IMPACT OF SHORT- AND LONG-TERM UNEMPLOYMENT ON MENTAL HEALTH IN BRAZIL

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ABSTRACT

This study analyzes the impact of unemployment on mental health in Brazil using a nationally representative dataset from the 2019 National Health Survey. As an empirical strategy, an instrumental variable ordered probit model is employed to address potential endogeneity issue and estimated using a conditional mixed process estimator. The results indicate that unemployment leads to worse mental health in both short and long-term, with stronger negative impact of prolonged unemployment. Long-term unemployment (more than 24 months) increases the probabilities of mild and moderate-to-severe mental disorders by 7.4 and 3.7 percentage points, respectively, compared to short-term unemployment (less than 30 days). The impact of unemployment is stronger for highly educated young (aged 18-32) and middle-aged (aged 45-65) adults. Considering the global burden of mental health disorders and the concern about this topic, the findings are relevant for policy and suggest employment status as an important aspect of mental health promotion strategies.

Keywords: Mental health; Depression; Employment; Economic recession.

RESUMO

Este estudo analisa o impacto do desemprego na saúde mental no Brasil. Para tanto, utiliza dados da Pesquisa Nacional de Saúde (PNS) de 2019. Como estratégia empírica, um modelo probit ordenado com variável instrumental é empregado devido à potencial endogeneidade. O modelo é estimado usando o estimador de processo misto condicional (Conditional Mixed Process - CMP). Os resultados indicam que o desemprego é associado a um pior estado de saúde mental no curto e longo prazo, com impacto negativo mais forte em situação de desemprego prolongado. O desemprego de longa duração (mais de 24 meses) aumenta, em média, 7,4 pontos percentuais a probabilidade de sintomas depressivos leves e 3,7 pontos percentuais a probabilidade de reportar sintomas depressivos moderadamente severos, em comparação com o desemprego de curta duração (menos de 30 dias). O impacto do desemprego é mais intenso para adultos jovens (18-32 anos) e de meia-idade (45-65 anos) com alta escolaridade. Considerando a carga global da saúde mental e a preocupação em torno deste tema, os resultados são relevantes para as políticas e evidenciam a condição de emprego do indivíduo como um aspecto importante das estratégias de promoção da saúde mental.

Palavras-chave: Saúde mental; Depressão; Emprego; Recessão econômica.

Classificação JEL: I12; J6

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INTRODUCTION

Macroeconomic shocks have a substantial impact on a population's health. The evidence covers a broad range of health dimensions, including mental, physical, and social facets (NORSTROM et al., 2019; CHARLES; DECICCA, 2008). During economic downturns, the mental aspect has drawn great attention because of its potentially rapid and intense deterioration (FARRÉ; FASANI; MUELLER, 2018), which includes suicide mortality (ANTONAKAKIS; COLLINS, 2015), suicide attempts and ideation (BROWNINGA; HEINESEN, 2012), psychiatric admissions (WANG; FATTORE, 2020), anxiety (GILI et al. 2012), major depressive episodes (AVDIC; NEW; KAMHÖFER, 2021; RODRIGUES; NUNES, 2018), psychotropic medication (BRADFORD; LASTRAPES, 2013; KASPERSEN et al., 2016) and substance disorders and alcohol and drug abuse (KALOUSOVA; BURGARD, 2014; HENKEL, 2011).

Unemployment can lead to higher levels of mental distress owing to different causes, such as income loss (THOMSON et al., 2022; BOYD-SWAN et al., 2016; BARBAGLIA et al., 2014), debt (DUNN; MIRZAIE, 2015; FITCH, 2011), feelings of uselessness (FARRÉ; FASANI; MUELLER, 2018), loss of self-perceived social status (KRUGA; EBERL, 2018), economic/job insecurity (CAROLI; GODARD, 2016; ROHDE et al., 2016; PRAUSE; HUH, 2009), and reduced utilization and access to medical care (SCHALLER; STEVENS, 2015).

Although there is strong evidence of a negative correlation between job losses and mental health (LATIF, 2015), some studies have found no or, at best, a weak relationship between unemployment and mental health (BUBONYAA; COBB-CLARKB; RIBAR, 2019; TEKIN; MCCLELLAN; MINYARD, 2018; SCHMITZ, 2011). Many of these studies show important differences in terms of labor market conditions, empirical approaches, and datasets (CYGAN-REHM; KUEHNLE; OBERFICHTNER, 2016).

Crucial aspects of this relationship include reverse causality and unobserved factors (e.g., lifestyle), given that an individual's mental health is likely to affect their selection in the labor market. To deal with endogeneity, extensive literature has used plant closures or mass layoffs as an exogenous source of unemployment (BROWNING; HEINESEN, 2012). Another widely used strategy is that of fixed-effect models, which control for unobserved individual-specific factors (SCHMITZ, 2011).

The current literature on how economic downturns affect mental health is concentrated on high-income countries (GUERRA; EBOREIME, 2021). Few studies have investigated the effect of unemployment on mental health for low- and middle-income countries (LMICs) (WEINMANN; KOESTERS, 2017), especially using a robust methodological approach. One of the main reasons for this lack of research is the limited availability of data sets, such as the absence of individual longitudinal data and information on the cause of unemployment (voluntary or involuntary mass layoffs). Economic downturns may have specific effects on health outcomes for populations living in nations with weaker social protection systems, more precarious labor markets, and limited access to quality health services (HONE et al., 2019; JACOB, 2017).

This study explores the case of Brazil, an upper-middle-income economy that faced severe economic recession starting in mid-2014, with the gross domestic product (GDP) dropping by 3.5% in 2015 and 3.3% in 2016. Since then, Brazil has experienced high unemployment rates, with the number of unemployed crossing 10 million in recent years (IBGE, 2022). Despite a slight economic recovery before the pandemic outbreak in 2020, Brazilian long-term unemployment continued to increase from 34.7% in 2013 to 42.5%

in 2019 (IBGE, 2020), far above the Organisation for Economic Co-operation and Development (OECD) average of 25.8% in 2019 (OECD, 2021). This study utilizes the Brazilian situation, which is marked by high and persistent levels of unemployment, to estimate the impact on individual health.

To deal with methodological issues related to potential endogeneity, this study employed an instrumental variable (IV) approach, which consists of identifying instruments that are correlated with individual's unemployment but exogenous to their mental health status. Based on annual enterprise demography, the instrument used was high-growth companies, which are active companies with 10 or more employees in the previous three years and an average growth of at least 20% per year in the number of employees during that period. The advantage of using this instrument is that it avoids the transition to entrepreneurship because of a lack of market opportunities. High-growth company rates are strongly correlated with variations in unemployment, but there is no reason to expect a direct effect on individual health.

In this context, this study aimed to investigate the short- and long-term effects of unemployment on mental health in Brazil, considering the duration of unemployment (< 1 month, 1–12 months, 13–24 months, > 24 months).

This study contributes to the literature in three ways: First, there is a lack of studies on the effect of unemployment on mental health in LMICs. In these regions, the effect of unemployment may differ considerably from that in high-income countries, as LMICs have limited policy measures to cushion the impact of economic downturns. Second, there is evidence of heterogeneous effects across group compositions (BLACK; JACKSON; JOHNSTON, 2022; JOFRE-BONET; SERRA-SASTREA; VANDOROS, 2018), with a stronger association with specific characteristics. Two groups were analyzed according to age and education. This stratification corroborated the recent and growing literature on macroeconomic fluctuations and their lasting effects on the health of young adults (MACLEAN, 2013). Labor market entrants are more vulnerable to adverse conditions and have persistent and negative effects on career outcomes (employment, earnings, and job quality) with long recovery periods (WACHTER, 2020). Finally, the impacts of each of the nine mental health criteria were estimated.

DATA AND METHODS

Data

This study used data from the 2019 National Health Survey (*Pesquisa Nacional de Saúde* – PNS), conducted by the Brazilian Institute of Geography and Statistics (IBGE; Portuguese acronym). Only individuals of working age (18–64 years old) were included. The initial sample consisted of 177,658 individuals. Those who did not answer questions about employment status and mental health status were excluded. The final sample comprised 43,671 individuals. Post-stratification of the sample weights was conducted following PNS guidance for complex survey data.

Mental health

The main outcome variable considered in the analysis was mental health disorder. The Patient Health Questionnaire-9 (PHQ-9) was used to assess the mental health status. This instrument has been validated by international and national studies (SANTOS et al., 2013; KROENKE et al., 2001). The questionnaire consists of nine criteria (see Appendix 1), similar to those used by the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV). The Likert scale was employed, where the responses to each criterion were converted into a code: 0 implied "not at all;" 1, "less than half of the days;" 2, "more than half of the days;" and 3, "nearly every day." The total score (sum of the nine criteria) ranged between 0 and 27. Following the score, the responses were categorized into five groups according to the severity of depression: 0–4 denoted "none-minimal;" 5–9, "mild;" 10–14, "moderate;" 15–19, "moderately severe;" and 20–27, "severe."

Employment

Employment was categorized into five groups according to two questions: "During the reference week, did you work for at least one hour in some paid activity?" and "Until the reference week, how long had you been without a job and looking for a job?" The categories were 1: "worked in the reference week;" 2: "looking for a job for less than 1 month;" 3: "looking for a job for more than or equal to 1 month and less than or equal to 12 months;" 4: "looking for a job for more than 12 months and less than or equal to 24 months;" and 5: "looking for a job for more than 24 months."

Additional controls

The model included as control a set of individual characteristics: education, age, sex, color, urban region, household income per capita, number of people living in the house, and self-reported health.

Education, age, household income, and self-reported health status were categorical variables. Education was grouped into three categories, namely, 1: "no formal education," "did not complete primary education," or "completed primary education;" 2: "did not complete secondary education," "completed secondary education," and "did not complete tertiary education;" and 3: "completed tertiary education." Age was grouped into three categories, namely, 1: "between 18 and 32 years old;" 2: "between 33 and 44 years old;" and 3: "between 45 and 65 years old." Household income was grouped into three categories, namely, 1: "1 minimum wage or less;" 2: "more than 1 minimum wage and less than 5 minimum wages;" and 3: "more than 5 minimum wages." Self-reported health was grouped into five categories, where 1 meant "very good;" 2, "good;" 3, "fair;" 4, "poor;" and 5 "very poor." The number of people living in the house was a discrete variable, ranging from 1, i.e., "only one person living in the house" to 15, "15 people living in the house."

The remaining control variables were dichotomous: Male, 1 if the individual was a man and 0 otherwise; White, 1 if the individual was White and 0 otherwise; Urban, 1 if the individual lived in an urban region and 0 otherwise.

Empirical strategy

The relationship between mental health (MH) and employment (E) was estimated using an ordered probit model, as MH is an ordered categorical variable. The model's empirical strategy can be written as:

$$MH_i^* = x'\gamma + \varepsilon_i, \tag{1}$$

where MH^* is the dependent variable and it is unobserved, x is a vector of explanatory variables, and γ is a vector of coefficients; ε_i is the error term, where $\varepsilon_i \sim N(0,1)$.

In the case of five categories, the link function is given below (GREENE, 2011)

$$
\begin{aligned}
MH &= 0 \text{ if } MH^* \leq 0 \\
&= 1 \text{ if } 0 < MH^* \leq \tau_1 \\
&= 2 \text{ if } \tau_1 < MH^* \leq \tau_2 \\
&= 3 \text{ if } \tau_2 < MH^* \leq \tau_3 \\
&= 4 \text{ if } \tau_3 \leq MH^*
\end{aligned} \tag{2}
$$

where τ corresponds to the unknown parameters determined together with β, which $0 < \tau_1 < \tau_2$. The categories, *MH*, change when the latent variable MH^* crosses a certain cut point.

The probability distribution function can be expressed as:

$$
\begin{aligned}
\text{Prob } (Y = 0 \mid X) &= F(-X'\beta) \\
\text{Prob } (Y = 1 \mid X) &= F(\tau_1 - X'\beta) - F(-X'\beta) \\
\text{Prob } (Y = 2 \mid X) &= F(\tau_2 - X'\beta) - F(\tau_1 - X'\beta) \\
\text{Prob } (Y = 3 \mid X) &= F(\tau_3 - X'\beta) - F(\tau_2 - X'\beta) \\
\text{Prob } (Y = 4 \mid X) &= 1 - F(\tau_3 - X'\beta)
\end{aligned} \tag{3}
$$

The vector of the explanatory variables includes employment and additional controls. A statistical concern is the potential endogeneity between the main explanatory variables of interest and mental health, as Farré et al. (2018) point out. In other words, unemployment may affect mental health status, but mental health may also affect employment status. In the presence of endogeneity, the assumptions of the classical model are violated. One strategy for dealing with this issue is the IV method. This method is based on an exogenous source of variation but is strongly correlated with the endogenous variable, i.e., an instrumental variable correlated with unemployment but uncorrelated with mental health. The challenge is to identify a suitable set of instruments.

To estimate an instrumental variable (IV) probit model with a categorical endogenous regressor, a conditional mixed process (CMP) estimator was used. This estimation technique is suitable in situations where the dependent and endogenous regressors are not continuous. In this study, both variables were categorical. The CMP provides consistent and efficient estimates compared to standard estimators (ROODMAN, 2011).

The following system of equations was used to estimate the ordered probit models for the first and second equations using the CMP estimator:

$$
\begin{aligned}
MH_i^* &= \alpha_1 + \alpha_2 E_i + \alpha_3 Z_i + \mu_i \\
E_i^* &= \omega_1 + \omega_1 V_i + \omega_1 Z_i + \mu_i
\end{aligned} \tag{4}
$$

for all $i=1, 2,..., n$ individuals. MH^* is the unobserved latent outcome variable; E is an endogenous employment variable; V is a vector of exogenous instruments; and X is the vector of the additional controls.

Two instruments were used in the study. The first was the variation in the number of high-growth companies between 2018 and 2019 by state. These included companies that had 10 or more employees in the last three years and showed an average growth of at least 20% per year in the number of employees over this period. Figure 1 shows a strong negative correlation between the annual variation in the number of unemployed and high-growth companies since 2013. This instrument is particularly useful because it does not include small companies that are formed during an economic recession. Opportunity entrepreneurs, who found a business based on a good opportunity, and necessity entrepreneurs, who start their own business because of the lack of opportunities in the job market, may differ in many aspects. This topic has been addressed in detail by Apergis and Payne (2016) and Fairlie (2013). The second instrument was any other source of income, including that from renting property, social security benefits from the federal government, private pensions, and financial support from someone external to the household. These variables are considered the determinants of the reservation wage and have a positive impact on reservation wages and duration of unemployment, as workers are more likely to wait for better opportunities in the job market (KOCHOVSKA, 2019; BROWN; TAYLOR, 2013). Deschacht and Vansteenkiste (2021) show that reservation wages decline with unemployment duration, with stronger declines occurring among those with higher reservation wages. Both variables are correlated with employment status, but there is no reason to believe that they affect mental health. This indicates that high-growth companies and other sources of income can be used as instrumental variables for employment status.
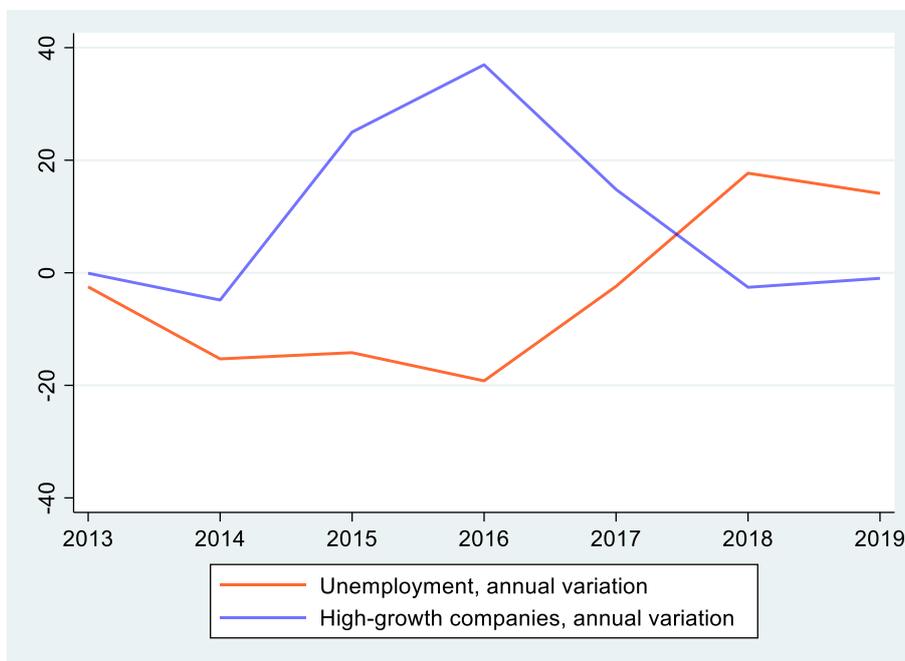
Figure 1 – Annual variation in the number of unemployed and high-growth companies, 2013–2019, Brazil

The Atanhrho values were reported for all estimations using the CMP. This provided a test of the correlation between the error terms of mental health and employment

equations. The statistical significance of the test implies that there are unobserved factors correlated with both employment and mental health status; thus, the IV approach would be appropriate, and ordinary least squares (OLS) estimates would not be consistent.

The CMP estimator does not provide standard tests of instrumental variables. To conduct these tests, the regressor was treated as a continuous variable using IV two-stage least squares (2SLS) estimation. First, Durbin and Wu–Hausman tests were conducted to test the null hypothesis of no endogeneity. Second, the Amemiya–Lee–Newey test of over-identifying restrictions was performed. This test's null hypothesis is that the instruments are valid; that is, they are not correlated with the error term. Therefore, if it is rejected, it is not possible to conclude the validity of the instruments. Finally, the power of the instruments was tested using F-statistics. This presents the joint significance of all instruments and is required to be over 10.

RESULTS AND DISCUSSION

Table 1 presents the descriptive statistics of the variables used in the model. Mental health and employment were categorical variables. Appendix 2 presents the number and proportion of individuals in each category.

Table 1 – Descriptive statistics, Brazil, 2019

	Mean	Linearized Std. Err.
Mental Health	1.381	0.006
(Un)employment	1.213	0.006
Education	1.873	0.006
Age	1.947	0.006
Male	0.548	0.004
White	0.440	0.004
Urban	0.881	0.001
Household income	1.623	0.005
Number of people living in the house	2.968	0.011
Self-reported health	2.103	0.006
Variation in the number of high-growth companies	14.745	0.024
Other sources of income	0.114	0.003

Table 2 shows the regression results for mental health and employment status. Overall, the coefficient is statistically significant at the 1% level using all estimation methods. Column (1) shows the ordered probit results that treat unemployment as an exogenous variable. Column (2) provides the IV-2SLS results, which treat the regressor as a continuous variable. The results of the three tests performed indicate that the hypothesis that mental health is exogenous is rejected and that the instruments are valid (uncorrelated with the error term in the second stage) and jointly significantly different from zero. Finally, the results in Column (3) are based on Equation (4), using the IV-ordered probit

approach. The CMP estimator, which treats the regressor as a categorical variable, is used. Employment has a positive effect on mental health status. In other words, unemployment is associated with higher mental health disorder scores. Atanhrho is negative and statistically significant at the 5% level. The first stage is reported in Appendix 3.

Table 2 – Estimation results for mental health, Brazil, 2019

	ORDERED PROBIT	IV-2SLS	IV- ORDERED PROBIT
(Un)employment	0.0864***	0.7097***	0.1632***
	(0.0116)	(0.1046)	(0.0401)
Education	0.0584***	-0.0045	0.0573***
	(0.0179)	(0.0073)	(0.0178)
Age	-0.0975***	-0.0049	-0.0923***
	(0.0154)	(0.0096)	(0.0156)
Male	-0.5152***	-0.1728***	-0.5024***
	(0.0230)	(0.0183)	(0.0244)
White	0.0466**	0.0241***	0.0470**
	(0.0236)	(0.0093)	(0.0235)
Urban	0.2484***	0.0500***	0.2386***
	(0.0276)	(0.0168)	(0.0280)
Household income	0.0203	0.1645***	0.0392
	(0.0227)	(0.0257)	(0.0244)
Number of people living in the house	-0.0131	-0.0078**	-0.0134
	(0.0085)	(0.0032)	(0.0085)
Self-reported health	0.5235***	0.2890***	0.5200***
	(0.0155)	(0.0066)	(0.0157)
Constant		-0.2873*	
		(0.1715)	
Atanhrho			-0.1251**
			(0.0620)
Wu-Hausman F test		60.7577***	
Amemiya–Lee–Newey test		1.1055	
F test		58.2738***	
Observations	43,654	43,654	43,654
Population size	35,626,278	35,626,278	35,626,278

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The marginal effects indicate that the effect of unemployment on mental health differs by the duration of unemployment across all severities of depression (mild, moderate, moderate-to-severe, and severe). For example, individuals looking for a job for more than

24 months are, on average, 10.1 percentage points more likely to report mild mental disorders than employed individuals and approximately 7.4 percentage points more likely to do so than individuals looking for a job for less than 1 month (Appendix 4). Considering moderate-to-severe mental disorders, the marginal effects are 3.7 percentage points for individuals looking for a job for more than 24 months when compared to those who are employed and 3.1 percentage points when compared to those looking for a job for less than 1 month.

The impact of unemployment on mental health was also examined by considering age and schooling groups (Table 3). Unemployment affects highly educated individuals twice as much as those with no education or low levels of education. In terms of age, younger and middle-aged workers show a large impact of unemployment on mental health.

When estimating Equation (4) by the criteria of mental health using the CMP, the unemployment coefficient is positive and statistically significant in eight out of the nine criteria (Table 4). It is worth noting that the coefficient magnitude presents an expressive difference based on these criteria. It was found a large impact of unemployment on thoughts about being dead or hurting yourself, trouble sleeping, and feeling bad about yourself. All statistically significant at the 1% level.

Table 3 – Estimation results for mental health by education and age groups, Brazil, 2019

	Education			Age		
	(A)	(B)	(C)	(A)	(B)	(C)
(Un)employment	0.1585**	0.0822	0.3716***	0.2092***	0.1189*	0.2205***
	(0.0653)	(0.0721)	(0.0786)	(0.0582)	(0.0703)	(0.0765)
Education				-0.0070	0.0081	0.1202***
				(0.0378)	(0.0311)	(0.0268)
Age	-0.1513***	-0.0806***	-0.0841**			
	(0.0256)	(0.0233)	(0.0386)			
Male	-0.5965***	-0.5085***	-0.3609***	-0.4931***	-0.5325***	-0.4938***
	(0.0403)	(0.0353)	(0.0570)	(0.0475)	(0.0425)	(0.0372)
White	0.0406	0.0421	0.0429	0.0339	0.0388	0.0607*
	(0.0376)	(0.0340)	(0.0585)	(0.0437)	(0.0416)	(0.0363)
Urban	0.1958***	0.3600***	0.1688*	0.2530***	0.3333***	0.1362***
	(0.0405)	(0.0424)	(0.0866)	(0.0478)	(0.0475)	(0.0483)
Household income	-0.0084	0.0211	0.0575	0.0634	0.0543	0.0320
	(0.0427)	(0.0379)	(0.0499)	(0.0451)	(0.0452)	(0.0366)
Number of people living in the house	-0.0061	-0.0145	-0.0332	-0.0332**	-0.0139	0.0002
	(0.0138)	(0.0124)	(0.0227)	(0.0152)	(0.0147)	(0.0148)
Self-reported health	0.5700***	0.4881***	0.5014***	0.4272***	0.5117***	0.5770***
	(0.0249)	(0.0246)	(0.0354)	(0.0329)	(0.0249)	(0.0257)
Atanhrho	-0.1409	-0.0205	-0.3468***	-0.2769***	-0.0119	-0.1694
	(0.1064)	(0.1134)	(0.1190)	(0.0937)	(0.1050)	(0.1207)
Observations	15,671	19,327	8,656	11,774	15,017	16,863
Population size	11,946,845	16,241,786	7,437,647	9,387,373	12,257,978	13,980,927

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Education – (A): "no formal education," "did not complete primary education," or "completed primary education;" (B): "did not complete secondary education," "completed secondary education," and "did not complete tertiary education;" and (C): "completed tertiary education."
Age – (A): "between 18 and 32 years old;" (B): "between 33 and 44 years old;" and (C): "between 45 and 65 years old."

Table 4 – Estimation results by mental health criteria, Brazil, 2019

	Trouble sleeping	Tired/little energy	Little interest/ pleasure	Trouble concentrating	Poor appetite or overeating	Moving/speaking slowly or restless/ fidgety	Feeling down/ depressed/ hopeless	Feeling bad about yourself	Thoughts about being dead or hurting yourself
(Un)employment	0.1718***	0.0774*	0.0785*	0.0675	0.1033*	0.0908**	0.1010**	0.1216***	0.2026***
	(0.0415)	(0.0402)	(0.0403)	(0.0439)	(0.0540)	(0.0431)	(0.0416)	(0.0414)	(0.0515)
Education	0.0583***	0.0736***	0.0403**	0.1114***	0.0015	0.0349*	-0.0123	0.0001	-0.1265***
	(0.0165)	(0.0160)	(0.0171)	(0.0186)	(0.0194)	(0.0194)	(0.0182)	(0.0214)	(0.0290)
Age	0.0663***	-0.0923***	-0.1166***	-0.1237***	-0.1788***	-0.0354**	-0.0352**	-0.1104***	-0.0928***
	(0.0141)	(0.0139)	(0.0147)	(0.0166)	(0.0172)	(0.0172)	(0.0157)	(0.0186)	(0.0269)
Male	-0.3290***	-0.4128***	-0.4334***	-0.3429***	-0.4365***	-0.3503***	-0.4756***	-0.3315***	-0.3288***
	(0.0214)	(0.0210)	(0.0225)	(0.0243)	(0.0270)	(0.0266)	(0.0242)	(0.0277)	(0.0401)
White	0.0540**	0.0473**	0.0042	-0.0148	0.0132	0.0267	0.0261	0.0402	0.0228
	(0.0212)	(0.0208)	(0.0218)	(0.0242)	(0.0257)	(0.0257)	(0.0241)	(0.0277)	(0.0402)
Urban	0.1252***	0.1716***	0.2160***	0.1204***	0.1692***	0.1263***	0.1701***	0.2296***	0.1075**
	(0.0256)	(0.0241)	(0.0256)	(0.0284)	(0.0290)	(0.0333)	(0.0273)	(0.0322)	(0.0511)
Household income	0.0484**	0.0788***	0.0209	0.0670***	0.0684**	0.0191	-0.0576**	-0.0512*	-0.0798**
	(0.0218)	(0.0213)	(0.0228)	(0.0250)	(0.0287)	(0.0288)	(0.0258)	(0.0300)	(0.0401)
Number of people living in the house	-0.0284***	0.0244***	-0.0071	0.0089	-0.0101	0.0024	-0.0277***	-0.0067	-0.0199
	(0.0078)	(0.0074)	(0.0080)	(0.0089)	(0.0089)	(0.0090)	(0.0085)	(0.0099)	(0.0141)
Self-reported health	0.3782***	0.4305***	0.4012***	0.3954***	0.3666***	0.3830***	0.4180***	0.3971***	0.3856***
	(0.0144)	(0.0141)	(0.0149)	(0.0161)	(0.0169)	(0.0166)	(0.0157)	(0.0178)	(0.0256)
Atanhrho	-0.1852***	-0.1323**	-0.0447	-0.0341	-0.0674	-0.0453	-0.0053	-0.0062	-0.2021**
	(0.0659)	(0.0630)	(0.0632)	(0.0684)	(0.0853)	(0.0663)	(0.0639)	(0.0653)	(0.0807)
Observations	43,654	43,654	43,654	43,654	43,654	43,654	43,654	43,654	43,654
Population size	35,626,278	35,626,278	35,626,278	35,626,278	35,626,278	35,626,278	35,626,278	35,626,278	35,626,278

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Finally, Table 5 presents the different specifications for testing the sensitivity of the results using the CMP estimator. Column (1) excludes self-reported health variable. Column (2) excludes individuals with a medical diagnosis of mental health disorder prior to unemployment. A total of 4,430 individuals were excluded from the sample. Again, the impact of unemployment on mental health is seen to be positive and significant.

Table 5 – Sensitivity analyses, Brazil, 2019

	(1)	(2)
(Un)employment	0.1599***	0.1539***
	(0.0396)	(0.0413)
Education	-0.0228	0.0161
	(0.0170)	(0.0201)
Age	0.0050	-0.0975***
	(0.0151)	(0.0174)
Male	-0.5533***	-0.4359***
	(0.0237)	(0.0263)
White	-0.0010	0.0265
	(0.0231)	(0.0257)
Urban	0.1880***	0.2190***
	(0.0271)	(0.0315)
Household income	-0.0633***	0.0253
	(0.0240)	(0.0258)
Number of people living in the house	-0.0167**	-0.0028
	(0.0084)	(0.0095)
Self-reported health		0.4612***
		(0.0176)
Atanhrho	-0.1072*	-0.1019
	(0.0603)	(0.0643)
Observations	43,654	39,225
Population size	35,626,278	31,379,509

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

These findings are in line with the vast majority of previous studies, which suggest that unemployment has a significant positive effect on mental health (BRIODYA; DOYLEB; KELLEHER, 2020; FARRÉ; FASANI; MUELLER, 2018; CYGAN-REHM; KUEHNLE; OBERFICHTNER, 2016; DRYDAKIS, 2015). Considering the duration of unemployment is also relevant. The results show that long-term unemployment has a stronger impact on mental illness, although a negative impact is already observed with one month of unemployment. These results are consistent with Cygan-Rehm, Kuehnle

and Oberfichtner (2016), which investigate three different durations of unemployment (less than 3 months, 3–12 months, and longer than 1 year) for four countries (Australia, Germany, United Kingdom, and United States). Unemployment was consistently associated with mental disorder, regardless of duration. Germany and Australia exhibit more negative effects in the long-term, whereas United Kingdom and United States in the short-term.

There is also a heterogeneous impact across different groups. As found for high-income countries, highly educated individuals are more likely to experience mental health disorders (LATIF, 2015). It is worth noting that this result is not a consent. For instance, Jofre-Bonet, Serra-Sastrea and Vandoros (2018) and Charles and DeCicca (2008) found that less-educated groups are more negatively affected by unemployment in England and in the United States, respectively.

Among the age groups, young (aged 18-32) and middle-aged (aged 45-65) adults are the most affected by unemployment. It is well-documented that the number of jobs responds strongly to economic cycles (BAL-DOMAŃSKA, 2022). The labor market entrants are more vulnerable to these shocks. Young people have less experience and face job-specific ability barriers (CALIENDO; SCHMIDL, 2016). Black, Jackson and Johnston (2022) show that young women (aged 20-29) are the most negatively affected, particularly those employed in an insecure job (e.g. causal or fixed-term) and from families of lower socioeconomic status.

The 9 criteria that comprise the survey exhibit a consistent sign pattern and corroborate those reported by Charles and DeCicca (2008). The authors investigate six questions from K6 scale of non-specific (sadness, hopelessness, worthlessness, restlessness, nervousness, and feelings of effort) and showed that an increase in the unemployment rate is related to a reduction in mental health.

In the context of low- and middle-income countries, there are only few studies on this topic. A major concern around these studies is that, in general, they assume the exogeneity of unemployment. Despite the different methodological approach of these studies, the results also suggest that unemployed individuals experience diminished mental health NOGHANIBEHAMBARI; TAVASSOLIB; NOGHANIC, 2021; FERNÁNDEZ-NIÑO et al., 2018; CAICEDO; VAN GAMEREN, 2016).

In the face of the 2008 financial crisis, World Health Organization (WHO, 2011) warned against the risk of secondary mental health effects and the relevance of policy measures in that context. Possible measures to mitigate the mental health effects of economic crisis included active labour market programmes, family support programmes, debt relief programmes, controls on the price and availability of alcohol, and mental health services for groups of high risk, oriented toward preventing and detection mental health issues early.

CONCLUSIONS

This study has shown how short- and long-term unemployment affects mental health in Brazil. A variety of studies have addressed this topic, but few have explored the context

of LMICs using robust methodological approaches. The evidence presented in this study indicates that unemployment leads to worse mental health, with the duration of unemployment affecting the severity of mental disorders. A longer duration of unemployment is associated with higher severity of mental health disorders. The study also revealed that the impact of job loss was the strongest on highly educated young and middle-aged adults. In addition, unemployment status showed a positive impact on eight of the nine criteria considered in the survey.

An important aspect of the ongoing debate about mental health disorders worldwide is the precise understanding of associated factors. This study reflects the relevance of including policies oriented toward promoting mental health during macroeconomic shocks, mainly in periods of high and persistent levels of unemployment, as a preventive strategy to ensure mental well-being.

REFERENCES

ANTONAKAKIS, N., COLLINS, A. The impact of fiscal austerity on suicide mortality: evidence across the 'Eurozone periphery'. **Soc. Sci. Med,** v. 145, 63–78, 2015.

APERGIS, N.; PAYNE, J. E. An empirical note on entrepreneurship and unemployment: Further evidence from U.S. States. **Journal of Entrepreneurship and Public Policy**. v. 5 n. 1, 2016, p. 73-81.

AVDIC, D.; NEW, S. C. de; KAMHÖFER, D. A. Economic downturns and mental health in Germany. **European Economic Review**, v. 140, 2021. https://doi.org/10.1016/j.euroecorev.2021.103915

BAL-DOMAŃSKA, B. The impact of macroeconomic and structural factors on the unemployment of young women and men. **Economic Change and Restructuring**, v. 55, 2022. https://doi.org/10.1007/s10644-021-09341-9

BARBAGLIA M.G.; HAVE; M.T.; DORSSELAER S.; ALONSO J; GRAAF R. Negative socioeconomic changes and mental disorders: a longitudinal study. **J Epidemiol Community Health,** v. 69, 2015. http://dx.doi.org/10.1136/jech-2014-204184

BLACK, N.; JACKSON, A.; JOHNSTON, D. W. Whose mental health declines during economic downturns? **Health Economics**, v. 31, 2022.

BOYD-SWAN, C.; HERBST; C. M.; IFCHER, J.; ZARGHAMEE. H. The earned income tax credit, mental health, and happiness. **Journal of Economic Behavior & Organization,** v. 126, 2016. http://dx.doi.org/10.1016/j.jebo.2015.11.004

BRADFORD, D. W.; LASTRAPES, W. D. A prescription for unemployment? recessions and the demand for mental health drugs. **Health Economics**, v.23, n. 11, 2013. https://doi.org/10.1002/hec.2983

BRIODYA, J.; DOYLEB, O.; KELLEHER, C. The effect of local unemployment on health: A longitudinal study of Irish mothers 2001-2011. **Economics and Human Biology**, v.37, 2020. http://dx.doi.org/10.1016/j.ehb.2020.100859

BROWN S.; TAYLOR, K. Reservation wages, expected wages and unemployment. Economic Letters, v.119. 2013 http://dx.doi.org/10.1016/j.econlet.2013.02.035

BROWNING, M.; HEINESEN, E. Effect of job loss due to plant closure on mortality and hospitalization, **Journal of Health Economics**, v. 31, n. 4, 599–616, 2012.

BUBONYAA, M.; COBB-CLARKB, D. A.; RIBAR, D. C. The reciprocal relationship between depressive symptoms and employment status. Economics and Human Biology, v. 35, 2019. https://doi.org/10.1016/j.ehb.2019.05.002

CAICEDO, M.; VAN GAMEREN, E. Unemployment and Mental Health among Mexican Immigrants and other Population Groups in the United States. **Migraciones internacionales**, v. 8, n. 4, 2016.

CALIENDO, M.; SCHMIDL, R. Youth unemployment and active labor market policies in Europe. **IZA Journal of Labor Policy**, v.5, n.1, 2016. https://doi.org/10.1186/s40173-015-0056-3

CAROLI, E.; GODARD, M. Does job insecurity deteriorate health? **Health Economics**, v. 25, 2016. https://doi.org/10.1002/hec.3122

CYGAN-REHM, K.; KUEHNLE, D.; OBERFICHTNER, M. Bounding the causal effect of unemployment on mental health: Nonparametric evidence from four countries. **Health Economics**, v.26, 2016 https://doi.org/10.1002/hec.3510

CHARLES, K.K.; DEDICCA, P. Local labor market fluctuations and health: Is there a connection and for whom? **Journal of Health Economics**. v.27, 2008.

DESCHACHT, N.; VANSTEENKISTE, S. The effect of unemployment duration on reservation wages: Evidence from Belgium. **Labour Economics**, v. 71, 2021. https://doi.org/10.1016/j.labeco.2021.102010

DRYDAKIS, N. The effect of unemployment on self-reported health and mental health in Greece from 2008 to 2013: A longitudinal study before and during the financial crisis. **Social Science & Medicine**, v. 128, 2015. http://dx.doi.org/10.1016/j.socscimed.2014.12.025

DUNN, L. F.; MIRZAIE, I. A. Consumer debt stress, changes in household debt, and the great recession. **Economic Inquiry**, v. 54, n. 1, 2016. http://dx.doi.org/10.1111/ecin.12218

FARRÉ, L.; FASANI, F.; MUELLER, H. Feeling useless: the effect of unemployment on mental health in the Great Recession. **IZA Journal of Labor Economics**, v.7, n.8, 2018. https://doi.org/10.1186/s40172-018-0068-5

FAIRLIE, R. W. Entrepreneurship, Economic Conditions, and the Great Recession. **Journal of Economics and Management Strategy**. v. 22, n. 2, 2013.

FERNÁNDEZ-NIÑO et al. Association between the employment status and the presence of depressive symptoms in men and women in Mexico. **Cad. Saúde Pública**, v. 34, 2018. https://doi.org/10.1590/0102-311X00219617

FITCH, C. et al. The relationship between personal debt and mental health: a systematic review. Mental Health Review Journal, v. 16, n. 4, 2011. http://dx.doi.org/10.1108/13619321111202313

GILI, M.; ROCA, M.; BASU, S.; MCKEE, M.; STUCKLER, D. The mental health risks of economic crisis in Spain: evidence from primary care centres, 2006 and 2010. **Mental health risks of economic crisis in Spain**, v. 23, n. 1, 2012.

GREENE, W. H. **Econometric analysis**. Prentice Hall, 7th ed., 2011.

GUERRA, O.; EBOREIME, E. The Impact of Economic Recessions on Depression, Anxiety, and Trauma-Related Disorders and Illness Outcomes—A Scoping Review. **Behav. Sci**, v.11, n.119, 2021. https://doi.org/10.3390/bs11090119

HENKEL, D. Unemployment and Substance Use: A Review of the Literature (1990-2010). **Current Drug Abuse Reviews**, 4, 2011.

HONE, T., MIRELMAN, A. J., RASELLA, D., PAES-SOUSA, R., BARRETO, M. L., ROCHA, R. & MILLETT, C. Effect of economic recession and impact of health and social protection expenditures on adult mortality: a longitudinal analysis of 5565 Brazilian municipalities. **Lancet Glob Health**, v. 7**,** e1575-e1583, 2019.

IBGE. Summary of Social Indicators - SIS. Rio de Janeiro: Brazilian Institute of Geography and Statistics. 2020.

IBGE. Instituto Brasileiro de Geografia e Estatística. 2022.

KALOUSOVA, L.; BURGARD, S. Unemployment, measured and perceived decline of economic resources: contrasting three measures of recessionary hardship and their implications of adopting negative health behaviors. **Soc. Sci. Med**, v.106, 2014.

KASPERSEN, S. L.; PAPE, K.; OSE, S. O.; GUNNELL, D.; BJØRNGAARD, J. H. Unemployment and initiation of psychotropic medication: a case-crossover study of 2,348,552 Norwegian employees. **Occup Environ Med**, v.73, 2016.

KRUGA, G.; EBERL, A. What explains the negative effect of unemployment on health? An analysis accounting for reverse causality. **Research in Social Stratification and Mobility**, v. 55, 2018. https://doi.org/10.1016/j.rssm.2018.03.001

KOCHOVSKA, T. Interplay Between Reservation Wage and Unemployment Duration: Evidence From North Macedonia. Fourteenth International Conference on European Integration – Innovating Europe, Skopje, 2019. https://doi:10.5281/zenodo.3533845

KROENKE, K., SPITZER, R. L.; WILLIAMS, J. B. 2001. The PHQ-9: validity of a brief depression severity measure. **J Gen Intern Med**, 16**,** 606-13.

JACOB, K. S. Mental health services in low-income and middle-income countries. **Lancet Psychiatry**, 2017. http://dx.doi.org/10.1016/

JOFRE-BONETA, M.; SERRA-SASTREA, V.; VANDOROS, S. The impact of the Great Recession on health-related risk factors, behaviour and outcomes in England. **Social Science & Medicine**, v. 197, 2018.

LATIF, E. The impact of economic downturn on mental health in Canada. International **Journal of Social Economics**, v.42, n.1, 2015.

NOGHANIBEHAMBARI, H.; TAVASSOLIB, N.; NOGHANIC, F. Labor demand shocks, unemployment, and suicide: evidence from provinces across Iran. **Middle East Development Journal**, 2021. https://doi.org/10.1080/17938120.2021.1959830

NORSTROM, F., WAENERLUND, A. K., LINDHOLM, L., NYGREN, R., SAHLEN, K. G. & BRYDSTEN, A. 2019. Does unemployment contribute to poorer health-related quality of life among Swedish adults? **BMC Public Health**, 19, 457.

OECD. 2022. Organisation for Economic Co-operation and Development. Long-term unemployment rate [Online]. Available: https://data.oecd.org/ [Accessed March 2022].

PRAUSE, J. A. D., D., HUH, J. Income Volatility and Psychological Depression. **American Journal of Community Psychology**, v.43, 1-2, 2009.

RODRIGUES, D.F.S.; NUNES, C. Inpatient Profile of Patients with Major Depression in Portuguese National Health System Hospitals, in 2008 and 2013: Variation in a Time of Economic Crisis. **Community Ment. Health J**, 54, 224–235, 2018.

ROHDE, N., TANG, K.K., OSBERG, L., RAO, P. The effect of economic insecurity on mental health: recent evidence from Australian panel data. **Soc. Sci. Med**. v.151, 2016.

ROODMAN, D. Fitting fully observed recursive mixed-process models with cmp. **The Stata Journal**, v. 11, n. 2, 2011.

SANTOS, I. S., TAVARES, B. F., MUNHOZ, T. N., ALMEIDA, L. S., SILVA, N. T., TAMS, B. D., PATELLA, A. M. & MATIJASEVICH, A. 2013. [Sensitivity and specificity of the Patient Health Questionnaire-9 (PHQ-9) among adults from the general population]. **Cad Saude Publica**, 29, 1533-43.

SCHALLER, J., STEVENS. A. H. Short-run effects of job loss on health conditions, health insurance, and health care utilization. **J Health Econ**, v.43, 2015.

SCHMITZ, H. Why are the unemployed in worse health? The causal effect of unemployment on health. **Labour Economics**, v. 18, 2011.

TEKIN, E.; MCCLELLAN, C.; MINYARD, K.J. Health and health behaviors during the great recession: a note on drinking, smoking, obesity, and physical activity. **Rev Econ Household**, v.16, n.4, 2018.

THOMSON, R. M.; IGELSTRÖM, E.; PURBA, A. K.; SHIMONOVICH, M.; THOMSON, H.; MCCARTNEY, G.; REEVES, A.; LEYLAND, A.; PEARCE, A.; KATIKIREDD, S. V. How do income changes impact on mental health and wellbeing for working-age adults? A systematic review and meta-analysis. **Lancet Public Health**, v. 7, 2022.

WANG, Y.; FATTORE, G. the impact of the great economic crisis on mental health care in Italy. **The European Journal of Health Economics**, v.21, 2020.

WACHTER, T. von. The Persistent Effects of Initial Labor Market Conditions for Young Adults and Their Sources. **The Journal of Economic Perspectives**, v. 34, n. 4, 2020, pp.168-194

WEINMANN S., KOESTERS, M. Economic crisis and mental health – findings from low- and middle-income countries. **Die Psychiatrie**, v.14, n. 2, 2017, pp. 86-89 https://doi:10.1055/s-0038-1669557

WHO. Impact of economic crisis on mental health. **World Health Organization**, Denmark, 2011. Available in <https://www.euro.who.int/__data/assets/pdf_file/0008/134999/e94837.pdf>

APPENDIX

Appendix 1 - Patient Health Questionnaire – 9 (PHQ-9)

Over the last 2 weeks, how often have you been bothered by any of the following problems?	Not at all	Less than half the days	More than half the days	Nearly every day
1. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
2. Feeling tired or having little energy	0	1	2	3
3. Little interest or pleasure in doing things	0	1	2	3
4. Trouble concentrating on usual things	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Moving or speaking slowly; or the opposite – being fidgety or restless	0	1	2	3
7. Feeling down, depressed, or hopeless	0	1	2	3
8. Feeling bad about yourself – or that you are a failure or have let yourself or your family down	0	1	2	3
9. Thoughts that you would be better off dead or of hurting yourself in some way	0	1	2	3

Appendix 2 – Number and proportion of individuals by mental health and employment status, Brazil, 2019

Mental Health			(Un)employment		
	N[a]	%[b]		N[a]	%[b]
None-minimal	33,399	75.71	Employed	40,395	92.45
Mild	6,482	15.15	Unemployed (< 1)[c]	338	0.87
Moderate	2,353	5.65	Unemployed (> 1 and < 12)[c]	1,068	2.57
Moderate-severe	951	2.31	Unemployed (> 12 and < 24)[c]	509	1.13
Severe	486	1.19	Unemployed (> 24)[c]	1,361	2.99
TOTAL	43,671	100	TOTAL	43,671	100

[a]Unweighted numbers
[b]Weighted percentage
[c]Months

Appendix 3 – Estimation results for mental health, first stage, Brazil, 2019

	IV-ORDERED PROBIT
High-growth companies	-0.0022***
	(0.0008)
Other sources of income	0.2647***
	(0.0526)
Education	0.0249
	(0.0273)
Age	-0.1994***
	(0.0236)
Male	-0.3467***
	(0.0305)
White	-0.0082
	(0.0340)
Urban	0.3075***
	(0.0386)
Household income	-0.8019***
	(0.0396)
Number of people living in the house	0.0110
	(0.0109)
Self-reported health	0.0773***
	(0.0217)
Observations	43,654
Population size	35,626,278

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 4 – Predict value, CPM estimator, 2019, Brazil

	Margin	Std. Err.	T	P>|t|	[95% Conf. Interval]	
1 1	0.7893	0.0040	197.7	0.0000	0.7815	0.7971
1 2	0.7392	0.0114	64.7	0.0000	0.7168	0.7616
1 3	0.6835	0.0264	25.9	0.0000	0.6318	0.7353
1 4	0.6234	0.0433	14.4	0.0000	0.5386	0.7082
1 5	0.5601	0.0607	9.2	0.0000	0.4411	0.6790
2 1	0.1466	0.0031	46.6	0.0000	0.1404	0.1528
2 2	0.1736	0.0062	28.1	0.0000	0.1615	0.1857
2 3	0.2004	0.0120	16.7	0.0000	0.1768	0.2239
2 4	0.2255	0.0166	13.6	0.0000	0.1929	0.2580
2 5	0.2473	0.0186	13.3	0.0000	0.2108	0.2838
3 1	0.0448	0.0017	25.8	0.0000	0.0414	0.0482
3 2	0.0588	0.0037	15.8	0.0000	0.0515	0.0661
3 3	0.0753	0.0083	9.1	0.0000	0.0591	0.0915
3 4	0.0939	0.0138	6.8	0.0000	0.0668	0.1209
3 5	0.1140	0.0197	5.8	0.0000	0.0755	0.1526
4 1	0.0144	0.0009	15.6	0.0000	0.0126	0.0162
4 2	0.0205	0.0020	10.2	0.0000	0.0166	0.0245
4 3	0.0286	0.0046	6.2	0.0000	0.0196	0.0376
4 4	0.0389	0.0084	4.6	0.0000	0.0224	0.0554
4 5	0.0514	0.0134	3.8	0.0000	0.0250	0.0778
5 1	0.0050	0.0004	11.5	0.0000	0.0041	0.0058
5 2	0.0079	0.0010	7.6	0.0000	0.0058	0.0099
5 3	0.0122	0.0026	4.6	0.0000	0.0070	0.0174
5 4	0.0184	0.0055	3.4	0.0010	0.0077	0.0292
5 5	0.0272	0.0101	2.7	0.0070	0.0074	0.0469

Obs.: Delta-method