemployment through the studied period.

Figure 11: Survival analysis for the unemployment duration considering high OCH and sex, Brazil, 2012-2021.

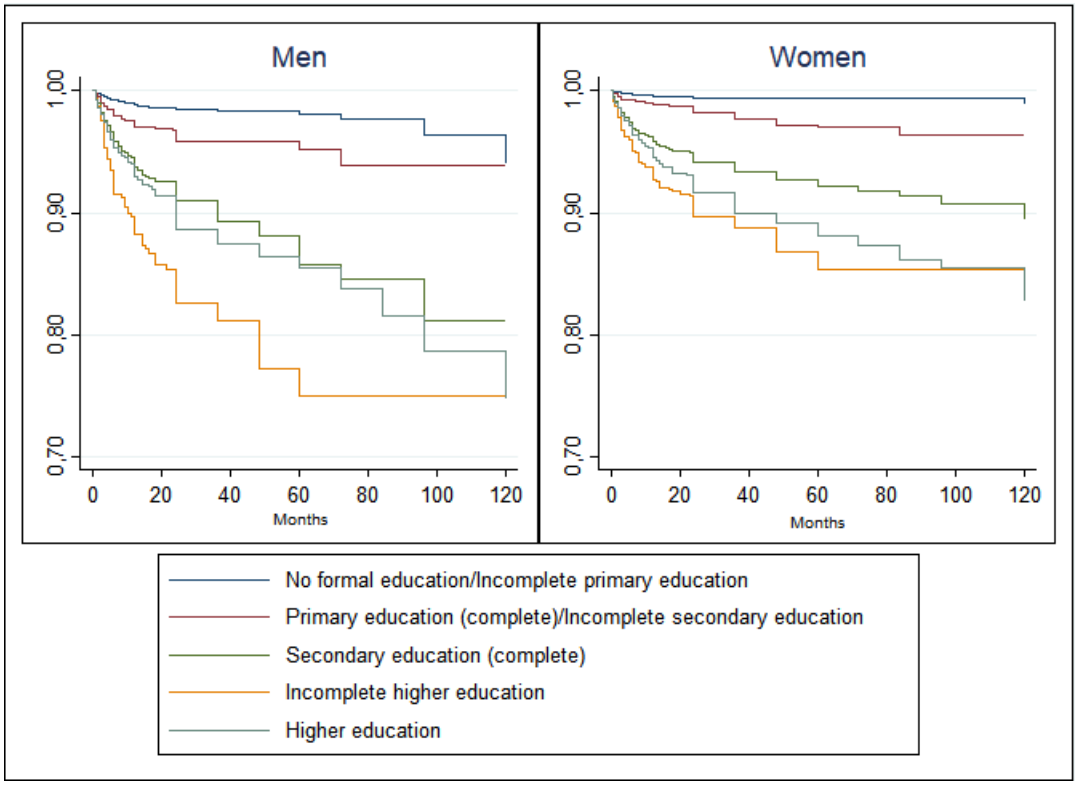


Source: Own elaboration based on the PNAD-C, 2012-2021.

Figure 12 exhibits the survival analysis considering the probability of leaving unemployment to medium socio-economic ranked occupations by sex and educational attainments. Those with incomplete higher education present the lowest survival function, both for men and women (whilst men exit unemployment faster than women), demonstrating that they are more likely to find a medium socio-economic ranked occupation. This educational group is followed by those with higher education, albeit men presenting a very similar survival function to those in secondary education. For women, however, those with higher education are in much better condition than those with complete secondary education.

In this scenario, although men with the lowest educational attainment have slightly higher chances of exiting unemployment, women with the same schooling levels tend to remain in unemployment. From observing those with primary education (complete) and incomplete secondary education, one can note that the chances of transitioning from unemployment to a medium OCH occupation is higher, compared previously to higher OCH occupations (figure 11).

Figure 12: Survival analysis for the unemployment duration considering medium OCH and sex, Brazil, 2012-2021.

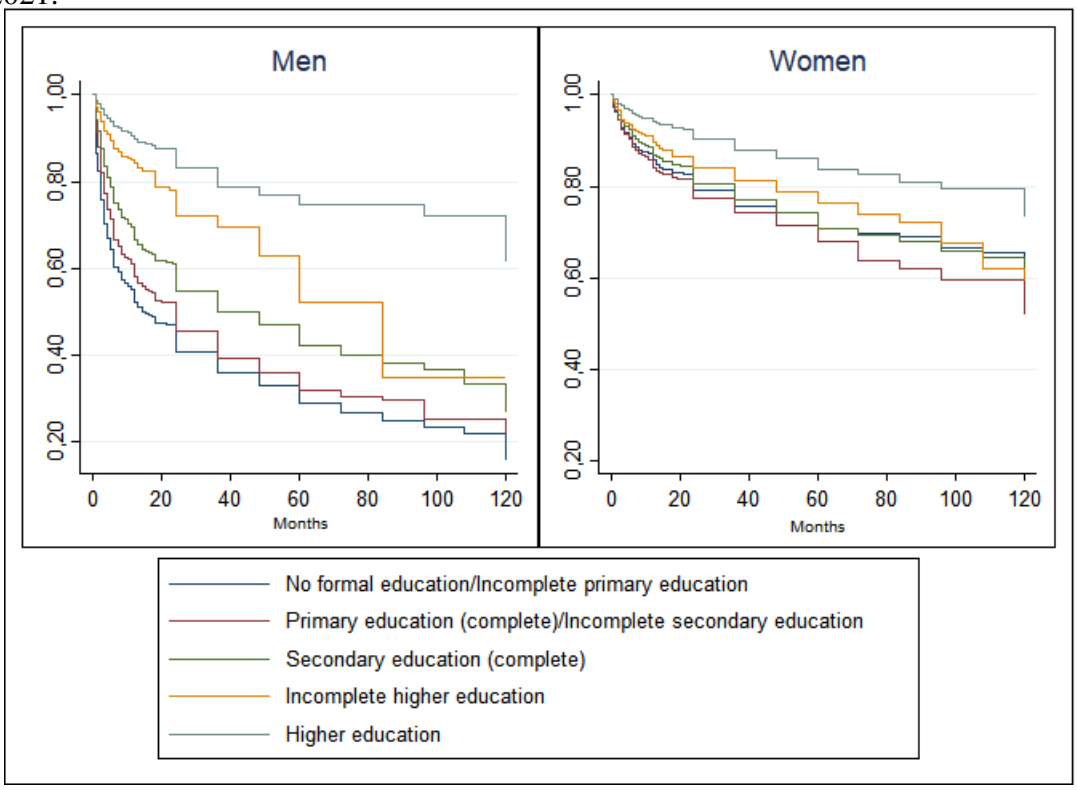


Source: Own elaboration based on the PNAD-C, 2012-2021.

Finally, figure 13 displays the survival analysis considering the probability of leaving unemployment to lower socio-economic ranked occupations by sex and educational attainments. There is a stark contrast between men and women, where women have higher chances of remaining unemployed than men, when considering transitions to lower socio-economic ranked occupations. Moreover, the results are the antipode of the ones observed in figure 11 (higher OCH), entailing those with lower educational attainment with shorter durations of unemployment and those with higher educational attainment present longer duration of unemployment in this setting[2]. Hence, those with lower educational attainments are more likely to find a low socio-economic ranked occupation.

[2]The log–rank test, used to compare survival curves, can be found in the appendix. According to Kleinbaum and Klein (2010), the null hypothesis is that all survival curves are the same, meaning that there is no difference between two or more independent groups. The results reject the null hypothesis for all the analysed covariates. Furthermore, the Wilcoxon, which is a variation of the log rank test was also estimated and the same results were found.

Figure 13: Survival analysis for the unemployment duration considering low OCH and sex, Brazil, 2012-2021.



Source: Own elaboration based on the PNAD-C, 2012-2021.

Mainly, those results pose concerns for sex and different schooling attainments, as they may result in better or worse conditions to exit unemployment. When considering sex, throughout the complete analysis, women present higher chances of longer unemployment duration and thus, are more vulnerable than men in any given scenario.

Furthermore, it is important to highlight that the duration of unemployment only increases as educational attainment increases when employment types are not being considered (figure 10). From the other figures, the outcome emphasises that while the risk of exiting unemployment increase for those with lower educational attainments when shifting down the OCH rank to analyse unemployment duration, this risk decreases for those with higher educational attainments. This is an issue, in the sense that lower OCH occupations usually present worse employment conditions, with lower wages and less stability. The duration analysis has indicated that educational attainment might be intrinsically related to the ranking in socio-economic occupations. Thus, better opportunities in education may result in better quality of life and may constitute a manner of social mobility.

Albeit being an important initial analysis, the Kaplan-Meier estimator only allows for an univariate analysis. Thus, this results in separate analysis for each covariate in the unemployment

duration (as it can be seen above). To analyse the simultaneous effect of the covariates in the duration of unemployment, a multivariate analysis has been used. Through this method, it will be possible to verify if these variables together are significant in explaining unemployment duration.

Choosing the most appropriate parametric model depends on evaluating which underlying distribution fits best the unemployment duration analysis. According to Kleinbaum and Klein (2010), the Akaike's information criterion (AIC), calculated as 2 log likelihood + 2p (where p is the number of parameters in the model and the addition of 2 times p is the penalty for added non predictive parameters), can be used to compare distributions and the preferred model is the one with the smallest AIC value. Also, the best model will present the closest log-likelihood to the Generalized Gamma baseline model. Therefore, the following table presents the possible distributions for unemployment duration: Weibull, Exponential and Gompertz.

Table 9: AIC statistics to compare the fit of different models, Brazil, 2012-2021.

Distribution	**Log-likelihood**	**AIC**	**BIC**
Generalized Gamma	-60959,265	-	-
Weibull	-62073,266	**124216,5**	124532,3
Exponential	-65425,728	130919,5	131226,2
Gompertz	-62587,421	125244,8	125560,6

Source: Own elaboration based on the PNAD-C.

Based on table 9, the Weibull model is the best model for unemployment duration. For both the AIC and for the log-likelihood this model provided to be the best fit, indicating that the Weibull distribution should be used for the duration analysis.

Therefore, six models with a Weibull baseline were estimated separately for the three different levels in the OCH, namely high, medium and low, and for both sexes. The main purpose was to capture how different socio-economic traits, the household factors, different regions and, finally, the macroeconomic scenario affect unemployment duration, given different types of occupation when transitioning to employment. Accordingly, the covariates used in the models were sex, race, age (through groups), education attainment, region, position in the household, being in a metropolitan area, being in an urban area, temporal dummies (year effect to indirectly capture the macroeconomic scenario) and the quarters (to indirectly control for seasonal effect).

Table 10 presents the results for all models, calibrated by relative risks, meaning that if the risk is greater than 1, the probability of the considered group finding a job is higher than the other groups. Therefore, there is a higher risk of finding employment compared to other groups.

	OCH – High Men	OCH – High Women	OCH - Medium Men	OCH - Medium Women	OCH – Low Men	OCH – Low Women
Baseline: No formal education/Incomplete primary education						
Primary education (complete)/Incomplete secondary education	1,299	1,836	2,052***	3,079***	0,839***	1,103*
	(1,06)	(1,45)	(4,82)	(5,18)	(-6,26)	(2,22)
Secondary education (complete)	3,199***	9,547***	4,760***	9,840***	0,662***	0,972
	(6,71)	(7,47)	(13,39)	(12,61)	(-16,10)	(-0,78)
Incomplete higher education	7,900***	32,24***	8,355***	16,05***	0,374***	0,801**
	(9,27)	(10,87)	(14,11)	(13,79)	(-12,34)	(-2,80)
Higher education	24,45***	115,4***	5,376***	12,65***	0,221***	0,479***
	(19,39)	(16,10)	(12,15)	(13,46)	(-22,19)	(-11,74)
Black/brown	1,095	0,950	1,097	1,074	0,888***	0,976
	(0,89)	(-0,65)	(1,17)	(1,01)	(-5,07)	(-0,70)
Baseline: Head of the household						
Partner	0,859	0,941	0,887	0,857*	0,960	0,811***
	(-1,21)	(-0,72)	(-1,20)	(-2,00)	(-1,63)	(-6,30)
Son/daughter	0,452***	0,707***	0,515***	0,966	0,542***	0,721***
	(-6,67)	(-3,43)	(-7,28)	(-0,39)	(-21,11)	(-6,53)
Other relative	0,549**	0,986	0,593***	0,796	0,661***	0,888
	(-2,82)	(-0,08)	(-3,35)	(-1,38)	(-8,73)	(-1,58)
Baseline: Southeast						
North	1,357*	0,803	0,979	0,678***	1,238***	1,009
	(2,04)	(-1,82)	(-0,17)	(-3,60)	(6,20)	(0,18)
Northeast	1,068	0,919	0,995	0,640***	1,024	0,906*
	(0,53)	(-0,90)	(-0,05)	(-5,08)	(0,93)	(-2,54)
South	1,582***	1,218	1,375**	1,464***	1,248***	1,562***
	(3,49)	(1,76)	(2,87)	(3,89)	(6,14)	(9,43)
Midwest	1,181	0,990	1,535***	0,987	1,560***	1,193**
	(1,01)	(-0,08)	(3,44)	(-0,12)	(11,75)	(3,13)
Baseline: 30 to 34 years old						
35 to 39 years old	0,977	0,899	0,857	0,915	0,927**	1,049
	(-0,18)	(-1,17)	(-1,62)	(-1,09)	(-2,60)	(1,17)
40 to 44 years old	1,062	0,660***	0,671***	0,755**	0,848***	0,964
	(0,43)	(-3,74)	(-3,49)	(-2,93)	(-5,28)	(-0,81)
45 to 49 years old	0,998	0,784*	0,576***	0,667***	0,754***	0,974
	(-0,01)	(-2,02)	(-4,35)	(-3,52)	(-8,40)	(-0,53)
50 to 54 years old	0,854	0,823	0,472***	0,579***	0,640***	0,843**

	(-0,98)	(-1,42)	(-5,32)	(-3,87)	(-12,18)	(-2,91)
55 to 59 years old	0,545**	0,484***	0,413***	0,334***	0,513***	0,749***
	(-3,05)	(-3,36)	(-5,55)	(-4,61)	(-15,86)	(-3,67)
60 to 64 years old	0,531**	0,231**	0,437***	0,300**	0,400***	0,764*
	(-2,65)	(-2,90)	(-4,24)	(-2,90)	(-15,89)	(-2,19)
Urban	1,541*	0,641***	2,458***	1,400*	0,856***	0,901*
	(2,14)	(-3,76)	(5,40)	(2,51)	(-6,26)	(-2,41)
Metropolitan	1,091	0,794**	1,027	1,239**	0,827***	0,968
	(0,90)	(-2,94)	(0,35)	(3,05)	(-7,31)	(-0,92)
Baseline: 2012	1,259	0,903	1,162	1,095	1,085	1,095
2013	(1,09)	(-0,61)	(0,95)	(0,62)	(1,73)	(1,29)
	1,181	1,119	1,190	1,046	1,091	1,095
2014	(0,79)	(0,68)	(1,12)	(0,30)	(1,82)	(1,27)
	0,936	0,859	0,839	0,932	1,025	1,074
2015	(-0,32)	(-0,95)	(-1,12)	(-0,49)	(0,55)	(1,04)
	0,846	0,673*	0,718*	0,743*	0,823***	0,913
2016	(-0,85)	(-2,48)	(-2,23)	(-2,12)	(-4,50)	(-1,38)
	0,655*	0,794	0,532***	0,727*	0,796***	0,979
2017	(-2,13)	(-1,55)	(-4,06)	(-2,32)	(-5,36)	(-0,33)
	0,703	0,543***	0,632**	0,669**	0,876**	0,882
2018	(-1,80)	(-3,88)	(-3,08)	(-2,89)	(-3,09)	(-1,93)
	0,653*	0,693*	0,535***	0,688**	0,878**	0,896
2019	(-2,15)	(-2,43)	(-4,00)	(-2,73)	(-3,00)	(-1,71)
	0,226***	0,378***	0,465***	0,372***	0,481***	0,446***
2020	(-4,79)	(-4,72)	(-4,02)	(-5,08)	(-12,26)	(-8,66)
	0,381***	0,419***	0,282***	0,412***	0,517***	0,492***
2021	(-3,51)	(-4,34)	(-5,29)	(-4,74)	(-10,59)	(-8,11)
Baseline: 1st quarter						
2nd quarter	0,939	0,564***	1,000	0,860	1,034	1,002
	(-0,53)	(-6,13)	(-0,00)	(-1,74)	(1,22)	(0,05)
3rd quarter	0,809	0,473***	0,990	0,825*	1,012	1,045
	(-1,76)	(-7,70)	(-0,10)	(-2,22)	(0,44)	(1,10)
4th quarter	0,695**	0,507***	0,874	0,729***	0,919**	0,861***
	(-2,81)	(-6,86)	(-1,32)	(-3,42)	(-2,95)	(-3,42)
N	28885	32340	28885	32340	28885	32340
ln_p						
p						
1/p						

Exponentiated coefficients; *t* statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Through the results, considering the significant coefficient, it is possible to observe that black/brown men present a lower risk than white men of finding a low socio-economic occupation (low OCH). Reis and Aguas (2014) also found that black workers have higher chances of transitioning to more vulnerable jobs than white workers. Although the other predictors do not have significant coefficients, one can notice black/brown women also have a lower risk than white women of finding a high or low socio-economic occupations. However, this does not seem to hold for women in medium OCH and for men in high and medium OCH. In both cases, black/brown people present higher risks than white people of finding a job, which yields shorter periods in unemployment. Comparatively, there is also no consensus in literature regarding race: while Andrade (2004) has found that black tend to remain longer in unemployment, Arruda et al. (2017) have conversely found that they tend to stay shorter periods in unemployment than white.

When considering the position in the household, the risks of finding a job are always lower if the individual is not the head of the household, independently of the socio-economic occupation (OCH). Thus, the risks of finding a job are lower for partners than for heads of the households. Much in agreement, Menezes-Filho and Picchetti (2000); Andrade (2004); Monte et al. (2009); Arruda et al. (2017) have found that household chiefs present lower unemployment duration than other household members. Moreover, the results also highlight that sons/daughter present lower risks than heads of the households of finding a job. On that account, Barros et al. (1997) also found higher unemployment rates for those considered to be sons/daughters in the household.

Broadly speaking, concerning region predictors that had significant coefficients, being in the North and Northeast regions of Brazil results in lower risks of finding a job compared to the Southeast region, the very same way being in the South and in the Midwest regions of Brazil yields higher risks of finding a job than being in the Southeast region. However, it is worth noting that men in the Northern region of Brazil presented higher risks of finding a low socio-economic occupation than men in the Southern region of Brazil. Although higher risks are associated with better chances of getting a job, still in this case, this could be viewed with precaution, for those men would be getting a job in lower socio-economic occupations.

As the model is controlled for individual traits, it is possible to see how age affects the risks of finding a job. According to Barros et al. (1997), Antigo and Machado (2006) and Andrade (2004) older people present lower probabilities of leaving unemployment than younger people. From Table 7, the age groups presented lower risks than those between 30 and 34 years old of finding an occupation, providing the same evidence as previous literature that the probability of leaving unemployment decreases with age. It seems of utmost importance to emphasise that predictors that had significant coefficients indicate that, no matter the type of socio-economic classification occupation, older people have lower risks of finding a job. Those results are especially accurate for

two age groups, namely 55 to 59 years old and 60 to 64 years old. This drawback might be related to the fact that those age groups represent ages closer to the retirement age in Brazil and this would incur higher costs for the employee.

Analysing the dummies for years allows for indirectly capturing how different macroeconomic scenarios affect the risks of finding a job. Table 7 shows that from 2016 onwards, the risks of finding employment are lower than for 2012 (baseline) for both sexes and all types of occupations, being especially lower and significant for 2020 and 2021.Those results highlight the stagnant economic conditions that the Brazilian labour market has been facing since the first economic downturn in 2015 and, therefore, its severe impact on society at large.

The relative risks considering the educational attainments reveals some interesting facts for the socio-economic classification for occupations. The risks for those with higher education of finding a high OCH occupation are much higher than those with no formal education or incomplete primary education, for both sexes, but particularly for women. These risks are accordingly higher when compared to other schooling levels. However, when analysing the risks of finding a medium OCH occupation, it is perceptible that those with complete secondary education and incomplete higher education (intermediate schooling levels) present higher risks than the baseline group, as well as other educational levels. Finally, when analysing the risks of finding a low OCH occupation, those with no formal education or incomplete primary education present higher risks of finding a job than the rest of the educational attainment groups. Therefore, one could make the analogy of a ladder: while higher steps would represent higher socio-economic occupations, medium steps would represent middle socio-economic occupations and lower steps would represent lower socio-economic occupations. The probability of rising in this job ladder depends on higher, medium or lower educational attainments. Therefore, the higher the schooling levels are, higher are the chances of being atop the ladder. Those results indicate the persistence of hierarchical relations, especially for obtaining employment[3].

Mainly, results in this chapter have shown that the mean time in unemployment is 48 months in Brazil during the analysed period. Worse still, through the survival analysis, it was possible to observe that only 2% of the unemployed Brazilians found a job after a month and only 9% of the unemployed individuals found a job after 48 months. Bearing in mind that the unemployment exit rate is a decreasing function of duration, this result highlights that workers are

[3]An extended Cox model was fitted to incorporate unobserved heterogeneity. The results are in the appendix. Broadly speaking, given that the relative risks in the extended cox models are like the relative risks in the parametric model, the Weibull model in the parametric analysis seems to fit appropriately for the unemployment analysis. One advantage of a parametric model compared to a Cox model is that the parametric likelihood easily accommodates right-censored, left-censored, or interval-censored data.

entering unemployment and remaining in that position, thus indicating immobility within this state. Moreover, this immobility was also observed within other labour market states, as results have shown higher probabilities of remaining in the same labour market state as of the first interview, independently of the sex. On that matter, it was interesting to see that those in higher socio-economic classifications had lower probabilities of being unemployed, inactive, discouraged or in lower OCHs. The outputs obtained in the parametric model indicate that men present lower risks than white men of finding a low socio-economic occupation (low OCH) and also that the probability of leaving unemployment decreases with age. Furthermore, risks of finding a job are always lower if the individual is not the head of the household, independently of the socio-economic occupation (OCH). Moreover, regarding the regions, being in the North and Northeast regions of Brazil results in lower risks of finding a job compared to the Southeast region, while being in the South and in the Midwest regions of Brazil yields higher risks of finding a job than being in the Southeast region. Finally, regarding the macroeconomic scenario, the probabilities of being unemployed and finding employment have been much lower from 2016 onwards.

5 Theoretical Model

In an effort to analyse if unemployed workers suffer from the "stigma effect" of long-term unemployment, a microeconomic theoretical job search model based on Vishwanath (1989) was developed and then parametrized considering the Brazilian labour market. As for parameters, all waves were utilized, namely the first, second, third, fourth and fifth interviews, enabling an individual to be followed along the PNAD-C. Using the complete panel allowed for the analysis of long-term unemployment and hence the stigma effect. Moreover, the complete panel provided means for analysing conditional probabilities and possible transitions in the labour market.

Following this preamble, a few properties and hypothesis that were taken into consideration when developing the model shall be presented. The first hypothesis is that educational attainment is employed as a proxy for firms to analyse productivity. Thus, unemployed workers with higher educational attainments would have higher reservation wages. These reservation wages, however, are expected to decrease with time in unemployment, but this decrease is yet higher for those with lower educational attainments. Also, it is expected, as seen before, that women will be in a more vulnerable situation than men, with lower reservation wages and lower chances of getting a job. These sex differences yield different levels of inequality within the labour market and thus require different policies targeting them. Therefore, firms discriminate individuals with longer unemployment spells, given offered wages, offering a smaller wage to those who have longer unemployment duration.

Furthermore, it is important to acknowledge that, while the theoretical model has the advantage of assessing policymakers when it comes to long-term unemployment, and identifying people in these vulnerable conditions, these come at the cost of simplifying a fairly complex issue that can affect people differently. However, for the Brazilian case, this restriction is already imposed by lack of data for long-term unemployment, job search and how the employer views unemployment. Therefore, combining the theoretical model with the previous analysis is rather a positive tool for policymakers when analysing the labour market. The job search model is stated in the following paragraphs.

Consider the follow discrete time model of a risk-neutral (expected income maximising) worker searching for a job in a decentralised labour market. Let $\lambda > 0$ be the probability that a firm has a job vacancy. Associated with each job vacancy is an offer, which, for simplicity, is assumed to be the lifetime discounted income from the job - also referred as wage. It is important to highlight that as the probability does not change over time and the number of firms in each period is constant, a large number of failures in the matching process implies in a higher unemployment length.

Each offer is an independent random draw from the cumulative probability distribution: $F(w; I)$, where I denotes the information the firm knows about the worker. The search cost of

visiting a firm is represented by $c > 0$.

The only difference between jobs is the wage offer. Therefore, if there is a job vacancy, the worker can decide to either continue the job search or to accept the match. The latter occurs with a probability p. Furthermore, if the match is successful, the worker will be employed for a lifetime at the offered wage.

In addition, the number of match failures can be seen as an indicator of the worker's quality: as failures increase, i. e. unemployment length increases, firms tend to believe that the worker presents a lower productivity. Based on that, the stigma effect can be formally incorporated into the model.The stigma effect is formally introduced through the following assumption:

Assumption 1. *The probability of a match in the next period decreases if in the current period the worker decides to explore an offer but does not secure the job. It is worth mentioning that the probability depends on I. Therefore, if $p_{k^{s,e}}$ denotes the match probability after k match failures throughout the unemployment duration (indexed for sex and educational attainment), then $p_{k^{s,e}} \geq p_{(k^{s,e}+1)}$ for $k^{s,e} = 0, 1, 2, 3, ...$*

Therefore, firms may attempt to estimate the worker's productivity from the worker's unemployment history. Associating larger numbers of failures with longer unemployment duration, it is possible to show that the match probability falls in every period. The longer the number of failures, the more inclined firms are to believe the worker is of bad quality and it is reasonable to expect the match probability to fall with the number of failures. The following discussion serves to justify assumption 1.

Remark. *The property of the probability is a consequence of the signaling model.*

Proof. Let's suppose five types of unemployment workers, with different productivity levels:

$$0 < \theta_1 < \theta_2 < \theta_3 < \theta_4 < \theta_5$$

being θ_5 the highest level of productivity.

Also suppose that firms analyse, in an ex-ante manner, the worker's educational attainments. Aware of the schooling signal as a proxy to productivity, they offer different contracts.

A worker of type $i = 1, 2, 3, 4, 5$ can get e years of education at cost $c(e) = \theta_i e$. Utility is then given by:

$$u(w * (e)) - c(e, \theta_i)$$

Obtaining higher levels of education is more costly if the individual is by nature not very productive. This can be observed by the Spence-Mirlees condition, also known as the single crossing condition

$$u' > 0 \quad u'' < 0$$

$$\frac{\partial c}{\partial e} > 0 \quad \frac{\partial c}{\partial \theta} > 0 \quad \frac{\partial^2 c}{\partial^2 \theta} > 0 \quad \frac{\partial^2 c}{\partial \theta \partial r} > 0$$

Thus, two types of constraints must hold:

- Individual rationality: each worker must prefer their contract to the outside option;
- Individual compatibility: each worker must prefer their own contract to any other

$$\theta_i e_i - c(\theta_i, e_i) \geq \theta_i e_j - c(\theta_j, e_j), \forall i \neq j \quad \epsilon \quad 1, 2, 3, 4, 5 \quad (IC)$$

$$\theta_j e_j - c(\theta_j, e_j) \geq 0 \forall i \quad (IR)$$

For the individual compatibility constraint, one can prove that if $\theta_3 e_3 - c(\theta_3, e_3) \geq \theta_3 e_2 - c(\theta_2, e_2)$ it is possible to slightly increase $c(\theta_3, e_3)$ without violating other restrictions. Thus, the worker's utility can be higher (it has not reached its maximum) and IC_{32} is active. Following the same reasoning IC_{21} is also active. $IC_{12} + IC_{21}$ yields:

$$\theta_1 e_1 - c_1 + \theta_2 e_2 - c_2 \geq \theta_1 e_2 - c_2 + \theta_2 e_1 - c_1$$

$$\theta_2(e_2 - \theta_1) - \theta_1(e_2 - e_1) \geq 0$$

$$\theta_2 \theta_1)(e_2 - e_1) \geq 0$$

$$e_2 \geq e_1$$

Considering that IC_{31}:

$$\theta_3 e_3 - c_3 = \theta_3 e_2 - c_2$$

$$= \theta_3 e_2 - (\theta_2 e_2 - \theta_2 e_1 + c_1)$$
$$= \theta_3 e_1 - \theta_3 e_1 + \theta_3 e_2 - \theta_2 e_2 + \theta_2 e_1 - c_1)$$
$$= \theta_3 e_1 - c_1 + \theta_3(e_2 - e_1) - \theta_2(e_2 - e_1)$$
$$= \theta_3 e_1 - c_1 + (\theta_3 - \theta_2)(e_2 - e_1) \geq 0$$

Therefore

$$(IC_{ij} + IC_{ji}) : (\theta_j - \theta_i)(e_j - e_i) \geq 0$$

If $j > i$, then $e_j > e_i$. On this point, one can consider only ICs that are active. Considering IC_j, $j - 1$ is active. By induction:

$$\theta_i e_i - c_i = \theta_i e_i - c_j + (\theta_i - \theta_j)(e_{i-1} - e_j) + (...)$$
$$\theta_i e_i - c_i = \theta_i e_j - c_j$$

On the one hand, the least productive person has no incentive to acquire education, give that he/she is getting the worse possible wage. On the other, the one with highest productivity is getting the highest possible wage. Then, incentive compatible requires:

$$\theta_i - \theta_{i-1} e_i \leq \theta_{i-1}$$
$$\theta_i - \theta_i e_i \geq \theta_{i-1}$$

Therefore:

$$\theta_5 - \theta_4 e_5 \leq \theta_4$$
$$\theta_4 - \theta_3 e_4 \leq \theta_3$$
$$\theta_3 - \theta_2 e_3 \leq \theta_2$$
$$\theta_2 - \theta_1 e_2 \leq \theta_1$$

Otherwise individuals with lower productivity would prefer to acquire higher levels of education. Also:

$$\theta_5 - \theta_5 e_5 \geq \theta_4$$
$$\theta_4 - \theta_4 e_4 \geq \theta_3$$

$$\theta_3 - \theta_3 e_3 \geq \theta_2$$

$$\theta_2 - \theta_2 e_2 \geq \theta_1$$

$$\theta_1 - \theta_1 e_1 \geq 0$$

Otherwise, high productivity workers would prefer to acquire less education and a smaller wage.

Therefore, the only intuitive equilibrium is a separating equilibrium, which gives:

$$e_1 = 0$$

$$e_2 = (\theta_2 - \theta_1)\theta_1$$

$$e_3 = e_2 + (\theta_3 - \theta_2)\theta_2$$

$$e_4 = e_3 + (\theta_4 - \theta_3)\theta_3$$

$$e_5 = e_4 + (\theta_5 - \theta_4)\theta_4$$

Yielding that the lowest type takes no education and the highest type takes enough to separate from the others (middle types). It is important to recall here that firms analyse educational attainment beforehand.

Let's suppose that educational attainment obtained by workers are independent random variables $g_i e$ and $G_i e$ for the five educational levels, represented respectively by the density and cumulative functions.

It is reasonable to assume that higher educational attainments are more likely related to the worker with higher productivity. Hence, the likelihood ratio $\frac{g_5(e)}{g_4(e)}$ is increasing in e and, likewise, $\frac{g_4(e)}{g_3(e)}$ is also increasing in e. Thus, $\frac{g_i(e)}{g_{i-1}(e)}$, where i represents the productivity levels, is also increasing in e.

Then, given the educational level e, it can be shown that the probability that the worker is of the highest type, denoted $P(\theta_5|e)$ is increasing in e. From Bayes' rule:

$$P(\theta_5|e) = \frac{P(e|\theta_5)P(\theta_5)}{\sum_{r_j=1}^{r_j} P(e|\theta_j)P(\theta_j)}$$

Where $\theta_j = (1, 2, 3, 4)$ and r represents the productivity levels.Taking the derivatives, it is readily established that $\frac{\partial P(\theta_5|e)}{\partial e} \geq 0$ for all e if, and only if, $\frac{\partial \log[\frac{g_i}{g_{i-1}(e)}]}{\partial e}$ is positive, which is assured

by the increasing likelihood-ratio assumption. Thus, the minimum educational level needed to have a probability equal to b is given by e^*.

Moreover, if $b_{k^{s,e}}$ represents the ex-ante probability that the worker is of type r_5 given that he/she has experienced $k^{s,e}$ failures, it is possible to show that:

$$b_{k^{s,e}} > b_{k^{s,e}+1} \; for \; k^{s,e} = 0, 1, 2, 3, ...$$

To verify this, one can observe from Baye's rule that for $k^{s,e} = 0, 1, 2, 3, ..., N$:

$$b_{k+1} = \frac{G_5[e^*(b_{k^{s,e}})]b_{k^{s,e}}}{G_5[e^*(b_{k^{s,e}})]b_{k^{s,e}} + \sum_{i=1}^{i=4} G_i[e^*(b_{k^{s,e}})](1 - b_{k^{s,e}})}$$

Thus, $b_{k+1} \leq b_k$ if $G_i(e) \leq G_{i-1}(e)$ for all e. This condition is implied by the assumption of increasing likelihood ratio, as shown below. Consider the hazard $h_i(e) \equiv \frac{}{t} o \Theta g_i(e)[1 - G_i(e)]$ for all $i = 1, 2, 3, 4, 5$. By virtue of increasing ratio $\frac{f_5(e)}{f_4(e)}$, we have:

$$h_5(e) \leq \frac{g_5(e)}{\left\{ \int_{x \geq e} \frac{g_4(x) g_5(e)}{g_4(e)} \, dx \right\}} = h_4(e)$$

Then, the required result follows from expressing $1 - G_i(e)$ in terms of the hazard as equal to $exp[-\int_0^e h_i(s)ds]$. The increasing-ratio assumption is equivalent to likelihood-ratio ordering of distributions, which implies first order stochastic dominance.

As the number of match failures increases, the prior belief that the worker is of high productivity decreases. If $e^*(b)$ is the minimum schooling level needed to have a probability equals to b, the match probability stated as $1 - G_i[e^*(b_k)]$ is decreasing in k for all types of unemployed workers. Thus, as a consequence of the firm behaviour, there is a decline in the match probability. This arises as a natural consequence of firm behaviour, justifying the assumption 1. □

In accordance with Vishwanath (1989), it is also assumed that the information set I indicates only the number of match failures, to observe the stigma effect alone. Thereby, $F(w; k^{s,e})$ is the offer distribution for a worker who has experienced $k^{s,e}$ match failures. In addition, as firms may discriminate wage offers according to the worker's unemployment history (number of failures), it is further assumed that:

$$F(w; k^{s,e} + 1) = F(w - a_{k^{s,e}}; k^{s,e})$$

In which, $a_k \leq 0$ is a constant. This equation means that after each failure, the distribution is shifted downward. It is worth mentioning that one of the biggest differences between this model

and Vishwanath (1989) can be observed here: as there is no given test prior to the job offer, the vacancy is explicitly offered to the job seeker.

Assuming that the unemployed worker knows the match probability and the offer distribution parameters, the optimal job search will be stated below for $p_{k^{s,e}} \neq 0$ is

$$V_{k^{s,e}} = \lambda \int_0^\infty max \left\{ p_{k^{s,e}} w + (1 - p_{k^{s,e}}) V_{k^{s,e}+1}, V_{k^{s,e}}, \right\} dF(w, k^{s,e}) - c$$

Where, $V_k^{s,e}$ denotes the expected net income deriving from a search for a worker with k failures. Also, the state of the unemployed job seeker is the number of match failures throughout the unemployment duration. If a wage offer, w, is made, the optimal decision is to continue the search if $p_k w + (1 - p_k) V_{k+1} < V_k$. Consequently, the reservation wage in state $k^{s,e}$ is:

$$R_{k^{s,e}} = [V_{k^{s,e}} - (1 - p_{k^{s,e}}) V_{k^{s,e}+1}] / p_{k^{s,e}}$$

Based on the reservation wage, it is possible to re-write the optimal job search as it can be seen below:

$$V_{k^{s,e}} = \int_0^\infty max \left\{ p_{k^{s,e}} w + (1 - p_{k^{s,e}}) V_{k^{s,e}+1}, V_{k^{s,e}}, \right\} dF(w, k^{s,e}) - c$$

$$\frac{V_{k^{s,e}}}{\lambda} = \frac{P_{k^{s,e}}}{\lambda} \int_0^\infty max \left\{ (w, r_{k^{s,e}}) \right\} dF(w, k^{s,e}) + \frac{(1 - p_{k^{s,e}}) V_{k^{s,e}+1}}{\lambda} - \frac{c}{\lambda}$$

or

$$\frac{R_{k^{s,e}}}{\lambda} = \int_0^\infty max \left\{ (w, r_{k^{s,e}}) \right\} dF(w, k^{s,e}) - \frac{c}{\lambda p_{k^{s,e}}}$$

or, finally,

$$\lambda \int_0^\infty max \left(w, r_{k^{s,e}} \right), dF(w, k^{s,e}) = \frac{c}{p_{k^{s,e}}}$$

$$\int_{R_{k^{s,e}}}^\infty (w - \frac{R_{k^{s,e}}}{\lambda}) dF(w, k^{s,e}) = \frac{c}{\frac{q_{k^{s,e}}}{1 - F(R_{k^{s,e}}, k^{s,e})}} \tag{15}$$

Therefore, the only solution to the equation is the reservation wage of a worker with $k^{s,e}$ failures. In addition, $q_{k^{s,e}}$, that represents the escape probability from unemployment in state $k^{s,e}$, is:

$$q_{k^{s,e}} \equiv \lambda p_{k^{s,e}} [1 - F(R_{k^{s,e}}; k^{s,e})]. \tag{16}$$

To determine the escape-rate behaviour from unemployment, one must define the conditional expectation for any s:

$$\alpha_{k^{s,e}}(s) \equiv E[W_k - s | W_{k^{s,e}} > s] = \int_s^{\infty} (w-s) \frac{dF(w, k^{s,e})}{[1 - F(s; k^{s,e})]} \tag{17}$$

Therefore, for $k^{s,e} \geq 1$, $\alpha_{k^{s,e}}(s)$ is decreasing in s if $\alpha_0(s)$ is decreasing in s. The reservation wage and escape rate behaviour are explained in the proposition below.

Proposition 1. *In the model, as unemployment spells increases, the reservation wages decreases, $R_{k^{s,e}} \geq R_{k^{s,e}+1}$ for all $k^{s,e}$. Furthermore, an individual's probability of exiting unemployment decreases when the period of unemployment increases (escape rate is non-increasing over the unemployment spell) . Therefore, unemployment duration is a signal of lower productivity for the firms and, thus, this entails discrimination in the firm's hiring process.*

Proof. To determine the escape-rate behaviour from unemployment, one must assume the following restrictions:

1. $F(w; k^{s,e} + 1) = F(w - a_{k^{s,e}}; k^{s,e})$
2. $\int_{R_{k^{s,e}}}^{\infty} (w - \frac{R_{k^{s,e}}}{\lambda}) dF(w, k^{s,e}) = \frac{c}{\lambda P_{k^{s,e}}}$

And define $\overline{R}_{k^{s,e}+1} = R_{k^{s,e}+1} - a_{k^{s,e}}$ for $k^{s,e} > 0$. Substituting equation 1 into equation 2 and changing variables with $y = w - a_{k^{s,e}}$:

$$\int_{R_{k^{s,e}}}^{\infty} (w - \frac{R_{k^{s,e}}}{\lambda}) dF(w, k^{s,e}) = \frac{c}{\lambda p_{k^{s,e}}}$$

$$\int_{R_{k^{s,e}+1}}^{\infty} (w - a_{k^{s,e}} - \frac{\overline{R}_{k^{s,e}+1}}{\lambda}) dF(w - a_{k^{s,e}}, k^{s,e}) = \frac{c}{\lambda p_{k^{s,e}+1}}$$

$$\int_{R_{k^{s,e}+1}}^{\infty} (y - \frac{\overline{R}_{k^{s,e}+1}}{\lambda}) dF(y, k^{s,e}) = \frac{c}{\lambda p_{k^{s,e}+1}}$$

$$> \frac{c}{\lambda P_{k^{s,e}}} = \int_{R_{k^{s,e}}}^{\infty} (y - \frac{R_{k^{s,e}+1}}{\lambda}) dF(y, k^{s,e})$$

Since $k^{s,e} > 0$, $\overline{R}_{k^{s,e}+1} < R_{k^{s,e}}$, the first part of the proposition is proved. From the second equation, the escape probability from unemployment in state $k^{s,e}$ can be written as:

$$\int_{R_{k^{s,e}}}^{\infty} (w - \frac{R_{k^{s,e}}}{\lambda}) dF(w, k^{s,e}) = \frac{c[1 - F(R_{k^{s,e}}; k^{s,e})]}{q_{k^{s,e}}} \tag{18}$$

Thus,

$$q_{k^{s,e}} = \frac{c[1 - F(R_{k^{s,e}}; k^{s,e})]}{\int_{R_{k^{s,e}}}^{\infty} (w - \frac{R_{k^{s,e}}}{\lambda}) dF(w, k^{s,e})}$$

$$q_{k^{s,e}} = \frac{c}{E[w_{k^{s,e}} - R_{k^{s,e}} | w_{k^{s,e}} > R_{k^{s,e}}]}$$

$$q_{k^{s,e}} = \frac{c}{\alpha_{k^{s,e}}(R_{k^{s,e}})} \tag{19}$$

Therefore, the escape rate is non-increasing over the unemployment spell. □

To see the dependence of the reservation wage and the escape rate, one must take the derivatives in $\int_{R_{k^{s,e}}}^{\infty} (w - \frac{R_{k^{s,e}}}{\lambda}) dF(w, k^{s,e}) = \frac{c}{\lambda P_{k^{s,e}}}$:

$$\frac{\partial R_{k^{s,e}}}{\partial c} = \frac{-1}{\lambda p_{k^{s,e}}}[1 - F(R_{k^{s,e}}; k^{s,e})] = \frac{-1}{q_{k^{s,e}}}$$

Therefore, the escape rate, $q_{k^{s,e}}$ is increasing in c for each $k^{s,e}$. Also, for each $k^{s,e}$, the reservation wage is positively dependent on λ and $p_{k^{s,e}}$.

The result of this model shows that the higher the reservation wage, the higher the unemployment duration. In the same line, an individual's probability of exiting unemployment decreases when the period of unemployment increases. Therefore, unemployment duration is a signal of lower productivity for firms and, thus, this entails discrimination in the firm's hiring process. Furthermore, the stigma effect also influences the worker's environment, since as unemployment spells increases, the reservation wage decreases. Those results will be better discussed when analysing the Brazilian labour market in the following paragraphs.

In order to observe the stigma effect for the Brazilian labour market, by sex, equation 15 (optimal job search strategy) was parameterized using a Weibull distribution in accordance with the duration models in the previous chapter. Firstly, the selected data and variables for the model's parameterization are presented and then results are shown. In equation 15, w represents the monthly mean wages, deflating to 2021 values, in the Brazilian labour market by sex and educational attainment. This can be seen in the table below.

Table 10: Wages by educational attainment and sex, Brazil

Highest educational attainment	Women	Men
No formal education/Incomplete primary education	986,1886	1535,642
Primary education (complete)/Incomplete secondary education	1228,362	1944,797
Secondary education (complete)	1589,353	2522,032
Incomplete higher education	1868,003	3163,217
Higher education	4167,877	7002,453

Source: Own elaboration based on the PNAD-C.

From table 11, one can observe the gender gap pay: women earn less than men, independently of the educational attainment. This is a visible example of sex discrimination in the labour force, which leads to inequalities within the labour force dynamic. While there are some facts that partly explain this gender gap, such as working hours and women being more likely to take career breaks to look after children or ill members of the family, there is another part of the gap related to sex discrimination, inasmuch as the previous aspects mentioned do not account for the whole gap (ILO (2019b)). Based on that, one can hypothesize that these differences most likely represent one of the reasons for women having lower reservation wages than men. This calls attention not only to the importance of evaluating possible sex bias for those employed, but also for unemployed, as this issue may also arise when women are looking for a job.

In addition, in equation 15, lambda, λ is the probability of having a job vacancy in the labour market with an attributed value of 0.7. As there is no available data on job vacancy within the household survey that was utilized, the employment rate, which is roughly 70% independently of the sex, is used as a proxy for the probability of a job vacancy. Moreover, q_k is the escape probability from unemployment, therefore represented by the conditional probability of leaving unemployment given unemployment duration. Those probabilities can be seen in the tables below.

Table 11: Conditional probability of leaving unemployment given elapsed time in this situation, Women, Brazil.

Time in unemployment	No formal education/Incomplete primary education	Primary education (complete)/Incomplete secondary education	Secondary education (complete)	Incomplete higher education	Higher education
0 to 6 months	0,3695	0,3433	0,4017	0,4081	0,4577
7 to 12 months	0,3430	0,3306	0,4225	0,4067	0,4130
13 to 18 months	0,3288	0,3044	0,4011	0,4001	0,4136
19 to 24 months	0,2778	0,2969	0,2972	0,3023	0,3147
24 months or more	0,2550	0,2420	0,2821	0,3133	0,2883

Source: Own elaboration based on the PNAD-C.

Table 12: Conditional probability of leaving unemployment given elapsed time in this situation, Men, Brazil.

Time in unemployment	No formal education/Incomplete primary education	Primary education (complete)/Incomplete secondary education	Secondary education (complete)	Incomplete higher education	Higher education
0 to 6 months	0,5295	0,5039	0,5288	0,4600	0,5374
7 to 12 months	0,4919	0,4506	0,5091	0,4524	0,5209
13 to 18 months	0,5270	0,4574	0,5411	0,5274	0,5297
19 to 24 months	0,4700	0,3833	0,4182	0,4124	0,4159
24 months or more	0,4059	0,3696	0,3591	0,3712	0,3578

Source: Own elaboration based on the PNAD-C.

The conditional probabilities in tables 12 and 13, respectively for women and men, show duration dependence. The longer the elapsed time in unemployment, lower are the chances of leaving this condition (those results were also found by Heckman and Borjas (1980)). In agreement with previous findings (see Barros et al. (1997); Andrade (2004); Antigo and Machado (2006); Reis and Aguas (2014)), women are more likely to remain unemployed than men, also indicating sex inequalities within the labour market. The conditional probabilities of leaving unemployment are especially low for long-term unemployment (24 months or more), possibly indicating a previous hint on the stigma effect in Brazil. However, one cannot assume that as the proper stigma, as the reduction in the probability may also account for workers reducing their search intensity, thus becoming discouraged.

Also, it is important to highlight that w, wages, and k, match failures given by different elapsed unemployment duration, were adjusted on the probability density function and cumulative density function of the Weibull distribution, in order to assure first order stochastic dominance considering each educational attainment level. It is important to assure that as time in unemployment increases, the paid wage for workers tend to decrease. This adjustment, given by α_k and seen in equation 19, is shown in the table below:

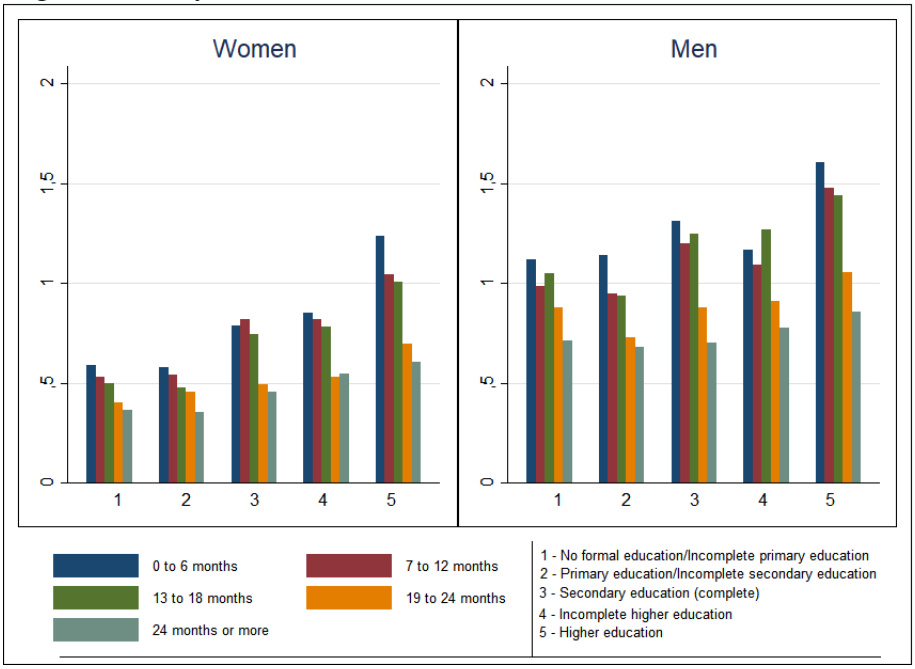
Table 13: Adjustment by educational attainment and sex, Brazil

Highest educational attainment	**Women**	**Men**
No formal education/Incomplete primary education	0,95706	0,97713
Primary education (complete)/Incomplete secondary education	0,95318	0,9691
Secondary education (complete)	0,94673	0,96233
Incomplete higher education	0,95603	0,95882
Higher education	0,95054	0,95835

Source: Own elaboration based on the PNAD-C.

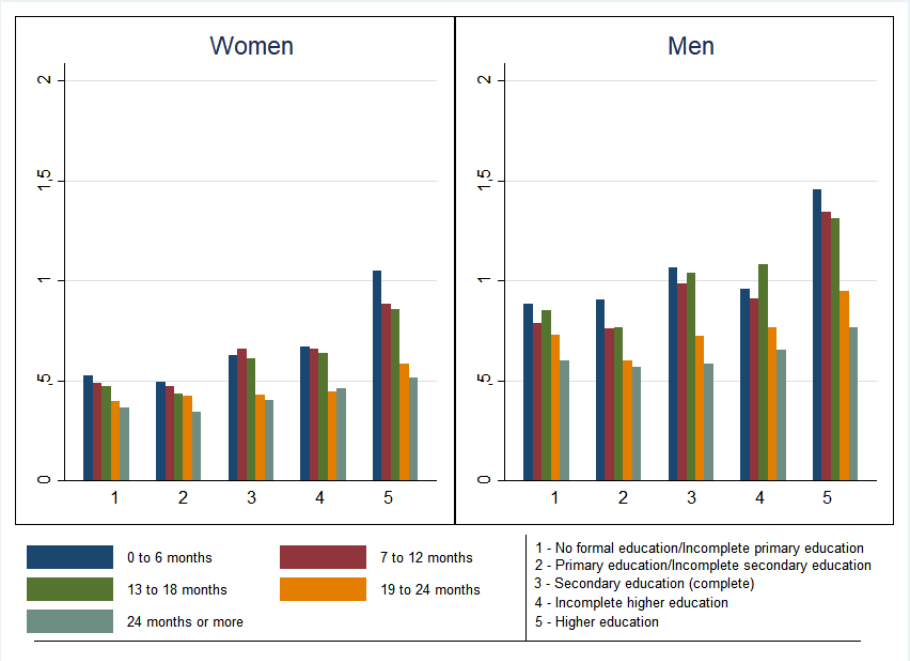
Finally, in equation 15 c represents the search cost. This parameter will represent the cost of living, thus the minimum amount needed to cover basic expenses. In this matter, two different thresholds for costs of living were taken into account. The first is a cost of R$210,00, used as an eligibility criterion for the Auxílio Brasil aid (cash transfer program that replaced Bolsa Família and the emergencial aid during the Covid-19 pandemic), albeit being very low in meeting basic needs (Neri and Hecksher (2022)). The second threshold is exactly the Auxílio Brasil aid of R$400,00. Therefore, results for the parameterized theoretical model are presented below. Results for q_k, the match probabilities after elapsed time in unemployment, which is precisely the stigma effect, is shown below.

Figure 14: Stigma effect by sex and educational attainment with c=R$210, Brazil, 2012-2021.



Source: Own elaboration based on the PNAD-C, 2012-2021.

Figure 15: Stigma effect by sex and educational attainment with c=R$400, Brazil, 2012-2021.



Source: Own elaboration based on the PNAD-C, 2012-2021.

Results in Figures 14 and 15 depict the stigma effect in the Brazilian labour market, as an increase in elapsed time in unemployment decreases the match probability of finding a job. Thus, there is a negative duration dependence of unemployment, which, in general, decreases the probability in the following observed period. For instance, those unemployed for 24 months or more (considered to be long-term unemployment in Brazil) present the lowest probabilities of finding a job, regardless of the highest educational attainment. In this sense, firms regard unemployment as a negative signal of productivity and loss of human capital (see Acemoglu (1995), Vishwanath (1989), Eriksson and Rooth (2014) and Van Belle et al. (2017)).

Nevertheless, the probabilities increase as the highest educational attainment increases, indicating, for example, that those with higher education present higher chances of finding a match than those with complete secondary education. For instance, those with complete secondary education have higher chances of finding a match than those with no formal education or incomplete primary education. Hence, this indicates again that education is a valuable asset in assuring lower chances of being both in unemployment and in more liable situations in the labour market. Moreover, it indicates that the stigma effect is lower for higher educational attainments. This might be associated with the fact that there is a lower information asymmetry for those with higher schooling levels, as they can inform firms and employers the maximum degree obtained, which is a good proxy for productivity (in line with previous found results by Camargo and Reis (2005)). Also, women present

worse match probabilities than men, calling attention once more to the more vulnerable situation that they encounter in the labour market.

Furthermore, it is worth noting that the match probability is lower when the cost of living is higher. This can be explained by the fact that the observed probability that, q, it is the one that depends on the cost. The job seeker must have a higher salary to pay for all the expenses when the cost increases, then the probability of having a matching is lower. However, since q is fixed, it seems that when the cost increases the probability of offering a job increases accordingly (being a matter of perspective). Also, the probabilities that are higher than one can be interpreted as the possibility of having multiple job vacancies available. On this, it is interesting to observe, especially for the highest cost of living, that the probability of the q_k being greater than one is mostly perceived amongst those with higher educational levels.

Moreover, the following table presents the reservation wages considering elapsed time in unemployment in the theoretical model and considering the cost of R$210,00. Table 15 shows the reservation wages for women given the elapsed unemployment duration considering all the other parameters in the model. One can observe that women with lower educational attainments than incomplete higher education present a decline in their reservation wage as time in unemployment increases, thus highlighting that those women are adjusting their labour market expectations to find a job. Moreover, as time in unemployment elapses, individuals with lower educational levels usually cannot rely on any savings (given their low wages) and thus become deprived (or even aggravating such condition) with time, willing to accept whatever offer is available. On this matter, it is important to note that the lack of income yields other types of deprivations. The behaviour on the reservation wage is different for women with incomplete higher education and higher education: as time in unemployment increases, their reservation wage also increases. This can be related to the fact that highly educated workers, given their previous income, are able to use their savings and choose to stay longer in unemployment to acquire a desired vacancy in the job market. According to Eriksson and Rooth (2014) the negative effect for long-term unemployment spells is not found for highly educated workers in the Swedish labour market.

Table 14: Reservation wage with c=R$210 by educational attainment for women, Brazil

Unemployment duration	0 to 6 months	7 to 12 months	13 to 18 months	19 to 24 months	24 months or more
No formal education/ Incomplete primary education	387,00	378,70	387,54	319,75	299,44
Primary education (complete)/ Incomplete secondary education	585,30	601,35	586,88	608,79	504,38
Secondary education (complete	1068,71	1145,87	1160,35	1006,00	1012,77
Incomplete higher education	1356,91	1407,58	1448,75	1306,98	1383,94
Higher education	3943,68	3981,93	4085,19	3980,60	4003,37

Source: Own elaboration based on the PNAD-C.

Table 15: Reservation wage with c=R$210 by educational attainment for men, Brazil

Unemployment duration	0 to 6 months	7 to 12 months	13 to 18 months	19 to 24 months	24 months or more
No formal education/ Incomplete primary education	1112,62	1118,29	1193,36	1176,53	1136,80
Primary education (complete)/ Incomplete secondary education	1533,09	1523,95	1583,68	1528,56	1554,61
Secondary education (complete	2192,64	2237,66	2332,05	2250,65	2212,34
Incomplete higher education	2817,57	2888,43	3052,51	2985,83	2990,37
Higher education	7087,68	7237,14	7407,93	7419,32	7465,37

Source: Own elaboration based on the PNAD-C.

For this incurring cost of search, the reservation wages for men either increase or remain the same independently of the educational attainment. Although this result differs from what theory suggests (see Vishwanath (1989); Cahuc et al. (2014)), this might stem from the fact that such a low threshold is not an ideal parameter for assessing individual choices and changes in preferences and expectations due to longer periods of unemployment for men. With this in mind, the following tables present the reservation wage considering the threshold of $c = R\$400$.

Table 16: Reservation wage with c=R$400 by educational attainment for men, Brazil

Unemployment duration	0 to 6 months	7 to 12 months	13 to 18 months	19 to 24 months	24 months or more
No formal education/ Incomplete primary education	703,85	694,64	797,00	753,34	677,50
Primary education (complete)/ Incomplete secondary education	1083,38	1041,89	1114,94	1003,33	1024,10
Secondary education (complete	1739,53	1777,30	1901,72	1725,99	1629,98
Incomplete higher education	2290,00	2361,81	2598,95	2433,08	2395,76
Higher education	6599,37	6741,59	6927,15	6823,61	6789,58

Source: Own elaboration based on the PNAD-C.

Table 17: Reservation wage with c=R$400 by educational attainment for women, Brazil

Unemployment duration	0 to 6 months	7 to 12 months	13 to 18 months	19 to 24 months	24 months or more
No formal education/ Incomplete primary education	-36,56	-54,26	-50,94	-170,46	-225,61
Primary education (complete)/ Incomplete secondary education	89,78	106,41	81,61	104,06	-66,12
Secondary education (complete	562,49	665,29	671,17	430,08	430,39
Incomplete higher education	832,62	891,10	934,98	698,35	797,91
Higher education	3396,29	3391,10	3504,11	3254,81	3233,57

Source: Own elaboration based on the PNAD-C.

Table 17 presents the reservation wage for men considering the monthly cost of living of R$400. Those results are now aligned with the literature: the longer in unemployment, the lower the reservation wage for all educational attainments, solely for those with higher education. The same trend is observed for women, in table 18, but their reservation wages are much lower than men. The negative reservation wage for women with no formal education or incomplete primary education may indicate that from the moment they enter unemployment, they are willing to work for any wage to be employed and thus back in the job market. This might also suggest that their deprivation levels when unemployed are much higher than men, considering that they usually are responsible for assuming responsibilities with children. This result, once again, is confirming the horizontal inequalities within the labour market regarding sex.

Moreover, these tables call attention that those with lower educational attainments and in long-term unemployment not only face the stigma effect of finding a job, but they might be facing monetary hardships that also affect other aspects in life and well-being. Therefore, those reservation

wages, especially for women, indicate that long periods in unemployment might be contributing to an increase in poverty levels. Worse still, the theoretical model displays the stigma effect in the Brazilian labour market, indicating that firms are less likely to hire an unemployed worker as they regard this as a negative signal (Nickell (1979), Clark et al. (1979), Heckman and Borjas (1980), Vishwanath (1989), Blanchard and Diamond (1994), Acemoglu (1995)). Specifically, women and those with lower levels of educational attainments present the worst results, raising, on the one hand even more concerns about long-term unemployment as those groups were previously more vulnerable in the labour market. On the other, this highlights the importance and need of specific public policies targeting women and education.

6 Conclusions

The main goal of this dissertation thesis was to analyse unemployment considering its dynamic within the labour market in Brazil, between 2012 and 2021, using the PNAD-C. In light of the recent economic crises (2015 and the pandemic), the country has faced a considerable increase in unemployment levels during the last eight years, resurfacing old issues for Brazilian workers. This is particularly noteworthy given dire social consequences it may cause, namely increase in poverty levels, increase in inequalities within the labour market and social exclusion.

From this standpoint, in chapter 2 I first reviewed the theoretical work on unemployment and the job search theory. Namely, many authors have used signalling theory to address the unemployment issue, to explain long-term unemployment and the "scarring" effect. On this matter, the duration of unemployment and the transitions in the labour force status have also been used. Recently, audit studies have been used to understand the relation between job search outcomes and the duration dependence of unemployment. Mainly, they have demonstrated that long-term unemployment is viewed as a negative signal by employers, as individuals with longer unemployment spells received fewer call-backs than job applicants with identical traits, but shorter unemployment spells. Concerning the empirical review, I focused on unemployment in Brazil and how individual, household and macroeconomic factors have influenced the duration of unemployment and the transitions within the labour force status. The empirical review highlighted some important features of those in unemployment that were taken into consideration when applying the methodological approaches.

In the third chapter, the methodological approach was explained. Based on the PNAD-C interviews, it was possible to create a panel following the individuals and its dynamic within the labour market in more than one period of time. This is one of the main contributions of this work, since, to my knowledge, no one has used the PNAD-C panel to analyse unemployment through 2012 and 2021 (some papers have focused on shorter periods of time), as well as to analyse the labour market dynamic considering socio-economic classification of occupations.

In the fourth chapter results show that the state in the first interview strongly influences the state in the second interview, denoting that there is duration dependence. For instance, individuals unemployed in the first interview present higher chances of remaining in this state than of transitioning to other states in the labour market. Furthermore, it demonstrated the importance of considering occupations and socio-economic traits to analyse disparities within the labour market, as individuals with higher educational attainments present higher chances of finding higher socio-economic occupations than those with lower educational attainments. Hence, those with higher educational attainments present higher chances of being in better quality employment than those with lower

educational attainments. Conversely, as those with lower educational attainments present higher chances of being in lower socio-economic occupations, they are more prompted to be in worse quality types of employment.

In the same manner, Survival analysis has demonstrated that distributional differences, such as sex, race, age group and educational attainments, are important to consider when analysing the Brazilian labour market as these differences yield different levels of inequality within the labour market. Finally, the last chapter employed a theoretical job search model incorporating the "stigma effect" of unemployment. Results from the parameterized model have shown that firms are less likely to hire long-term unemployed individuals. Worse still, women and individuals with lower educational attainments suffer the most from the scarring effect.

The obtained results in this dissertation thesis shed light on the importance of narrowing the gender gap and implementing educational social policies to diminish inequalities within the labour market. Concerning the gender gap within the Brazilian labour market, Chapter 5 has shown the wage difference between sexes and the importance of stimulating equal pay in a country where, despite applicable legislation against gender bias discrimination within the same position, there are still large differences in wages. Thus, actively promoting law enforcement, encouraging wage transparency between peers, strengthening collective bargaining and the minimum wage system can positively contribute to decrease the wage gap. Regarding education, whilst historically Brazil has advanced and obtained universal access to basic education, such advance was not accompanied by improvements in quality, nor efficacy in keeping the students enrolled and attending school in the long run. As a result, high school dropout rate is still very high and the school quality remains undesirably very low. Hence, this negatively influences individuals' educational attainments and their opportunities in the labour market, urgently demanding policies targeting the improvement of quality in education in general, and high schools in particular, as well as enhancing the access to higher education. Those two features can be a powerful tool in reducing inequalities in the labour market and as a way of promoting social mobility, as higher educational attainments results not only in higher chances of being in a more secure position in the labour market, but it is also a way of moving towards better quality employment in the labour market.

Moreover, although unemployment trends are improving with the recent and yet slight economic recovery, job finding rates amongst the long-term unemployed continue to be low, illustrating the importance of public policies targeting this group to diminish the negative impact of unemployment on individuals and on society. Recent measures in Brazil, such as the provisional measure number 905 (Medida Provisória 905), also known as "Contrato de Trabalho Verde e Amarelo", and the provisional measure number 1045, known as "Programa Emergencial de Manutenção do Emprego e da Renda (BEm)", have insofar failed to thrive (Figueiredo (2022)). The former provi-

sional measure had two intended fronts, namely creating qualification programs for those presenting difficulties in finding employment and also helping those aged between 18 and 29 years old (youth) in obtaining their first formal job contract, through diminished bureaucracy in the hiring process for the employer. The latter provisional measure is a monetary benefit aimed to employees who had their job contracted formally interrupted or employees with reduced working hours during the Covid-19 pandemic.

Accordingly, social policies targeting long-term unemployment could be designed in Brazil mirroring, for example, European social policies for this group. In this sense, the European Commission (2019) recommended four steps in tackling long-term unemployment in the EU countries. Within the first step, States should to encourage registration of the long-term unemployed with an employment service, as this is essential for re-integration into the labour market. On that, the State may also provide information about the program to non-registered individuals (i.e. inactive individuals) as means to encourage them to also register. In Malta, this is achieved via cooperation with NGOs and educational institutions. The second step is to increase individualised support for long-term unemployed, to assess potential needs one might have and also to ensure a job-integration agreement. This job integration agreement is a contract that indicates available re-integration measures to the labour market, objectives and mutual obligations for both parties (unemployed individual and government). This very tailored individual assessment is what guarantees the success of re-inserting people into the market, as they might have different traits. Croatia, for example, has designed a statistical profiling tool that estimates the probability of employment within 12 months of the registered individual. Those with worse employment probabilities and, thus, with higher risks of long-term unemployment receive additional in-depth counselling. The third step is to coordinate available services to long-term unemployed through a single point of contact, as a means of reducing the multiple barriers people in this situation may face. In Finland, through a coordinated system, the municipality provides social and health care services, while the Social Insurance Institution provides vocational rehabilitation either from the same physical location or from a mobile facility. This is especially important, given that those in long-term unemployment may be experiencing vulnerabilities in other aspects of life. Thus, providing coordinated mechanisms may also avoid a process of social exclusion. Finally, the fourth step is to encourage employers, social services, education and training providers to develop partnerships. In France, the government has developed the “Territoires zero chômeur de longue durée” project, in which the government creates employment-oriented companies based on community needs. Long-term unemployed individuals are then trained to develop skills and reintegrated into the labour market with paid permanent contracts. All those steps and examples could be adapted for the Brazilian reality and used as a reference when designing effective public policies towards long-term unemployed individuals, as, in fact, taking into account previous experiences in other countries is a way of reducing the chances of a failed

public policy.

Hence, issues arising from unemployment are of utmost importance on the individual and on the societal level. On the former, not having an income from work yields higher chances of being exposed to deprivations and vulnerable situations. Worse still, it may result in lack of control over one's life and lack of freedom to develop other aspects of life. On the latter, unemployed individuals are not contributing to economic growth, social protection and taxation systems. Hence, unemployment should be seen as a very serious social problem requiring collective redress.

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8 Appendix

Table 18: Log-rank test

Considering	Covariate	Log-rank test	Wilcoxon test
Unemployment duration	Schooling level	893,77	1181,84
		0,000	0,000
Unemployment duration for men	Schooling level	517,61	706,18
		0,000	0,000
Unemployment duration for women	Schooling level	45,88	68,45
		0,000	0,000
Unemployment duration considering transitions to high-quality jobs for men	Schooling level	1321,00	1043,77
		0,000	0,000
Unemployment duration considering transitions to high-quality jobs for women	Schooling level	2176,9	1938,89
		0,000	0,000
Unemployment duration considering transitions to medium-quality jobs for men	Schooling level	475,7	340,33
		0,000	0,000
Unemployment duration considering transitions to medium-quality jobs for women	Schooling level	503,27	413,66
		0,000	0,000
Unemployment duration considering transitions to low-quality jobs for men	Schooling level	1334,14	1345,19
		0,000	0,000
Unemployment duration considering transitions to low-quality jobs for women	Schooling level	251,41	253,51
		0,000	0,000

Note: chi2 and p-values in parentheses

Source: Own elaboration based on the PNAD-C.

Table 19: Relative risks for covariates in the extended cox model by sex, 2012-2021, Brazil.

	OCH – High Men	OCH – High Women	OCH - Medium Men	OCH - Medium Women	OCH – Low Men	OCH – Low Women
Baseline: No formal education/Incomplete primary education						
Primary education (complete)/Incomplete secondary education	1,299	1,836	2,052***	3,079***	0,839***	1,103*
	(1,06)	(1,45)	(4,82)	(5,18)	(-6,26)	(2,22)
Secondary education (complete)	3,199***	9,547***	4,760***	9,840***	0,662***	0,972
	(6,71)	(7,47)	(13,39)	(12,61)	(-16,10)	(-0,78)
Incomplete higher education	7,900***	32,24***	8,355***	16,05***	0,374***	0,801**
	(9,27)	(10,87)	(14,11)	(13,79)	(-12,34)	(-2,80)
Higher education	24,45***	115,4***	5,376***	12,65***	0,221***	0,479***
	(19,39)	(16,10)	(12,15)	(13,46)	(-22,19)	(-11,74)
Black/brown	1,095	0,950	1,097	1,074	0,888***	0,976
	(0,89)	(-0,65)	(1,17)	(1,01)	(-5,07)	(-0,70)
Baseline: Head of the household						
Partner	0,859	0,941	0,887	0,857*	0,960	0,811***
	(-1,21)	(-0,72)	(-1,20)	(-2,00)	(-1,63)	(-6,30)
Son/daughter	0,452***	0,707***	0,515***	0,966	0,542***	0,721***
	(-6,67)	(-3,43)	(-7,28)	(-0,39)	(-21,11)	(-6,53)
Other relative	0,549**	0,986	0,593***	0,796	0,661***	0,888
	(-2,82)	(-0,08)	(-3,35)	(-1,38)	(-8,73)	(-1,58)
Baseline: Southeast						
North	1,357*	0,803	0,979	0,678***	1,238***	1,009
	(2,04)	(-1,82)	(-0,17)	(-3,60)	(6,20)	(0,18)
Northeast	1,068	0,919	0,995	0,640***	1,024	0,906*
	(0,53)	(-0,90)	(-0,05)	(-5,08)	(0,93)	(-2,54)
South	1,582***	1,218	1,375**	1,464***	1,248***	1,562***
	(3,49)	(1,76)	(2,87)	(3,89)	(6,14)	(9,43)
Midwest	1,181	0,990	1,535***	0,987	1,560***	1,193**
	(1,01)	(-0,08)	(3,44)	(-0,12)	(11,75)	(3,13)
Baseline: 30 to 34 years old						
35 to 39 years old	0,977	0,899	0,857	0,915	0,927**	1,049
	(-0,18)	(-1,17)	(-1,62)	(-1,09)	(-2,60)	(1,17)
40 to 44 years old	1,062	0,660***	0,671***	0,755**	0,848***	0,964
	(0,43)	(-3,74)	(-3,49)	(-2,93)	(-5,28)	(-0,81)
45 to 49 years old	0,998	0,784*	0,576***	0,667***	0,754***	0,974
	(-0,01)	(-2,02)	(-4,35)	(-3,52)	(-8,40)	(-0,53)
50 to 54 years old	0,854	0,823	0,472***	0,579***	0,640***	0,843**
	(-0,98)	(-1,42)	(-5,32)	(-3,87)	(-12,18)	(-2,91)
55 to 59 years old	0,545**	0,484***	0,413***	0,334***	0,513***	0,749***
	(-3,05)	(-3,36)	(-5,55)	(-4,61)	(-15,86)	(-3,67)
60 to 64 years old	0,531**	0,231**	0,437***	0,300**	0,400***	0,764*
	(-2,65)	(-2,90)	(-4,24)	(-2,90)	(-15,89)	(-2,19)
Urban	1,541*	0,641***	2,458***	1,400*	0,856***	0,901*
	(2,14)	(-3,76)	(5,40)	(2,51)	(-6,26)	(-2,41)
Metropolitan	1,091	0,794**	1,027	1,239**	0,827***	0,968
	(0,90)	(-2,94)	(0,35)	(3,05)	(-7,31)	(-0,92)
Baseline: 2012	1,259	0,903	1,162	1,095	1,085	1,095
2013	(1,09)	(-0,61)	(0,95)	(0,62)	(1,73)	(1,29)
	1,181	1,119	1,190	1,046	1,091	1,095
2014	(0,79)	(0,68)	(1,12)	(0,30)	(1,82)	(1,27)
	0,936	0,859	0,839	0,932	1,025	1,074
2015	(-0,32)	(-0,95)	(-1,12)	(-0,49)	(0,55)	(1,04)
	0,846	0,673*	0,718*	0,743*	0,823***	0,913
2016	(-0,85)	(-2,48)	(-2,23)	(-2,12)	(-4,50)	(-1,38)
	0,655*	0,794	0,532***	0,727*	0,796***	0,979
2017	(-2,13)	(-1,55)	(-4,06)	(-2,32)	(-5,36)	(-0,33)
	0,703	0,543***	0,632**	0,669**	0,876**	0,882
2018	(-1,80)	(-3,88)	(-3,08)	(-2,89)	(-3,09)	(-1,93)
	0,653*	0,693*	0,535***	0,688**	0,878**	0,896
2019	(-2,15)	(-2,43)	(-4,00)	(-2,73)	(-3,00)	(-1,71)
	0,226***	0,378***	0,465***	0,372***	0,481***	0,446***
2020	(-4,79)	(-4,72)	(-4,02)	(-5,08)	(-12,26)	(-8,66)
	0,381***	0,419***	0,282***	0,412***	0,517***	0,492***
2021	(-3,51)	(-4,34)	(-5,29)	(-4,74)	(-10,59)	(-8,11)
Baseline: 1st quarter						
2nd quarter	0,939	0,564***	1,000	0,860	1,034	1,002
	(-0,53)	(-6,13)	(-0,00)	(-1,74)	(1,22)	(0,05)
3rd quarter	0,809	0,473***	0,990	0,825*	1,012	1,045
	(-1,76)	(-7,70)	(-0,10)	(-2,22)	(0,44)	(1,10)
4th quarter	0,695**	0,507***	0,874	0,729***	0,919**	0,861***
	(-2,81)	(-6,86)	(-1,32)	(-3,42)	(-2,95)	(-3,42)
N	28885	32340	28885	32340	28885	32340

Source: Own elaboration based on the PNAD-C.