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Reskilling and Resilience*

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Abstract

This paper shows that effective reskilling can have profound mental health benefits for workers and their partners. Using institutional variation in access to higher education after work accidents in Denmark, we find that reskilling prevents one case of depression for every three injured workers. Strikingly, the spillover effects on partners are just as large. These mental health gains are accompanied by higher partner employment and increased separation rates, suggesting that reskilling frees partners from costly relationship commitments. Together, the mental health and partner benefits add 83% to the direct labor earnings gains from reskilling.

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Losing work can cause harms that extend well beyond the labor market, including declines in mental health and increased burdens on partners (Marcus (2013)). This paper shows that effective reskilling can mitigate many of these harms, protecting not only the well-being of displaced workers but also delivering meaningful benefits to their partners.

The setting for our analysis is work accidents—a sudden and severe shock to workers' ability to continue in their occupations. To identify the causal effect of reskilling, we exploit institutional variation in access to reskilling among otherwise similar injured workers: In Denmark, some vocational degrees grant direct entry to relevant higher education programs, while other comparable degrees do not. We conduct a host of validation checks to confirm that workers with and without access to reskilling are comparable in background characteristics, labor market histories, partner characteristics, and health. As Humlum, Munch, and Plato (2025) show, these reskilling opportunities have transformative labor market effects for the about 11% of injured workers who take them, enabling individuals who would otherwise rely on disability benefits to transition into better-paid employment.

In this paper, we go beyond the job and examine how reskilling impacts workers' mental health and partner outcomes. To do so, we leverage Danish register data that link the labor market and health records of injured workers and their partners. Our analysis proceeds in four parts.

We begin by examining the mental health of injured workers. Although we focus exclusively on physical injuries, 10-15% of affected workers end up on antidepressants. Our first key result is that reskilling substantially reduces this mental burden, preventing one case of depression for every three reskilled. Notably, these mental health benefits are greatest while workers are still in school—before any income gains materialize—suggesting that current engagement or improved future prospects play a key role in supporting the well-being of displaced workers. By contrast, once workers transition into their long-term outcomes—better-paid jobs rather than disability support—the mental health benefits largely recede.

Next, we turn to the partners of injured workers and find substantial spillover effects.

Although not directly affected by the accidents, about 7% of partners begin taking antidepressants. Remarkably, the mental health benefits of reskilling are just as large for partners: one case of partner depression is prevented for every three workers reskilled. Moreover, unlike the effects for injured workers, these effects grow over time, such that the long-run mental health benefits from reskilling accrue primarily to partners.

These improvements for injured workers and their partners extend to a range of "diseases of despair," including indicators of alcoholism and opioid abuse. They do not, however, translate into reductions in "deaths of despair," largely because the work accidents we study do not increase mortality in the first place—leaving little scope for reskilling to save additional lives.

Third, we examine the circumstances that make reskilling so pivotal for partners. Without access to reskilling, negative outcomes reflect loyal partners who are dragged down in the aftermath of injury. These partners experience substantial declines in both employment and mental health, yet are more likely to remain in the relationship. Strikingly, when injured workers can reskill, the pattern reverses: separation rates increase after accidents, while partner employment and mental health remain stable, suggesting that reskilling may free partners from otherwise burdensome relationship commitments.

As a final step, we assess the economic significance of the mental health and partner spillovers from reskilling. To do so, we monetize our estimated effects on antidepressant use using existing lower-bound estimates of quality-adjusted life year (QALY) losses associated with depression. Incorporating these into a cost-benefit framework, we estimate that mental health and partner spillovers add $224,000 in benefits per reskilled worker, equivalent to an additional $3.2 in return for every dollar invested. These returns reflect mental health benefits of $56,000 for injured workers and $78,000 for their partners, as well as $90,000 from increased partner employment. In total, these spillover gains amount to 83% of the direct labor earnings gains from reskilling among injured workers.

In summary, our evidence shows that reskilling does more than restore labor market prospects—it also substantially protects the well-being of affected workers and their partners. In this sense, our paper helps fill an important gap in the literature. While the psychosocial costs of career shocks are well documented (Charles and Stephens (2004); Sullivan and Von Wachter (2009); Kuhn, Lalive, and Zweimüller (2009); Marcus (2013)), much less is known about how to mitigate these costs (Hussam et al. (2022)). At the same time, although a large literature—including our prior paper (Humlum, Munch, and Plato (2025))—has examined the direct effects of active labor market policies on treated workers (Card, Kluve, and Weber (2018)), we know far less about their spillover effects on mental health and family well-being (Baekgaard et al. (2024)). We fill this gap by showing how reskilling can yield profound mental health benefits for both treated workers and their partners.

1 Data and Institutional Setting

Studying the mental health and partner spillovers of reskilling requires unusually rich data linkages. We leverage comprehensive Danish register data that combine work accidents, reskilling activities, labor market outcomes, health care utilization, and partner relationships at the individual level from 1995 to 2017. We summarize our data and institutional setting below.

1.1 Institutional Features

Denmark is known for its welfare state and flexicurity model. In brief, the government provides health care and education free of charge. Firms can hire and fire workers with relative ease, and displaced individuals are supported by generous transfers from the government.

Disability insurance is the most relevant transfer program for injured workers. Disability benefits are set at 19,000 DKK (2,700 USD) per month, equivalent to 50-80% of injured workers' prior earnings.[1] Injured workers who participate in formal education may receive *reskilling benefits* of 19,000 DKK per month, effectively closing the gap in financial support relative to DI.

[1] In terms of eligibility criteria, replacement rates, and benefit duration, the Danish disability insurance matches the Social Security Disability Insurance (SSDI) in the United States (Krueger and Meyer (2002); Autor and Duggan (2003); Reno, Thompson Williams, and Sengupta (2003)).

In sum, we study individuals with strong institutional support to invest in their human capital and minimal financial barriers to seeking health care. In particular, Denmark's universal health care system mitigates a common concern that individuals' decisions to seek health care are influenced by their economic circumstances (Currie and Madrian (1999)).

1.2 Data Sources

Our shocks to worker ability arise from *work accidents*—sudden events during the course of work that result in occupational injury. Danish law requires employers to report these incidents within 14 days.[2] Work accidents are common: each year, about 0.6% of Danish workers are injured in such events—a rate slightly higher than displacement from mass layoffs (Humlum, Munch, and Plato (2025)). We obtain comprehensive records of work accident reports from the Labor Market Insurance (AES), including detailed information on the cause of the accident and the nature of the injury.

We measure *human capital investment* using the Education Register (UDDA), which records all formal degree enrollments and completions. As described in Section 2.2, our identification strategy focuses on transitions from vocational degrees to higher education programs, all of which are fully captured in the Education Register.

Employment outcomes are sourced from the Integrated Database for Labor Market Research (IDA), which provides detailed records on earnings, occupations, and employers.

Our data on *health care* combine comprehensive registers on hospitalizations (National Patient Registry), primary care and specialist visits (Health Insurance Registry), and prescription drug purchases (Prescription Drug Database). These allow us to track health diagnoses and treatments over time.[3]

Finally, we obtain *partner linkages* from the Population Register (BEF), which tracks both registered partnerships and cohabiting relationships. This allows us to extend the analysis beyond injured workers and examine how reskilling affects the health and labor market outcomes of their partners.

[2]Workers, unions, or medical professionals may also report accidents within one year of occurrence.
[3]Fadlon and Nielsen (2019) use the same registers to study family spillovers in health behaviors.

1.3 Analysis Sample

Following Humlum, Munch, and Plato (2025), we apply a series of sample restrictions to hone in on a well-defined set of injury events.

First, we restrict the sample to physical injuries that result in a permanent loss of earning capacity.[4] Second, we limit the sample to individuals with stable pre-injury employment, defined as full-time work in all three years preceding the accident. Third, to implement the identification strategy of Humlum, Munch, and Plato (2025) (see Section 2.2), we focus on craft workers with vocational degrees prior to injury. Finally, because these work accidents are overwhelmingly experienced by men (98%), we restrict our main analysis to men to ease the interpretation of partnership dynamics.[5] These additional sample restrictions do not affect the severity of the injuries considered in the analysis (see Appendix Table A.2). The injuries in our analysis sample are relatively severe, with an average estimated earning capacity loss of 35% among injured workers.

Table 1, Column (1) reports the characteristics of workers in the year before their accident, focusing on those whose vocational degrees provide access to higher education. The typical injured worker is a 42-year-old man employed in a physically demanding occupation. Column (4) shows that 72% have partners, all of whom are female, and 88% of these partners are employed full-time. The strong labor market attachment of these partners reflects Denmark's norms of gender equality (Kleven, Landais, and Søgaard (2019)).

2 Empirical Strategy

The central question of this paper is how access to reskilling modifies the consequences of work accidents. Answering this question involves two steps: What are the impacts of work accidents? And how does access to reskilling modify those impacts? We address the first in Section 2.1 and turn to the second in Section 2.2.

[4]As Humlum, Munch, and Plato (2025) show, workers do not pursue reskilling after cognitive or temporary injuries.

[5]Appendix C.3.1 shows that our main estimates are robust to keeping the female injured workers in the analysis sample.

2.1 Leveraging Quasi-Random Work Accidents

Our first step is to estimate what would have happened to injured workers had their accident not occurred. Following Humlum, Munch, and Plato (2025), we exploit the quasi-random nature of work accidents within occupations to implement a matched difference-in-differences design: for each injured worker, we select a random match with the same age, gender, education, occupation, industry, and access to higher education in the year prior to the accident. Because our analysis focuses on partner outcomes, we additionally match on pre-injury indicators for having a stable partner and being a parent. Appendix Table A.3 shows that the "Injury" and "Match" groups are similar across all these factors, including a range of outcomes we do not match on, supporting the assumption that these are valid comparisons.

We estimate the simple differences-in-differences in outcomes Y between the injured workers ($I = 1$) and their matches ($I = 0$) around work accidents, indexed to the year before the accident:

$$Y_{it} = \beta_1 I_i + \sum_k \beta_{0k} \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -1} \beta_{1k} I_i \mathbf{1}_{\{t=e+k\}} + \varepsilon_{it}, \tag{1}$$

where $\mathbf{1}_{\{t=e+k\}}$ are event-time dummies that switch on if the event year e occurred k years ago, and β_{1k} are our coefficients of interest, identifying the causal effects of work accidents under parallel trends. We estimate Equation (1) by OLS and cluster the standard errors at the match-cell level. For partner outcomes, we follow workers' initial partners (defined in the year before the accidents), regardless of whether they stay in the relationship.

2.2 Identifying the Effects of Reskilling

To identify the causal effect of reskilling, we follow Humlum, Munch, and Plato (2025) and exploit that similar vocational degrees grant different access to higher education. For example, while carpenters, electricians, and welders can enroll directly in higher education programs, comparable trades such as blacksmiths, iron and metal workers, and manufacturing technicians must first complete three years of high school to become eligible.

These institutional rigidities of the Danish education system allow us to identify comparable workers in similar occupations and with similar amounts of schooling who differ in their access to higher education only due to their different vocational specializations. To find these comparable workers, we follow Humlum, Munch, and Plato (2025) and implement an inverse probability weighting (IPW) strategy detailed in Appendix B.1. The reweighing allows us to compare workers of similar demographics, years of schooling, earnings, work experiences, drug prescriptions, and injuries who differ in their access to higher education.

Table 1 reports characteristics of workers with access to reskilling (Column (1)) and reweighted workers without access (Column (2)), along with their standardized mean differences in Column (3). Following Stuart and Rubin (2008), standardized differences above 25% are commonly used to indicate imbalance. The table shows that the groups are well balanced across covariates, including many not directly targeted by the IPW procedure. We comment on these characteristics in Section 2.3 below, which provides additional placebo checks of the comparability of the worker groups.

To compare the effects of work accidents across the two groups, we estimate Equation (1) separately for workers with and without access to reskilling. To isolate the causal effect of reskilling access, we then take the difference between these estimates, effectively implementing a triple-difference approach.

2.3 Placebo Checks

The key identifying assumption of our analysis is that, absent differences in access to higher education, "Access" and "No Access" workers would have experienced similar outcomes following work accidents. Humlum, Munch, and Plato (2025) assess the validity of this assumption through a series of falsification checks focused on the injured workers. We extend these checks to include mental health and partner outcomes.

First, Column (3) of Table 1 shows that injured workers in the two groups display similar characteristics and outcomes before their accidents, including demographics, employment, and health. They are also balanced on a range of attributes not explicitly targeted by the IPW procedure, supporting the validity of the comparison.[6]

Second, Columns (4)–(6) extend these checks to the partners of injured workers. About 72% of injured workers in each group have partners before their accidents, all of whom are female. Although the IPW procedure does not target partner characteristics, the two partner groups are highly similar across a range of observables, including age, education, employment, earnings, occupation, and health.

Third, to verify that the two groups experience similarly severe injuries, Figures B.1–B.2 show that injured workers experience similar hospitalization rates following the accidents. Likewise, partners in both groups show no increase in hospitalizations around the time of the accident.

Finally, we examine milder accidents that do not cause permanent loss of earning capacity.[7] Because these temporary injuries do not lead to reskilling, they serve as a placebo test for whether the two groups follow similar trajectories in the absence of reskilling (Humlum, Munch, and Plato (2025)). Using these "placebo" injuries, Figure B.3 shows that mental health, relationship dynamics, and partner employment evolve similarly across groups following the accidents.

2.4 Setting the Stage: Labor Supply Effects of Reskilling

Figure 1 shows how work accidents affect the labor supply of injured workers. Panel (i) presents separate estimates by access to reskilling using the difference-in-differences specification in Equation (1). Panel (ii) isolates the role of reskilling access by differencing these estimates, effectively implementing a triple-difference design.

On average, work accidents lead to adverse outcomes for both groups: ten years after the event, about 20–30% of injured workers receive disability insurance rather than remain in employment (Panel (i)).

However, outcomes differ notably by access to reskilling: Among those with access, 11% enroll in higher education following the accident. Over time, these individuals tran-

[6]Humlum, Munch, and Plato (2025) show that the workers were also similar at age 16—when they chose their vocational specialization—with comparable primary school grades and youth employment. Moreover, the groups have similar parental backgrounds in terms of education, employment, and wealth.

[7]Earning capacity loss is estimated upfront by the Labor Market Insurance (AES).

sition into full-time employment instead of disability insurance. Hence, taking the triple differences in Panel (ii) shows that access to reskilling enables this subset of workers to pursue additional schooling, ultimately returning to stable employment rather than long-term benefit receipt.

Figure 1 captures the central result from Humlum, Munch, and Plato (2025): access to reskilling helps workers who would otherwise rely on disability benefits to reenter the labor market, eventually earning about 25% more than before their injuries. These results for labor supply set the stage for our further analysis. In the following sections, we ask: How do these reskilling effects spillover to workers' mental health and partner outcomes?

To facilitate continued comparisons to the labor supply dynamics, we divide the post-period into four stages (indicated by the vertical dashed lines in Figure 1): *accident* (the year of the accident), *program* (years 1-4, when treated workers are enrolled in education), *transition* (years 5-7, when workers transition out of the programs), and *placement* (year 8 and beyond, when workers settle into their long-run outcomes: employment or disability insurance, respectively). Although we prefer these dynamic estimates for their transparency, they are also data demanding. Hence, to support the statistical power of our conclusions, we also present more pooled estimates in Appendix C.1.

3 Results

3.1 Mental Health

Figure 2 shows individuals' take-up of antidepressant drugs around work accidents. Panel (i) presents separate estimates by injured workers' access to reskilling, while Panel (ii) isolates the differential effects of reskilling access. Subpanels (a) display outcomes for injured workers; Subpanels (b) show corresponding outcomes for their partners.[8]

Losing work ability causes substantial mental tolls: Despite suffering exclusively physical injuries, about 10-15% of injured workers resort to antidepressants. These mental burdens are largest in the year 1-4 before converging to a long-run effect of about 7

[8]As Section 2.1 describes, we follow workers' initial partners (defined in the year before the accidents), regardless of whether they remain in the relationship.

percentage points higher antidepressant use.

Comparing these effects by workers' access to reskilling distills our first key result: Reskilling can substantially reduce the mental burdens of losing work ability. Scaling the triple-difference estimates in years 1-4 by the take-up of reskilling (about 11%, cf. Figure 1) implies that reskilling prevents one case of depression for every 2-3 participants. Notably, these mental health benefits are greatest while workers are still in school—before any income gains materialize. By contrast, once workers transition into their long-term outcomes—better-paid jobs rather than disability support—the mental health benefits largely recede. This suggest that current engagement or improved future prospects play a key role in supporting the well-being of displaced workers (Hussam et al. (2022)).

In Subpanels (b) of Figure 2, we turn to the partners of injured workers and find substantial spillover effects. Although not directly affected by the accidents, about 7% of partners in the "No Access" group begin taking antidepressants, with steadily growing rates over time. Remarkably, access to reskilling can mitigate much of this harm: only about 2% of partners in the "Access" group initiate antidepressant use. The long-run effects for partners are just as large as the short-run benefits for injured workers: one case of long-run partner depression is prevented for every 2-3 workers reskilled. Moreover, unlike the effects for injured workers, these effects grow over time, such that the long-run mental health benefits from reskilling accrue primarily to partners.

3.2 Partner Dynamics

Why is reskilling so consequential for partner well-being? Figure 3 presents results for partners' outcomes, focusing on relationship stability (Subpanels (a)) and labor market attachment (Subpanels (b)). The findings point to a stark contrast based on reskilling access.

Without access to reskilling, negative outcomes reflect loyal partners who are dragged down in the aftermath of injury. These partners experience a substantial decline of 5 percentage points in labor market attachment, yet are 5 percentage points *more* likely to remain in the relationship.

By contrast, when injured workers can reskill, the patterns shift. Separation rates increase by about 3 percentage points, while partner employment and mental health remain much more stable. This reversal suggests that reskilling may offer both members of the couple a path out of an otherwise burdensome situation.

These findings support the view that labor market shocks can affect marital stability through channels beyond financial considerations (Charles and Stephens (2004)). The fact that partners in the "no access" group remain in the relationship—despite suffering mentally—is consistent with sociological theories that caregiving burdens can trap individuals in strained relationships, especially women (Hochschild and Machung (2012)).[9] By contrast, when injured workers can regain labor market attachment through reskilling, partners may feel less obligated to stay. In addition, reskilling may alter workers' life trajectories and aspirations, potentially reducing the match quality of the original relationship (Becker, Landes, and Michael (1977)).

3.3 Disease and Deaths of Despair

The preceding sections show that reskilling has meaningful implications for the mental health of injured workers and their partners. But how far do these effects extend? Job loss has been linked to a range of adverse lifestyle outcomes—including opioid and alcohol misuse—that can ultimately lead to "deaths of despair" (Sullivan and Von Wachter (2009); Case and Deaton (2015); Pierce and Schott (2020)). In Appendix C.2, we leverage the comprehensive Danish health records to examine whether reskilling mitigates these broader health risks. We summarize the main findings here.

Figure C.1 begins by examining opioid prescriptions. In the year of the accident, opioid use rise by a similar 30 percentage points for injured workers with and without access to reskilling, reflecting their use as pain relief for physical injuries. In the following years, however, a substantial gap emerges: injured workers without access to reskilling are 5 percentage points more likely to stay on opioids. This difference is persistent and remains stable for up to 10 years after the accident. By contrast, we find no evidence

[9] As Charles and Stephens (2004) note, the nature of the shock—losing ability—may also heighten the social stigma of divorce, as married couples vow to remain together "in sickness and in health."

that work accidents affect opioid use among partners, nor that reskilling modifies this pattern.

In Figure C.2, we turn to alcoholism-related diagnoses, including alcohol poisoning and liver disease. Among workers without access to reskilling, work accidents lead to such diagnoses for 3% of injured workers, with effects rising slowly over time. Notably, access to reskilling can offset most of these harms: the estimated effect of accidents falls to about 1%, although with wide confidence bands. As with opioid use, we find no evidence that work accidents affect alcohol-related diagnoses among partners, nor that reskilling alters this pattern.

Finally, Figures C.3 and C.4 examine suicide and overall mortality. In contrast to our findings for depression, opioid use, and alcoholism, the work accidents we study do not affect mortality, whether self-inflicted or otherwise. Consequently, access to reskilling does not influence "deaths of despair" either.[10]

4 Quantifying the Broader Returns to Reskilling

Taking stock, we find that reskilling has far-reaching impacts beyond the labor market outcomes of injured workers, substantially improving well-being for both them and their partners. In this final section, we assess the economic significance of these spillover effects by embedding our estimates into a simple cost-benefit framework. This allows us to compare the magnitude of spillover effects relative to the direct costs and labor market gains of reskilling.

While monetizing spillovers to partner earnings is relatively straightforward, valuing improvements in mental health is more complex. Our goal is to provide a conservative and transparent lower-bound estimate. Following the literature, we convert reductions in antidepressant use into quality-adjusted life years (QALYs), as detailed in Appendix D.1. We adopt a lower-bound estimate of 0.2 QALYs lost per year of depression from Jia et al.

[10]Moreover, Figures C.5–C.6 show that the groups exhibit similar rates of cardiovascular and respiratory diagnoses following the accidents. This underscores that the impacts of reskilling are concentrated on mental health and disease of despair outcomes, rather than reflecting a general effect on healthcare utilization.

(2015), and assign a monetary value of \$100,000 per QALY based on modal estimates from Neumann, Cohen, Weinstein, et al. (2014). Our valuation also incorporates the cost of antidepressant medication. Appendix D.1 shows our conclusions are robust across a range of published QALY valuations. Because we focus only on the antidepressant effect, these estimates likely understate the broader mental health benefits of reskilling. For instance, Section 3.3 shows additional gains across a wider set of "diseases of despair."

Table 2 presents the results of our cost-benefit analysis. The first two rows replicate the direct costs and earnings benefits from Humlum, Munch, and Plato (2025), showing that reskilling injured workers is already a highly worthwhile investment based on direct impacts alone: it transforms a worker who would otherwise rely on disability insurance into a high-wage earner. In total, for every dollar spent on reskilling (including tuition and income support), the program generates \$3.9 in additional labor earnings for injured workers.[11]

The remaining rows incorporate spillover effects—the key contribution of this paper. First, accounting for gains in partner earnings significantly raises total benefits. When injured workers are able to reskill, their partners face fewer economic and emotional burdens and contribute more to the labor market. For every dollar spent on reskilling, partners gain \$1.3 in additional earnings.

The final rows include mental health benefits. Each dollar spent on reskilling yields mental health improvements valued at approximately \$0.8 for injured workers and \$1.1 for their partners.

Taken together, spillover gains from partner earnings and mental health amount to 83% of the direct labor market gains. These results underscore the importance of incorporating broader spillover effects when evaluating the full returns to reskilling programs.

[11] As Humlum, Munch, and Plato (2025) show, even when considering only these direct costs and benefits, public spending on tuition and reskilling benefits pays for itself four times over through increased taxable employment and reduced disability payments. In the terminology of Hendren and Sprung-Keyser (2020), subsidizing reskilling for injured workers has an infinite Marginal Value of Public Funds (MVPF).

5 Conclusion

Losing work has been linked to social and psychological decline, yet little is known about how to mitigate these harms. This paper shows that effective reskilling can safeguard mental health and partner outcomes from setbacks in the labor market. We reach these conclusions in the context of work accidents, which cause sudden and severe setbacks in the ability of workers to continue in their occupation.

These spillovers on mental health and partners are substantial: one case of depression, for both injured workers and partners, is prevented for every three reskilled. The profound effects on partners reflect that reskilling prevents them from being dragged down in the aftermath of injury, allowing them to maintain their labor market attachment and mental health. Taken together, the spillover effects adds 83% to the direct labor earnings gains from reskilling injured workers.

Many advanced countries, especially the United States, face rising social disparities, persistent non-employment, growing disability rolls, and diseases of despair (Case and Deaton (2015); Autor and Duggan (2003); Abraham and Kearney (2020)), with evidence linking these trends to worker struggles adjusting to labor market disruptions (Pierce and Schott (2020); Autor, Dorn, and Hanson (2019)). We show that effective reskilling programs can serve as a first line of defense against these broader harms—helping vulnerable workers regain their footing in the labor market while substantially protecting the well-being of both themselves and their partners.

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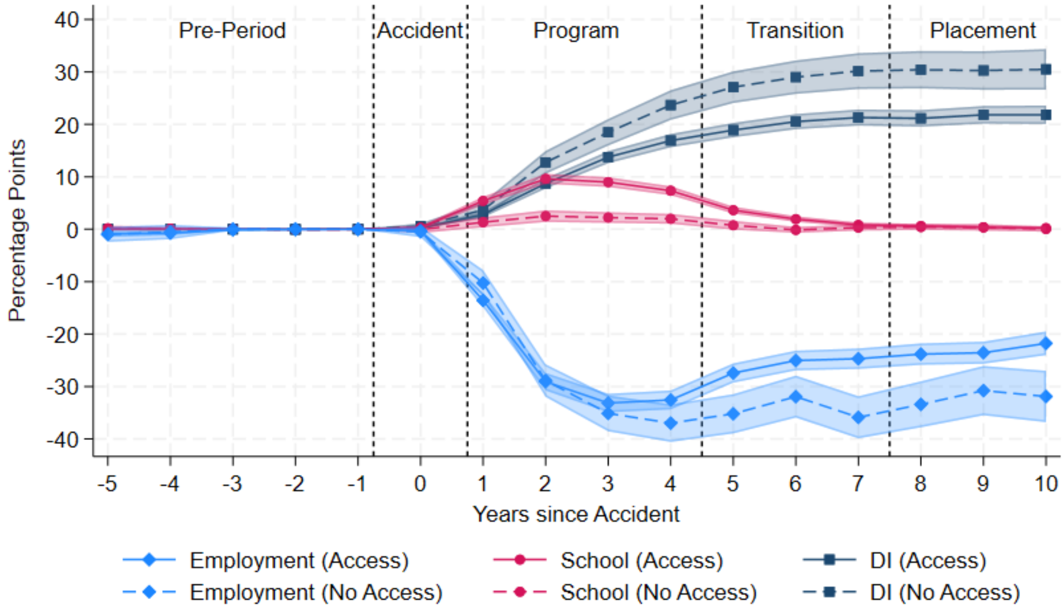
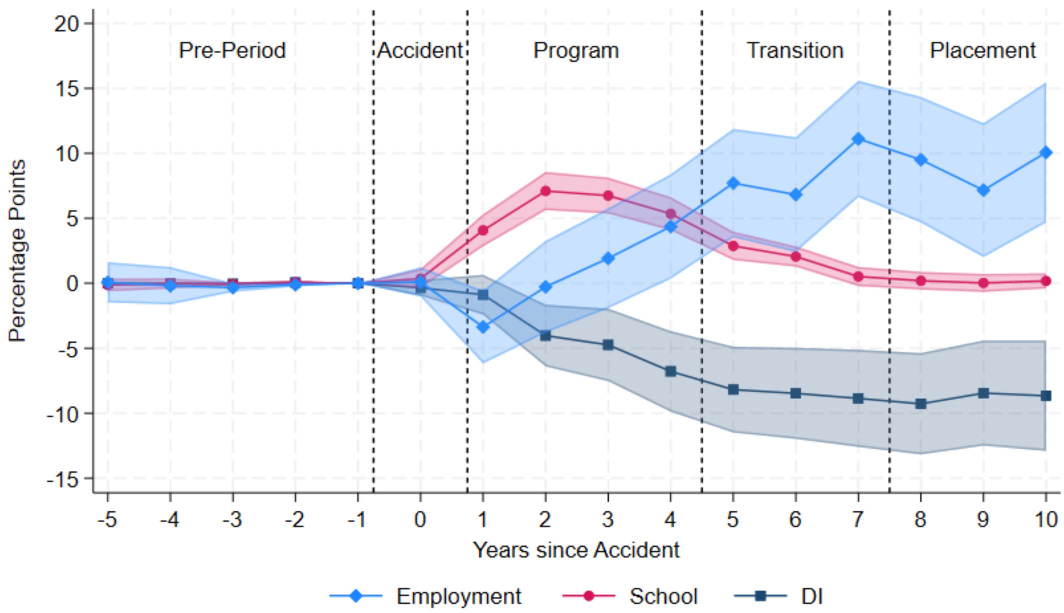
6 Figures and Tables

Figure 1: Labor Supply Around Work Accidents

(i) By Access to Reskilling



(ii) Triple Differences

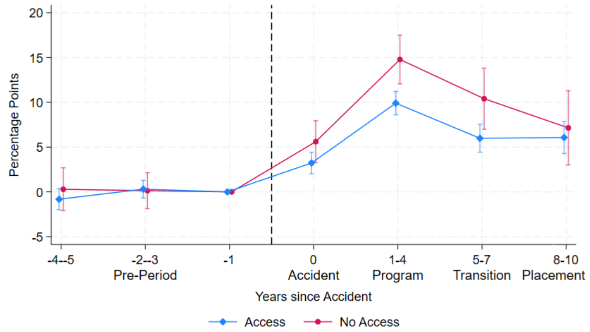


Notes: This figure shows the labor supply trajectories of workers around the time of work accidents, separated by whether they had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Panel (a) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year −1. Panel (b) presents the difference between the two differences-in-differences estimates, a "triple difference" estimator. Shaded areas represent 90% confidence intervals. The estimated triple-difference effect on reskilling (defined as participation in higher education by year +10) is 10.7 percentage points.

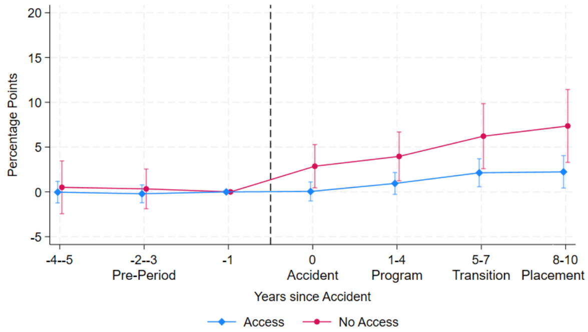
Figure 2: Antidepressant Prescriptions Around Work Accidents

(i) By Access to Reskilling

(a) Injured Worker

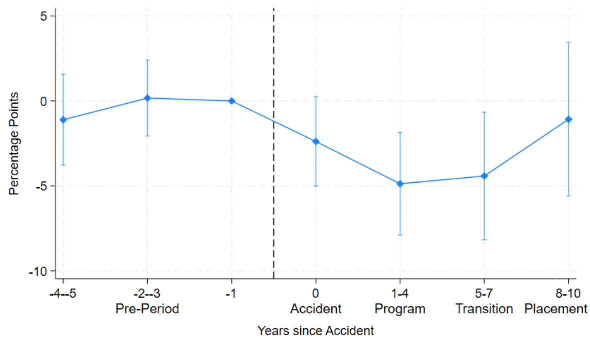


(b) Partner

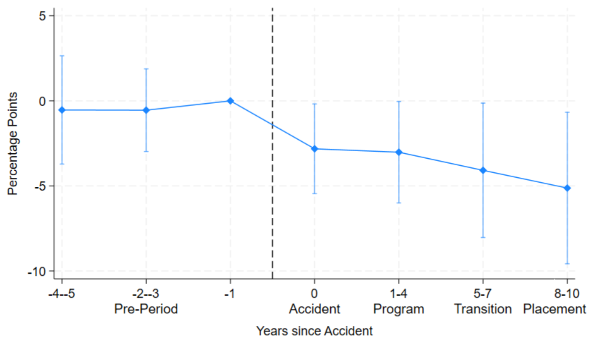


(ii) Triple Differences

(a) Injured Worker



(b) Partner

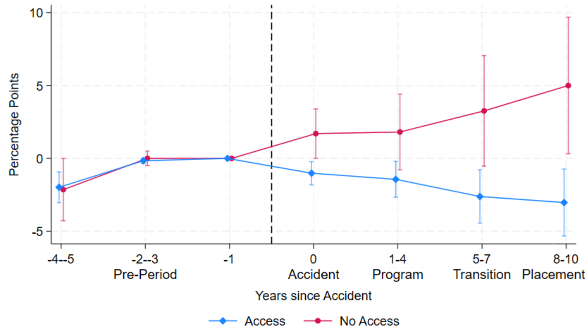


Notes: This figure shows the antidepressant prescriptions of injured workers and their partners. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Subpanels (a) shows the prescriptions of antidepressants among injured workers, and Subpanels (b) shows antidepressant prescriptions of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year -1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year +10) is 10.7 percentage points.

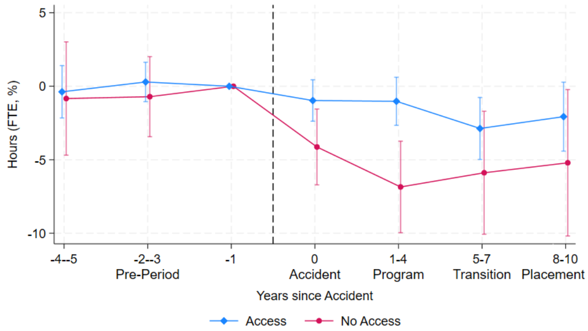
Figure 3: Partner Outcomes Around Work Accidents

(i) By Access to Reskilling (Diff-in-Diff)

(a) Staying with Injured Worker

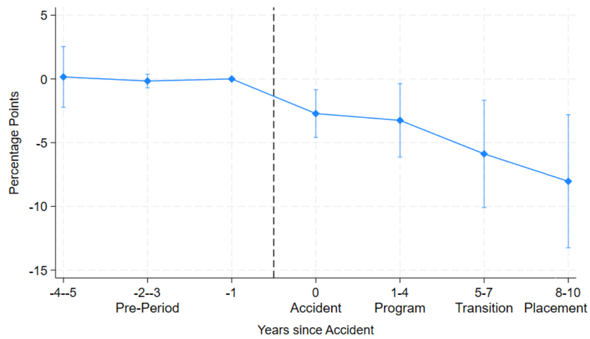


(b) Hours worked

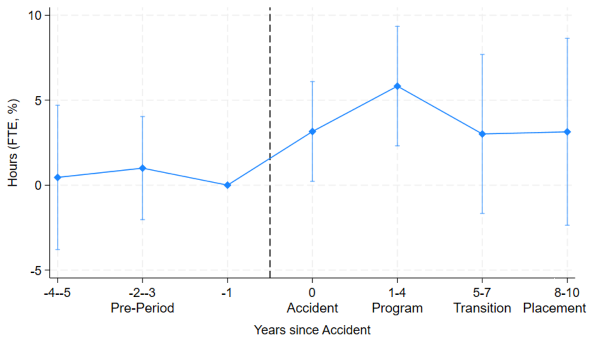


(ii) Triple Differences

(a) Staying with Injured Worker



(b) Hours worked



Notes: This figure shows the outcomes of partners of injured workers around the time of work accidents, separated by whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Partners). Partners are in a registered relationship in the three years leading up to the accident. Subpanels (a) shows the share of partners who remain in the relationship. Subpanels (b) shows their hours worked as percentage of a full-time equivalent (FTE) work year. Panel (i) display differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3 (Partners), with outcomes indexed to year -1. Panel (ii) present the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year $+10$) is 10.7 percentage points.

Table 1: Outcomes of Injured Workers and Their Partners Before the Accident

	Injured worker			Partner		
	Access	No Access (IPW)	Std. Diff.	Access	No Access (IPW)	Std. Diff.
Panel A. Demographics						
Age (Years)	42.09	42.69	-5.7%	42.54	42.36	1.8%
	(11.05)	(10.24)		(10.06)	(9.58)	
Female (%)	0.00	0.00	0.0%	100.00	100.00	0.0%
	(0.00)	(0.00)		(0.00)	(0.35)	
Stable partner (%)	72.14	70.77	3.0%	100.00	100.00	0.0%
	(44.84)	(45.50)		(0.00)	(0.00)	
Panel B. Education						
Years of schooling	14.43	14.37	15.8%	12.73	12.56	6.8%
	(0.15)	(0.47)		(2.41)	(2.54)	
Primary (%)	0.00	0.00	0.0%	33.38	33.47	-0.2%
	(0.00)	(0.00)		(47.17)	(47.22)	
Vocational (%)	100.00	100.00	0.0%	44.94	46.02	-2.2%
	(0.00)	(0.00)		(49.75)	(49.88)	
Secondary (%)	0.00	0.00	0.0%	3.85	4.12	-1.4%
	(0.00)	(0.00)		(19.25)	(19.90)	
Post-secondary (%)	0.00	0.00	0.0%	17.83	16.39	3.8%
	(0.00)	(0.00)		(38.29)	(37.04)	
Panel C. Employment						
Labor income (1000DKK)	402.82	405.99	-2.7%	205.04	208.47	-2.4%
	(118.99)	(116.64)		(133.98)	(151.18)	
Full-time (%)	100.00	100.00	0.0%	88.16	87.96	0.6%
	(0.00)	(0.00)		(32.32)	(32.58)	
Hours worked (FTE, %)	87.08	87.37	-0.9%	83.50	83.95	-1.9%
	(34.23)	(26.08)		(24.76)	(22.25)	
Hourly wage (1000DKK)	254.81	251.98	1.9%	144.81	148.95	-10.2%
	(162.09)	(140.76)		(43.20)	(38.32)	
Labor market experience (Years)	21.26	20.26	10.1%	16.56	15.13	15.4%
	(9.51)	(10.04)		(9.23)	(9.30)	
Union (%)	91.29	91.79	-1.8%	81.46	77.91	8.8%
	(28.21)	(27.46)		(38.88)	(41.51)	
Panel D. Occupation						
Physical-cognitive ability gap	0.31	0.24	9.6%	-0.37	-0.23	-12.3%
	(0.55)	(0.72)		(1.15)	(1.11)	
Panel E. Health Outcomes						
Anti-depressants (%)	5.11	5.77	-2.9%	8.61	9.55	-3.3%
	(22.03)	(23.32)		(28.05)	(29.41)	
Hospital visits (# visits)	0.92	1.00	-5.0%	0.91	1.00	-5.0%
	(1.59)	(1.64)		(1.65)	(1.79)	
Accidents (x 100, acc.)	0.18	0.16	5.8%	0.06	0.06	-0.1%
	(0.38)	(0.36)		(0.23)	(0.23)	
Cardiovascular diagnoses (x 100, acc.)	0.02	0.03	-5.1%	0.02	0.02	0.4%
	(0.15)	(0.18)		(0.15)	(0.15)	
Respiratory diagnoses (x 100, acc.)	0.01	0.01	-2.5%	0.01	0.01	4.3%
	(0.10)	(0.11)		(0.12)	(0.10)	
Broad alcohol diagnoses (x 100, acc.)	0.00	0.00	-5.3%	0.00	0.00	0.0%
	(0.03)	(0.06)		(0.00)	(0.00)	
Opioid drugs (%)	8.40	8.10	1.1%	8.13	8.83	0.0%
	(27.75)	(27.29)		(27.34)	(28.40)	
Suicide attempts (x 100, acc.)	0.00	0.00	0.0%	0.00	0.00	0.0%
	(0.00)	(0.00)		(0.00)	(0.00)	
Mortality (%, acc.)	0.00	0.00	0.0%	0.00	0.00	0.0%
	(0.00)	(0.00)		(0.00)	(0.00)	
Panel F. Injury						
Year of Injury	2005.21	2005.32	-2.2%	2005.28	2005.41	0.0%
	(4.91)	(4.84)		(4.94)	(4.85)	
Observations	2915	1093		2103	774	

Notes: This table shows the characteristics of injured workers and their partners in the year before their work accidents. Standard deviations are in parentheses. The "Access" column shows workers with a vocational degree that grants access to higher education. The "No Access" columns show workers ineligible for a higher degree. The "IPW" column implements an Inverse Probability Weighing (IPW) of the workers according to a logistic regression of access to higher degrees on the covariates reported in this table. Appendix B.1 details the IPW procedure. The "Std. Mean Diff" column shows the standardized mean difference between the "Access" and "IPW" workers, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin (2008)). See Table A.1 for definitions of the outcome variables.

Table 2: Costs and Benefits of Reskilling (PDV for Compliers and their Partners)

	Per reskilled worker ($)	Per dollar of education	Percent of total
	(1)	(2)	(3)
Education costs	-69,695	-1.0	-16.4
Labor earnings			
Injured Workers	270,062	3.9	63.6
Partners	90,146	1.3	21.2
Mental health			
Injured Workers	56,019	0.8	13.2
Partners	77,806	1.1	18.3
Total	424,338	6.1	100.0

Notes: This table shows the present discounted values of providing a higher degree for an injured worker of age 32, the average among the instrument compliers. *Education Costs* include tuition, reskilling benefits, and State Education Support (SU) for the injured workers. *Earnings* are the labor earnings of the injured worker and their partner. *Mental health effects* capture the monetized value of changes in Quality-Adjusted Life Years (QALYs) as well as expenditures for medication for the injured worker and their partners. Appendix D details our approach to the cost-benefit calculations.

Supplementary Appendix
Reskilling and Resilience

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A Institutional Setting and Data

A.1 Variable Definitions

Table A.1: Variable Definitions

	Variable	Defition
Panel A. Demographics		
(1)	Age (Years)	Age by 31st of December.
(2)	Female (%)	Dummy indicating the individual is registered as female.
(3)	Stable partner (%)	Dummy indicating cohabiting (including marriages) with the same partner for 3 consecutive years.
Panel B. Education		
(4)	Years of schooling	Prescribed years of study associated with highest completed degree counting from grade 1.
(5)	Primary (%)	Dummy indicating pre-school educations, primary education, preparatory courses, or Danish language courses at language centers as highest completed degree.
(6)	Vocational (%)	Dummy indicating Vocational Education and Training (VET), qualifying educational programmes, or labor market educations (AMU) as highest completed degree.
(7)	Secondary (%)	Dummy indicating upper secondary education as highest completed degree.
(8)	Post-secondary (%)	Dummy indicating short cycle higher education, vocational bachelors educations, bachelors-, masters-, or PhD programmes as highest completed degree.
Panel C. Employment		
(9)	Labor income (1000DKK)	Total labor market income, including bonuses, amenities, wages payed under sick- and parental leave, and employer contributions to pension saving schemes.
(10)	Full-time (%)	Dummy indicating full-time work according to the Danish Register-Based Labour Force Statistics (RAS), defined by normal working hours above 32 hours/week.
(11)	Hours worked (FTE, %)	From 2008-2017: Yearly number of payed hours. From 1995-2007: Yearly labor income (9) divided by hourly wage rates (12). Divided by full-time equivalent yearly hours, 1924, corresponding to 37 hours/week.
(12)	Hourly wage (DKK)	From 2008-2017: Yearly total labor income (9) divided by yearly hours worked (11). From 1995-2007: Average hourly wage rate in November job. Due to issues with the data quality, we only have reliable hourly wage rates for individuals working more than 20 hours a week in this early part of the sample.
(13)	Labor market experience (Years)	Labor market experience measured in years since 1964.
(14)	Union (%)	Dummy indicating union membership. Measured by a positive deductible amount reported by the unions to the tax authorities.
(15)	Employment (%)	Dummy indicating full-time work while simultaneously not being in School (16) or receiving DI (17).
(16)	School (%)	Enrollment in post-secondary degree (8) program in the given year.
(17)	DI (%)	Dummy indicating any amount of weeks within a year spent receiving disability insurance.
Panel D. Occupation		
(18)	Physical-cognitive ability gap	Defined as ln(Physical Ability Requirements/Cognitive Ability Requirements). Physical Ability Requirements are defined as the average importance of Static Strength, Explosive Strength, Dynamic Strength, Trunk Strength, and Stamina, as measured by O*NET. Cognitive Ability Requirements are defined as the average importance of Fluency of Ideas, Originality, Problem Sensitivity, Deductive Reasoning, Inductive Reasoning, Information Ordering, Category Pleribility, Mathematical Reasoning, and Number Facility, as measured by O*NET. Both measurements are normalized.
Panel E. Health Outcomes		
(19)	Anti-depressants (%)	Dummy indicating a prescription for drugs in the "N06A: Antidepressants" ATC-classification.
(20)	Hospital visits (# visits)	Number of visits to a hospital, both for admission, outpatient treatment, and ER visits.
(21)	Accidents (x100, acc.)	Accumulated number of hospitalizations where the reason for contact is registered as an accident.
(22)	Cardiovascular diagnoses (x100, acc.)	Accumulated number of hospital diagnoses within the ICD-10 category "I: Diseases of the circulatory system"
(23)	Respiratory diagnoses (x100, acc.)	Accumulated number of hospital diagnoses within the ICD-10 category "J: Diseases of the respiratory system"
(24)	Alcohol diagnoses (x100, acc.)	Accumulated number of hospital diagnoses related to alcohol from Browning and Heinesen (2012). Includes alcohol poisoning, addiction syndrome, delirious abstinence, alcohol psychosis, varicose vein on gullet, alcoholic disease of the liver, alcoholic disease of pancreas. Corresponds to the following ICD-10 codes: F100, F102, F104, F105, I85, K70, K860, T500, T510.
(25)	Opiod drug (%)	Dummy indicating a prescription for drugs in the "N02A: Opioids" ATC-classification.
(26)	Suicide attempts (x100, acc.)	Accumulated number of hospitalizations where the reason for contact is registered as a suicide attempt.
(27)	Mortality (%, acc.)	Accumulated mortality, defining an individual as diseased from the year of death.
Panel F. Injury		
(28)	Year of Injury	Calender year of the workplace accident. Non-injured control workers are assigned the year of injury of their matched injured workers.

Notes: This table defines the variables used in the analysis.

A.2 Analysis Sample

Appendix Table A.2 shows how our sample restrictions shrink the analysis data. Column (3) shows that the restrictions do not affect the severity of the injuries considered in the analysis.

Table A.2: Work Accident Sample Reduction

Sample Step	# Injury Events (1)	# Stable Partners (2)	Earnings Cap. Loss (%) (3)
1. All work accidents with ECL >0	31,129	-	36.18
2. Exclude psychological shock	29,875	-	35.86
3. Collapse to person-year	29,853	-	35.89
4. Person exists in register data	29,783	18,262	35.88
5. Full-time employed before injury	13,365	9,483	36.58
6. Vocational degrees with access	4,157	2,976	34.31
7. Male craft workers	2,915	2,103	34.92

Notes: This table shows how our sample restrictions shrink the analysis data, starting from the universe of work accidents that cause loss of earnings capacity from 1998 to 2017. Step 6 corresponds to the "Injury" column of Table A.3. *Earning capacity loss* (ECL) represents AES upfront estimate of the loss of work capacity in the workers' occupation.

Table A.3: Outcomes of Injured Workers and Their Partners Before the Accident

	Injured worker			Partner		
	Injury	No Injury (Match)	Std. Diff.	Injury	No Injury (Match)	Std. Diff.
Panel A. Demographics						
Age (Years)	42.09	42.09	0.0%	42.54	42.76	-2.2%
	(11.05)	(11.05)		(10.06)	(10.08)	
Female (%)	0.00	0.00	0.0%	100.00	100.00	0.0%
	(0.00)	(0.00)		(0.00)	(0.00)	
Stable partner (%)	72.14	72.14	0.0%	100.00	100.00	0.0%
	(44.84)	(44.84)		(0.00)	(0.00)	
Panel B. Education						
Years of schooling	14.43	14.44	-5.6%	12.73	12.97	-10.3%
	(0.15)	(0.16)		(2.41)	(2.34)	
Primary (%)	0.00	0.00	0.0%	33.38	28.29	0.0%
	(0.00)	(0.00)		(47.17)	(45.05)	
Vocational (%)	100.00	100.00	0.0%	44.94	48.03	0.0%
	(0.00)	(0.00)		(49.75)	(49.97)	
Secondary (%)	0.00	0.00	0.0%	3.85	4.18	0.0%
	(0.00)	(0.00)		(19.25)	(20.03)	
Post-secondary (%)	0.00	0.00	0.0%	17.83	19.50	0.0%
	(0.00)	(0.00)		(38.29)	(39.63)	
Panel C. Employment						
Labor income (1000DKK)	402.82	407.52	-3.9%	205.04	218.17	-9.7%
	(118.99)	(120.51)		(133.98)	(137.54)	
Full-time (%)	100.00	100.00	0.0%	88.16	88.79	0.0%
	(0.00)	(0.00)		(32.32)	(31.56)	
Hours worked (FTE, %)	87.08	87.74	-2.3%	83.50	84.63	-4.4%
	(34.23)	(20.58)		(24.76)	(26.61)	
Hourly wage (1000DKK)	254.81	247.09	5.6%	144.81	147.20	-5.6%
	(162.09)	(107.34)		(43.20)	(41.54)	
Labor market experience (Years)	21.26	22.02	-8.0%	16.56	17.34	-8.5%
	(9.51)	(9.50)		(9.23)	(9.23)	
Union (%)	91.29	90.46	2.9%	81.46	80.46	2.5%
	(28.21)	(29.38)		(38.88)	(39.66)	
Panel D. Occupation						
Physical-cognitive ability gap	0.31	0.31	-0.3%	-0.37	-0.47	8.6%
	(0.55)	(0.53)		(1.15)	(1.15)	
Panel E. Health Outcomes						
Anti-depressants (%)	5.11	2.57	13.2%	8.61	7.18	5.3%
	(22.03)	(15.84)		(28.05)	(25.82)	
Hospital visits (# visits)	0.92	0.61	21.9%	0.91	0.77	9.1%
	(1.59)	(1.29)		(1.65)	(1.49)	
Accidents (x 100, acc.)	0.18	0.13	15.1%	0.06	0.06	-2.0%
	(0.38)	(0.33)		(0.23)	(0.24)	
Cardiovascular diagnoses (x 100, acc.)	0.02	0.02	2.9%	0.02	0.02	5.8%
	(0.15)	(0.14)		(0.15)	(0.12)	
Respiratory diagnoses (x 100, acc.)	0.01	0.01	3.4%	0.01	0.01	8.0%
	(0.10)	(0.08)		(0.12)	(0.08)	
Alcohol diagnoses (x 100, acc.)	0.00	0.00	0.0%	0.00	0.00	0.0%
	(0.03)	(0.03)		(0.00)	(0.00)	
Opioid drugs (%)	8.40	3.70	19.8%	8.13	5.75	0.0%
	(27.75)	(18.89)		(27.34)	(23.29)	
Suicide attempts (x 100, acc.)	0.00	0.00	0.0%	0.00	0.00	0.0%
	(0.00)	(0.00)		(0.00)	(0.00)	
Mortality (%, acc.)	0.00	0.00	0.0%	0.00	0.00	0.0%
	(0.00)	(0.00)		(0.00)	(0.00)	
Panel F. Injury						
Year of Injury	2005.21	2005.21	0.0%	2005.28	2005.28	0.0%
	(4.91)	(4.91)		(4.94)	(4.94)	
Observations	2915	2915		2103	2103	

Notes: This table shows the characteristics of injured workers and their partners in the year before their work accidents. Standard deviations are in parentheses. The "Injury" column shows the average outcomes of workers in the year before a work accident. The "No Injury (Match)" column shows averages for workers with the same age, gender, education level, occupation, industry, access to higher education, partnership- and parental status as the "Injury" workers in the year before the injury (one-to-one random match within cells). Appendix B.1 details the IPW procedure. The "Std. Mean Diff" column shows the standardized mean difference between the "Injury" and "Match" workers, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin (2008)). See Table A.1 for definitions of the outcome variables.

B Identification Strategy

B.1 Inverse Probability Weighting

This section describes our inverse probability weighting (IPW) procedure for finding comparable workers who differ in their eligibility for higher education. The procedure follows Abadie (2005).

We first estimate propensity scores for having access to higher education:

$$p(\text{Access}_{ie-1} = 1) = \mu(X_{ie-1}), \tag{2}$$

where μ is a logistic link function, and X include first-order terms of the variables listed in the "*Demographics*", "*Education*", "*Employment*", "*Occupation*", and "*Injury*" panel of Table 1, as well as a dummy variable indicating antidepressant drug prescriptions. To be specific, X includes age, gender, stable partner indicator, years of schooling, labor market income, hours worked, hourly wages, labor market experience, union membership status, the physical-/ cognitive ability requirement gap, dummy variable for prescription of antidepressant medication, and the year of injury.

We then reweight our "No Access" workers to have the same average propensity score as our "Access" group. In particular, we assign each "No Access" worker i a weight of

$$w_i = \frac{\hat{p}(X_{ie-1})}{1 - \hat{p}(X_{ie-1})}. \tag{3}$$

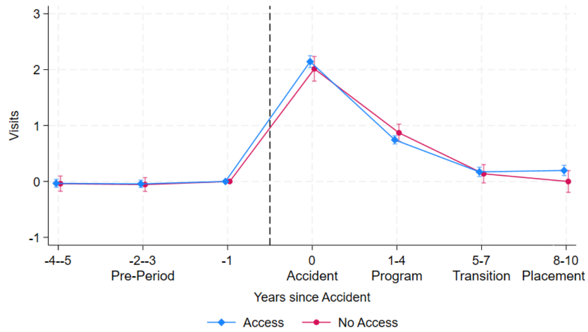
We estimate the propensity scores for injured workers and assign the same weight to the control worker within the match. Table 1 validates that the IPW-weighted "No Access" workers are comparable to the "Access" group on the observables X.

B.2 Placebo Checks

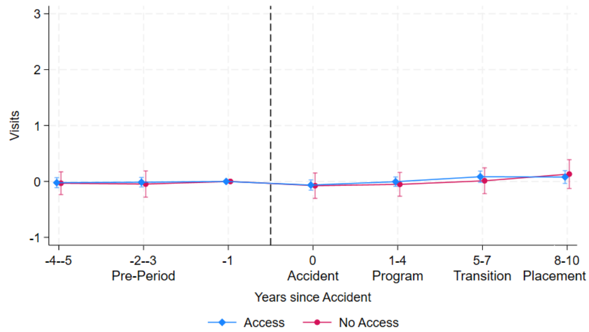
Figure B.1: Hospital Visits around Work Accidents

(i) By Access to Reskilling (Diff-in-Diff)

(a) Injured Worker

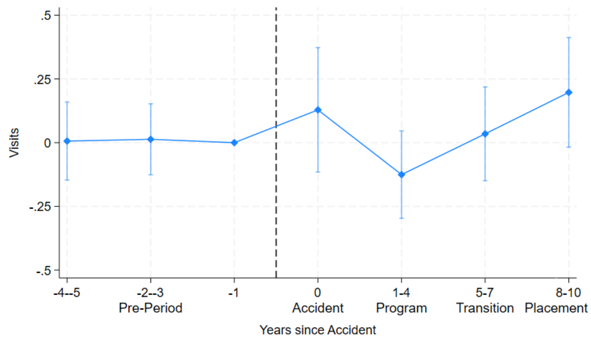


(b) Partner

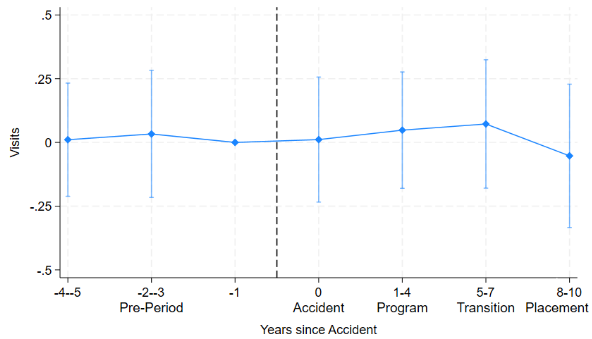


(ii) Triple Differences

(a) Injured Worker



(b) Partner

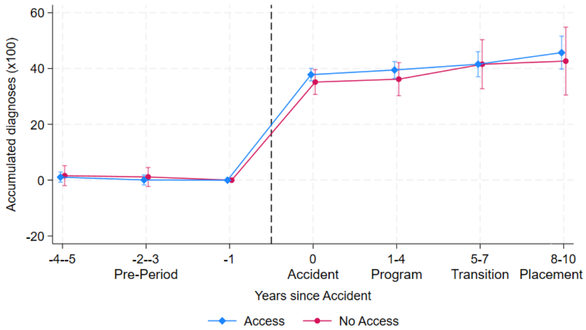


Notes: This figure shows the hospital visits of injured workers and their partners. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Subpanels (a) shows the hospital visits among injured workers, and Subpanels (b) shows hospital visits of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year −1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year +10) is 10.7 percentage points.

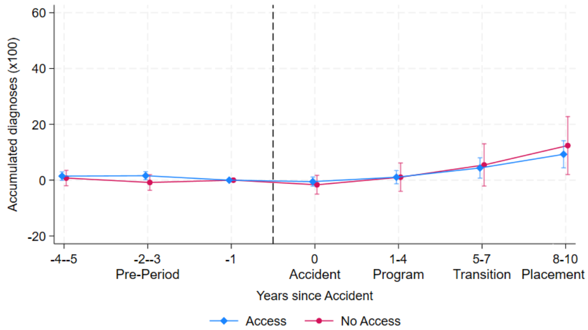
Figure B.2: Hospitalizations due to Accidents

(i) By Access to Reskilling (Diff-in-Diff)

(a) Injured Worker

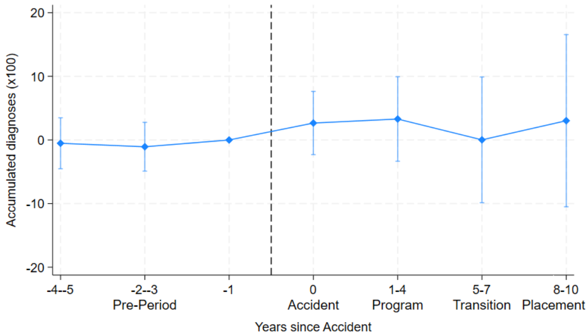


(b) Partner

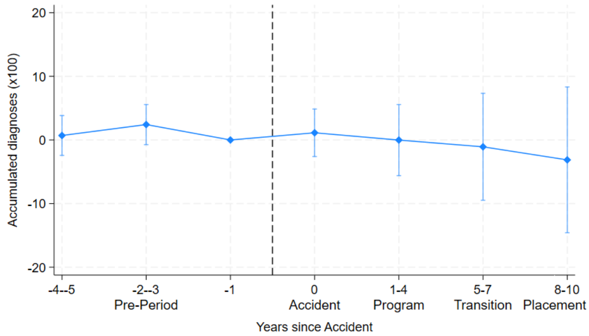


(ii) Triple Differences

(a) Injured Worker



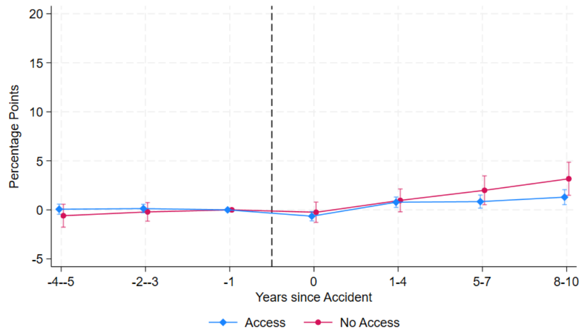
(b) Partner



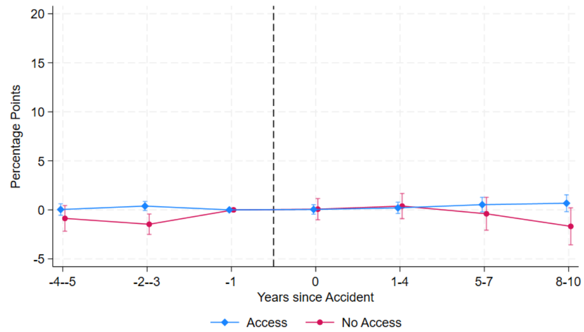
Notes: This figure shows the hospitalizations due to accidents of injured workers and their partners. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the “Access” and “No Access, IPW” columns in Table 1 (Injured worker). Subpanels (a) shows the hospitalizations among injured workers, and Subpanels (b) shows hospitalizations of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing “Injury” and “Match” workers from Table A.3, with outcomes indexed to year -1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a “triple difference” estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year +10) is 10.7 percentage points.

Figure B.3: Outcomes around Temporary Injuries by Access to Reskilling (Diff-in-Diff)

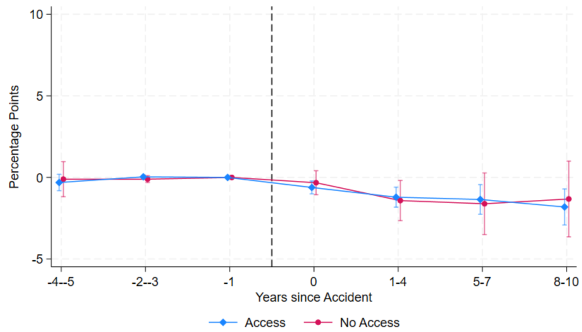
(a) Antidepressants of Injured Worker



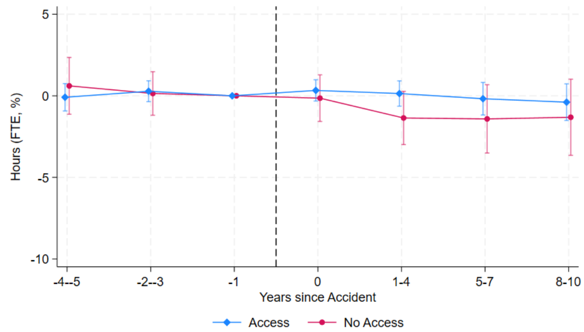
(b) Antidepressants of Partner



(c) Partner Staying with Injured Worker



(d) Hours Worked of Partner



Notes: The figure studies temporary work injuries, defined as work accidents that AES assesses did not cause permanent loss of earning capacity or personal impairment to the worker. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). The figure displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year -1. Subpanel (a) shows the prescriptions of antidepressants among injured workers, and Subpanel (b) shows antidepressant prescriptions of their original partners (defined as their stable partners in the year before the accident). Subpanel (c) shows the share of partners who remain in the relationship, while Subpanel (d) shows their hours worked as percentage of a full-time equivalent (FTE) work year. Whiskers represent 90% confidence intervals.

C Results

C.1 Pooled Estimates

Table C.1: Triple-Difference Estimates (Reduced Form)

	Dynamic Estimates				Pooled Estimates		
	Year 0	Years 1-4	Years 5-7	Years 8-10	Years 0-10	Years 1-10	Years 5-10
Panel A. Main outcomes							
Antidepressant prescriptions (%)							
Injured worker	-1.78	-5.02	-3.64	-0.77	-3.39	-3.57	-2.35
	(0.179)	(0.001)	(0.046)	(0.723)	(0.016)	(0.018)	(0.196)
Partner	-2.82	-3.02	-4.08	-5.12	-3.74	-3.85	-4.55
	(0.079)	(0.096)	(0.089)	(0.058)	(0.042)	(0.049)	(0.055)
Staying with injured worker (%)							
Partner	-2.83	-3.26	-5.88	-8.04	-4.98	-5.23	-6.85
	(0.013)	(0.063)	(0.022)	(0.011)	(0.011)	(0.014)	(0.011)
Hours worked (FTE, %)							
Partner	3.16	5.83	3.01	3.14	4.19	4.30	3.07
	(0.077)	(0.006)	(0.290)	(0.348)	(0.054)	(0.064)	(0.282)
Panel B. Placebo checks							
Hospital visits (# visits)							
Injured worker	0.13	-0.13	0.02	0.19	0.00	-0.01	0.10
	(0.387)	(0.203)	(0.859)	(0.153)	(0.987)	(0.897)	(0.370)
Partner	0.01	0.04	0.06	-0.08	0.02	0.02	0.00
	(0.959)	(0.780)	(0.696)	(0.648)	(0.898)	(0.896)	(0.990)
Accidents (x 100, acc.)							
Injured worker	2.66	3.29	0.02	3.03	2.31	2.27	1.40
	(0.378)	(0.415)	(0.997)	(0.713)	(0.638)	(0.667)	(0.838)
Partner	1.13	-0.02	-1.08	-3.13	-0.82	-1.04	-1.96
	(0.619)	(0.996)	(0.833)	(0.653)	(0.842)	(0.813)	(0.733)
Cardiovascular diagnoses (x 100, acc.)							
Injured worker	0.12	-1.01	-2.83	-1.12	-1.37	-1.54	-2.03
	(0.913)	(0.640)	(0.456)	(0.843)	(0.645)	(0.635)	(0.647)
Partner	-0.90	-0.03	0.63	-2.43	-0.45	-0.40	-0.73
	(0.425)	(0.991)	(0.883)	(0.698)	(0.890)	(0.911)	(0.882)
Respiratory diagnoses (x 100, acc.)							
Injured worker	-0.45	-1.37	-1.89	0.38	-1.01	-1.07	-0.86
	(0.587)	(0.329)	(0.439)	(0.906)	(0.585)	(0.595)	(0.751)
Partner	-0.43	-0.57	0.07	-1.98	-0.68	-0.71	-0.85
	(0.650)	(0.730)	(0.980)	(0.560)	(0.737)	(0.749)	(0.767)

Notes: This table summarizes the estimation results from our main outcomes and placebo checks. p-values are in parentheses. The table reports "triple differences" in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 1), each measured relative to their "No Injury" matches (from Table A.3), and indexed to year -1. The first four columns replicates ("Dynamic Estimates") the dynamic estimates also shown in figures. The next three columns ("Pooled Estimates") shows estimation results with pooled post-accident years: years 0-10, years 1-10, and years 5-10, respectively. See Table A.1 for definitions of the outcome variables.

C.2 Disease and Death of Despair

Table C.2: Triple-Difference Estimates (Reduced Form)

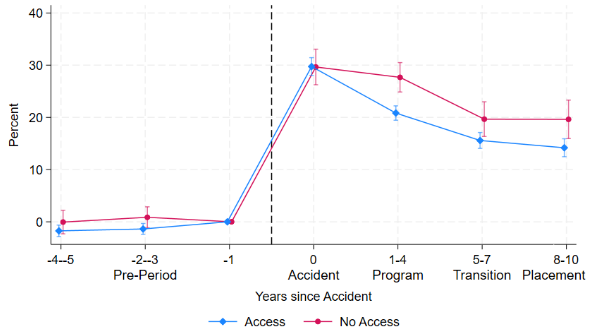
	Dynamic Estimates				Pooled Estimates		
	Year 0	Years 1-4	Years 5-7	Years 8-10	Years 0-10	Years 1-10	Years 5-10
Panel A. Disease and death of despair							
Alcohol diagnoses (x 100, acc.)							
Injured worker	0.13	-1.18	-2.18	-1.65	-1.41	-1.59	-1.94
	(0.743)	(0.121)	(0.126)	(0.418)	(0.200)	(0.189)	(0.248)
Partner	-0.02	-0.35	-0.67	-0.30	-0.39	-0.43	-0.51
	(0.318)	(0.228)	(0.279)	(0.756)	(0.415)	(0.417)	(0.508)
Opioid drugs (%)							
Injured worker	0.08	-6.75	-3.74	-5.01	-4.88	-5.45	-4.32
	(0.971)	(0.000)	(0.088)	(0.037)	(0.006)	(0.003)	(0.040)
Partner	1.56	0.71	-0.68	-2.22	-0.22	-0.43	-1.37
	(0.429)	(0.675)	(0.737)	(0.373)	(0.894)	(0.804)	(0.504)
Suicide attempts (x 100, acc.)							
Injured worker	0.00	0.00	-0.06	0.30	0.05	0.06	0.11
	(1.000)	(0.990)	(0.892)	(0.613)	(0.869)	(0.869)	(0.827)
Partner	-0.05	0.10	0.11	0.42	0.16	0.18	0.25
	(0.317)	(0.317)	(0.331)	(0.026)	(0.139)	(0.119)	(0.070)
Mortality (%, acc.)							
Injured worker	-0.13	-0.76	-0.12	0.25	-0.29	-0.31	0.05
	(0.278)	(0.052)	(0.894)	(0.848)	(0.638)	(0.652)	(0.962)
Partner	0.12	-0.12	-0.19	-0.41	-0.18	-0.21	-0.29
	(0.696)	(0.844)	(0.864)	(0.790)	(0.828)	(0.814)	(0.820)

Notes: This table summarizes the estimation results from our disease and death of despair outcomes. p-values are in parentheses. The table reports "triple differences" in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 1), each measured relative to their "No Injury" matches (from Table A.3), and indexed to year -1. The first four columns ("Dynamic Estimates") replicates the dynamic estimates also shown in figures. The next three columns ("Pooled Estimates") shows estimation results with pooled post-accident years: years 0-10, years 1-10, and years 5-10, respectively. See Table A.1 for definitions of the outcome variables.

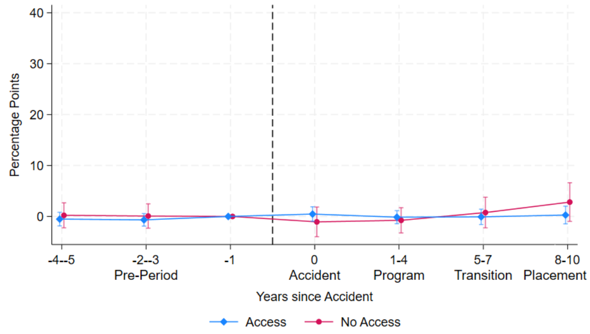
Figure C.1: Opioid Prescriptions in the Household

(i) By Access to Reskilling (Diff-in-Diff)

(a) Injured Worker

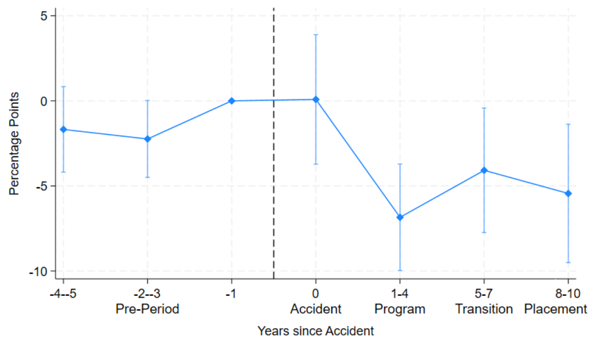


(b) Partner

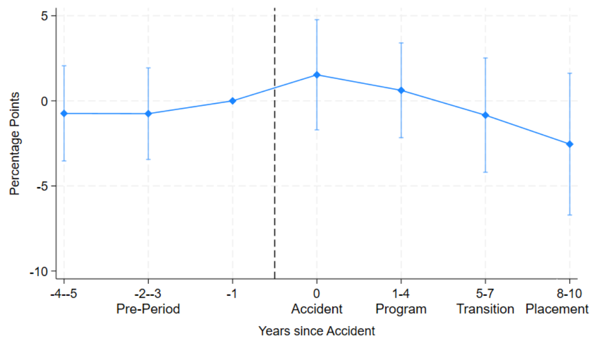


(ii) Triple Differences

(a) Injured Worker



(b) Partner

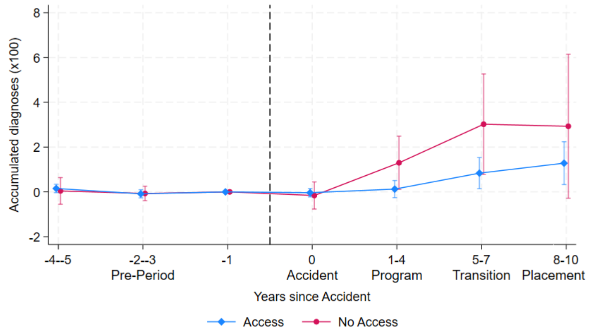


Notes: This figure shows the consumption of prescription opioid drugs among injured workers and their partners. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Subpanels (a) shows the consumption among injured workers, and Subpanels (b) shows consumption of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year -1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year $+10$) is 10.7 percentage points.

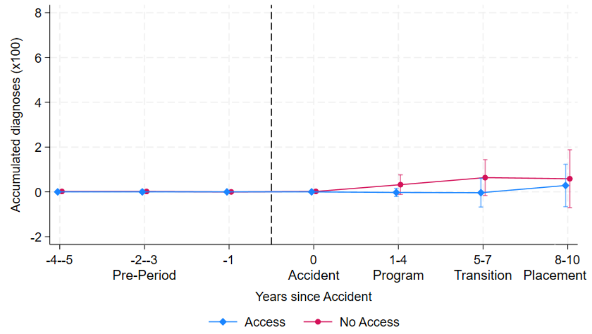
Figure C.2: Alcohol Diagnoses in the Household

(i) By Access to Reskilling (Diff-in-Diff)

(a) Injured Worker

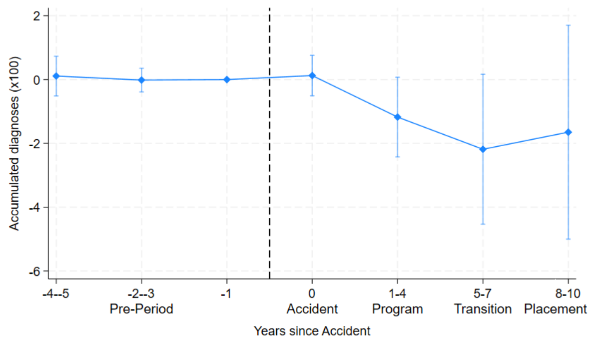


(b) Partner

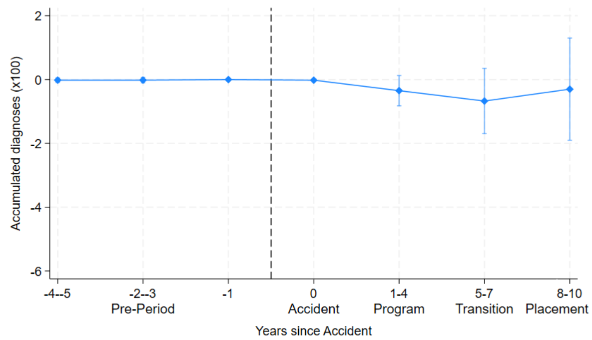


(ii) Triple Differences

(a) Injured Worker



(b) Partner

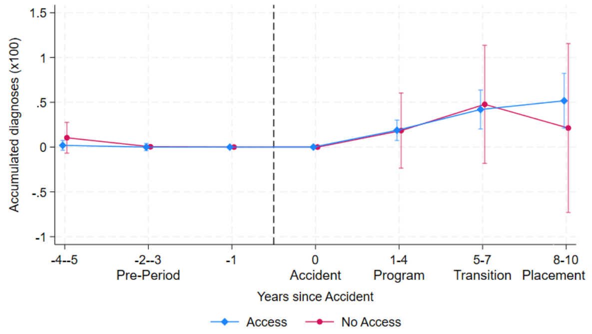


Notes: This figure shows the alcohol diagnoses of injured workers and their partners. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Subpanels (a) shows the diagnoses among injured workers, and Subpanels (b) shows diagnoses of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year -1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year $+10$) is 10.7 percentage points.

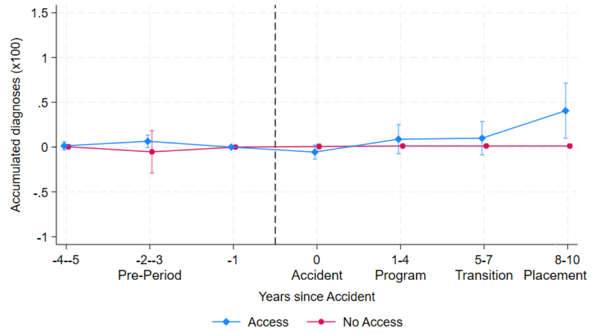
Figure C.3: Suicide Attempts in the Household

(i) By Access to Reskilling (Diff-in-Diff)

(a) Injured Worker

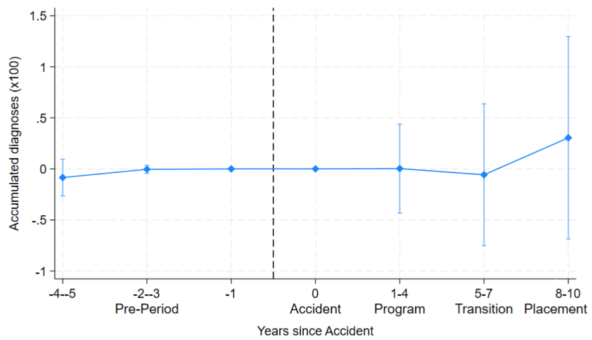


(b) Partner

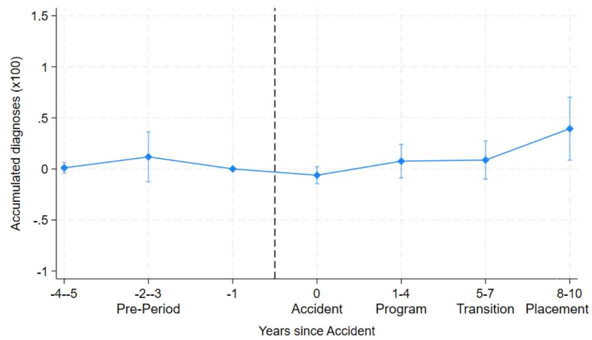


(ii) Triple Differences

(a) Injured Worker



(b) Partner

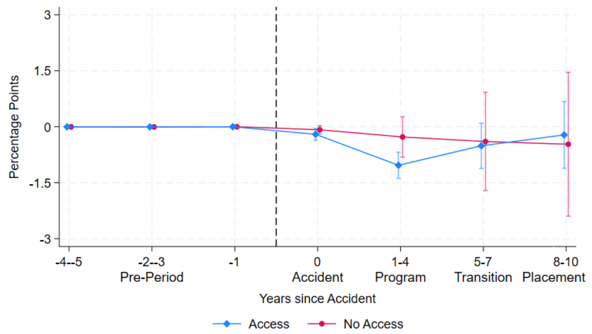


Notes: This figure shows the suicide attempts of injured workers and their partners. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Subpanels (a) shows the suicide attempts among injured workers, and Subpanels (b) shows suicide attempts of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year -1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year $+10$) is 10.7 percentage points.

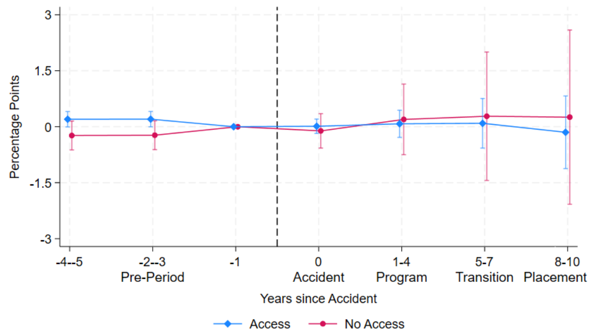
Figure C.4: Mortality in the Household (Cumulative)

(i) By Access to Reskilling (Diff-in-Diff)

(a) Injured Worker

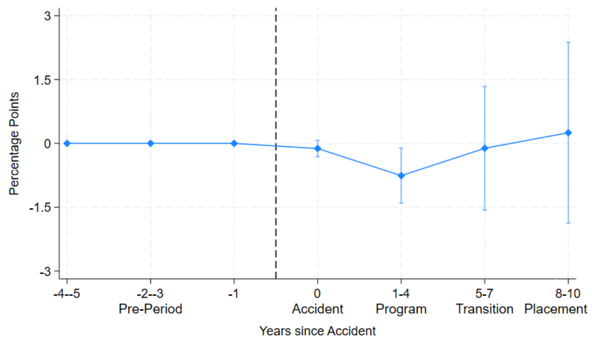


(b) Partner

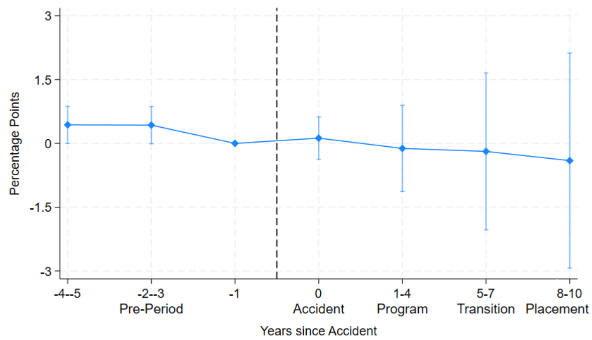


(ii) Triple Differences

(a) Injured Worker



(b) Partner

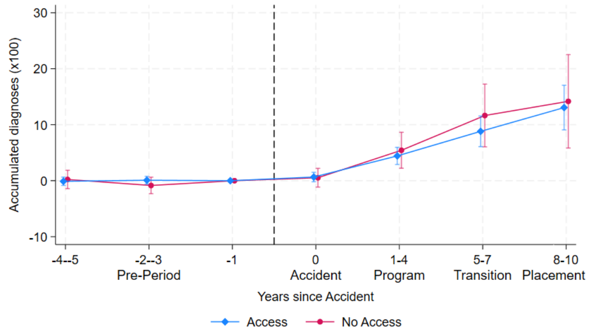


Notes: This figure shows the cumulative mortality of injured workers and their partners. The specification is not designed to estimate the effect of work accidents on short-term mortality immediately following the accident, as our sample focuses on work accidents that individuals survive. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Subpanels (a) shows the cumulative mortality among injured workers, and Subpanels (b) shows the cumulative mortality of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year -1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year $+10$) is 10.7 percentage points.

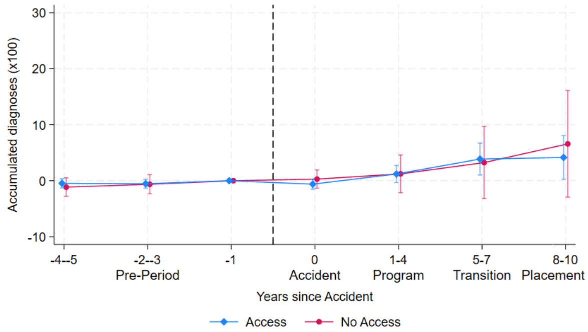
Figure C.5: Cardiovascular Diagnoses

(i) By Access to Reskilling (Diff-in-Diff)

(a) Injured Worker

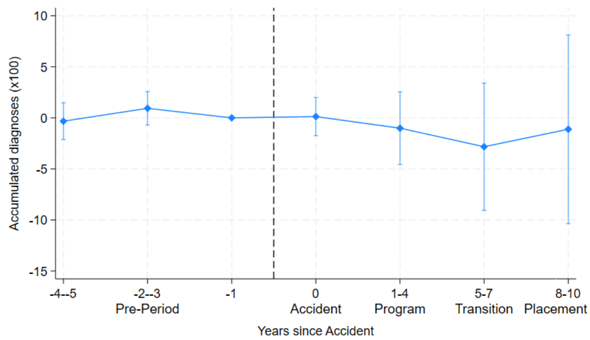


(b) Partner

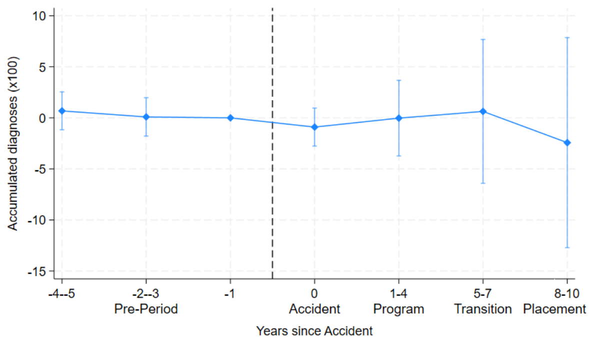


(ii) Triple Differences

(a) Injured Worker



(b) Partner

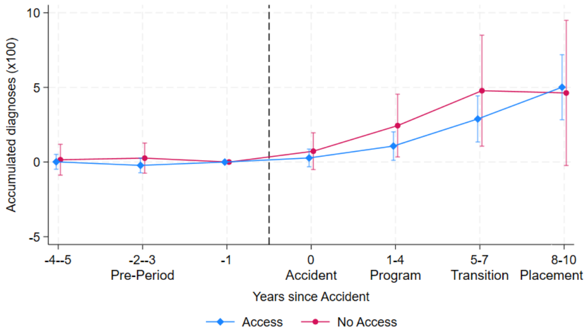


Notes: This figure shows the cardiovascular diagnoses of injured workers and their partners. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Subpanels (a) shows the diagnoses among injured workers, and Subpanels (b) shows diagnoses of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year -1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year $+10$) is 10.7 percentage points.

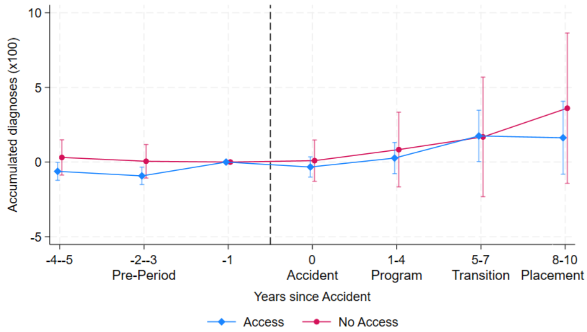
Figure C.6: Respiratory Diagnoses

(i) By Access to Reskilling (Diff-in-Diff)

(a) Injured Worker

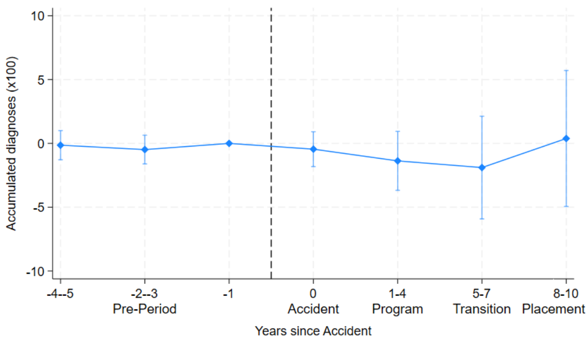


(b) Partner

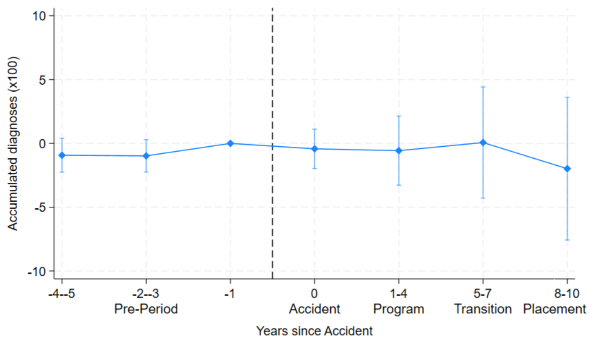


(ii) Triple Differences

(a) Injured Worker



(b) Partner



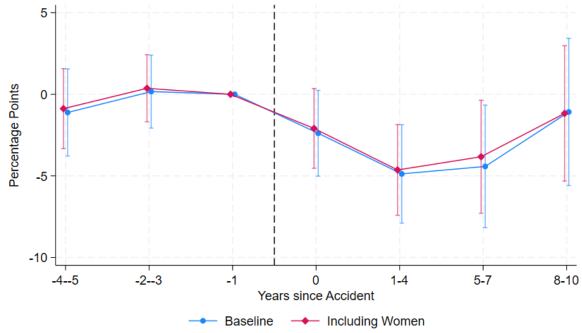
Notes: This figure shows the respiratory diagnoses of injured workers and their partners. The figure separates households based on whether the injured workers had access to higher education at the time of injury. The groups correspond to the "Access" and "No Access, IPW" columns in Table 1 (Injured worker). Subpanels (a) shows the diagnoses among injured workers, and Subpanels (b) shows diagnoses of their original partners (defined as their stable partners in the year before the accident). Panel (i) displays differences-in-differences estimates comparing "Injury" and "Match" workers from Table A.3, with outcomes indexed to year -1. Panel (ii) presents the corresponding difference between the two differences-in-differences estimates, a "triple difference" estimator. Whiskers represent 90% confidence intervals. For reference, the estimated triple-difference effect on reskilling (defined as participation in higher education by year +10) is 10.7 percentage points.

C.3 Robustness Analysis

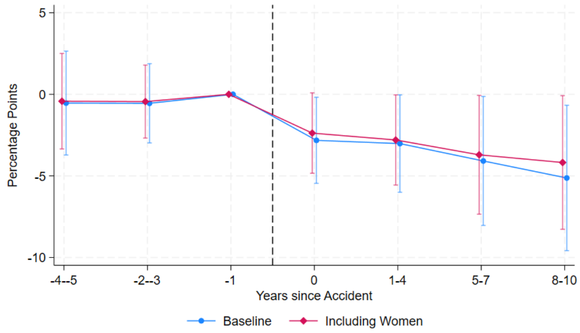
C.3.1 Including Women

Figure C.7: Main Results Including Female Injured Workers: Triple Differences

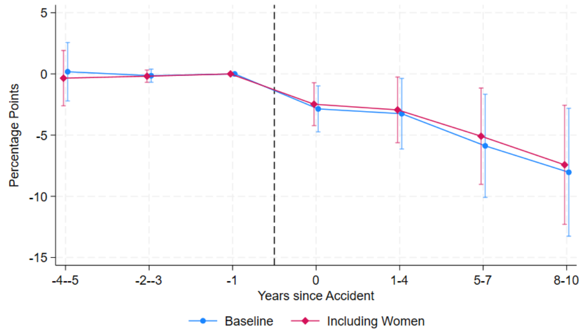
(a) Antidepressants: Injured Worker



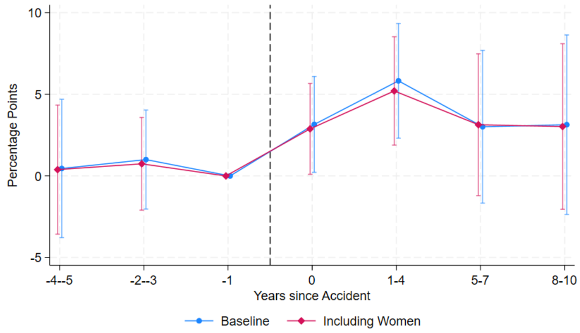
(b) Antidepressants: Partner



(c) Staying with Injured Worker



(d) Hours Worked of Partner



Notes: This figure shows the difference in outcomes of workers and their partners around work accidents split by whether or not we include female injured workers in the analysis sample. "Baseline" corresponds to our main specification in Figures 2 and 3, while "Including Women" include female injured workers in the analysis sample. The plots are triple differences, where the first difference is between the "Access" and "No Access (IPW)" workers (from Table 1), the second difference is between the "Injury" and "No Injury, Match" workers (from Table A.3), and the third difference is indexed to year -1. Subpanel (a) shows the prescriptions of antidepressants among injured workers, and Subpanel (b) shows antidepressant prescriptions of their original partners (defined as their stable partners in the year before the accident). Subpanel (c) shows the share of partners who remain in the relationship, while Subpanel (d) shows their hours worked as percentage of a full-time equivalent (FTE) work year. Whiskers represent 90% confidence intervals.

D Cost-Benefit Analysis

D.1 Valuing the Mental Health Benefits of Reskilling

To quantify the mental health benefits of reskilling, we focus on the effects of depression among injured workers and their partners. Our valuation includes both the cost of antidepressant medication and the monetized value of changes in Quality-Adjusted Life Years (QALYs).

We begin by estimating the annual out-of-pocket cost of antidepressants (ATC-code N06A). Using data from the Danish Medicines Agency, we compute the average price per Defined Daily Dose (DDD) within each detailed ATC category.[12] We multiply the average price per DDD by 365 to obtain the yearly cost of each type of medication. To isolate private costs, we apply official reimbursement thresholds from the Danish Medicines Agency[13] and include only the co-pay amounts borne by patients.

We use our dynamic triple-difference estimates to quantify the effect of reskilling on antidepressant use (Figure 2, Panel (ii)). We extrapolate the final post-treatment estimates (captured at "Placement") forward to the statutory retirement age of 65 and calculate present-discounted values using an annual real interview rate of 6%. To account for the presence of partners, we weight partner-level effects by the share of injured workers with partners in our data (72%).

To value QALY losses from depression, we use the lower bound estimate of 0.20 QALYs per year from Jia et al. (2015). We assign a monetary value of $100,000 per QALY, which lies in the mid-range of estimates in the literature (Neumann, Cohen, Weinstein, et al. (2014)).[14]

Finally, to assess the robustness of our conclusions, Table D.1 presents cost-benefit results under alternative QALY valuations. We consider $50,000 (a conservative lower-

[12] The DDD is defined by the World Health Organization and adapted by the Danish Medicines Agency to standardize drug consumption metrics. A full list of prescription drug prices is available at `www.medicinpriser.dk`.

[13] `https://laegemiddelstyrelsen.dk/en/reimbursement/calculate-reimbursement/reimbursement-thresholds/`

[14] Institute for Clinical and Economic Review (2020) recommends a range of $50,000 to $200,000 per QALY.

bound), \$100,000 (our preferred estimate), and \$150,000 (a plausible upper-bound). Even under the most conservative valuation, mental health improvements account for 20% of the total net return to reskilling (Panel C, Columns (4) and (5)).

Table D.1: Costs and Benefits of Reskilling (PDV for Compliers and their Partners)

	Education costs	Labor Earnings		Mental Health		Total
		Injured Worker	Partner	Injured Worker	Partner	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. \$ per reskilled worker						
QALY Estimate						
\$50,000	-69,695	270,062	90,146	28,361	39,392	358,265
\$100,000	-69,695	270,062	90,146	56,019	77,806	424,338
\$150,000	-69,695	270,062	90,146	83,676	116,221	490,411
Panel B: Per \$ of education						
QALY Estimate						
\$50,000	-1.0	3.9	1.3	0.4	0.6	5.1
\$100,000	-1.0	3.9	1.3	0.8	1.1	6.1
\$150,000	-1.0	3.9	1.3	1.2	1.7	7.0
Panel C: Percent of total						
QALY Estimate						
\$50,000	-19.5	75.4	25.2	7.9	11.0	100.0
\$100,000	-16.4	63.6	21.2	13.2	18.3	100.0
\$150,000	-14.2	55.1	18.4	17.1	23.7	100.0

Notes: This table shows the sensitivity of our cost-benefit analysis in Table 2 to different assumptions about the value of a Quality-Adjusted Life Year (QALY). The table repeats the cost-benefit analysis in Table 2 with QALY values of \$50,000, \$100,000, and \$150,000. The table present discounted values of providing a higher degree for an injured worker of age 32, the average among the instrument compliers. *Education Costs* include tuition, reskilling benefits, and State Education Support (SU) for the injured workers. *Earnings* are the labor earnings of the injured worker and their partner. *Mental health effects* capture the monetized value of changes in QALYs as well as expenditures for medication for the injured worker and their partners. Appendix D details our approach to the cost-benefit calculations.