Long-Term Consequences of Job Loss in Israel

Tslil Aloni Hadar Avivi*

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Abstract

This paper provides a detailed analysis of the consequences of job displacement in mass layoff events on earnings, employment, and crime incidence in in Israel from 1999-2009, using administrative employer-employee records. Our analysis reveals significant long-term earning losses of 15% eleven years after displacement, alongside by a drop of 10% in employment. Israeli workers demonstrate resilience compared to international counterparts, with faster recovery in employment and wages. Labor market losses are highly cyclical, with long-run losses in earnings twice as large during downturns. Job displacement losses exhibit further heterogeneity across individuals by pre-displacement income, firm characteristics, and age. We document that job displacement generates a temporary increase only in economically motivated crimes, with no effect on all other types of crimes. Our work also examines the job displacement's effects on children's educational outcomes. We find a notable decrease in high school education achievements, particularly among children from lower-income families, highlighting the social ramifications of job loss. These findings underscore the complex consequences of job displacement and emphasize the importance of targeted policy interventions to mitigate these impacts.

*Hadar Avivi: Economics Department, U.C. Berkeley. Email: havivi@berkeley.edu. Tslil Aloni: Economics Department, New York University. Email: aloni@nyu.edu. We are grateful to the Chief Economist at the Israeli Ministry of Finance and to Assaf Geva for supporting the research financially and conceptually. This research was conducted in the research room of the Central Bureau of Statistics based on files prepared by the Information Accessibility for Research Department. We are grateful to our colleagues at the Central Bureau of Statistics for making the data accessible.

1 Introduction

Job displacement has large negative impacts on workers' earnings and employment that last for decades (e.g. Jacobson et al., 1993; Couch and Placzek, 2010; Davis and von Wachter, 2011). These effects have been documented in several countries, with a large variation in effect sizes and duration Bertheau et al. (2022). Moreover, these impacts vary over the business cycle (Schmieder et al., 2023) and seem to be heterogeneous with respect to several worker characteristics (e.g. Illing et al., 2021; Aloni and Avivi, 2024).

In this paper, we use rich administrative data to document and study the effects of unexpected job displacement due to mass layoffs events in Israel in the years 2000 to 2009. To this end, we follow the seminal study of Jacobson et al. (1993) (henceforth JLS), and estimate the impacts workers experience following a mass layoff event at the firm level. In addition, we explore heterogeneity in the effects, examine their cyclicality, and conduct an international comparison. We study the effects of job loss on a wide variety of outcomes, including crime incidence. Lastly, we estimate the propagating effects of job loss on high-school education outcomes of workers' children.

Our findings suggest substantial consequences of job loss on yearly earnings and employment. Earnings plummet by 45 percent on average in the first year post-displacement, partially recovering over time to a 10-20 percent gap in the long run. This translates to an average loss of 26 percent of earnings over 11 years after a job loss, with some workers transitioning to self-employment post-job loss. A 70 percent re-employment rate is noted post-mass layoff events, with 7 percent of the long-term unemployed never returning to work. Moreover, we find evidence for added worker effect, as suggested in previous literature (Lundberg, 1985; Stephens, 2002). Spousal earnings increase after a displacement event, hinting at a labor supply reaction at the household level. Yet, this increase compensates for the job loss only in the year of displacement, in contrast to the finding in Halla et al. (2020), who finds a longer-lasting effect. Lastly, the study encompasses both mass layoffs and total firm closures, with more pronounced short-term effects evident in firm closure events.

The above findings generally agree with Milgrom (2023), who have estimated the job loss effects on earnings in Israel to find somewhat weaker effect, with a short run effect of 35 percent in the short-run, and between 10 to 15 percent in the long-run. In his paper, Milgrom focuses on manufacturing workers, and estimates the demand for workers' industry-specific skills to find that workers in highly specialized roles within shrinking industries experience significantly larger earnings losses, driven by enduring employment challenges.

In juxtaposition with international data, as documented in Bertheau et al. (2022) across sever European countries, our study underscores the unique resilience of the Israeli labor market post-job loss. While the large initial impact on earnings aligns with patterns observed in Italy and Spain, by the 5th year, Israeli workers demonstrate a rapid recovery in both employment and wage levels. Bertheau et al. (2022) suggest that the main driver of cross country differences in job loss effects is institutional, namely, the use of and spendings on active labor market policies. Furthermore, they find that international differences in effects cannot be explained by differences in worker characteristics.

They propose that these types of policies help mitigate reallocation to lower quality firms, measured using firm fixed effects. In this spirit, we find large heterogeneity in job loss effects with respect to firm fixed effects. Further investigation into the sources of the differences between Israel and its counterparts is warranted.

Key to these differences is that Southern European workers are less likely to find employment following job loss. Loss of employer-specific premiums explains a significant share of wage losses in all countries. The use of active labor market policies is the sole institution able to explain a significant portion of the cross-country heterogeneity in earnings losses.

Further, echoing Schmieder et al. (2023); Davis and von Wachter (2011), we find strong evidence for cyclicality in the short- and long-run effects of job loss, notably more pronounced during economic downturns. In the Israeli context, the magnitude of job loss repercussions during economic downturns is significantly heightened, with long-run effects being almost twice as severe as those experienced in non-crisis periods. The correlation is consistent across various timelines post-job loss (1, 2, 5, and 10 years), underscoring the long-lasting impact of the economic conditions prevailing at the time of job separation on both immediate and extended outcomes.

Delving into the heterogeneity of job loss effects, we document variations based on income levels, firm fixed effects, and age. High earners grapple with a persistent 30 percent decline post-displacement, whereas low earners see diminishing effects within seven years. Nevertheless, low earners face lasting employment challenges. In addition, we estimate firm wage premia using the AKM framework Abowd et al. (1999). We find that workers from firms that tend to pay higher wages, i.e., with high fixed effects, are especially susceptible to the effects of job loss, experiencing larger losses post-displacement (Schmieder et al., 2023; Lachowska et al., 2020). Expectantly, age emerged as a significant factor, with older workers bearing more pronounced impacts of job loss, emphasizing their heightened vulnerability in the labor market and the potential need for targeted interventions (as documented in, e.g., Seim, 2019; Von Wachter et al., 2009).

In addition, we estimate the impacts of job displacement on crime activity up to 11 years after displacement. We find that unexpected job displacement in a mass layoff event increases the probability of committing economically motivated crimes such as theft, fraud, and robbery. These results highlight an increase of around 200% in such crimes compared to baseline levels pre-displacement. This spike is however short-lived, predominantly appearing within the first year post job loss. Notably, violent crimes and other categories didn't exhibit a similar trend. This suggests that criminal actions post job loss is driven by economic incentives, rather than a broader sense of distress or upheaval. cite

Lastly, we evaluate the effects of job loss on children and find that parental job loss causes a substantial and significant drop in high school education outcomes. We measure education outcomes by performance in the *Bagrut* math exam and the probability of attaining a *Bagrut* certificate (or matriculation certificate), a series of standardized national exams taken in the last two years of high school, and a pre-requisite for university. We estimate a reduction of 1.4 percentage points in the probability of securing a Bagrut certificate due to parental job loss and almost one percentage point in the math exam. Interestingly, the mean results mask substantial heterogeneity. The entire effect is

driven by children from families with below-median income, amounting to a 3.7 (2.2) percentage points decrease in Bagrut certificate attainment (math scores), which is a reduction of almost 10 percent of the baseline average in this group. These findings suggest that low-income families have a limited capacity to shield their children from the adverse impacts of unforeseen employment shocks.

Echoing the results in Uguccioni (2021), we show that the impact of parental job loss on children's education diminishes with age at the time of job loss, implying younger children's heightened vulnerability. This finding is aligned with theories highlighting the importance of early years in human capital development (Cunha and Heckman, 2007), or those suggesting that effects accumulate over time (Chetty and Hendren, 2018a,b). In addition, we consider the effect of job loss on both fathers and mothers. Our data provide noisy, suggestive evidence that the impact is mainly due to paternal displacement.

The rest of this paper is outlined as follows: Section 2 provide detail on our dataset, sample constructing and restrictions, and job loss definition. Section 3 delves into the results, with the main impacts of job loss in Israel, international comparison, and the interplay of job loss effects and the business cycle. We further present results on the heterogeneity of the effects with respect to earning levels, firms, and the age of the workers. In Section 3.6 investigates the link between job loss and criminal activity. Lastly, 4 provides evidence on the effects of job loss on children's education outcomes. Section 5 concludes.

2 Data

In this work, we use administrative data assembled by the Israeli Central Bureau of Statistics (CBS). The data covers the entire registered Israeli citizens for the cohorts of 1950-1995, totaling roughly 100 thousand individuals per cohort on average. The data is composed of two main sources: Tax records, and the population registry. From the Tax Authority, the data includes employer-employee and self-employed tax records at a yearly level for the years 1995-2019. At the firm level, the data includes a unique firm id, number of employees, 3-digit industry code, and total payroll for each year. At the worker level, this data records separate jobs on a yearly basis at each employer, with the number of months of employment at each job and gross yearly earnings.

From the civil registry records, we match detailed information on demographics including gender, year of birth, date of immigration and country of origin of children, an identifier of a spouse, and the year of birth for every child.

The main labor market outcomes in our analysis are employment and yearly earnings from work. Employment status is defined by a dummy that receives the value one if the worker earned more than 10,000 Israeli Shekels (around 3,000 dollars) a year, and 0 otherwise. In addition to these outcomes, we also present results on the number of months that each worker worked during the year and monthly earnings.

We complement our data with administrative individual-level criminal conviction records, for the

years 2000-2020, provided by the Israeli Police. Criminal offenses are grouped into four categories: (1) Economic offenses, including property, fraud, economic, and administrative crimes, (2) violent offenses, including assault, murder, sex offenses, and moral crimes, (3) public order and safety, and (4) other crimes, such as traffic violations and uncategorized crimes.

Lastly, our data includes education records provided by the Ministry of Education for the sample of children matched to working parents. The primary outcomes for children in our study are educational achievements, specifically high school matriculation exam scores and attainment of the matriculation certificate, the "Bagrut". We define two primary outcomes for children. First, we define Bagrut certificate attainment as a binary variable assigned a value of 1 if the student has received the certificate and 0 otherwise. The second outcome is the math exam result, which is also a binary variable assigned a value of 1 if the student's score exceeds the mean within their cohort, and 0 otherwise. It's important to note that in both instances, a value of 0 is attributed to students who either fail or do not have a registered score.

2.1 Sample Restriction and Job Loss Definition

We focus on workers who are involuntarily separated from their jobs due to mass layoff events. Differentiating between workers who are fired and those who leave for other reasons is challenging, given the absence of explicit separation reasons in our administrative data. Therefore, we rely on methods established in previous literature to detect mass layoff events and worker displacement.[1]

A mass layoff event is defined in our data as an instance where a firm identifier disappears from the records and does not reappear, or if a firm experiences a minimum of 30 percent reduction in full-job equivalent worker count within a year, which is not offset the following year. We consider mass layoff events between 1999 and 2009. We restrict our analysis to firms with at least 50 employees due to their higher stability and the likelihood that they will truly represent mass layoffs. To mitigate concerns about firm mergers or re-identification, we track worker flows from closing firms to existing ones and omit those where over 20 percent of workers find employment in another continuing firm.

Our sample comprises two groups: displaced and non-displaced workers. Displaced workers are those who leave a firm during a mass layoff event and meet specific criteria. These include a minimum of three years of tenure at their primary employer, working at least 10 months each year for those three years, and no re-employment at the same firm post-displacement. The focus on tenured workers serves two purposes: it supports the assumption that the job loss is involuntary and unrelated to worker-specific characteristics, and it acknowledges that tenured workers experience greater losses when displaced.[2] In addition, we restrict our attention to workers between the ages of 25-54, and exclude workers who worked in the following sectors prior to their displacement: mining, public administration, and health, activities of private households and extra-territorial organizations, and industries that are led by government-owned companies.[3]

[1]For a discussion on the efficacy of this approach, see (Flaaen et al., 2019).

[2]For more on the implications of focusing on tenured workers, see Bertheau et al. (2022), Lachowska et al. (2020).

[3]Specifically, we omit workers from the following industries: B - Mining and quarrying, O - Local administration,

For the non-displaced worker group, we consider all workers who do not belong to the displaced worker category and were not employed at firms undergoing mass layoffs. We apply the same tenure, age, and sector restrictions criteria as for the displaced group. Each year a non-displaced worker meets these conditions becomes a potential job loss year, and they enter the sample K times, weighted by $\frac{1}{K}$.

Propensity Score Matching Having defined the treated (displaced) and non-treated populations in our data, we use one-to-one matching to pick a subset of non-displaced workers, such that they have similar observables as the treated workers. To this end, we estimate a logit-based propensity score to predict the probability of each worker experiencing a mass layoff event. We exploit the richness of our data by including a long list of features in the propensity estimation, including earnings in the three years prior to displacement independently interacted with gender, pre-displacement firm characteristics such as firm size and firm fixed effects, dummies for the year of birth, tenure, age, ethnic group, number of children born up to displacement year, area of residence at the time of displacement, and spouse's earnings. We match displaced workers to control workers within bins of characteristics. These bins are defined according to the displaced worker's industry, year of job loss, gender, and prior yearly earning quartiles. More information on the propensity score estimation and the matching can be found in the appendix.

2.2 Summary Statistics

Table 1 presents the means and standard deviation of workers' pre-displacement characteristics. Column (1) presents the characteristics of the non-displaced population who follow the tenure restrictions we introduce in Section 2.1, from which we draw workers to match the job loss population. Columns (2) and (3) present the treated and control groups after matching, while column (4) presents the difference between treatment and control means.

First, as evident from Column (3), we find that job loss workers are negatively selected compared to the pool of non-displaced workers (Column (1)). Job loss workers are more likely to earn less on average, are less educated, work in smaller, lower-paying firms, and are more likely to be of minority groups, such as Ethiopians and Arabs, or from the predominantly newer migrant group, the Former Soviet Union descendants. However, note that job losers have a similar gender ratio to the pool of non-displaced workers in our sample. Second, the covariates balance across the two groups after matching, making the matched non-job-loss workers similar to the job-loss workers on observables. Note that relative to the general Israeli workforce, without the tenure restrictions detailed in 2.1, both the restricted population (Column (1)) and the job loss workers (Column (3)) are on average *positively* selected, if we compare, for example, yearly salaries, which stood at around 110-125 thousand ILS in

public administration and defense; compulsory social security, P - Education, Q - Human health and social work activities, R.91 - Libraries, archives, museums, and other cultural activities, T - Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use, U - Activities of extraterritorial organizations and bodies, H.51 - Air transport

that period in Israel. This is to be expected given the tenure restriction we impose in our design.

3 Effects of Job Loss in Israel

To evaluate the impact of job loss, we present two types of results. First, we plot the averages of outcomes of workers who experienced job loss to a matched sample of workers who did not experience job loss, relative to the year of the event. The second type is the event-study coefficients estimated using the following regression:

$$y_{it} = \sum_{\tau=-5,\tau\neq-1}^{\tau=11} \gamma_\tau \mathbf{1}\left\{t = t_i^* + \tau\right\} + \sum_{\tau=-5,\tau\neq-1}^{\tau=11} \theta_\tau \mathbf{1}\left\{t = t_i^* + \tau\right\} \times \mathrm{D}_i + \alpha_{m(i)} + \varepsilon_{it} \tag{1}$$

where y_{it} is worker i's outcome variable t years after the job loss year t_i^*. D_i is an indicator of being displaced. We include a matched-pair fixed effect, $\alpha_m(i)$, where $m(i)$ is the matched pair identifier of worker i.[4][5]

3.1 Job Loss Effects on Labor Market Outcomes

Figures 1 and 2 present the effects of job loss on yearly earnings from work and self-employment, while Figure 3 presents the effects on employment. In addition, we present the effects on spousal and total couple earnings in Figure 4, and the effects on severance pay in Figure 5. Left-hand figures present raw means of the outcome variables by year, centered around the displacement event year ($t = 0$), while right-hand figures present the regression results corresponding to equation (1). As can be seen in panels (a) and (b) of Figure 1, yearly earnings drop by 45% on average in the first year relative to pre-displacement earnings[6], and partially recover to a gap of 10-20% in the long run. These effects are equivalent to around 60,000 NIS in the short run and 30,000 NIS in the long run as shown in panel (d). On average, across the 11 years after a job loss, earnings lost amount to around 26% of earnings in that period, or 350 thousand NIS in $t = 0$ present value terms (discounted by 3% yearly). Figure 2 shows that the income from self-employment increases after a job loss, suggesting that some workers switch to self-employment, but the overall effect on income is small on average. Note that the corresponding drop in total income, which includes income from self-employment, shown in Panel (f) of Figure 2, is very similar to the effect on earnings since the average increase in income from self-employment alone is small (Panel (b)). Panels (e) and (f) show that job loss-affected workers find jobs in worse firms in terms of their AKM fixed effects, with an initial average drop of 1.5 standard deviations in the firm

[4]Controlling for time-varying variables, such age, and age interacted with gender and ethnic group, as well as year fixed-effects, has very little effect on the estimates, given that observables are balanced between the displaced and the matched control observations.

[5]Note that the matched pairs $\alpha_{m(i)}$ are within gender, hence there is no $Female_i$ dummy term separately. Also, since matching is performed within the treatment year as well, this is akin to a matched-pair-cohort FE, which under treatment effect heterogeneity, addresses the concerns of estimating biased effects due to negative weights across treatment effect and cohort's groups (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021).

[6]Pre-displacement earnings are calculated as the average across the three years before displacement.

Table 1: Job loss balance table and descriptive statistics

		Matched sample		
	(1)	(2)	(3)	(4)
Variable	Population	Stayers	Displaced	Difference
Panel A: workers				
t=-1 Yearly earnings	162,953	133,556	132,787	-769
				(1,642)
t=-2 Yearly earnings	155,936	131,598	131,973	-375
				(1,919)
t=-3 Yearly earnings	144,927	124,111	126,446	-2,336
				(2,050)
Male	0.57	0.58	0.58	0.00
				(0.01)
Age at t=0	40.11	40.06	39.98	-0.09
				(0.11)
t=0 # children in HH	1.96	1.92	1.94	0.02
				(0.02)
Had a spouse	0.54	0.53	0.53	0.00
				(0.01)
Spouse earnings at t=-1	70,010	61,933	61,364	-568
				(1,427)
BA attainment	0.2	0.17	0.17	-0.00
				(0.00)
Arab	0.08	0.11	0.12	0.00
				(0.00)
Ethiopia descendent	0.01	0.02	0.02	0.00
				(0.00)
FSU descendent	0.24	0.31	0.30	-0.00
				(0.01)
Europe/Israel descendent	0.32	0.26	0.26	0.00
				(0.00)
North-African descendent	0.33	0.29	0.29	0.00
				(0.01)
Firm tenure	6.85	5.71	5.66	-0.04
				(0.03)
Panel B: firms				
Firm age	8.04	8.04	7.77	-0.28
				(0.04)
Hi-tech	0.11	0.11	0.12	0.01
				(0.00)
Avg. age in firm	44.95	45.14	45.19	0.05
				(0.04)
Firm share men	0.56	0.56	0.58	0.02
				(0.01)
Firm mean earnings	70,295	70,295	75,360	5,065
				(823)
Share firms closed	0	0	0.19	
Firm size	167	157	136	-20.56
				(14.77)
Num. firms	6,066	3,229	1,138	4,367
Num. individuals	443,778	13,361	13,361	26,722

Note: This table presents means of the main pre-displacement characteristics of workers who were displaced (column 3), non-displaced matched sample (column 2), and the pool of non-displaced individuals whose parents follow the baseline restrictions (column 1). In addition, column (4) presents the difference between columns (2) and (3) with stars showing the significance of the difference. *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$

fixed effect in the first year, which gradually decreases to around half a standard deviation in the long term.

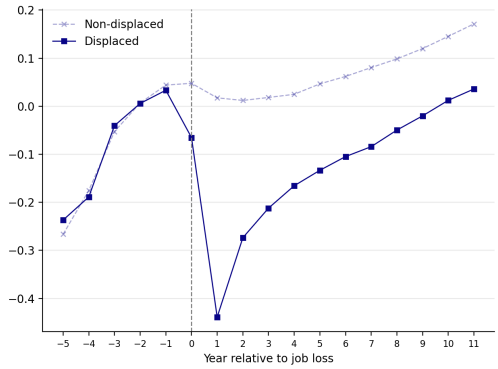
Panel (a) of Figure 3 shows that just above 70% of the workers who experienced a mass layoff event managed to find employment in a different firm in the following year. Panel (b) of the same figure shows the effect of job loss on employment relative to the natural attrition of similar workers, which is 25% in the first year, and shrinks to below 10% after 5 years and is at 7% at the end of our sample period. Panel (c) and (d) of Figure 3 show the dynamics of the permanent attrition due to job loss. The outcome variable used in the figures is a dummy variable that takes the value 1 in the first period that the worker stops working and never returns to work, and 0 otherwise. We find that almost all 7% of long-term unemployed stop working in the year of job loss and never return to work as employees. This means that there is no significant difference in attrition rates between those who experienced job loss and those who did not after the initial shock in the first year. This is not an obvious finding, in light of Jarosch (2023) who finds that the costs of job loss are driven by the inability to find a stable job after job loss. In such a case, one might expect that the attrition should also happen gradually in the years after the initial event, due to lower wages as well as worse job security. Notwithstanding the above, we find that the tendency to earn from self-employment increases by almost 4pp in the first year, a rate that gradually decreases to around 1.5% in the long term.

In addition, in Figure 4 we find that the effect on spousal earnings is positive and significant instantaneously at the year of displacement, suggesting a labor supply response at the household level. Interestingly, however, this response offsets the effect of job loss on total household earnings only in the year of displacement, and not in the year after nor in the long run (Panel (d) of Figure 4). This added-worker result is in the spirit of (Lundberg, 1985), who has first suggested measuring the added-worker effect of wives in the context of unexpected unemployment, rather than any unemployment spell or change in participation. Our results are also generally in line with the results in Stephens (2002), which shows that the spouse response is short-lived and small. However, we don't distinguish between husbands and wives, and treat either as the displaced worker or his/her spouse. Our results are somewhat at odds with Halla et al. (2020), who also find that the spouse labor response has limited effect on household total earnings, but is consistent and lasts for at least 5 years after husband displacement.

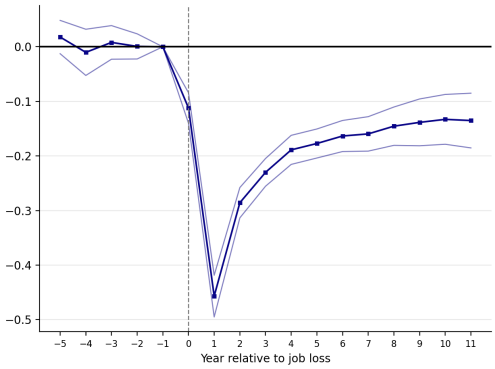
Lastly, from tax records, we can observe the amount of severance pay that an employee receives each year. In Figure 5 we present both the share of workers who received any severance pay in each year and the amounts paid. Reassuringly, we find a strong spike in compensations paid to job-loss workers, but not to the control group. It is important to mention that although severance pay in layoffs is mandatory, in some cases, such as in bankruptcy or legal disputes, these amounts are paid by the National Insurance Institute and not the employer, and would not be observed in our data.

Note that similar to the common practice in the literature, we include in our analysis both firm event types, i.e., both mass-layoffs, where the firm keeps operating after at least 30% of the employees are let go, and firms that cease operations altogether (e.g., Bertheau et al., 2022; Schmieder et al., 2023). In Appendix Figures A.1 we present the aggregate effect separately by each event type. In

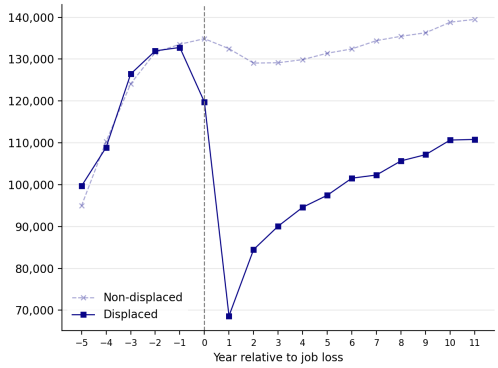
Figure 1: Effects of job loss on yearly earnings



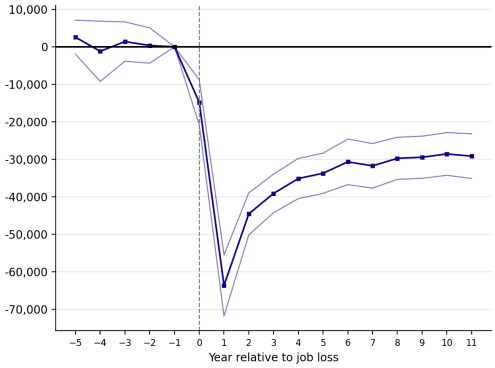
(a) yearly earnings rel. to $t < 0$



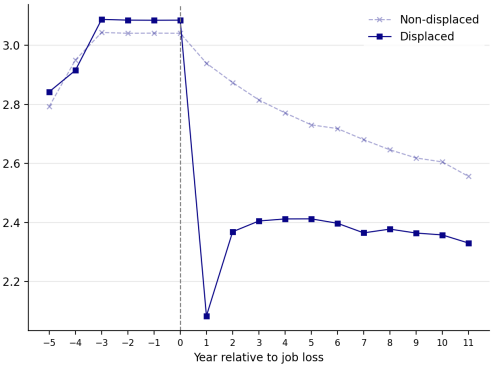
(b) Effects on yearly earnings rel. to $t < 0$



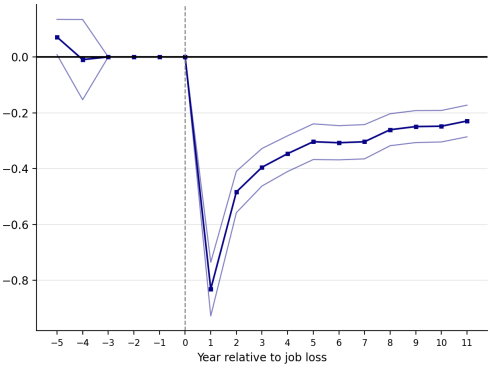
(c) yearly earnings (1NIS $\approx$ 0.3\$)



(d) Effects on yearly earnings (1NIS $\approx$ 0.3\$)



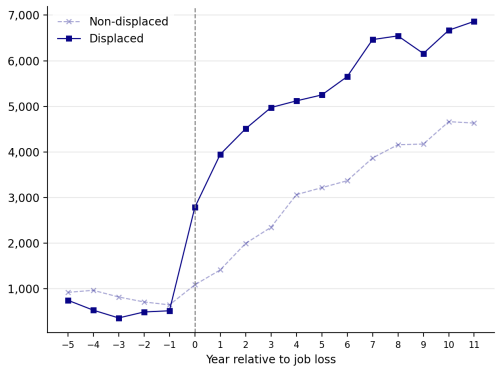
(e) firm fixed-effects



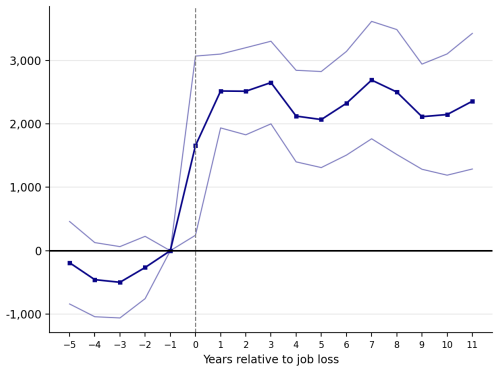
(f) Effects on firm fixed-effects

Note: This figure presents the effects of job loss on labor market outcomes. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on yearly earnings from salary and self-employment relative to the average earnings across the three periods before displacement. Panels (c) and (d) present the same effects on yearly earnings in Shekels. Panels (e) and (f) show the effects on firm fixed effects. Years with no reported earnings are coded as 0. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

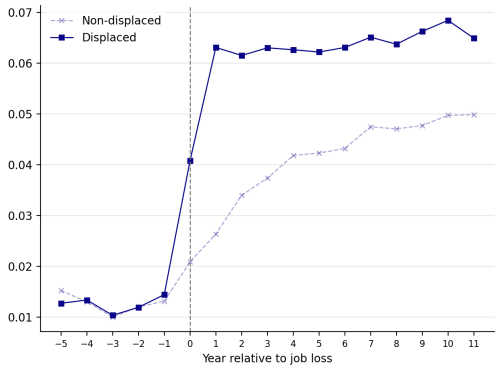
Figure 2: Effects of job loss on yearly earnings from self-employment



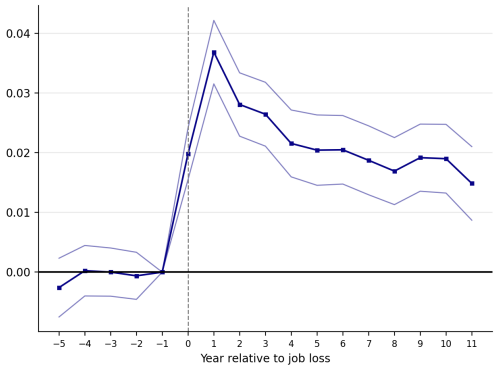
(a) Yearly income from self-employment



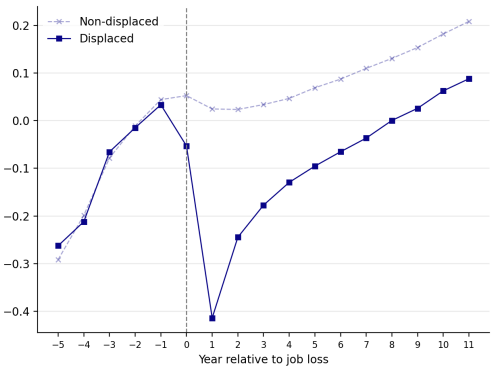
(b) Effects on income from self-employment



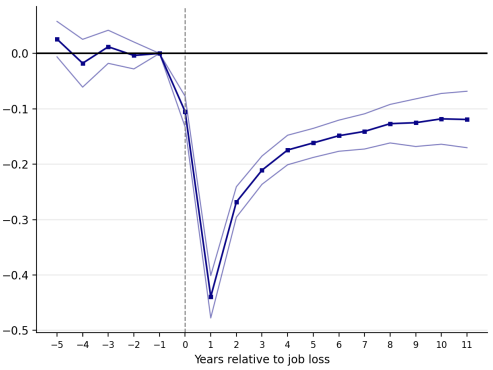
(c) Yearly self-employment



(d) Effects on self-employment



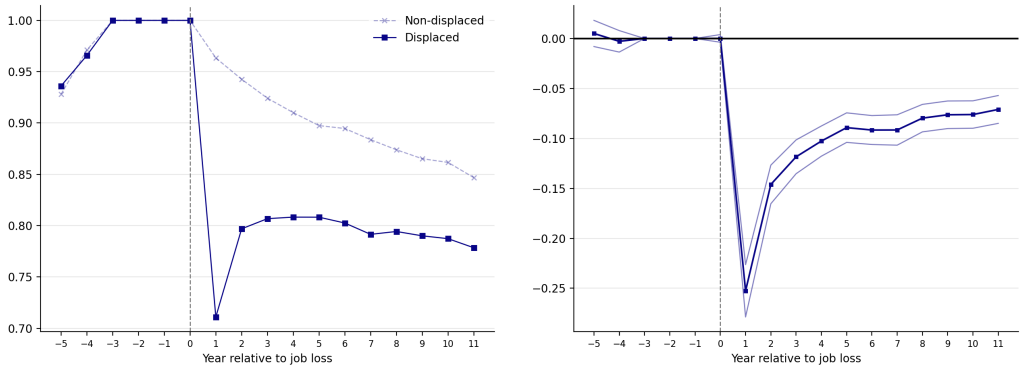
(e) Yearly total income from work rel. to $t < 0$



(f) Effects on total income from work rel. to $t < 0$

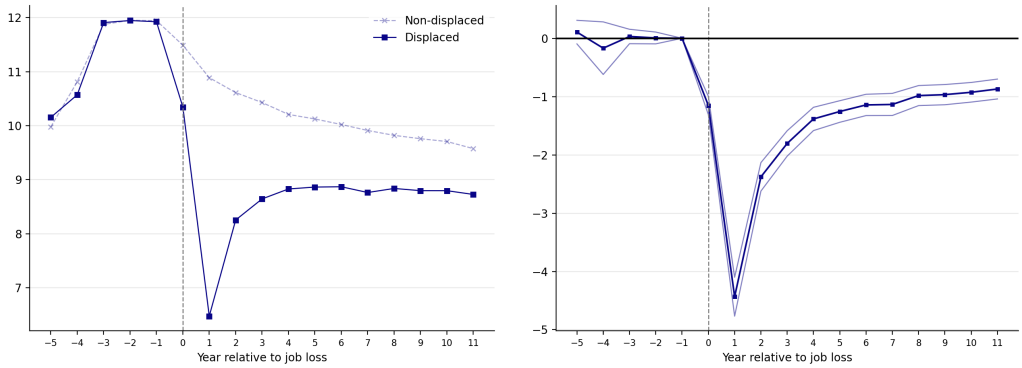
Note: This figure presents the effects of job loss on labor market outcomes. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on yearly earnings from self-employment in Shekels. Panels (c) and (d) present the effect on total earnings and salary relative to income before displacement. Years with no reported earnings are coded as 0. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

Figure 3: Effects of job loss on employment



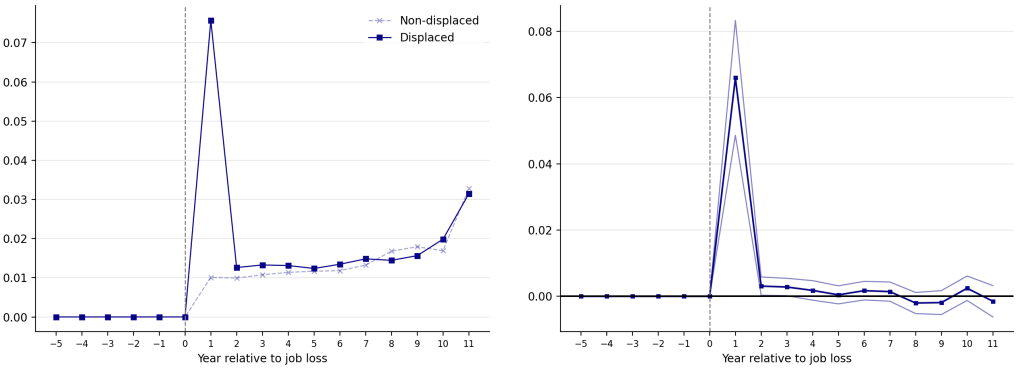
(a) Means of employment

(b) Effects on employment



(c) Means of # of months employed

(d) Effects on # of months employed

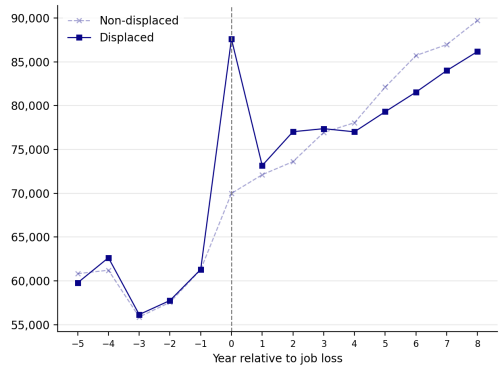


(e) Means of leaving the LF

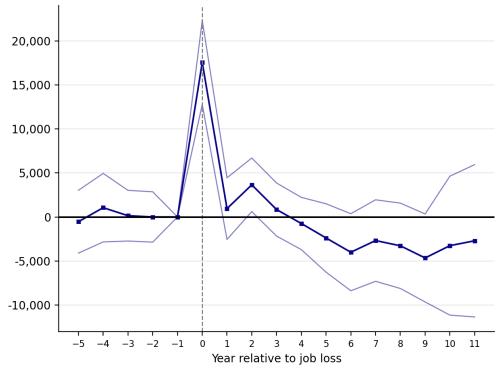
(f) Effects on leaving the LF

Note: This figure presents the effects of job loss on labor market outcomes. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effects on working and earning above 10,000 ILS (around 3,000 USD) during the calendar year, panels (c) and (d) present the effect on the number of months reported working and earning a positive amount, and panels (e) and (f) present the effects on a proxy for leaving the LF - switching to unemployment for the rest of the available panel years and up to 15 years after job loss. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

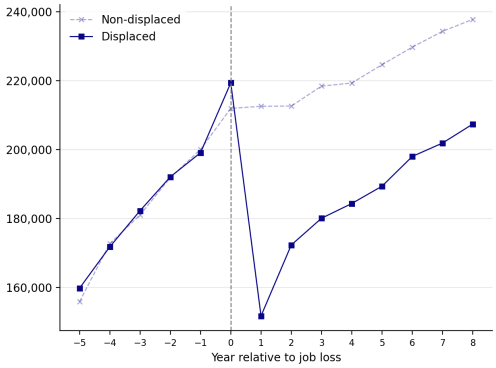
Figure 4: Effects of job loss on spouse earnings and total HH earnings



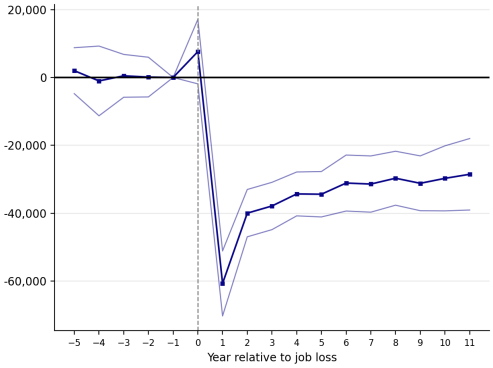
(a) Means of Spouse earnings



(b) Effects on Spouse earnings



(c) Means of Total HH earnings

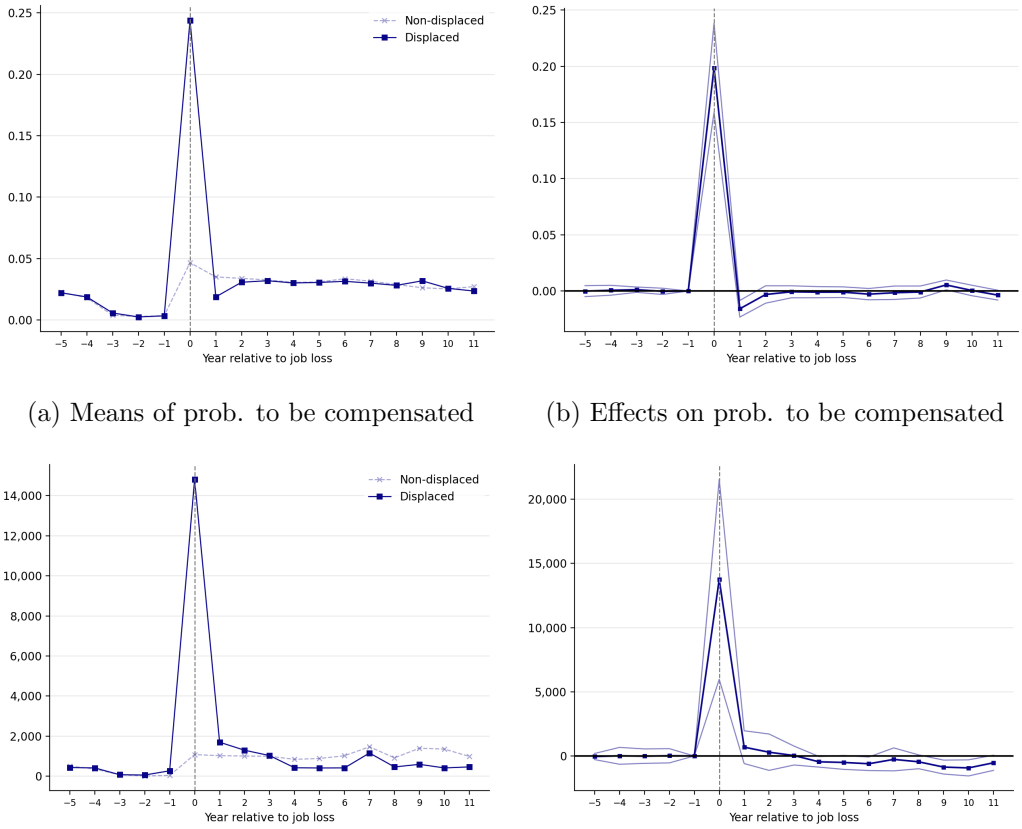


(d) Effects on Total HH earnings

Note: This figure presents the effects of job loss on labor market outcomes. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on spousal yearly earnings, and panels (c) and (d) present the effect on the sum of worker and spouse's yearly earnings. We code spousal earnings for workers with no spouses or spouses with no earnings as 0. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

general, we find larger effects, especially in the short-term, in firm closure events.

Figure 5: Effects of job loss on severance pay



(a) Means of prob. to be compensated

(b) Effects on prob. to be compensated

(c) Means of compensations amount

(d) Effects on compensations amount

Note: This figure presents the effects of job loss on labor market outcomes. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on the probability of receiving severance pay from the employer, and panels (c) and (d) present the effect on the amount received in severance pay from the employer in Shekels (1NIS $\approx$ 0.3\$). We code spousal earnings for workers with no spouses or spouses with no earnings as 0. Panels (e) and (f) show the effects on firm fixed effects. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

3.1.1 International Comparison

We compare our results to the most recent international comparison study by Bertheau et al. (2022). To alleviate concerns regarding the sensitivity of the results to differences in research design, such as treatment definitions, sample restrictions, and estimation approach, we employ a very similar methodology to (Bertheau et al., 2022).

For convenience, Figure 6 presents the results from Bertheau et al. (2022), with our results for

Israel added. Panel (a) shows the effect of job loss on earnings, while panel (b) presents the effect on employment. In general, our estimates are comparable to those in Bertheau et al. (2022). It is evident, however, that the effect of job loss in Israel on earnings is relatively high only in the first year after the event. The depth of the effects we find both on earnings and on employment are similar to those in Italy and Spain. In the longer term, however, workers in Israel go back to work faster and wages recover such that by the 5th year after a job loss, the effects are comparable to the lower half of the distribution of effects.

This distinctive dynamic in the Israeli labor market may be attributable to a variety of factors that warrant further exploration. Potential explanations could include the effectiveness of job retraining programs, social safety nets, or unique cultural or societal factors that encourage rapid re-employment. Understanding the exact mechanisms at play could provide valuable insights for policymakers seeking to mitigate the harmful effects of job loss in other countries.

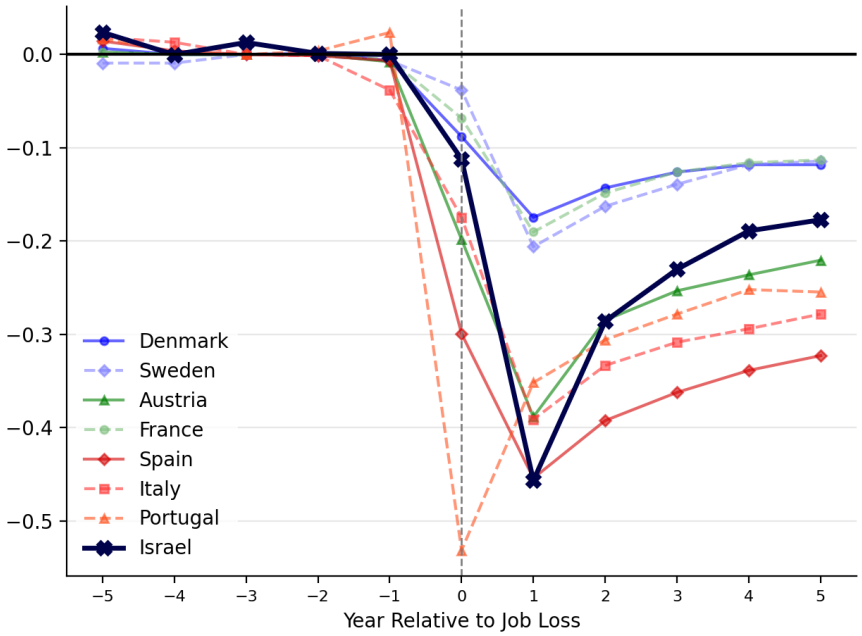
In conclusion, while the immediate impact of job loss on earnings in Israel is comparable to Italy and Spain, the longer-term outlook is more optimistic due to the rapid recovery of earnings and employment. This comparative study underscores the importance of considering temporal patterns when analyzing the economic ramifications of job loss, and highlights the potential for national policies and societal factors to influence these outcomes.

3.2 Job Loss Effects and the Business Cycle

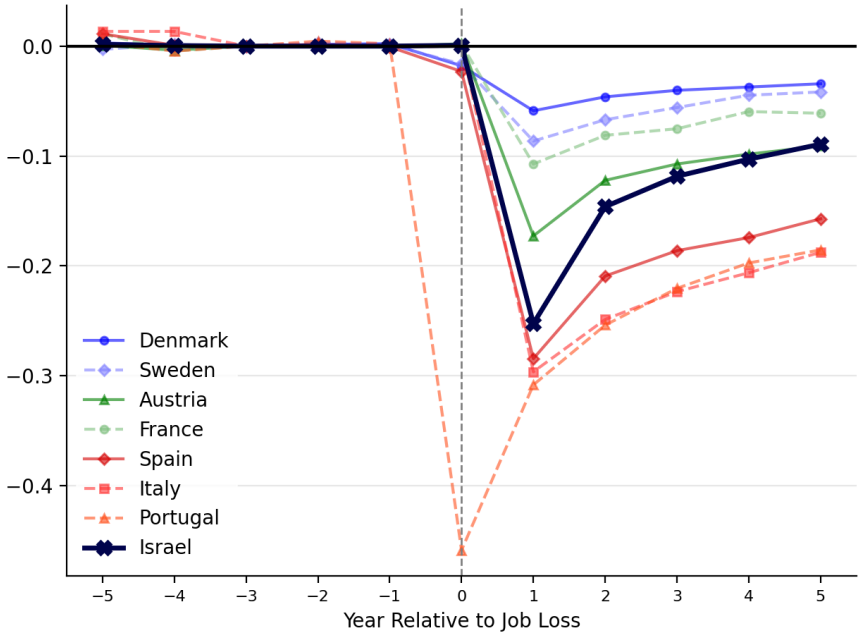
The effects of job loss have been found to be substantially higher when the worker-firm separation occurs in times of recessions (e.g., Davis and von Wachter, 2011). We document this phenomena in Israel. Figure 7 presents the effects of job loss against the participation and unemployment rate in the Israeli economy in each event year. Each point presents the average participation rate (Panel A) or unemployment rate (Panel B), against the job loss effect for the group of individuals laid off each year in the sample period, 1999-2009. We plot the effects in different time spans after the event, i.e., 1, 2, 5, and 10 years after job loss. First, there is an evident relation between the business cycle and the effects of job loss, both in the short term and in the long term, such that when unemployment is high (or participation is low), the effects of job loss are higher. The elasticity between the participation rate (unemployment rate) and the effect of job loss, i.e., the fitted average slope, is -0.11 (0.03). Second, note that the slopes in each time period (t=1,2,5,10) are almost perfectly parallel. This implies that the impact of market conditions during the year of job loss not only plays a significant role in the short-term effects but also determines the average impacts of job loss in the long term. However, this may also be due to differences in the characteristics of the workers and firms that experience job loss events under different market conditions.

The evidence that job loss effects are more severe during economic downturns could support the case for counter-cyclical unemployment insurance policies or targeted retraining programs, especially given the large cumulative effects of job loss over the long-term. This, however, crucially depends on the mechanisms behind this phenomena, which is outside the scope of this work. Notwithstanding this, the literature offers several explanations related to the business cycle's impact on job loss outcomes.

Figure 6: International comparison of the average effects of job loss



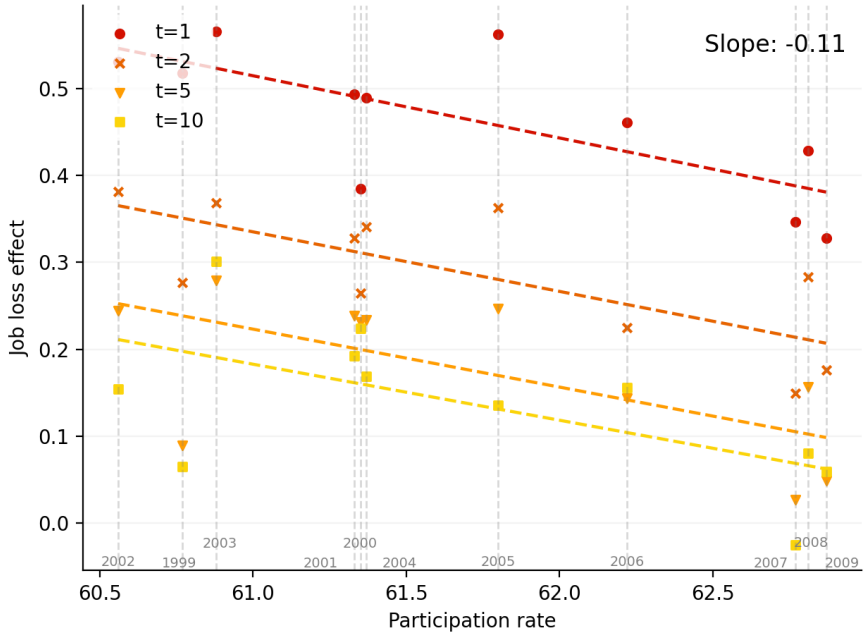
(a) Earnings



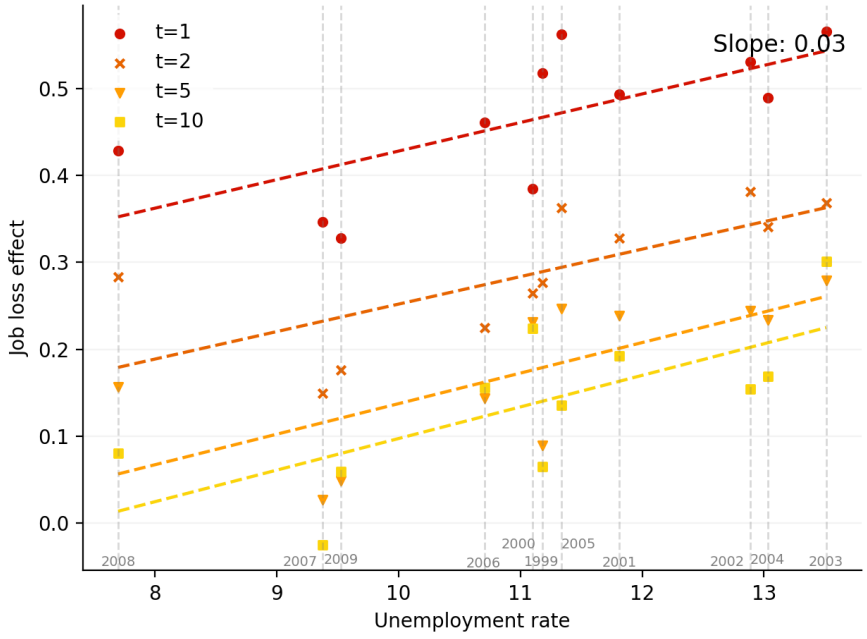
(b) Employment

Note: This figure presents the effects of job loss across countries, taken from Bertheau et al. (2022), with the addition of Israel.

Figure 7: The effects of job loss on earnings against the participation and unemployment rates



(a) Participation rate



(b) Unemployment rate

Note: This figure presents the effects of job loss on earnings in percentage points relative to earnings before displacement in each year and the time period after the mass-layoff event, against the employment and participation rates in the year of displacement. Labor market indicators are taken from the International Labour Organization: "Labour Force Statistics Database (LFS)" ILOSTAT. Accessed February 21, 2023.

The most immediate is the lower labor market tightness, prolonging unemployment duration which lowers reemployment wages and may also lead to skill depreciation, thereby exacerbating the long-term impacts of job loss (e.g., Schmieder et al., 2016; Jarosch, 2023). The strong long-run correlation we observe in the data between market conditions and the effects of job loss may also be explained by *cyclical downgrading* (McLaughlin and Bils, 2001). Under this hypothesis, high wage sectors and jobs are more sensitive to market cyclicality, creating larger average wage drops. All in all, recessions are periods with costly job switches across sectors, firms, and occupations. Marginally productive job reallocation may be economically efficient in the long term, but detrimental to the displaced workers (Schumpeter, 1942; Foster et al., 2016).

Our findings align with Schmieder et al. (2023), who document the high cyclicality of job loss effects. There, they find that the long term effects of job loss in recessions more than double the losses in booms. They provide insight into the mechanisms behind this variation, by examining the losses in firm wage premiums, the longer unemployment duration, and to losses in occupation and industry specific skills. Crucially, they attribute the cyclicality not to worker or firm composition, but to reductions in establishment wage premiums. Displaced workers in recessions face larger decreases in these premiums, which in turn explains a significant part of the cyclicality in wage losses. Furthermore, they show that other factors like unemployment duration and occupation and industry switches correlate with wage losses, but to a smaller extent than firm fixed effects.

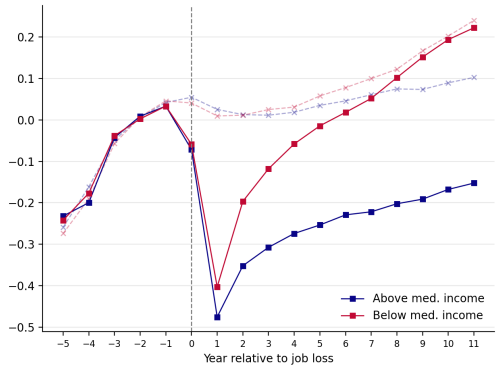
3.3 Earning Level Heterogeneity

Figure 8 presents the job loss effects separately by pre-displacement earnings levels, calculated as the average of yearly earnings in the three years before displacements, and split according to the within the event-year median. The different scar patterns noticeable in Panels (a) and (b) are that while the effect is large and persistent for high-earners at 30%, it fades completely after roughly 7 years for low-earners. In addition, the short-term effect is also somewhat smaller for lower earners. In contrast, as seen both in Panels (a) and (b) of Figure 9 for yearly employment and Panels (c) and (d) for monthly employment, employment drops of low-earners do not completely dissipate. Taken together, this suggests that there is an *increase* in wages for the low-earning displaced relative to the non-displaced. From panels (e) and (f) we learn that lower-earning job losers tend to return to employment and not leave the labor force more than high earners.[7]

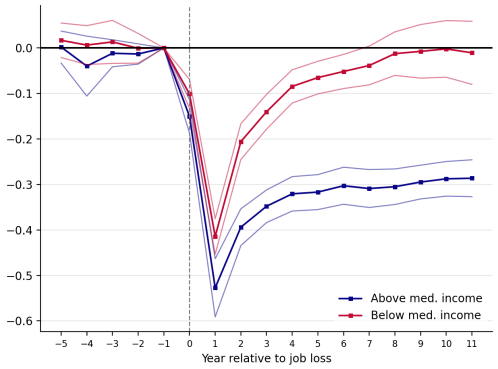
Although the effects are large in relative terms for both groups, in absolute terms (Panel (d) of Figure 8), the drops in earnings are much smaller for the lower-earning workers, as they start with much lower earnings prior to displacement (Panel (c) of Figure 8).

[7]In Appendix Figures A.2 and A.3 we present these results by quartiles.

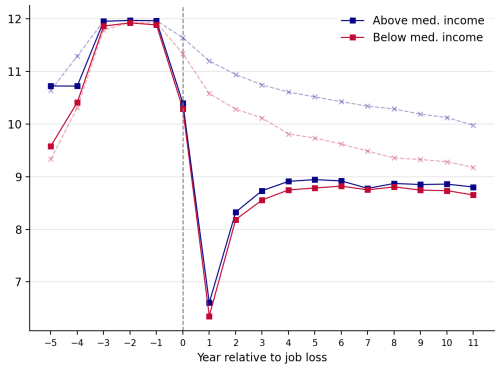
Figure 8: Effects of job loss on yearly earnings, by income levels



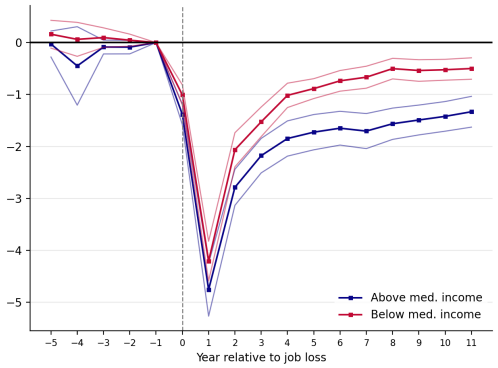
(a) Yearly earnings rel. to $t < 0$



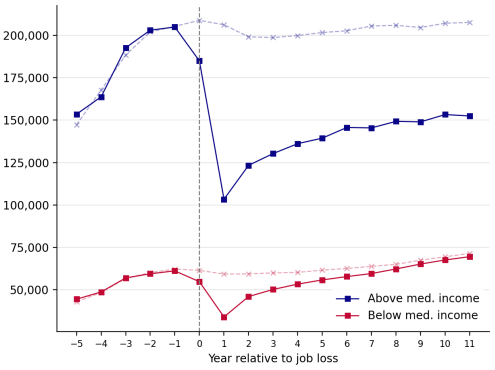
(b) Effects on yearly earnings rel. to $t < 0$



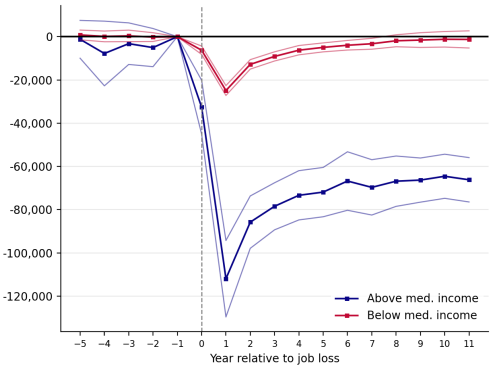
(c) Yearly # of months employed



(d) Effects on yearly # of months employed



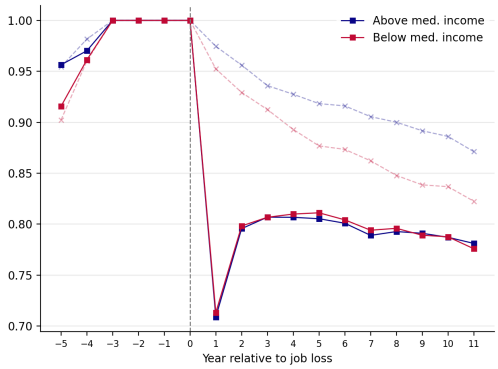
(e) Yearly earnings (1NIS $\approx$ 0.3\$)



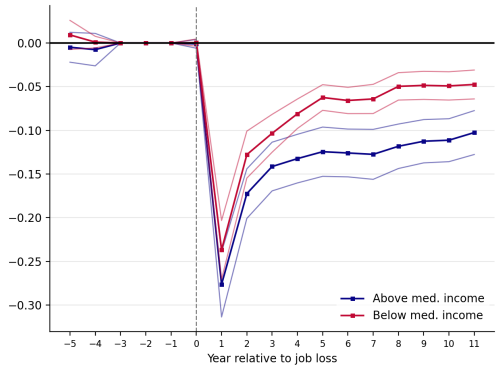
(f) Effects on yearly earnings (1NIS $\approx$ 0.3\$)

Note: This figure presents the effects of job loss on labor market outcomes, separately by high and low earnings levels, split by the median of pre-displacement. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on yearly earnings from salary and self-employment relative to the average earnings across the three periods before displacement. Panels (c) and (d) present the same effects on yearly earnings in Shekels. Years with no reported earnings are coded as 0. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

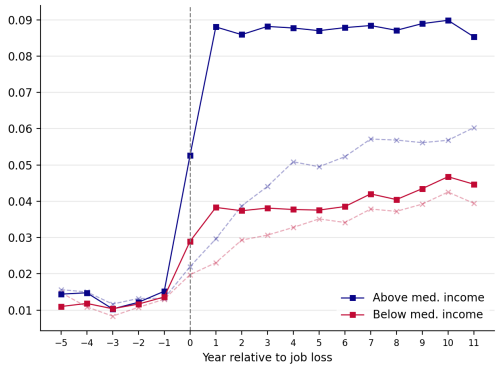
Figure 9: Effects of job loss on employment, by income levels



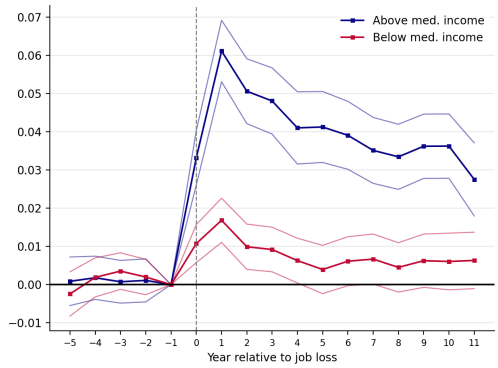
(a) Means of employment



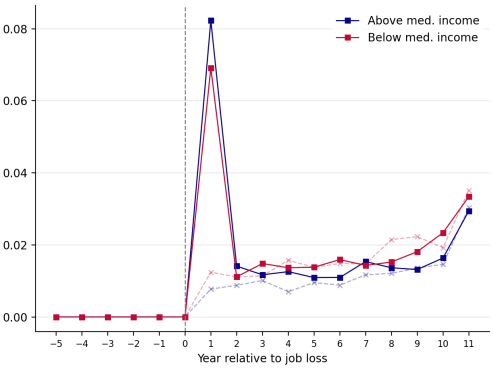
(b) Effects on employment



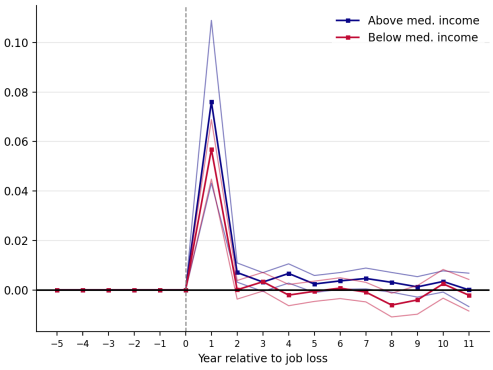
(c) Means of self employment



(d) Effects on self employment



(e) Means of leaving the LF



(f) Effects on leaving the LF

Note: This figure presents the effects of job loss on labor market outcomes, separately by high and low earnings levels, split by the median of pre-displacement. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effects on working and earning above 10,000 ILS (around 3,000 USD) during the calendar year, panels (c) and (d) present the effect on the number of months reported working and earning a positive amount, and panels (e) and (f) present the effects on a proxy for leaving the LF - switching to unemployment for the rest of the available panel years and up to 15 years after job loss. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

3.4 Firm Heterogeneity

Figures 10 and 11 present the job loss effects separately by firm fixed effect, estimated via a two-way fixed effects model proposed in Abowd et al. (1999) on all firms, not including laid-off workers[8]. Similarly to the pattern of effects by income levels, workers from higher fixed-effect firms suffer a greater loss both in absolute terms and relative to pre-displacement earnings. This suggests that firms and pre-displacement earnings and employer fixed effect both play an important role in predicting earnings losses in job loss. This pattern is similar to that found in Schmieder et al. (2023) using German administrative data.

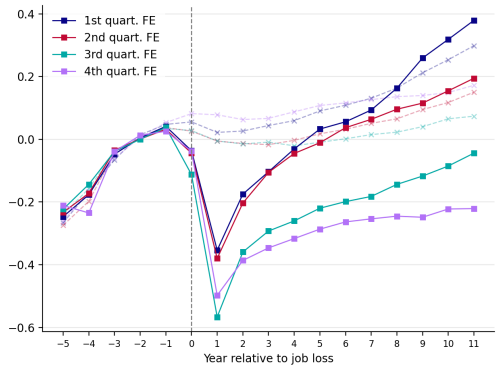
3.5 Age at Layoff Heterogeneity

The findings presented in Figures 12 and 13 highlight the impact of job loss on different age categories of workers in the labor market. The results show a consistent pattern across the figures: the older the worker is at the time of job loss, the more pronounced the effects are, both in the short term and in the long term. This suggests that older workers are more vulnerable to the negative impacts of job loss, and may experience greater difficulty in finding new employment and restoring their earnings to pre-displacement levels. This information provides valuable insight and highlights the need for targeted interventions to support this population in the aftermath of job loss. However, it is important to note that this relationship may not solely be attributed to age, as other factors may be correlated with age and also influence the results, such as income, gender, occupation, etc.

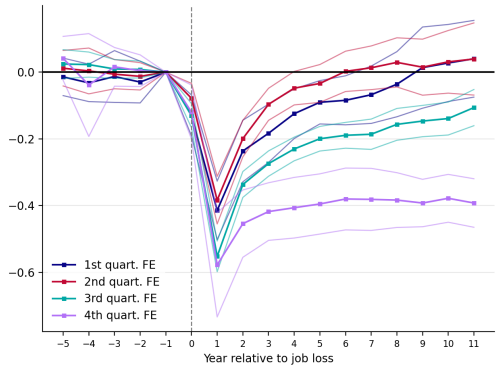
In a similar exercise done on Swedish data, Seim (2019) finds that young workers' wages recover faster than those of older workers, but that initial drops are similar between age groups. We find the same pattern of recovery, although short-term drops are significantly smaller for younger workers. Our results as well as those in Seim (2019), are at odds with Von Wachter et al. (2009), who find, using CPS data, that young workers (ages 25-34) suffer greater and more consistent drops in earnings, while workers in ages 35-54 have a full and quick recovery in earnings.

[8]AKM style effects have been estimated using a similar approach on Israeli administrative data in previous work, such as San (2020) and Dobbin and Zohar (2021)

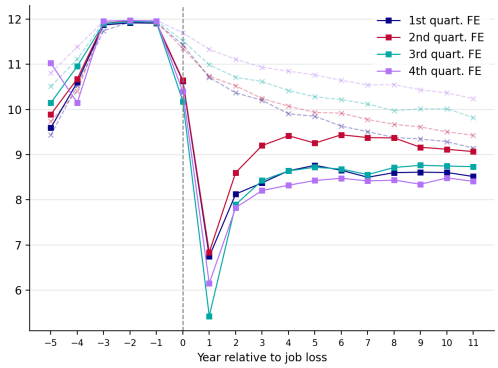
Figure 10: Effects of job loss on yearly earnings, by firm fixed effects



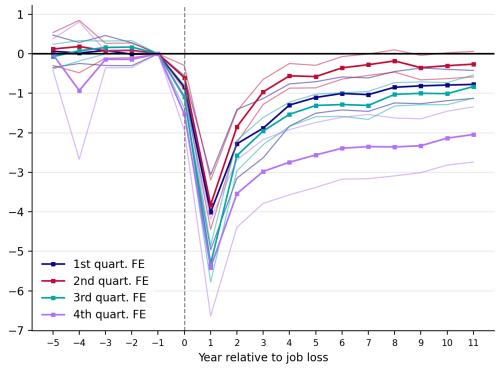
(a) Yearly earnings rel. to $t < 0$



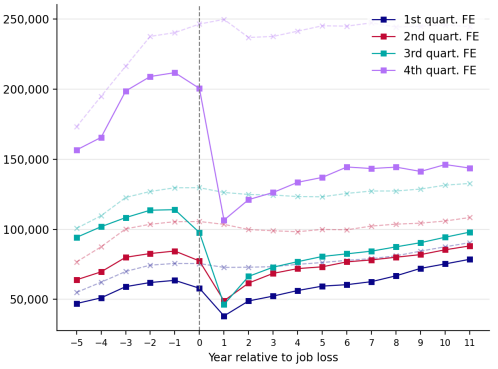
(b) Effects on yearly earnings rel. to $t < 0$



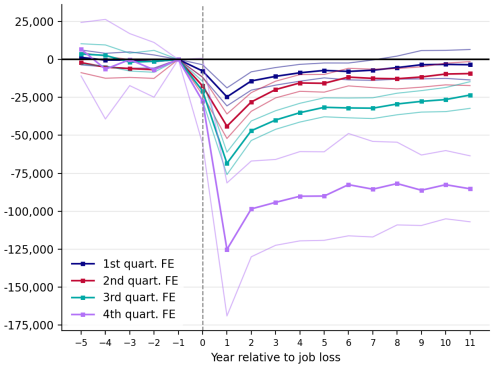
(c) Yearly # of months employed



(d) Effects on yearly # of months employed



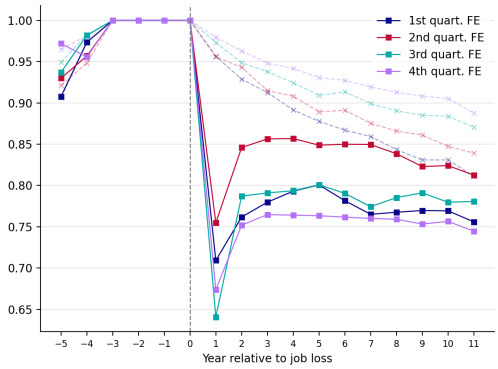
(e) Yearly earnings (1NIS $\approx$ 0.3\$)



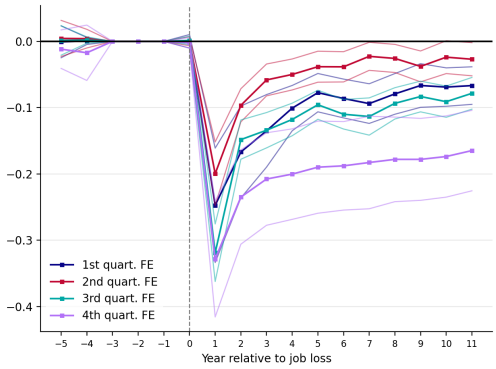
(f) Effects on yearly earnings (1NIS $\approx$ 0.3\$)

Note: This figure presents the effects of job loss on labor market outcomes, separately by 4 quartiles of firm fixed effects, estimated via a two-way fixed effects model. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on yearly earnings from salary and self-employment relative to the average earnings across the three periods before displacement. Panels (c) and (d) present the same effects on yearly earnings in Shekels. Years with no reported earnings are coded as 0. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

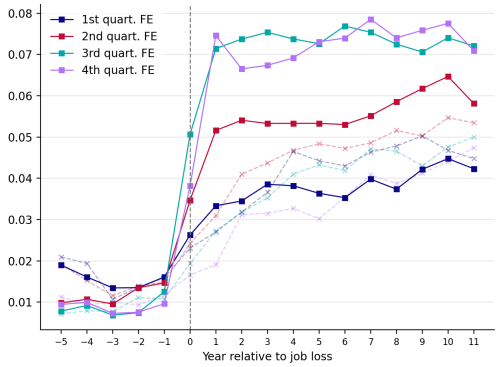
Figure 11: Effects of job loss on employment, by firm fixed effects



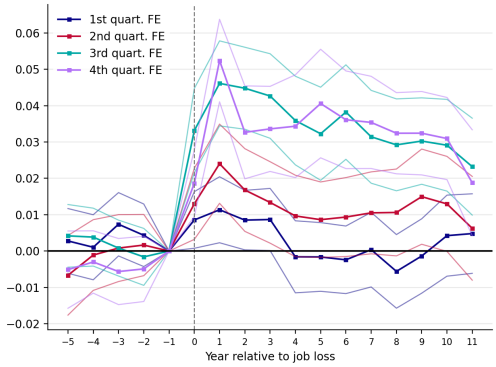
(a) Means of employment



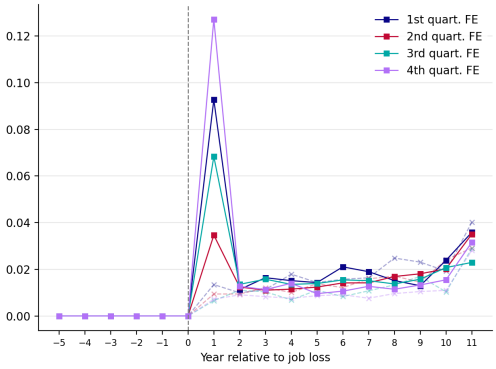
(b) Effects on employment



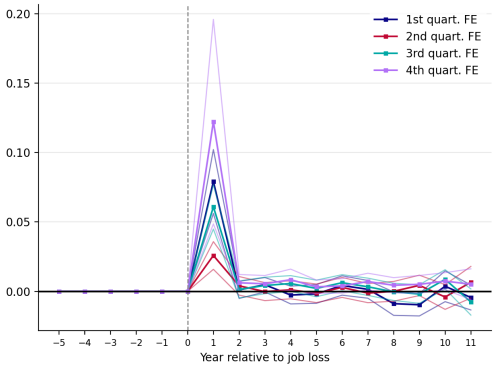
(c) Means of self employment



(d) Effects on self employment



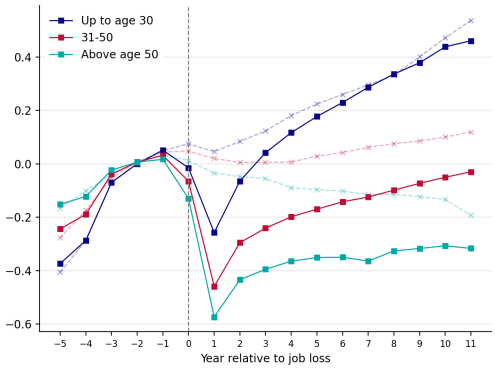
(e) Means of leaving the LF



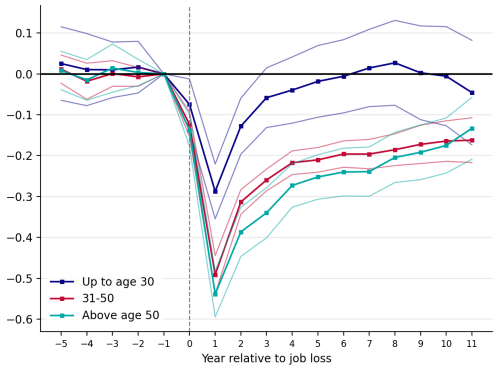
(f) Effects on leaving the LF

Note: This figure presents the effects of job loss on labor market outcomes, separately by 4 quartiles of firm fixed effects, estimated via a two-way fixed effects model. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effects on working and earning above 10,000 ILS (around 3,000 USD) during the calendar year, panels (c) and (d) present the effect on the number of months reported working and earning a positive amount, and panels (e) and (f) present the effects on a proxy for leaving the LF - switching to unemployment for the rest of the available panel years and up to 15 years after job loss. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

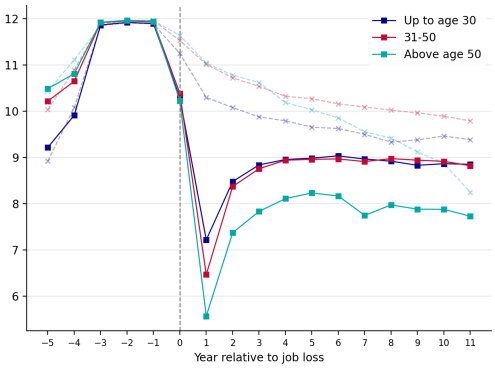
Figure 12: Effects of job loss on yearly earnings, by age



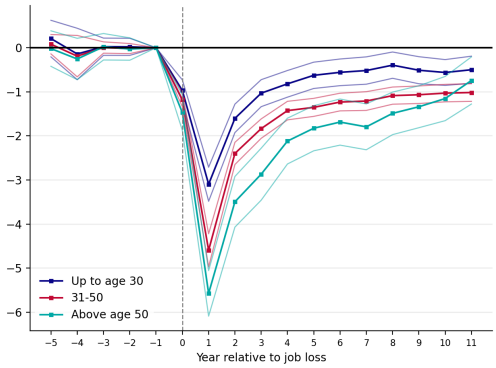
(a) Yearly earnings rel. to $t < 0$



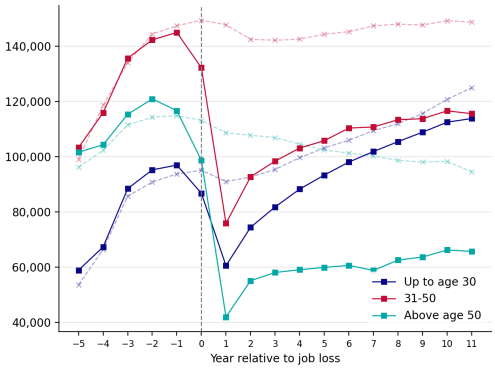
(b) Effects on yearly earnings rel. to $t < 0$



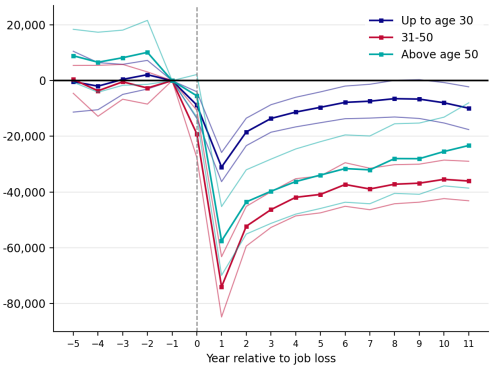
(c) Yearly # of months employed



(d) Effects on yearly # of months employed



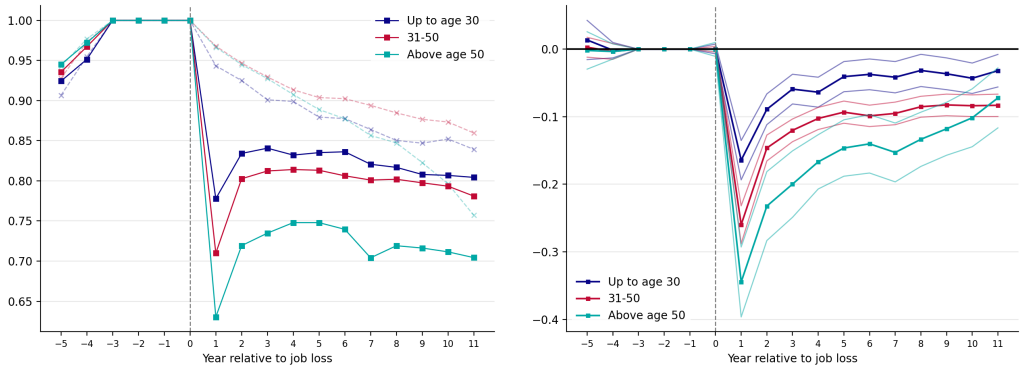
(e) Yearly earnings (1NIS $\approx$ 0.3\$)



(f) Effects on yearly earnings (1NIS $\approx$ 0.3\$)

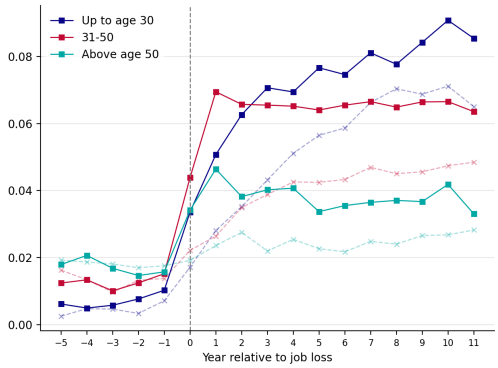
Note: This figure presents the effects of job loss on labor market outcomes, separately by three age groups: up to age 30, up to age 50, and above age 50. The age is determined by the job loss year. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on yearly earnings from salary and self-employment relative to the average earnings across the three periods before displacement. Panels (c) and (d) present the same effects on yearly earnings in Shekels. Years with no reported earnings are coded as 0. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

Figure 13: Effects of job loss on employment, by age

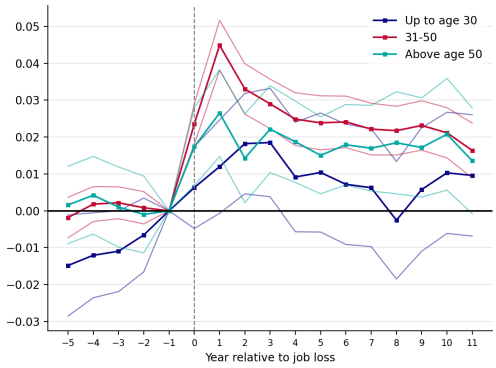


(a) Means of employment

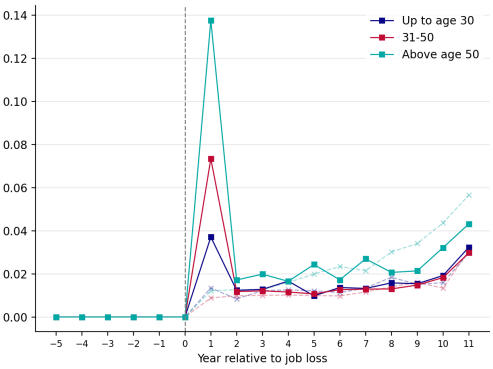
(b) Effects on employment



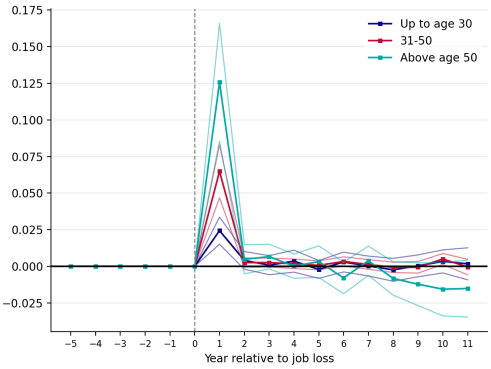
(c) Means of self employment



(d) Effects on self employment



(e) Means of leaving the LF



(f) Effects on leaving the LF

Note: This figure presents the effects of job loss on labor market outcomes, separately by three age groups: up to age 30, up to age 50, and above age 50. The age is determined by the job loss year. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effects on working and earning above 10,000 ILS (around 3,000 USD) during the calendar year, panels (c) and (d) present the effect on the number of months reported working and earning a positive amount, and panels (e) and (f) present the effects on a proxy for leaving the LF - switching to unemployment for the rest of the available panel years and up to 15 years after job loss. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

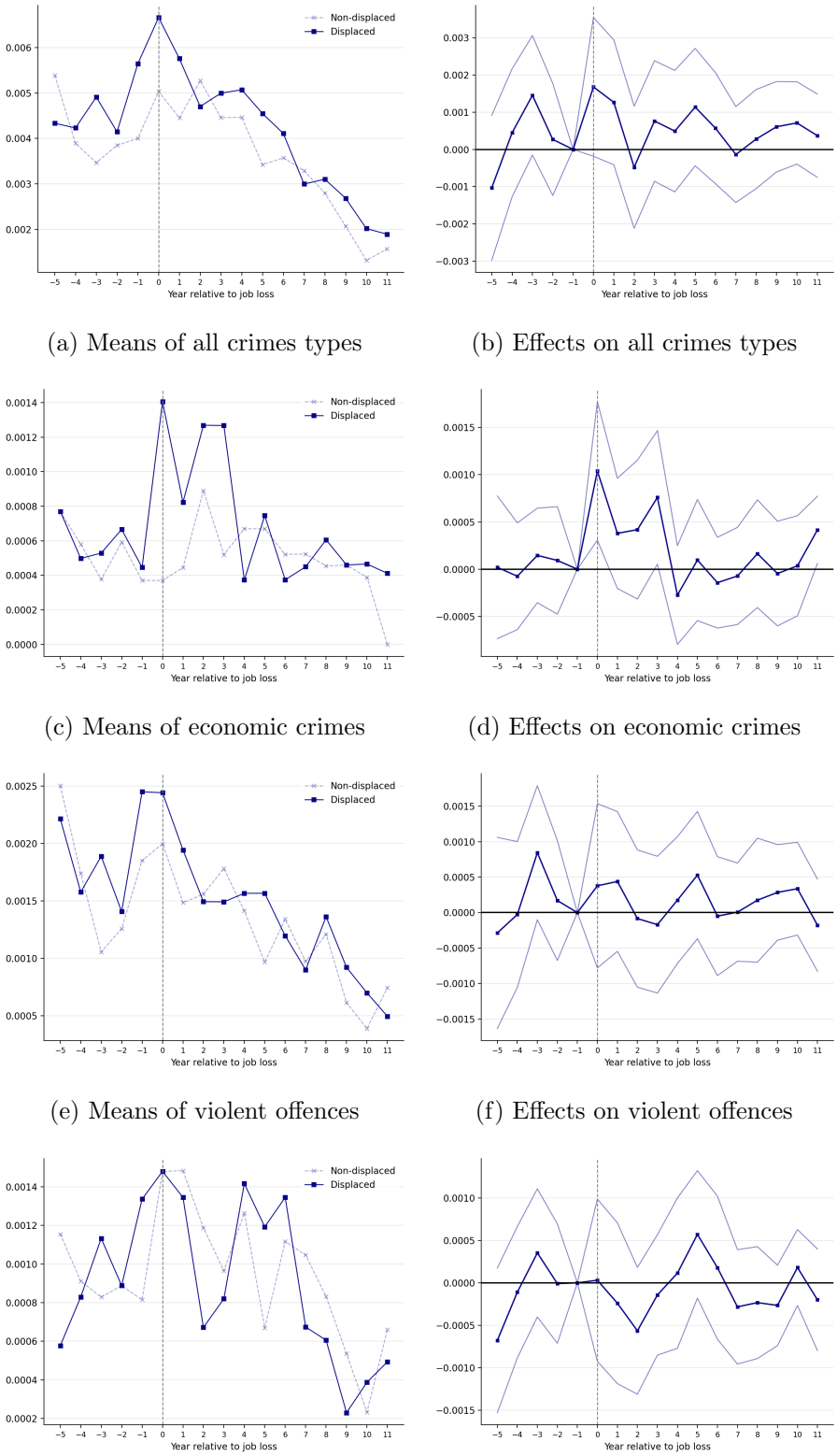
3.6 The Effects of Job Loss on Crime

Empirical evidence consistently demonstrates a higher prevalence of criminal activity among low-income earners and workers with weak labor market attachment Hsieh and Pugh (1993); Pratt and Cullen (2005). A long line of theoretical papers, starting with Becker (1968) and Ehrlich (1973), suggest that these patterns can be explained by diminishing incentives to avoid crime in the face of limited labor market prospects. However, establishing a causal link between labor market outcomes and criminal behavior presents a considerable challenge due to selection on unobservable factors.

Studies conducted in the United States and Brazil have estimated this relationship by focusing on the exogenous event of job loss Rose (2018); Britto et al. (2022). Their findings indicate that individuals who lose their jobs are more likely to engage in criminal activities. Motivated by these studies, we undertake a similar analysis in the Israeli context, linking administrative criminal records to our dataset. Our data allow us to observe the type of crime committed, shedding light on the motives driving criminal behavior in response to labor market shocks.

Figure 14 presents the effects of job loss on crime instances in Israel. The effect on all crime incidents in general, as shown in Panel (b) is positive but non-significant. We find, however, a significant but short-lived increase in economically motivated crimes, such as theft, fraud, or robbery. It suggests an increase of 0.1pp compared to the non-displaced workers, an increase of around 200% compared to the baseline level pre-displacement. This effect lasts only in the first years, although it is positive but not significant in the 3 years after job loss. In panels (f) and (h) we present the effects on violent crimes and other types of crime, with null effects. This supports the notion that the economic incentives created by the job loss motivate the crimes committed, and perhaps not any other distress associated with job loss.

Figure 14: Effects of job loss on crime



(a) Means of all crimes types

(b) Effects on all crimes types

(c) Means of economic crimes

(d) Effects on economic crimes

(e) Means of violent offences

(f) Effects on violent offences

(g) Means of other crimes

(h) Effects on other crimes

Note: This figure presents the effects of job loss on criminal behavior. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

It is, however, important to interpret these findings with caution, as the incidence of crime in Israel is relatively low compared to the settings analyzed in other studies[9]. As such, our results contribute to the broader understanding of the relationship between labor market outcomes and crime, while also highlighting the need for context-specific analyses in order to account for variations in crime rates and labor market conditions across different countries.

Herzog (2005) in the Palestinian setting in Israel, find no relation between economic hardships caused by drops in the employment of Palestinians in Israel due to the conflict and crime in general. They do find, however, an increase in car theft - an economically motivated crime.

4 The Inter-Generational Effects of Job Loss

Next, we turn to estimate the propagating effects of parental job loss on children's high school outcomes. We first estimate the aggregate effects of job loss and then turn to study the dynamics of the effects with age and their heterogeneity with respect to parental income and displaced parent's gender. In this Section, we focus on the subset of workers with children, and utilize a different econometric approach to propensity score matching for the comparison of displaced and non-displaced households. Instead, we employ inverse probability weighting, with propensity scores estimated at the child level, instead of at the worker level. We provide further detail into the methodology, its advantages in the current setting, as well as the sample characteristics and further analyses in Aloni and Avivi (2023).

In our analysis, we focus on the effects of parental job loss on key high school performance indicators: the probability of attaining a Bagrut certificate and the probability of completing all the math Bagrut exams and scoring above the median. Since these outcomes are realized between the ages 17-18, we estimate Δ^c as defined below separately for children whose parents were displaced before and after age 18. Therefore, the effect of job loss after age 18 serves as a placebo test. To estimate Δ^c by age groups, we run:

$$y_i = \sum_{k=1}^{J} \Delta_k^c \times \mathbb{1}\{age_i \in k\} \times \mathrm{D}_i + \sum_{k=1}^{J} \gamma_k \times \mathbb{1}\{age_i \in k\} + \varepsilon_i \tag{2}$$

Where D_i is a dummy for whether child i's parent experienced job loss, and age_i is the age of the child when the parent was displaced. $1, ..., J$ are the age bins of children's age at parent's displacement. Δ_k^c, therefore, gives the effect of parent job loss among children whose parent was displaced when she was in age group k.

Table 2 presents the estimation results of Equation 2 stratifying the age group to above and below age 18. Column (1) shows that children whose parents lost their jobs by age 18 are 1.4 percentage points less likely to secure a Bagrut certificate. The estimates for the effects post outcome realization (above 18) are small and insignificant, supporting our identification assumption of no selection into

[9]For example, homicide rates are 4 times higher in the U.S. and more than 10 times higher in Brazil. (link to source, retrieved May 11th, 2023)

treatment. Interestingly, the total mean effect masks substantial heterogeneity by family earnings. As seen in column (2), the effect on the matriculation certificate more than doubles in size when we introduce an interaction with a dummy for family income above the median. This implies that children born to below-median income families whose parents lost their jobs unexpectedly suffer from a 3.7 percentage points lower probability of securing a matriculation certificate, a reduction of more than 10 percent effect relative to the unconditional mean in Matriculation attainment in our sample. Columns (3) and (4) display a very similar pattern for the effect on math exam scores, which is an important indicator for performance in the matriculation exams, and found to be strongly related to later labor market outcomes (Lavy, 2020; Angrist and Lavy, 2009; Ben-David and Kimhi, 2020). This effect amounts to about 7 percent effect relative to the sample mean once we focus on lower-income families.

The coefficient of the interaction between job loss and high-income families is qualitatively small, positive, and statistically insignificant from zero, implying that the effects of job loss on children are concentrated among children from low-income families. Such results could be driven by several mechanisms. For example, financially constrained families may have a harder time coping with the loss of income and struggle to prevent the propagation of the shock to children, as suggested in Cooper and Stewart (2017). Another explanation could be that the time spent at home for higher income families, which are on average associated with higher human capital, could outweigh the effects of lost earnings, as suggested in Liu and Zhao (2014). The aggregate effects we find are in line with the general conclusions in the literature: job loss appears to have detrimental impacts on children's school performance, and the effects are stronger for low-income families.[10]. This result can be partly explained by the patterns in our data, regarding the effects of job loss on parents by income. There we show that these families enjoy much higher levels of income in absolute terms, even after job loss and despite the drop in earnings, which may mean lower elasticities of child human capital investments with respect to income. In addition, the earnings shock relative to pre-displacement levels is similar between low and high-income families, while the self-employment and spousal income responses somewhat dampen the effects in higher-earnings families.

[10]For a review, see Ruiz-Valenzuela (2020, 2021)

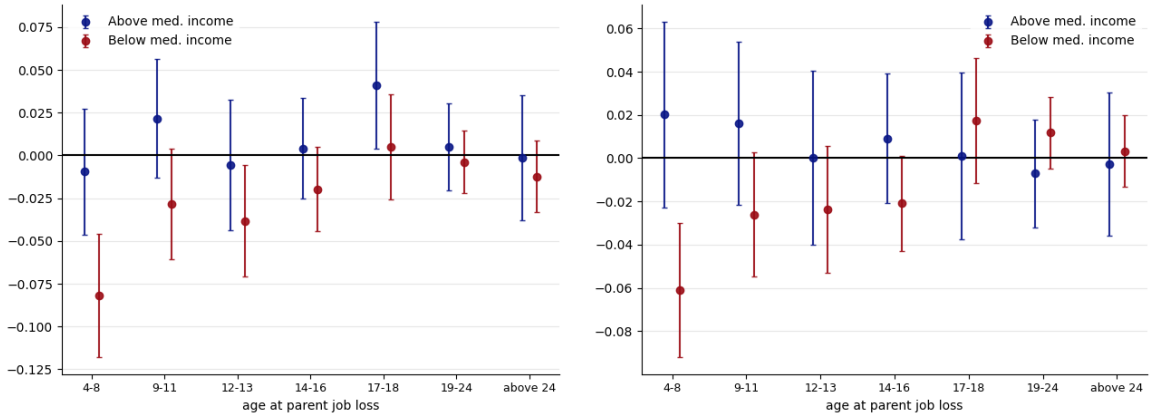
Table 2: The impacts of job loss on children's education outcomes

	Bagrut certificate		Math score	
	(1)	(2)	(3)	(4)
Under age 18	-0.014	-0.037	-0.009	-0.022
	(0.006)	(0.006)	(0.006)	(0.007)
Above age 18	0.001	0.001	-0.002	-0.002
	(0.006)	(0.008)	(0.005)	(0.0073)
Under age 18 X high inc.		0.044		0.031
		(0.012)		(0.012)
Above age 18 X high inc.		0.001		-0.02
		(0.13)		(0.13)
Adj. R sq.	0.15	0.16	0.12	0.12
Observations	452,141	452,141	452,141	452,141
Num. Treated	16,063	16,063	16,063	16,063

Note: This table presents the effects of parental job loss on children's education outcomes, by child age at the time of job loss, estimated via Equation 2. Columns (1) and (2) present the effects on Bagrut certificate attainment and columns (3) and (4) present the effect on taking the matriculation math exam and scoring above the median grade. In columns (2) and (4) we introduce an interaction between job loss before age 18 and a dummy for parents' income above the median, altering the interpretation of the first row coefficients from the aggregate effect of job loss to the effects of job loss on children from lower-income families. Standard errors clustered at the parent level are in parenthesis. For more detail, see Aloni and Avivi (2023).

Figure 15 extends this analysis to finer age groups at parental job loss and whether it was the father or mother displaced. Subfigure (a) presents the results from securing a Bagrut certificate, and subfigure (b) for math exam performance, i.e., scoring above the median in the matriculation math exam. First, in accord with the findings in Table 2, only children from lower-income families experience negative effects, and only before outcome realization.

Figure 15: The impacts of job loss on children's education outcomes, by child's age at the time of job loss and by household income



(a) Matriculation certificate

(b) Math score

Note: This figure presents the effects and confidence intervals of parental job loss on children's education outcomes by the age of the child at the year of parental job loss following equation 2. Panel (a) presents the effects on the attainment of the Bagrut certificate and Panel (b) presents the effects on the probability of taking the math exam and achieving a score above the median grade. Each figure is divided by earning levels, determined using the median total parental earnings prior to displacement. Bars indicate 95% confidence intervals based on standard errors clustered at the parent level.

Interestingly, we find substantial heterogeneity in the impacts of job loss on children by the child's age at the time of parental job loss, whereby the effects on children from low-income families decrease with age. That is, the younger the child is at parental job loss, the larger the harm to her education outcomes. The effects are as high as 6 percent on the math exam outcome and 8 percent on the Bagrut certificate for the younger age groups. While we find substantial heterogeneity in the impact of job loss on children by their age at loss, in Appendix Figure **??**, we do not find a similar pattern for parents. This suggests that the child age effect variation is not driven by variation in family characteristics that might be correlated with the age of the child at the time of displacement, such as parental age.[11]

The dynamic pattern of job loss effects by age could reflect different mechanisms of the human capital production function. On the one hand, in line with Cunha and Heckman (2007), it could be attributed to the excess importance of younger ages in human capital development. Another possibility is that due to the nature of the job loss scar, which lasts years after the layoff, a shock at a younger age implies longer exposure to a family with fewer resources. Such accumulating exposure effect was

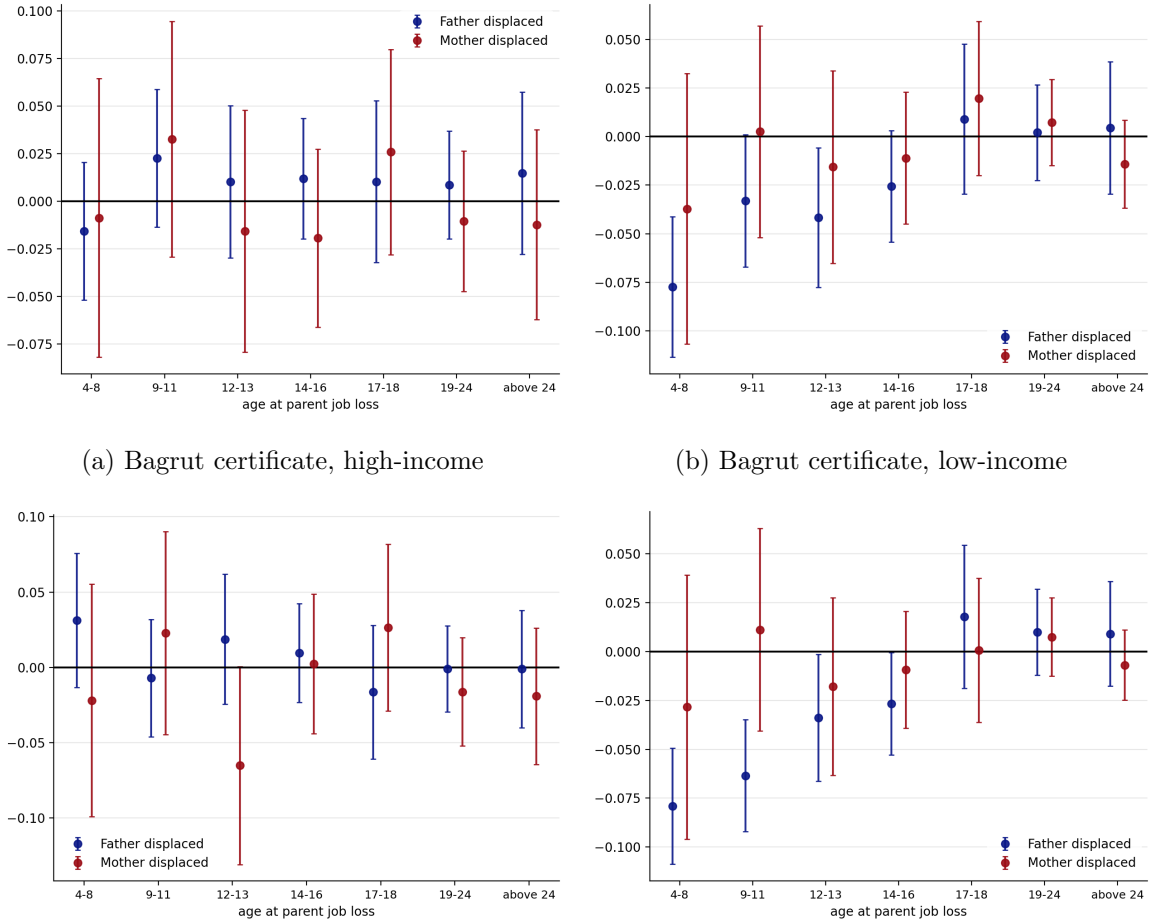
[11]This pattern of effects on children by age is similar to that found in Uguccioni (2021). The main difference to our approach is that Uguccioni (2021) uses UI recipients in Canada to identify job losers, as opposed to jobs lost via mass layoff events. Uguccioni (2021) estimates effects on college attainment and later earnings with a similar pattern to ours, from age two up to around age 12, and null thereafter. The effect on college attainment is around 2.5% and around three percentiles on income rank. Our findings are, however, at odds with the findings by Mörk et al. (2020), who use a similar design on Swedish data. They find no effects on children's education outcomes, perhaps due to the relatively small job loss effects on parents that they observe in their setting and the comprehensive social welfare instituted in Sweden.

also found in the literature on neighborhood effects on children outcomes (Chetty et al., 2016; Chetty and Hendren, 2018a,b). As of now, exploring the mechanisms behind the age-dependent pattern of effects is outside the scope of this paper.

While in this work we present the effects of job loss experienced by both mothers and fathers, the more common practice in the literature is to focus on fathers only (e.g. Oreopoulos et al., 2008). Figure 16 presents the dynamic effects of job loss by the gender of the parent who was displaced. Interestingly, the effects appear to be mainly driven by fathers' displacement.[12] This pattern is in line with the models in which investment in child's human capital can be either acquired in the market or produced at home using time (Gronau, 1977; Galor and Weil, 1993), acknowledging the fact that home child care and career aspirations are trade-offs that mothers, rather than fathers, face under the current social norms (Goldin, 1995; Bertrand et al., 2010; Goldin, 2014; Wasserman, 2023). Therefore, if mothers are more effective in rearing and home production of children's human capital, there is a tradeoff between the effects of job loss on the family resources on the one hand and the added childcare home production on the other. This pattern could also be explained by the fact that women are less likely to be the "breadwinners" in the household, and losing their jobs has less of an impact on family resources.

[12] We caveat that the children whose mothers were displaced are a smaller group, hence the noisier estimates

Figure 16: The impacts of job loss on children's education outcomes, by child's age at the time of job loss and by parent's gender



(a) Bagrut certificate, high-income

(b) Bagrut certificate, low-income

(c) Math score, high-income

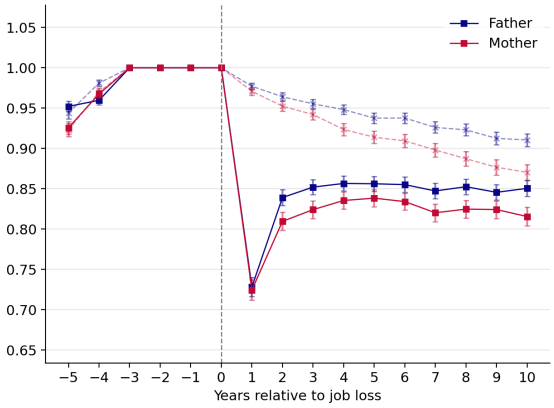
(d) Math score, low-income

Note: This figure shows the effects of parental job loss on children's educational outcomes, segmented by the child's age at the time of displacement, estimated via equation 2, separately by the gender of the parent who was affected by job loss. The top panels present the effects on Bagrut certificate attainment, and the bottom panels present the effects on the probability of taking the math matriculation exam and scoring above the median grade. The left panels, (a) and (c), present the effects on children from high-income families defined by the total parental pre-displacement earnings median, while the right panels, (b) and (d), present the effects on low-income families. Bars indicate 95% confidence intervals based on standard errors clustered at the parent level. For more detail, see Aloni and Avivi (2023).

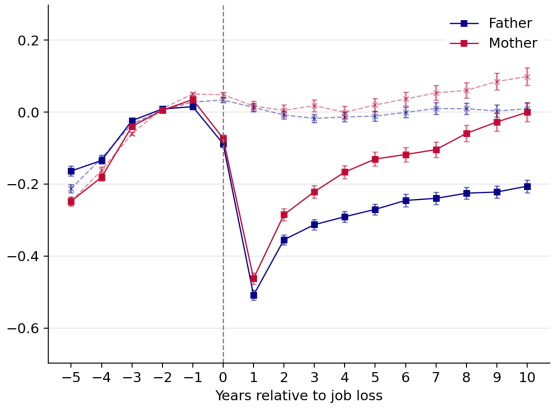
To further shed light on this matter, we circle back to the effects of job loss on parents. Figure 17 presents the effects of job loss on parents by the gender of the parent. There we see large differences in earnings and a large difference in the tendency to turn to self-employment, whereby fathers who experience job loss increase their income from other sources almost three times more than mothers, while mothers tend to remain unemployed slightly more than men after the first year of job loss, implying that mothers are more likely to turn to home production compared to fathers after job loss. Notwithstanding this, it is also evident that the proportion of earnings of fathers out of the total

family income is twice as large as that of mothers, meaning that the loss of a father's job is more impactful for family resources than the loss of a mother's job on average.

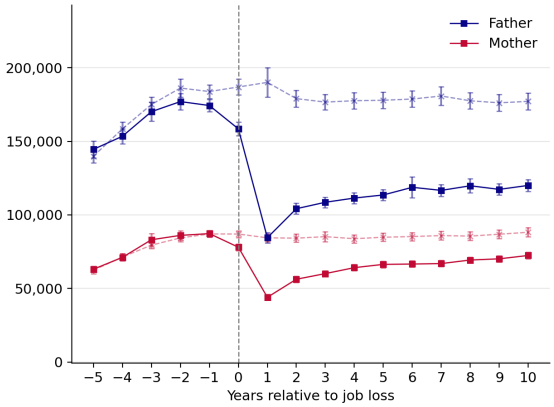
Figure 17: Effects of job loss on household income and employment by the displaced parent's gender



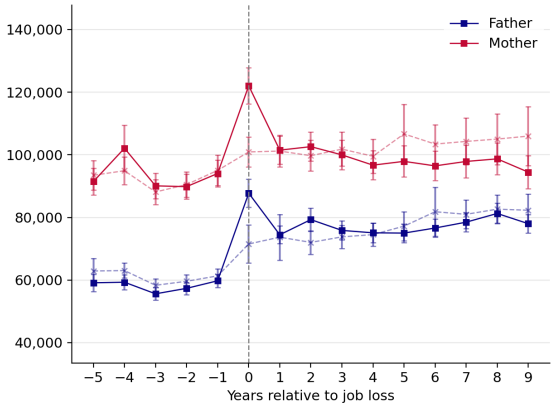
(a) Employment status



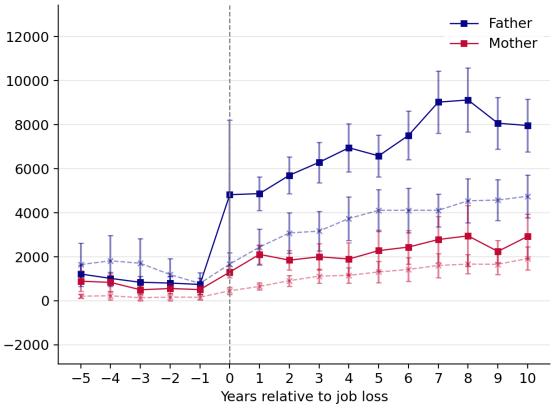
(b) Yearly earnings relative to $t < 0$



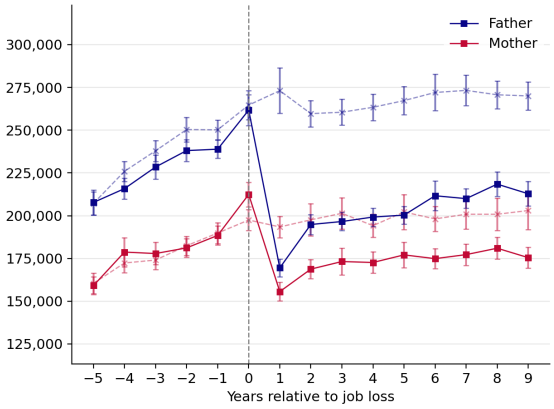
(c) Earnings (1ILS $\approx$ 0.3\$)



(d) Spouse earnings (1ILS $\approx$ 0.3\$)



(e) Self-employment earnings (1ILS $\approx$ 0.3\$)



(f) Total household earnings (1ILS $\approx$ 0.3\$)

Note: These figures present the impacts of job loss on labor market outcomes, by the gender of the parent who was displaced. They depict the raw means of the treatment and control groups. The first three figures show the (a) mean employment status, defined as working and earning above 10,000 ILS (around 3,000 USD) during the calendar year, (b) average annual earnings relative to the average of the three years of earnings before displacement, and (c) average annual earnings in Israeli Shekels. The next three figures present the (d) spouse's annual earnings, (e) earnings from self-employment, and (f) total household income, including both employment and self-employment earnings for the individual and their spouse. For more detail, see Aloni and Avivi (2023).

To test for the validity of our identification assumption, we add a placebo test by introducing outcomes that are realized even sooner than high-school graduation, and before job loss. To do so, we utilize the children's scores in the national standardized school evaluation exams, *Meitzav*, administered by the Israeli Ministry of Education.[13] The *Meitzav* exams cover several key subjects, including mathematics, science, English, and Hebrew/Arab language skills, mimics the PISA exam administrated by the OECD. This exam is administered at a random representative sample of schools, which in our sample amounts to a tenth of the children in the full analysis sample. The Meitzav exams are taken by students in the 5th and 8th grades. Hence, if the parental shock affects performance, we expect to find null effects in the years after the exam is taken, and not only after age 18, as we saw in the effects on high-school matriculation exams.

Table 3 presents Δ^c in terms of standard deviations by three age groups. Column (1) presents Δ^c for the 5th-grade exam, and column (2) presents the results for the 8th-grade exam. In the rows, we look at Δ^c by age categories of the child at parent's displacement: before the exam age (before age 11 for the 5th-grade exam, and before age 13, for the 8th-grade exam), after the exam age but still in school (up to age 18), and after age 18. Due to the small number of observations, of around a tenth of the full job loss sample size, the results are noisy. However, focusing on the point estimates, we do find a large negative point estimate for the effects before the exam of around 0.024 to 0.031 lower standard deviations. In addition, the point estimates after the realization of the exam are much smaller and closer to zero.

[13] "Meitzav" is an acronym in Hebrew that translates to "School Efficiency and Growth Measures".

Table 3: The effects of job loss on early standardized exams scores, pre job loss

	5th Grade (1)	8th Grade (2)
Before the exam	-0.031	-0.024
	(0.031)	(0.033)
After the exam and below 18	0.012	0.019
	(0.037)	(0.04)
Above 18	-0.002	-0.022
	(0.076)	(0.061)
# of treated obs.	1,867	2,614
Adj. R Squared	0.312	0.523

Note: This table shows the impact of job loss on the composite score in the Meitzav standardized exams, for the subset of students who experienced job loss before taking the exams. These exams are administered to a subset of schools in grades 5 or 8 (ages 11 or 14). The rows denote the children's ages at the time of their parent's job displacement. Observations are of children affected by job loss. Standard errors clustered at the family level are in parentheses. For more detail, see Aloni and Avivi (2023).

5 Conclusions

This paper studies the impacts of job loss on workers in Israel. We find that, akin to patterns observed in Italy and Spain, there is a significant initial decline in workers' earnings followed by a notable re-employment and wage restoration, with long-run effects closer to those found in countries like Austria, Sweden, and France.

In addition, we identify a clear relationship between the business cycle and job loss effects. Economic conditions during the time of job loss significantly influence both short-term and long-term labor market outcomes. In addition, differences in effects arise based on income levels and firm fixed effects. High earners and workers from high fixed-effect firms face more pronounced effects post-displacement.

Using criminal records data, we find a short-term increase in economically motivated crimes following job loss, such as theft and fraud. However, no significant link between job loss and violent crimes was identified.

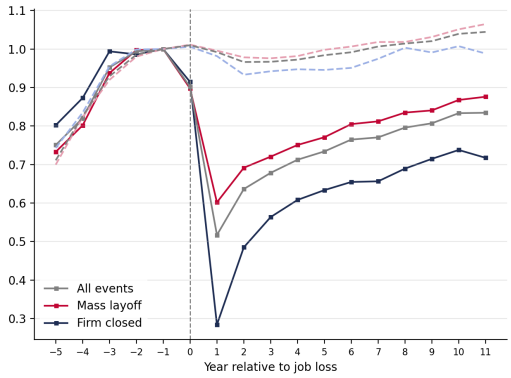
Lastly, we delve into the intergenerational impacts of job loss, focusing on its ramifications for children's educational outcomes. Our findings indicate that parental job loss, particularly before children reach the age of 18, significantly decreases the likelihood of these children achieving key

educational milestones, such as obtaining a Bagrut certificate and excelling in math exams. This effect is especially pronounced among lower-income families, underscoring the role of economic status in exacerbating the adverse effects of job loss.

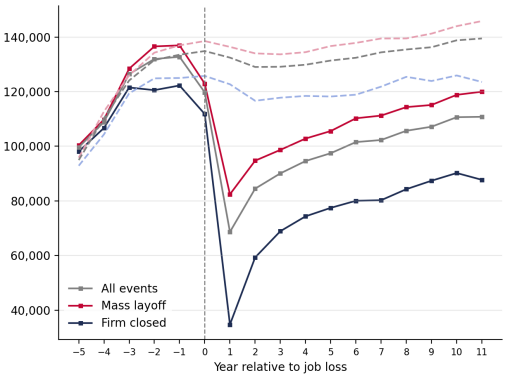
In conclusion, This study provides a comprehensive analysis of the multifaceted effects of job loss in Israel, incorporating both the immediate labor market repercussions and the broader intergenerational impacts. While offering valuable insights, the findings also highlight the complex and varied nature of job loss implications, emphasizing the need for ongoing research and analysis.

A Appendix Tables and Figures

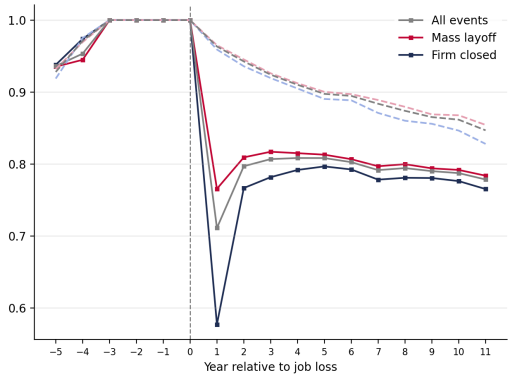
Figure A.1: Effects of job loss, by firm event type



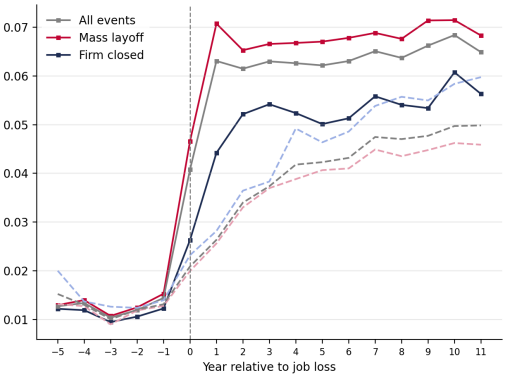
(a) Effects on yearly earnings rel. to $t < 0$



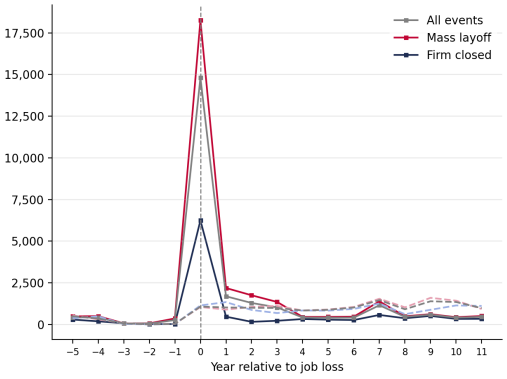
(b) Effects on yearly earnings (1NIS $\approx$ 0.3\$)



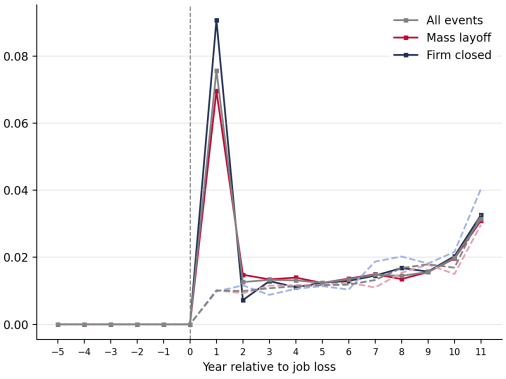
(c) Effects on yearly employment



(d) Effects on yearly self-employment



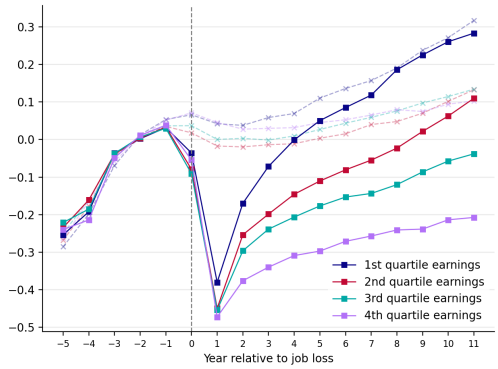
(e) Effects on yearly compensations amount



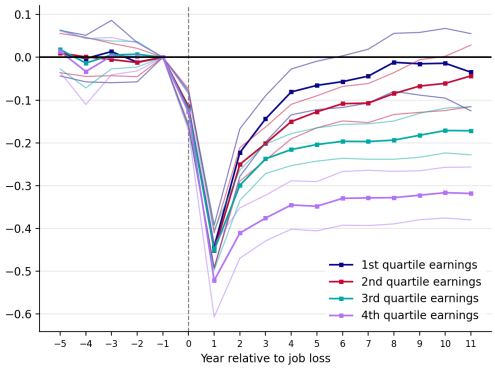
(f) Effects on yearly leaving the LF

Note: This figure presents the effects of job loss on labor market outcomes, separately by the type of event the firm underwent: whether it fully closed or laid off at least 30% of the employees but kept operating after the event. All panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on yearly earnings from salary and self-employment. Panel (c) presents the effects on employment, while (d) presents the effects on compensations received from employers. Panels (e) and (f) present the effects on the probability of leaving the labor force. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

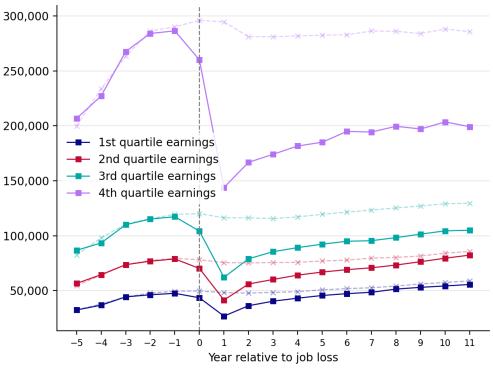
Figure A.2: Effects of job loss on yearly earnings, by income quartiles



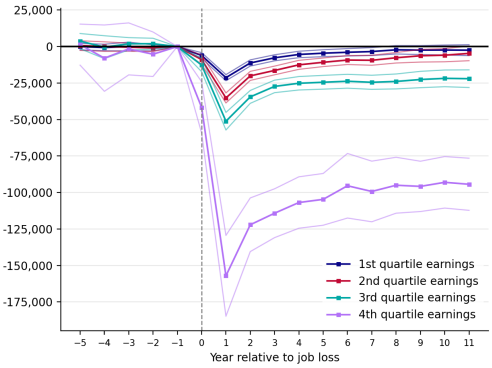
(a) Yearly earnings rel. to $t < 0$



(b) Effects on yearly earnings rel. to $t < 0$



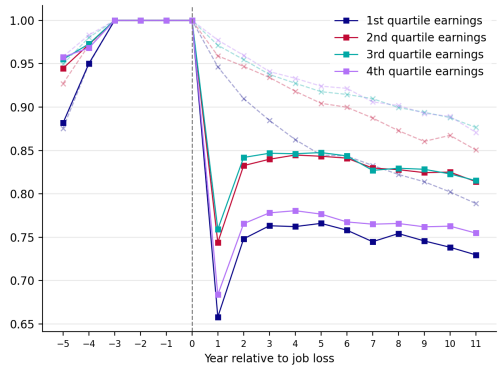
(c) Yearly earnings (1NIS $\approx$ 0.3\$)



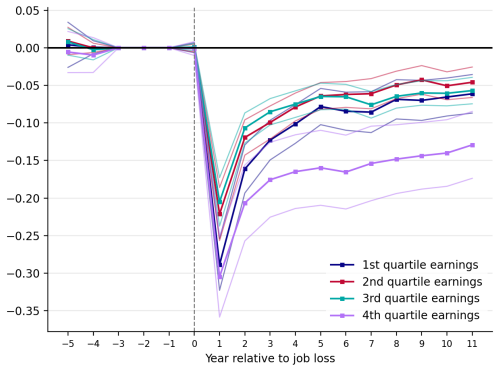
(d) Effects on yearly earnings (1NIS $\approx$ 0.3\$)

Note: This figure presents the effects of job loss on labor market outcomes, separately by four quartiles of earnings levels, split by pre-displacement earnings. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effect on yearly earnings from salary and self-employment relative to the average earnings across the three periods before displacement. Panels (c) and (d) present the same effects on yearly earnings in Shekels. Years with no reported earnings are coded as 0. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

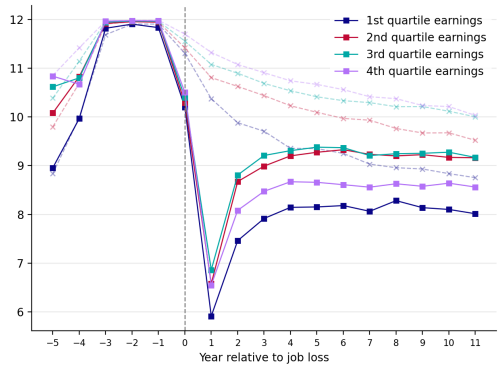
Figure A.3: Effects of job loss on employment, by income levels



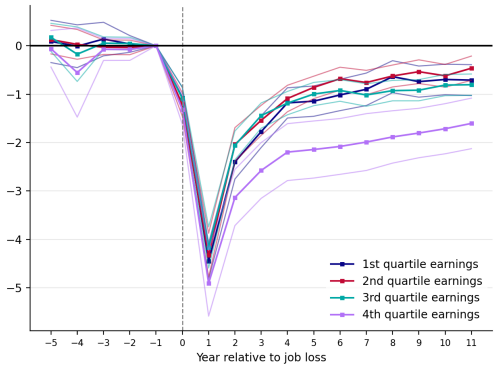
(a) Means of employment



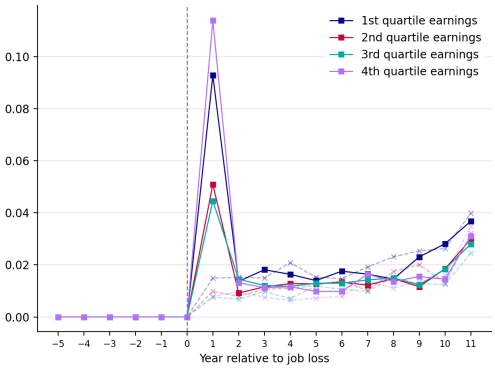
(b) Effects on employment



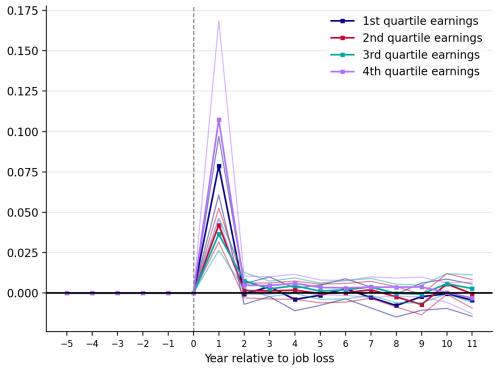
(c) Means of # of months employed



(d) Effects on # of months employed



(e) Means of leaving the LF



(f) Effects on leaving the LF

Note: This figure presents the effects of job loss on labor market outcomes, separately by four quartiles of earnings levels, split by pre-displacement earnings. The left panels present the sample means by period relative to the event year with dashed lines depicting the control group, while the right panels present the estimates according to Equation 1. Panels (a) and (b) present the effects on working and earning above 10,000 ILS (around 3,000 USD) during the calendar year, panels (c) and (d) present the effect on the number of months reported working and earning a positive amount, and panels (e) and (f) present the effects on a proxy for leaving the LF - switching to unemployment for the rest of the available panel years and up to 15 years after job loss. Standard errors used to construct the confidence intervals on the right panels are clustered at the firm level.

B Propensity Score Matching

Propensity Score Matching We estimate a logit-based propensity score to predict the probability of belonging to the treatment group of workers displaced in a mass layoff event. The logit equation for estimating the propensity score is given by:

$$\text{logit}(P(T = 1|X)) = \alpha + \beta X$$

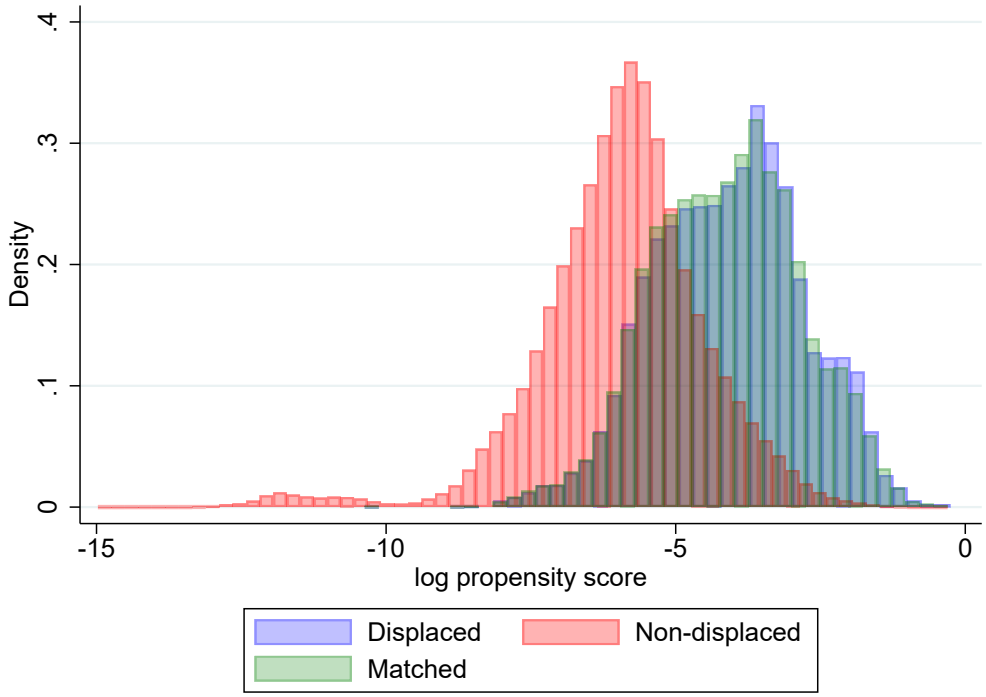
where $\text{logit}(P(T = 1|X))$ represents the log-odds of belonging to the treatment group given the covariates X. We exploit the richness of our data by including a long list of features in our estimation:

- 2nd order polynomial of earnings in the three years prior to displacement
- Gender
- Pre-displacement firm characteristics (firm size rank decile dummies, total firm payroll decile dummies)
- Firm tenure years
- Cubic age times gender
- Ethnic group
- Commuting zone at the time of displacement
- Spouse's earnings in the two years prior to displacement

With the predicted propensity score for the non-treatment population, we employ a one-to-one matching within characteristics bins. We define bins according to the displaced worker's 1-digit industry, job loss year, gender, and yearly earning quartiles prior to displacement.

Appendix Figure B.1 presents the overlap in the predicted propensity to be displaced for each of the groups, and after the matching procedure.

Figure B.1: Propensity score overlap histogram



Note: This figure presents the distributions of the log of predicted probability of being displaced for the displaced and non-displaced population, and after the matching procedure.

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