Effect of Working Hours on Mental Health: Empirical Evidence in the USA

Group X [Word Count: 2500]

1 Introduction

Nowadays, long working hours have become a widespread phenomenon across organizations and companies, as shareholders seek to maximize value through extended employee work hours. At the same time, mental illness has surged globally. According to Statista (2023), nearly 39% of adults in the U.S. have been diagnosed with depression, raising concerns about the psychological costs of prolonged work hours. While long working hours are often associated with mental health risks, work itself can also provide psychological benefits by offering a sense of purpose, financial stability, and personal achievement, making the relationship between working hours and mental well-being more complex.

Existing literature presents conflicting evidence regarding the relationship between working hours and mental health outcomes. Several studies suggest that prolonged working hours significantly increase the risk of depression and psychological distress through heightened stress levels and reduced work-life balance (Virtanen et al., 2018). However, other research highlights the potential psychological benefits of work, arguing that employment provides essential elements for mental well-being, including financial security, and a sense of achievement (Aitken et al., 2024). These contradictory findings suggest that the relationship between working hours and mental health is more complex than initially assumed, potentially varying across different population segments and working conditions.

This study aims to solve these complex relationships by examining how working hours affect mental health outcomes, specifically focusing on depression and sadness in the United States, using nationally representative data from the IPUMS Health Survey (2013-2018). Recognizing that the impact of working hours may not be uniform across all individuals, we pay particular attention to how this relationship is moderated by educational attainment and gender. By investigating these heterogeneous effects, this research seeks to provide more nuanced insights into when and for whom extended working hours may be particularly beneficial or detrimental to mental health, thereby informing more targeted and effective labor policies.

The remainder of our paper is structured as follows. **Section 2** provides detailed descriptions of the IPUMS Health Survey data and key variables used in our analysis. **Section 3** introduces our empirical strategy, including the OLS and logistic regression models. **Section 4** presents our main empirical results and robustness checks. **Section 5** explores heterogeneity analyses across gender and education levels. Finally, **Section 6** concludes with a discussion of limitations and implications for future research.

2 Data Description

This study employs data from the IPUMS Health Survey (NHIS) from 2013 to 2018, focusing on working individuals below 85 years of age across all genders. **Table 1** provides brief descriptions and definition for all variables involved in the analyses. **Table 2** presents relevant descriptive statistics of key variables.

As shown in **Table 1**, we will examine two mental health outcomes as dependent variables: depression frequency (DEPFREQ), measured as a binary variable (1 = ever felt depressed, 0 = never felt depressed) transformed from an original five-point scale. The second, sadness (ASAD), measured as an ordered categorical variable (0-4) indicating the frequency of feeling sad in the past 30 days.

The primary explanatory variable is working hours (HOURSWRK), which we categorize into five groups: part-time (<35 hours), standard full-time (35-40 hours, reference), moderate overtime (41-48 hours), high overtime (49-60 hours), and excessive overtime (<60 hours).

We control for several sociodemographic characteristics: age (continuous variable up to 85), sex (binary: 1 = male, 2 = female), marital status (five categories: married, separated, divorced, widowed, never married), and education attainment (eight categories from no schooling to graduate degree). Health status serves as a mediating variable, measured on a five-point scale from excellent to poor.

Note that all missing or invalid data are dropped through filtering to ensure overall integrity. Also, given NHIS's complex sampling design, sampling weights are employed to ensure national representativeness: regression techniques are adjusted correspondingly, see **Section 3**.

Table 1: Variable Descriptions and Definitions

Variables	Description	Definition
Mental Health		
DEPFREQ	Dependent variable indicating depression frequency	Binary variable: 1=ever felt depressed 0 = never felt depressed[1]
ASAD	Dependent variable indicating sadness frequency	Ordered categorical variable with value (0-4) with increasing frequency of feeling sad in past 30 days: 0 = None; 1 = A little; 2 = Some time; 3 = Most time; 4 = All the time
Working Hours		
HOURSWRK	Working hours	Total hours worked last week or usually
Part-time	Part-time work	<35 hours
Standard Full-time	Standard hours (reference)	35-40 hours
Moderate Overtime	Moderate overtime	41-48 hours
High Overtime	High overtime	49-60 hours
Excessive Overtime	Excessive overtime	>60 hours
Control Variables		
AGE	Age	Continuous variable (up to 85 years)
EDUCATION	Education attainment	Ordered categorical (1-8) with increasing level of education: 1=No schooling; 2=Elementary school; 3=Middle school; 4=No high school diploma; 5=High school graduate; 6=Some college without diploma; 7=Bachelor's degree; 8=Graduate degree
SEX	Sex	Binary: 1=Male, 2=Female
MARITAL	Marital status	Unordered categorical variable (1-5) representing different marital status: 1=Married; 2=Separated; 3=Divorced; 4=Widowed; 5=Never married
HEALTH_STATUS	Health status	Ordered categorical variable(1-5) with decreasing level of health status: 1=Excellent; 2=Very good; 3=Good; 4=Fair; 5=Poor

1: Transformed from a primary ordered categorial variable with value 1 to 5 corresponding to depression frequency of daily, weekly, monthly, a few times a year, and never. Value 1-4 are recoded into value 1 and value 5 is recoded into value 0.

Table 2: Descriptive Statistics

Name	Obs	Mean	St. Dev.	Min	Median	Max
Panel A: Working Hours						
Working Hours	58,467	39.79	12.98	5	40	95
Part time	12,894	22.08	7.75	5	24	34
Standard Full Time	28,369	39.49	1.39	35	40	40
Moderate Overtime	5,500	44.95	1.78	41	45	48
High Overtime	9,468	53.78	4.33	49	50	60
Excessive Overtime	2,236	73.91	8.95	61	70	95
Panel B: Mental Health						
Depression Frequency	58,467	0.37	0.48	0	0	1
ASAD (Sadness Frequency)	58,467	0.33	0.71	0	0	4
Panel C: Control Variables						
Education Attainment	58,467	6.08	1.28	1	6	8
Martial Status	58,467	2.68	1.76	1	3	5
Age	58,467	43.44	14.22	18	43	85
Sex	58,467	0.5	0.5	0	1	1
Panel D: Mediation Variable						
Health Status	58,467	2.07	0.92	1	2	5

3 Empirical Strategy

Since the data are derived from a complex survey design, the two models elaborated below are estimated using survey-weighted regression ($svyglm()$), which appropriately integrates sampling weights ($weights$ in $svydesign()$) to adjust for unequal probabilities of selection and produce representative estimates.

3.1 Model 1: Ordinary Least Squares (OLS)

$$Y_{it} = \beta_0 + \beta_1 \times HOURSWRK_{it} + \gamma X_{it} + \varepsilon_{it} \tag{1}$$

An OLS regression model is employed to analyze the determinants of sadness. In this model, i and t denote the individual and year, respectively. The dependent variable, Y_{it}, represents the self-reported level of sadness for individual i in year t.

The independent variable, $HOURSWRK_{it}$, captures an individual's total working hours last week, while X_{it} encompasses a set of control variables, including age, gender, education level, and marital status, which may influence emotional well-being. ε_{it} denotes the standard error term.

3.2 Model 2: Logistic Regression (Logit)

$$logit[P(Y_{it} = 1)] = \beta_0 + \beta_1 \times HOURSWRK_{it} + \gamma X_{it} + \varepsilon_{it} \tag{2}$$

where logit function is given by:

$$logit[P(Y_{it} = 1)] = \ln \frac{P(Y_{it} = 1)}{1 - P(Y_{it} = 1)} = \ln(odds) \tag{3}$$

Since multiple levels of depression have been consolidated into two dummy variables, a Logit model is employed to examine the relationship between working hours and mental health. In this framework, i and t also represent the individual and year. The dependent variable, Y_{it}, is a binary indicator, where 1 denotes the presence of different level of depression symptoms, and 0 indicates no depression. $HOURSWRK_{it}$, X_{it}, and ε_{it} are defined and constructed the same way as in **Model 1**.

To overcome the limitations associated with using a linear probability model (LPM) for binary variables, the logit model transforms probabilities into odds, eliminating the constraints of probability values being bound between 0 and 1. Furthermore, the Logit model applies a log-odds transformation, allowing for a linear relationship between the dependent and independent variables. This approach enables the estimation of the probability of an individual experiencing severe depression as a function of working hours while accounting for other demographic and health-related factors.

4 Empirical Results and Robustness Check

4.1 Empirical Results

Table 3: Regression Results

	Dependent variable:	
	Sadness	Depression
	(1)	(2)
Part-time (<35h)	0.033	0.111*
	(0.021)	(0.065)
Moderate Overtime (41-48h)	-0.002	0.099***
	(0.010)	(0.033)
High Overtime (49-60h)	-0.017	0.215***
	(0.012)	(0.041)
Excessive Overtime (>60h)	0.077***	0.323***
	(0.011)	(0.029)
Age	0.001***	0.002**
	(0.0003)	(0.001)
Sex	0.117***	0.434***
	(0.008)	(0.025)
Education Level	-0.047***	0.040***
	(0.003)	(0.009)
Marital Status	0.032***	0.104***
	(0.002)	(0.007)
Constant	0.399***	-1.512***
	(0.024)	(0.081)
Model Type	Linear	Logistic
Joint test statistic	F = 16.17	Chi2 = 31.68
Joint test p-value	0	0
Observations	58,467	58,467
Log Likelihood	-71,550.210	
Akaike Inf. Crit.	143,118.400	

Note: The sample covers years 2013 to 2018. The standard errors are reported in parentheses, clustered at individual level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

This section evaluates the relationship between working hours and mental health using both OLS and logit model. The regression results in **Table 3** indicate that working excessive overtime has different impacts across the two mental health measures. We observe that excessive overtime (>60h) has the strongest association with both sadness and depression, showing coefficients of 0.077 and 0.323 respectively. While moderate overtime (41-48h) and high overtime (49-60h) don't significantly affect sadness, they show substantial positive associations with depression, with coefficients of 0.099 and 0.215 respectively. Part-time work (<35h) also shows a marginally significant positive relationship with depression (0.111).

To better interpret the logistic regression results for depression (Model 2), we specifically visualized the odds ratios (**Figure 1**), as they provide a more intuitive interpretation of the logistic coefficients through exponential transformation. The odds ratio visualization demonstrates a clear ascending pattern in the risk of depression as working hours increase. While part-time work and moderate overtime show relatively modest elevations in odds ratios, the risk for high overtime workers increases significantly. Most strikingly, excessive overtime workers (>60h) show the highest odds ratio of approximately 1.4, indicating a 40% higher likelihood of experiencing depression compared to standard working hours.

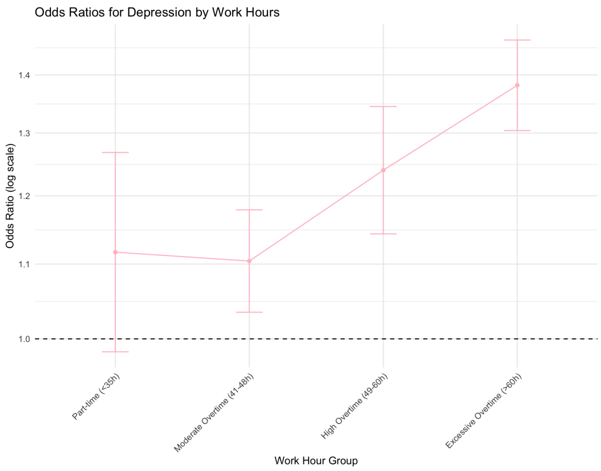

Figure 1: Odds ratios for Depression by Working Hours

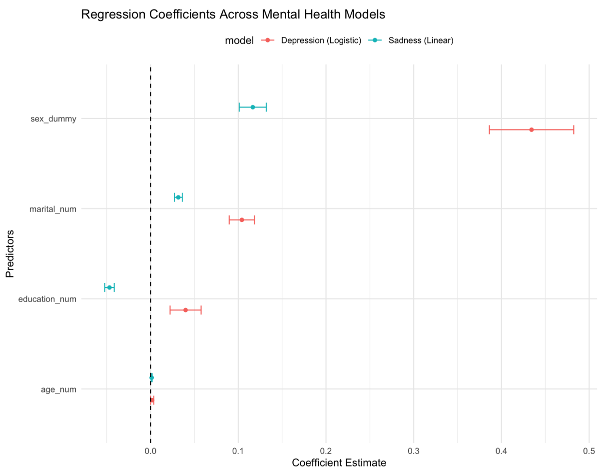

Figure 2: Regression Coefficients across Mental Health Models

Figure 2 presents the visualisation of coefficient comparison regarding demographic factors in the models, revealing substantial and significant effects on mental health outcomes. Sex emerges as the strongest predictor among control variables, with a coefficient of 0.434 for depression and 0.117 for sadness. Marital status shows consistent positive associations across both outcomes, while education level demonstrates an interesting divergence, with a negative relationship to sadness but a positive relationship to depression.

4.2 Mediation Analysis

To extend our understanding beyond the direct relationships identified in our regression analysis between working hours and mental health outcomes, we conducted mediation tests (shown in **Table 4** and **Table 5)** to investigate whether physical health status acts as a mediating factor in this relationship.

First, part-time work shows significant indirect effects on both depression (0.021) and sadness (0.007), indicating that part-time employment may affect mental health through its impact on physical health conditions. This may be because part-time workers often face financial constraints due to lower income, limiting their access to quality healthcare. Also, they may have limited access to employer-provided health benefits and wellness programs typically available to full-time employees (Petrova, 2012). These factors collectively contribute to poorer physical health outcomes, which in turn affect mental well-being. Secondly, for high overtime group, we observe significant negative indirect effects for both depression (-0.012) and sadness (-0.004), with a particularly high mediation proportion for sadness (59.2%). This unexpected buffering effect tends to be rather unintuitive, thus requiring further investigation in future research.

In contrast, excessive overtime shows minimal and non-significant indirect effects through health status for both mental health outcomes. This suggests that for excessive overtime workers, the impact on mental health is primarily driven by direct effects rather than by physical health deterioration. One possible explanation is that the immediate psychological strain from extreme work demands, such as work-life conflict and job stress, has a more immediate and overwhelming impact on mental well-being, whereas physical health problems develop more gradually over time (Somaraju et al., 2022).

Table 4: Mediation Test for Depression

Working Hour Category	Indirect Effect	Standard Error	Z score	P Value	Total Effect	Proportion Mediated
Excessive overtime	0.001	0.011	0.100	0.920	0.111	0.010
High overtime	-0.012	0.006	-2.148	0.032	0.089	-0.134
Moderate overtime	0.013	0.007	1.852	0.064	0.219	0.057
Part time	0.021	0.005	3.766	0.000	0.368	0.056

Table 5: Mediation Test for Sadness

Working Hour Category	Indirect Effect	Standard Error	Z score	P Value	Total Effect	Proportion Mediated
Excessive overtime	0.000	0.004	0.100	0.920	0.032	0.011
High overtime	-0.004	0.002	-2.146	0.032	-0.06	0.592
Moderate overtime	0.004	0.002	1.850	0.064	-0.017	-0.234
Part time	0.007	0.002	3.757	0.000	0.088	0.075

5 Heterogeneity Analysis

While the main findings presented in **Table 3** demonstrate the overall relationship between working hours and mental health, this average effect may have important variations across different groups and contexts. To gain a deeper understanding of the potential mechanisms through which working hours affect mental health, we conduct heterogeneity analyses along two important dimensions.

5.1 Sex Heterogeneity

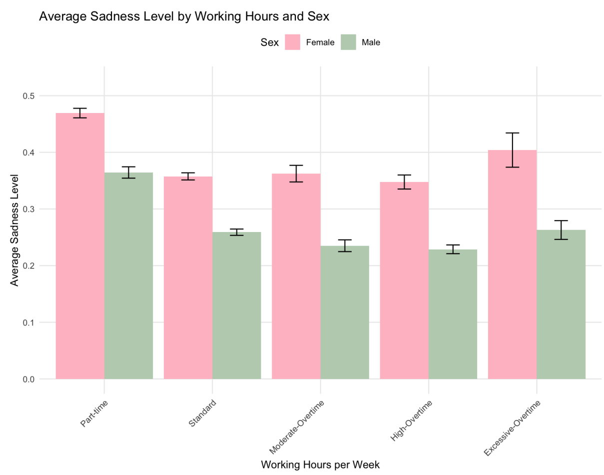

Figure 3: Average Sadness Level by Working Hours and Sex

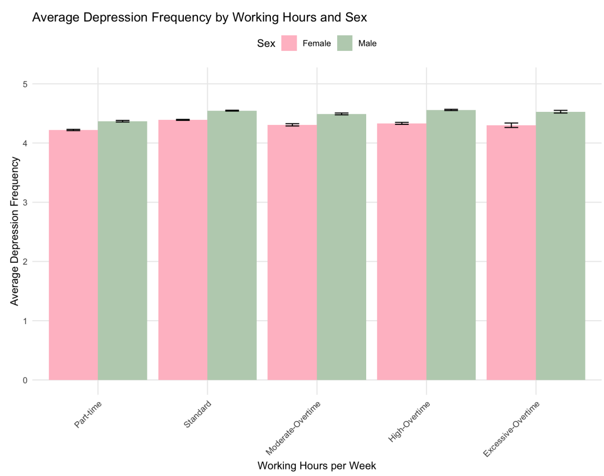

Figure 4: Average Depression Frequency by Working Hours and Sex

To investigate the gender-wise impact heterogeneity of working hours on mental health, we first look at the average mental health status distribution of male and female (as shown in **Figure 3**) in different working hour groups. There seems to be apparent cross-group differences in average sadness levels for male and female, while the difference in average depression frequency appears to be less distinctive. However, such relationships require further statistical investigation, which will be conducted in following parts.

To formally test these gender differences, we conduct a heterogeneity analysis by sex. Relevant regression results are documented in **Table 6**, and corresponding Chow test results are shown in **Table 7**.

For depression, males show stronger and more significant responses to overtime work compared to females. Specifically, excessive overtime (0.254 vs 0.035) and high overtime (0.210 vs 0.034) have substantially larger effects on depression for males than females. This gender difference is statistically significant as confirmed by the Chow test (F-statistic = 40.06, p-value <0.00001). This idea is supported by Roche et al. (2016), who argue that men may be more susceptible to depression from long working hours than women due to traditional masculine norms and the societal stigma that discourages openness about mental health struggles. Moreover, compared to women, men generally have lower mental health literacy, which makes them less likely to identify symptoms of depression. Consequently, they are less inclined to seek medical help or openly discuss their mental well-being, further exacerbating the negative impact of excessive work hours. However, for sadness, the gender differences are less pronounced and not statistically significant, as indicated by the Chow test with p-value of 1.0. Overall, these findings demonstrate that overtime work has a significantly stronger effect on depression for male workers compared to female workers, while its impact on sadness is similar across both genders.

Table 6: Heterogeneity Analysis by Sex

	Dependent variable:			
	Depression		Sadness	
	Female	Male	Female	Male
	(1)	(2)	(1)	(2)
Excessive Overtime	0.035	0.254**	0.018	0.061
	(0.079)	(0.111)	(0.024)	(0.039)
High Overtime	0.034	0.210***	-0.016	0.021
	(0.045)	(0.052)	(0.012)	(0.017)
Moderate Overtime	0.160***	0.283***	-0.021	-0.010
	(0.056)	(0.056)	(0.014)	(0.018)
Part time	0.306***	0.331***	0.068***	0.083***
	(0.049)	(0.036)	(0.017)	(0.014)
Age	0.002*	0.001	0.001***	0.001***
	(0.001)	(0.001)	(0.0003)	(0.0005)
Education Level	0.060***	0.014	-0.031***	-0.068***
	(0.012)	(0.014)	(0.004)	(0.005)
Marital Status	0.130***	0.076***	0.029***	0.033***
	(0.011)	(0.010)	(0.003)	(0.004)
Constant	-1.695***	-0.849***	0.321***	0.636***
	(0.112)	(0.114)	(0.029)	(0.040)
Chi-square	10.76	24.36	6.71	9.25
p-value	0	0	0	0
Observations	29,212	29,240	29,212	29,240

Note: The sample covers years 2013 to 2018. The standard errors are reported in parentheses, clustered at individual level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 7: Chow Test for Sex Heterogeneity

	Depression Model	Sadness Model
F-statistics	40.06041	-9.743997
p-value	0.00000	1

5.2 Education Heterogeneity

Following the analysis of gender heterogeneity, we further examine the effect of education level on the relationship between working hours and mental. In terms of the overall distribution, there were observable differences in the level of sadness and relatively small differences in the level of depression among people with different education levels. A heterogeneity analysis on education level is then conducted to test whether these differences are statistically significant.

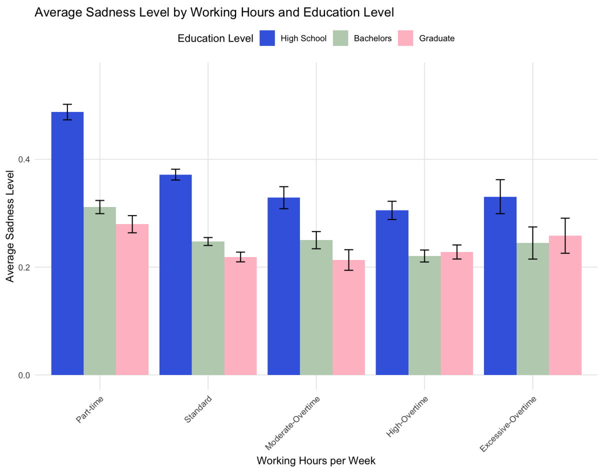

Figure 5: Average Sadness Level by Working Hours and Education

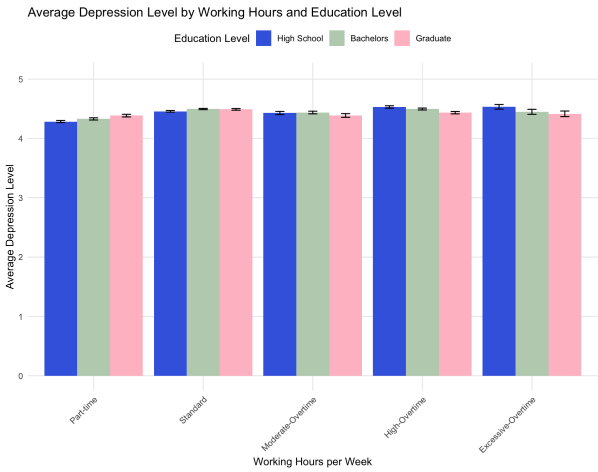

Figure 6: Average Depression Level by Working Hours and Education

The heterogeneity analyses regression results are included in **Table 8**, and their corresponding Chow test results are presented in **Table 9**. For depression in moderate-overtime group, as shown in the first two columns of **Table 8**, there is a stronger positive association among high-educated workers (0.214) compared to those with lower education (0.145). This disparity may be attributed to the cumulative impact of overtime work: while highly achievement-oriented employees may initially perceive overtime as an opportunity for professional growth, prolonged exertion appears to take a greater toll on their mental health (McAllister et al., 2017). In contrast, for part-time work, the effect tends to be slightly larger for the low-education group (0.382) than for the high-education group (0.380), though the differences seem less pronounced. The overall differences between education groups for the depression model are then confirmed by the Chow test to be significant with a p-value near 0.

For the sadness model, the results in the third and fourth columns of **Table 8** show that low education group exhibits stronger associations with working conditions compared to the high education group. Specifically, the results reveal an interesting dynamic related to reference group theory (Richer, 1976) and achievement orientation (Elliot and Harackiewicz, 1994) in behavioral economics. Moderate overtime shows a significant negative effect on sadness only in the low education group, while its impact is not significant for the highly educated group. The low-education group, with a lower reference point, may find it easier to derive satisfaction from overtime work, viewing it as an opportunity for additional income and personal achievement. Moreover, their achievement-oriented mindset might initially lead them to perceive overtime as a valuable opportunity rather than a burden. Part-time work, however, demonstrates robust and significant positive associations with sadness across both education levels, with a notably stronger effect among those with lower education (0.105) compared to those with higher education (0.059), suggesting that reduced working hours might negatively impact satisfaction and achievement feelings, particularly for those with lower education levels. The overall differences between education groups for the sadness model are then verified as well by the Chow test to be significant with a p-value near 0.

Table 8: Heterogeneity Analysis by Education

	Dependent variable:			
	Depression		Sadness	
	Low Edu (1)	High Edu (2)	Low Edu (1)	High Edu (2)
Excessive Overtime	0.009	0.036	0.004	0.019
	(0.083)	(0.095)	(0.028)	(0.029)
High Overtime	-0.007	0.053	-0.029*	-0.016
	(0.044)	(0.049)	(0.015)	(0.012)
Moderate Overtime	0.145***	0.214***	-0.039**	-0.009
	(0.051)	(0.062)	(0.016)	(0.016)
Part time	0.382***	0.380***	0.105***	0.059***
	(0.035)	(0.052)	(0.014)	(0.014)
Age	0.003**	0.0001	0.002***	0.001**
	(0.001)	(0.001)	(0.0004)	(0.0004)
Sex	0.078***	0.184***	-0.033***	-0.015
	(0.016)	(0.036)	(0.006)	(0.010)
Marital Status	0.090***	0.129***	0.035***	0.026***
	(0.009)	(0.011)	(0.003)	(0.003)
Constant	-1.487***	-2.353***	0.353***	0.250***
	(0.112)	(0.272)	(0.037)	(0.076)
Chi-square	31.9	15.88	21.34	6.23
p-value	0	0	0	0
Observations	36,349	22,095	36,349	22,095

Note: Sample covers 2013 to 2018. Standard errors reported in parentheses, clustered in individual. *p<0.1, **p<0.05, ***p<0.01.

Table 9: Chow Test for Education Heterogeneity

	Depression Model	Sadness Model
F-statistics	8.400964	16.33871
p-value	0.00000	0.00000

6 Conclusion and Limitation

This study investigates the complex relationship between working hours and mental health outcomes (depression and sadness) in the United States using IPUMS Health Survey data from 2013-2018. Through OLS and logistic regression analyses, supplemented by mediation tests and heterogeneity analyses across gender and education levels, we provide nuanced insights into how different working hour patterns affect mental well-being.

However, several limitations warrant consideration. First, our study faces potential selection bias by focusing solely on employed individuals, excluding the unemployed population whose mental health conditions might differ systematically. Second, reverse causality presents a significant concern, as individuals with poor mental health might self-select into reduced working hours, potentially overstating the negative association between shorter hours and mental health outcomes. Third, omitted variable bias may exist due to data limitations in IPUMS Health Survey, as several unobserved factors affecting both working hours and mental health, such as workplace environment, job satisfaction, and personal circumstances, are not captured in our dataset.

While we deliberately used pre-2020 data to avoid COVID-19's confounding effects, this decision limits our findings' applicability to the modern workplace, which has undergone substantial transformation through remote work adoption and evolving work-life integration patterns. Future research should address these endogeneity concerns through instrumental variable approaches or natural experiments, while also examining how the relationship between working hours and mental health has evolved in the post-pandemic era.

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Statement of Contributions

- Code: Yiduo Zou, Xueyang Zhang
- Introduction: Sashi Ghimiray
- Data Description: Xintong Gao
- Empirical Strategy: Feifan Zhang
- Result: Yiduo Zou, Xueyang Zhang
- Data Visualization: Yuhua Hong
- Conclusion and Limitation: Yiduo Zou
- Final Compilation and LaTeX Transformation: Yiduo Zou

Public Link

`https://github.com/zhang-xueyang/GroupX-Skywalkers.git`