JDE Journal of Developing Economies

JDE (Journal of Developing Economies)
https://e-journal.unair.ac.id/JDE/index

MENTAL HEALTH EFFECTS ON JOB RETENTION IN INDONESIA

M. Arizal*[1]

I Dewa Gede Karma Wisana[2]

[1, 2] Department of Economics, Universitas Indonesia, Depok, Indonesia

ABSTRACT

This study examines the effect of mental health proxied by depression on job retention. The primary independent variable is the change in depression scores in 2007 and 2014. It discovers the number of individuals whose depression scores remained, decreased, and increased. The dependent variable was being employed or unemployed in 2014. The data used in this study are from the Indonesia Life Family Survey (IFLS). The method used is logistic regression. The test results from 9675 observations showed that individuals who experienced symptoms of depression in the previous period decreased their work retention by 5.55%. Both men and women in this study showed significant results. This study confirms the long-term effect of depressive disorders on job retention.

ARTICLE INFO

Received: July 12th, 2022
Revised: January 16th, 2023
Accepted: January 26th, 2023
Online: June 15th, 2023

*Correspondence:
M. Arizal
E-mail:
zari3789@gmail.com

Keywords: *Mental Health, Depression, Employment*
JEL: 114; 118; C35

To cite this document: Arizal, M., & Wisana, I. D. G. K. (2023). Mental Health Effects on Job Retention in Indonesia. *JDE (Journal of Developing Economies)*, *8*(1), 1-20. https://doi.org/10.20473/jde.v8i1.37445

Introduction

Mental health has become an exciting issue and has received special worldwide attention, especially since the 2000s (Lagomarsino & Spiganti, 2020; McGovern, 2014). It is due to the various impacts that mental health can have in various aspects in developed and developing countries (Frijters et al., 2014). Moreover, no less than 80% of individuals with mental health disorders do not receive treatment in middle and low-income countries (WHO, 2013). This condition is also exacerbated by the fact that there are no facilities related to collecting and reporting data related to mental health in no less than 27% of countries in the world (Giang et al., 2006). There are economic costs and losses that certain parties must bear due to the direct and indirect effects of mental health problems (Lanuza, 2013; Rudolph & Eaton, 2016). One of these effects is to create a burden on the work environment. Therefore, the World Health Organization seeks to upgrade various priority agendas related to mental health.

Furthermore, one type of mental health disorder that is commonly discussed is depression because of the distribution of cases and the high economic costs it incurs (Asami et al., 2015; Bubonya et al., 2019). According to the National Institute of Mental Health (NIMH) (2021), depression can cause severe mood disorders and impact individuals' thoughts, feelings, appetite, and work activities. Data in America show the development of cases of depression that continues to increase from 2010 to 2018, from less than 15.5 million to 17.5 million adults. In line with the increasing number of cases, from 2010 to 2018, there has always been an increase in the economic burden due to depression, from the initial $236 billion to $326 billion. More interestingly, costs related to work activities due to depression increased to 61% from 41% (Greenberg et al., 2015, 2021). Not only related to the cost of work activities, but the WHO also reports on the estimation of the global disease burden, explaining that an average of 54.8% of health losses due to disability are caused by depression (WHO, 2020). More broadly, WHO also published that at least in 2015, as many as 322 million people in the world had experienced depression which spread to several regions of the world (as shown in figure 1.) or equivalent to 4.4% of the world's population (WHO, 2017). Figure 1. shows that the distribution of cases of depression is highest in the area around Southeast Asia. As detailed again in the WHO report, Indonesia has the second highest case occurring in Southeast Asia, with more than 9 million cases.

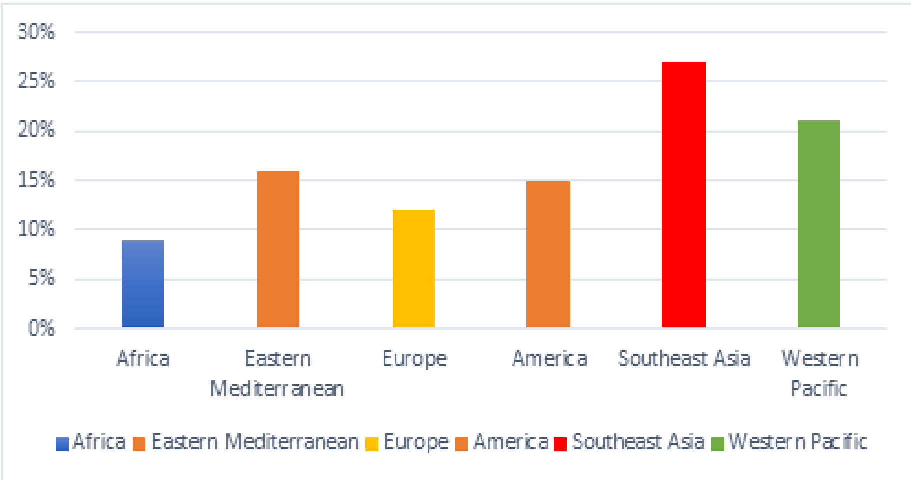

Figure 1: Distribution Case Depression

Source: WHO (2017)

Data from the Indonesian Ministry of Health show an increase in cases of mental health disorders by 7% in 2018 compared to 2013, which was only 1.7% for people in the category of mental disorders. From 2013 to 2018, there was also an increase from only 6% to 9.7% for emotional and mental disorders (Ministry of Health, 2020). Suppose it is more specific to cases of depression in 2018, based on the RISKESDAS report. There 12 million people have experienced it, or about 6% of the population, and only about 9% of those who get treatment. Based on this report, of the 12 million people who experience depression, working-age individuals have a high prevalence of depression. Ages 15-24 years recorded a total of 6.2% of cases, while in that age range, only 5.25% received treatment, even though this age is significant in shaping the quality of human resources. If you look at data from other sources, namely the Indonesia Family Life Survey from 2007 to 2014, the number of people screened for depression in Indonesia has more than doubled (Zulfa, 2017).

Departing from the many cases of mental health, such as depression in various countries that can affect individuals of working productive age, many studies specifically link the effect to labor outcomes (Johar & Truong, 2014; Layard, 2013; Peng et al., 2016). The effect on the labor outcome is that the probability of becoming a worker and productivity is usually lower (Bryan et al., 2022; Jain et al., 2013). Low productivity can be caused by absenteeism and presenteeism by workers with depression symptoms. Absenteeism is the absence of workers at work, while presenteeism is for workers who do not work optimally in the work environment. Bubonya et al. (2017) found that low mental health led to a 5% higher absenteeism from work in Australia, while a study by Rudolph & Eaton (2016) found that depression can cause a 37% risk of being fired from work for women and 18% for men. This negative relationship between mental health and labor outcomes has been estimated through various studies.

According to Chatterji et al. (2011), there are three channels in how mental health affects labor outcomes. First, individuals with mental health disorders will find it challenging to get and stay at work due to low productivity, concentration, and motivation. A study by Saffer & Dave (2005) found that mental health problems such as depression lead to unhealthy behaviors such as smoking, alcohol, and drug consumption. This unhealthy behavior may affect the quality of the individual. Depression can also affect the level of happiness, perception of life, sleep disturbances, and feelings of fatigue, which impact work activities (Ringdal & Rootjes, 2022). Second, the company or employer will not want to incur additional costs to accommodate this problem. Third, the potential for acts of discrimination if the history of mental health disorders is known by the work environment. These three channels will significantly affect the quality of work of individuals with mental health disorders. If it is associated with the theory of labor demand, companies will only hire employees if their productivity exceeds the costs incurred. In other words, the company will hire employees with high productivity.

The previous study still finds debate on how labor outcomes can be affected by mental health. Some studies have found a negative relationship (Frijters et al., 2021; Mitra & Jones, 2017; Ruiz-Tagle & Troncoso, 2018). A study conducted by Mitra & Jones (2017) found that decreased mental health increased the chances of becoming unemployed, and improved health increased the chances of becoming employed. However, other studies found a non-significant effect of mental health disorders on labor outcomes (Sohn, 2018). Differences in results were also found when estimating gender differences. Several studies have found that the effect of mental health on labor outcomes is more influential in males. In their study, Ojeda et al. (2010) explained that male individuals with mental health disorders had more influence on the possibility of working than women, while a study conducted by Zulfa (2017) found that mental health, such as depression, only affected female individuals. The ambiguity of the differences in mental health effects by gender makes this study still interesting.

So far, we have yet to find studies in Indonesia that discuss mental health's effects on job retention. Previous studies have focused more on the correlation between mental health problems and employment opportunities for those who have not previously worked. In addition, several studies related to mental health in Indonesia have yet to include the variable of mental change itself, so we cannot see the long-term effects of mental health problems. This study believes that mental health disorders have a long-term effect on job retention, so the change variable of mental health conditions is essential to include in the model. To fill this research gap, this study includes a variable change in mental health conditions proxied by the change in depression scores in 2007 and 2014. This study also includes many relevant control variables so that it can overcome the problem of unobserved heterogeneity.

This study aims to investigate the effect of depression on job retention or the likelihood of remaining employed using IFLS longitudinal data in Indonesia. The question is whether depressive symptoms will reduce worker retention or the probability of remaining employed for both men and women in Indonesia. A provisional assumption is that depression can reduce the probability of being able to remain in work or work retention. So far, we have not found studies with Indonesian characteristics that focus on the effect of depression or mental health disorders on job retention. The main contribution of this study is to enrich the literature on the effects of depression on job retention by filling the gap in research in Indonesia.

This study uses IFLS4 2007 data, consisting of individual characteristics, socioeconomic, and health, and comprehensively includes sectors and employment characteristics. Mental health measures use the Center of Epidemiological Studies Depression Scale (CES-D), self-reported. IFLS5 2014 data are used regarding individual employment and mental health status. This study also calculated how many individuals between 2007 and 2014 had depression scores that remained, decreased, and increased and then looked at the effect on work retention. Then, estimation is also carried out by differentiating gender to see the difference in the effect because, in some literature, it is stated that there are differences in characteristics between men and women in responding to mental health disorders, so separate regression between men and women can minimize heterogeneity. The method used is logistic regression because the dependent variable is a dummy. The use of logistic regression in this study was able to overcome the problem of reverse causality because what was used as an independent variable was the change in mental health scores in 2007 and 2014.

The results of this study indicate that individuals who experienced symptoms of depression in 2007. However, they did not have symptoms of depression again in the next period of 2014. Compared to individuals who had never had symptoms of depression in both periods, their work retention decreased by 5.55%. These findings confirm that there is indeed a long-term effect of depressive disorders on the ability to maintain a job. It indicates that individuals with depressive symptoms in 2007 are more at risk than individuals who do not experience them or have recently experienced depressive symptoms in 2014 for their chances of retaining their jobs in 2014. In a study conducted by Burcusa & Iacono (2007), it was explained that depression has a high recurrence rate, at least five years to nine years. It means that, in that period, many things will cause a low ability to maintain a job. Individuals in this range experience disability at work because symptoms of depression tend to recur. They are in the process of being treated and treated so they cannot work again. Even though their score improved in 2014, it will take time to get back into the work environment.

Literature Review

Two points will be discussed in the literature review: theoretical reviews and previous research.

Neoclassical Labor Supply Theory

In economic theory, it can be concluded that physical and mental illnesses such as depression can affect an individual's decision to join employment. Several studies have found that mental health disorders have a significant negative relationship with labor outcomes (Banerjee et al., 2017; Bir & Frank, 2001; Bryan et al., 2022). Neoclassical labor supply theory is based on consumer choices in maximizing utility by dealing with the tradeoff between consumption/work and leisure (Cahuc et al., 2004). It is also called time allocation because the choice to consume is obtained from the time used to work to earn earnings, and leisure time is not used for work (leisure time). The basic model of this neoclassical theory is U = (C, L), where if C, the working time used, increases, and L leisure time also increases, the individual will achieve satisfaction. However, remember that individuals have constraints in the form of total available time, so working or not working is a decision/choice. Individuals must determine how much the allocation of C and L is with the condition that if C increases, L will decrease.

Cahuc et al. (2004) suppose L0 is the total time in a day, and L is leisure time, so the time used for work can be written as h=L0 – L. When you want to increase h, it means that L must be reduced in allocation because L0 is limited, but, conversely, when you want to increase L, h must be reduced. Therefore, the relationship between h and L is called a tradeoff due to a constraint. The maximum combination of h/C and L can be seen on the indifference curve. If the indifference curve is further away from the origin, it represents the maximum level of utility.

In dealing with the tradeoff between work and leisure, we recognize the term reservation wage, namely with a certain wage level where individuals are willing to reduce their leisure time used for work. In the initial equation, where the time used for work can be written as h = L0 - L or the total time L0 = h + L, the individual chooses whether to work or leisure. For example, if there is an illness condition S, there will be a new total allocation, namely L0', which is a reduction in the total time with the length of illness L0' = L0 - S, so we can rewrite the time allocation that can be used to work h' = L0' - L'. The allocation of available time used for work is reduced due to illness which implies a decrease in the reservation wage received. The decline in the reservation wage will affect a person's decision to participate in becoming a worker.

Health Theory as Human Capital Investment

One of the literature that discusses the theoretical framework related to health effects and labor outcomes is the model adopted by Currie & Madrian (1999), which was pioneered and sourced from the human capital theory of Becker (1964) and Grossman (1972) who both emphasize the importance of health as human capital that affects income. Specifically, Grossman (1972) states that past health is related to future health, which can also affect future income. The study by Peng et al. (2013) seeks to explain how the theory of Becker and Grossman in an objective function to maximize utility related to the relationship between labor supply and health capital. The objective function consists of maximizing the consumption of goods, current health, and leisure time. However, this maximization has health production functions, budget constraints, total time constraints, wage constraints, sick time, working hours constraints, and income constraints.

With the objective function and budget constraint, after maximizing utility, it can be concluded that health problems can increase sick time, which can reduce the total time allocation, both time for work, time for health products, and free time. As stated by Becker (1964), investment in health is an essential human resource investment that can increase healthy time, which means it can add healthy days, then the implications for productivity or working hours. Referring to the definition of health according to Law 36 of 2009, one of the conditions a person is in a healthy state is mentally healthy. Therefore, people who experience mental health disorders have the potential to increase their sick time, which can affect work participation.

Previous Research

The relationship between mental health disorders such as depression and labor outcomes is still inconclusive because there are differences in the results of previous empirical studies. This difference is caused by various things, such as differences in data, proxies, measurements, and methodologies used. Furthermore, several studies have found that mental health disorders have a significant negative relationship with labor outcomes (Banerjee et al., 2017; Bir & Frank, 2001; Bryan et al., 2022; Ringdal & Rootjes, 2022; Zulfa, 2017). However, other studies show no relationship between these variables (Sohn, 2018).

Ringdal and Rootjes's (2022) study conducted in the Netherlands using a fixed effect and correlated random error and controlling for unobserved heterogeneity found that the presence of depressive symptoms in women did not affect work participation but did affect the probability of having a paid job by 1.6% points while in men effect both on participation and as a paid worker, which is 2.1%. Their study also tried to overcome the reverse causality problem by using mental health lag as an independent variable. Bubonya et al. (2017), using panel data and also controlling for unobservable heterogeneity, found that low mental health led to a 5% higher absenteeism from work in Australia. Another study from Bubonya et al. (2019), still in Australia, using panel data with a bivariate random effect, found that poor mental health caused men to be 3.3% likely not to work and women 2.8% points. This study also uses lag from mental health to overcome the issue of reverse causality. A study in France by Barnay & Defebvre (2019) using a bivariate probit model and using mental health time lag found that mental health reduced work retention in men by 12% points.

Fletcher (2013), using mental health lag and the Mincer model, found that depressive symptoms resulted in a 5% reduction in employment opportunities and a 15% reduction in income in adolescents. Then, Chatterji et al. (2011) looked more at the difference in the effect of gender. Women experience a decreased chance of becoming workers by 14%, of which men are only 9%. Interestingly, Banerjee et al. (2017) found the opposite result using the Structural Equation Model, with a more significant effect in men. Meanwhile, Mitra & Jones (2017) estimated using a dynamic model using the lag of mental health and the first difference to see the effects of transitions to mental health changes. The study using lag found a decrease in the probability and working hours of mental health. A study by Wang et al. (2014) found that the risk of becoming unemployed and job turnover was higher, with the possibility of becoming unemployed by 1.44 points and a job change or job turnover of 3.28 points. The study by Lerner et al. (2014) found an increased risk of unemployment by 12% and a higher probability of turnover, while a study by Rudolph & Eaton (2016) found that depression can cause the risk of the possibility of women being fired from work by 37% and men by 18%.

Several other literatures to address the endogeneity of mental health generally use instrumental variables. Ruiz-Tagle & Troncoso (2018) use IV for the number of families who died, families who had experienced depression, and family violence. Banerjee et al. (2017) used the experience of depression in youth. Barnay & Defebvre (2019) distinguish instruments for men and women, namely for men who have experienced violence and parents who have been divorced and for women who have experienced violence and were raised by one parent. Frijters et al., (2014) used IV death of closest friends. Lagomarsino and Spiganti (2020) use social acceptance or support, as well as Hamilton et al. (1997), who use the same IV and include IV stress events experienced, while Ettner et al. (1997) used the psychological condition of parents.

For research in Indonesia, we have not found a study discussing the effects of depression on work retention. The research in Indonesia focuses more on the effects of depression on individuals who have not previously worked, working hours, and income (Bir & Frank, 2001; Sohn, 2018; Zulfa, 2017). Sohn (2018) found no significant relationship between depression and several labor outcome variables, such as the probability of being employed, hours worked, and income. Zulfa (2017) found a relationship between depression and the likelihood of becoming a worker and being fired from work in individual women. Bir & Frank (2001) also found the effect of depression on the likelihood of working and working hours in Indonesia. These existing studies show an inconclusive relationship because there are differences in results. Therefore, apart from no research on job retention in Indonesia, this study also tried to include relevant control variables, considering changes in depressive symptom scores and differentiating estimates by gender to explain how depression relates to labor outcomes in Indonesia.

Data and Research Methods

Data

For the measurement of mental health scores the Center of Epidemiological Studies Depression Scale (CES-D) is used. This study uses secondary data from longitudinal survey data from the Indonesia Family Life Survey (IFLS). IFLS 4 and IFLS 5 are used because questions related to mental health, namely depression as measured by CES-D, only started in IFLS 4. The unit of analysis in this study is individuals aged 15-64 years who answered mental health questions in IFLS 4 and IFLS 5, namely in 2007 and 2014, and had complete data in waves 4 and 5. This study wants to measure the impact of mental health on labor outcomes, namely the possibility of participating as a worker or job retention. Therefore, the unit of analysis also includes individuals who answered the question in IFLS 5, namely, working or not working in 2014.

The working status variable is taken from Book 3A section TK1 IFLS 5 (2014), the primary dependent variable. Here it consists of two categories, namely working or not working. BPS defines work as an economic activity carried out by individuals to help earn income or profit for at least 1 hour a week. This variable category can be written as follows.

1 = If the individual worked in the last week in 2014

0 = If the individual did not work in the last week in 2014

Mental health, namely depression, is the primary independent variable in this study. Depression was measured using the Center of Epidemiological Studies Depression Scale (CES-D), self-reported. This depression variable is sourced from Book 3B Section KP IFLS 4 and IFLS 5. The CES-D used in IFLS is a short version containing ten questions, of which the full CES-D contains 20 question items (Andersen et al., 1994). In CES-D 10, there are two questions about positive moods and eight about negative ones. This question was asked based on the frequency of how often the mood was felt in the past week. There are four categories of frequency, namely rarely (<1 day), a little (1-2 days), sometimes (3-4 days), and often (5-7 days). If you choose (<1 day), it is given a score of 0, and a little (1-2 days) is given a score of 1. Sometimes (3-4 days) is given a score of 2, and often it is given a score of 3 (5-7 days). The scoring method applies to all questions except for questions E and H which are the opposite because they ask positive questions. The scores that can be obtained range from 0-30, and the higher the score, the higher the symptoms of depression (Radloff, 1977).

In interpreting the CES-D score, some use it in continuous form, and there are categories. Sohn (2018) uses continuous and categorical (>10) as depression. Some use it in continuous form only (Magin et al., 2009). Regarding the use of categorical form, Fletcher (2013) uses a cut-off point to determine depression or not. Andresen et al. (1994) have validated using the cut-off point of eight, which has a high sensitivity value equivalent to the cut-off point of 16 in CES-D 20. So this study adopts the cut-off from Andresen et al. (1994) with the category specification in the form of a dummy which can be written as follows.

1= There are depressive symptoms (score ≥ 8)
0= There are no depressive symptoms (score < 8)

This study also looked at how many individuals experienced depressive symptoms in 2007 and 2014, resulting in four categories, namely remaining not depressed (not depressed in

2007 and 2014, better (depressed in 2007 and not depressed in 2014), worse (not depressed in 2007 and depressed in 2014), and remained depressed (depressed in 2007 and 2014). This study used several control variables related to past health conditions, socio-demography, job characteristics, and others.

Table 1: Description of Control Variables

Variable	Description	Category
Individual Characteristics 2007		
Age	15-64 years old	Numerical
Gender	1= female, 0= male	Dummy
Marital status	1= Married, 0 others	Dummy
Location	1=Urban, 0= Rural	Dummy
Past Health & Economic Conditions 2007		
Habit Smoke	1= Smoking, 0= no	Dummy
Chronic Pain	1= Have sick chronic, 0= no	Dummy
Comorbid	1= Have comorbid 0= no	Dummy
Per Capita Income Log	Expenditure Per Capita	Numerical
Jobs Characteristics 2007		
Work Sector	Agriculture; Services Mining; Manufacturing	Dummy
Amount Worker	Number of workers in the work-place	Numerical
Others 2014		
Education	year of schooling	Numerical
Happiness	Min 1 and max 4	Ordinal
Migration	1= Yes , 0= no	Dummy
Married	1= Married , 0= other	Dummy

Research Method

This study uses two analyses, namely descriptive analysis, and inferential analysis. Descriptive analysis will be presented in tables, graphs, diagrams, and data centers, while for inferential analysis, this study adopts the model from Barnay & Defebvre (2019) that used logistic regression. The selection of the logistic regression model is carried out because the dependent variable has a qualitative value (dummy), which is 1 or 0. If you use a linear probability model, there is a possibility that the predictive value of the dependent variable is more than one or less than 0, so it is less efficient to use. This study also includes a variable change in mental health, namely mental health scores in 2007 and 2014, to obtain the final mental health status. It aims to overcome the problem of reverse causality. Previous studies on the relationship between mental health and working status have shown a two-way relationship between these variables if estimated in the same year. Therefore, when including the variable of change in mental health status, the reverse causality problem can be overcome so that it becomes an advantage in this model compared to previous studies. This model is as follows:

$$Y_{i2014} = \alpha + \beta ChangeDepression_{i2007-2014} + \gamma Cov_{i2007} + \varphi Cov_{i2014} + \varepsilon_i \quad (1)$$

Where is the labor outcome variable employed (1) or being employed (0) in 2014, is the primary independent variable of changes in mental health status, consisting of four dummy categories. The first category was those who remained not depressed in 2007 and 2014, and this first category was the basis for the regression of this mental health change variable. The second category is those whose depression status has improved, namely those experiencing depression in 2007 and no longer experiencing depression in 2014. The third category is those whose depression status is worse, namely those who did not experience depression in 2007 but experienced depression in 2014. The last category is those in a permanent depression status, namely those who experienced depression in 2007 and 2014 in both years.   was the control variable in 2007, was the control variable in 2014, and is the error term. The control variables consist of individual characteristics, health, economy, employment characteristics, and several other variables such as migration and happiness.

Finding and Discussion

Finding

This section will present an overview of the research units used based on data from IFLS 4 and IFLS 5, which are the units of analysis in this study to see how the effect of depression on retention works in Indonesia. The presentation will be presented in graphs, tabulations, and descriptive analysis. The aim is to see how the data distribution and the relationship between variables are before being estimated using inferential analysis. This study generally uses a sample of 9675 respondents. The distribution of individuals with depression symptoms from 9675 respondents can be seen in Figures 2 and 3, comparing depression in 2007 and 2014. Using a cut-off point of eight it can be seen that, in 2007, the distribution of answers was concentrated at values below eight, which amounted to 13.53% of respondents—who experienced symptoms of depression with a proportion of 52.3% or 685 experienced by women. Compared to 2014, there was an increase in answers with a value of more than the cut-off point of eight, and women with symptoms of depression also increased to 1616 respondents.

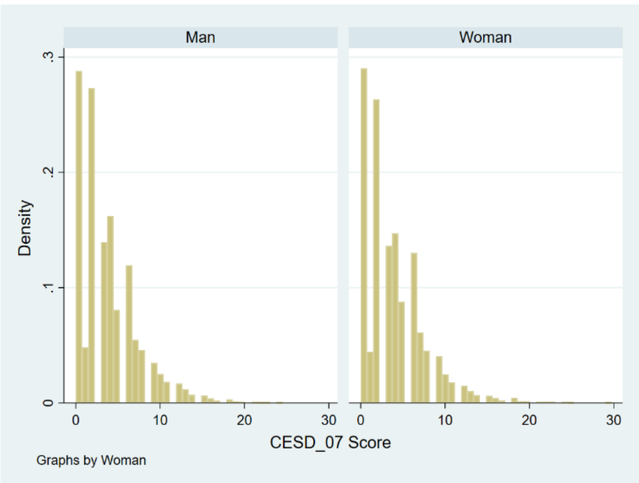

Figure 2: Distribution 2007 CES-D Answers By Gender

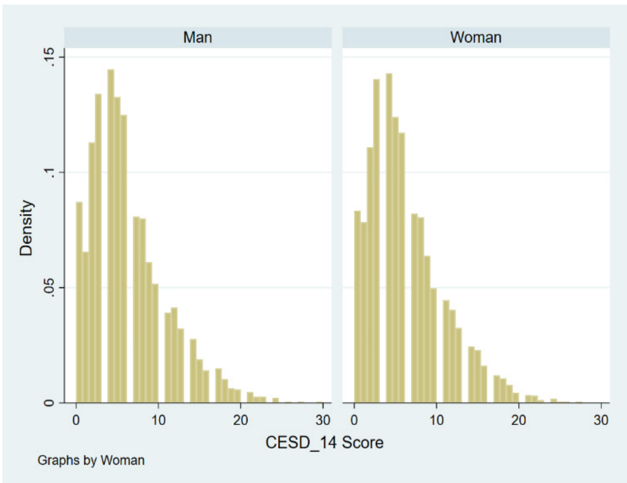

Figure 3: Distribution 2014 CES-D Answers By Gender

After seeing how the 2007 and 2014 CES-D answers spread, it is essential to look at how depression scores changed in 2007 and 2014. It is done to see how long and short-term the effects of depression symptoms are. By calculating the change in depression scores in 2007 and 2014, we can find how many people between the two periods remained depressed (depressed in both periods), better (depressed in 2007 and not depressed in 2014), worse (not depressed in 2007 and depressed in 2007), and even those who had never experienced symptoms of depression. This complete information can be seen in Table 2 below.

Table 2: Changes in Depression Score 2007 and 2014

	Code	Freq.	Percent	cum.
Fixed (no depression --> no depression)	0	5693	58.84	58.84
Better (depression --> no depression)	1	863	8.92	67.76
Worse (no depression --> depression)	2	2673	27.63	95.39
Fixed (depression --> depression)	3	446	4.61	100.00
Total		9675	100.00	

In Table 2 above, it can be seen that, from 2007 to 2014, 5693 people did not experience symptoms of depression in that year, equivalent to 58.84%. There were as many as 863 people, or 8.92%, who experienced an improved score of depressive symptoms, meaning that, in 2007, they were screened for experiencing symptoms of depression. However, in 2014 they did not experience it anymore. Unlike the case with 2673 people, or 27.63%, who experienced deteriorating mental health, i.e., they did not experience symptoms of depression in 2007 but experienced symptoms of depression in 2014. As many as 446 people, or 4.61% from 2007 and 2014, still experienced symptoms of depression. The distribution of changes in depression symptom scores at work or not working individuals in 2014 can be seen in Table 3 and Table 4 below.

Table 3: Changes in Depression Score with Status Working & Not Working 2014

Delta Score Depression	Working		
	Not Working	Working	Total
Fixed (no depression --> no depression)	1934	3759	5693
Better (depression --> no depression)	338	525	863
Worse (no depression --> depression)	946	1727	2673
Fixed (depression --> depression)	154	292	446
Total	3372	6303	9675

Table 4: Changes in Depression Score with Individual Work 2014

	Freq.	Percent	cum.
Fixed (no depression --> no depression)	3759	59.64	59.64
Better (depression --> no depression)	525	8.33	67.97
Worse (no depression --> depression)	1727	27.40	95.37
Fixed (depression --> depression)	292	4.63	100.00
Total	6303	100.00	

Table 4 shows that 3759 individuals did not have symptoms of depression in 2007 and 2014 had the highest probability of working in 2014, equivalent to 59.64% of the entire sample who worked in 2014. Individuals with depression symptoms in 2007 and without symptoms of depression in 2014 had a relatively small chance of working, which was only 8.38% or equivalent to 525 people. Individuals with no symptoms of depression in 2007 and symptoms of depression in 2014 had a higher chance of working in 2014, 27.40% or equivalent to 1727 people. Individuals who had the slightest opportunity to work in 2014 were individuals who in 2007 and 2014 still had symptoms of depression, as many as 292 people or around 4.63%. This phenomenon captures that there is indeed a persistent effect of mental health problems such as these depressive symptoms.

Furthermore, the general characteristics of the sample to answer research questions related to the effect of depression on the likelihood of working or work retention can be seen in Table 5. Table 5 shows that of the 9675 final respondents, 65.15% were working individuals, or the equivalent of 6,303 respondents, while the remaining 34.15% did not work. For the distribution of depression in 2007, 13.5% had symptoms of depression with an average CES-D score of 3.8. Variations can be seen from the standard deviation of the CES-D scores. Table 5 shows that, from 2007 to 2014, 5693 people did not experience symptoms of depression in each of these years, equivalent to 58.84%. There were as many as 863 people, or 8.92%, who experienced an improved score of depressive symptoms, meaning that, in 2007, they were screened for experiencing symptoms of depression. However, in 2014 they did not experience anymore.

In contrast to the case with 2673 people, or 27.63%, who experienced deteriorating mental health, namely not experiencing symptoms of depression in 2007 but experiencing symptoms of depression in 2014, as many as 446 people, or 4.61%, between 2007 and 2014 still experienced symptoms of depression. The sample size is female, married, and lives in urban areas. For the sample of job characteristics, in this study, the most employed were in the manufacturing sector at 38.7% or equivalent to 3,745 respondents, then the agriculture sector at 29.13%, services at 26.5%, and mining at 5.7%.

Table 5: Summary Statistics

Variable	Obs	mean	Std. Dev.	Min	Max
Working	9675	0.651	0.477	0	1
Depression07	9675	0.135	0.342	0	1
Depression14	9675	0.322	0.467	0	1
Cesd Score 07	9675	3.834	3.607	0	29
Cesd Score 14 Delta Depression Score	9675	6.274	4.643	0	30
Fixed Not Depressed	9675	0.588	0.492	0	1
Better	9675	0.089	0.285	0	1
Worse	9675	0.276	0.447	0	1
Fixed Depression	9675	0.046	0.21	0	1
Age	9675	33.818	12.586	15	64
Age Square	9675	1302.05	947.985	225	4096
Woman	9675	0.516	0.5	0	1
Marry	9675	0.687	0.464	0	1
City	9675	0.56	0.496	0	1
Smoke	9675	0.912	0.284	0	1
Chronic	9675	0.349	0.477	0	1
Comorbid	9675	0.464	0.499	0	1
Revenue Log	9675	13.08	0.728	10.231	16.427
Amount Worker	9675	83.904	861.03	0	50000
Agriculture	9675	0.291	0.454	0	1

Variable	Obs	mean	Std. Dev.	Min	Max
Service	9675	0.265	0.441	0	1
Mining	9675	0.057	0.231	0	1
Manufacture	9675	0.387	0.487	0	1
Education	9675	8.23	6.063	0	22
Migration	9675	0.274	0.446	0	1
Married 2014	9675	0.702	0.457	0	1
Very Unhappy	9675	0.012	0.108	0	1
Not Happy	9675	0.081	0.272	0	1
Happy	9675	0.771	0.42	0	1
Very Happy	9675	0.137	0.343	0	1

Table 6 shows the relationship between changes in depression scores with job retention or the possibility of working in 2014. For all models, there is a negative and significant relationship between depression symptoms and job retention. Model (1) only includes a variable change in depression scores. Without including a control variable, it appears that individuals with better categories (depressed in 2007 and not depressed in 2014), when compared to individuals who do not have symptoms of depression (base), both in 2007 and 2014, have a low probability of working in 2014 of 5.22%. Meanwhile, for model (2), by including all control variables, the effect increased by 5.55%, which means that individuals in the better category (depressed in 2007 and not depressed in 2014) when compared to individuals without symptoms of depression (base), both in 2007 and 2014, have a low probability of working in 2014 of 5.55%. Then in model (3) and model (4), regression separated by sex, it appears that the effect of changing depressive symptoms is better (depression in 2007 and not depression in 2014), reducing the probability of working retention in males by 5.62% and females by 5.84% compared to individuals who did not have symptoms of depression in both periods.

In Table 6 model (2) for the control variable, only the education variable significantly affects work retention. Increasing one year of schooling reduces the opportunity to keep working by 0.23%. However, an interesting finding is that when separate estimates were made between men and women, it was found that the effect of education on job retention was more significant for women than for men. For model (3) and model (4), it can be seen that several control variables significantly affect job retention in Indonesia. In model (3), the smoking variable significantly affects the probability of men working by 5.2% more than men who do not smoke. It is more due to cigarette consumption which tends to be high in Indonesia. Of 260 million people, no less than 25% are smokers, and from 2005 to 2015, there was no decrease in smoking prevalence in Indonesia (Reitsma et al., 2017). A study by Amalia et al. (2019) showed an increasing pattern of smokers from 2007 to 2014, and those who smoked tended to work in 2014. The variable married in model (3) also significantly affected work retention; married men will increase their chances of working by 3.13% compared to unmarried men. It is because employers prefer married men over unmarried men. Married men in several studies show high loyalty and responsibility at work, so they are preferred (Jordan & Zitek, 2012). For model (4), there are several significant control variables: location of residence and education. In model (4), it can be seen that women living in urban areas reduce their chances of continuing to work by 2.43% compared to women living in rural areas. It is because job competition is very tight in urban areas compared to rural areas, it could be due to the flow of urbanization, or it could also be due to a high level of education in urban areas (Winarsih & Lisna, 2015). Then in model (4), it is also seen that the education variable also affects work retention. An additional year of schooling reduces the probability of women to keep working by 0.31%. It could be due to the issue of gender inequalities in developing countries such as Indonesia. A study conducted by Samarakoon & Parinduri (2015) in Indonesia shows that increasing the number of years of schooling for women does not increase their authority in making household decisions regarding employment status. Women who receive more education may be able to increase their knowledge, skills, and cognitive abilities but cannot change deep-rooted social customs and habits regarding decision-making in which men in the household can make their own decisions (Kevane et al., 2003).

Table 6: Relationship Changes in Depression and Retention Score Working

	(1)	(2)	(3)	(4)
	Working	**Working**	**Man**	**Woman**
Better (d)	**-0.0522****	**-0.0556****	**-0.0562****	**-0.0584****
	(0.0179)	(0.0181)	(0.0258)	(0.0255)
Worse (d)	-0.0143	-0.0154	-0.0142	-0.0182
	(0.0113)	(0.0113)	(0.0162)	(0.0159)
Fixed Depression (d)	-0.00564	-0.0118	-0.0287	0.00299
	(0.0236)	(0.0240)	(0.0356)	(0.0326)
Age		-0.000485	-0.00249	-0.000369
		(0.00258)	(0.00382)	(0.00358)
Age Square		0.0000152	0.0000269	0.0000251
		(0.0000332)	(0.0000477)	(0.0000469)
Married (d)		-0.00858	-0.00437	0.00226
		(0.0127)	(0.0208)	(0.0169)
City (d)		-0.0142	-0.00281	**-0.0245***
		(0.00978)	(0.0140)	(0.0137)
Smoking (d)		0.0242	**0.0528****	-0.00423
		(0.0174)	(0.0254)	(0.0238)
Chronic (d)		0.00248	0.0211	-0.0157
		(0.0102)	(0.0146)	(0.0142)
Comorbid (d)		0.0111	0.00248	0.0177
		(0.00987)	(0.0141)	(0.0138)
Income Log		0.00136	0.000577	0.00197
		(0.00673)	(0.00983)	(0.00928)
The number of workers		0.0000946	0.0000147	0.00000672
		(0.00000669)	(0.0000129)	(0.00000804)
Services (d)		0.00508	-0.00262	0.0150
		(0.0132)	(0.0183)	(0.0195)
Mining (d)		-0.0106	-0.00793	-0.00504
		(0.0226)	(0.0314)	(0.0326)
Manufacturing (d)		-0.0129	-0.0262	0.00147
		(0.0122)	(0.0168)	(0.0181)
Education		**-0.00230****	-0.00155	**-0.00317****

	(1)	(2)	(3)	(4)
	Working	**Working**	**Man**	**Woman**
		(0.000798)	(0.00113)	(0.00113)
Migration (d)		0.0119	0.0244	-0.000165
		(0.0108)	(0.0156)	(0.0151)
Married 2014 (d)		0.00998	**0.0311****	-0.0105
		(0.0106)	(0.0154)	(0.0148)
Not Happy (d)		0.0126	-0.0442	0.0520
		(0.0473)	(0.0744)	(0.0611)
Happy (d)		-0.0108	-0.0363	0.00468
		(0.0447)	(0.0650)	(0.0614)
Very Happy (d)		-0.0216	-0.0836	0.0257
		(0.0475)	(0.0738)	(0.0618)
No. of Obs.	9675	9675	4683	4992
Prob > chi2	0.025	0.017	0.062	0.027
Pseudo R2	0.001	0.003	0.005	0.005

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* p<0.10, **p<0.05, ***p<0.001

Discussion

Men and women have the same opportunity to experience depression (NIMH, 2022). Sometimes depression is challenging to detect and has high recurrence rates. It decreases the accumulation of human capital in men and women and can affect their work activities. This effect stems from the increasing marginal disutility of work in both men and women due to sleep disturbances, loss of concentration, and difficulty making decisions that have implications for maintaining a job in the long term. In addition, the presence of these symptoms of depression makes their marginal consumption decrease so that the labor supply becomes reduced. In Indonesia, the effect of depression on both men and women has a significant effect on job retention. However, there is a slight difference in the coefficient between the two, with women having a slightly higher coefficient. Depressive symptoms that influence job retention may be caused by only a small percentage of people who experience depression who get treatment and medication. RISKESDAS data in 2018 showed that only about 9% of people with depression received treatment, so there may be long-term effects experienced by most people who do not get treatment. This study shows that individuals with better categories (depressed in 2007 and not depressed in 2014) compared to individuals who do not have symptoms of depression (base), both in 2007 and 2014, have a low probability of working in 2014 of 5.22%. These results are consistent with previous research that there is a negative effect of depressive symptoms on work status (Banerjee et al., 2017; Bubonya et al., 2017; Ringdal & Rootjes, 2022). The effect of depression on work status in this study follows Becker (1964) and Grossman's (1972) theory of human resource accumulation.

These findings confirm that there is indeed a long-term effect of depressive disorders on the ability to maintain a job. It indicates that individuals with depressive symptoms in 2007 are more at risk than individuals who do not experience them or have recently experienced depressive symptoms in 2014 for their chances of retaining their jobs in 2014. In a study conducted by Burcusa & Iacono (2007), it was explained that depression has a high recurrence rate, at least five years to nine years. It means that, in that period, many things will cause a low ability to maintain a job. Individuals in this range experience disability at work because symptoms of depression tend to recur. They are in the process of being treated, so they cannot work again. Even though their score improved in 2014, it will take time to get back into the work environment. Then, when we do regression separated by sex, it appears that the effect of changing depressive symptoms is better (depression in 2007 and not depression in 2014), reducing the probability of working retention in males by 5.62% and females by 5.84% compared to individuals who did not have symptoms of depression in both periods. It follows a study by Barnay & Defebvre (2019), which found the effect of depressive symptoms on both men and women with almost the same coefficient.

Conclusion

Economists are interested in mental health because of its role and impact. One of the most commonly discussed types of mental health disorders is depression. Mental health disorders can reduce a person's ability, one of which is in the work environment. Due to mental health disorders, decreased ability and productivity in the work environment can incur certain costs. Research shows that the economic burden in the work environment increased from 41% to 61% due to mental health disorders (Greenberg et al., 2015, 2021). Not only that, previous studies have found that depressed individuals have a lower tendency to work and keep their jobs.

This study used IFLS 4 and IFLS 5 data to see the effects of mental health disorders, namely depression, on the ability to maintain a job or work retention. The logistic regression test showed that depressive symptoms in the previous period were proven to reduce the probability of an individual retaining his job in the next period, which could cause his job retention to be low in the following period. Policies to carry out early and continuous screening to identify whether individuals experience depressive symptoms are important, especially for individuals who are in a work environment. In addition to screening for early symptoms of depression, treating depression earlier and expanding people's access to treatment is essential, given the long-term effects caused by mental health disorders such as depression. Then other factors that cause job retention to decrease apart from symptoms of depression are the location of residence and length of the school year for women, but not men. Women who live in urban areas have lower job retention than those who live in rural areas. It can happen because of the tight competition for jobs in urban areas because many are looking for jobs in urban areas. Therefore, women's abilities and capacities must be continuously improved, for example, by having specific skills or participating in various pieces of training. The length of school years for women in this study also reduces job retention. It may be due to the lack of gender equality in Indonesia. Women tend to take care of the household more, more decisions are made by men, or some companies only employ unmarried women. Improving gender equality and women's competitiveness may improve their ability to hold jobs.

Declaration

In this section, I declare that this research: (1) does not conflict with anyone's interests (2) Availability of data and materials, (3) there are the author's contributions, (4) there is a source of funding and (5) and acknowledgments.

Conflict of Interest

We certify that there are no significant financial, professional or personal competing interests that might affect performance as a result of this research.

Availability of Data and Materials

Data and research materials can be provided upon request. Data Sharing does not apply to this article as no new data was generated or analyzed in this study.

Authors' Contribution

The author's contribution to this study was writing, reviewing, and editing the manuscript, as well as writing the original draft.

Funding Source

This research was funded by Lembaga Pengelola Dana Pendidikan (LPDP) Kementerian Keuangan RI.

Acknowledgment

We would like to express our sincere gratitude to the academic community at the Faculty of Economics and Business, University of Indonesia, for their support and valuable insights throughout this research.

References

Amalia, B., Cadogan, S. L., Prabandari, Y. S., & Filippidis, F. T. (2019). Socio-demographic inequalities in cigarette smoking in Indonesia, 2007 to 2014. *Preventive Medicine*, *123*, 27–33. https://doi.org/10.1016/j.ypmed.2019.02.025

Andresen, E. M., Malmgren, J. A., Carter, W. B., & Patrick, D. L. (1994). Screening for Depression in Well Older Adults: Evaluation of a Short Form of the CES-D. *American Journal of Preventive Medicine*, *10(2)*, 77–84. https://doi.org/https://doi.org/10.1016/S0749-3797(18)30622-6

Asami, Y., Goren, A., & Okumura, Y. (2015). Work Productivity Loss With Depression, Diagnosed and Undiagnosed, Among Workers in an Internet-Based Survey Conducted in Japan. *Journal of Occupational and Environmental Medicine*, *57*(1), 105–110. https://doi.org/10.2307/48500661

Banerjee, S., Chatterji, P., & Lahiri, K. (2017). Effects of Psychiatric Disorders on Labor Market Outcomes: A Latent Variable Approach Using Multiple Clinical Indicators. *Health Economics (United Kingdom)*, *26*(2), 184–205. https://doi.org/10.1002/hec.3286

Barnay, T., & Defebvre, É. (2019). Gender Differences in the Influence of Mental Health on Job Retention. *LABOUR*, *33*(4), 507–532. https://doi.org/https://doi.org/10.1111/labr.12154

Becker, G. (1964). *A Theoretical and Empirical Analysis*, with Special Reference to Education, Third Edition. In The University of Chicago Press.

Bir, A., & Frank, R. G. (2001). *Mental Illness and the Labor Market in Developing Nations.* (CMH Working Paper Series). https://library.cphs.chula.ac.th/Ebooks/HealthCareFinancing/WorkingPaper_WG1/WG1_6.pdf

Bryan, M. L., Rice, N., Roberts, J., & Sechel, C. (2022). Mental Health and Employment: A Bounding Approach Using Panel Data. *Oxford Bulletin of Economics and Statistics*, *84*(5), 1018–1051. https://doi.org/https://doi.org/10.1111/obes.12489

Bubonya, M., Cobb-Clark, D. A., & Ribar, D. C. (2019). The reciprocal relationship between depressive symptoms and employment status. *Economics & Human Biology*, *35*, 96–

106. https://doi.org/https://doi.org/10.1016/j.ehb.2019.05.00

Bubonya, M., Cobb-Clark, D. A., & Wooden, M. (2017). Mental health and productivity at work: Does what you do matter? *Labour Economics*, *46*, 150–165. https://doi.org/10.1016/j.labeco.2017.05.001

Burcusa, S. L., & Iacono, W. G. (2007). Risk for recurrence in depression. *Clinical psychology review*, *27*(8), 959–985. https://doi.org/10.1016/j.cpr.2007.02.005

Cahuc, P., Carcillo, S., & Zylberberg, A. (2004). *Labor Economics* (2nd edn.). The MIT Press.

Chatterji, P., Alegria, M., & Takeuchi, D. (2011). Psychiatric disorders and labor market outcomes: Evidence from the National Comorbidity Survey-Replication. *Journal of Health Economics*, *30*(5), 858–868. https://doi.org/10.1016/j.jhealeco.2011.06.006

Currie, J., & Brigitte Madrian, N. C. (1999). Health, Health Insurance And The Labor Market. In: O.C. Ashenfelter & D.Card (eds.), *Handbook of Labor Economics*, Vol 3, C, pp. 3309-3416.

Ettner, S. L., Frank, R. G., & Kessler, R. C. (1997). The Impact of Psychiatric Disorders on Labor Market Outcomes. *Industrial and Labor Relations Review, 51*(1), 64–81. https://doi.org/10.2307/2525035

Fletcher, J. (2013). Adolescent Depression and Adult Labor Market Outcomes. *Southern Economic Journal*, *80*(1), 26–49. https://doi.org/10.4284/0038-4038-2011.193

Frijters, P., Johnston, D. W., & Shields, M. A. (2014). The effect of mental health on employment: Evidence from Australian panel data. *Health Economics (United Kingdom)*, *23*(9), 1058–1071. https://doi.org/10.1002/hec.3083

Frijters, P., Johnston, D. W., & Shields, M. A. (2021). Mental Health and Labour Market Participation: Evidence from IV Panel Data Models. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1595524

Giang, B. K., Allebeck, P., Kullgren, G., & van Tuan, N. (2006). The Vietnamese version of the Self Reporting Questionnaire 20 (SRQ-20) in detecting mental disorders in rural Vietnam: A validation study. *International Journal of Social Psychiatry*, *52*(2), 175–184. https://doi.org/10.1177/0020764006061251

Greenberg, P. E., Fournier, A. A., Sisitsky, T., Simes, M., Berman, R., Koenigsberg, S. H., & Kessler, R. C. (2021). The Economic Burden of Adults with Major Depressive Disorder in the United States (2010 and 2018). *PharmacoEconomics*, *39*(6), 653–665. https://doi.org/10.1007/s40273-021-01019-4

Greenberg, P. E., Fournier, A.-A., Sisitsky, T., Pike, C. T., & Kessler, R. C. (2015). The Economic Burden of Adults With Major Depressive Disorder in the United States (2005 and 2010). *The Journal of Clinical Psychiatry*, *76*(02), 155–162. https://doi.org/10.4088/JCP.14m09298

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *Journal of Political Economy, 80*(2), 223–255. http://www.jstor.org/stable/1830580

Hamilton, V. H., Merrigan, P., & Dufresne, E. (1997). Down and out: estimating the relationship between mental health and unemployment. *Health economics, 6*(4), 397–406. https://doi.org/10.1002/(sici)1099-1050(199707)6:4<397::aid-hec283>3.0.co;2-m

Jain, G., Roy, A., Harikrishnan, V., Yu, S., Dabbous, O., & Lawrence, C. (2013). Patient-reported depression severity measured by the PHQ-9 and impact on work productivity: Results from a survey of full-time employees in the United States. *Journal of Occupational and Environmental Medicine*, *55*(3), 252–258. https://doi.org/10.1097/JOM.0b013e31828349c9

Johar, M., & Truong, J. (2014). Direct and indirect effect of depression in adolescence on adult wages. *Applied Economics*, *46*(36), 4431–4444. https://doi.org/10.1080/00036846.2014.962227

Jordan, A. H., & Zitek, E. M. (2012). Marital Status Bias in Perceptions of Employees. *Basic and Applied Social Psychology*, *34*(5), 474–481. https://doi.org/10.1080/01973533.2012.711687

Kevane, M., & Levine, D. I. (2000). The Changing Status of Daughters in Indonesia. *UC Berkeley: Institute for Research on Labor and Employment*. Retrieved from https://escholarship.org/uc/item/09m817c0

Lagomarsino, E., & Spiganti, A. (2020). No gain in pain: psychological well-being, participation, and wages in the BHPS. *European Journal of Health Economics*, *21*(9), 1375–1389. https://doi.org/10.1007/s10198-020-01234-4

Lanuza, V. (2013). The Consequences of Mental Illness on Labor Market Decisions. *CMC Senior Thesis*. http://scholarship.claremont.edu/cmc_theses/669

Layard, R. (2013). Mental health: the new frontier for labour economics. *IZA Journal of Labor Policy, 2*(1), 2. https://doi.org/10.1186/2193-9004-2-2

Lerner, D., Adler, D. A., Chang, H., Lapitsky, L., Hood, M. Y., Perissinotto, C., Reed, J., McLaughlin, T. J., Berndt, E. R., & Rogers, W. H. (2004). Unemployment, Job Retention, and Productivity Loss Among Employees With Depression. *Psychiatric Services*, *55*(12), 1371–1378. https://doi.org/10.1176/appi.ps.55.12.1371

Magin, P., Sibbritt, D., & Bailey, K. (2009). The relationship between psychiatric illnesses and skin disease: a longitudinal analysis of young Australian women. *Archives of dermatology, 145*(8), 896–902. https://doi.org/10.1001/archdermatol.2009.155

McGovern, P. (2014). Why should mental health have a place in the post-2015 global health agenda? *International Journal of Mental Health Systems, 8*(1), 38. https://doi.org/10.1186/1752-4458-8-38

Ministry of Health. (2020). *Rencana Aksi Kegiatan 2020-2024 [Action Plan for 2020-2024 Activities]*. Ministry of Health. http://p2p.kemkes.go.id/wp-content/uploads/2023/04/FINAL-RAK-Setditjen-P2P-Tahun-2022-2024.pdf

Mitra, S., & Jones, K. (2017). The impact of recent mental health changes on employment: new evidence from longitudinal data. *Applied Economics*, *49*(1), 96–109. https://doi.org/10.1080/00036846.2016.1192274

National Institute of Mental Health (NIMH). (2021). *Depression*. https://www.nimh.nih.gov/health/topics/depression

NIMH. (2022). *Men and Depression*. https://www.nimh.nih.gov/health/publications/men-and-depression#part_6071

Ojeda, V. D., Frank, R. G., Mcguire, T. G., & Gilmer, T. P. (2010). Mental illness, nativity, gender and labor supply. *Health Economics*, *19*(4), 396–421. https://doi.org/10.1002/hec.1480

Peng, L., Meyerhoefer, C. D., & Zuvekas, S. H. (2013). *The Effect Of Depression On Labor Market Outcomes*. http://www.nber.org/papers/w19451

Peng, L., Meyerhoefer, C. D., & Zuvekas, S. H. (2016). The Short-Term Effect of Depressive Symptoms on Labor Market Outcomes. *Health Economics (United Kingdom)*, *25*(10), 1223–1238. https://doi.org/10.1002/hec.3224

Radloff, L. S. (1977). The CES-D Scale: A Self-Report Depression Scale for Research in the General Population. *Applied Psychological Measurement*, *1*(3), 385–401. https:/-/doi.org/10.1177/014662167700100306

Reitsma, M. B., Fullman, N., Ng, M., Salama, J. S., Abajobir, A., Abate, K. H., Abbafati, C., Abera, S. F., Abraham, B., Abyu, G. Y., Adebiyi, A. O., Al-Aly, Z., Aleman, A. v., Ali, R., Alkerwi, A. al, Allebeck, P., Al-Raddadi, R. M., Amare, A. T., Amberbir, A., … Gakidou, E. (2017). Smoking prevalence and attributable disease burden in 195 countries and territories, 1990-2015: A systematic analysis from the global burden of disease study 2015. *The Lancet*, *389*(10082), 1885–1906. https://doi.org/10.1016/S0140-6736(17)30819-X

Ringdal, C., & Rootjes, F. (2022). Depression and labor supply: Evidence from the Netherlands. *Economics & Human Biology, 45*, 101103. https://doi.org/https://doi.org/10.1016/j.ehb.2021.101103

Rudolph, K. E., & Eaton, W. W. (2016). Previous anxiety and depression as risk factors for early labour force exit. *Journal of epidemiology and community health, 70*(4), 390–395. https://doi.org/10.1136/jech-2015-206202

Ruiz-Tagle, J., & Troncoso, P. (2018). Labor Cost of Mental Health: Evidence from Chile. *Repositorio Academico de La Universidad de Chile*. https://ueconomia.uchile.cl/wp-content/uploads/2018/10/Labor-Cost-of-Mental-Health.pdf

Saffer, H., & Dave, D. (2005). Mental Illness And The Demand For Alcohol, Cocaine, And Cigarettes. *Economic Inquiry*, *43*(2), 229–246. https://doi.org/https://doi.org/10.1093/ei/cbi016

Samarakoon, S., & Parinduri, R. A. (2015). Does Education Empower Women? Evidence from Indonesia. *World Development*, *66*, 428–442. https://doi.org/10.1016/j.worlddev.2014.09.002

Sohn, K. (2018). Depressive Symptoms Are Not Related To Labor Market Outcomes In Indonesia. *Hitotsubashi Journal of Economics*, *59*(2). http://www.jstor.org/stable/44866220

Wang, X., Guo, J., Zhang, X., Qu, Z., Tian, D., & Ma, S. (2014). The effects of depression and chronic diseases on the work outcomes of employees: A prospective study in Northwest China. *Public Health*, *128*(8), 734–742. https://doi.org/10.1016/j.puhe.2014.06.007

WHO. (2013). *Mental Health Action Plan 2013-2020*. https://www.who.int/publications/i/item/9789240031029

WHO. (2017). *Depression and Other Common Mental Disorders Global Health Estimates*. https://apps.who.int/iris/bitstream/handle/10665/254610/WHO-MSD-MER-2017.2-eng.pdf

WHO. (2020). *WHO methods and data sources for global burden of disease estimates 2000-2019*. http://www.who.int/gho/mortality_burden_disease/en/index.html

Winarsih, W., & Lisna, V. (2015). *Statistics on Informality in Indonesia*. BPS. https://www.unsiap.or.jp/e-learning/el_material/3_Population/3_2_labor/1507_Informal/cr/Indonesia_cp1.pdf

Zulfa, A. H. (2017). *Depresi usia muda: dampaknya terhadap status dan stabilitas kerja di Indonesia [Early onset depression: the effect on status and work stability in Indonesia]*. Universitas Indonesia Library. https://lib.ui.ac.id/file?file=pdf/abstrak/id_abstrak-20458042.pdf