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**Balancing Work and Earnings: The Long-Term Impact on Mental Health**

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# Balancing Work and Earnings: The Long-Term Impact on Mental Health


## Abstract

Earnings and work hours (e.g., weekly work hours) are key determinants of one's mental health. While higher earnings are linked to better mental health due to reduced financial stress, they may come at the cost of longer work hours harmful for mental health. Therefore, balancing work hours with earnings is crucial for mental health. Using the 2015, 2017, and 2019 waves of the Panel Study of Income Dynamics (N = 6,776), this study explores how one's earnings and work hours combine to influence mental health using growth mixture modeling and a negative binomial regression model, with generalized propensity score weighting for causal inference. The findings reveal that working 40 hours a week with earnings two to three times the US federal poverty threshold benefits mental health. However, earning more by working 60 hours a week does not provide additional mental health benefits. Additionally, individuals with a history of low earnings face a high risk of psychological distress, even as their earnings improve over time. This risk is similar to that experienced by those consistently earning low incomes. Our findings highlight the importance of clarifying work-earning balance for one's mental health as well as identifying people with mental health needs from a longitudinal perspective.


**Keywords:** earnings, weekly work hours, mental health, negative binomial regression, growth mixture modeling, generalized propensity score weighting, causal inference

## Highlights

[1]. Better mental health found at: 40 hr/week with earnings 2 to 3 times the poverty line
[2]. Higher earnings achieved via 60 hr/week do not yield more mental health benefits
[3]. Benefit of higher earnings for mental health could be outweighed by longer work hours
[4]. One-time and persistent low earnings could be similarly harmful for mental health
[5]. long-term patterns of work hours and earnings determine one's mental health

## Introduction

The importance of maintaining good mental health is widely documented due to its profound impact on overall daily life (Ungar & Theron, 2020). Evidence shows that individuals facing economic hardships (e.g., low income) or long work hours (e.g., 60 hours per week) are disproportionately vulnerable to hardships in maintaining mental health (Bannai & Tamakoshi, 2014; Frech & Damaske, 2019; Shields-Zeeman & Smit, 2022; Thomson et al., 2022; Virtanen et al., 2012). Despite substantial studies have explored these topics, how one's earnings and work hours coalesce to influence mental health outcomes remains inadequately explored. For example, while higher income is associated with better mental health due to fewer financial worries, it could be at the cost of long work hours that may harm one's mental health. On the other hand, while avoidance of long work hours could benefit one's mental health, lower earnings could lead to financial worries that worsen one's mental health.

To better clarify the amount of sufficient earnings with the appropriate work hours that best benefit one's mental health, it is important to understand how one's earnings and work hours coalesce to influence mental health outcomes. For this purpose, this study first investigates the patterns of co-existence of earnings and work hours and then its impacts on one's mental health. These analyses results are pivotal to clarify the balance between manageable work hours and sufficient income, which benefit one's mental health. It could provide important insights into targeted strategies to improve mental health outcomes from the work perspective.

*Low income and long work hours are risk factors for people's mental health*

Lower income is a risk factor leading to higher levels of problems in mental health, especially for economically vulnerable populations (Asebedo & Wilmarth,2017; Conger et al., 2010; Masarik & Conger, 2017). Empirical studies support this viewpoint. Landers-Potts et al. (2015) observed that unmet material needs, hardships in making ends meet, and financial cutbacks induced by low income are predictive of depressive symptoms, feelings of discouragement, and hopelessness. Iruka et al. (2012) reported that lower income-to-needs ratios were associated with more depression, somatization, and anxiety. Evidence has also shown that improvement in economic well-being is conducive to one's mental health. Lee et al. (2013) observed that reductions in chronic family economic stress are protective factors to address both short-term and long-term parental stress. A systematic review and meta-analysis showed that an increase and decrease in one's income is associated with improving and decreasing mental health outcomes, respectively (Thomson et al., 2022). These findings show that financial strain creates a challenging environment where stress can manifest, underscoring the critical link between income levels and mental health outcomes.

Empirical evidence demonstrates an association between work hours and mental health outcomes. Virtanen et al. (2011) observed that employees working more than 55 hours per week are at greater hazard ratio of developing depressive and anxiety symptoms compared with employees working 35 to 40 hours per week. Another study shows similar findings even controlling for one's socioeconomic demographic features as well as chronic physical disease and the use of smoking and alcohol among participants with no psychological morbidity at baseline (Virtanen et al., 2012). In Japan, Kato et al. (2014) observed the risk of the new onset of depressive disorder is more than four times higher for employees working with 60 or more hours per week than for those working 50 or lower hours per week. Along with these studies, a systematic review showed that longer working hours are associated with a greater risk of problems in mental health (Bannai & Tamakoshi, 2014). Biological evidence supports the association between long work hours and mental health. Parent-Lamarche & Marchand (2018) reported that long work hours without adequate rest can contribute to chronic physiological arousal and dysregulation of stress hormones, such as cortisol, which are linked to one's mental health. Together, these insights collectively the detrimental effects of long work hours on mental health, underscoring the critical link between work hours and mental health outcomes.

*The importance of considering the co-existence of income and work hours across time*

When evaluating the impact of income and work hours on mental health, it is imperative to consider their co-existence rather than examining each factor in isolation. The interplay between income and work hours provides a more nuanced and comprehensive understanding of an individual's overall well-being. High income can alleviate financial stress, thereby enhancing mental health (McCarthy, 2011). However, if it comes at the cost of excessively long work hours, the benefits may be mitigated by increased burnout, chronic stress, and reduced quality of life (Hu et al., 2016; Fontinha et al., 2019; Fordjour et al., 2020). Excessively long work hours can lead to fatigue and poor work-life balance, which are detrimental to mental health (Afonso et al., 2017; Kowitlawkul et al., 2019; Park et al., 2020; Rose et al., 2017). On the other hand, shorter work hours may contribute to better mental health by allowing more personal time to enhance life satisfaction (Kamerāde et al., 2020). However, if these reduced hours result in insufficient income, financial insecurity, and associated stress can offset the mental health benefits gained from having more free time (Alexander & Haley-Lock, 2015). In addition to the possibility that higher income may come at the cost of longer working hours, potentially harming one's mental health, it is also possible that people with similar work hours have different levels of earnings. Therefore, rather than only focusing on one's earnings or work hours, the integrated perspective acknowledges both dimensions and its impacts on mental health. Such analyses advance our understanding of how to necessitate multifaceted interventions and policies to improve one's mental health.

When evaluating the impact of one's earnings and work hours on mental health, employing longitudinal measures rather than a single time point offers a more robust and dynamic understanding of the co-existence of both earnings and work hours. Longitudinal data captures the trends in both income and work hours across time, providing insights into how changes in these variables may affect mental health. For example, longitudinal measures can show whether consistent overwork leads to mental health deterioration, or consistently higher income eventually alleviates financial stress despite long work hours. On the other hand, a single time point measure may capture a period of high income and long work hours, but it cannot help us to understand whether this is a sustained condition or a transient spike. A longitudinal perspective is therefore essential for a more nuanced understanding of how income and work hours influence mental health outcomes.

*Research gaps and the current study*

Examining the co-existence of both earnings and work hours across time offers insights that surpass those gained from analyzing each factor in isolation at a single time point. Despite the potential advantages, there remains a significant gap in our understanding of the co-existence of earnings and work hours across time and its impacts on one's mental health. This study aims to clarify the co-existence of earnings and work hours across time and its impacts on one's mental health. Recognizing that not all people exhibit the same pattern in the co-existence of earnings and work hours across time, this research first investigates the heterogeneity in these co-existing trajectories. Following this, the study examines how variations in these co-existing trajectories predict different levels of mental health outcomes. These analyses enable us to better understand how earnings and work hours coalesce to influence one's mental health outcomes, a key for policy and intervention implications to improve one's mental health through figuring out the balance between manageable work hours and sufficient earnings.

## Method

### *Data*

This study uses the Panel Study of Income Dynamics (PSID), a longitudinal study based on interviews with a nationally representative sample of families. The PSID contains detailed information on economic information (e.g., an individual's earnings, family income, assets) and other demographic information, including but not limited to age, gender, race and ethnicity, marital status, employment status, educational attainments, mental health, and family composition. The PSID was conducted annual between 1968 and 1997 and biennially thereafter. The current study draws on the 2015, 2017, and 2019 waves (Survey Research Center, 2015, 2017, 2019). Given that the US retirement age for full benefits under Social Security is between 66 and 67, this study is aligned with Chen et al. (2021) to restrict analyses to adults aged between 18–65. The analytic sample consisted of 6,776 observations.

***Measures***

Earnings are coded as a continuous variable that represents the ratio of an individual's annual employment earnings to the U.S. official poverty line. This ratio takes into account the number of family members to adjust for family size (U.S. Census Bureau, n.d.). A value of 1.0 represents earnings exactly at the poverty threshold for that family size. Values greater than 1.0 indicate that earnings are above the poverty line, while values less than 1.0 signify earnings below the poverty line. For example, a ratio of 0.5 means that the individual earns only half of what is considered necessary to meet the basic needs of their family, while a ratio of 2.0 indicates double the poverty threshold.

Working hours are coded as a continuous variable that represents the average weekly hours worked throughout the year. It is recorded in numeric form, with values corresponding to the average number of hours per week. For instance, a value of 40 indicates a standard full-time work schedule, while values lower than 40 might indicate part-time work, and higher values suggest overtime or extended work hours.

Psychological distress is coded as a continuous variable by summing item scores from the Kessler Psychological Distress Scale (Kessler et al., 2002), which consists of six items assessing mental health (felt nervous, hopeless, restless, that everything was an effort, feeling sad or worthless). The items are scored by the PSID as follows: A response of 'All of the Time' = 4 points, 'Most of the Time' = 3 points, 'Some of the Time' = 2 points, 'A Little of the Time' = 1 point, and 'None of the Time' = 0 points. The total score is calculated by adding up all item responses, yielding a composite score where higher values indicate greater psychological distress.

Demographic covariates reflecting one's demographic characteristic included age (years), gender (female or male), race and ethnicity (non-Hispanic White American, non-Hispanic Black American, non-Hispanic Others, or Hispanic), family structures (with or without spouse & with or without children), educational attainment (college or above degree), other household income sufficiency (yes or no), household wealth sufficiency (yes or no), and living place (metro areas or not). Other household income sufficiency is a binary variable reflecting whether the total of all income other than one's earnings (e.g., income from other family members) is above the US federal poverty threshold or not, accounting for variability in the number of family members. Household wealth sufficiency is a binary variable (sufficient or not). Following definitions pioneered by Caner and Wolff (2004) and Haveman and Wolff (2004), households are defined as wealth insufficiency if their wealth is insufficient for meeting needs for a period of three months, which also can be described as wealth below one quarter of the US federal poverty threshold. Based on data set availability, household wealth includes savings and other assets (e.g., farm or business, bonds, stocks, vehicles) minus all debts. Baseline psychological distress, as measured by the Kessler Psychological Distress Scale in the 2015 PSID, is included as a covariate. By including baseline mental health as a covariate, we control for pre-existing differences in mental health status, allowing us to more accurately isolate the effects of co-existing earnings and work hours on subsequent mental health outcomes.

***Statistical analyses***

Following Asparouhov and Muthén (2014), this study utilized a three-step approach to investigate the heterogeneity in co-existing trajectories of earnings and working hours across time and its impacts on psychological distress. In the first step, we estimated heterogeneity in co-existing trajectories of earnings and working hours across time using growth mixture modeling, which classified people into different groups (i.e., classes) based on their earnings and working hours between 2015 and 2019. People sharing similar co-existing trajectories of earnings and working hours were categorized into the same class. In growth mixture modeling, a trajectory within a class does not imply that everyone follows the same trajectory; instead, it indicates that individuals with similar patterns of trajectory across time are grouped into the same class (Nguefack et al., 2020; Ram & Grimm, 2009). Earnings and working hour trajectories were constructed by measuring earnings and working hours at the 2015 data wave, the 2017 data wave, and the 2019 data wave. The detection of two or more classes indicates there is heterogeneity in co-existing trajectories of earnings and working hours across time.

The second step was to determine the optimal number of classes, for which we used the following goodness-of-fit statistics indexes: log-likelihood value (LogL), the Akaike's information criterion (AIC), the Bayesian information criterion (BIC), and the sample size adjusted BIC (SABIC). Generally, the method of determining the optimal number of classes is to choose higher LogL values or lower AIC, BIC, and SABIC values (Chen et al., 2017; Nylund et al., 2007). This study also employed entropy values to determine the optimal number of classes. A higher entropy value indicates a more precise classification. Following Nylund et al. (2007), for class membership assessment, this study utilized the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR) and the Adjusted Lo-Mendell-Rubin likelihood ratio test (ALMR). A significant result ($p < 0.05$) from these likelihood ratio tests indicates that the model with ***k*** classes is superior to the model with ***k-1*** classes. To ensure sufficient power to detect differences between classes, Nylund et al. (2007) suggested that each class should contain at least 5% of the sample. Growth mixture modeling and class determination based on the aforementioned goodness-of-fit statistics indexes were conducted using M*plus* 6.12. These analyses enabled us to clarify whether there were two or more patterns of co-existing trajectories (i.e., classes) of earnings and working hours across time (indicating heterogeneity in co-existing trajectories of earning and working hours).

In the third step, the class membership was utilized as a categorical variable to predict the risk of psychological distress while controlling for sociodemographic characteristics. To account for over-dispersed Poisson distribution of the outcome, this study applied a negative binomial regression model for analyses. As post-estimation, the linear combination of coefficients test was conducted to compare the strength of relationships linking class memberships to psychological distress. The negative binomial regression model applied with generalized propensity score weighting and its post-estimation of coefficient comparison were conducted using the Stata 13.0 MP version.

For causal inference that accounts for potential selection bias in different classes (i.e., co-existing trajectories of earnings and working hours), this study conducted analyses applied with generalized propensity score weighting. As a quasi-experimental method, generalized propensity score weighting was employed to ensure observations across different classes share similar demographic characteristics and similar baseline psychological distress. In such a case, it enables us to better assess the impacts of earnings and working hours patterns on one's psychological distress.

Following Guo and Fraser (2015), to create a generalized propensity score weight, a multinomial logistic regression model was first run to predict the probability of each pattern of earnings and working hours across time, $\boldsymbol{P_n}$, where $\boldsymbol{n}$ represents the number of class memberships determined using growth mixture modeling. Demographic characteristics and baseline psychological distress were included as independent variables to predict probability $\boldsymbol{P_n}$. Next, we utilized the predicted probability $\boldsymbol{P_n}$ to create a generalized propensity score by the inverse probability, namely $\boldsymbol{1/ P_n}$. As table 4 shows, this study conducted the balance tests and observed that application of generalized propensity score weighting make baseline demographic features and baseline psychological distress not statistically different between classes. Specifically, by ensuring baseline psychological distress similar across different classes, the application of generalized propensity score weight enables us to account for the potential reverse causality that shows the impacts of psychological distress on class memberships.

## Results

*Class memberships*. Class memberships were examined in order to explore the heterogeneity in co-existing trajectories of earnings and working hours. In Table 1, the VLMR and ALMR tests show that the model containing six classes did not fit the data in a significantly better way than the model containing five classes. For this reason, models containing two, three, four, or five classes were considered. The VLMR and ALMR tests show that five-class solution is better than the lower-class solutions. Also, given the higher values of log-likelihood as well as lower values of AIC, BIC, and SABIC, this study concluded that the five-class solution is more appropriate than the lower-class solutions to identify the heterogeneity of earnings and working hours across time.

Figure 1 and figure 2 respectively show the trend of earnings and working hours across time in each class. For class 1, *the improving class*, both earnings ratio and weekly work hours increase across time. For class 2, *the worsening class*, both earnings ratio and weekly work hours decrease across time. For class 3, *the persistently high class*, both earnings ratio and weekly work hours are persistently high. For class 4, *the persistently low class*, both earnings ratio and weekly work hours are persistently low. For class 5, *the sufficient class*, both earnings ratio and weekly work hours are persistently stable, but not as high as those shown in class 3.

*Descriptive results by class memberships*. Table 2 shows that demographic characteristics vary by class memberships. For example, a greater portion of people in the classes featured with stable earnings and working hours across time (i.e., class 3 and 5) have college degrees. For people in the class 4 (persistently low earnings and work hours), a greater proportion are non-Hispanic Black Americans, live without spouse or child, and have higher psychological distress scores. People in the class 1 (low earnings and work hours that improve with time), show low household income and household assets at baseline.

*Negative binomial regression model applied with generalized propensity score weighting*. To support causal inference that demonstrates the impacts of class memberships on psychological distress, this study applied generalized propensity score weighting to the negative binomial regression model. Table 4 shows that application of generalized propensity score weighting makes the demographic differences between class memberships become non-significant. By ensuring people in different class memberships share similar demographic features and baseline psychological distress, such a quasi-experimental approach is able to more validly illustrate the impacts of class memberships on one's psychological distress.

Table 3 shows that the risk of psychological distress for people in class 3 is statistically lower than the risk of psychological distress for people in class 4 (Log incidence Rate Ratio = - 0.27, $p<0.01$). Table 3 shows that the risk of psychological distress for people in class 5 is statistically lower than the risk of psychological distress for people in class 4 (Log incidence Rate Ratio = - 0.20, $p<0.01$). Table 3 shows that the risk of psychological distress for people in class 1 or class 2 is non-statistically different from the risk of psychological distress for people in class 4 ($p>0.05$). Post-estimation shows that the risk of psychological distress for people in class 3 is non-statistically different from the risk of psychological distress for people in class 5 ($p>0.05$).

The risk of psychological distress for people in class 5 is significantly lower than the risk of psychological distress for people in class 1 ($p<0.05$) and people in class 2 ($p<0.001$). The risk of psychological distress for people in class 1 and people in class 2 is non-statistically different from each other ($p>0.05$).

## Discussion

This study shows the heterogeneity in the co-existence of earnings and work hours trajectories and how such heterogeneity impacts on one's psychological distress. Findings of our study suggest the importance of getting sufficient income with a manageable work hour. More specifically, findings show that earning an income four times the US federal poverty threshold at the cost of working 60 hours per week does not necessarily lead to lower psychological distress compared to earning an income two to three times the US federal poverty threshold at the cost of working 40 hours per week. Therefore, even with higher earnings from working 60 hours a week, the risk of psychological distress is not significantly lower compared to those working 40 hours a week. There are several reasons. Longer working hours can cause not only feelings of tiredness but also strained relationships with family and friends which interfere with the access to social support and overall life satisfaction (Shafer et al., 2018). Also, it may impair hormone release that determines cognitive functions and emotional regulation, making individuals more susceptible to depressive and anxiety symptoms (Gerding & Wang, 2022). Thus, the benefits of additional income could be outweighed by the negative impacts of longer work hours on well-being, making a moderate income with a manageable work hour an option that contributes to less psychological distress and in turn, contribute to better overall mental health.

Results also show that the risk of psychological distress in class 1 (i.e., *the improving class*) is not significantly different from that in class 4 (*the persistently low class*). Although earnings and work hours may increase over time, some individuals might still face psychological challenges. These previous economic difficulties may have a lasting effect, where the stress and anxiety from those times continue to influence individuals even after their situation improves (Perreault et al., 2020). This suggests that the mental health effects of financial struggles could persist. Consequently, it is important to provide mental health support to those who have ever experienced economic hardship, as past experiences may continue to affect their mental health even if their present economic situation is stable.

Results show that the risk of psychological distress for people in class 5 (*the sufficient class*) is significantly lower than the risk of psychological distress for people in class 1 (*the improving class*) and people in class 2 (*the worsening class*). These findings suggest that a stable employment providing sufficient earnings across time plays an important role in maintaining one's mental health. This viewpoint aligns with empirical findings, which show that the lack of a stable job can pose a comparable threat to mental health as unemployment does (Flint et al., 2013; Kim & von dem Knesebeck, 2015).

Our results also suggest that people with similar work hours could have different levels of earnings. More specifically, even though weekly work hours among people in class 1 (*the improving class*) increase to a similar level to people in class 5 (*the sufficient class*) in 2019, earnings of the former group are only half of earnings of the latter group. Such findings suggest barriers to better earning opportunities among these populations. Relevantly, our results show that class 4 (*the persistently low class*) simultaneously experience consistently low earnings and work hours, risk factors worsening one's mental health. Reasons include the high cost of moving upward in the socioeconomic status ladder (Conger et al., 2010). In modern society, this trend may exacerbate with time, especially with rising demand in specialized fields like high-tech jobs, further restricting access to lucrative job markets for the socioeconomically vulnerable populations (Autor & Salomons, 2018). Although obtaining higher employment skill levels or educational attainments could be a strategy, nowadays, it has become more financially cost for people with lower socioeconomic status (Hout, 2021; Oreopoulos & Salvanes, 2011; Wyner et al., 2020). More efforts are required to coordinate educational and employment interventions and policies to ensure the socioeconomically vulnerable populations to succeed in the modern job markets.

The relationship between earnings, work, and mental health outcomes can be understood through a series of interrelated pathways. Higher earnings can lead to improved mental health by providing financial stability, reducing stress associated with economic insecurity (Thomson et al., 2022). Work environment also play a crucial role; positive work conditions and a sense of accomplishment can enhance mental health, while job strain and poor work conditions may contribute to mental health challenges (Kato et al., 2014). Additionally, the interaction between earnings and work-related factors, such as work-life balance and social support, further influences mental health (Obrenovic et al., 2020; Shafer et al., 2018). These empirical findings suggest that mental health outcomes are shaped not only by the direct effects of earnings and work conditions but also indirectly through subjective well-being reflected in one's working environment, financial stability, and work-life balance.

While a macro-level intervention such as raising minimum wage standards is a key to enhancing work-earning balance (Carr, 2023), it is also important to know that achieve a healthy work-earning balance is intricately tied to the micro-level dynamics within a workplace. Company culture significantly impacts work-life integration by setting the tone for flexibility, remote work options, and support for personal development. Effective communication and support from supervisors can foster open communication, understanding of personal needs, and opportunities for growth, leading to open access to opportunities for a work-life balance (Susanto et al., 2022; Webber et al., 2010). Thus, while a macro-level intervention through policy reform provides a structural framework, it is the micro-level dynamics such as organizational culture and interpersonal relationships that profoundly shape one's ability to achieve a harmonious work-earning balance. Notably, small and medium enterprises could adopt more flexible, but less formal, approaches, while larger organizations might follow more structured processes and have dedicated teams in work arrangements (Harney & Dundon, 2006). Furthermore, acknowledging the role of trade unions is crucial given unions can significantly influence work-life balance agreements by negotiating work arrangements (Tremblay, 2016). Therefore, interventions improving these conditions are also suggested.

To better understand how to address disparities in earnings and work hours, it is crucial to analyze these gaps across various demographic characteristics. Evidence highlights gender-based differences in income and work hours, reflecting broader systemic inequalities that persist despite efforts to reduce them (Weeden et al., 2016). While this study adopts a quasi-experiment design using generalized propensity score weight to ensure all socioeconomic covariates, including baseline mental health, do not significantly differ between people when evaluating the impacts of work hour and earnings on mental health, future studies are encouraged to further explore potential mechanisms resulting in these disparities by demographic features.

While this study focuses on investigating the impacts of co-existence patterns of working hours and earnings on mental health, it is important to know that gender is a key determinant of the complex systems interplayed by working hour, earnings, and mental health. More specifically, gender plays a significant role in shaping the relationship between work hours, earnings, and mental health, often due to societal expectations and workplace dynamics (Dinh et al., 2017; Dembe & Yao, 2016; Krieger, 2020; Moortel, 2020). Women, particularly those balancing family responsibilities, tend to experience higher rates of part-time work or reduced hours, leading to lower overall earnings compared to men. This earnings gap is exacerbated by occupational segregation, where women are more likely to work in lower-paid industries. Longer work hours, common in male-dominated fields, can strain mental health across genders, but women may face additional mental health challenges from the cumulative demands of unpaid caregiving and work, which enlarges the disparity in working hour and earnings by gender (Son-Hing et al., 2023). These disparities underscore how gender norms and expectations influence financial stability and well-being, often intensifying stress and impacting mental health differently across genders (Dinh et al., 2017; Dembe & Yao, 2016; Krieger, 2020; Moortel, 2020). Overall, these studies suggest that how working hour and earnings determine one's mental health could not be fully identical for female and male.

To further have a clearer picture, this study conducts a sensitivity analysis stratified by gender. Results of a sensitivity analysis shown in Table 5 demonstrate that the findings based on the main model are similarly applicable to both male and female. More specifically, long-term and stable work hours and earnings are key to one's mental health, and having higher earnings at the costs of longer working hours does not significantly further improve one's mental health. While these results are applicable to both female and male, it does not mean that gender is not an important factor. Rather, results based on Table 2 show that there are lower proportions of female belonging to Class 3 (i.e., high earnings and work hours) and Class 5 (sufficient earnings and work hours). Noticeably, both Class 3 and Class 5 have lower proportions of educational attainment equal to or above college. Also, these two classes have higher proportions of simultaneously living with a spouse and children, which could reflect the possibility that female could support male's working for earnings. These results suggest that there could be possible interconnections between these factors, which could shrink female's capacity to fully engage in a stable work that provides with sufficient earnings.

To address disparities in work hours and earnings, policies must prioritize equal access to education, job training, and career advancement opportunities for underrepresented groups (Tomaskovic-Devey & Avent-Holt, 2019). Implementing wage transparency, raising minimum wage standards, and enforcing stronger laws can help ensure fair compensation (Abbott, 2013). Achieving universally fair wage-to-hours ratios requires a combination of governmental regulation, corporate accountability, and collective bargaining efforts to promote equitable work environments and reduce systemic biases (Tomaskovic-Devey & Avent-Holt, 2019).

This study's findings are subject to several limitations. One limitation of our study is that, as there is no perfect data set that contains all variables, we did not include other factors influencing psychological distress, such as genetic and environmental variables. To mitigate this, we included baseline psychological distress applied with generalized propensity score weighting to account for pre-existing differences in mental health status. Future research that incorporates these additional factors could provide a more comprehensive understanding and allow for comparisons with our findings to see how results may vary. Physical health is an important factor affecting one's capacity to work. When available, future studies are encouraged to include comprehensive physical health conditions for analyses and compare results with ours to investigates how the impacts of work hours and earnings on mental health may vary by this factor. Also, this study does not include employment type for analyses for the following reasons. First, while this study simultaneously includes earnings and work hours for analyses, an addition of employment type could lead to a multicollinearity issue. The reason could be attributed to the fact that both work time and earnings are already key components of one's employment (Merriman, 2014). Second, an empty cell effect hinders coefficient estimation. For instance, none of the unemployed belong to the overworking class, and no military or police personnel fall into the long-term no earnings and work hour class. When including the employment type into the analyses, the coefficient estimation would be hindered. Therefore, to avoid multicollinearity and the empty cell effect, this study does not include job type to ensure a valid estimation of the impact of class simultaneously embodied by work hour and earnings on mental health. Additionally, like any other mental health measures, the Kessler Psychological Distress Scale utilized as a mental health measure in this study cannot capture every dimension of one's mental health. Future studies are encouraged to apply different mental health measures to explore how the impacts of differences in work hours and earnings on mental health may vary.

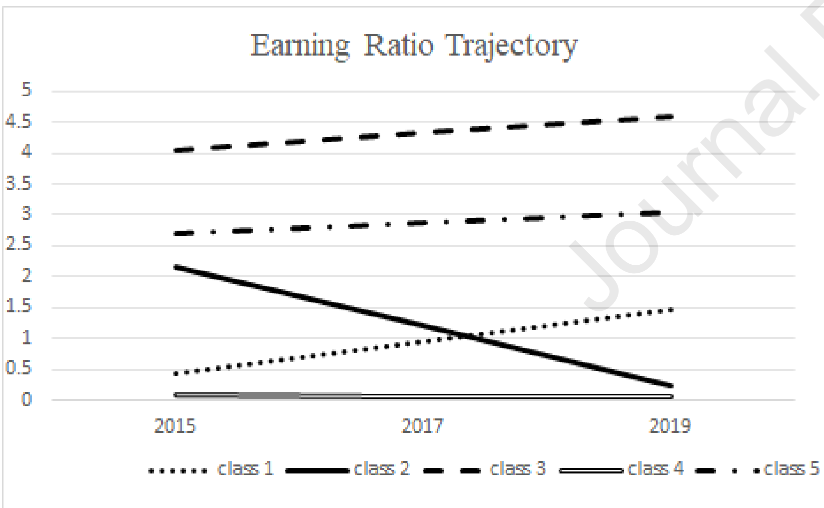
**Conclusions**

Manageable work hours (about 40 hours per week) with annual earnings two to three times the official US federal poverty threshold have positive impacts on one's mental health. Higher earnings at the cost of longer work hours (about 60 hours per week) do not have more positive changes to one's mental health. People with past experiences in low earnings are at higher risk of more severe mental health issues even though for those whose earnings are improving across time. Thes findings underscore the importance of providing mental health support alongside economic aid to help individuals fully recover from the impacts of economic hardships. Policymakers and employers should consider implementing comprehensive support systems that address both the economic and psychological aspects of recovery for the economically vulnerable populations.

Table 1. Growth Mixture Modeling Model Fit Indexes of the Class Membership

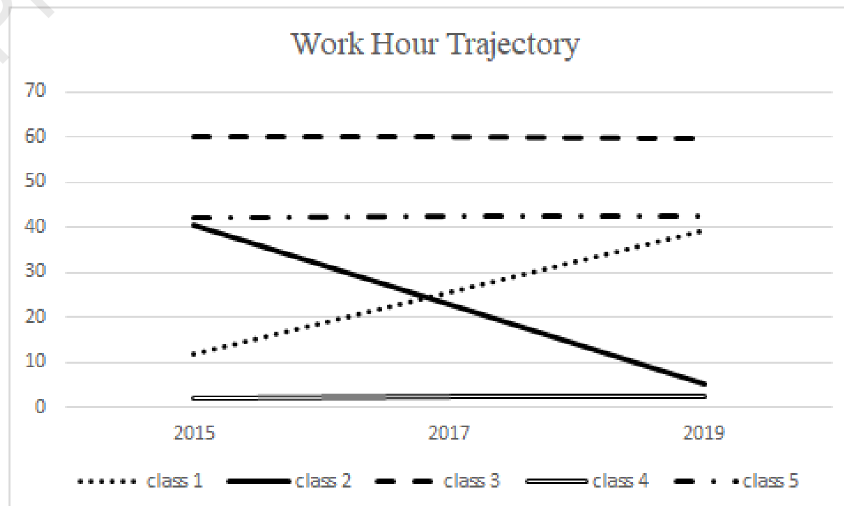
| Classes | LogL | Entropy | AIC | BIC | Adj. BIC | VLMR (*p*) | ALMR (*p*) | Smallest Class (%) |
|---|---|---|---|---|---|---|---|---|
| 2 | -151312.03 | 0.961 | 302644.06 | 302712.27 | 302680.50 | < 0.001 | < 0.001 | 19.9 |
| 3 | -148633.92 | 0.903 | 297297.85 | 297400.17 | 297352.50 | < 0.001 | < 0.001 | 14.6 |
| 4 | -146051.53 | 0.930 | 292143.07 | 292279.49 | 292215.94 | < 0.001 | < 0.001 | 8.4 |
| **5** | **-143857.14** | **0.945** | **287764.28** | **287934.81** | **287855.37** | **< 0.001** | **< 0.001** | **7.4** |
| 6 | -143048.52 | 0.923 | 286157.03 | 286361.67 | 286266.33 | > 0.05 | > 0.05 | 2.3 |

Figure 1. Earnings ratio trajectory




Note: vertical axis reflects the ratio of earnings to the US poverty threshold

Figure 2. Weekly work hour trajectory




Note: vertical axis reflects working hours per week

Table 2. Descriptive Results Based on Latent Classes (N=6,776)

| | Class 1 ($N$ = 503, 7.4%) | Class 2 ($n$ = 554, 8.2%) | Class 3 ($n$ = 808, 11.9%) | Class 4 ($n$ = 830, 12.3%) | Class 5 ($n$ = 4,081, 60.2%) |
|---|---|---|---|---|---|
| Age*** | 36.9 (SD=12.2) | 47.1 (SD=13.5) | 40.0 (SD=10.8) | 50.0 (SD=10.3) | 39.0 (SD=11.5) |
| Female*** | 49.1% | 39.4% | 16.8% | 43.6% | 31.7% |
| Ethnicity and Race*** | | | | | |
| non-Hispanic White | 33.0% | 42.4% | 56.5% | 37.1% | 50.3% |
| non-Hispanic Black | 56.5% | 46.6% | 32.7% | 55.7% | 37.7% |
| non-Hispanic others | 1.4% | 2.7% | 2.8% | 2.0% | 2.2% |
| Hispanic | 9.1% | 8.3% | 8.0% | 5.2% | 9.8% |
| College degree or higher*** | 17.3% | 21.0% | 38.5% | 11.9% | 32.1% |
| Insufficiency of other household income*** | 66.6% | 58.1% | 50.7% | 48.2% | 55.7% |
| Insufficiency of household assets*** | 82.3% | 64.1% | 48.4% | 74.0% | 62.9% |
| Family structure*** | | | | | |
| w/o child & w/o spouse | 41.2% | 39.2% | 24.9% | 47.0% | 31.4% |
| w/o child & w/ spouse | 11.7% | 27.8% | 23.1% | 22.5% | 20.6% |
| w/ child & w/o spouse | 31.6% | 17.7% | 9.8% | 19.0% | 17.2% |
| w child & w spouse | 15.5% | 15.3% | 42.2% | 11.5% | 30.8% |
| Urban | 86.1% | 84.6% | 82.5% | 82.1% | 85.3% |
| Baseline psychological distress*** | 4.5 (SD=4.8) | 3.5 (SD=4.4) | 3.2 (SD=3.6) | 5.4 (SD=5.6) | 3.2 (SD=3.5) |

* $p < 0.05$; ** $p < 0.005$; *** $p < 0.001$

Table 3. Negative binomial regression model applied with generalized propensity score weighting (Outcome: psychological distress)

| Predictors | Coefficient | *p*-value | 95% C.I. |
|---|---|---|---|
| Class of earnings and weekly work hours | | | |
| Class 4: persistently low earnings and work hours (ref) | | | |
| Class 1: low earnings and work hours that improve by time | -0.04 | 0.680 | [-0.21, 0.14] |
| Class 2: decreasing earnings and work hours | 0.05 | 0.527 | [-0.11, 0.22] |
| Class 3: high earnings and work hours | **-0.27** | **0.001** | **[-0.43, -0.11]** |
| Class 5: sufficient earnings and work hours | **-0.20** | **0.004** | **[-0.33, -0.06]** |
| Age | **-0.01** | **<0.001** | **[-0.02, -0.00]** |
| Female | 0.09 | 0.191 | [-0.05, 0.23] |
| Ethnicity and Race | | | |
| non-Hispanic White (ref) | | | |
| non-Hispanic Black | **0.15** | **0.004** | **[0.05, 0.26]** |
| non-Hispanic others | 0.26 | 0.060 | [-0.01, 0.53] |
| Hispanic | **0.19** | **0.048** | **[0.00, 0.38]** |
| College degree or higher | -0.10 | 0.077 | [-0.21, 0.01] |
| Insufficiency of other household income | -0.00 | 0.957 | [-0.11, 0.00] |
| Insufficiency of household assets | **0.16** | **0.005** | **[0.05, 0.27]** |
| Family Structure | | | |
| w/o child & w/o spouse (ref) | | | |
| w/o child & w/ spouse | **-0.22** | **0.010** | **[-0.38, -0.05]** |
| w/ child & w/o spouse | **-0.16** | **0.023** | **[-0.30, -0.02]** |
| w child & w spouse | -0.04 | 0.604 | [-0.19, 0.11] |
| Urban | -0.08 | 0.185 | [-0.19, 0.04] |
| Baseline psychological distress | **0.10** | **<0.001** | **[0.09, 0.11]** |

Post estimation using the linear combination of coefficients test shows that coefficient strength of class 3 is not statistically different from coefficient strength of class 5 ($\beta$ = - 0.07, p=0.158; 95% C.I.= [-0.18, 0.03]).
95% C.I.: the 95% confidence interval.

Table 4. Balance Test of Generalized Propensity Score Weighting [b]

| | P-value before weighting | P-value after weighting [a] |
|---|---|---|
| Age | **P<0.001** | P=0.349 |
| Female | **P<0.001** | P=0.243 |
| Ethnicity and Race | **P<0.001** | P=0.714 |
| College degree or higher | **P<0.001** | P=0.070 |
| Sufficiency of other household income | **P<0.001** | P=0.487 |
| Sufficiency of household assets | **P<0.001** | P=0.362 |
| Family structure | **P<0.001** | P=0.637 |
| Urban | P=0.071 | P=0.851 |
| Baseline psychological distress | **P<0.001** | P=0.959 |

[a] After applying generalized propensity score weighting, this study found that people in different class memberships share similar baseline demographic features and baseline psychological distress (i.e., no significant difference in baseline demographic features and baseline psychological distress between different class memberships).
[b] By ensuring all people share similar baseline demographic features and similar baseline psychological distress, such a balance test justifies the use of generalized propensity score weighting to get a valid causal inference of how class memberships impact psychological distress.

Table 5. Sensitivity analysis: Negative binomial regression model stratified by gender (Outcome: psychological distress)

| Predictors | Coefficient | *p*-value | 95% C.I. |
|---|---|---|---|
| Class of earnings and weekly work hours (Female) | | | |
| Class 4: persistently low earnings and work hours (ref) | | | |
| Class 1: low earnings and work hours that improve by time | -0.08 | 0.421 | [-0.27, 0.11] |
| Class 2: decreasing earnings and work hours | 0.01 | 0.882 | [-0.18, 0.21] |
| Class 3: high earnings and work hours | **-0.38** | **0.002** | **[-0.63, -0.14]** |
| Class 5: sufficient earnings and work hours | **-0.22** | **0.004** | **[-0.37, -0.07]** |
| Class of earnings and weekly work hours (Male) | | | |
| Class 4: persistently low earnings and work hours (ref) | | | |
| Class 1: low earnings and work hours that improve by time | -0.19 | 0.182 | [-0.38, 0.01] |
| Class 2: decreasing earnings and work hours | -0.07 | 0.398 | [-0.25, 0.10] |
| Class 3: high earnings and work hours | **-0.31** | **<0.001** | **[-0.46, -0.15]** |
| Class 5: sufficient earnings and work hours | **-0.30** | **<0.001** | **[-0.43, -0.17]** |

Female: Post estimation using the linear combination of coefficients test shows that coefficient strength of class 3 is not statistically different from coefficient strength of class 5 (β = - 0.16, p=0.126; 95% C.I.= [-0.37, 0.05]).
Male: Post estimation using the linear combination of coefficients test shows that coefficient strength of class 3 is not statistically different from coefficient strength of class 5 (β = - 0.01, p=0.868; 95% C.I.= [-0.11, 0.10]).
95% C.I.: the 95% confidence interval.

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**Balancing Work and Earnings: The Long-Term Impact on Mental Health**

**Highlight**

**[1]**. Better mental health found at: 40 hr/week with earnings 2 to 3 times the poverty line

**[2]**. Higher earnings achieved via 60 hr/week do not yield more mental health benefits

**[3]**. Benefit of higher earnings for mental health could be outweighed by longer work hours

**[4]**. One-time and persistent low earnings could be similarly harmful for mental health

**[5]**. long-term patterns of work hours and earnings determine one's mental health