Revista Brasileira de Economia. 2024, V. 78: e222024 Original article

Exploring the 'stigma effect' of unemployment on the Brazilian labour market: Evidence from a theoretical job search model

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A theoretical job search model incorporating the "stigma effect" of long-term unemployment was developed to analyse the Brazilian labour market considering different educational levels between 2012 and 2021. Results from the parameterized model indicate 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.

Keywords. Unemployment, Schooling levels, Duration, Labour market.

JEL classification. J01, J64, I20, I24.

1. Introduction

Economic theory suggests that 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). Blanchard and Diamond (1994), for example, show not only that employers prefer to employ people who have experienced shorter periods of unemployment, but also that those who have experienced longer periods of unemployment may take longer in transitioning from unemployment to employment. Thus, the unemployment exit rate is a decreasing function of duration, which, in turn, indicates that the longer the duration of unemployment, the more difficult it becomes for a worker to transition from unemployment to employment (see Clark et al., 1979;

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 https://doi.org/10.5935/0034-7140.20240022

Heckman and Borjas, 1980; Jackman and Layard, 1991; Acemoglu, 1995; Biewen and Steffes, 2010; Cockx and Picchio, 2013; Van Belle et al., 2018). Furthermore, Acemoglu (1995) highlights that duration in unemployment may also result in human capital loss.

Adding to the woes, workers who remain unemployed during periods of 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 a worker who is presently, or who has recently been, unemployed because they tend to regard the status of unemployment as a negative signal: it indicates possibly 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.

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, such as the conditional cash transfer to low-income families, Bolsa Familia. 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 hit 6.6%, its minimum level in almost twenty years. However, by 2015 it reached 14.7% in the first trimester of 2021 according to the IBGE (2021) (Brazilian Institute of Geography and Statistics). Worse still, in the final trimester of 2021, Lameiras et al. (2022) demonstrate that the percentage of workers who remained unemployed for a period greater than two years exceeded 30%, which reached a record for the historical series. Our findings are substantially similar. Using the PNAD Contínua between 2012 and 2021, results indicate that after one month in unemployment, the exit rate of unemployment was 2%. This suggests that a 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. In other words, the probability of remaining unemployed in Brazil is exceedingly high. Hence, this portrays a serious problem in the Brazilian labour market, as workers are entering unemployment and remaining in that position.

As this was an old issue resurfacing, there are very few new studies which cover unemployment and job search theory in Brazil recently. Given these circumstances, this paper develops and adopts a microeconomic theoretical model of job search in light of the Brazilian labour market as means of assessing long-term unemployment and its behaviour in Brazil considering educational levels. To our knowledge there is no previous research for the topic in the country. Thus, it can be seen as a new tool to assess long-term unemployment in Brazil and for developing labour market policies.

Besides this introductory section, the paper is organised as follows: section 2 reviews the theoretical literature on unemployment. The following section 3 will present methods and an analysis of the Brazilian labour market. Results for the theoretical model are shown in section 4. Finally, section 5 concludes and discusses the implications of unemployment and its possible public policies.

2. Background

Heckman and Borjas (1980) develop 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:

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

The density function is, therefore,

$$f_{12}(t_{12}) = a_{12}\exp(-a_{12}t_{12}) \tag{2}$$

$$E(t_{12}) = \frac{1}{a_{12}} \tag{3}$$

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) modify the “waiting time” in the distribution function of time to unemployment (1). In this manner, they index 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 adjust 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) determine “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 use 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” (p. 254 Heckman and Borjas, 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

$$\frac{\partial h_{ij}(t_{ij})}{\partial t_{ij}} < 0, \quad i,j = 1,2,\ i \neq j \tag{4}$$

Equation (4) 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 is stated in Cahuc et al. (2014), a decrease in the reservation wages results in a positive duration dependence.

Nickell (1979) is 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 estimates the conditional probabilities of an individual leaving unemployment and then used those probabilities to understand the expected durations of unemployment. Results show different probabilities of leaving unemployment over the duration of an unemployment spell. Also, and in accordance with Heckman and Borjas (1980), he finds negative duration dependence, as the probability of transitioning from unemployment to employment decreases considerably after six months.

Clark et al. (1979) highlight 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. (2019) create 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 show 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) develops 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) indicate 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) develop 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 highlight 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) show 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 test if the classifications unemployed and out of the labour force were behaviourally meaningless distinctions and rejected this hypothesis.

Mainly, authors emphasize 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 is 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) develops 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 analyses 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 show 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) develops 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) finds 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) also highlight 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) consider 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 considers 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 show 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) employ 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 indicate 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 show 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) analyse, through a field experiment, how the employers’ behaviour affected the adverse effect of long-term unemployment in 100 U.S cities. The authors 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 show 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 find 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) predict in their continuous-time model of heterogeneity, Eriksson and Rooth (2014) haven’t find “lagged duration dependence” to be an important factor in the employers’ hiring decision in Sweden.

Van Belle et al. (2018) propose 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 demonstrate 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 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 show 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 find that there’s a negative effect of holding an interim job when applying to a high-skilled position. Finally, the authors employ 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 show 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) show 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) shows 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) highlight 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.

3. Methodology

3.1 *Brazilian data*

The PNAD Contínua, carried by IBGE (Brazilian Institute of Geography and Statistics), provides continuous information concerning demographic and educational features of the Brazilian labour market. This survey was analysed between 2012 and 2021 to understand unemployment and its dynamic in Brazil for those aged between 30 and 64 years old.

The interviews adhere to a 1-2(5) rotating scheme and the sample is marked by repeated cross section data. It is possible to see the rotating scheme in the households in Table 1. 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.

Hence, a similar methodology to Ribas and Soares (2008) was employed considering that IBGE does not provide the individual identification. In order to create the panel for the PNAD Contínua, we have used individuals' date of birth (day, month, and year), sex,

Table 1.: Rotating scheme of the PNAD Contínua

	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

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.

Table 2 compares the panel size and the first interview. Considering that panel data involves repeated observations, it is feasible to have sample attrition and, thus, missing data. Given that deprived individuals may be more likely to drop out of the panel sample, this missing data may cause attrition bias (Cameron and Trivedi, 2005). A graphical analysis comparing indicators in the cross-section data with the panel data from the PNAD Contínua was made and results indicate that the the panel is not adding considerable bias to the data. The panel data impart a slightly optimistic outlook when compared to the cross-section data, but both types of data analysis follow the same trend.

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

	Interview	Observations	Panel size	Data loss	Panel only with adults (30 to 64 years old)
	1st	4 174 244			
Panel following the	1st and 2nd	3 193 774	76.51%	23.49%	2 008 983
	1st, 2nd and 3rd	2 833 589	67.88%	32.12%	1 780 449
	1st, 2nd, 3rd and 4th	2 560 487	61.34%	38.66%	1 607 691
	1st, 2nd, 3rd, 4th and 5th	2 338 383	56.02%	43.98%	1 467 502

It is essential to provide background on the Brazilian labour market between 2012 and 2021. First, it is crucial to highlight the distinct trends observed between men and women. While men’s employment rate has remained consistently high at approximately 75%, women’s employment rate has lagged behind at around 55%. In addition, women have experienced a significantly higher inactivity rate of approximately 40% compared to men, who have an inactivity rate of around 15% during the analysed period. This discrepancy has been further exacerbated by the COVID-19 pandemic, which resulted in a sharp increase in the inactivity rate, particularly among women. Costa et al. (2021) argue that the pandemic has increased the risks of transitioning to inactivity, particularly for women, black individuals, and young people.

Furthermore, there has been a noticeable decline in the employment rate for both sexes, accompanied by an increase in the unemployment rate. The trend in unemployment is also noteworthy, with women experiencing slightly higher rates of unemployment than men throughout the period. Since the 2015 economic crisis, the Brazilian labour market has been grappling with reduced employment and increased unemployment rates, particularly affecting women. Moreover, the unemployment rates have not only remained above their 2015 pre-crisis levels in the subsequent years, but have indeed surged significantly. Adding to the economic distress, the COVID-19 pandemic has caused an even greater disruption, resulting in historically high unemployment rates of nearly 12% for men and 15.5% for women in 2020. Thus, the observed differences between men and women underscore the need to analyse the labour market by sex.

An examination of a more extensive range of economic indicators provides further insight into the differences within the labour market, especially in terms of educational attainment. Although the disparity between men and women persists, it narrows for individuals with higher educational attainment, such as higher education or incomplete higher education. Furthermore, individuals with higher levels of educational attainment exhibit higher employment rates than those with lower levels of education, highlighting the stark contrast between unemployment rates among these groups. Those with lower levels of education often face difficulties in securing better employment opportunities that require higher educational qualifications, leading to a twofold increase in labour market insecurity.

Finally, Figure 1 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., 2018). 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.

The survival data analysis in Table 3 was 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).

Table 3 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 0.578, 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.

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

Figure 1. Unemployment rate by time (in months) in this condition by sex, 2012-2021, Brazil.

Table 3. 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	61 225	0.066	0.934	0.0010	0.932	0.936
1	52 574	0.027	0.909	0.0012	0.907	0.911
2	49 417	0.048	0.866	0.0014	0.863	0.869
4	39 036	0.028	0.806	0.0017	0.803	0.809
6	33 673	0.040	0.755	0.0019	0.751	0.758
12	24 503	0.038	0.684	0.0022	0.679	0.688
18	17 864	0.019	0.643	0.0024	0.639	0.648
24	15 874	0.093	0.578	0.0026	0.573	0.583
36	9 338	0.082	0.531	0.0029	0.525	0.536
48	5 697	0.060	0.499	0.0032	0.493	0.505
60	3 915	0.084	0.457	0.0037	0.450	0.464

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).

4. 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 utilised, namely the first, second, third, fourth and fifth interviews, enabling an individual to be followed along the PNAD Contínua. 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 $k^{s,e} = 0,1,2,3,\ldots$.

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 1. 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

$$u' > 0 \qquad u'' < 0 \qquad\qquad \frac{\partial c}{\partial e} > 0 \qquad \frac{\partial c}{\partial \theta} > 0 \qquad \frac{\partial^2 c}{\partial^2 \theta} > 0 \qquad \frac{\partial^2 c}{\partial \theta \partial r} > 0$$

Thus, two types of constraints must hold: (i) **Individual rationality**: each worker must prefer their contract to the outside option; (ii) **Individual compatibility**: each worker must prefer their own contract to any other.

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

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

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}:

$$\begin{aligned}
\theta_3 e_3 - c_3 &= \theta_3 e_2 - c_2 \\
&= \theta_3 e_2 - (\theta_2 e_2 - \theta_2 e_1 + c_1) \\
&= \theta_3 e_1 - \theta_3 e_1 + \theta_3 e_2 - \theta_2 e_2 + \theta_2 e_1 - c_1) \\
&= \theta_3 e_1 - c_1 + \theta_3(e_2 - e_1) - \theta_2(e_2 - e_1) \\
&= \theta_3 e_1 - c_1 + (\theta_3 - \theta_2)(e_2 - e_1) \geq 0
\end{aligned}$$

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:

$$\begin{aligned}
\theta_i e_i - c_i &= \theta_i e_i - c_j + (\theta_i - \theta_j)(e_{i-1} - e_j) + (\cdots) \\
&= \theta_i e_j - c_j
\end{aligned}$$

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 $g_5(e)/g_4(e)$ is increasing in e and, likewise, $g_4(e)/g_3(e)$ is also increasing in e. Thus, $g_i(e)/g_{i-1}(e)$, 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:

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

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

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

To verify this, one can observe from Bayes’ rule that for $k^{s,e} = 0,1,2,3,\ldots,N$:

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

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 $h_i(e) \equiv \frac{g_i(e)}{[1-G_i(e)]}$ for all $i = 1,2,3,4,5$. By virtue of the increasing ratio $\frac{f_5(e)}{f_4(e)}$, we have:

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

Then, the required result follows from expressing $1-G_i(e)$ in terms of the hazard as equal to $\exp[-\int_0^e h_i(s)\,\mathrm{d}s]$. 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

$$V_{k^{s,e}} = \lambda \int_0^\infty \max\{p_{k^{s,e}}w + (1-p_{k^{s,e}})V_{k^{s,e}+1}, V_{k^{s,e}},\}\,\mathrm{d}F(w,k^{s,e}) - c$$

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:

$$V_{k^{s,e}} = \lambda \int_0^\infty \max\{p_{k^{s,e}} w + (1-p_{k^{s,e}})V_{k^{s,e}+1}, V_{k^{s,e}}\} \, \mathrm{d}F(w, k^{s,e}) - c$$

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

or

$$\frac{R_{k^{s,e}}}{\lambda} = \int_0^\infty \max\{(w,r_{k^{s,e}})\} \, \mathrm{d}F(w,k^{s,e}) - \frac{c}{\lambda p_{k^{s,e}}},$$

or, finally,

$$\lambda \int_0^\infty \max(w,r_{k^{s,e}}) \, \mathrm{d}F(w,k^{s,e}) = \frac{c}{p_{k^{s,e}}}$$

$$\int_{R_{k^{s,e}}}^\infty \left(w - \frac{R_{k^{s,e}}}{\lambda}\right) dF(w,k^{s,e}) = \frac{c}{\frac{q_{k^{s,e}}}{1-F(R_{k^{s,e}},k^{s,e})}} \tag{5}$$

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:

$$q_{k^{s,e}} \equiv \lambda p_{k^{s,e}}[1 - F(R_{k^{s,e}}; k^{s,e})]. \tag{6}$$

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

$$\alpha_{k^{s,e}}(s) \equiv E[W_k - s | W_{k^{s,e}} > s] = \int_s^\infty (w - s) \frac{\mathrm{d}F(w,k^{s,e})}{[1 - F(s;k^{s,e})]} \tag{7}$$

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. $\int_{R_{k^{s,e}}}^\infty \left(w - \frac{R_{k^{s,e}}}{\lambda}\right) \mathrm{d}F(w,k^{s,e}) = \frac{c}{\lambda P_{k^{s,e}}}$

And define $\overline{R}_{k^{s,e}+1} = R_{k^{s,e}+1} - a_{k^{s,e}}$ for $k^{s,e} > 0$. Substituting $F(w;k^{s,e}+1) = F(w - a_{k^{s,e}};k^{s,e})$ in $\int_{R_{k^{s,e}}}^{\infty}\left(w - \frac{R_{k^{s,e}}}{\lambda}\right)\mathrm{d}F(w,k^{s,e}) = \frac{c}{\lambda P_{k_{s,e}}}$ and changing variables with $y = w - a_{k^{s,e}}$:

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

$$\begin{aligned}\int_{R_{k^{s,e}+1}}^{\infty}\left(y - \frac{\overline{R}_{k^{s,e}+1}}{\lambda}\right)\mathrm{d}F(y,k^{s,e}) &= \frac{c}{\lambda p_{k^{s,e}+1}}\\ &> \frac{c}{\lambda P_{k^{s,e}}} = \int_{R_{k^{s,e}}}^{\infty}\left(y - \frac{R_{k^{s,e}+1}}{\lambda}\right)\mathrm{d}F(y,k^{s,e})\end{aligned}$$

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:

$$\int_{R_{k^{s,e}}}^{\infty}\left(w - \frac{R_{k^{s,e}}}{\lambda}\right)\mathrm{d}F(w,k^{s,e}) = \frac{c[1 - F(R_{k^{s,e}};k^{s,e})]}{q_{k^{s,e}}} \tag{8}$$

Thus,

$$\begin{aligned}q_{k^{s,e}} &= \frac{c[1 - F(R_{k^{s,e}};k^{s,e})]}{\int_{R_{k^{s,e}}}^{\infty}\left(w - \frac{R_{k^{s,e}}}{\lambda}\right)\mathrm{d}F(w,k^{s,e})}\\ &= \frac{c}{E[w_{k^{s,e}} - R_{k^{s,e}}|w_{k^{s,e}} > R_{k^{s,e}}]}\\ q_{k^{s,e}} &= \frac{c}{\alpha_{k^{s,e}}(R_{k^{s,e}})}\end{aligned} \tag{9}$$

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 $\int_{R_{k^{s,e}}}^{\infty}(w - \frac{R_{k^{s,e}}}{\lambda})\mathrm{d}F(w,k^{s,e}) = \frac{c}{\lambda P_{k^{s,e}}}$:

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

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 (5) (optimal job search strategy) was parameterized using a Weibull distribution. Firstly, the selected data and variables for the model's parameterization are presented and then results are shown. In (5), 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 Table 4.

Table 4. Wages by educational attainment and sex, Brazil

Highest educational attainment	Women	Men
No formal education/Incomplete primary education	986.19	1 535.64
Primary education (complete)/Incomplete secondary education	1 228.36	1 944.80
Secondary education (complete)	1 589.35	2 522.03
Incomplete higher education	1 868.00	3 163.22
Higher education	4 167.88	7 002.45

From Table 5, 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, 2019). 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 (5), 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 Tables 5 and 6.

The conditional probabilities in Tables 5 and 6, 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

Table 5. 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	0.37	0.34	0.40	0.41	0.46
7 to 12 months	0.34	0.33	0.42	0.41	0.41
13 to 18 months	0.33	0.30	0.40	0.40	0.41
19 to 24 months	0.28	0.30	0.30	0.30	0.31
24 months or more	0.26	0.24	0.28	0.31	0.29

Table 6. 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	0.53	0.50	0.53	0.46	0.54
7 to 12 months	0.49	0.45	0.51	0.45	0.52
13 to 18 months	0.53	0.46	0.54	0.53	0.53
19 to 24 months	0.47	0.38	0.42	0.41	0.42
24 months or more	0.41	0.37	0.36	0.37	0.36

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 (9), is shown in Table 7:

Table 7. Adjustment by educational attainment and sex, Brazil

Highest educational attainment	Women	Men
No formal education/Incomplete primary education	0.957 1	0.977 1
Primary education (complete)/Incomplete secondary education	0.953 2	0.969 1
Secondary education (complete)	0.946 7	0.962 3
Incomplete higher education	0.956 0	0.958 8
Higher education	0.950 5	0.958 4

Finally, in equation (5) 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 in Figures 2 and 3. Results for q_k, the match probabilities after elapsed time in unemployment, which is precisely the stigma effect is observed in Figures 2 and 3 depending on the threshold.

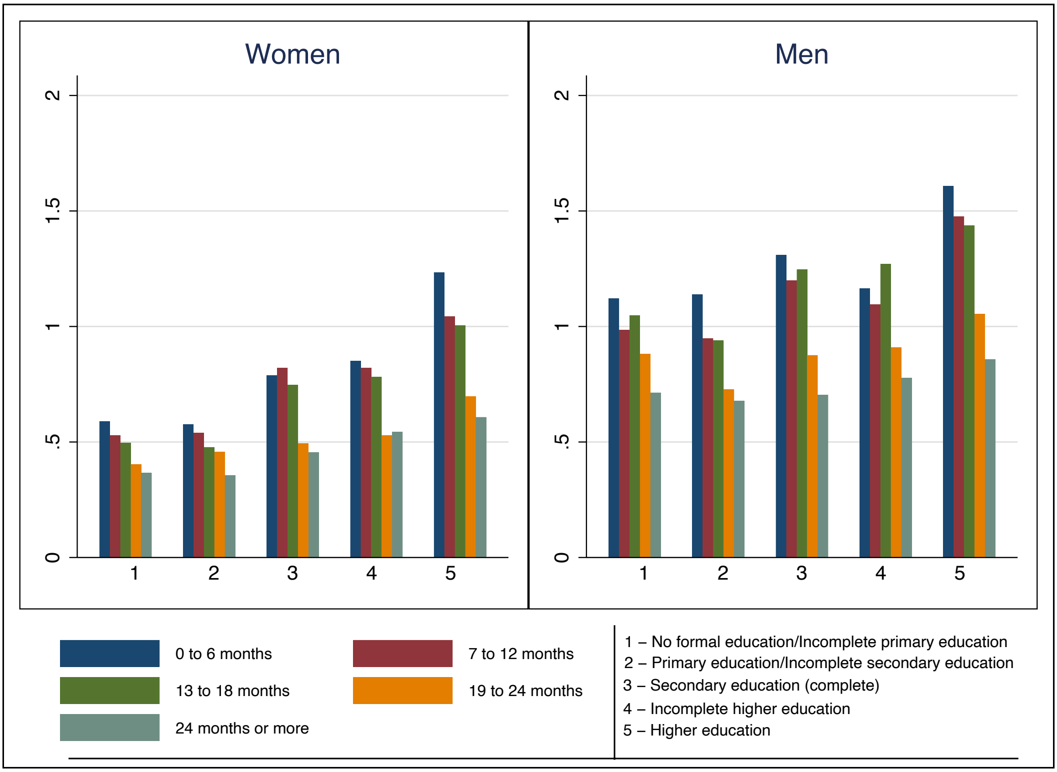

Figure 2. Stigma effect by sex and educational attainment with c = R$210, Brazil, 2012-2021.

Results in Figures 2 and 3 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; Van Belle et al., 2018).

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

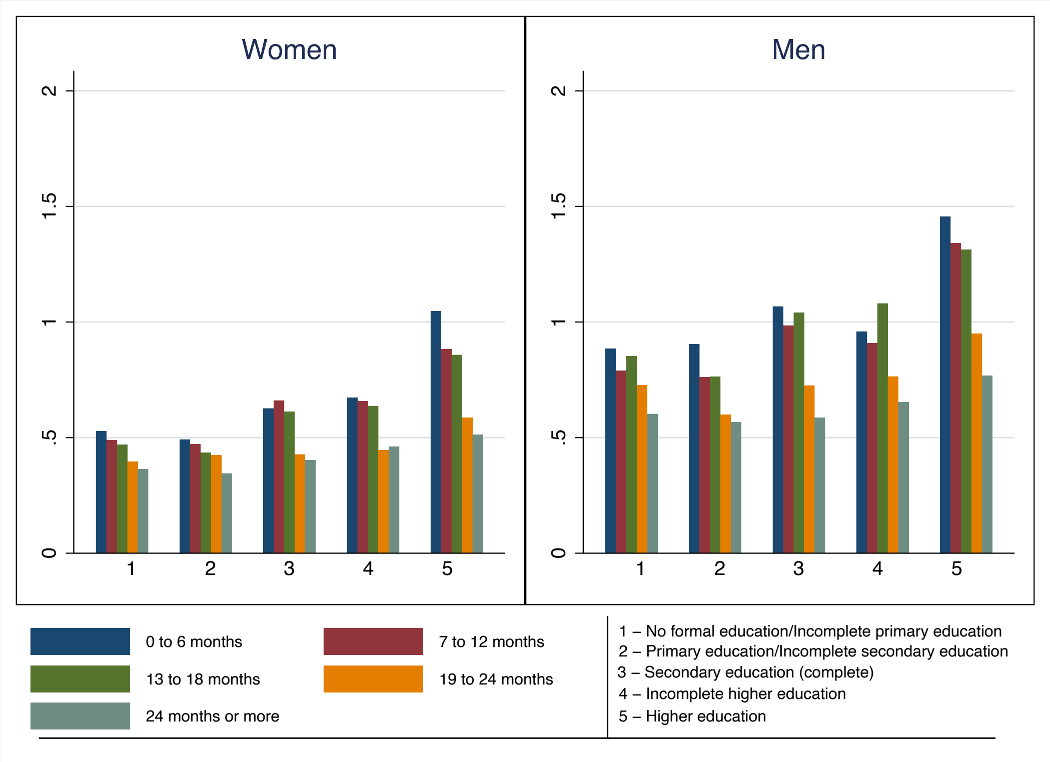

Figure 3. Stigma effect by sex and educational attainment with c = R$400, Brazil, 2012-2021.

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, Table 8 and Table 9 present the reservation wages considering elapsed time in unemployment in the theoretical model and considering the cost of R$210.00. Table 8 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.

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, Tables 10 and 11 present the reservation wage considering the threshold of $c = R\$400$.

Table 10 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 11, 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, Tables 10 and 11 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

Table 8.: 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)	1 068.71	1 145.87	1 160.35	1 006.00	1 012.77
Incomplete higher education	1 356.91	1 407.58	1 448.75	1 306.98	1 383.94
Higher education	3 943.68	3 981.93	4 085.19	3 980.60	4 003.37

Table 9.: 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	1 112.62	1 118.29	1 193.36	1 176.53	1 136.80
Primary education (complete)/Incomplete secondary education	1 533.09	1 523.95	1 583.68	1 528.56	1 554.61
Secondary education (complete)	2 192.64	2 237.66	2 332.05	2 250.65	2 212.34
Incomplete higher education	2 817.57	2 888.43	3 052.51	2 985.83	2 990.37
Higher education	7 087.68	7 237.14	7 407.93	7 419.32	7 465.37

Table 10.: 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	1 083.38	1 041.89	1 114.94	1 003.33	1 024.10
Secondary education (complete)	1 739.53	1 777.30	1 901.72	1 725.99	1 629.98
Incomplete higher education	2 290.00	2 361.81	2 598.95	2 433.08	2 395.76
Higher education	6 599.37	6 741.59	6 927.15	6 823.61	6 789.58

Table 11.: 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	3 396.29	3 391.10	3 504.11	3 254.81	3 233.57

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.

5. Conclusions

The main goal of this paper was to analyse long-term unemployment considering its dynamic within the labour market in Brazil, between 2012 and 2021, using the PNAD Contínua and a theoretical model. 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, we have 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 paper 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, the theoretical model 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 provisional 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.

Bibliography

Abraham, Katharine G, John C Haltiwanger, Kristin Sandusky, and James R Spletzer (2019): "The consequences of long-term unemployment: Evidence from linked survey and administrative data," *Industrial and Labor Relations Review*, 72 (2), 266–299, versão anterior disponível como NBER Working Paper No. 22472, 2016. [4]

Acemoglu, Daron (1995): "Public policy in a model of long-term unemployment," *Economica*, 161–178. [2, 4, 5, 11, 12, 22, 27]

Andrade, Claudia Sá Malbouisson (2004): "Duração do desemprego na Região Metropolitana de Salvador: Mensuração e análise," *Revista Econômica do Nordeste*, 35 (3), 315–338. [20]

Antigo, Mariangela Furlan and Ana Flávia Machado (2006): "Transições e duração do desemprego: Uma revisão da literatura com novas evidências para Belo Horizonte," *Nova Economia*, 16, 375–406. [20]

Barros, Ricardo Paes de, José Márcio Camargo, and Rosane Silva Pinto de Mendonça (1997): "A estrutura do desemprego no Brasil," *Instituto de Pesquisa Econômica Aplicada (Ipea)*. [20]

Biewen, Martin and Susanne Steffes (2010): "Unemployment persistence: Is there evidence for stigma effects?" *Economics Letters*, 106 (3), 188–190. [2, 5, 6, 11]

Blanchard, Olivier Jean and Peter Diamond (1994): "Ranking, unemployment duration, and wages," *The Review of Economic Studies*, 61 (3), 417–434. [1, 2, 5, 6, 12, 27]

Cahuc, Pierre, Stéphane Carcillo, and André Zylberberg (2014): *Labor Economics*, MIT press. [4, 24]

Camargo, José Márcio and Maurício Cortez Reis (2005): "Desemprego: O custo da desinformação," *Revista Brasileira de Economia*, 59, 381–425. [23]

Cameron, A Colin and Pravin K Trivedi (2005): *Microeconometrics: Methods and applications*, Cambridge university press. [10]

Clark, Kim B and Lawrence H Summers (2007): *The Dynamics of Youth Unemployment*, University of Chicago Press. [8]

Clark, Kim B, Lawrence H Summers, Charles C Holt, Robert E Hall, Martin Neil Baily, and Kim B Clark (1979): "Labor market dynamics and unemployment: A reconsideration," *Brookings Papers on Economic Activity*, 1979 (1), 13–72. [1, 2, 4, 5, 11, 12, 27]

Cockx, Bart and Matteo Picchio (2013): "Scarring effects of remaining unemployed for long-term unemployed school-leavers," *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 176 (4), 951–980. [2, 11]

Coles, Melvyn G and Eric Smith (1998): "Marketplaces and matching," *International Economic Review*, 239–254. [5]

Costa, Joana Simões, Ana Luiza Neves de Holanda Barbosa, and Marcos Hecksher (2021): "Desigualdades no mercado de trabalho e pandemia da Covid-19," Tech. Rep., Texto para Discussão. [10]

Eriksson, Stefan and Dan-Olof Rooth (2014): "Do employers use unemployment as a sorting criterion when hiring? Evidence from a field experiment," *American economic review*, 104 (3), 1014–39. [7, 8, 22, 24]

European Commission (2019): "Report from the commission to the council. Evaluation of the Council Recommendation on the integration of the long-term unemployed into the labour market," . [28]

Farber, Henry S, Chris M Herbst, Dan Silverman, and Till Von Wachter (2019): "Whom do employers want? The role of recent employment and unemployment status and age," *Journal of Labor Economics*, 37 (2), 323–349. [7]

Figueiredo, Erik Alencar de (2022): "Comentários sobre o desempenho recente do mercado de trabalho brasileiro e a taxa de desemprego de longo prazo," *Instituto de Pesquisa Econômica Aplicada (Ipea)*, texto para Discussão 2799. [28]

Flinn, Christopher J and James J Heckman (1983): "Are unemployment and out of the labor force behaviorally distinct labor force states?" *Journal of labor economics*, 1 (1), 28–42. [5]

Heckman, James J and George J Borjas (1980): "Does unemployment cause future unemployment? Definitions, questions and answers from a continuous time model of heterogeneity and state dependence," *Economica*, 47 (187), 247–283. [1, 2, 3, 4, 5, 7, 11, 12, 20, 27]

ILO (2019): "Women in business and management: The business case for change," . [20]

——— (2021): "World Employment and Social Outlook: Trends 2021," *International Labour Office – Geneva: ILO, 2021*. [2, 11]

Jackman, Richard and Richard Layard (1991): "Does long-term unemployment reduce a person's chance of a job? A time-series test," *Economica*, 93–106. [2, 11]

Kroft, Kory, Fabian Lange, and Matthew J Notowidigdo (2013): "Duration dependence and labor market conditions: Evidence from a field experiment," *The Quarterly Journal of Economics*, 128 (3), 1123–1167. [6, 7]

Lameiras, Maria Andrea Parente, CH Corseuil, Lauro Ramos, and Felipe Mendonça Russo (2022): “Desempenho recente do mercado de trabalho e perspectivas,” *Carta de conjuntura*, (54). [2]

Ljungqvist, Lars and Thomas J Sargent (1998): “The European unemployment dilemma,” *Journal of political Economy*, 106 (3), 514–550. [6]

Lockwood, Ben (1991): “Information externalities in the labour market and the duration of unemployment,” *The Review of Economic Studies*, 58 (4), 733–753. [6]

Neri, Marcelo and Marcos Hecksher (2022): “A montanha-russa da pobreza,” Tech. Rep., Centro de Políticas Sociais, FGV. [21]

Nickell, Stephen (1979): “Estimating the probability of leaving unemployment,” *Econometrica: Journal of the Econometric Society*, 1249–1266. [2, 4, 8, 12, 27]

Reis, Maurício and Marina Aguas (2014): “Duração do desemprego e transições para o emprego formal, a inatividade e a informalidade,” *Economia Aplicada*, 18, 35–50. [20]

Ribas, Rafael Perez and Sergei Suarez Dillon Soares (2008): “Sobre o painel da Pesquisa Mensal de Emprego (PME) do IBGE,” Tech. Rep., Texto para discussão, texto para Discussão 1348. [8]

Van Belle, Eva, Ralf Caers, Marijke De Couck, Valentina Di Stasio, and Stijn Baert (2018): “Why is unemployment duration a sorting criterion in hiring?” *European Journal of Work and Organizational Psychology*, 27 (6), 715–728. [2, 7, 11, 22]

Vishwanath, Tara (1989): “Job search, stigma effect, and escape rate from unemployment,” *Journal of Labor Economics*, 7 (4), 487–502. [2, 5, 6, 12, 13, 17, 22, 24, 27]