EL COLEGIO DE MÉXICO
CENTRO DE ESTUDIOS ECONÓMICOS

MAESTRÍA EN ECONOMÍA

TRABAJO DE INVESTIGACIÓN PARA OBTENER EL GRADO
DE MAESTRO EN ECONOMÍA

"GENDER DIFFERENCES IN MENTAL HEALTH AND LABOR MARKET OUTCOMES IN MEXICO"

LAURA ELIZABETH BONILLA MEDINA

PROMOCIÓN 2022-2024

ASESOR:

DR. RAYMUNDO M. CAMPOS VÁZQUEZ

AGOSTO 2024

Agradecimientos

A mi madre, Ivonne Medina, y a mi padre, Edmar Bonilla por brindarme su apoyo y amor incondicional en cada paso que doy. Sin ustedes no sería quien soy ni hubiera sido posible continuar por este camino.

A mi hermana, Karla, por ser una fuente de luz y amor en mi vida. Gracias por siempre recordarme que la vida está compuesta por simples momentos, que hay que disfrutarla junto con las personas que más amamos, y por alentarme a siempre seguir adelante recordándome que soy capaz de cumplir lo que me proponga.

A todas y todos mis familiares cercanos que estuvieron presentes durante esta etapa. Han sido fuente de inspiración, motivación y amor. Gracias por sus buenos deseos y ánimo de siempre.

A mis mejores amigas, Ximena López y Fernanda Granados. Ustedes me han enseñado el verdadero valor de la amistad y me han acompañado en los grandes momentos de mi vida, tanto los buenos como los malos. Junto a ustedes he aprendido a navegar esta vida.

A Cristian Gudiño, por su compañía, paciencia y cariño durante esta etapa. Gracias por alentarme a cada día ser mejor y dar un poco más de mi en todo lo que hago. También, por recordarme que, aunque a veces parezca que retrocedo diez pasos, en realidad siempre estoy avanzando uno.

A mis amigos Mario Lechuga, Diego Garrido, Santiago Bautista, y Héctor Deschamps por compartir esta experiencia conmigo y aligerar la carga de todos los días. Sin duda, aportaron a que esta etapa sea inolvidable. Gracias por su apoyo, sus comentarios, y las enseñanzas que me llevo de cada uno de ustedes.

A mis compañeros y compañeras. Gracias por las palabras de aliento compartidas, el apoyo, y el ambiente de cooperación y compañerismo que todos juntos creamos durante estos dos años.

A mis compañeras y profesoras por ser una fuente de inspiración y motivación. Su compañía en estos años ha alumbrado el camino y lo han hecho menos solitario.

Al Dr. Jorge Mora por depositar su confianza en mí desde el primer día. Sin su ejemplo no habría seguido este camino. Gracias por todas las enseñanzas dentro y fuera del aula, por las pláticas que me han motivado y que me recuerdan que no importa lo que hagamos, siempre hay que tener claro el por qué.

A mi asesor, el Dr. Raymundo Campos por su acompañamiento y asesoramiento durante este proceso. Gracias por permitirme aprender de usted y confiar en mis ideas.

Al Colegio de México, por abrirme las puertas y brindarme esta gran oportunidad. Sin duda me llevo más de lo que traía cuando llegue. Gracias a todos los docentes que han contribuido a mi formación y educación.

Por último, a mis perritas Zury, Niki y Muñeca por brindarme paz, tranquilidad y amor con tan sólo una mirada. Gracias por acompañarme en desveladas y brindarme alegrías todos los días.

Abstract

Mental health disorders, particularly depression and anxiety, significantly impact labor market outcomes. This research investigates the gender differences in the effects of depressive symptoms on employment status and labor force participation in Mexico using data from the National Health and Nutrition Survey (ENSANUT) from 2012 to 2022. The study employs instrumental variables (IV) and instrumented differences-in-differences (IDID) methodologies to address endogeneity and reverse causality issues. While no significant effects were found on the extensive margin of employment, the study reveals intriguing gender differences. Depression appears to have a positive association with employment for women but a negative one for men, highlighting the necessity of considering gender-specific strategies in mental health and labor market policies. Moreover, the findings suggest an effect on the intensive margin of employment, showing a greater effect for women. This research underscores the complex interplay between mental health and economic outcomes, emphasizing the need for targeted interventions to support vulnerable groups and improve labor market participation among individuals with mental health disorders.

Contents

1 Introduction

Mental disorders are common in all countries. According to the World Health Organization (2022), one in every eight people experience some type of disorder at least once in their lifetime, and the most common disorders are anxiety and depression. Furthermore, mental health issues have increased in the last 10 years and the COVID-19 pandemic caused a sharp increase in depression and anxiety of 25% just in its first year (WHO, 2022). This raises a concern since mental health is of vital importance for enjoying a fulfilling life. It has been well documented that experiencing a mental disorder is associated with a decline in cognitive abilities, which affects people´s daily activities, including work outcomes and decisions (Abramovitch et al., 2021; Bauermeister and Bunce, 2015; Bunce et al., 2008; Jokela, 2022). Yet evidence on the effect of mental health on economic outcomes is limited, especially for low- and middle-income countries. This research presents evidence of the effect of mental health in labor market outcomes in Mexico using 2012 - 2022 cross-sectional data from the *National Health and Nutrition Survey* (ENSANUT by its Spanish acronym) which contains information regarding depressive symptoms of the Mexican population and labor market variables such as labor force participation and formality. Furthermore, it analyzes the heterogeneous effects among men and women, shedding light on the effect of gender differences in mental health on labor market outcomes. An instrumental variable approach is used alongside an instrumented differences-in differences model to provide robustness to the estimates.

Economics and mental health are intertwined in multiple ways (Knapp and Wong, 2020). On one hand, individuals who experience a mental illness have pessimistic expectations and lose time due to ruminiation - uncontrollable and repetitive preocuppation with one´s negative thoughts. As a result they work less, consume less, invest less in risky assets, and forego treatment, which in turn reinforces mental illness (Abramson et al., 2024). Additional to productivity losses, there are also high treatment costs associated with mental disorders, which is concerning because poor mental health contributes to reduced productivity at work, greater likelihood of absence due to sickness, and a higher probability of unemployment (McDaid et al., 2019; OECD, 2021; Hoedeman, 2012; for Economic Co-operation and Development, 2015). Government expenditure on mental health treatment is meager, and even though spending on mental health care has grown, it does not match needs. In 2020 the estimated global median expenditure on mental health was only US$2.5 per person annually, accounting for less than 2% of government health expenditure globally. To have an idea of the magnitude of the problem, currently in the US a psychotherapy session is estimated to be, on average, on a range from USD$100 to USD$200 per session (Lauretta, n.d.), and in a middle-income country like Mexico is estimated to be, on average, 500 (approximately 29.98 USD) pesos per session but the price can rise to 2,000 pesos (119.93 USD approximately) or more in Mexico City (Galindo, n.d.). This low expenditure is a major reason for the wide gap between mental health needs and provision of intervention, particularly in low-and middle-income countries (Knapp and Wong, 2020; Lund et al., 2024). Median domestic expenditure on mental health is 2.1% of health expenditure globally, but only 1.05, 1.1 and 1.60% in low, lower-middle and upper-middle income countries (WHO, 2022). Over 80% of people who need treatment for common mental disorders cannot access it, a substantially higher proportion than those who cannot access treatment for major physical health conditions (Chisholm et al., 2016).

On the other hand, economic disadvantage is associated with a greater likelihood of mental illness. Those with the lowest incomes are typically 1.5 to 3 times more likely than the rich to experience depression or anxiety due to worry, worse physical health, early-life conditions, violence and crime, and social status, creating then a "poverty trap" of mental health (Ridley et al., 2020; Haushofer and Salicath, 2023). Given this bidirectional relationship between mental health and economic conditions it is essential to analyze it through the lens of economics in order to provide valuable information regarding the magnitude and direction of the relationship to make the best policy recommendations with a good allocation of resources.

Even though existing investigations have shown that interventions to treat mental illness have positive effects on economic individual outcomes such as hours worked and earnings in developed and developing countries (Ridley et al., 2020; Lund et al., 2024) it is important to understand and quantify the effects of mental illness on labor market outcomes to be able to create policies aimed at the most vulnerable groups and also to understand the causes and mechanisms in order to address them from different perspectives, and not just focus the policies on treatment that could be costly.

Mental health encompasses the ability to relate, cope, handle difficulties, and thrive. It exists on a complex continuum, with experiences ranging from optimal well-being to debilitating states of significant suffering and emotional pain. While individuals with mental disorders are more likely to experience lower levels of mental well-being, this is not always the case nor necessarily so (WHO, 2022). There is still a lot to research and learn about mental disorders, but it is extremely necessary to investigate how they relate to the economic decisions and labor market outcomes of the population, even more so in the context of increasing health and income inequality, as well as increasing poverty and violence. Individuals with mental health conditions experience significantly lower employment rates, higher unemployment rates, lower wages and incomes, and greater reliance on various working-age benefits. The overall cost of mental health is estimated to be at least 4% of GDP, factoring in labor market costs such as decreased productivity and increased absenteeism, social spending costs, and direct healthcare system expenses (OECD, 2021). The previous facts shed light on the strong relationship between mental health and labor market outcomes, but the direction and magnitude of the relationship is not clear.

In Mexico, an annual prevalence of approximately 19.9% of people with mental disorders and addictions is estimated, and about 5% of the population will experience a severe disorder (de Salud, n.d.). Additionally, there is an increasing concern for the youngest groups since they report a high prevalence of mental disorders, and not only do they have less access to medical services, but they also underuse them (Molina, n.d.). Recent findings by Blanchflower et al., 2024 confirm this trend across 34 countries including Mexico. They explore the subjective well-being which was thought to have a

U-shape in age and the subjective ill-being which was thought to follow a hump shape. They find that the hump shape in ill-being has been replaced by a monotonic decrease by age, primarily because of the deterioration in young people´s mental health, both absolutely and relatively to older people.

Even though mental health problems affect any person and can begin since childhood, they affect younger generations more. However, there is also another group that shows greater vulnerability: women. It has been documented that there is a gender gap in mental health, particularly in depressive and anxiety disorders. On average, women of working age are 45% more likely to report mental health conditions than men of the same age (OECD, 2021). Since the 1990s, a ratio of approximately 2:1 in depressive symptoms between women and men has been maintained in developed countries. However, in developing countries, there is significant variance, and interesting differences in symptoms have been found. Men tend to exhibit more aggressive behaviors when experiencing depressive symptoms, whereas women are more likely to seek social activities - such as attending church - to seek help (Culbertson, 1997) and show more prosocial behaviors in comparison to men (Alarcón and Forbes, 2017). Also, it has been documented that social norms, traumas, and coping strategies affect women and men differently and that genetic differences or biological factors do not play a role in explaining the gender differences in depression (Piccinelli and Wilkinson, 2000). These differences could imply contrasting life outcomes for men and women suffering from a mental disorder, and they could also indicate varying relationships between mental health and labor outcomes due to persistent gender gaps in education and income. Therefore, it is important to analyze how these gaps interact.

Despite the existing literature on the causal effect between poor mental health and labor outcomes, there is a notable gap in this literature as it fails to analyze the differences in effects for men and women, as well as their potential mechanisms. This research makes two significant contributions to the literature on the effect of mental disorders on labor market outcomes.

First, it examines the effect of depressive symptoms on labor market outcomes in a developing country like Mexico, addressing a major gap since most studies focus on developed countries. This research uses 2012 - 2022 cross-sectional data from the *National Health and Nutrition Survey* (ENSANUT by its Spanish acronym) to establish a causal relationship between depression and labor market outcomes. To address endogeneity and reverse causality issues, it employs two distinct methodologies: instrumental variables (IV) and a novel approach, instrumented differences-in-differences (IDID). Both approaches rely on three main assumptions: the exclusion restriction, independence, and relevance of the instrument. By using instruments that are correlated with the endogenous explanatory variables and uncorrelated with the error term, these methods help correct for endogeneity and reverse causality bias. Novel instruments are used for the endogenous variables - the score obtained on the CES-D7 scale to diagnose depressive symptoms in a population sample, and a dichotomous variable for depression. For the IV model, the instrument is violence or attack experienced by a household member, and for the IDID approach, the instrument is living in a state with COVID-19 deaths greater than or equal to 3,000. Interestingly, this research does not find a causal effect of depression on the extensive margin of employment, contrary to previous findings in developed countries. However, the results suggest that there is an effect on the intensive margin.

Second, this research explicitly analyzes the different effects by gender and examines the issue from a gender perspective. Although causal effects on the extensive margin are not found, the results suggest an intriguing difference in the relationship between depression and employment by gender; a positive relationship for women and a negative one for men. Additionally, the results suggest that the effect on the intensive margin is greater for women than for men.

The next section presents a literature review of the bidirectional relation between mental health and economic outcomes. Section 3 describes the data and depression measure. Section 4 outlines the Instrumental Variables and Instrumented Differences-in-Differences research designs and the variables used. The main results and heterogeneous effects are shown and analyzed in Section 5. Section 6 presents further evidence for the reliability and validity of the instruments used. Section 7 discusses the findings and potential mechanisms. Section 8 concludes.

2 Literature Review

Evidence regarding the relationship between mental disorders and economic outcomes is not new. However, establishing a causal effect is challenging due to the potential issues of reverse causality and endogeneity, which can bias estimates. Reverse causality implies that the dependent variable may affect the independent variable, such as employment potentially impacting mental health while trying to assess the effect of mental health on employment. An endogeneity problem occurs when the independent variable is correlated with the error term, often due to omitted variables, measurement errors, or simultaneity. This is particularly pertinent as mental health issues are likely correlated with both observable and unobservable individual characteristics that also influence personal life outcomes, including labor decisions and outcomes.

Due to these issues, earlier studies on the relationship between mental health and labor outcomes often relied on correlation analyses. The first article to investigate the relationship used Ordinary Least Squares (OLS) estimates to assess the impact of different diseases on earnings and hours worked, making a significant contribution by using physician-diagnosed diseases rather than self-reported well-being. They found that psychoses or neurosis negatively affected labor supply by 45% and reduced earnings by about 42%. Although these estimates were biased, they established a strong relationship between mental disorders and labor outcomes (Bartel and Taubman, 1979).

Recent studies have explored more specific relationships. Watson and Osberg, 2018 examined the relationship between job insecurity and mental health and found that, for males and females aged 25-64, job insecurity is associated with an increase between 0.10-0.12 SD in psychological distress. Kessler et al., 2008 investigated the impact of serious mental illness on earnings in the US, finding that a DSM-IV serious mental illness in the preceding 12 months reduced earnings by $16,306 ($26,435 among men, $9,302 among women). In Mexico, using the Mexican Family Life Survey (MxFLS) and municipality-level administrative data on labor markets from the Mexican Institute of Social Security (IMSS), Gunes and Tsaneva, 2022 found that an increase in the employment rates positively affected men's physical and mental health, with no significant effects observed for women.

Job insecurity and unemployment not only affect mental health by causing distress and feelings of worry that negatively impact the productivity of workers but it has also been found that a perceived increase in job destruction worsens the mental health of adolescents and lowers academic performance, which in turn reduces education and increases income inequality in college attendance (Ananat et al., 2017). Thus, mental health issues not only affect adults but also impact children and adolescents, which in turn influences the labor decisions and outcomes of their parents, creating a vicious cycle of worsening economic conditions within households (Golberstein et al., 2016; Eriksen et al., 2021).

Similar to the documented relationship between parent´s and children´s physical health (Case et al., 2002; Smith, 2009), there has also been found an intergenerational transmission of mental health, and there is evidence that in utero exposure to maternal stress from family ruptures affects later mental health (Bütikofer et al., 2024; Persson and Rossin-Slater, 2018). This transmission of mental disorders and its effect on children and adolescents perpetuates inequalities in health and income.

Despite these insights, many studies fail to establish a causal relationship between mental health and economic outcomes. Understanding the direction, causes, and effects of the relationship is crucial for improving treatment, access to medical services for the most vulnerable groups, and for creating public policies to enhance mental health and alleviate its causes.

Recently, studies have begun to address this gap and have shown that there exists a bidirectional causal relationship. Haushofer and Salicath, 2023 summarized research on the bidirectional causal effects of income on psychological distress and Ridley et al., 2020 showed that mental illness reduces employment and income. The mechanisms behind the causal effect of poverty on mental illness are worries and uncertainty, environmental factors, physical health, early-life conditions, trauma, violence, crime, social status, shame and isolation. Conversely, the research shows that treating mental illnesses has a positive impact on employment and earnings, through a literature review of RCTs. The mechanisms behind this relationship are cognitive function, beliefs, preferences, stigma, labor supply and productivity, health expenditures, women´s empowerment, intergenerational effects, and human capital accumulation.

So, the causal research on the relationship between mental health and labor market outcomes can be divided into observational and experimental studies. Observational studies often use instrumental variables (IV) or fixed-effects panel models to address endogeneity and reverse causality. Ettner et al., 1997 used the National Comorbidity Survey (NCS) to examine the impact of psychiatric disorders on employment, hours worked, and income. They found that psychiatric disorders significantly reduced employment among both men and women, using information on mental health history and mental health of the respondent´s partner as instruments. Marcotte and Wilcox-Gok, 2003 estimated the effect of depression, dysthymia, anxiety disorder, and anti-social personality disorder on earnings in the 1990-1992 NCS, using parental health as an instrument. They found that suffering from an anxiety disorder in the past year reduced earnings by 49% for women and found no statistically significant effect for men. Chatterji et al., 2011 estimated the effect of a past-year psychiatric disorder on employment and earnings in the 2001-2003 NCS, using childhood mental health and religiosity as instruments. They found that a past-year psychiatric disorder reduced the likelihood of employment by 17 percentage points for men and 9 percentage points for women; however, they found no evidence of negative effects on earnings. Ojeda et al., 2010 estimated the effect of an increase in the K6 Scale of Mental Illness on labor supply for natives and immigrants in the 2002 National Survey on Drug Use and Health in the US, using social support as an instrument. Their findings show that immigrant labor supply is less responsive to mental health problems than native labor supply. Using the Mexican Family Life Survey for 2002-2005, Michaelsen, 2012 estimates the causal effect of depressive symptoms on the extensive margin and intensive margin of labor supply for working-aged men and women, using ongoing violent conflicts and homicide rates related to drug trafficking networks as instruments. The results showed that depressive symptoms decreased the probability of working by 26% and reduced by 12 the hours worked in a week for men. No statistically significant effects were found for women and the instruments were not reliable for the women sample. Germinario et al., 2022 used the National Longitudinal Survey of Youth-1979 cohort (NLSY79) panel study in the US to establish a causal effect of mental health on labor market outcomes, using a novel approach that relaxes some of the assumptions made on IV methods and the adolescents AGQT scores as an instrument. They found that going from having "no vs. little" or "little vs. mild" depressive symptoms reduces employment by at most 4%, while going from "moderate vs. mild" and "severe vs. moderate" lowers employment by at most 10% and 16%, respectively. Also, they found that the population causal average effect of going from having no to severe depression symptoms decreases earnings by 11-44%. Shen, 2023 used data from the 2012 Canadian Community Health Survey-Mental Health (CCHS-MH) to analyze the effect of depressive symptoms on the extensive margin of labor using a family member´s mental health problem(s) as an instrument. The results show that having depression reduces employment by 26 percentage points. For men, the effect is a reduction of 57 percentage points, and no effect is found for women. Also, the estimates for people aged less than 45 are significant (-30.4pp) while for older people, they are not significant. On the other hand, there are several studies that use panel data with fixed-effects methods to estimate causal effects. Biasi et al., 2021 estimated the causal effect of bipolar disorder by exploiting the exogenous change in the use of lithium as a treatment for this disorder. They used differences-in-differences and event study estimations and found that access to treatment eliminates one third of the earnings penalty associated with BD and greatly reduces the risks of low or no earnings. Bryan et al., 2022 used nine waves of the UK Household Longitudinal Study and estimated individual fixed-effects regressions which showed that depression reduces employment by 1.6 percentage points. Frijters et al., 2014 estimated the effect of mental health on employment by using 10 waves of the Household, Income and Labour Dynamics (HILDA) in Australia survey and the death of a close friend as an instrument. They estimated IV regressions with individual fixed effects and found that a one standard deviation decrease in mental health decreased employment by 30 percentage points and found that the effect is larger for women (32 percentage points) than for men (27 percentage points). Peng et al., 2016 showed that depression reduced the probability of employment by 2.6 percentage points but didn´t affect earnings using data from the 2004–2009 Medical Expenditure Panel Survey. They also estimated the effect of depression on work impairment and found that exhibiting depressive symptoms increases annual work loss days by about 1.4 days. Ringdal and Rootjes, 2022 estimated the relationship between depression and labor market outcomes using 2008 - 2018 data from the Netherland´s Longitudinal Internet Studies for the Social Sciences (LISS) panel. They found a significant effect in labor force participation for men but not for women; however, they found that a one standard deviation increase in women's mental health increases the likelihood of her having paid employment by 1.1–1.6% point. Bubonya et al., 2017 estimated the effect of mental health issues on absenteeism and presenteeism using the HILDA survey, finding that the odds that men (women) in poor mental health report diminished productivity at work is 6.17 (6.91) times higher than those of otherwise similar men (women) in good mental health. They also found that the absence rate of men (women) who report being in poor health is 4.9 (5.3) percent higher than otherwise similar men (women) in good mental health. This last study sheds light on the effect on productivity among workers with mental health problems.

The second group of studies are RCTs (Random Controlled Trials), which are used to establish a more robust causal link between mental health and labor outcomes. These studies, in general, show a causal effect of treating mental illness on employment. Lund et al., 2024 conducted a meta-analysis that aggregated results across 31 RCTs in developing countries, showing a positive average effect of various interventions to treat mental illness on labor supply, with effects similar to those in developed countries. Their main findings are that interventions aimed at improving common mental disorders increase job search by 0.16 standard deviations and the effect is larger for severe mental disorders, 0.30 standard deviations.

In sum, the findings of the IV and panel studies have consistently found a negative effect of mental health on employment, but mixed effects on earnings and distinct effects among men and women. Although these results and methods are powerful they have some limitations. IV studies often rely on personal characteristics as instruments, raising questions about exogeneity. Panel data studies, typically involving smaller samples, face issues of statistical power. This research addresses these limitations by using exogenous instruments, thus not depending on individual characteristics, and a novel instrumented differences-in-differences method, combining the strengths of both instrumental variables and differences-in-differences.

There is a notable gap in the literature regarding the causal effect of mental health on labor outcomes in developing countries. Chatterji et al., 2007 used data from the National Latino and Asian American Study (NLAAS) to estimate the effect of psychiatric disorders on labor market outcomes in Latin and Asian descent, which are mostly immigrants. They found that meeting diagnostic criteria for any psychiatric disorder reduced the probability of being employed by about 11 percentage points for Latino males and by about 22 percentage points for Latino females, and increased the probability of being absent from work in the last month by 19 percentage points for males and 16 percentage points for females. The recent research by Lund et al., 2024 shed light on the effect in these countries and emphasized that the evidence from high income countries might have limited relevance for economic outcomes in low- and middle-income countries because mental health treatments in LMICs are often modified to limit costs and labor market characteristics differ substantially; they tend to have more informal work and weaker labor market regulations -like provisions for sick leave - which people may use to manage their conditions. Furthermore some of the more recent RCTs in developing economies find mixed evidence of the effects of mental health treatments on economic outcomes Lund et al., 2024). Barker et al., 2022 found that a psychosocial intervention improved mental and physical health in rural Ghana after one to three months. In contrast, Haushofer et al., 2020 found no impact of a psychosocial intervention in rural Kenya neither in mental health nor economic outcomes. Baranov et al., 2020 and Bhat et al., 2022 found consistent improvements in mental health but no effect on labor supply from psychosocial interventions among all or mostly female populations in South Asia. The results of these studies reinforce the need to continue investigating the effects of mental health on labor outcomes in middle-income countries like Mexico, which is the primary objective of this research.

Additionally, there is a lack of analysis on gender differences in mental health. Although some studies include heterogeneous effects, most find no significant impacts on women and do not explore underlying causes. Given the higher rates of depression and anxiety among women, it is crucial to understand the mechanisms behind these findings, as it remains a critical public health issue.

The limited existing literature has focused on the effect of the wage gap or employment inequality on women´s mental health. Platt et al., 2016 used data from a 2001–2002 US nationally representative survey of 22,581 working adults ages 30–65 and a Oaxaca Blinder decomposition analysis along with propensity score matching methods and found that when the gender wage gap is higher the likelihood of mental disorders were significantly higher among women versus men, and when females earned more than their male counterparts, the higher likelihoods for women for mental disorders were significantly attenuated. Yu, 2018 utilized global data for depressive disorders and socioeconomic data from the United Nations' World Bank databases and Global Burden of Disease database to demonstrate the correlation between social inequality and gender disparities in mental health. They found a high correlation between inequalities and gender disparities in mental health. de Mola et al., 2020 using data from a birth cohort in Brazil found that differences in income and schooling are correlated with differences in mental health by gender. They found that women earn less and that explains 1/6 of their higher risk of MD (major depression), GAD (generalized anxiety disorder) and CMD (common mental disorders), also they found that earning the same reduces women´s higher risk of MD and GAD in less than half, and that studying more than 12 years reduces women´s higher risk of MD by a half. Batool, 2020 conducted a systematic review and established a cause-effect relationship between gender disparities in the workplace and mental health in the UK.

However, the inverse relationship has not been explicitly analyzed. As of the date of this research, no articles have been found regarding the inverse effect of gender differences in mental health on inequalities by gender on labor market outcomes. This study contributes to this literature by examining the effect of depression on employment from a gender perspective and discussing the possible mechanisms behind the results.

3 Data

This section demonstrates that there is a vast array of tools for measuring depression. However, some are more reliable and have been proven to perform better for population samples, including the one used for the objective of this investigation. Also, a description of the data and variables that were used for the estimations is provided.

Measurement of depression

The way of measuring and diagnosing mental disorders is not singular, and most existing tools are for clinical diagnosis performed by experts. Given the growing interest in investigating the causes and effects of mental health in different populations, scales have emerged that work to measure and diagnose mental illnesses in large population samples that do not require a specialized interviewer or are self-diagnosed (Ridley et al., 2020). The most widely used internationally and found in the literature are listed in Table 1:

Table 1: Main tools for reliable diagnosis of depression and/or anxiety used worldwide in surveys for the general population

Scale	**What does it measure**	**How does it measure it**
PHQ-9	Major depressive disorder	9 questions from the DSM-IV criteria
GAD-7	Generalized anxiety disorder	7 questions from the symptoms exposed in the DSM-IV
SRQ-20	Non-psychotic mental disorders	20 questions created by WHO
CES-D	Depressive symptoms	20 questions created from clinical diagnostic questionnaires.
CES-D 7	Depressive symptoms	A shortened version of the CES-D with a higher likelihood of completing the survey and reduced administrative time while maintaining the same reliability
GHQ-5	Common mental disorders	Shortened version of GHQ measuring the individual's current mental health status.

It has been found that these tools are capable of predicting professional diagnoses with a predictive power and sensitivity greater than 50% and a specificity of over 90% [1] (Ridley et al., 2020; Ali et al., 2016; Patel et al., 2008; Levine, 2013; Spitzer et al., 2006; Kroenke and Spitzer, 2002).

There is a wide variety of surveys and tools for diagnosing mental disorders apart from the main ones mentioned earlier, but most of them are lengthy, require administration by a specialized person, or their reliability, sensitivity, and specificity have not been adequately tested, such as the Hamilton Rating Scale for Depression (HAM-D), the 21-item Beck Depression Inventory, and the Hospital Anxiety and Depression Scale (HADS).

For these reasons, the scales presented in Table 1 have been accepted in the literature to estimate the prevalence of certain disorders in population samples. In the particular case of depressive symptoms, the most used scales are the PHQ-9 and the CES-D. The

[1] The specificity of a test is the probability that a healthy subject will have a negative test result.

Patient Health Questionnaire (PHQ-9) asks nine questions for each of the symptoms that are used to define major depressive disorder according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) created by the American Psychiatric Association. The latter, the Center for Epidemiologic Studies Depression Scale (CES-D) is a screening scale for detecting probable cases of depression. It was designed based on studies in clinical and general populations and is a popular measure among studies of the effect of economic interventions or shocks on mental health (Ridley et al., 2020). It has the advantage of providing a structured and brief measurement in a self-report format. Through 20 items, it allows for the investigation of various components of depression in the past week and has consistently shown to be satisfactory in different sociocultural contexts, populations, and genders (González-Forteza et al., 2011). The CES-D7 is a shortened version of the CES-D with only 7 questions, it was created because it was noticed that the CES-D was too large and had a high likelihood of incompleted survey. Also, the CES-D7 reduced administrative time while maintaining the same reliability as the 20 questions version (Andersen et al., 1994; Tuunainen et al., 2001).

Although these tools have been validated internationally and their validity has been tested, they are not exempt from possible measurement errors, as there are factors that could affect individuals´ responses. For example, there may be social desirability bias, meaning that individuals report fewer symptoms due to stigma or shame, which could lead to a systematic underestimation of depression. Physical ailments or health problems could also bias the results. Therefore, it is important to continue improving and regularly analyzing the validity and reliability of these instruments to obtain increasingly accurate estimates. Nonetheless, they remain good instruments for estimating depressive symptoms in population samples and are not believed to have systematic measurement error, but rather possible random measurement errors since they are highly correlated with clinic diagnosis.

Ensanut

To estimate the effects of depression on labor market outcomes in the Mexican population, this research uses cross-sectional data from the *National Health and Nutrition Survey* (ENSANUT by its Spanish acronym) as it includes information about depressive symptoms in adults and adolescents along with the individuals´ sociodemographic characteristics, which include labor force participation, type of occupation, among others labor outcomes that are used as dependent variables. This survey has included the CES-D7 questionnaire since 2012 to assess the prevalence, effects and consequences of depressive symptoms. Additionally, the reliability of the CES-D 7 has been tested internationally, and furthermore, there are studies validating the cutoff points of this scale in the case of Mexico (Salinas-Rodríguez et al., 2013; Salinas-Rodríguez et al., 2014), which gives confidence to use it for measuring depression.

ENSANUT is a survey created to assess the health status and nutritional conditions of various population groups in Mexico. In its early years, it was conducted every six years, but since 2018, it has been conducted every year to quantify and provide information to study the environmental, socioeconomic, and cultural factors determining the health-disease process, including dietary patterns, physical activity, and other lifestyle-related factors; to provide useful information to describe the population´s perception of the coverage, quality, accessibility, and utilization of priority health and nutrition programs; and to identify future challenges for the health system. This survey has been used in several social sciences studies. Gračner et al., 2022 analyze changes in weight-related outcomes among adolescents following consumer price increases of taxed sugar-sweetened beverages; Ponce-Alcala et al., 2021 study the association between household food insecurity and obesity in Mexico; Rivera-Hernandez et al., 2016 estimate the impact of social health insurance (*Seguro Popular*) on diabetes and hypertension process indicators among older adults in Mexico; among others (Stabridis and van Gameren, 2018; Doubova et al., 2023; Del Valle, 2021; Sosa-Rubi et al., 2009). Thus, its use is reliable and recognized both nationally and internationally.

The Health Questionnaire - used in this research - includes information about the socioeconomic characteristics of the household and individuals, alongside information about use and access to health care services (Household Questionnaire); information about the physical and mental health status of adolescents and adults (Adults Questionnaire, ages 20 and older; and Adolescents Questionnaire, ages 10-19); and information regarding the physical health and development of children (Children Questionnaire, ages 0-9). The data obtained from the questionnaires that conform the Health Questionnaire were merged for every year that included the CES-D7 questions: 2012, 2018, 2019, 2021, and 2022. Then the datasets for every year where merged creating a final database of 183, 667 observations that was used to create the variables used in the final estimations[2]. After creating the necessary variables, the sample was restricted to individuals between 20 and 65 years old, and observations for which the variable *married* was a missing value were removed, resulting in a final database of 95,500 observations.

The CES-D7 questions included in the 2012, 2018, 2019, 2021, and 2022 questionnaires are shown in Table 2. According to the frequency of symptom occurrence in the past week, a value of 0 to 3 is assigned. For example, when asked "Did it seem like everything you did was an effort?", the person responded that during the past week she felt like everything was an effort for about 3 or 4 days, then a value of 2 was recorded for question d). By summing the value recorded in each question, a depression score is obtained for each individual, with the lowest possible score being zero and the highest possible being 21. The cutoff point to determine moderate to severe depression symptoms for adults is a score of 9 or higher, while for adults over 60 years old, the cutoff point is 5 points (Salinas-Rodríguez et al., 2013; Salinas-Rodríguez et al., 2014). Since a cutoff point has not been established for teenagers, the sample was restricted to individuals aged between 20 and 65 years, the upper age range was chosen to exclude retired people.

[2] A detailed description of the variables and how they were created is available in the Appendix

Table 2: CES-D7 questions in the Ensanut questionnaire

During last week...					
		Rarely or never (less than one day)	Occasionally or some-times (1 - 2 days)	A con-siderable number of times (3 - 4 days)	All the time or most of the time (5- 7 days)
a)	Did you feel like you couldn't shake off sadness?	0	1	2	3
b)	Did you have trouble concen-trating on what you were do-ing?	0	1	2	3
c)	Did you feel depressed?	0	1	2	3
d)	Did it seem like everything you did was an effort?	0	1	2	3
e)	Did you sleep poorly?	0	1	2	3
f)	Did you enjoy life?	0	1	2	3
g)	Did you feel sad?	0	1	2	3

Note: In the original questionnaire, the possible answers had values ranging from 1 to 4. However, to utilize the cutoff points provided in the literature, the variables had to be recoded so that they range from 0 to 3, as shown in the table. The recoding of variables can be seen in the Appendix.

4 Empirical Framework

Outcome variables

The main outcome variable analyzed is employed, which was defined as a binary variable that is equal to one if the respondent worked for at least an hour during the past week. Additional variables of labor market outcomes are investigated: labor force participation, which takes the value of one if the respondent worked for at least an hour or did not work but was searching for a job during the past week; formality, which is equal to one if the worker receives social security from their job; preseenteism, which was defined as a binary variable if the respondent had trouble concentrating and felt like everything was an effort for 3 days or more during the past week, and variables that indicate if the worker is an employee, employer or self-employed.

Mental health variables

The endogenous variables used in the model were the CES-D7 score and a binary variable that is equal to one if the individual has moderate or severe depressive symptoms according to the cutoff points and zero otherwise.

Estimation strategy

As it has been stated, establishing a causal effect of poor mental health in labor market outcomes is hard because of possible endogeneity and reverse causality. To address these issues and obtain unbiased and consistent estimates, two methods are used: instrumental variables and instrumented difference-in-differences.

Instrumental Variables

The first approach used is a two-stage least squares (2SLS) implementing the following equations:

$$MH_i = \alpha I + X_i\beta + C_t + d_s + \epsilon_i \tag{1}$$

$$L_i = \gamma MH_i + X_i\delta + C_t + d_s + \eta_i \tag{2}$$

Equation 1 corresponds to the first stage and equation 2 is the second stage. MH_i denotes the mental health variables, I is the instrument, X_i is a vector of sociodemographic characteristics, C_t and d_s are time and state fixed effects to account for possible unobservable factors that affect mental health during a given year or in a certain state, L_i is a labor market outcome, and ϵ_i, η_i are the error terms. All regressions were weighted with the survey sampling weights.

Instrumented Differences-in-Differences

A second approach is used as a robustness check for the IV estimates. The instrumented-differences-in differences (IDID) model explicitly utilizes external randomness in exposure trends and accounts for unmeasured confounding in repeated cross-sectional studies. The instrumented DID method estimates a convex combination of average causal effects, similar to Angrist and Imbens, 1995, based on a set of exclusion, parallel trends, and monotonicity assumptions that are common in both Difference-in-Differences (DD) and Instrumental Variables (IV) designs (Ye et al., 2023; DiazOrdaz, 2023; Hudson et al., 2017). This model is useful when the instrument is present only during some periods, so that the individuals are not exposed to the instrument until a certain period.

$$MH_i = \alpha I + \vartheta Post + \mu I \cdot Post + X_i\beta + C_t + d_s + \epsilon_i \tag{3}$$

$$L_i = \gamma MH_i + \tau Post + X_i\delta + C_t + d_s + \eta_i \tag{4}$$

Equation 3 corresponds to the first stage and equation 4 is the second stage. MH_i denotes the mental health variables, I is the instrument, *Post* is a binary variable that takes the value of 1 after year 2020, X_i is a vector of sociodemographic characteristics, C_t and d_s are time and state fixed effects, L_i is a labor market outcome, and ϵ_i, η_i are the error terms. All regressions were weighted with the survey sampling weights.

Instruments

In both the IV and IDID methods the main assumptions are the exclusion restriction, independence, and relevance of the instrument. In addition, for the latter, the parallel trends assumption must hold in the sense that the instrument must not affect the outcomes during the previous years. The exclusion restriction states that the instrument must not be correlated with the error term of the second stage, the relevance assumption requires that the instrument is correlated with the endogenous variable and for the independence assumption to hold the instrument must not directly affect the outcome. In the context of this research, the instrument must affect depression and not be correlated with the error term so that it affects the dependent variables only through depression.

For the IV model, the chosen instrument is violence or attack suffered by at least one member of the household in the past year excluding domestic violence or abuse. It has been documented that violence and crime have a negative effect on the mental health of both victims and non-victims (Cornaglia et al., 2014; De Jong et al., 2003; Murthy and Lakshminarayana, 2006; Brück and Müller, 2010; Giacaman et al., 2007), so it suggests that it is sufficiently correlated with the endogenous variable used in this research. Since violence or attacks that were considered for the construction of the instrumental variable are external to the individual[3], it is believed that they are not correlated with unobservable variables that affect labor outcomes. For example, the fact that a person within the household has experienced a traffic incident or robbery outside the household in the past year does not affect investment decisions in education or the type of position the individual holds at work. The exclusion restriction could be violated if, for example, the individual lives in a more dangerous neighborhood or if a certain year is more violent, which could affect both her mental health and her

[3] In the Appendix the violence and attacks that were used for the construction of the dummy instrument for violence/attack are listed.

labor market decisions. For these reasons, state fixed effects and year fixed effects are included to ensure that violence or attack suffered for at least a member of the household is not indirectly correlated with local labor demand shocks. Additionally, in Figures A4 A5 and A6 in the Appendix it is shown the incidence of the instrument and the unemployment rate by state and no clear pattern is observed, which gives more confidence that the exclusion restriction holds.

The instrument chosen for the IDID estimation is a binary variable that is equal to 1 if COVID-19 deaths per state are greater or equal to 3,000 deaths[4]. Since it was an exogenous shock to the whole population, it satisfies the parallel trends assumption. Landa-Blanco et al., 2021 find a negative effect of the COVID-19 pandemic on the mental health of various populations, including Mexico, which suggests that the instrument is correlated with depression. Covid deaths per state are not believed to be correlated with the error term of the second stage because individual observable characteristics that predict labor market outcomes do not determine the number of deaths per state. Additionally, Covid deaths per state are not believed to directly explain labor market outcomes since it was expected to be a transitory shock. Again, the exclusion restriction assumption could be violated if, for example, the individual lives in a state with more incidence of COVID-19 or less health care services, which could be correlated with sociodemographic characteristics like education and age, variables that are known to be correlated with labor outcomes. To control for these factors sociodemographic characteristics are included in each regression alongside state and year fixed effects.

To assess the impact of unobserved factors on the relationship in order to have more confidence in the instruments chosen and that the exclusion restriction is satisfied, observed individual variables were sequentially excluded from the baseline models to simulate omitted variable bias (Maruyama and Heinesen, 2020; Oster, 2019; Shen, 2023). If the estimates from these simulations do not vary significantly with each exclusion, then omitted variable bias does not significantly impact the instruments, meaning that

[4]Results using different instruments in per capita terms and different thresholds are shown in Tables A1 and A2 in the Appendix

the instrument is not likely to be correlated with the error term of the second stage. The validity and reliability of the instruments are further explored in Section 6.

The literature has used different instruments to analyze the effect of poor mental health on labor market outcomes, such as social support, religiosity, family member(s) with mental disorders, among others. In order to choose the best instrument for the IV model, two main criteria were used. First, the predictability of the instrument seen in Table 3, that is, how much do the known factors together explain the incidence of the instrument (e.g degree of randomness of the instrument) such that it gives confidence that the unknown factors are unlikely to bias the IV estimates significantly. Second, the strength of the first stage [5]. For the IDID instrument, the dummy variable covid deaths per state ≥ 3,000 was chosen because it seems a stronger instrument than the variable of covid deaths per capita by state and the dummy covid deaths per capita by state ≥ 100 (which is above the mean of 74.28) and they yield similar results for the second stage for almost every variable, some of the differences are due to the fact that not all instruments have a strong first stage for each dependent variable. [6]

Socioeconomic variables

The control variables used in both estimations are age, sex, a binary variable indicating if the person is married, years of education, and a binary variable indicating if the individual lives in a rural area. These covariates were chosen because it is well documented that they affect labor market outcomes and mental health. Additionally, state and year fixed effects are included in all the estimations to control for differences in the incidence of violence and COVID-19 infections that individuals face according to their place of residence.

[5] The estimations of the first stage for each instrument can be found in Tables A1 and A2 in the Appendix

[6] Results are shown in Table A5 in the Appendix

Table 3: Predictability of instruments

Dependant variable	Incidence	R^2 (IV)	R^2 (IDID)
Attack/violence	1.79%	0.013	
Accident of child	1.19%	0.017	
Partner with depression	0.09%	0.006	
Parent(s) with depression	0.01%	0.001	
Family members with depression	0.14%	0.009	
Covid infections by municipality			0.485
Covid deaths per state			0.668
Covid deaths per state ≥ 3,000	85.66%		0.781
Covid deaths per state ≥ 1,000	15.46%		0.600
Covid deaths per capita by state			0.064
Covid deaths per capita by state ≥ 75	89.21%		0.063
Covid deaths per capita by state ≥ 100	86.31%		0.063

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The table displays the incidence of the instrument in the complete analyzed sample and the corresponding R^2 for the regression of each instrument with the controls used in the baseline models.

5 Results

Descriptive analysis

Figure 1 shows the prevalence of severe or moderate depressive symptoms by gender and labor force participation for the entire 2012-2022 sample. The figure was constructed by calculating the mean with sample weights of the variable *Depression* by gender and labor force participation status: employed, unemployed or out of the labor force. As seen in the figure, the prevalence is higher for women than for men. In other words, there is a greater proportion of women with severe or moderate depressive symptoms in comparison to men among the Mexican population. Consistent with the literature (Culbertson, 1997), the ratio is approximately 2:1 for the employed - with women experiencing depression twice as often as men - and almost a 10% higher prevalence for the unemployed and outside the labor force. Additionally, depressive symptoms are more common among the unemployed compared to the employed for both genders, suggesting that there is a relationship between employment status and depression, that is, is possible that people with worse mental health stay unemployed or out of the labor force and that those with a better mental health self-select into employment.

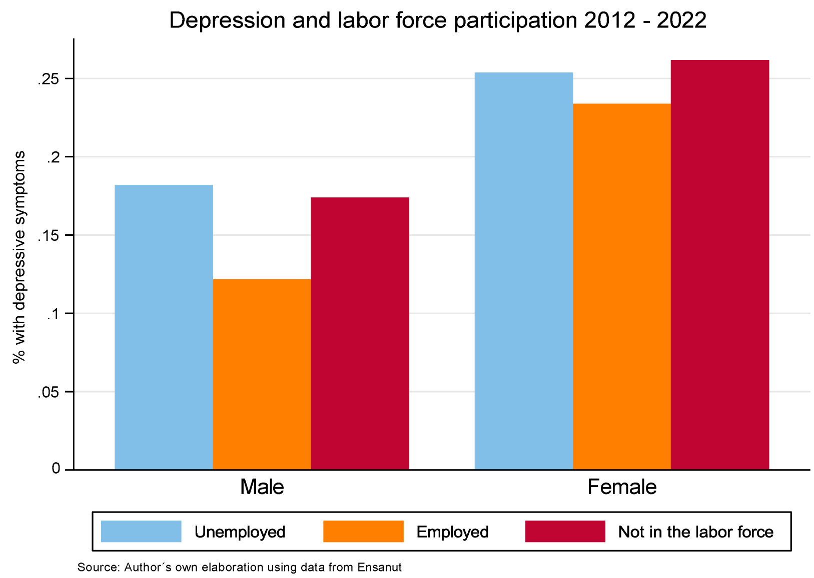


Figure 1: Depression and labor force participation 2012 - 2022 (%)

When disaggregating the analysis by year, Figure 2 shows that throughout the entire study period, the prevalence of depression is higher among women. The ratio of 2:1 is observed in every period, which means that the proportion of women with severe or moderate depressive symptoms has been at least twice than the proportion of men since 2012 and the trend has prevailed until recent years. Interestingly, in the figure is not observed an increase in the prevalence of depression after the 2020 COVID-19 pandemic.

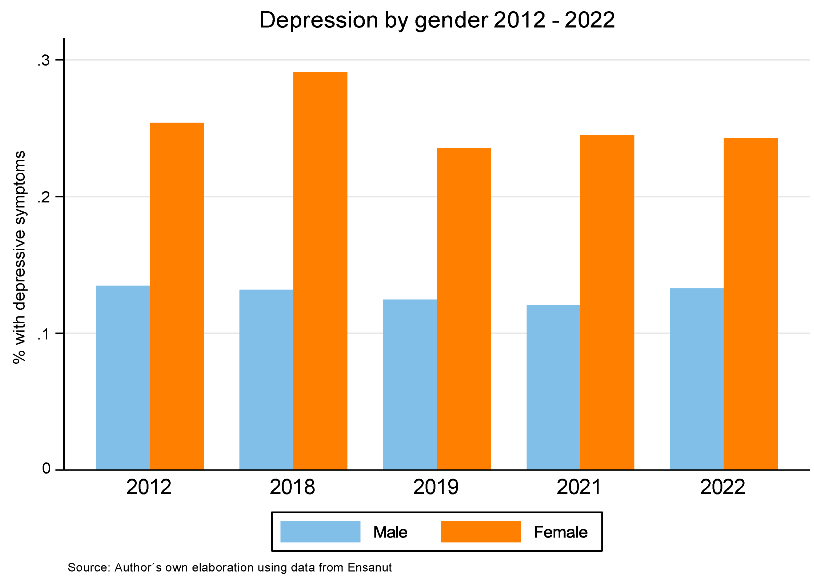
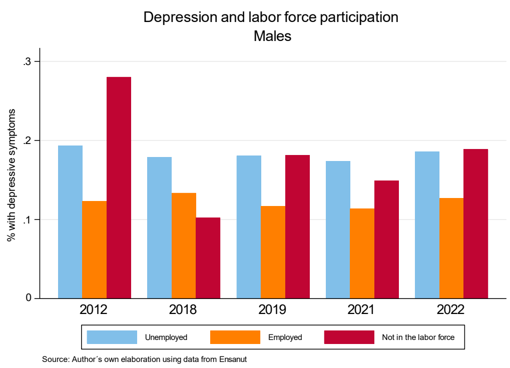
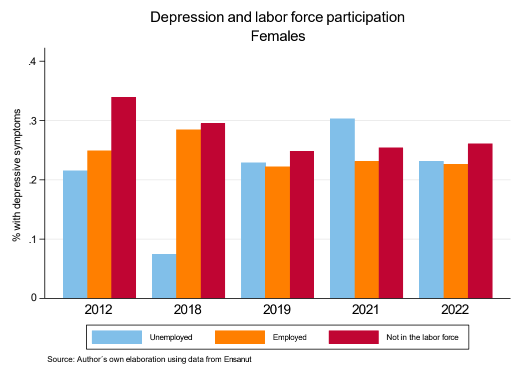


Figure 2: Depression by gender 2012 - 2022 (%)

Figure 3 shows the prevalence of depression by labor force participation and gender over time. It was constructed in the same way as Figure 1 but separately by period. It shows an interesting pattern. For men, depression is more common among the unemployed or those outside the labor force. In contrast, for women, there is a higher prevalence of depression among the employed and those outside the labor force from 2012 to 2018. After 2018, the proportions become very similar across all three labor force participation states for women but not for men, where the differences persist. This pattern suggests that women do not self-select into the labor force or employment like men do, and that there is a strong positive relationship between unemployment and depression for men - with a proportion of almost 20% of unemployed men with depressive symptoms versus approximately 12% of employed men with depressive symptoms -, while this pattern is not observed for women. It is worth noting that in 2018, the prevalence of women with depressive symptoms among the unemployed was particularly low, at less than 8%. This could potentially bias the results, making estimates particularly sensitive to this year. However, as mentioned earlier, fixed effects by year were included in all regressions to address this concern. Fixed effects by year allow to control for temporal variability that might influence both the dependent and independent variables. This means that any systematic changes over time (such as policies, macroeconomic events, or general trends) will not bias the estimation results.



(a) Males 2012 - 2022



(b) Females 2012 - 2022

Figure 3: Depression and labor force participation by gender 2012 - 2022 (%)

In Table 4 means and standard deviations of all the variables used in this study are reported, the number of observations is 95,500 and the statistics were calculated using sample means.

As observed in the table, from top to bottom, the mean age is 39 and half years old which means that the middle-aged people are more present in the sample, this could overestimate the results since it is thought that as people get older they tend to feel more depressed. The mean CES-D 7 score is 5.636, below the cutoff point for adults but higher than the cutoff for older adults, this means that there are not too many people in the sample with moderate or severe symptoms, since the average age is 39 years and the cutoff point for people under 60 years old is 9 points on the score. In addition, the proportion with moderate or severe depressive symptoms is almost 20%, which is not a large part of the population; if people with depression where over-represented in the sample then the estimates could be overestimated because the sample would not accurately reflect the proportion of depressed individuals in the general population and the results could not be generalized to the population. Women represent 54% of the sample, which is fairly the half of the sample; 64.6% are employed, higher than the prevailing employment rate in Mexico - 58.6% in 2022 according to INEGI; 66% belong to the labor force, this number is close to the prevailing labor force size in Mexico - 60% in 2022 according to INEGI. The latter could bias the results as the sample over-represents those who are already employed, potentially masking the true effect of depression on employment status. However, the difference is not too large to create serious concerns about the validity of the results. Among workers, those in formality represent the 42.3%, really close to the proportion of formal workers in 2022 according to INEGI- 44.9%; the proportion of individuals suffering from presenteeism is 4.43%, which means that a very little fraction of the sample feel like everything is an effort and had problems concentrating during the past week. If people with preseenteism were over-represented the estimates would be bias upwards because it is thought that people with depressive symptoms would suffer more from ruminiation which could affect the answer to the questions used to create the variable. Those married represent 68%, this could bias the results if it is thought that people with a couple are more happy and tend to feel less depressed; the mean years of education is 10.10 which is less than high school completed, so the sample over-represent less educated people which could also tend to have more depressive symptoms; the employees represent 41.3%; employers are the 9.47%; the self-employed are the 17.2%; and the proportion living in rural areas is 37.7%. Overall, the composition of the sample does not suggest that the results could be biased since some of the over-represented variables like married, and years of education are used as covariates to precisely control for these factors that could affect both depression and labor market outcomes. In the bottom part of the table, the descriptive statistics for the instruments used in the estimations are shown. The proportion of individuals who had at least one household member that suffered an attack or violence during the past 12 months is 1.79%; those who had a children that suffered an accident during past last year represent 1.19%; and people living in states where covid deaths were greater or equal to 3,000 represent 69.6%.

Table 4: Descriptive statistics full sample 2012-2022

Variable	(1) N	(2) mean	(3) sd	(4) min	(5) max
Age	95,500	39.45	12.36	20	65
CES-D 7 score	95,500	5.636	3.667	0	21
Depression	95,500	0.193	0.395	0	1
Sex	95,500	0.540	0.498	0	1
Employment status	95,500	0.646	0.478	0	1
Labor force participation	95,500	0.667	0.471	0	1
Formal worker	57,658	0.423	0.494	0	1
Presenteeism	95,500	0.0443	0.206	0	1
Married	95,500	0.681	0.466	0	1
Years of education	95,500	10.10	4.016	0	23
Employee	95,500	0.413	0.492	0	1
Employer	95,500	0.00947	0.0969	0	1
Self-employed	95,500	0.172	0.378	0	1
Rural	95,500	0.377	0.485	0	1
Instruments:					
Attack/violence	95,500	0.0179	0.133	0	1
Accident of a child	95,500	0.0119	0.108	0	1
Covid deaths per state ≥ 3,000	95,500	0.696	0.460	0	1

Notes: Depression is a dummy variable that takes the value 1 if the individual exhibits moderate or severe depressive symptoms, *Sex* takes the value 1 if the individual is female, *Employment status* takes the value 1 if the person is employed, *Formal worker* takes the value 1 if the individual is a formal worker, *Married* is equal to 1 if the person is married, and *Rural* is a dummy variable indicating whether the individual lives in a rural area.

Table 5 presents the differences in means for the outcome and sociodemographic variables between depressed and non-depressed individuals. All variables are significantly different except for the dummy variable indicating whether the individual lives in a rural area and the instrument for the IDID estimation. In general, depressed individuals are more likely to be women, self-employed, older, not married, have fewer years of education, are less likely to be part of the labor force or employed, and have more incidence of attack or violence in a member of the household. The latter could bias the results if individuals with depression tend to engage in violent behaviors or are more often involved in risky situations. However, this is unlikely, as the dummy variable for violence or attack indicates whether any household member experienced it, not necessarily the person reporting depressive symptoms. It is possible that the incidence of violence is related to the place of residence, which in turn could be correlated with the individual's mental health status. Nonetheless, as mentioned earlier, fixed effects by region are included to control for unobserved factors associated with the place of residence. Additionally, controls such as education and rural, which are related to socioeconomic status, are included. This, along with the evidence presented in Sections 4 and 6 regarding the validity of the instrument, suggests that the results are not biased due to these factors.

Table 5: Difference in means by depression status

	Not depressed	Depressed		
Variable	Mean	Mean	% difference	p-value
Sex	0.5509	0.7287	-24.399%	0.0000
Employed	0.6390	0.5259	21.500%	0.0000
Labor force participation	0.6586	0.5446	20.921%	0.0000
Formal worker	0.4228	0.3371	25.409%	0.0000
Presenteeism	0.0003	0.2318	-99.863%	0.0000
Employee	0.4049	0.3029	33.696%	0.0000
Employer	0.0106	0.0074	42.354%	0.0001
Self-employed	0.1707	0.1892	-9.755%	0.0000
Age	39.341	44.490	-11.573%	0.0000
Married	0.7157	0.6489	10.295%	0.0000
Years of education	9.7332	8.2555	17.901%	0.0000
Rural	0.5011	0.4981	0.609%	0.4465
Violence/attack	0.0109	0.0181	-39.869%	0.0000
Covid deaths per state ≥3,000	0.8570	0.8556	0.1534%	0.6383

Notes: Depression is a dummy variable that takes the value 1 if the individual exhibits moderate or severe depressive symptoms, *Sex* takes the value 1 if the individual is female, *Employment status* takes the value 1 if the person is employed, *Formal worker* takes the value 1 if the individual is a formal worker, *Married* is equal to 1 if the person is married, and *Rural* is a dummy variable indicating whether the individual lives in a rural area.

Main results

Table 6 reports the regression results for the first stage of the 2SLS and the IDID for the whole sample. Panel A shows the results of the CES-D7 score and Panel B presents the results of the dummy of depression, the coefficients of both instruments are statistically significant at 1% and positive for the full sample. Put differently, violence or attack suffered by a member of the household during the past year increases the CES-D7 score by 1.680 points and the probability of having depression by 0.124 percentage points (pp). Living in a state where covid deaths per state exceed 3,000 increases the CES-D7 score by 0.549 points and the probability of having depression by 0.0406pp. The magnitude and direction of the coefficients are consistent with expectations from the literature and the F statistics are well above the cutoff value of 10 proposed by (Staiger and Stock, 1994) in all estimations.

In Table 7 the same results are presented by gender. Again, both instruments perform well for the two endogenous variables, although the F statistic for the male sample is much smaller, suggesting that the instruments are weak, especially for the CES-D7 score. To address this concern, results were estimated using the LIML method as suggested in Angrist and Pischke, 2009 and it yielded very similar results. [7] As seen in Panel A of Table 7 both instruments are highly significant both for females and males. A violence or attack suffered by a member of the household during the past year increases the CES-D7 score by 2.148 points for women and 1.287 for men. Living in a state with covid deaths greater or equal to 3,000 increases the CES-D7 score by 0.537 points for females and 0.565 for males. Panel B of the table shows that a violence or attack suffered by a member of the household during the past year increases the likelihood of having depression by 0.16pp for women and 0.093pp for men. Living in a state with covid deaths greater or equal to 3,000 increases the probability of having depression by 0.036pp for females and 0.0463pp for males. This results imply

[7] This results can be found in Table A3 in the Appendix

Table 6: First stage regression results

VARIABLES	(1) IV	(2) IDID
Panel A. Dependent variable: CES-D7 score		
Attack/violence	1.680***	
	(0.357)	
Covid deaths per state ≥ 3,000		0.549***
		(0.113)
Constant	6.433***	6.045***
	(0.192)	(0.218)
Observations	95,500	95,500
R-squared	0.053	0.050
F	34.75	35.91
Panel B. Dependent variable: Depression		
Attack/violence	0.124***	
	(0.0321)	
Covid deaths per state ≥ 3,000		0.0406***
		(0.0118)
Constant	0.149***	0.121***
	(0.0186)	(0.0211)
Observations	95,500	95,500
R-squared	0.066	0.064
F	44.45	43.92

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Both estimations include the sociodemographic variables as controls and fixed effects of year and state. Mean CES-D 7 score is 5.63 and the mean for depression is 0.19.

that women, in general, are more affected by perceived violence than men, while the COVID-19 pandemic affected both genders in a similar way. It is noteworthy that both instruments are stronger for the female subsample.

In Table A6, Ordinary Least Squares (OLS) results with and without controls, the second-stage (2SLS), and second-stage (IDID) results are reported. The results in the case of the IV and the IDID estimations should be interpreted as local average treatment effects (LATE). For the IV estimations, the coefficients show the effect on the population that actually experienced a mental health impact from being a victim of an attack or living in the same household as a victim of an attack or violence in the past year. For the IDID estimations, the coefficients show the effect on the population that experienced a mental health impact due to living in a state with more than 3,000 COVID-19 deaths during the year. It is evident that the magnitudes of the coefficients between OLS and IV, as well as IDID, exhibit contrasting patterns across all variables, except for presenteeism, employer, and self-employed. For example, OLS estimations with controls suggest that increasing one point in the CES-D7 scale is associated with a decrease in the likelihood of employment of 0.00207pp, while the IV estimation suggests that there is an increase on the likelihood of employment of 0.0275pp, close to the coefficient of the IDID model (0.0229pp). In contrast, column (2) of Panel B shows that suffering depression increases the likelihood of being self-employed by 0.0133pp, and columns (3) and (4) also suggest an increase in the probability of being self-employed (0.152pp and 0.258pp) although the magnitudes are greater. However, no statistically significant effects are observed, except for presenteeism, with both endogenous variables and in both models.

In Panel A, the coefficient for presenteeism indicates that a 1-point increase in the CES-D7 score raises the probability of experiencing presenteeism by 0.0455pp in the IV model and by 0.0376pp in the IDID model. Conversely, as demonstrated in Panel B, having depression increases the probability of presenteeism by 0.548pp and 0.509pp in the IV and IDID models, respectively. In terms of elasticity, a 1% increase in the

Table 7: First stage regression results by gender

	Female		Male	
Instruments	IV	IDID	IV	IDID
Panel A. Dependent variable: CES-D7 score				
Attack/violence	2.148***		1.287***	
	(0.683)		(0.257)	
Covid deaths per state ≥ 3,000		0.537***		0.565***
		(0.163)		(0.154)
Constant	7.742***	7.330***	6.286***	5.901***
	(0.276)	(0.322)	(0.260)	(0.286)
Observations	56,153	56,153	39,347	39,347
R-squared	0.034	0.030	0.019	0.016
F	14.75	14.90	5.204	5.163
Panel B. Dependent variable: Depression				
Attack/violence	0.160***		0.0930***	
	(0.0598)		(0.0262)	
Covid deaths per state ≥ 3,000		0.0360**		0.0463***
		(0.0177)		(0.0150)
Constant	0.255***	0.228***	0.156***	0.124***
	(0.0268)	(0.0313)	(0.0250)	(0.0279)
Observations	56,153	56,153	39,347	39,347
R-squared	0.053	0.051	0.033	0.032
F	20.44	19.23	10.03	10.33

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Both estimations include the sociodemographic variables, except the sex dummy, as controls and fixed effects of year and state. For females, the mean CES-D7 score is 6.21 and the mean for depression is 0.25. For males, the respective means are 4.96 and 0.13.

CES-D7 score increases the probability of having presenteeism by 5.82%; and a 1% increase in the probability of having depression, increases the probability of having presenteeism by 1.75%. It is noteworthy that the magnitudes and directions of the coefficients closely resemble those of the OLS with controls.

Given the absence of significant effects apart from presenteeism, the gender analysis concentrated on employment status and presenteeism. Table 9 presents the results for the female sample. Again, no statistically significant effects where found on employment status, but the IV and IDID results suggest that there is a positive relationship between and increase in the CES-D7 score or depression with the probability of being employed. The presenteeism coefficient in Panel A implies that an increase of 1 point in the CES-D7 score raises the probability of presenteeism by 0.035pp in the IV model with a 5% significance and by 0.041pp in the IDID model with a 1% significance. Furthermore, having depression implies an increase of 0.44pp (IV) and 0.62pp (IDID) in the likelihood of experiencing presenteeism, although the IV coefficient is marginally significant. In terms of elasticity, these results suggest that a 1% increase in the probability of having depression increases the probability of having presenteeism by approximately 3.1%.

In Table 10, the results for the IDID estimations are displayed alongside the OLS with and without controls since there was no first-stage for the IV model using the male subsample. Although the coefficients for presenteeism are statistically significant and positive, they exhibit lower magnitudes compared to females. The presenteeism coefficient in Panel A implies that an increase of 1 point in the CES-D7 score raises the probability of presenteeism by 0.033pp in the IDID model with a 5% significance, similar magnitude as columns (1) and (2). Coefficient for presenteeism in Panel B implies that having depression increases the likelihood of experiencing presenteeism by 0.402pp at the 5% significance level.

In terms of elasticity, these results suggest that a 1% increase in the probability of having depression increases the probability of having presenteeism by approximately 3.1% for females. Conversely, for men, a 1% increase in the probability of having

Table 8: OLS, second stage 2SLS and instrumented DID regression results

Dependant variable	(1) OLS	(2) OLS with controls	(3) IV	(4) IDID	Mean
Panel A. Endogenous variable: CES-D7 score					
Employment status	-0.0131***	-0.00207***	0.0275	0.0229	0.646
	(0.000834)	(0.000782)	(0.0212)	(0.0251)	
Labor force participation	-0.0126***	-0.000843	0.0259	0.0422*	0.667
	(0.000827)	(0.000736)	(0.0210)	(0.0250)	
Formal worker	-0.00871***	-0.00370***	0.0236	-0.0255	0.423
	(0.00112)	(0.00103)	(0.0257)	(0.0416)	
Presenteeism	0.0435***	0.0436***	0.0455**	0.0376***	0.0443
	(0.000631)	(0.000640)	(0.0188)	(0.0103)	
Employee	-0.0112***	-0.00190**	0.0323	0.0123	0.413
	(0.000812)	(0.000794)	(0.0219)	(0.0280)	
Employer	-0.000404***	-0.000104	-0.00148	0.00294	0.00947
	(0.000134)	(0.000128)	(0.00222)	(0.00518)	
Self-employed	0.00164***	0.00170***	0.0112	0.0191	0.172
	(0.000637)	(0.000641)	(0.0126)	(0.0208)	
Panel B. Endogenous variable: Depression					
Employment status	-0.125***	-0.0353***	0.372	0.310	0.646
	(0.00784)	(0.00731)	(0.299)	(0.350)	
Labor force participation	-0.124***	-0.0281***	0.350	0.571	0.667
	(0.00778)	(0.00690)	(0.293)	(0.368)	
Formal worker	-0.0767***	-0.0205**	0.335	-0.299	0.423
	(0.0102)	(0.00952)	(0.375)	(0.495)	
Presenteeism	0.329***	0.330***	0.548**	0.509***	0.0443
	(0.00671)	(0.00685)	(0.247)	(0.165)	
Employee	-0.122***	-0.0309***	0.438	0.166	0.413
	(0.00740)	(0.00734)	(0.307)	(0.381)	
Employer	-0.00170	7.67e-05	-0.0200	0.0398	0.00947
	(0.00127)	(0.00126)	(0.0302)	(0.0705)	
Self-employed	0.0270***	0.0133**	0.152	0.258	0.172
	(0.00636)	(0.00628)	(0.173)	(0.287)	
N	95,500	95,500	95,500	95,500	

Notes: Column (1) shows the estimates of an OLS regression without controls. Columns (2), (3) and (4) include controls and fixed effects of year and state. Columns (3) and (4) show the 2SLS estimates for the IV and IDID models. The variable *Presenteeism* takes the value of 1 if the person had difficulty concentrating on what they were doing and felt that everything was an effort for 3 days or more. Note: An incident involving a child at home was used as the instrument for the presenteeism variable since the violence variable could have issues with reverse causality. The F-statistic of the first stage is 42.80 and the first-stage results can be found in Panel A of Table A4 on the Appendix. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

depression increases the probability of having presenteeism by 1.3%. These results are in concordance to those found by Bubonya et al., 2017, where they found that women experience an increase of 6.9% in the odds of having presenteeism due to poor mental health, while for men the increase is of 6.1%. Although the results are not directly comparable, the coefficients are significant and positive, and women experience larger effects too.

It is noteworthy that, while there is no significant effect for employment status, the direction of the relationship is opposite for females and males, suggesting a positive association between employment and depression for women and a negative association for men. For females, a 1% increase in the probability of depression is associated with a 0.29% increase in the probability of employment. For men, a 1% increase in the probability of depression is associated with a 0.019% decrease in the probability of being employed.

Table 9: OLS and second stage 2SLS regression results - females

Dependant variable	(1) OLS	(2) OLS with controls	(3) IV	(4) IDID	Mean
Panel A. Endogenous variable: CES-D7 score					
Employment status	-0.00154	0.000816	0.0441	0.0535	0.443
	(0.00101)	(0.00104)	(0.0392)	(0.0390)	
Presenteeism	0.0471***	0.0470***	0.0346**	0.0415***	0.088
	(0.000736)	(0.000728)	(0.0169)	(0.0155)	
Panel B. Endogenous variable: Depression					
Employment status	-0.0366***	-0.0178*	0.593	0.799	0.443
	(0.00934)	(0.00947)	(0.556)	(0.678)	
Presenteeism	0.344***	0.345***	0.443*	0.620**	0.088
	(0.00803)	(0.00806)	(0.233)	(0.313)	
N	56,153	56,153	56,153	56,153	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Column (1) shows the estimates of an OLS regression without controls. Columns (2) and (3) include controls and fixed effects of year and state. Column (3) shows the 2SLS estimates for the IV model. The variable *Presenteeism* takes the value of 1 if the person had difficulty concentrating on what they were doing and felt that everything was an effort for 3 days or more. Note: An incident involving a child at home was used as the instrument for the presenteeism variable since the violence variable could have issues with reverse causality. The F-statistic of the first stage is 18.92 and can be found in Panel B of Table A4 on the Appendix.

Table 10: OLS and second stage 2SLS regression results - males

Dependant variable	(1) OLS	(2) OLS with controls	(3) IDID	Mean
Panel A. Endogenous variable: CES-D7 score				
Employment status	-0.00597***	-0.00604***	-0.00998	0.884
	(0.00117)	(0.00115)	(0.0300)	
Presenteeism	0.0368***	0.0369***	0.0329**	0.040
	(0.00120)	(0.00120)	(0.0129)	
Panel B. Endogenous variable: Depression				
Employment status	-0.0468***	-0.0546***	-0.122	0.884
	(0.0106)	(0.0105)	(0.365)	
Presenteeism	0.296***	0.299***	0.402**	0.040
	(0.0122)	(0.0124)	(0.162)	
N	39,347	39,347	39,347	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Column (1) shows the estimates of an OLS regression without controls. Columns (2) and (3) include controls and fixed effects of year and state. Column (3) shows the 2SLS estimates for the IV model. The variable *Presenteeism* takes the value of 1 if the person had difficulty concentrating on what they were doing and felt that everything was an effort for 3 days or more.

Heterogeneity effects

Given the absence of significant effects apart from presenteeism, the heterogenous effects analysis is also concentrated on employment status and presenteeism.

Age groups

In Figure 4 the coefficients for the 2SLS estimates for employment status are shown for different age groups. The figure was created by estimating the IV model with controls and fixed effects by year and state for each age subsample, then the coefficients of depression on employment status for each age group were plotted. Although the effects are not significant and are quite noisy with large confidence intervals, the results suggest that there is a positive relationship between depression and employment and this relation is stronger among the youngest and oldest groups, while the middle-age groups hold a smaller relation.

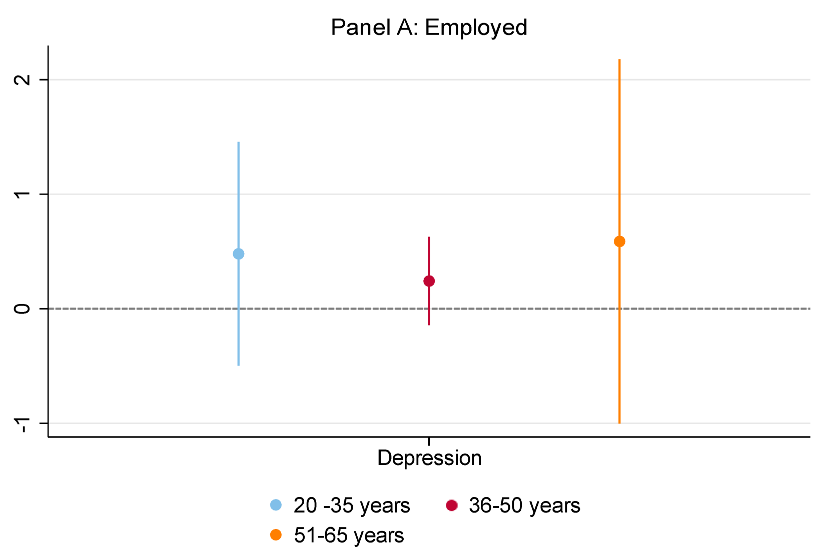
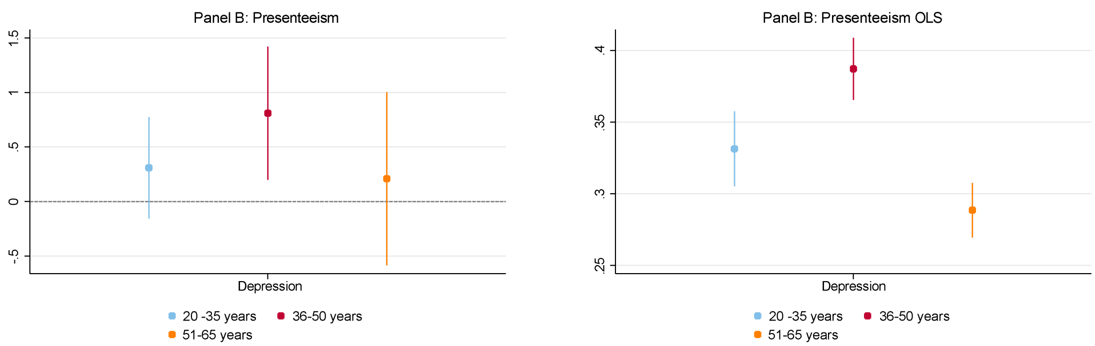


Figure 4: Effect of depression on employment status by age group - 2SLS

Figure 5 presents the effect of depression on presenteeism by age group. Estimates of the main results showed that OLS, IV and IDID yielded very similar results, and since the instruments does not work well for every subsample, the OLS estimates are shown in 5b along with the IDID results in 5a. In both figures, it can be appreciated that the most affected group is the middle-aged followed by the youngest. This means that having depression increases the likelihood of having presenteeism- not being able to concentrate and feel like everything is an effort during 3 or more days a week- in greater magnitude for people aged between 36 and 50 years. This raises concern since there is a greater proportion of middle-aged people inside the workforce, which could affect the productivity and production.



(a) IDID

(b) OLS

Figure 5: Effect of depression on preseenteism by age group

Sociodemographic groups

In Figure 6, the effects of depression on employment status across sociodemographic groups are depicted. While the coefficients lack significance, it is noteworthy that a consistent pattern emerges - the same observed in Tables 9 and 10: males exhibit a negative association between depression and employment, whereas the opposite holds true for females. This trend persists across all educational and age groups.

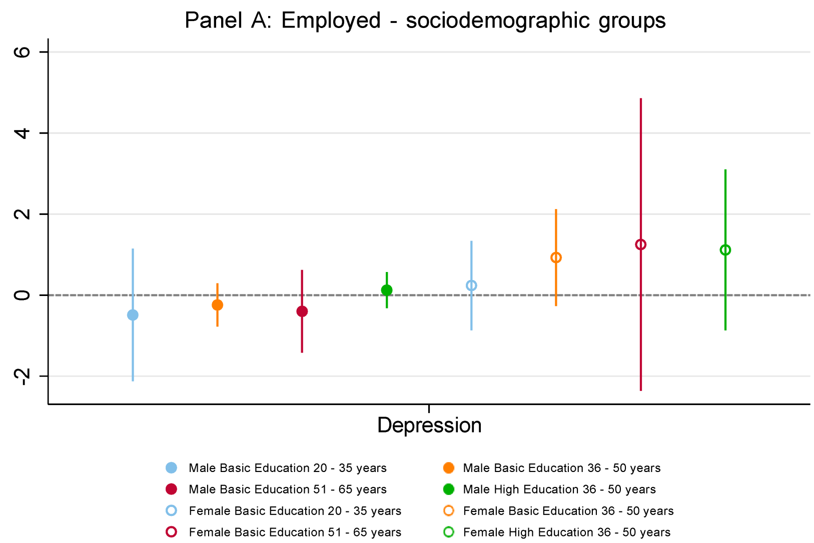


Figure 6: Effects of depression on presenteeism by sociodemographic group - 2SLS [8]

For presenteeism, the instrument lacked validity across most groups, thus only the OLS coefficients are depicted in Figure 7 to highlight the diversity in effects on this variable. The more affected groups are Male and Female with Basic Education 36-50 years, Male and Female with High Education 36-50 years, and Male and Female with Basic Education 20-35 years. These findings align with the earlier results, indicating that individuals in the middle age range exhibit the greatest likelihood of experiencing presenteeism if they are affected by depression and that, in general, women are more affected by depressive symptoms.

[8]The sociodemographic groups with very large confidence intervals were omitted; the graph including all sociodemographic groups can be found in the Appendix.

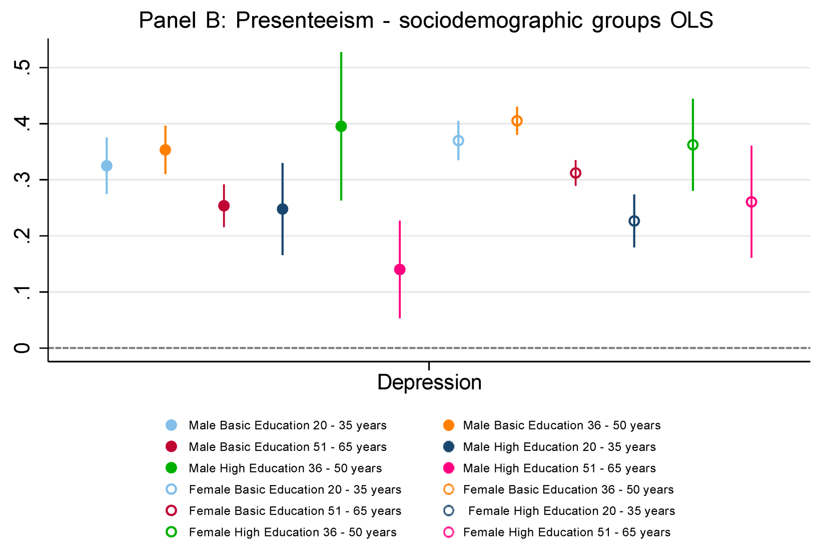


Figure 7: Effects of depression on presenteeism by sociodemographic group - OLS

6 Further evidence for the reliability of the instruments

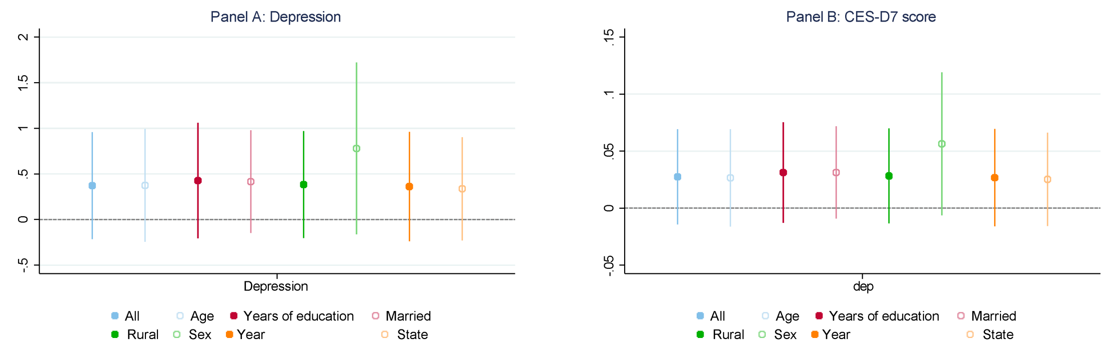
A number of arguments about the validity of the instruments used has been provided. In this section further evidence about the validity and reliability of the instrument is shown to provide more support to the IV and IDID estimations.

Omitted variable bias

One way to infer the size of potential bias due to unkown characteristics of the individual that affect depression is to examine how the results are affected if the observable characteristics are omitted one by one sequentially from the baseline models.

Figure 8 illustrates the simulation of omitted variable bias for the IV estimation. Each dot in the graphs represents the coefficient for depression (Figure 8a) or the CES-D7 score (Figure 8b) on employment when excluding the corresponding control variable such as years of education, married, or sex. The caps around the dots represent the 95% confidence interval. Overall, the estimates do not vary significantly when each set of observed individual characteristic or fixed effects by year or state are excluded. This means that the instruments is not affected by the excluded variable and gives confidence that the exclusion restriction is satisfied because if the instrument is not correlated with observable characteristics that affect both mental health and labor market outcomes it is believed that is also not correlated with unobservable factors or that the bias is not significant. The first dot is the baseline model with all the controls included, and no significant differences are observed. For Figure 8a in most cases the differences point estimates are less than 10% or 5% [9], suggesting characteristics of the individual are not likely affecting the instrument as unobserved omitted variables (Maruyama and Heinesen, 2020; Shen, 2023). For Figure 8b similar results can be seen, in most cases the differences in point estimates are 0.1% or less than 0.3%. The significance and signs are unaffected, although when excluding the sex dummy for both endogenous variables the difference is statistically significant for the IV model, suggesting that sex could be affecting the instrument as unobservable omitted variable. This result does not suggest that the instrument is invalid nor that there are possible unobserved factors that could be biasing the results because it has been documented that women are more affected by direct and indirect violence (Javdani et al., 2014), so when excluding the sex dummy it biases the results upward because being female is related with having less probability of employment and is correlated with the instrument.

[9] In Panel A and Panel B of Table A7 the coefficients of all the estimations excluding covariates are shown.



(a) Depression

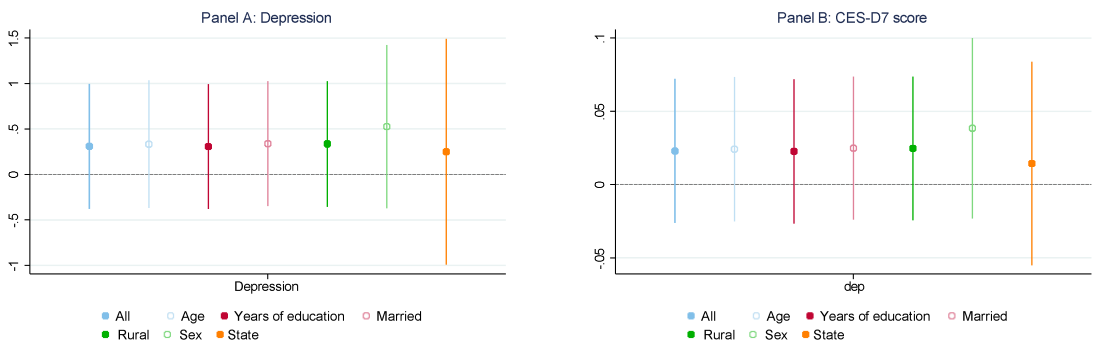
(b) CES-D7 score

Figure 8: Omitted variable bias simulation for IV instrument

Figure 9 shows the same simulation of omitted variable bias for the IDID estimations. In this case, the year dummies where not excluded since they are obviously correlated with the instrument because covid deaths only occurred after the year 2020. Again, each dot in the graphs represents the coefficient for depression (Figure 9a) or the CES-D7 score (Figure 9b) on employment when excluding the corresponding control variable such as years of education, married, or sex. The caps around the dots represent the 95% confidence interval. Overall, the estimates do not vary significantly when each set of observed individual characteristic or fixed effects by year or state are excluded. The first dot is the baseline model with all the controls included, and no significant differences are observed. For Figure 9a in all cases the differences point estimates are less than 10% and most are below 5% [10], suggesting characteristics of the individual are not likely affecting the instrument as unobserved omitted variables. For Figure 8b similar results can be seen, in most cases the differences in point estimates are 0.1% or less than 0.3%. The only significant difference found is again when excluding the sex dummy. It has been found that women have more sentiments of worry and are more affected about health shocks, especially for mothers (Eriksen et al., 2021; Eriksen et al., 2016; Kristofferzon et al., 2003; Herrera-Añazco et al., 2022) which sheds light on this

[10]In Panel C and Panel D of Table A7 the coefficients of all the estimations excluding covariates are shown.

important correlation between covid deaths, depression and gender (Pieh et al., 2020). This relation does not mean that the instrument is invalid or that the estimates could be significantly biased by unobserved factors.



(a) Depression (b) CES-D7 score

Figure 9: Omitted variable bias simulation for IDID instrument

The same simulations where made for the IV and IDID estimations of depression on presenteeism. The results are shown in Table A8 and Figure A2 on the Appendix. Overall the results suggest that the instruments are valid and are not probable to be affected by unobserved characteristics. Furthermore, the estimations remain very similar between specifications.

Placebo tests

Table 11 shows placebo test that provide additional support for the validity of the instruments. In columns (1) and (2) the baseline estimations from the first stage of the instruments on depression and CES-D7 score are presented, and in column (3) the coefficient is the regression of the instruments on diabetes, a physical health measure. While it is expected that the violence or attack suffered from a member of the household to impact the depression score and the probability of suffering moderate or severe depressive symptoms it is not expected to affect the physical health of the individual that is not a wound or any injury directly related to the attack if the individual was the one who suffered the violence directly. This is shown in Panel A of Table 11 , the instrument used in the IV model has a positive and statistically significant effect in both the depression dummy and the CES-D7 score while it does not have a statistically significant effect on diabetes which is a chronic condition that is highly predicted by sociodemographic characteristics (Cutler and Lleras-Muney, 2010; Cutler et al., 2008; Goldman and Smith, 2002). In Panel B of 11 the same is shown using as instrument the dummy for covid deaths per state ≥ than 3,000, there is a significant and positive effect on depression and CES-D7 but no effect on Diabetes. If the instruments simply reflected unobservable heterogeneity then we would expect these unobservable heterogeneties to impact upon both physical and mental health (Frijters et al., 2014).

Table 11: Placebo test for instruments

VARIABLES	(1) Depression	(2) CES-D7	(3) Diabetes
Panel A: Instrumental variables estimation			
Attack/violence	0.124***	1.680***	0.0416
	(0.0321)	(0.357)	(0.0350)
Constant	0.149***	6.433***	-0.143***
	(0.0186)	(0.192)	(0.0140)
Observations	95,500	95,500	95,500
R-squared	0.066	0.053	0.081
F	44.45	34.75	44.64
Panel B: Instrumented differences-in-differences estimation			
Covid deaths per state ≥ 3,000	0.0406***	0.549***	0.00411
	(0.0118)	(0.113)	(0.00833)
Constant	0.121***	6.045***	-0.146***
	(0.0211)	(0.218)	(0.0152)
Observations	95,500	95,500	95,500
R-squared	0.064	0.050	0.080
F	43.92	35.91	29.21

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The placebo tests presented in this section along with the results of the omitted variable simulation, enhance confidence in the validity of the instruments used in this research. They also provide assurance that the results are robust and that the IV and IDID estimates are valid.

7 Discussion

This research has contributed to establishing a causal relationship between depression and labor outcomes in a middle-income country through a methodology of instrumental variables and instrumented difference-in-differences. The instruments used were violence or attack suffered by a household member during the past year, and living in a state with more than 3,000 COVID-19 deaths. These are external variables not directly affected by individual characteristics, contrary to variables used as instruments in other studies, such as religiosity, social support, or family member(s) with mental health issues.

The main findings suggest that having depression or increasing the score of the CES-D7 scale has no effect on the extensive margin of labor supply, contrary to most of the existing research (Ettner et al., 1997; Chatterji et al., 2011; Michaelsen, 2012; Germinario et al., 2022; Shen, 2023; Bryan et al., 2022; Frijters et al., 2014; Peng et al., 2016; Chatterji et al., 2007. However, it is important to recall that all of these articles used data from developed countries, and the context varies greatly in a developing country, where the informal sector is significant, there is less access to medical services, people could be conscious about their own mental health status, or there could still be a lot of stigma regarding mental illness. The only comparable article found is the one by Michaelsen, 2012, also for Mexico, although the instruments used could produce biased estimates because ongoing violence and homicides related to drug trafficking could directly affect employment decisions, and the instrument resulted not valid for females. On the contrary, the instruments used in the present research appear to be more reliable and are valid for the whole sample.

Additionally, the results for *presenteeism* suggest that there is an effect on the intensive margin of labor supply. A recommendation to the National Institute of Statistics and Geography (INEGI in Spanish) is extended to include variables about individual earnings and hours worked per week again in the ENSANUT questionnaires, as these were removed from the 2020 survey. Also, it could contribute to the literature about the effects of mental health on labor market outcomes to include variables about absenteeism in the workplace to analyze how depression affects people already inside the labor force.

Moreover, the coefficients for men and women, although not significant, show opposite signs. These results could be explained by depression in men being associated with aggressive behaviors, while depressive symptoms in women could be related to prosocial behaviors (Alarcón and Forbes, 2017; Piccinelli and Wilkinson, 2000). These findings are similar to the majority of those found in the literature that include heterogeneity effects by gender - there are no effects of mental disorders on employment for females (Shen, 2023; Michaelsen, 2012; Ringdal and Rootjes, 2022). However, the effects on presenteeism are higher for women, in accordance with the investigation of Bubonya et al., 2017 that found that depression diminishes productivity, especially for women. The heterogeneous effects by age and sociodemographic groups indicate that middle-aged people and the youngest are more affected by depression - with greater effects on presenteeism. This finding is in accordance with the new findings of Blanchflower et al., 2024 that the change in the hump-shape for ill-being by age has been replaced by a monotonic decreasing relationship between ill-being and age driven particularly by an increasing deterioration in the mental well-being of the youngest generations. Also, it is interesting to note that for all age groups, the results suggest a positive relationship between depression and employment, contrary to previous findings. This result could be explained by coping strategies, and that being employed might reduce or "alleviate" depressive symptoms, especially for women who - when experiencing depressive symptoms - tend to enroll in more social activities.

Overall, this research contributes to a more nuanced understanding of how mental health issues intersect with labor market dynamics in developing countries. The findings advocate for targeted mental health policies and improved data collection to better address the complex interplay between depression and employment.

8 Conclusion

Despite existing literature establishing a causal effect of depression or poor mental health on employment, this has primarily focused on developed countries. No evidence of this causal relationship has been found in developing countries. It is important to consider that contexts matter and play a role in people´s experiences and feelings, making it relevant to analyze the case of developing countries.

For this reason, this research contributes to the existing gap of the relationship between mental health and labor market outcomes in a developing country. The results show differences with the ones found in previous literature, suggesting that maybe, in the case of developing countries, the strong causal relationship is from employment or socioeconomic status to depression or poor mental health, and conversely, the effect is null or very low.

Although the methods used in this research are powerful and appear to be robust it is important to consider the limitations of the investigation. One possible limitation is the instrument used for the IV estimation. Although it yielded similar results to the IDID estimations, the incidence of the instrument is very low, meaning that the Local Average Treatment Effect (LATE)- the average treatment effect for the subset of the population whose treatment status is affected by an instrumental variable- only is valid for a very little part of the population. There is also a need for more variables included in the survey that can be used as valid instruments that affect a greater portion of the population. Another potential limitation is the measurement of depression. Although the CES-D7 scale is validated and generally reliable, it may not be as reliable for the Mexican population and could be subject to measurement errors. Men might under-report depressive symptoms due to shame and social norms that dictate men should not show their feelings and should appear strong at all times. Conversely, women might over-report depressive symptoms due to persistent and high levels of violence against women in Mexico and significant gender disparities in various aspects of life, which could cause systematic measurement errors in depression reporting. These considerations should be taken into account in future research to develop reliable tools for measuring depression in contexts like Mexico, where social problems such as inequality and ongoing violence could bias the results.

Additionally, different mental disorders should be included in ENSANUT, along with variables for individual earnings, hours worked, absenteeism, and variables that can be used as instruments. This would enable future research to analyze the effects of various mental health issues on labor market outcomes and life decisions of the Mexican population, considering possible heterogeneous effects by gender, age, and education level. Obtaining more robust results will be crucial for making policy recommendations aimed at reducing mental illness and improving the quality of life and productivity of individuals experiencing mental disorders.

References

Abramovitch, A., Short, T., & Schweiger, A. (2021). The c factor: Cognitive dysfunction as a transdiagnostic dimension in psychopathology. *Clinical Psychology Review*, *86*, 102007.

Abramson, B., Boerma, J., & Tsyvinski, A. (2024). *Macroeconomics of mental health* (tech. rep.). National Bureau of Economic Research.

Alarcón, G., & Forbes, E. E. (2017). Prosocial behavior and depression: A case for developmental gender differences. *Current behavioral neuroscience reports*, *4*, 117–127.

Ali, G.-C., Ryan, G., & De Silva, M. J. (2016). Validated screening tools for common mental disorders in low and middle income countries: A systematic review. *PloS one*, *11* (6), e0156939.

Ananat, E. O., Gassman-Pines, A., Francis, D. V., & Gibson-Davis, C. M. (2017). Linking job loss, inequality, mental health, and education. *Science*, *356* (6343), 1127–1128.

Andersen, 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.

Angrist, J. D., & Imbens, G. W. (1995). Two-stage least squares estimation of average causal effects in models with variable treatment intensity. *Journal of the American statistical Association*, *90* (430), 431–442.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Baranov, V., Bhalotra, S., Biroli, P., & Maselko, J. (2020). Maternal depression, women's empowerment, and parental investment: Evidence from a randomized controlled trial. *American economic review*, *110* (3), 824–859.

Barker, N., Bryan, G., Karlan, D., Ofori-Atta, A., & Udry, C. (2022). Cognitive behavioral therapy among ghana's rural poor is effective regardless of baseline mental distress. *American Economic Review: Insights*, *4*(4), 527–545.

Bartel, A., & Taubman, P. (1979). Health and labor market success: The role of various diseases. *The Review of Economics and Statistics*, 1–8.

Batool, F. (2020). Gender discrimination at workplace and mental health of women: A systematic literature review. *PalArch's Journal of Archaeology of Egypt/Egyptology*, *17*(8), 622–633.

Bauermeister, S., & Bunce, D. (2015). Poorer mental health is associated with cognitive deficits in old age. *Aging, Neuropsychology, and Cognition*, *22*(1), 95–105.

Bhat, B., De Quidt, J., Haushofer, J., Patel, V. H., Rao, G., Schilbach, F., & Vautrey, P.-L. P. (2022). *The long-run effects of psychotherapy on depression, beliefs, and economic outcomes* (tech. rep.). National Bureau of Economic Research.

Biasi, B., Dahl, M. S., & Moser, P. (2021). *Career effects of mental health* (tech. rep.). National Bureau of Economic Research.

Blanchflower, D. G., Bryson, A., & Xu, X. (2024). *The declining mental health of the young and the global disappearance of the hump shape in age in unhappiness* (tech. rep.). National Bureau of Economic Research.

Brück, T., & Müller, C. (2010). Comparing the determinants of concern about terrorism and crime. *Global Crime*, *11*(1), 1–15.

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.

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.

Bunce, D., Tzur, M., Ramchurn, A., Gain, F., & Bond, F. W. (2008). Mental health and cognitive function in adults aged 18 to 92 years. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *63*(2), P67–P74.

Bütikofer, A., Ginja, R., Karbownik, K., & Landaud, F. (2024). (breaking) intergenerational transmission of mental health. *Journal of Human Resources*, *59* (S), S108–S151.

Case, A., Lubotsky, D., & Paxson, C. (2002). Economic status and health in childhood: The origins of the gradient. *American Economic Review*, *92* (5), 1308–1334.

Chatterji, P., Alegria, M., Lu, M., & Takeuchi, D. (2007). Psychiatric disorders and labor market outcomes: Evidence from the national latino and asian american study. *Health economics*, *16* (10), 1069–1090.

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.

Chisholm, D., Sweeny, K., Sheehan, P., Rasmussen, B., Smit, F., Cuijpers, P., & Saxena, S. (2016). Scaling-up treatment of depression and anxiety: A global return on investment analysis. *The Lancet Psychiatry*, *3* (5), 415–424.

Cornaglia, F., Feldman, N. E., & Leigh, A. (2014). Crime and mental well-being. *Journal of human resources*, *49* (1), 110–140.

Culbertson, F. M. (1997). Depression and gender: An international review. *American Psychologist*, *52* (1), 25.

Cutler, D. M., & Lleras-Muney, A. (2010). Understanding differences in health behaviors by education. *Journal of health economics*, *29* (1), 1–28.

Cutler, D. M., Lleras-Muney, A., & Vogl, T. (2008). Socioeconomic status and health: Dimensions and mechanisms.

De Jong, J. T., Komproe, I. H., & Van Ommeren, M. (2003). Common mental disorders in postconflict settings. *The lancet*, *361* (9375), 2128–2130.

Del Valle, A. (2021). The effects of public health insurance in labor markets with informal jobs: Evidence from mexico. *Journal of Health Economics*, *77*, 102454.

de Mola, C. L., Carpena, M. X., Gonçalves, H., de Avila Quevedo, L., Pinheiro, R., dos Santos Motta, J. V., & Horta, B. (2020). How sex differences in schooling and income contribute to sex differences in depression, anxiety and common mental disorders: The mental health sex-gap in a birth cohort from brazil. *Journal of Affective Disorders*, *274*, 977–985.

de Salud, S. (n.d.). *2° diagnóstico operativo de salud mental y adicciones*. https://www.gob.mx/cms/uploads/attachment/file/730678/SAP-DxSMA-Informe-2022-rev07jun2022.pdf (accessed: 23.05.2024).

DGE. (n.d.). *Datos abiertos dirección general de epidemiología*. https://www.gob.mx/salud/documentos/datos-abiertos-152127 (accessed: 03.04.2024).

DiazOrdaz, K. (2023). Discussion on: Instrumented difference-in-differences, by ting ye, ashkan ertefaie, james flory, sean hennessy and dylan s. small. *Biometrics*, *79* (2), 597–600.

Doubova, S. V., Ortiz-Panozo, E., & Pérez-Cuevas, R. (2023). The neglected problem of obesity during pregnancy in mexico: Secondary data analysis of the 2018 national survey of health and nutrition. *Maternal and Child Health Journal*, *27* (1), 70–81.

Eriksen, T. L. M., Gaulke, A., Skipper, N., & Svensson, J. (2021). The impact of childhood health shocks on parental labor supply. *Journal of Health Economics*, *78*, 102486.

Eriksen, T. L. M., Hogh, A., & Hansen, Å. M. (2016). Long-term consequences of workplace bullying on sickness absence. *Labour Economics*, *43*, 129–150.

Ettner, S. L., Frank, R. G., & Kessler, R. C. (1997). The impact of psychiatric disorders on labor market outcomes. *ILR Review*, *51* (1), 64–81.

for Economic Co-operation, O., & Development. (2015). *Fit mind, fit job: From evidence to practice in mental health and work*. OECD Publishing.

Frijters, P., Johnston, D. W., & Shields, M. A. (2014). The effect of mental health on employment: Evidence from australian panel data. *Health economics*, *23* (9), 1058–1071.

Galindo, J. (n.d.). *El costo de la salud mental, ¿cuánto cuesta ir al psicólogo?* https://www.eleconomista.com.mx/finanzaspersonales/El-costo-de-la-salud-mental-Cuanto-cuesta-ir-al-psicologo-20220222-0084.html (accessed: 26.05.2024).

Germinario, G., Amin, V., Flores, C. A., & Flores-Lagunes, A. (2022). What can we learn about the effect of mental health on labor market outcomes under weak assumptions? evidence from the nlsy79. *Labour Economics*, *79*, 102258.

Giacaman, R., Shannon, H. S., Saab, H., Arya, N., & Boyce, W. (2007). Individual and collective exposure to political violence: Palestinian adolescents coping with conflict. *The European Journal of Public Health*, *17*(4), 361–368.

Golberstein, E., Gonzales, G., & Meara, E. (2016). *Economic conditions and children's mental health* (tech. rep.). National Bureau of Economic Research.

Goldman, D. P., & Smith, J. P. (2002). Can patient self-management help explain the ses health gradient? *Proceedings of the National Academy of Sciences*, *99* (16), 10929–10934.

González-Forteza, C., Solís Torres, C., Jiménez Tapia, A., Hernández Fernández, I., González-González, A., Juárez García, F., Medina-Mora, M. E., & Fernández-Várela Mejía, H. (2011). Confiabilidad y validez de la escala de depresión ces-d en un censo de estudiantes de nivel medio superior y superior, en la ciudad de méxico. *Salud mental*, *34*(1), 53–59.

Gračner, T., Marquez-Padilla, F., & Hernandez-Cortes, D. (2022). Changes in weight-related outcomes among adolescents following consumer price increases of taxed sugar-sweetened beverages. *JAMA pediatrics*, *176*(2), 150–158.

Gunes, P. M., & Tsaneva, M. (2022). Labour market conditions and adult health in mexico. *Canadian Journal of Economics/Revue canadienne d'économique*, *55* (1), 106–137.

Haushofer, J., Mudida, R., & Shapiro, J. P. (2020). *The comparative impact of cash transfers and a psychotherapy program on psychological and economic well-being* (tech. rep.). National Bureau of Economic Research.

Haushofer, J., & Salicath, D. (2023). The psychology of poverty: Where do we stand? *Social Philosophy and Policy*, *40*(1), 150–184.

Herrera-Añazco, P., Urrunaga-Pastor, D., Benites-Zapata, V. A., Bendezu-Quispe, G., Toro-Huamanchumo, C. J., & Hernandez, A. V. (2022). Gender differences in depressive and anxiety symptoms during the first stage of the covid-19 pandemic: A cross-sectional study in latin america and the caribbean. *Frontiers in Psychiatry*, *13*, 727034.

Hoedeman, R. (2012). Oecd. sick on the job? myths and realities about mental health and work. parijs: Oecd publishing, 2012. *Tbv–tijdschrift Voor Bedrijfs-En Verzekeringsgeneeskunde*, *20*, 234–235.

Hudson, S., Hull, P., & Liebersohn, J. (2017). Interpreting instrumented difference-in-differences. *Metrics Note, Sept*.

Javdani, S., Abdul-Adil, J., Suarez, L., Nichols, S. R., & Farmer, A. D. (2014). Gender differences in the effects of community violence on mental health outcomes in a sample of low-income youth receiving psychiatric care. *American journal of community psychology*, *53*, 235–248.

Jokela, M. (2022). Why is cognitive ability associated with psychological distress and wellbeing? exploring psychological, biological, and social mechanisms. *Personality and Individual Differences*, *192*, 111592.

Kessler, R. C., Heeringa, S., Lakoma, M. D., Petukhova, M., Rupp, A. E., Schoenbaum, M., Wang, P. S., & Zaslavsky, A. M. (2008). Individual and societal effects of mental disorders on earnings in the united states: Results from the national comorbidity survey replication. *American Journal of Psychiatry*, *165* (6), 703–711.

Knapp, M., & Wong, G. (2020). Economics and mental health: The current scenario. *World Psychiatry*, *19* (1), 3–14.

Kristofferzon, M.-L., Löfmark, R., & Carlsson, M. (2003). Myocardial infarction: Gender differences in coping and social support. *Journal of advanced nursing*, *44* (4), 360–374.

Kroenke, K., & Spitzer, R. L. (2002). The phq-9: A new depression diagnostic and severity measure.

Landa-Blanco, M., Mejía, C. J., Landa-Blanco, A. L., Martínez-Martínez, C. A., Vásquez, D., Vásquez, G., Moraga-Vargas, P., Echenique, Y., Del Cid, G. M., & Montoya,

B. D. (2021). Coronavirus awareness, confinement stress, and mental health: Evidence from honduras, chile, costa rica, mexico and spain. *Social science & medicine*, *277*, 113933.

Lauretta, A. (n.d.). *How much does therapy cost in 2024?* https://www.forbes.com/health/mind/how-much-does-therapy-cost/ (accessed: 26.05.2024).

Levine, S. Z. (2013). Evaluating the seven-item center for epidemiologic studies depression scale short-form: A longitudinal us community study. *Social psychiatry and psychiatric epidemiology*, *48*, 1519–1526.

Lund, C., Orkin, K., Witte, M., Walker, J. H., Davies, T., Haushofer, J., Murray, S., Bass, J., Murray, L., Tol, W., et al. (2024). *The effects of mental health interventions on labor market outcomes in low-and middle-income countries* (tech. rep.). National Bureau of Economic Research.

Marcotte, D. E., & Wilcox-Gok, V. (2003). Estimating earning losses due to mental illness: A quantile regression approach. *Journal of Mental Health Policy and Economics*, *6* (3), 123–134.

Maruyama, S., & Heinesen, E. (2020). Another look at returns to birthweight. *Journal of Health Economics*, *70*, 102269.

McDaid, D., Park, A.-L., & Wahlbeck, K. (2019). The economic case for the prevention of mental illness. *Annual review of public health*, *40*, 373–389.

Michaelsen, M. M. (2012). Mental health and labour supply–evidence from méxico's ongoing violent conflicts. *Ruhr Economic Paper*, (378).

Molina, A. (n.d.). *La importancia de la salud mental*. https://www.espm.mx/blog/importancia-salud-mental/ (accessed: 23.05.2024).

Murthy, R. S., & Lakshminarayana, R. (2006). Mental health consequences of war: A brief review of research findings. *World psychiatry*, *5* (1), 25.

OECD. (2021). *Fitter minds, fitter jobs: From awareness to change in integrated mental health, skills and work policies*.

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.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, *37* (2), 187–204.

Patel, V., Araya, R., Chowdhary, N., King, M., Kirkwood, B., Nayak, S., Simon, G., & Weiss, H. (2008). Detecting common mental disorders in primary care in india: A comparison of five screening questionnaires. *Psychological medicine*, *38* (2), 221–228.

Peng, L., Meyerhoefer, C. D., & Zuvekas, S. H. (2016). The short-term effect of depressive symptoms on labor market outcomes. *Health Economics*, *25* (10), 1223–1238.

Persson, P., & Rossin-Slater, M. (2018). Family ruptures, stress, and the mental health of the next generation. *American economic review*, *108* (4-5), 1214–1252.

Piccinelli, M., & Wilkinson, G. (2000). Gender differences in depression: Critical review. *The British Journal of Psychiatry*, *177* (6), 486–492.

Pieh, C., Budimir, S., & Probst, T. (2020). The effect of age, gender, income, work, and physical activity on mental health during coronavirus disease (covid-19) lockdown in austria. *Journal of psychosomatic research*, *136*, 110186.

Platt, J., Prins, S., Bates, L., & Keyes, K. (2016). Unequal depression for equal work? how the wage gap explains gendered disparities in mood disorders. *Social Science & Medicine*, *149*, 1–8.

Ponce-Alcala, R. E., Luna, J. L. R.-G., Shamah-Levy, T., & Melgar-Quiñonez, H. (2021). The association between household food insecurity and obesity in mexico: A cross-sectional study of ensanut mc 2016. *Public Health Nutrition*, *24* (17), 5826–5836.

Ridley, M., Rao, G., Schilbach, F., & Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*, *370* (6522), eaay0214.

Ringdal, C., & Rootjes, F. (2022). Depression and labor supply: Evidence from the netherlands. *Economics & Human Biology*, *45*, 101103.

Rivera-Hernandez, M., Rahman, M., Mor, V., & Galarraga, O. (2016). The impact of social health insurance on diabetes and hypertension process indicators among older adults in mexico. *Health Services Research*, *51* (4), 1323–1346.

Salinas-Rodríguez, A., Manrique-Espinoza, B., Acosta-Castillo, G. I., Franco-Núñez, A., Rosas-Carrasco, Ó., Gutiérrez-Robledo, L. M., & Sosa-Ortiz, A. L. (2014). Validación de un punto de corte para la versión breve de la escala de depresión del centro de estudios epidemiológicos en adultos mayores mexicanos. *salud pública de méxico*, *56* (3), 279–285.

Salinas-Rodríguez, A., Manrique-Espinoza, B., Acosta-Castillo, I., Téllez-Rojo, M. M., Franco-Núñez, A., Gutiérrez-Robledo, L. M., & Sosa-Ortiz, A. L. (2013). Validación de un punto de corte para la escala de depresión del centro de estudios epidemiológicos, versión abreviada (cesd-7). *salud pública de méxico*, *55*, 267–274.

Shen, Y. (2023). Mental health and labor supply: Evidence from canada. *SSM-Population Health*, *22*, 101414.

Smith, J. P. (2009). The impact of childhood health on adult labor market outcomes. *The review of economics and statistics*, *91* (3), 478–489.

Sosa-Rubi, S. G., Galárraga, O., & Harris, J. E. (2009). Heterogeneous impact of the "seguro popular" program on the utilization of obstetrical services in mexico, 2001–2006: A multinomial probit model with a discrete endogenous variable. *Journal of health economics*, *28* (1), 20–34.

Spitzer, R. L., Kroenke, K., Williams, J. B., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The gad-7. *Archives of internal medicine*, *166* (10), 1092–1097.

Stabridis, O., & van Gameren, E. (2018). Exposure to firewood: Consequences for health and labor force participation in mexico. *World development*, *107*, 382–395.

Staiger, D. O., & Stock, J. H. (1994). Instrumental variables regression with weak instruments.

Tuunainen, A., Langer, R. D., Klauber, M. R., & Kripke, D. F. (2001). Short version of the ces-d (burnam screen) for depression in reference to the structured psychiatric interview. *Psychiatry research*, *103* (2-3), 261–270.

Watson, B., & Osberg, L. (2018). Job insecurity and mental health in canada. *Applied Economics*, *50* (38), 4137–4152.

WHO. (2022). World mental health report: Transforming mental health for all.

Ye, T., Ertefaie, A., Flory, J., Hennessy, S., & Small, D. S. (2023). Instrumented difference-in-differences. *Biometrics*, *79*(2), 569–581.

Yu, S. (2018). Uncovering the hidden impacts of inequality on mental health: A global study. *Translational psychiatry*, *8*(1), 98.

Appendix

Creation of variables

As described in the main body of the research, the questionnaires used were: Household Questionnaire;Adults Questionnaire, ages 20 and older; Adolescents Questionnaire, ages 10-19; and Children Questionnaire, ages 0-9. The following outlines how the outcome variables, instruments, and control variables were created.

Outcome variables

- Employment status: dummy variable that takes the value of 1 if the respondent answered yes to the question: "Did you work at least one hour last week?" and 0 if the respondent answered that he did not work but was searching for a job (unemployed).

- Labor force participation: dummy variable that takes the value of 1 if the respondent is employed (worked at least an hour during the past week) or unemployed (did not work but was searching for a job), and 0 otherwise.[11]

- Formal worker: dummy variable that takes the value of 1 if the respondent was employed and answered to the question: "Do you receive for your work:" one or more of the next options: medical insurance (IMSS, ISSSTE or other).

- Employee: dummy variable that takes the value of 1 if the respondent answered "Employee or laborer?" to the question: "Last week, in your job, were you:" and takes the value of 0 otherwise.

- Employer: dummy variable that takes the value of 1 if the respondent answered "Employer or employer? (hires workers)" to the question: "Last week, in your job, were you:" and takes the value of 0 otherwise.

[11] It is important to mention that people with a disability were taken out of the sample.

- Self-employed: dummy variable that takes the value of 1 if the respondent answered "Self-employed? (does not hire workers)" to the question: "Last week, in your job, were you:" and takes the value of 0 otherwise.

- Presenteeism: dummy variable that takes the value of 1 if the respondent answered "A considerable number of times (3 - 4 days)" to both questions: During last week, "Did you have trouble concentrating on what you were doing?" and "Did it seem like everything you did was an effort?". Takes the value of 0 otherwise.

Depression variables

Durante la última semana...

Entrevistador: <u>lea las opciones</u> de respuesta para cada pregunta y anote sólo una.

	No, Rara vez o nunca (menos de un día)	Pocas veces o alguna vez (1-2 días)	Un número de veces considerable (3-4 días)	Todo el tiempo o la mayoría del tiempo (5-7 días)
A. ¿Sentía como si no pudiera quitarse de encima la tristeza?	1	2	3	4
B. ¿le costaba concentrarse en lo que estaba haciendo?	1	2	3	4
C. ¿se sintió deprimido/a?	1	2	3	4
D. ¿le parecía que todo lo que hacía era un esfuerzo?	1	2	3	4
E. ¿no durmió bien?	1	2	3	4
F. ¿disfrutó de la vida?	1	2	3	4
G. ¿se sintió triste?	1	2	3	4

Figure A1: CES-D7 questions in the ENSANUT Adults Questionnaire

Figure A1 shows the original CES-D7 questions in the Adults Questionnaire. Since the cutoff points for moderate to severe depressive symptoms are 5 and 9 for older adults and adults, respectively, the variables had to be recoded so that the lowest possible score was zero. Otherwise, if a person responded that she did not feel any of the symptoms that are used to diagnose depression she would still have obtained a score of 7, and if she was older than 65 years she would then be categorized as a depressive person when she is not. The variables were recoded in the following way:

- Rarely or never (less than one day) had a value of 1, and was recoded to have instead a value of 0.

- Occasionally or sometimes (1-2 days) had a value of 2, and was recoded to have instead a value of 1.

- A considerable number of times (3-4 days) had a value of 3, and was recoded to have instead a value of 2.

- All the time or most of the time (5-7 days) had a value of 4, and was recoded to have instead a value of 3.

After the variables where recoded, a score was obtained for each observation by summing the values obtained in each of the seven questions.

The dummy variable for depression was coded in the next way:

- For adults between 20 and 60 years old: depression==1 if CES-D7 score ≥ 9, and depression==0 if CES-D7 score < 9.

- For adults older than 60 years: depression==1 if CES-D7 score ≥ 5, and depression==0 if CES-D7 score < 5.

Instruments

- Violence/ attack: dummy variable that takes the value of 1 if at least one member of the family answered "yes" to having an attack during the past 12 months. The attacks taken into account were: robbery, traffic incident, fight with strangers, kidnapping, detention or raping by a stranger. This variable excluded violence perpetuated by family members or inside the household.

- Accident of a child: dummy variable that takes the value of 1 if at least one child inside the household suffered an accident during the past 12 months.

- Partner with depression: dummy that takes the value of 1 if the respondent´s partner has depression (depression==1). The respondent´s partners were matched according to the variable "kinship with the head of the household" and by household folio.

- Parent(s) with depression: dummy that takes the value of 1 if the respondent´s mother or father has depression (depression==1). The respondent´s parents were matched according to the variable "kinship with the head of the household" and by household folio.

- Family members with depression: dummy that takes the value of 1 if the respondent´s family member(s) that share household with her have depression (depression==1). The respondent´s family members were matched according to the variable "kinship with the head of the household" and by household folio.

For the COVID-19 instruments, first the databases of The General Directorate of Epidemiology concerning COVID cases (DGE, n.d.) were downloaded and the covid deaths per year in 2021 and 2022 were calculated by entity and a database was created with the next variables: state, municipality, year, covid deaths. The database was then merged with the Ensanut final database created using state, municipality and year. Then a dummy variable was created, taking the value of 1 if covid deaths in the state of residence of the individual where greater or equal to 3,000. This threshold was chosen because was close to the mean deaths per state (3,820) and yielded the best results.

The variable of covid infections by municipality was created based on questions that were aggregated in the 2021 and 2022 Household questionnaires of Ensanut:

- 2021: a dummy was created (*covid*) that took the value of 1 if the individual responded yes to the next question: "From January 2021 to the present date, were you diagnosed with COVID-19 by any healthcare personnel?" and responded "with a test" or "both" (with a test and symptoms) to the question "Was it with a test or by symptoms?"

- 2022: a dummy was created (*covid*) that took the value of 1 if the answer to the question "Since February 2020, how many times has (NAME) been diagnosed with COVID-19 by healthcare personnel?" was greater or equal to 1.

Then to count the infections by municipality, the dummy *covid* multiplied by the weights sample was summed by locality which is a variable that concatenates the number of state and municipality.

Sociodemographic characteristics

- Age: corresponds to the age reported in the questionnaire by each individual.
- Years of education: variable created based on the last level of education completed by the individual. For example, if the last level completed was high school, then years of education takes the value of 12 and if the last level completed was primary school, the variable takes the value of 6.
- Married: dummy variable that takes the value of 1 if the respondent is married or lives with her partner in free union. Takes the value of 0 otherwise.
- Rural: dummy variable that takes the value of 1 if the individual lives in a rural area.
- Sex: dummy variable that takes the value of 1 if the respondent is female.

Estimations for the selection of the instrument

Table A1: First stage regression results - comparison of instruments

VARIABLES	(1) IV	(2) IDID
Dependent variable: CES-D7 score		
Attack/violence	1.680***	
	(0.357)	
F-statistic	34.75	
Accident	0.381***	
	(0.140)	
F-statistic	34.63	
Partner with depression	0.703**	
	(0.340)	
F-statistic	29.92	
Parent(s) with depression	2.838	
	(2.556)	
F-statistic	23.62	
Family member(s) with depression	0.727**	
	(0.360)	
F-statistic	34.57	
Covid deaths per state ≥ 3,000		0.549***
		(0.113)
F-statistic		35.91
Covid deaths per state		0.00004***
		(9.95e-06)
F-statistic		36.07
Covid infections by municipality		6.63e-07*
		(3.76e-07)
F-statistic		34.74
Covid deaths per capita by state		0.0047***
		(0.00126)
F-statistic		35.40
Covid deaths per capita by state ≥ 75		-0.0454
		(0.195)
F-statistic		34.53
Covid deaths per capita by state ≥ 100		0.3236***
		(0.1121)
F-statistic		35.37

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Both estimations include the sociodemographic variables as controls and fixed effects of year and state. The sample size for all estimations is 95,500 observations except for the estimations of partner with depression and parent(s) with depression, which have an N of 78,942 and 58,372 respectively.

Table A2: First stage regression results - comparison of instruments

VARIABLES	(1) IV	(2) IDID
Dependent variable: Depression		
Attack/violence	0.124***	
	(0.032)	
F-statistic	44.45	
Accident	0.031**	
	(0.014)	
F-statistic	42.80	
Partner with depression	0.047	
	(0.033)	
F-statistic	37.095	
Parent(s) with depression	0.151	
	(0.194)	
F-statistic	27.24	
Family member(s) with depression	0.037	
	(0.029)	
F-statistic	42.82	
Covid deaths per state ≥ 3,000		0.041***
		(0.011)
F-statistic		43.92
Covid deaths per state		3.13e-06***
		(1.06e-06)
F-statistic		43.87
Covid infections by municipality		5.20e-08
		(3.94e-08)
F-statistic		42.90
Covid deaths per capita by state		0.000366**
		(0.000139)
F-statistic		43.80
Covid deaths per capita by state ≥ 75		-0.019
		(0.02290)
F-statistic		42.83
Covid deaths per capita by state ≥ 100		0.023*
		(0.0119)
F-statistic		43.49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Both estimations include the sociodemographic variables as controls and fixed effects of year and state. The sample size for all estimations is 95,500 observations except for the estimations of partner with depression and parent(s) with depression, which have an N of 78,942 and 58,372 respectively.

Results

LIML vs 2SLS for males subsample

As can be observed in Table A3 both methods yield very similar results for both endogenous variables and both the IV and the IDID models. This gives confidence to use the instruments even though they have a weak first stage in the male subsample. If the instruments are weak there is a chance that the 2SLS estimates are biased in a very similar way to OLS. LIML is a linear combination of OLS and 2SLS that is approximately unbiased, so if it yields similar results to 2SLS it gives confidence that the 2SLS estimates are unbiased (Angrist and Pischke, 2009).

Table A3: 2SLS and LIML regression results - males

Dependant variable	(1) 2SLS-IV	(2) LIML-IV	(3) 2SLS-IDID	(4) LIML-IDID
Panel A. Endogenous variable: CES-D7 score				
Employment status	-0.00300	-0.00300	-0.00998	-0.00998
	(0.0243)	(0.0243)	(0.0300)	(0.0300)
Labor force participation	-0.00441	-0.00441	0.00957	0.00957
	(0.0230)	(0.0230)	(0.0265)	(0.0265)
Formal worker	0.0235	0.0235	-0.0312	-0.0312
	(0.0331)	(0.0331)	(0.0608)	(0.0608)
Employee	0.0263	0.0263	-0.00207	-0.00207
	(0.0289)	(0.0289)	(0.0439)	(0.0439)
Employer	-0.00197	-0.00197	0.00401	0.00401
	(0.00504)	(0.00504)	(0.00939)	(0.00939)
Self-employed	0.00250	0.00250	0.0206	0.0206
	(0.0229)	(0.0229)	(0.0348)	(0.0348)
Presenteeism	0.0312***	0.0312***	0.0329**	0.0329**
	(0.0118)	(0.0118)	(0.0129)	(0.0129)
Panel B. Endogenous variable: Depression				
Employment status	-0.0416	-0.0416	-0.122	-0.122
	(0.336)	(0.336)	(0.365)	(0.365)
Labor force participation	-0.0610	-0.0610	0.117	0.117
	(0.319)	(0.319)	(0.326)	(0.326)
Formal worker	0.309	0.309	-0.383	-0.383
	(0.451)	(0.451)	(0.760)	(0.760)
Employee	0.364	0.364	-0.0252	-0.0252
	(0.410)	(0.410)	(0.536)	(0.536)
Employer	-0.0273	-0.0273	0.0489	0.0489
	(0.0699)	(0.0699)	(0.115)	(0.115)
Self-employed	0.0345	0.0345	0.252	0.252
	(0.318)	(0.318)	(0.426)	(0.426)
Presenteeism	0.381**	0.381**	0.402**	0.402**
	(0.152)	(0.152)	(0.162)	(0.162)
N	39,347	39,347	39,347	39,347

Notes: Columns (1) and (3) show estimates of the second stage using 2SLS method for the IV model and IDID model respectively. Columns (2) and (4) show estimates of the second stage using LIML method for the IV model and IDID model respectively. All estimations include sociodemographic characteristics as control, excluding sex, and year and state fixed effects. Note: An incident involving a child at home was used as the instrument for the presenteeism variable in the IV model since the violence variable could have issues with reverse causality. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

First stage results using accident of the child as instrument

Table A4: First stage regression results using accident as instrument

VARIABLES	(1) CES-D7	(2) Depression
Panel A. Full sample		
Accident	0.382***	0.0318**
	(0.140)	(0.0138)
Constant	6.463***	0.152***
	(0.195)	(0.0188)
Observations	95,500	95,500
R-squared	0.050	0.064
F	34.63	42.80
Panel B. Female subsample		
Accident	0.677***	0.0527**
	(0.207)	(0.0216)
Constant	7.734***	0.254***
	(0.281)	(0.0271)
Observations	56,153	56,153
R-squared	0.030	0.051
F	14.45	18.92

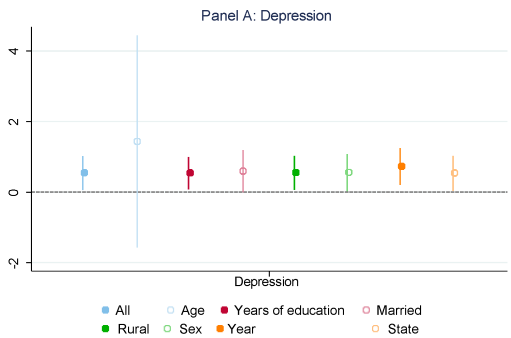
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All estimations include the sociodemographic variables as controls and fixed effects of year and state. The coefficients show the first-stage results for the IV model using accident of the child as instrument. In Panel A the results are shown for the whole sample, and in Panel B the results are shown for females.

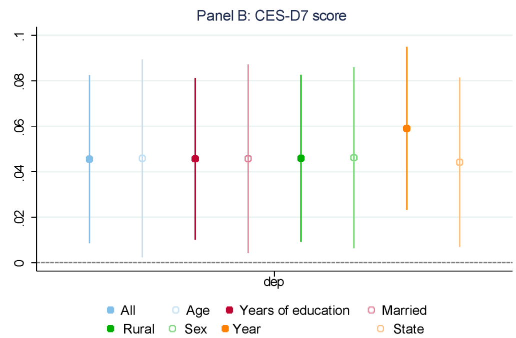
IDID estimations using different instruments

Results excluding 2018

Omitted variable bias simulation

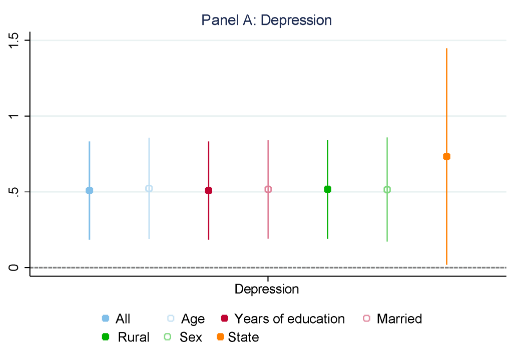


(a) Depression

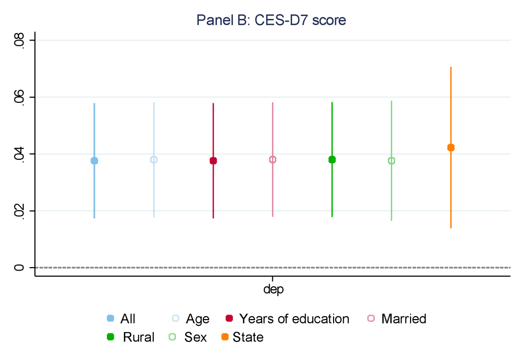


(b) CES-D7 score

Figure A2: Omitted variable bias simulation for IV instrument



(a) Depression



(b) CES-D7 score

Figure A3: Omitted variable bias simulation for IV instrument

Table A5: Second stage instrumented DID regression results with different instruments

Dependant variable	(1)	(2)	(3)
Panel A. Endogenous variable: CES-D7 score			
Employment status	-0.00355	0.0222	0.0229
	(0.0333)	(0.0424)	(0.0251)
Labor force participation	0.0216	0.0635	0.0422*
	(0.0327)	(0.0451)	(0.0250)
Formal worker	-0.106**	-0.149**	-0.0255
	(0.0512)	(0.0614)	(0.0416)
Presenteeism	0.0460***	0.0340*	0.0376***
	(0.0139)	(0.0177)	(0.0103)
Employee	-0.0728*	-0.101*	0.0123
	(0.0400)	(0.0582)	(0.0280)
Employer	-0.00985	-0.00461	0.00294
	(0.00771)	(0.00934)	(0.00518)
Self-employed	0.0613*	0.110**	0.0191
	(0.0331)	(0.0511)	(0.0208)
Panel B. Endogenous variable: Depression			
Employment status	-0.0507	0.312	0.310
	(0.475)	(0.616)	(0.350)
Labor force participation	0.309	0.893	0.571
	(0.481)	(0.738)	(0.368)
Formal worker	-1.382*	-1.827**	-0.299
	(0.780)	(0.888)	(0.495)
Presenteeism	0.656**	0.478*	0.509***
	(0.266)	(0.287)	(0.165)
Employee	-1.038	-1.421	0.166
	(0.657)	(0.977)	(0.381)
Employer	-0.141	-0.0648	0.0398
	(0.119)	(0.134)	(0.0705)
Self-employed	0.875	1.544*	0.258
	(0.553)	(0.935)	(0.287)
N	95,500	95,500	95,500

Notes: Column (1) shows estimates using Covid deaths per capita by state as instrument. Column (2) shows estimates using Covid deaths per capita by state ≥100 as instrument. Column (3) shows estimates using Covid deaths per state ≥3,000 as instrument. All estimates include sociodemographic variables as controls alongside state and year fixed effects. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A6: OLS, second stage 2SLS and instrumented DID regression results excluding 2018

Dependant variable	(1) OLS	(2) OLS with controls	(3) IV	(4) IDID
Panel A. Endogenous variable: CES-D7 score				
Employment status	-0.0131***	-0.00207***	0.0275	0.0229
	(0.000834)	(0.000782)	(0.0212)	(0.0251)
Labor force participation	-0.0126***	-0.000843	0.0259	0.0422*
	(0.000827)	(0.000736)	(0.0210)	(0.0250)
Formal worker	-0.00871***	-0.00370***	0.0236	-0.0255
	(0.00112)	(0.00103)	(0.0257)	(0.0416)
Presenteeism	0.0435***	0.0436***	0.0455**	0.0376***
	(0.000631)	(0.000640)	(0.0188)	(0.0103)
Employee	-0.0112***	-0.00190**	0.0323	0.0123
	(0.000812)	(0.000794)	(0.0219)	(0.0280)
Employer	-0.000404***	-0.000104	-0.00148	0.00294
	(0.000134)	(0.000128)	(0.00222)	(0.00518)
Self-employed	0.00164***	0.00170***	0.0112	0.0191
	(0.000637)	(0.000641)	(0.0126)	(0.0208)
Panel B. Endogenous variable: Depression				
Employment status	-0.125***	-0.0353***	0.372	0.310
	(0.00784)	(0.00731)	(0.299)	(0.350)
Labor force participation	-0.124***	-0.0281***	0.350	0.571
	(0.00778)	(0.00690)	(0.293)	(0.368)
Formal worker	-0.0767***	-0.0205**	0.335	-0.299
	(0.0102)	(0.00952)	(0.375)	(0.495)
Presenteeism	0.329***	0.330***	0.548**	0.509***
	(0.00671)	(0.00685)	(0.247)	(0.165)
Employee	-0.122***	-0.0309***	0.438	0.166
	(0.00740)	(0.00734)	(0.307)	(0.381)
Employer	-0.00170	7.67e-05	-0.0200	0.0398
	(0.00127)	(0.00126)	(0.0302)	(0.0705)
Self-employed	0.0270***	0.0133**	0.152	0.258
	(0.00636)	(0.00628)	(0.173)	(0.287)
N	95,500	95,500	95,500	95,500

Notes: Column (1) shows the estimates of an OLS regression without controls. Columns (2), (3) and (4) include controls and fixed effects of year and state. Columns (3) and (4) show the 2SLS estimates for the IV and IDID models. The variable *Presenteeism* takes the value of 1 if the person had difficulty concentrating on what they were doing and felt that everything was an effort for 3 days or more. Note: An incident involving a child at home was used as the instrument for the presenteeism variable since the violence variable could have issues with reverse causality. The F-statistic of the first stage is 42.80 and the first-stage results can be found in Panel A of Table A4 on the Appendix. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Omitted variable bias simualtion - employment

VARIABLES	(1) Panel A: Depression	(2) Panel B: CES-D7	(3) Panel C: Depression	(4) Panel D: CES-D7
All	0.372	0.0275	0.310	0.0229
	(0.299)	(0.0212)	(0.350)	(0.0251)
Age	0.374	0.0266	0.332	0.0242
	(0.316)	(0.0217)	(0.358)	(0.0252)
Years of education	0.427	0.0312	0.307	0.0227
	(0.322)	(0.0225)	(0.350)	(0.0251)
Married	0.416	0.0313	0.337	0.0249
	(0.287)	(0.0207)	(0.350)	(0.0248)
Rural	0.383	0.0283	0.335	0.0247
	(0.299)	(0.0212)	(0.352)	(0.0250)
Sex	0.779	0.0564*	0.526	0.0384
	(0.480)	(0.0320)	(0.458)	(0.0314)
Year	0.362	0.0267		
	(0.305)	(0.0217)		
State	0.337	0.0253	0.249	0.0144
	(0.288)	(0.0208)	(0.633)	(0.0354)
Observations	95,500	95,500	95,500	95,500

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the estimations excluding sequentially the control variables. Columns (1) and (2) use the IV model and columns (3) and (4) correspond to the IDID estimations. The first row is the baseline model including all the covariates.

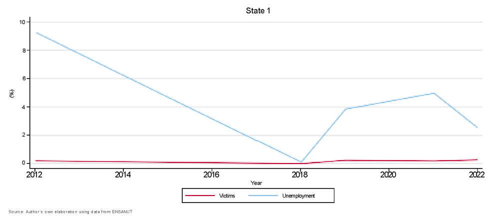
Table A8: Omitted variable bias simualtion - presenteeism

VARIABLES	(1) Panel A: Depression	(2) Panel B: CES-D7	(3) Panel C: Depression	(4) Panel D: CES-D7
All	0.548**	0.0455**	0.509***	0.0376***
	(0.247)	(0.0188)	(0.165)	(0.0103)
Age	1.437	0.0459**	0.523***	0.0380***
	(1.534)	(0.0222)	(0.170)	(0.0103)
Years of education	0.544**	0.0457**	0.509***	0.0376***
	(0.235)	(0.0181)	(0.165)	(0.0103)
Married	0.595*	0.0457**	0.517***	0.0380***
	(0.305)	(0.0212)	(0.166)	(0.0103)
Rural	0.554**	0.0459**	0.517***	0.0380***
	(0.247)	(0.0187)	(0.166)	(0.0103)
Sex	0.561**	0.0462**	0.515***	0.0376***
	(0.270)	(0.0203)	(0.175)	(0.0107)
Year	0.731***	0.0590***		
	(0.268)	(0.0183)		
State	0.542**	0.0442**	0.734**	0.0423***
	(0.254)	(0.0190)	(0.364)	(0.0145)
Observations	95,500	95,500	95,500	95,500

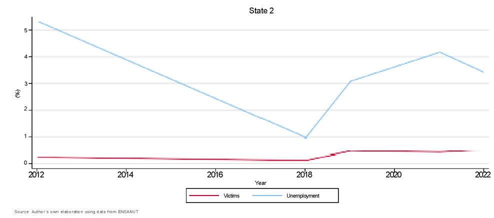
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents the estimations excluding sequentially the control variables. Columns (1) and (2) use the IV model and columns (3) and (4) correspond to the IDID estimations. The first row is the baseline model including all the covariates.

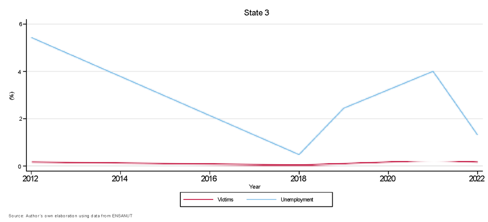
Violence and unemployment



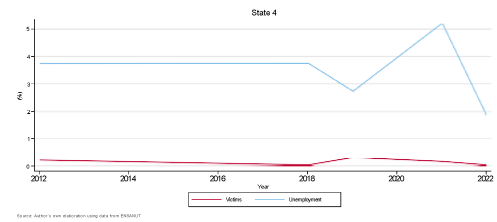
(a) Aguascalientes



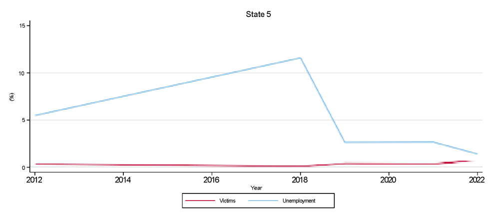
(b) Baja California



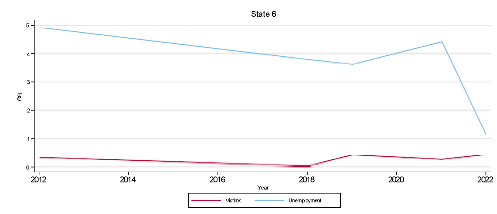
(c) Baja California Sur



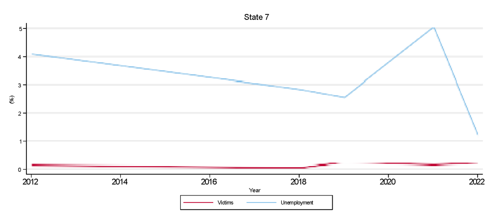
(d) Campeche



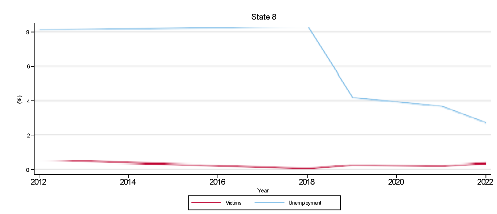
(e) Coahuila



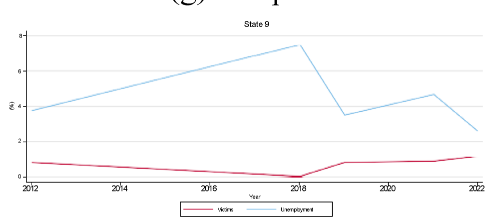
(f) Colima



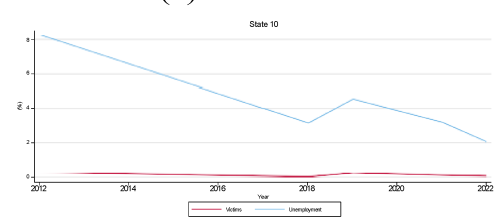
(g) Chiapas



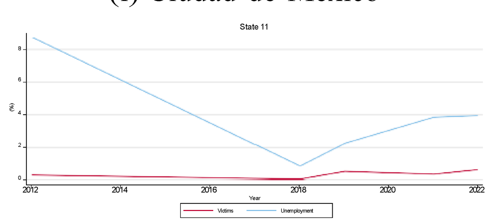
(h) Chihuahua



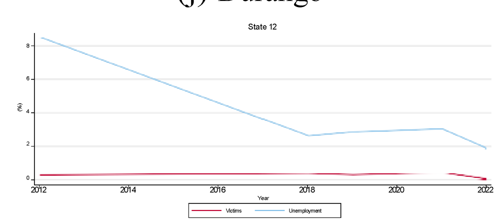
(i) Ciudad de México



(j) Durango

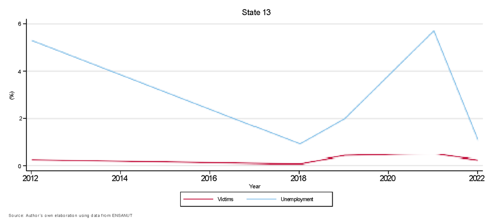


(k) Guanajuato

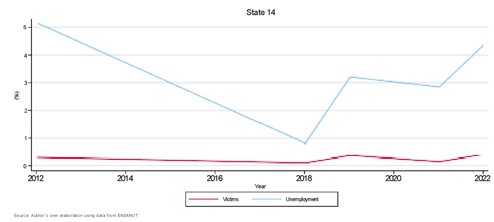


(l) Guerrero

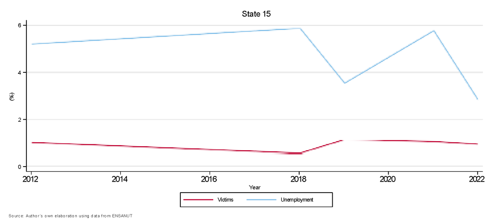
Figure A4: Violence and unemployment by state 2012 - 2022 (%)



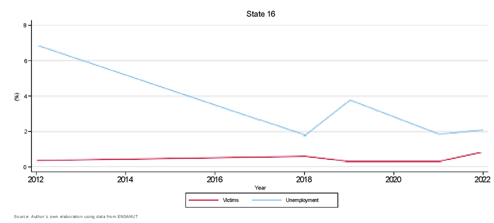
(a) Hidalgo



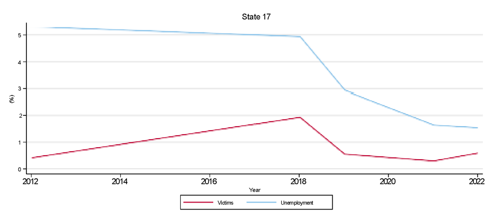
(b) Jalisco



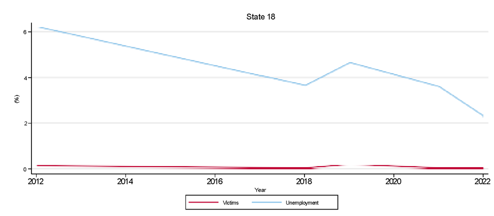
(c) Estado de México



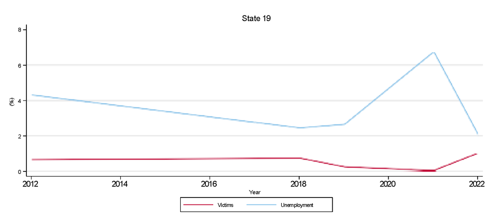
(d) Michoacán



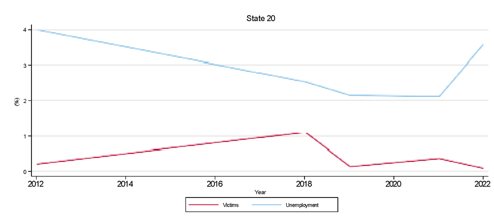
(e) Morelos



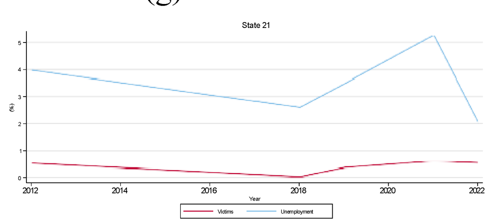
(f) Nayarit



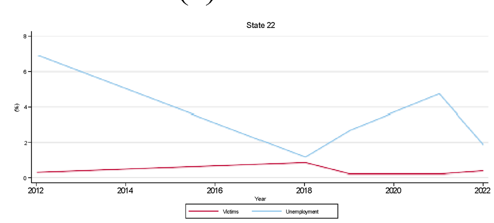
(g) Nuevo León



(h) Oaxaca

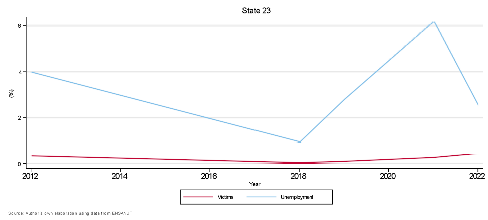


(i) Puebla

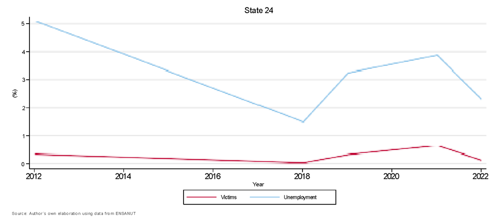


(j) Querétaro

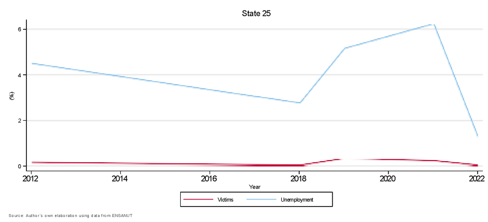
Figure A5: Violence and unemployment by state 2012 - 2022 (%)



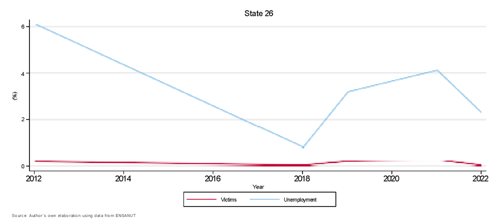
(a) Quintana Roo



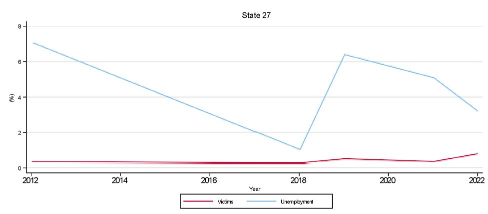
(b) San Luis Potosí



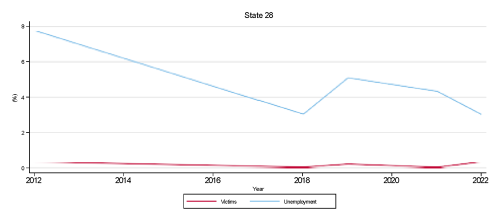
(c) Sinaloa



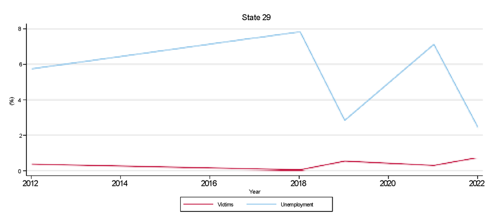
(d) Sonora



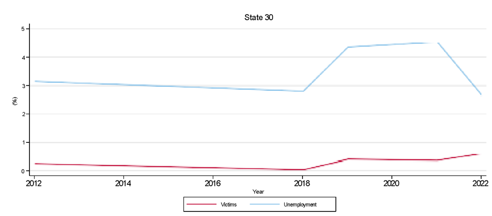
(e) Tabasco



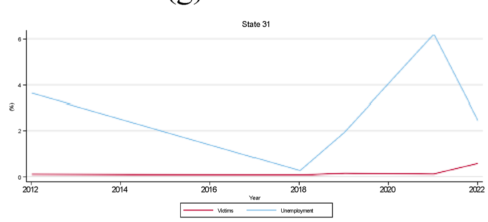
(f) Tamaulipas



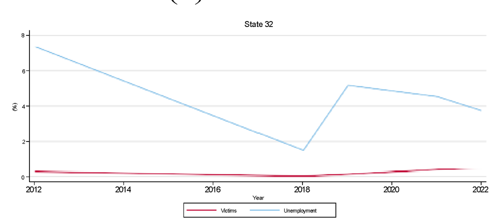
(g) Tlaxcala



(h) Veracruz



(i) Yucatán



(j) Zacatecas

Figure A6: Violence and unemployment by state 2012 - 2022 (%)

List of Figures

List of Tables