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Long-term Effects of Job Displacement on Earnings and Mental Health: Evidence from Population-wide Administrative Data

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Abstract

This paper analyzes the impacts of job displacement on earnings and mental health in Taiwan. Findings reveal an immediate 67-68% earnings loss after displacement, with incomplete recovery after a decade. Mental health suffers in the long term, with 15-16% more outpatient visits and 57-62% higher medical costs.

JEL codes: J63, I12

Keywords: Job Displacement, Earning Loss, Mental Health

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1 Introduction

Worker displacement can result in long-term earnings losses (Ruhm, 1991; Jacobson et al., 1993; Lachowska et al., 2020) as well as heightened risks of health issues and increased mortality rates (Strully, 2009; Sullivan and von Wachter, 2009; Kuhn et al., 2009; Schaller and Stevens, 2015; Eliason and Storrie, 2009b,a; Browning and Heinesen, 2012; Lee et al., 2023). Despite significant research, the relationship between job loss and mental health remains ambiguous, and as yet there is no consensus on the extent of its effects (Cygan-Rehm et al., 2017; Salm, 2009; Keefe et al., 2002). On one hand, job loss can result in financial difficulties, loss of status, and social disconnection (Coope et al., 2015; Canavan et al., 2021), which can contribute to anxiety and depression. On the other hand, job loss may alleviate some of the mental health problems associated with working.

In this paper, we investigate the long-term effects of job loss on earnings and mental health. Using administrative data from the entire population of Taiwan, we track earnings and healthcare use, including both outpatient and inpatient care, of the same individuals over a 16-year period. This feature sets our study apart from most existing studies that rely on survey data (Schmitz, 2011; Marcus, 2013; Drydakis, 2015; Cygan-Rehm et al., 2017), as surveys usually do not track the same individuals over extended periods and often only examine outcomes at a single point in time.[1] In addition, our study benefits from Taiwan's National Health Insurance, a mandatory single-payer system, reducing data attrition issues common in studies reliant on employer-based health insurance systems.[2]

[1]Several studies (Kuhn et al., 2009; Bíró and Elek, 2020) using large administrative data also only examined the short-run impact of job loss on health due to data limitation. A notable exception is the study by Browning and Heinesen (2012), which tracked inpatient mental health care utilization over 20 years and found significant long-term effects of job displacement on hospitalization due to mental disorders. However, most mental health issues require outpatient rather than inpatient care. Our dataset includes both types of care, providing a more complete picture of the impact of job loss on mental health.

[2]Health insurance coverage, often tied to employment, poses a challenge for studies using health claim data. Job loss or transition to self-employment can lead to loss of employer-based insurance, as seen in the systems like the U.S., necessitating the exclusion of such individuals from samples (Huang et al., 2014). Additionally, some health insurance systems do not cover the self-employed (Kuhn et al., 2009; Bíró and Elek, 2020), further complicating data representation.

A major challenge in estimating displacement effects is distinguishing between causation and selection, as less healthy workers may be more prone to displacement (Zimmer, 2021). To address selection bias, we follow prior studies (Jacobson et al., 1993; Sullivan and von Wachter, 2009; Browning and Heinesen, 2012; Salm, 2009; Classen and Dunn, 2012) and focus on mass layoffs and plant closures, acting like natural experiments since mass layoffs and plant closures occur irrespective of individual productivity or health. Further, we use the entropy balancing (EB) to establish a control group with similar characteristics to the treatment group, and implement a difference-in-differences (DID) design to compare trends in earnings and mental health between those who experienced job loss via mass layoffs or plant closures and those who remained steadily employed.

Our study yields two key findings. First, mass layoffs (plant closures) lead to a substantial 68% (67%) reduction in earnings for displaced workers in the following year, with only a partial recovery seen even after ten years. Second, mental health significantly worsens post-displacement, mainly due to stress, evidenced by a 15% (16%) increase in mental health-related outpatient visits and a 62% (57%) rise in associated medical costs. Notably, this adverse effect on mental health is more acute among lower-earnings workers, men, and older individuals.

2 Data and Sample

We used 2000-2017 administrative data from Taiwan's Health and Welfare Data Science Center (HWDC) to track individuals with scrambled national identification numbers, leveraging three HWDC sources: NHI enrollment records, outpatient care claim files, and inpatient care claim files.

With the NHI enrollment records, we calculate annual earnings by summing up the monthly earnings, capped at 182,000 NTD.[3] Furthermore, we use enrollment records to es-

[3]These enrollment records, maintained by the NHI Administration, are primarily for premium collection and statistical analysis. The premiums individuals pay are based on details in these records, including earnings, employment sector, and other relevant factors.

tablish individual characteristics, including gender, age, residential locations, and work locations. These records also provide firm identifiers, enabling us to ascertain firm characteristics such as size, average employee wage and age, and the proportion of female employees.

We also use NHI claim files for outpatient and inpatient care to track service utilization dates, types, and quantities, along with physician diagnoses.[4] This data helps us determine mental health outcomes: the number of outpatient visits and medical expenses associated with healthcare utilization for mental disorders.[5]

Our sample comprises individuals aged 20–65 who were employed in a firm with at least five employees in the baseline year. We define displaced workers, our treatment group, as those who were employed for a minimum of five years prior to losing their jobs and underwent a mass layoff (plant closure) in a given year between 2005 and 2007. A mass layoff (plant closure) is characterized by a firm reducing its employment by over 50% (90%) compared to the previous year. We track these workers for 16 years: five pre- and ten post-job loss.

The control group consists of non-displaced workers who had positive earnings each month during the sample period and worked in stable firms, with less than a 30% annual employment decrease. This mirrors the criteria of Lachowska et al. (2020), who used workers with positive quarterly earnings while staying with a single employer during the sample period, and Aaronson et al. (2019), who defined their control group as workers with at least 13 years at a single firm.[6] The final sample consists of 29,543 workers who experienced mass layoffs and 9,700 workers who experienced plant closures in the treatment group, along with 332,720 workers in the control group. Summary statistics and trends for both groups are shown in Table B.1 and Figure B.1 of the Online Appendix.[7] After the EB re-weighting,

[4] Service quantities can be converted to expenses using unit values set by a global budget system; one unit (dot) equals approximately one NTD.

[5] Mental illness is defined by ICD9 codes 290–319.

[6] Note that our control group did not necessarily stay in the same firm, but they remained continuously employed in stable firms throughout the study period.

[7] Compared to the mass layoff group, the characteristics of the control group are more similar to those of the treatment group that experienced plant closures, as evidenced by the smaller differences in pre-displacement outcomes (e.g., annual earnings and mental healthcare utilization) between the control group and the plant closure group.

differences between the groups almost disappear, with displaced workers' pre-displacement outcomes closely aligning with those of the re-weighted non-displaced workers.

3 Dynamic Difference-in-Differences Design

Our empirical strategy to identify the dynamic effects of displacement on earnings and mental health involves estimating the following regression:

$$Y_{it} = \sum_{k=-5}^{10} \delta_k \cdot Disp_i \times \mathbf{I}[t = c + k] + \sum_{k=-5}^{10} \gamma_k \cdot \mathbf{I}[t = c + k] + \alpha_i + \pi_t + X_{it}\beta + \varepsilon_{it}. \tag{1}$$

Y_{it} is the outcome of interest for worker i in year t, incorporating: (1) Annual earnings; (2) Cumulative number of mental illness visits; and (3) Cumulative medical expenses for mental illnesses (including both outpatient and inpatient care). $Disp_i$ indicates whether worker i is a displaced worker. $\mathbf{I}[t = c + k]$ is a dummy variable indicating k years after (pseudo) mass layoff year, c, where k does not include -2 since we consider two years prior to a job loss as the reference year.[8] γ_k represents the evolution of outcomes among non-displaced workers. δ_k is the coefficient of interest, which measures the change in outcomes among displaced workers with respect to the reference year ($k = -2$), relative to the change of non-displaced workers. We also control for individual fixed effects (α_i), calendar-year fixed effects (π_t), and other controls (X_{it}), mainly a quartic function of worker's age and county/municipality level unemployment rate.[9] Equation (1) is estimated using weighted least squares with EB-derived weights, and standard errors are clustered at the individual level.

Since previous research has shown that workers experienced some earnings loss one year prior to displacement (Lachowska et al., 2020; Schmieder et al., 2023), we allow for displaced workers to have a different pre-displacement trend one year prior to displacement. Given parallel trends prior to the reference year, we can therefore interpret δ_{-1} to δ_{10} as

[8] The control group's (pseudo) mass layoff (plant closure) year is the year we use to confirm the firm did *not* experience a mass layoff (plant closure) and had no more than a 30% reduction in size.

[9] See Table 1's notes for details on the controls.

displacement effects.

4 Results

Figure 1a (1b) from our model (1) illustrates the dynamic effects of displacement on earnings for mass layoffs (plant closures). Prior to displacement, the earnings trends for both groups—those who will face displacement and those who will not—are similar, with a minor yet significant decline observed one year before displacement.[10] After displacement, a stark divergence occurs: Workers displaced due to mass layoff (plant closure) experience an initial drop in annual earnings by about 230,000 (270,000) NTD, which increases to 310,000 (340,000) NTD the following year, approximately 68% (67%) less than their pre-displacement earnings. Although a slight recovery is observed two years later, pronounced long-term effects persist, even a decade after the displacement. Table 1 Panel A details the long-term earnings losses from model (1): a decrease of 279,500 (306,000) NTD, or 61% (60%) from the pre-displacement average, in the tenth year post-displacement due to mass layoff (plant closure).[11]

Figures 1c-1f illustrate the dynamic impact of displacement on mental health, showing that trends in mental healthcare use were similar for both the treatment and control groups until two years before displacement. In the year prior, coinciding with small earnings losses, there was a small but significant increase in both the cumulative number of outpatient visits and expenses for mental illness among those who were later displaced. Over time, the differences between the groups grew. As detailed in Table 1, a mass layoff (or plant closure) led to an increase of 0.517 (0.496) in outpatient visits and a 2,418 (2,028) NTD increase in medical expenses, representing approximately 15% (16%) and 62% (57%) increases, respectively,

[10] Jacobson et al. (1993), Lachowska et al. (2020), and Schmieder et al. (2023) also found significant earnings losses prior to displacement using data from the U.S. and Germany.

[11] In the Online Appendix C, we decompose the earnings loss due to mass layoffs (and plant closures) into extensive and intensive margins. Our results suggest that approximately 54% (48%) of earnings losses can be attributed to the loss of employment (i.e., the extensive margin).

compared to the control group over the same period.[12]

Table 2 presents the long-term impact of displacement on various types of mental disorders, including affective, nervous, and stress-related mental disorders, alcohol psychoses, drug psychoses, and other types of mental disorders, with the increases in mental health problems being largely due to affective, nervous, and stress-related mental disorders. Interestingly, in cases of plant closures, alcohol-related psychoses actually decrease—we observe a 79% reduction in the cumulative number of outpatient visits (Panel A of Column 6) and a 70% decrease in cumulative medical costs for these disorders (Panel B of Column 6). However, mass layoff has a null effect on alcohol-related psychoses (Panels A and B of Column 2).

Online Appendix D discusses a number of robustness checks for our main findings, including different matching techniques, estimation methods, and sample choices. In general, our main results are also robust to other changes. Moreover, we conduct a set of subgroup analyses in Online Appendix E. These analyses suggest that the negative effects of job displacement on mental health appear to be more pronounced among lower-income workers, men, and older individuals.

5 Conclusion

Using Taiwan's administrative data, we investigated the impact of job displacement on earnings and mental health. The study highlights two key findings. First, displaced workers experience a 67–68% earnings loss in the year following displacement. Despite a partial recovery, these levels do not return to pre-displacement level even after ten years. Second, workers' mental health deteriorates following displacement due to mass layoff (plant closure), primarily due to stress, causing a 15% (16%) increase in outpatient visits for mental health

[12] In Table D2 of the Online Appendix, where we adjusted the mass layoff cutoff from 30% to 80%, our estimates remained robust. For instance, the estimated earnings loss for workers at firms reducing employment by over 30% was 283,668 NTD, a 62% decrease from pre-displacement levels. This displacement led to a 0.624 increase in outpatient visits and a 2,615 NTD increase in medical expenses, representing about 18% and 66% rises, respectively, relative to the baseline mean.

and a 62% (57%) rise in medical costs, particularly among lower-earning, male, and older workers.

Our estimated mental health effects are inferred from healthcare utilization, hinting that the true mental impact of job loss could be more significant than our results suggest. This is because some displaced workers might not seek or recognize the value of mental health care. Future studies incorporating additional data, like biochemical examination data (Lee et al., 2023) or surveys on displaced workers' post-displacement experiences, would provide a more comprehensive understanding of this issue.

Tables

Table 1: Long-term Impact of Job Displacement on Earnings and Mental Disorders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mass Layoffs				Plant Closures			
Panel A: Annual Earnings (1,000 NTD)								
$Disp_i \times \mathbf{I}[t = c + 10]$	-279.5***	-279.4***	-279.4***	-279.5***	-305.9***	-305.4***	-305.4***	-306.0***
	(2.117)	(2.117)	(2.117)	(2.182)	(3.950)	(3.949)	(3.951)	(4.083)
Control baseline mean	458.188				509.637			
Panel B: Cumulative # of Visits for Mental Illness								
$Disp_i \times \mathbf{I}[t = c + 10]$	0.508***	0.509***	0.508***	0.517***	0.494***	0.496***	0.501***	0.496***
	(0.119)	(0.119)	(0.119)	(0.123)	(0.185)	(0.185)	(0.185)	(0.191)
Control baseline trend	3.340				3.123			
Panel C: Cumulative Medical Expenses of Mental Illness (1,000 NTD)								
$Disp_i \times \mathbf{I}[t = c + 10]$	2.408***	2.407***	2.407***	2.418***	2.024**	2.027**	2.028**	2.028**
	(0.472)	(0.472)	(0.472)	(0.487)	(0.807)	(0.807)	(0.807)	(0.832)
Control baseline trend	3.897				3.571			
Observations	5,796,208				5,478,720			
Basic DID + Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Individual control		✓	✓			✓	✓	
Firm control			✓				✓	
Individual FE + UNRATE				✓				✓

Notes: This table displays the estimated coefficients of δ_{10} from Equation (1), representing the impact of mass layoffs (plant closures) in the tenth year after the displacement year (c). Standard errors clustered at the individual level are reported in parentheses. All regressions are weighted with EB weights. The control baseline mean is the EB-weighted mean for the control group in the baseline year ($t = -2$). Individual controls are gender, birth month, wage, and county/municipality of residence in the pre-treatment period. Firm characteristics include location, number of employees, average monthly wage, average age, and proportion of females in the pre-treatment period. Finally, the unemployment rate (UNRATE) refers to county/municipality-level unemployment rate.
*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Table 2: Long-term Impact of Job Displacement on Types of Mental Disorders

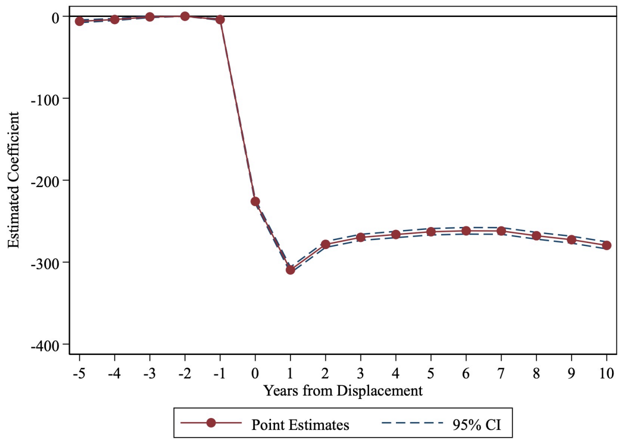
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mass Layoffs				Plant Closures			
	Stress-Related	Alcoholic	Drug	Others	Stress-Related	Alcoholic	Drug	Others
Panel A: Cumulative # of Visits for Mental Illness								
$Disp_i \times \mathbf{I}[t = c + 10]$	0.479***	0.004	0.016**	0.019	0.489***	-0.006***	0.029*	-0.017
	(0.115)	(0.004)	(0.008)	(0.032)	(0.182)	(0.001)	(0.016)	(0.037)
Control baseline trend	2.758	0.008	0.133	0.441	2.575	0.007	0.132	0.409
Panel B: Cumulative Medical Expenses of Mental Illness (1,000 NTD)								
$Disp_i \times \mathbf{I}[t = c + 10]$	2.375***	0.001	0.012	0.030	2.062**	-0.015**	0.021	-0.040
	(0.482)	(0.010)	(0.008)	(0.037)	(0.830)	(0.006)	(0.016)	(0.032)
Control baseline trend	3.416	0.024	0.083	0.374	3.133	0.021	0.083	0.335
Observations	5,796,208				5,478,720			

Notes: This table displays the estimated coefficients of δ_{10} from Equation (1), representing the cumulative impact of mass layoffs (plant closures) in the tenth year after the displacement year (c). Standard errors clustered at the individual level are reported in parentheses. All regressions are weighted with EB weights and include the covariates as Column (7) in Table 1. The control baseline trend is the difference in the outcome variable (EB-weighted) for the control group in the tenth year after and the second year previous to the (pseudo) displacement year. The outcomes of columns (1) and (5) are affective, nervous, and stress-related disorders, defined as illnesses with ICD9 codes 295–297, 300, 306, 308, 309, or 311. The outcomes of columns (2) and (6) are alcoholic psychoses, defined as illnesses with ICD9 codes 292, 304, and 305. The outcomes of columns (3) and (7) are drug psychoses, defined as illnesses with ICD9 codes 291 or 303. The outcomes of columns (4) and (8) are other mental disorders, defined as illnesses with ICD9 codes from 290 to 319 but not included in the above categories.
*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

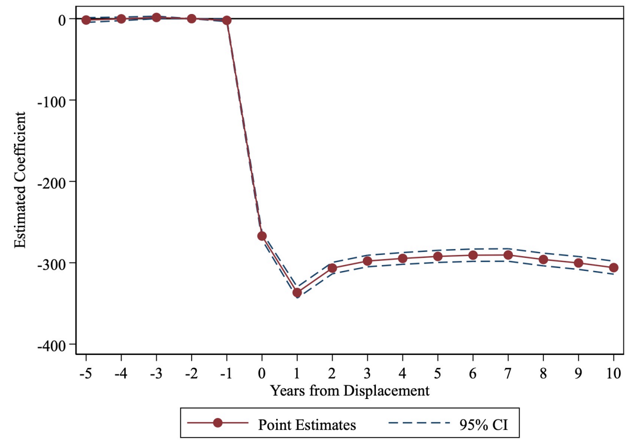
Figures

Figure 1: Dynamic DID Estimates

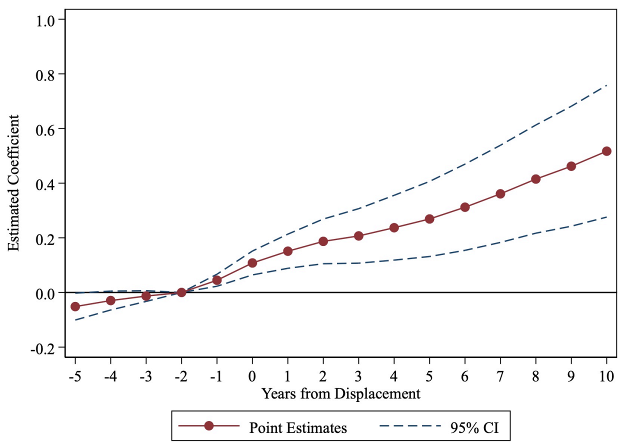
(a) Mass Layoffs: Annual Earnings (1,000 NTD)



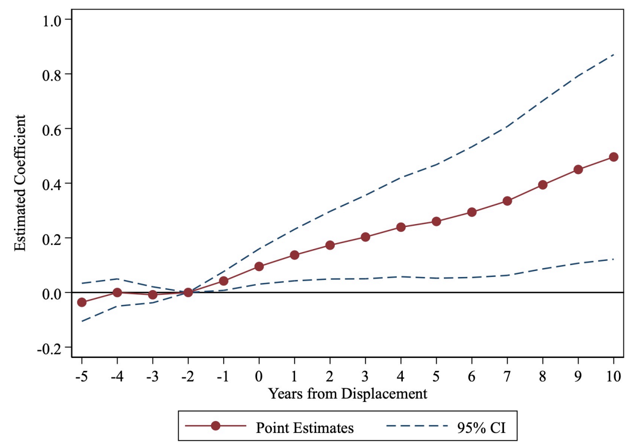
(b) Plant Closures: Annual Earnings (1,000 NTD)



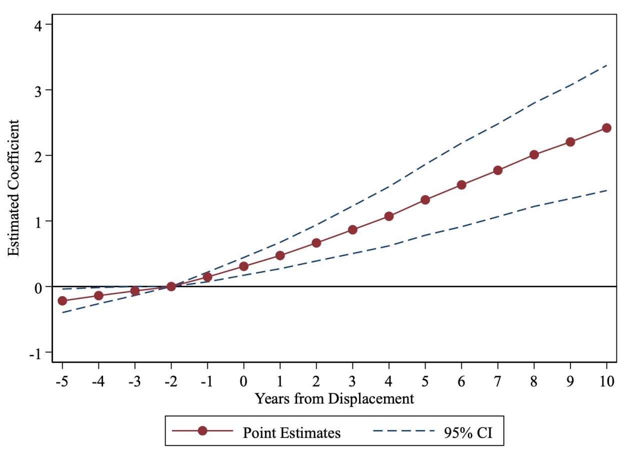
(c) Mass Layoffs: Cumulative Visits for Mental Illness



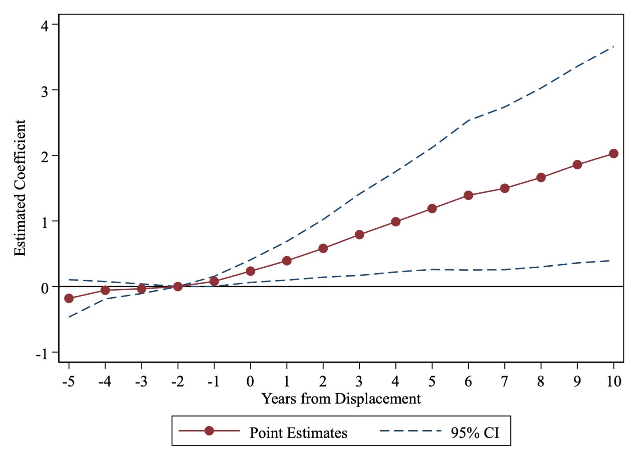
(d) Plant Closures: Cum. Visits for Mental Illness



(e) Mass Layoffs: Cumulative Medical Expenses of Mental Illness (1,000 NTD)



(f) Plant Closures: Cumulative Medical Expenses of Mental Illness (1,000 NTD)



Notes: These figures display the estimated coefficients of δ_k from Equation (1). The outcomes shown is annual earnings (1,000 NTD). The solid line denotes the point estimates. The dashed line denotes the 95% confidence interval. The horizontal axis refers to the number of years from the (pseudo) displacement.

References

Aaronson, D., S. Agarwal, L. J. Hotchkiss, and T. Kelley (2019). Job displacement and financial outcomes. *Economics Letters 177*, 18–21.

Bíró, A. and P. Elek (2020). Job loss, disability insurance and health expenditure. *Labour Economics 65*, 101856.

Browning, M. and E. Heinesen (2012). Effect of job loss due to plant closure on mortality and hospitalization. *Journal of Health Economics 31*, 599–616.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230.

Canavan, M., W. T. Gallo, and G. L. Marshall (2021). The moderating effect of social support and social integration on the relationship between involuntary job loss and health. *Journal of Applied Gerontology 40*(10), 1272–1279.

Classen, T. J. and R. A. Dunn (2012). The effect of job loss and unemployment duration on suicide risk in the united states: A new look using mass-layoffs and unemployment duration. *Health Economics 21*, 338–350.

Coope, C., J. Donovan, C. Wilson, M. Barnes, C. Metcalfe, W. Hollingworth, N. Kapur, K. Hawton, and D. Gunnell (2015). Characteristics of people dying by suicide after job loss, financial difficulties and other economic stressors during a period of recession (2010–2011): A review of coroners' records. *Journal of Affective Disorders 183*, 98–105.

Cygan-Rehm, K., D. Kuehnle, and M. Oberfichtner (2017). Bounding the causal effect of unemployment on mental health: Nonparametric evidence from four countries. *Health Economics 26*(12), 1844–1861.

Drydakis, N. (2015). The effect of unemployment on self-reported health and mental health in greece from 2008 to 2013: a longitudinal study before and during the financial crisis. *Social Science & Medicine 128*, 43–51.

Eliason, M. and D. Storrie (2009a). Does job loss shorten life? *Journal of Human Resources 44*(2), 277–302.

Eliason, M. and D. Storrie (2009b). Job loss is bad for your health–Swedish evidence on cause-specific hospitalization following involuntary job loss. *Social Science & Medicine 68*(8), 1396–1406.

Golosov, M., M. Graber, M. Mogstad, and D. Novgorodsky (2021). How Americans respond to idiosyncratic and exogenous changes in household wealth and unearned income. *National Bureau of Economic Research Working Paper*. https://www.nber.org/papers/w29000.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*(2), 254–277.

Huang, J., J. Birkenmaier, and Y. Kim (2014). Job loss and unmet health care needs in the economic recession: different associations by family income. *American Journal of Public Health 104*(11), e178–e183.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993). Earnings losses of displaced workers. *American Economic Review 83*(4), 685–709.

Keefe, V., P. Reid, C. Ormsby, B. Robson, G. Purdie, J. Baxter, and N. K. I. Incorporated (2002). Serious health events following involuntary job loss in New Zealand meat processing workers. *International Journal of Epidemiology 31*(6), 1155–1161.

Kuhn, A., R. Lalive, and J. Zweimüller (2009). The public health costs of job loss. *Journal of Health Economics 28*, 1099–1115.

Lachowska, M., A. Mas, and S. Woodbury (2020). Sources of displaced workers' long-term earnings losses. *American Economic Review 110*(10), 3231–3266.

Lee, J., J. Hwang, and H. B. Kim (2023). The impact of job loss on health: Evidence from administrative and biomarker data. Working Paper.

Marcus, J. (2013). The effect of unemployment on the mental health of spouses–evidence from plant closures in Germany. *Journal of Health Economics 32*, 546–558.

Ruhm, C. J. (1991). Are workers permanently scarred by job displacements? *American Economic Review 81*, 319–324.

Salm, M. (2009). Does job loss cause ill health? *Health Economics 18*(9), 1075–1089.

Schaller, J. and A. H. Stevens (2015). Short-run effects of job loss on health conditions, health insurance, and health care utilization. *Journal of Health Economics 43*, 190–203.

Schmieder, J., T. von Wachter, and J. Heining (2023). The costs of job displacement over the business cycle and its sources: Evidence from Germany. *American Economic Review 113*(5), 1208–1254.

Schmitz, H. (2011). Why are the unemployed in worse health? the causal effect of unemployment on health. *Labour Economics 18*, 71–78.

Strully, K. W. (2009). Job loss and health in the US labor market. *Demography 46*, 221–246.

Sullivan, D. and T. von Wachter (2009). Job displacement and mortality: an analysis using administrative data. *Quarterly Journal of Economics 124*(3), 1265–1306.

Zimmer, D. M. (2021). The effect of job displacement on mental health, when mental health feeds back to future job displacement. *The Quarterly Review of Economics and Finance 79*, 360–366.

Online Appendix for Paper: Long-term Effects of Job Displacement on Earnings and Mental Health: Evidence from Population-wide Administrative Data

Section A	NHI Data: Details
Section B	Summary Statistics
Section C	Decomposition of Earning Impacts: Extensive and Intensive Margins
Section D	Robustness Checks
Section E	Heterogeneous Effects

A NHI Data: Details

In March 1995, Taiwan introduced the National Health Insurance (NHI), a government-managed, single-payer health insurance system. Before the NHI, health coverage was provided by three main social insurance plans: labor insurance for private sector workers, government-employee insurance for public employees, and farmers' insurance for farmers and fishermen. These plans covered about 57% of Taiwan's population, excluding mainly the elderly, children under 14, and the unemployed. The launch of NHI significantly increased the coverage rate to 92% by the end of 1995, and since 2000, it has consistently covered over 99% of the population. Thus, NHI data nearly represents the entire Taiwanese population. In our study, we utilize three specific NHI datasets:

NHI enrollment records: Managed by the NHI Administration for collecting premiums and conducting statistical analyses, these records contain details necessary for calculating an individual's premium, such as earnings, employment sector, and demographic information (age, gender, township of residence). They also include firm identifiers, which help determine characteristics of firms like size, average wage and age of employees, and the proportion of female employees.

NHI claim files for outpatient care: These files, submitted by medical providers for payment, include data on the date, type, and amount of services used, out-of-pocket costs, physician IDs, and diagnoses made by physicians. The service usage is translated into total costs based on the unit price of services, set by a global budget system. We use these records to assess parents' mental health, identifying mental disorders with ICD-9 codes 290-319.

NHI inpatient claim files: Similar to outpatient files, they additionally provide information on the duration of hospital stays, types of surgeries, and total costs for hospital admissions.

Researchers interested in accessing these datasets need to submit a written request to the Health and Welfare Data Science Center (HWDC) in Taiwan. The application must include a comprehensive research proposal detailing the objectives and methodology, a list of required data variables, funding sources, and approval from an Institutional Review Board (IRB). All data analysis must be conducted in a designated computer room at HWDC.

B Summary Statistics

Table B.1 displays summary statistics for the treatment and control groups, covering instances of mass layoffs and plant closures. Compared to non-displaced employees, displaced workers are older, live in urban areas and tend to be female. They are also more likely to be employed in smaller firms with lower wages. To make the characteristics of treatment and control group more similar, we apply EB to re-weight the control group based on individual and firm characteristics listed in Table B.1. EB is a re-weighting approach that minimizes the differences in selected variables and moments between two groups. It balances not only the mean but also higher moments, accounting for potential non-linear relationships. After the EB process, differences between the groups have almost disappeared. Although pre-treatment outcome variables are not included in the EB process, they also reach balance after matching on individual and firm characteristics in the case of plant closure.

Figures B.1a and B.1b show that annual earnings decline sharply in the year following displacement and only recover slightly by ten years after displacement. Specifically, we note an approximate 60% reduction in annual earnings ten years after the year of displacement. Consistent with graphical evidence on labor market outcomes, Figures B.1c and B.1e, as well as Figures B.1d and B.1f, suggest that compared to the control group, displaced workers had higher utilization of medical services due to mental illness. Importantly, prior to layoff, the outcomes for displaced workers closely align with those of their non-displaced counterparts, suggesting that the post-displacement differences are not driven by differential pre-trends between the treatment and control groups.

Table B.1: Summary Statistics

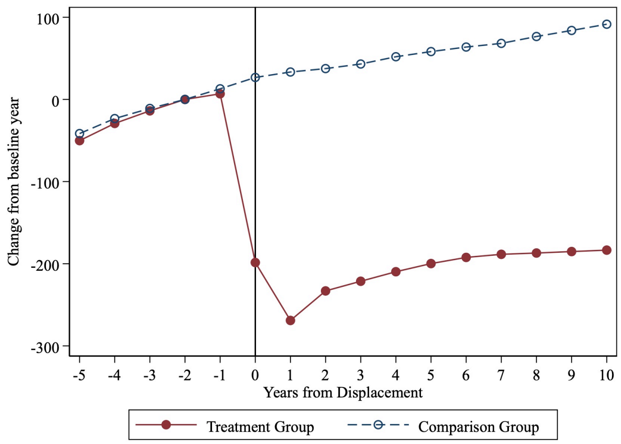
		Mass Layoffs			Plant Closures		
	Control	Treat	Difference pre-matching	Difference post-matching	Treat	Difference pre-matching	Difference post-matching
Individual Characteristics							
Female	0.460	0.569	0.109***	0.000	0.564	0.104***	0.000
	(0.498)	(0.495)	[0.003]	[0.003]	(0.496)	[0.005]	[0.005]
Age at displacement	38.775	42.509	3.734***	0.002	41.526	2.750***	0.014
	(7.556)	(9.420)	[0.047]	[0.057]	(9.092)	[0.078]	[0.094]
Live in urban area	0.737	0.763	0.025***	0.000	0.790	0.053***	0.000
	(0.440)	(0.425)	[0.003]	[0.003]	(0.407)	[0.005]	[0.004]
Work in urban area	0.804	0.835	0.031***	0.000	0.849	0.045***	0.000
	(0.397)	(0.371)	[0.002]	[0.002]	(0.358)	[0.004]	[0.004]
Firm Characteristics							
Number of employees (K)	1.495	0.226	-1.269***	-0.004	0.376	-1.119***	-0.036**
	(3.852)	(0.803)	[0.022]	[0.005]	(1.324)	[0.039]	[0.016]
Female proportion	0.436	0.481	0.045***	0.000	0.491	0.055***	0.000
	(0.224)	(0.209)	[0.001]	[0.001]	(0.212)	[0.002]	[0.002]
Average monthly wage	36.745	32.055	-4.690***	-0.004	34.392	-2.353***	-0.040***
(1,000 NTD)	(13.518)	(11.774)	[0.081]	[0.071]	(13.011)	[0.005]	[0.005]
Average age	36.971	38.658	1.687***	0.002	37.530	0.559***	0.010
	(5.042)	(5.774)	[0.031]	[0.035]	(5.364)	[0.052]	[0.055]
Outcome Variables in the Second Year Prior to the Displacement							
Real annual earnings	541.102	458.146	-82.956***	-0.042	509.170	-31.932***	-0.468
(1,000 NTD)	(257.066)	(235.832)	[1.550]	[1.432]	(262.076)	[2.649]	[2.702]
Cum. mental illness	0.450	0.636	0.186***	0.038	0.554	0.104***	0.004
outpatient visits	(3.543)	(4.419)	[0.022]	[0.025]	(3.824)	[0.037]	[0.041]
Cum. medical expenses	0.585	1.063	0.478***	0.273***	0.807	0.221**	0.098
of mental illness (1,000 NTD)	(9.831)	(19.186)	[0.066]	[0.077]	(11.344)	[0.102]	[0.112]
Number of observations	332,720	29,543			9,700		

Notes: Standard deviations in parentheses, and standard errors in brackets. The control group comprises workers who were employed at a stable firm (no more than a 30% employment decrease in a given year) and were continuously employed during the sample period. The mass layoffs treatment group comprises workers who underwent a mass layoff (firm reducing its employment by over 50%). The plant closures treatment group comprises workers who underwent a plant closure (firm reducing its employment by over 90%). All dollars are adjusted with CPI and displayed in 2016 NTD (1 NTD $\approx$ 0.033 USD). The cumulative number of outpatient visits and cumulative medical expenses of mental illness are calculated from the fifth to second years prior to the (pseudo) displacement. The statistics in the *Post-Matching* columns are weighted by EB. The variables included in the matching process are all variables in the *Individual Characteristics* and *Firm Characteristics* panels.

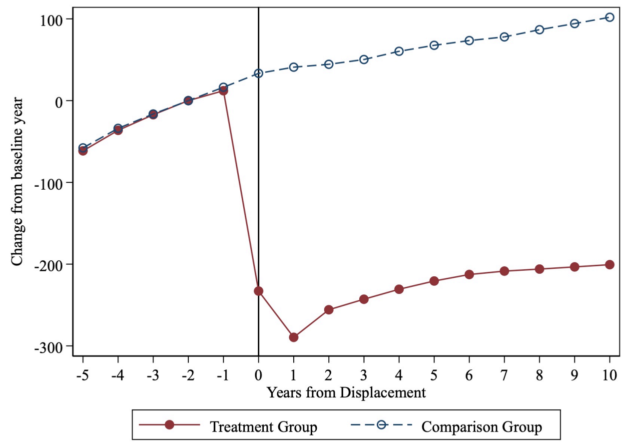
*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Figure B.1: Trends in Annual Earnings and Healthcare Use for Mental Disorders

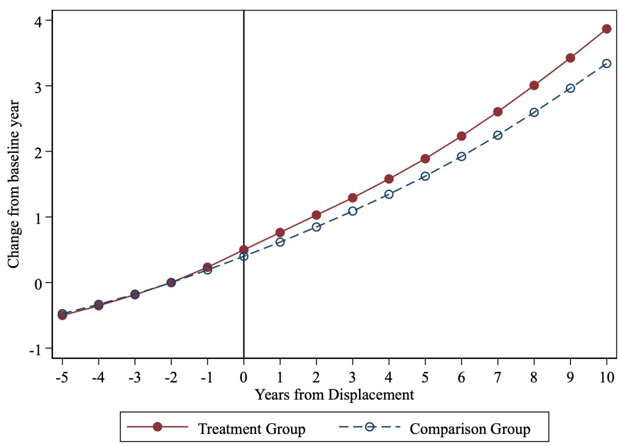
(a) Mass Layoffs: Annual Earnings (1,000 NTD)



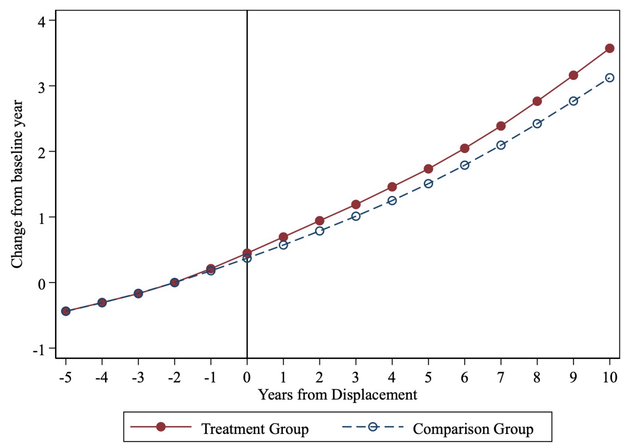
(b) Plant Closures: Annual Earnings (1,000 NTD)



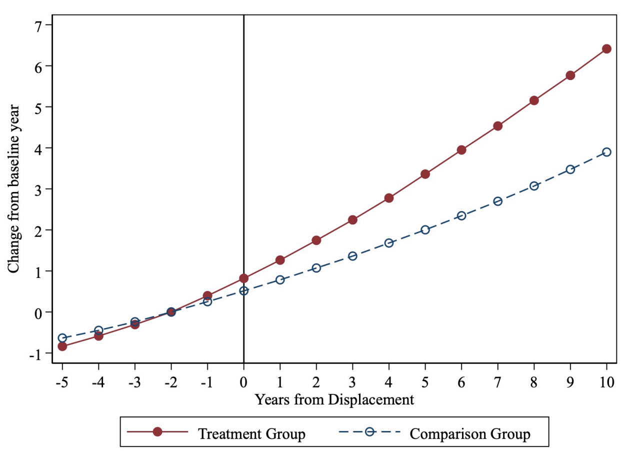
(c) Mass Layoffs: Cumulative Visits for Mental Illness



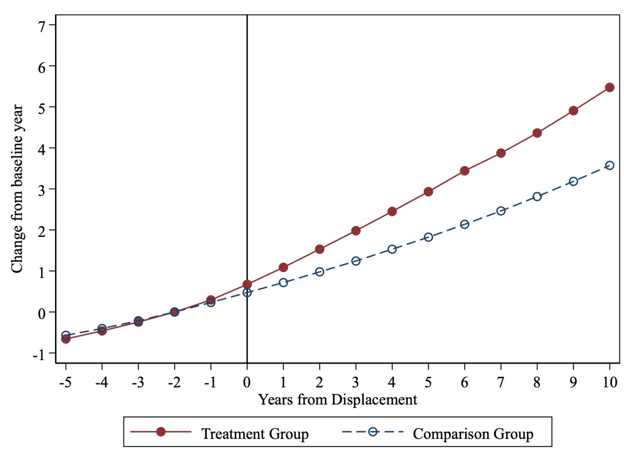
(d) Plant Closures: Cum. Visits for Mental Illness



(e) Mass Layoffs: Cumulative Medical Expenses of Mental Illness (1,000 NTD)



(f) Plant Closures: Cumulative Medical Expenses of Mental Illness (1,000 NTD)



Notes: These figures illustrate the change (from the baseline year) in the outcomes of interest for the treatment group (i.e., displaced workers) and the control group (i.e., non-displaced workers) from five years before to ten years after the (pseudo) displacement year. The vertical axis displays the outcomes at event time t relative to the baseline year ($t = -2$). The horizontal axis refers to the number of years from the (pseudo) displacement year.

C Decomposition of Earning Impacts: Extensive and Intensive Margins

Following Golosov et al. (2021), we decompose the impact of displacement on earnings into extensive (due to loss of job) and intensive margins (due to reduction in earning conditional on employed). Specifically, we decompose the earning effect γ_k^{DD} in period k years from the mass layoff event (as obtained from Equation (1)) into two elements:

1. The difference in expected earnings between the treated (laid-off workers) and control group multiplied by the probability that the treatment group is employed in period k—denoted as α_k (Equation (C.1))

2. The expected earnings for the treatment group if employed multiplied by the difference in the probability of employment between the treatment and control groups in period k—denoted as β_k (Equation (C.2))

The earning effect in period k driven by intensive (extensive) margins is then defined as the difference between the respective α_k (β_k) terms in period k and the baseline period $k = -2$, as shown in Equation (C.3). Further details of this decomposition approach can be found in Golosov et al. (2021).

$$\begin{aligned}\alpha_k = \Big(&\mathbb{E}[Earnings_{it}|Disp_i = 1, Employed_{it} = 1] - \\ &\mathbb{E}[Earnings_{it}|Disp_i = 0, Employed_{it} = 1]\Big) \times \mathbb{P}[Employed_{it}|Disp_i = 1]\end{aligned} \tag{C.1}$$

$$\begin{aligned}\beta_k =&\mathbb{E}[Earnings_{it}|Disp_i = 1, Employed_{it} = 1] \times \\ &\Big(\mathbb{P}[Employed_{it}|Disp_i = 1] - \mathbb{P}[Employed_{it}|Disp_i = 0]\Big)\end{aligned} \tag{C.2}$$

$$\gamma_k^{DD} = \underbrace{\alpha_k - \alpha_{k=-2}}_{\text{Intensive Margins}} + \underbrace{\beta_k - \beta_{k=-2}}_{\text{Extensive Margins}} \tag{C.3}$$

Based on this decomposition, we calculate the share of the total displacement effect attributable to extensive margins for whole sample and across different income quantiles. Table C.1 shows the results. For the case of mass layoffs (plant closures), 54% (48%) of the earnings loss response at $t = 10$ is due to non-employment (i.e. extensive margins), while the remaining 46% (52%) can be attributed to intensive margins (Column 1). We perform a similar decomposition by income quantile. The results suggest that compared to higher pre-displacement wage workers, the earnings loss of lower pre-displacement wage workers is mainly driven by extensive margins. Specifically, for the lowest income quantile group, 73–77% of the earnings loss is attributable to extensive margins (Column 2). In contrast, for the highest income quantile group, only 40% is due to extensive margins (Column 6). The other income quantiles fall in between.

Table C.1: Decomposition of Earnings Response into Extensive and Intensive Margins

	(1)	(2)	(3)	(4)	(5)	(6)
	All Sample	Income Quantile				
		Q1	Q2	Q3	Q4	Q5
Panel A: Mass Layoffs (Workforce Reduction > 50%)						
Share Extensive Margins	0.54	0.77	0.63	0.54	0.47	0.40
Panel B: Plant Closures (Workforce Reduction > 90%)						
Share Extensive Margins	0.48	0.73	0.61	0.53	0.46	0.40

Notes: This table details the proportion of the total impact on earnings that is due to the extensive margins. This is calculated using Equations (C.1), (C.2), and (C.3). We define income quantiles based on earnings before treatment. Panel A demonstrates the results of the estimated effect of mass layoffs (firm reducing its employment by over 50%). Panel B demonstrates the results of the estimated effect of plant closures (firm reducing its employment by over 90%). Significance levels are marked as follows: *** for 1%, ** for 5%, and * for 10%.

D Robustness Checks

Table D.1 displays various robustness checks for our main findings, including alternative matching techniques, sample selections, and estimation methods. We compare these results with those in Column (4) for mass layoffs and Column (8) for plant closures in Table 1.

Columns (1) and (2) (Columns (6) and (7)) in Table D.1 apply different matching methods to construct a control group for displaced workers. Column (1) (Columns (6)) adopts propensity score matching (PSM)—we use a logit regression to predict the treatment status with a series of individual and firm characteristics to construct the propensity score.[13] For each displaced worker, we assign the non-displaced workers with the closest propensity scores.[14] On the other hand, Column (2) (Columns (7)) uses a coarsened exact matching (CEM) approach to ensure a balanced sample of the treatment and control groups.[15] As we can see, the results using these two matching methods are very similar to our main results using EB weighting.

Our baseline sample considers workers employed at firms with at least 5 employees. Columns (3) and (4) (Columns (8) and (9)) restrict samples to larger firms: firms with 10 or more employees and firms with 30 or more employees, respectively. The resulting estimates suggest that the earnings loss and negative impact on mental health are larger for workers displaced from larger firms. Lastly, Column (5) (Column (10)) considers an alternative definition that allows the possibility for the control group to experience job loss

[13] The variables included in the regression are gender, monthly earnings, age, whether living in an urban area, whether working in an urban area, and firm characteristics (number of employees, average wage, average age, and proportion of female employees).

[14] Specifically, we apply 1 to 20 matching to search for the nearest neighbours (with the closest propensity score) for each displaced worker. Finally, the control units that matched with the displaced workers are included in the analysis, with those matched multiple times receiving a weight equal to the number of times they matched.

[15] Specifically, our matching variables include gender, whether living in an urban area, whether working in an urban area, and coarsened-grouped variables for individual earnings and age, and firms' number of employees, average wage, average age, and proportion of female employees. Each control unit is matched with the treatment units in the exact "strata" constructed by the above variables. The analysis weights for the control units are determined by the ratio of sample size for the treatment and the control group in each stratum. Those who fail to find a match (i.e., no common support) are excluded from the analysis.

in the post-displacement period. We observe a less pronounced impact on mental health due to displacement. This finding aligns well with the smaller decline in earnings reported in the same column.

In our primary analysis, we define mass layoffs as instances where firms witness a reduction of over 50% in their workforce. Examining the robustness of our findings, Table D.2 delves into alternative mass layoff thresholds, spanning from 30%, 40%, 60%, 70%, and 80%. The outcomes indicate that our estimations remain robust to different mass layoff thresholds. To be specific, the assessed earnings loss for employees spans from 278,437 to 292,136 NTD across diverse cutoffs, contrasting with our primary outcome of 305,988 NTD. The influence on the cumulative count of outpatient visits for mental health conditions fluctuates from 0.463 to 0.624, close to or larger than our principal finding of 0.496. The effect on the escalation of medical expenses ranges from 2,311 to 2,615 NTD, slightly higher than our primary outcome of 2,028 NTD.

One concern for our main results is that there is variation in the timing of displacement. Recent development in DID design has identified some complications associated with staggered DID design when there is variation in treatment timing (Goodman-Bacon, 2021). In particular, the estimates from staggered DID design can be biased if the control group contains an always-treated group. Since our control group is composed of workers who are continually employed before and after (pseudo) mass layoff (plant closure), it does not include an always-treated cohort. Nevertheless, in Figure D.1, we apply the estimator proposed by Callaway and Sant'Anna (Callaway and Sant'Anna, 2021) (CSDID), which is robust to multiple treatment periods in a DID setting.[16] Our main findings are not sensitive to the use of the CSDID estimator.

[16]The CSDID estimator is computed by separately estimating the treatment effect of each cohort (workers who experience job loss in a given year), then taking the average for all the possible combinations. The estimator only compares treatment units to the never-treated (i.e., the control group) and the not-yet treated (i.e., the later-treated cohorts). That is, the already treated group (earlier-treated cohort) would not be used as a control group in the analysis.

Table D.1: Robustness Checks: Different Estimation Models and Sample Selections

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mass Layoffs					Plant Closures				
	PSM	CEM	Employees ≥ 10	Employees ≥ 30	All Control	PSM	CEM	Employees ≥ 10	Employees ≥ 30	All Control
Panel A: Annual Earnings (1,000 NTD)										
$Disp_i \times \mathbf{I}[t = c + 10]$	-266.2***	-271.2***	-308.6***	-292.9***	-168.7***	-303.6***	-307.6***	-320.6***	-345.1***	-194.8***
	(2.149)	(2.121)	(3.093)	(2.044)	(2.217)	(4.108)	(4.073)	(4.277)	(5.429)	(4.067)
Control baseline mean	457.415	455.914	510.343	458.188	458.136	509.153	504.137	529.130	563.586	509.611
Panel B: Cumulative # of Visits for Mental Illness										
$Disp_i \times \mathbf{I}[t = c + 10]$	0.460***	0.745***	0.682***	0.907***	0.181	0.443**	0.694***	0.715***	0.759***	0.199
	(0.119)	(0.112)	(0.148)	(0.113)	(0.116)	(0.195)	(0.192)	(0.199)	(0.245)	(0.189)
Control baseline trend	3.397	3.117	2.627	3.340	3.662	3.170	2.925	2.860	2.523	3.418
Panel C: Cumulative Medical Expenses of Mental Illness (1,000 NTD)										
$Disp_i \times \mathbf{I}[t = c + 10]$	2.282***	2.559***	2.423***	3.115***	1.599***	1.980**	2.192***	2.483***	2.716**	1.340
	(0.485)	(0.477)	(0.571)	(0.475)	(0.498)	(0.839)	(0.834)	(0.896)	(1.093)	(0.831)
Control baseline trend	4.038	3.768	2.790	3.897	4.755	3.629	3.419	3.204	2.656	4.272
Observations	4,103,168	5,713,504	3,810,720	5,796,208	9,370,944	2,236,768	5,055,424	4,700,000	3,646,768	9,053,456

Notes: This table displays the estimated coefficients of δ_{10} from Equation (1), representing the (cumulative) impact of a mass layoff in the tenth year after the displacement year (c). Standard errors clustered at the individual level are reported in parentheses. Column (1) uses PSM with 1 to 20 nearest neighbors matching to select the control group. Column (2) uses CEM to re-weight the control group. Both PSM and CEM use the same matching variables as the EB method described in the main text. Columns (3) and (4) restrict our samples to firms with more than 10 and more than 30 employees in the baseline period, respectively. Column (5) does not restrict the control group's post-treatment employment records.
*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

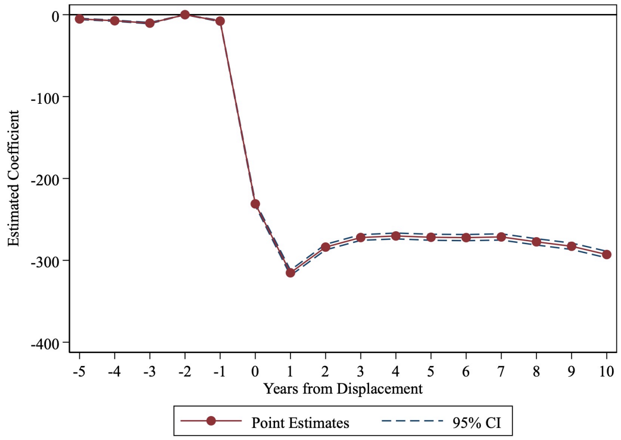
Table D.2: Robustness Checks: Different Mass Layoffs Cutoff

	(1)	(2)	(3)	(4)	(5)
	Mass Layoffs Cutoff				
	30%	40%	60%	70%	80%
Panel A: Annual Earnings (1,000 NTD)					
$Disp_i \times \mathbf{I}[t = c + 10]$	-283.668***	-278,437***	-283.653***	-286.482***	-292.136***
	(1.829)	(1.989)	(2.389)	(2.588)	(2.779)
Control Baseline Mean	451.821	451.953	467.328	475.006	482.753
Panel B: Cumulative # of Visits for Mental Illness					
$Disp_i \times \mathbf{I}[t = c + 10]$	0.624***	0.522***	0.474***	0.478***	0.463***
	(0.110)	(0.116)	(0.126)	(0.134)	(0.139)
Control Baseline Trend	3.408	3.384	3.290	3.230	3.195
Panel C: Cumulative Medical Expenses of Mental Illness (1,000 NTD)					
$Disp_i \times \mathbf{I}[t = c + 10]$	2.615***	2.542***	2.311***	2.421***	2.418***
	(0.411)	(0.461)	(0.531)	(0.592)	(0.642)
Control Baseline Trend	3.983	3.957	3.825	3.735	3.680
Observations	6,025,840	5,893,856	5,725,184	5,666,400	5,625,728

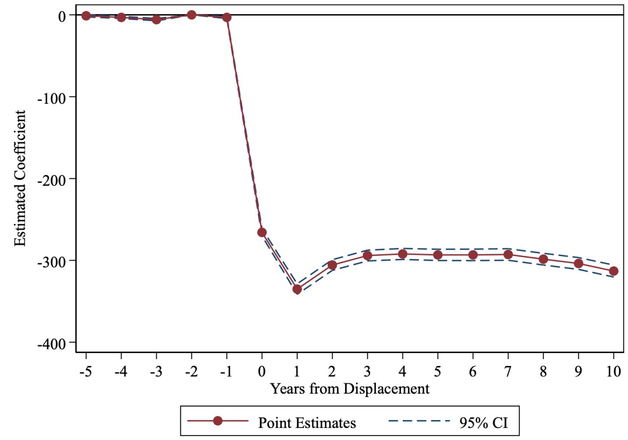
Notes: This table displays the estimated coefficients of δ_{10} from Equation (1), representing the impact of a mass layoff in the tenth year after the displacement year (c). We show the estimates by mass layoff cutoff from 30% to 80%. Each regression is adjusted using EB weights and incorporates the same covariates as shown in Column (7) of Table 1. The control baseline mean is the EB-weighted mean for the control group in the baseline year ($t = -2$). Standard errors clustered at the individual level are reported in parentheses. *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Figure D.1: Robustness Checks: Callaway and Sant'Anna DID Estimator

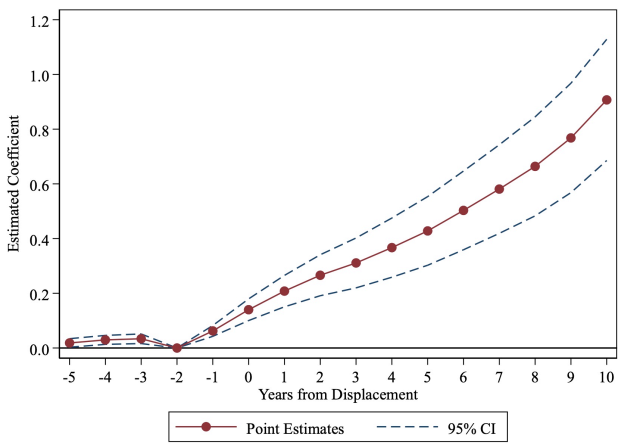
(a) Mass Layoffs: Annual Earnings (1,000 NTD)



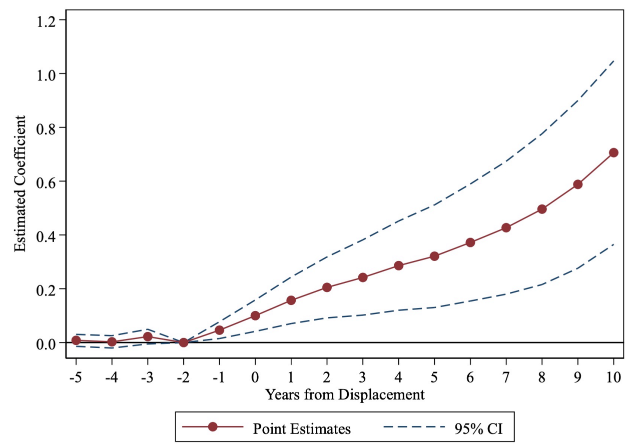
(b) Plant Closures: Annual Earnings (1,000 NTD)



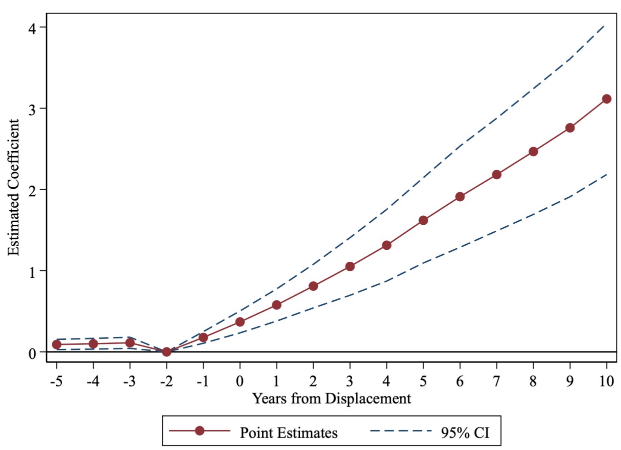
(c) Mass Layoffs: Cumulative Visits for Mental Illness



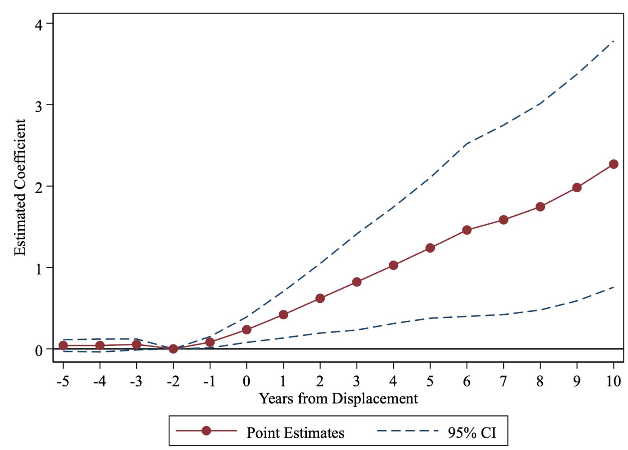
(d) Plant Closures: Cum. Visits for Mental Illness



(e) Mass Layoffs: Cumulative Medical Expenses of Mental Illness (1,000 NTD)



(f) Plant Closure: Cumulative Medical Expenses of Mental Illness (1,000 NTD)



Notes: These figures display the estimated coefficients of δ_k from Equation (1) with the Callaway and Sant'Anna estimator(Callaway and Sant'Anna, 2021). The outcomes shown are (a) annual earnings (1,000 NTD), (b) the cumulative number of outpatient visits for mental illness (cumulative from five years before to ten years after the [pseudo] displacement year), and (c) the cumulative total medical expenses (1,000 NTD) for mental illness (including both inpatient and outpatient care). The solid line denotes the point estimates. The dashed line denotes the 95% confidence interval. The horizontal axis refers to the number of years from the (pseudo) displacement.

E Heterogeneous Effects

To explore the mechanisms underlying the effects of displacement on mental health, we conduct a set of subgroup analyses by previous earnings, gender, and age in Table E.1.

As shown in Table E.1, workers whose previous earnings were above the median experienced a larger earnings loss than lower-earning workers, but this does not induce a larger negative impact on their mental health. In fact, higher-earning workers experienced a 57% (67%) long-term earnings loss following displacement due to mass layoffs (plant closures), yet their healthcare utilization does not significantly increase in the ten years following job loss. On the contrary, for lower-earning workers, cumulative outpatient visits for mental illness increase by 24% (27%), and the corresponding medical expenses rise by 74% (63%) in the decade after displacement. Table E.2 reports estimates of the displacement impact on mental health expenditures by quintile/percentile of prior earnings. We find the increase in mental health spending to be concentrated among workers in the bottom 20th percentile of pre-displacement earnings. This indicates the mental health consequences of job loss disproportionately affect lower-paid workers. In addition, older workers experience both larger earnings losses and a larger negative impact on mental health. These results provide suggestive evidence that financial difficulties and insecurity are more salient than the magnitude of income loss in explaining displacement's effects on mental health.

Finally, although the earnings loss is roughly the same in percentage terms for males and females, displacement has a larger effect on mental healthcare utilization for males than for females, suggesting that feelings of shame, loss of self-esteem, or loss of social status can be more pronounced for men due to societal gender norms. To sum up, these analyses suggest that the negative effects of job displacement on mental health appear to be more pronounced among lower-income workers, men, and older individuals.

Table E.1: Subgroup Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Mass Layoffs						Plant Closures					
	Previous Earnings		Gender		Age		Previous Earnings		Gender		Age	
	Low	High	Male	Female	< 45	≥ 45	Low	High	Male	Female	< 45	≥ 45
Panel A: Annual Earnings (1,000 NTD)												
$Disp_i \times \mathbf{I}[t = c + 10]$	-184.3***	-455.9***	-347.8***	-228.2***	-185.7***	-409.3***	-171.3***	-479.9***	-380.8***	-248.0***	-210.4***	-466.2***
	(1.793)	(4.766)	(3.905)	(2.380)	(2.475)	(3.456)	(3.214)	(7.706)	(7.228)	(4.481)	(4.505)	(6.802)
Control Baseline Mean	323.295	680.998	543.070	393.874	431.979	493.949	333.522	713.375	601.968	438.430	477.898	562.502
Panel B: Cumulative # of Mental Illness Outpatient Visits												
$Disp_i \times \mathbf{I}[t = c + 10]$	0.818***	-0.052	0.670***	0.403**	0.345**	0.759***	0.865***	0.0201	0.649**	0.374	0.425*	0.611*
	(0.165)	(0.174)	(0.182)	(0.167)	(0.135)	(0.226)	(0.283)	(0.246)	(0.316)	(0.235)	(0.226)	(0.343)
Control Baseline Trend	3.366	3.297	3.126	3.503	2.664	4.263	3.173	3.064	3.006	3.213	2.546	4.084
Panel C: Cumulative Medical Expenses of Mental Illness (1,000 NTD)												
$Disp_i \times \mathbf{I}[t = c + 10]$	3.117***	1.047*	2.935***	2.025***	1.680***	3.450***	2.447*	1.550	2.365*	1.753*	1.546*	2.830*
	(0.6942)	(0.547)	(0.835)	(0.575)	(0.559)	(0.868)	(1.256)	(1.102)	(1.314)	(1.058)	(0.851)	(1.709)
Control Baseline Trend	4.207	3.384	3.848	3.934	3.243	4.790	3.915	3.174	3.561	3.579	2.979	4.558
Observations	2,827,136	2,969,072	3,077,232	2,718,976	4,356,592	1,439,616	2,604,320	2,874,400	2,941,072	2,537,648	4,179,232	1,299,488

Notes: This table displays the estimated coefficients of δ_{10} from Equation (1). The coefficient stands for the (cumulative) impact of mass layoffs (plant closures) in the tenth year after the displacement year (c). Standard errors clustered at the individual level are reported in parentheses. All regressions are weighted with EB weights. The control baseline mean is the EB-weighted mean for the control group in the baseline year ($t = -2$). The control baseline trend is the difference in the outcome variable (EB-weighted) for the control group in the tenth year after and the second year previous to the (pseudo) displacement year. Columns (1) and (2) separate samples by pre-treatment earnings. The low-earnings group comprises workers with earnings lower than the median, and the high-wage group comprises workers with earnings equal to or greater than the median. Columns (3) and (4) separate samples by gender. Columns (5) and (6) separate samples by pre-treatment age. The same subgroup definition applies to columns (7) to (12).

*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

Table E.2: Subgroup Analysis by Income Quantile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mass Layoffs					Plant Closures				
Income Quantile	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A: Annual Earnings (1,000 NTD)										
$Disp_i \times \mathbf{I}[t = c + 10]$	-147.9***	-198.0***	-262.9***	-380.2***	-671.9***	-135.0***	-179.8***	-239.6***	-361.5***	-709.3***
	(2.465)	(2.737)	(4.235)	(5.199)	(11.12)	(4.636)	(4.787)	(7.023)	(8.366)	(15.624)
Control baseline mean	255.5	360.3	474.5	582.6	919.4	258.753	364.491	478.968	591.076	935.864
Panel B: Cumulative # of Mental Illness Outpatient Visits										
$Disp_i \times \mathbf{I}[t = c + 10]$	1.035***	0.692***	0.338	0.142	-0.145	1.288***	0.687	0.409	0.294	-0.201
	(0.288)	(0.226)	(0.244)	(0.276)	(0.283)	(0.458)	(0.446)	(0.387)	(0.419)	(0.363)
Control baseline trend	3.985	2.859	2.688	3.378	3.436	3.815	2.752	2.522	3.112	3.192
Panel C: Cumulative Medical Expenses of Mental Illness (1,000 NTD)										
$Disp_i \times \mathbf{I}[t = c + 10]$	4.893***	2.023**	0.575	2.225**	0.247	3.971	2.17	0.201	3.528	0.299
	(1.364)	(0.801)	(0.363)	(1.082)	(0.493)	(2.515)	(1.856)	(0.434)	(2.457)	(0.639)
Control baseline trend	5.484	3.184	2.656	3.451	3.638	5.185	3.105	2.523	3.216	3.360
Observations	1,110,256	1,180,432	954,544	1,390,464	1,160,512	1,000,848	1,096,672	904,912	1,342,080	1,134,208

Notes: This table displays the estimated coefficients of δ_{10} from Equation (1). The coefficient stands for the (cumulative) impact of mass layoffs (plant closures) in the tenth year after the displacement year (c). Standard errors clustered at the individual level are reported in parentheses. All regressions are weighted with EB weights. The control baseline mean is the EB-weighted mean for the control group in the baseline year ($t = -2$). The control baseline trend is the difference in the outcome variable (EB-weighted) for the control group in the tenth year after and the second year previous to the (pseudo) displacement year. Columns (1) to (10) separate samples by pre-treatment earnings quantiles.

*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.