Supplemental Appendix

Changing Tracks:
Human Capital Investment after Loss of Ability

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A Variable Definitions

Table A.1: Variable Definitions

	Variable	Definition
Panel A. Demographics		
(1)	Age	Age by 31st of December.
(2)	Female	Dummy indicating the individual is registered as female.
(3)	Cohabiting	Dummy indicating married couples and couples co-habiting at the same address.
(4)	School-aged Children	Dummy indicating children aged 6-16 cohabiting with the parent.
(5)	Property Owner	Dummy indicating that the public cash valuation of property owned by the individual exceeds 0 DKK.
Panel B. Education		
(6)	Years of Schooling	Prescribed years of study associated with highest completed degree counting from grade 1.
(7)	Primary	Dummy indicating pre-school educations, primary education, preparatory courses, or Danish language courses at language centers as highest completed degree.
(8)	Vocational	Dummy indicating Vocational Education and Training (VET), qualifying educational programmes, or labor market educations (AMU) as highest completed degree.
(9)	High School	Dummy indicating upper secondary education as highest completed degree.
(10)	Post-Secondary	Dummy indicating short cycle higher education, vocational bachelors educations, bachelors-, masters-, or PhD programmes as highest completed degree.
Panel C. Employment		
(11)	Hours Worked	From 2008-2017: Yearly number of payed hours. From 1995-2007: Yearly labor income (12) divided by hourly wage rates (13).
(12)	Labor Income	Total labor market income, including bonuses, amenities, wages payed under sick- and parental leave, and employer contributions to pension saving schemes.
(13)	Hourly Wage	From 2008-2017: Yearly total labor income (12) 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.
(14)	Job Tenure	Number of years in a row where the main job in November is registered with the same firm identifier.
(15)	Labor Market Experience	Labor market experience measured in years since 1964.
(16)	Public Sector	Dummy indicating work within the public sector (measured by 2-digit industry codes)
(17)	Union Membership	Dummy indicating union membership. Measured by a positive deductible amount reported by the unions to the tax authorities.
(18)	Sick Leave	Share of weeks within a year where the individual (or the individual's employer) have received sickness benefit transfers.
Panel D. Wealth		
(19)	Debt-to-Income Ratio	"Debt" include debt to banks, pension funds, insurance- and finansial companies, credit card debt, and study loans in banks. "Debt" is then divided by labor income (12).
(20)	Savings-to-Income Ratio	"Savings" primarily covers liquid savings and include bank deposits, bond values, and value of mortgage deeds. "Savings" is then divided by labor income (12).
Panel E. Occupation		
(21)	Physical Ability Requirement	Average importance of Static Strength, Explosive Strength, Dynamic Strength, Trunk Strength, and Stamina, as measured by O*NET. Standardized.
(22)	Cognitive Ability Requirement	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. Standardized.
(23)	Injury Rate	Number of accepted (not necessarily compensated) work accidents per full time employee.
Panel F. Reskilling		
(24)	Access to Higher Education	Defined as having direct access to higher education, either through a high school diploma or a vocational degree. See section 4.1. for more details.
(25)	Travel Time to Higher Education	Shortest travel time in minutes (by car) from the zip code of residence to the zip code of the nearest training facility that offers a relevant higher degree. Travel times are measured as in Harmon (2015). We measure travel times seperately for the "Access" workers in "Craft", "Care", and "Other" educational groups. For workers without access, we impute their travel time as a weighted average of the aforementioned groups based on the zip code of residence.
Panel G. Injury		
(26)	Earnings Capacity Loss	Loss of earnings capacity in percent as assessed by The Labor Market Insurance (AES). See section 2.1.1. for more details.
(27)	Personal Impairment	Degree of personal impairment in percent based on injury diagnosis. See section 2.1.1. for more details.
(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.
Panel H. Primary school grades (at age 16)		
(29)	Overall GPA	Grade point average of all grades given in grade 9 (compulsory) and grade 10 (not compulsory). Normalized to lie between 0 and 100.
(30)	Math GPA	Grade point average of all grades given in the subject "Math" in grade 9 (compulsory) and grade 10 (not compulsory). Normalized to lie between 0 and 100.
Panel I. Educational outcomes		
(31)	Degree courses	Formal education programmes registered in the Education Register (UDDA)
(32)	Non-degree courses	Non-degree courses registered in the Course Participation Register (VEUV)
(33)	Basic	Include courses at Primary- (7) and High School (9) educational programmes.
(34)	Vocational	Include courses at Vocational (8) educational programmes.
(35)	Higher	Include courses at Post-Secondary (10) educational programmes.
(36)	Training Rate	Share of workers enrolling in a higher degree measured within six years after a work accident.
(37)	Participation (flow)	Enrollment in higher degrees in the given year.
(38)	Participation (stock)	Accumulated enrollment in higher degrees.
Panel J. Health outcomes		
(39)	No. of hospital visits	Number of visits to a hospital, both for admission, outpatient treatment, and ER visits.
(40)	Days in Hospital	Number of days hospitalized. For admitted patients, both the admission- and release date are recorded. Outpatient treatment and ER visits are coded as 1-day visits.
Panel K. Labor market outcomes		
(41)	Employed	Dummy indicating full-time work while simultaneously not being in School (42), being on Sick Leave (43) or receiving DI (44).
(42)	School	Enrollment in higher degree. Same as (37).
(43)	Sick Leave	Dummy indicating more than 15% of weeks within a year are spend receiving sickness benefit transfers (18).
(44)	DI	Dummy indicating any amount of weeks within a year spend receiving disability insurance.
(45)	Other	Residual dummy from (41)-(44). Mainly covers part-time work, other unemployment and non-participation.

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

B Work Accidents

This section describes the prevalence and incidence of workplace accidents and benchmarks the magnitudes to those of mass layoffs.

Table B.1 lists the five occupations with the highest rates of work accidents. Accidents predominantly occur in physically demanding jobs, such as building and construction. For example, among every 100 carpenters, about 1 to 2 suffer a workplace injury per year. Back injuries from fall accidents are the most common workplace injury.

Table B.1: Occupations with the Highest Accident Rates

Occupation	Injuries/	Most Common Injury	
	1000 FTEs	Event	Body Part
Carpenters	15.54	Fall Injury	Back, incl. spine
Elementary workers, n.e.c.	15.51	Fall Injury	Back, incl. spine
Joiners and carpenters, n.e.c.	15.08	Fall Injury	Back, incl. spine
Heavy truck and lorry drivers	13.47	Fall Injury	Back, incl. spine
Plumbers and pipe fitters	13.43	Fall Injury	Back, incl. spine

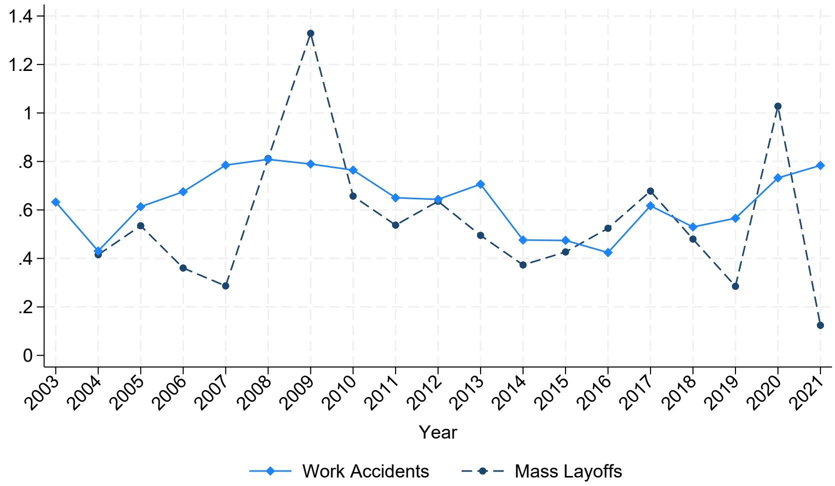
Notes: This table shows the five occupations (employing at least 10,000 full-time equivalents) with the highest rate of work accidents between 1996 and 2017. The table only includes accepted claims. The "Most Common Injury" columns report characteristics of the most common injuries that caused loss of earning capacity.

B.1 Benchmark to Mass Layoffs

Figure B.1 shows the time series of work accidents and mass layoffs in Denmark. The graphs are based on public data from the AES and the Danish Agency for Labour Market and Recruitment.

Every year, about 0.6% of workers in Denmark are injured in a work accident. For comparison, the risk of being displaced in a mass layoff is about 0.5% in a typical year. Mass layoffs are more pro-cyclical than work accidents.

Figure B.1: Work Accidents and Mass Layoffs per 100 Workers

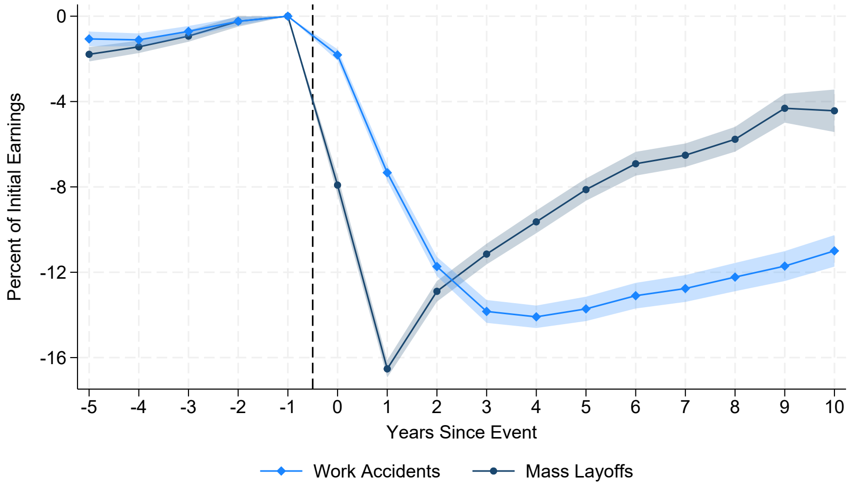


Notes: This figure shows the number of workers who experience a work accident or mass layoff in percent of the total employment in Denmark. The graphs are based on public data from the AES and the Danish Agency for Labour Market and Recruitment.

Figure B.2 compares the impacts of work accidents and mass layoffs on the earnings of workers. We measure mass layoffs in the micro-data following Davis and Von Wachter (2011); see Section B.1.1 for details. We use all work accidents that are accepted with compensation.

Work accidents cause more persistent earnings losses than mass layoffs. Ten years after the events, workers displaced in a mass layoff have recovered about 75% of the initial loss (from 16% to 4% of initial earnings). By contrast, injured workers barely recover any of their earnings losses.

Figure B.2: Labor Earnings around Work Accident vs. Mass Layoff



Notes: This figure compares the labor earnings of workers around work accidents and mass layoffs. Mass layoffs are defined as in Davis and Von Wachter (2011). We include all work accidents accepted with compensation. We match each injured/displaced worker to a control worker, following the procedure in Table 1. The graphs show the difference-in-differences in outcomes between the injured/displaced workers and their matches. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

B.1.1 Measuring Mass Layoffs

To measure mass layoffs in the micro-data, we follow Davis and Von Wachter (2011) and say that a worker is displaced in a mass layoff event if the worker separates from firm j in year t, and the following conditions are met:

1. Firm j had more than 50 employees in year t-*2*.
2. Employment at firm j contracts by 30-99 percent from t-*2* to t.
3. Employment at firm j in t-*2* is no more than 130 percent of employment in t-*3*.
4. Employment at firm j in t+*1* is less than 90 percent of employment in t-*2*.

C Human Capital Investment after Loss of Ability

C.1 Identification Strategy

Appendix Table C.1 shows how our sample restrictions shrink the analysis data. Columns (3) and (4) show that the restrictions do not affect the severity or earning capacity losses caused by the injuries considered in the analysis.

Table C.1: Work Accident Sample Reduction

Sample Step	Injury Events (1)	Distinct Individuals (2)	Injury Severity (3)	Earnings Cap. Loss (4)
1. All work accidents with ECL >0	31,129	30,693	12.84	36.18
2. Exclude psychological shock	29,875	29,482	12.77	35.86
3. Collapse to person-year	29,853	29,482	12.78	35.89
4. Person exists in register data	29,783	29,413	12.75	35.88
5. Full time employed before injury	14,623	14,510	12.52	36.57
6. Exclude Military Workers	14,481	14,369	12.45	36.63

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 1. For definitions of *earning capacity loss* (ECL), see Section I.A.

C.1.1 Robustness Analysis

Table C.2 shows that injured and non-injured workers are similar on a host of covariates when only matching workers' occupations.[1] The robust similarity between the "Injury" and "Match" workers supports the identifying assumption that work accidents are quasi-random within occupations such that workers with and without injuries are valid comparisons.[2]

Figure C.1 shows that the difference-in-differences estimates are robust to relaxing the covariates that the treatment and control workers are required to match on before the events. The robustness further corroborates that our baseline estimates identify the causal impacts of work accidents.

Figure C.2 shows that our estimates are also virtually identical when using the IPW method to find the non-injury match workers.

[1] Work accidents are more prevalent in physical occupations, cf. Table B.1.

[2] Altonji, Elder, and Taber (2005) and Oster (2019) provide conditions under which the similarity of workers on observables supports the quasi-exogeneity of work accidents.

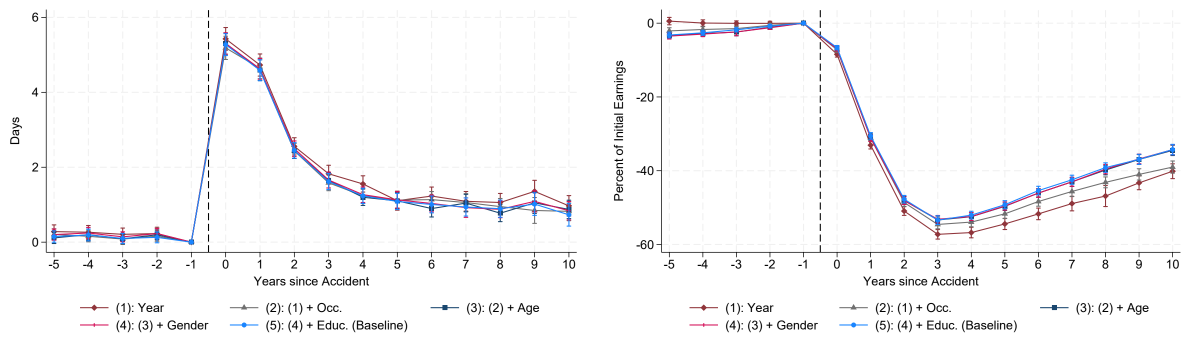
Table C.2: Worker Outcomes before Accident (Relaxing the Matching the Variables)

	Injury	No Injury				
		(1)	(2)	(3)	(4)	(5)
Panel A. Demographics						
Age	43.32	42.10	41.84	43.32	43.32	43.32
	(10.14)	(10.57)	(10.67)	(10.14)	(10.14)	(10.14)
Female (%)	39.16	44.71	38.06	38.11	39.16	39.16
	(48.81)	(49.72)	(48.55)	(48.57)	(48.81)	(48.81)
Cohabiting (%)	70.62	72.52	71.22	71.33	71.42	71.74
	(45.55)	(44.64)	(45.28)	(45.22)	(45.18)	(45.03)
School-aged Children (%)	33.47	32.18	31.67	32.04	32.32	32.17
	(47.19)	(46.72)	(46.52)	(46.67)	(46.77)	(46.72)
Property Owner (%)	58.57	63.82	59.90	61.43	61.67	61.63
	(49.26)	(48.05)	(49.01)	(48.68)	(48.62)	(48.63)
Panel B. Education						
Years of Schooling	12.85	13.86	12.94	12.93	12.90	12.91
	(2.63)	(2.87)	(2.92)	(2.90)	(2.91)	(2.56)
Primary (%)	31.54	19.69	28.38	28.01	28.77	31.54
	(46.47)	(39.77)	(45.08)	(44.91)	(45.27)	(46.47)
Vocational (%)	51.18	42.03	49.61	50.45	49.80	51.18
	(49.99)	(49.36)	(50.00)	(50.00)	(50.00)	(49.99)
High School (%)	1.60	4.65	2.76	2.67	2.65	1.60
	(12.53)	(21.07)	(16.39)	(16.11)	(16.07)	(12.53)
Post-Secondary (%)	15.68	33.62	19.25	18.88	18.78	15.68
	(36.36)	(47.24)	(39.43)	(39.14)	(39.05)	(36.36)
Panel C. Employment						
Hours Worked (Yearly)	1705.78	1731.18	1698.65	1725.68	1719.33	1739.58
	(531.57)	(1147.91)	(641.19)	(1140.94)	(1136.46)	(850.76)
Labor Income (1000 DKK)	377.40	432.95	376.79	381.94	379.80	380.96
	(126.45)	(239.26)	(145.50)	(149.12)	(139.10)	(142.02)
Hourly Wage (DKK)	236.80	257.35	232.27	230.01	228.36	229.71
	(171.44)	(188.40)	(224.65)	(138.86)	(123.94)	(125.28)
Job Tenure (Years)	3.62	4.02	3.91	4.03	3.99	4.02
	(3.22)	(3.43)	(3.38)	(3.47)	(3.45)	(3.45)
Labor Market Experience (Years)	19.53	19.50	19.59	20.64	20.62	20.76
	(9.33)	(9.78)	(9.61)	(9.39)	(9.39)	(9.37)
Public Sector (%)	30.07	25.95	30.07	30.07	30.07	30.07
	(45.86)	(43.84)	(45.86)	(45.86)	(45.86)	(45.86)
Union Membership (%)	91.11	82.34	89.02	89.32	89.70	89.77
	(28.46)	(38.14)	(31.26)	(30.89)	(30.39)	(30.31)
Panel D. Wealth						
Debt-to-Income Ratio (%)	28.49	22.87	24.22	23.33	23.78	23.71
	(27.35)	(25.27)	(25.64)	(25.31)	(25.23)	(25.44)
Savings-to-Income Ratio (%)	14.02	17.82	16.12	16.77	16.46	16.31
	(23.64)	(27.53)	(25.05)	(26.22)	(25.76)	(25.43)
Panel E. Occupation						
Physical Ability Requirement (Std.)	0.75	-0.06	0.72	0.72	0.72	0.71
	(0.93)	(1.10)	(0.92)	(0.92)	(0.92)	(0.92)
Cognitive Ability Requirement (Std.)	-0.39	0.07	-0.35	-0.36	-0.36	-0.37
	(0.84)	(0.94)	(0.87)	(0.86)	(0.87)	(0.86)
Injury Rate (x 1000)	10.35	5.69	10.04	10.04	10.04	10.08
	(5.03)	(4.93)	(4.87)	(4.77)	(4.96)	(4.94)
Panel F. Reskilling						
Access to Higher Education (%)	48.82	57.14	51.46	51.41	50.70	48.82
	(49.99)	(49.49)	(49.98)	(49.98)	(50.00)	(49.99)
Travel Time to Higher Education (Min.)	34.08	31.41	31.75	31.85	31.75	33.49
	(24.29)	(26.90)	(25.65)	(26.26)	(25.71)	(24.84)
Panel G. Injury						
Earnings Capacity Loss (%)	36.58	0.00	0.00	0.00	0.00	0.00
	(22.20)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Personal Impairment (%)	12.44	0.00	0.00	0.00	0.00	0.00
	(10.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year of Injury	2004.92	2004.92	2004.92	2004.92	2004.92	2004.92
	(4.84)	(4.84)	(4.84)	(4.84)	(4.84)	(4.84)
Match variables						
Year		✓	✓	✓	✓	✓
Occupation			✓	✓	✓	✓
Age				✓	✓	✓
Gender					✓	✓
Education						✓
Observations	14481	14481	14481	14481	14481	14481

Notes: This figure shows how the comparison of "Injury" and "No Injury" workers (Table 1) are affected by relaxing which covariates that workers are required to match on. Workers are one-to-one matched in the specified cells. Specification 1 matches workers on the year of the event. Specification 2 also matches workers on their occupation before the event. Specification 3 furthermore matches workers' age. Specification 4 furthermore matches workers' gender. Specification 5 (our baseline specification) also matches workers' level of education.

Figure C.1: Worker Outcomes around Accident (Relaxing the Matching Variables)

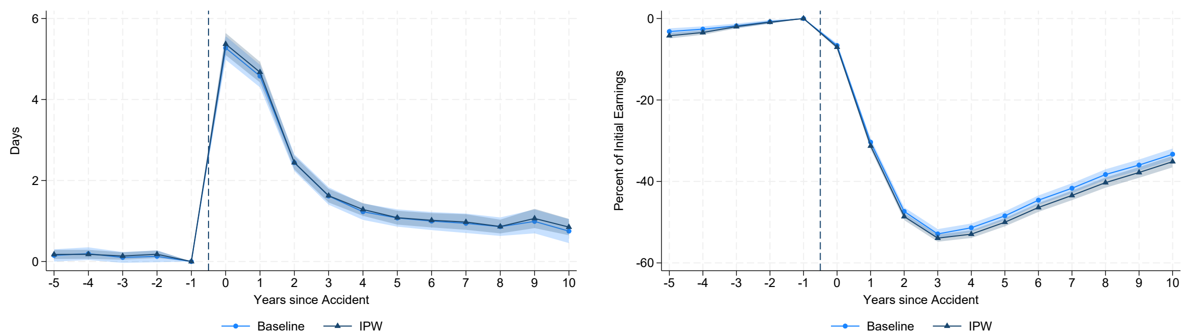
(a) Days in Hospital (b) Income



Notes: This figure shows how the difference-in-differences estimates of the impact of work accidents (Figure C.4) are affected by relaxing which covariates that injured and control workers are required to match on. Injured and control workers are one-to-one matched in the specified cells. Specification 1 matches workers on the year of the event. Specification 2 also matches workers on their occupation before the event. Specification 3 furthermore matches workers' age. Specification 4 furthermore matches workers' gender. Specification 5 (our baseline specification) also matches workers' level of education.

Figure C.2: Worker Outcomes around Accident (Comparison of Matching Methods)

(a) Days in Hospital (b) Income

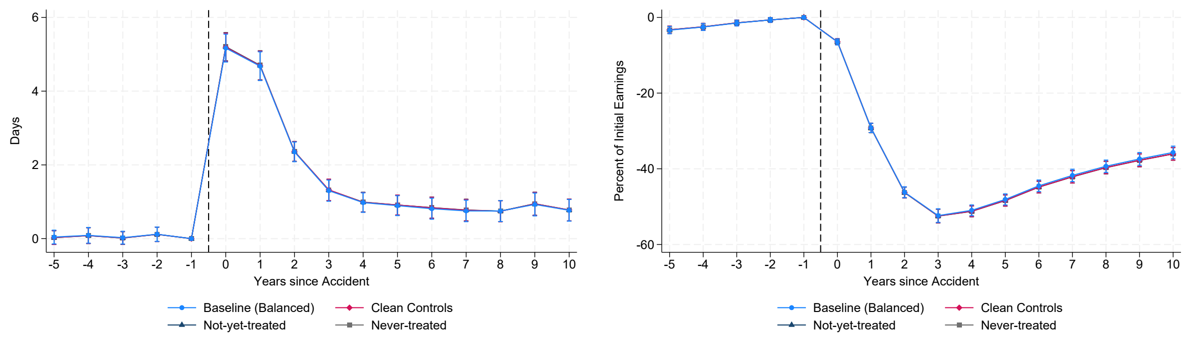


Notes: This figure shows how the difference-in-differences estimates of the impact of work accidents (Figure C.4) are affected by changing the matching method. *Baseline* refers to our specification in Figure C.4. *IPW* is based on an Inverse Probability Weighing (IPW) of the workers according to a logistic regression of injury on worker covariates (year of event, age, gender, occupation, industry, education, and access to higher education in the year before event). Appendix D.2 details the IPW procedure.

Figure C.3 verifies that our baseline estimates are virtually identical to the estimators of Callaway and Sant'Anna (2021), Sun and Abraham (2021), and De Chaisemartin and d'Haultfoeuille (2024) implemented on never-treated units. Finally, in our main analysis of human capital investment (Sections 4 and 5), we compare injured workers who differ in their access to education, where the non-injured match workers merely serve as placebo checks.

Figure C.3: Worker Outcomes around Accident (Comparison of Estimators)

(a) Days in Hospital (b) Income



Notes: This figure compares our baseline estimates (Figure C.4) with estimators that address identification issues that may arise in difference-in-differences designs when treatments are staggered (Gardner (2022); Roth et al. (2023); De Chaisemartin and d'Haultfoeuille (2023)). The estimators impose successively stricter requirements on the treatment and control groups. "Baseline (Balanced)" plots our baseline estimates on a balanced sample from years -5 to 10 (the event window). "Clean Controls" requires that control workers are not treated in the event window, corresponding to the specification in Cengiz et al. (2019). "Not-yet-treated" focuses on the first events of our treatment group and further requires that control workers are not treated before or during the event window, corresponding to the estimators developed in (Callaway and Sant'Anna (2021); De Chaisemartin and d'Haultfoeuille (2024)). "Never-treated" further requires that control workers are not treated throughout our data period, corresponding to the estimators developed in Callaway and Sant'Anna (2021), Sun and Abraham (2021), and De Chaisemartin and d'Haultfoeuille (2024).

C.2 Health and Income

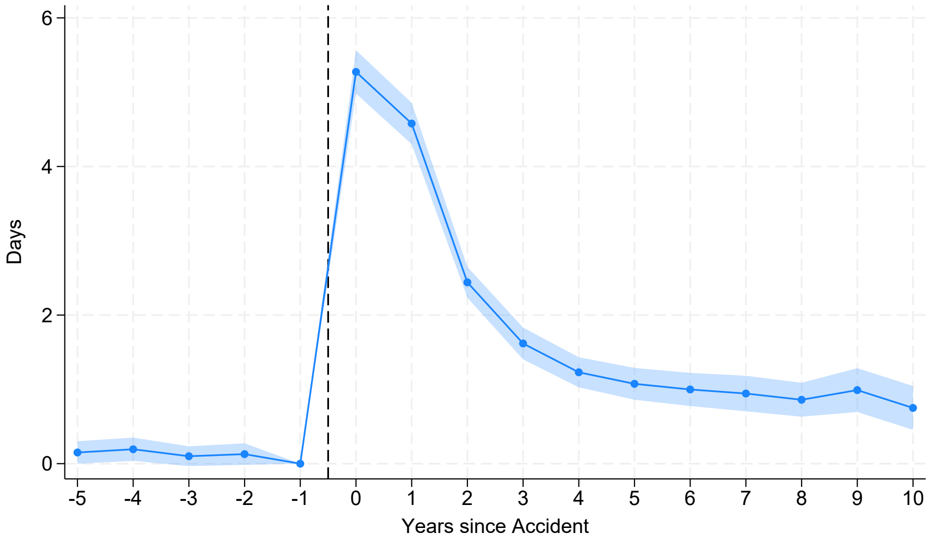
Figure C.4 shows the impact of work accidents on the health and income of workers.

The figure delivers four insights. First, before experiencing a work accident, workers have a similar evolution of health and earnings as other workers in their occupations. The flat pre-trends support the assumption that work accidents happen quasi-randomly within occupations. Second, work accidents severely shock workers' health, with days spent in hospital spiking for two years after the accidents. Third, work accidents cause persistent damage to workers, whose labor earnings suffer a persistent loss of about 40% (Panel (b)). Finally, although public transfers cover some of the economic losses, work accidents are a severe shock to the well-being of workers. After the accidents, workers' labor income (including transfers) decreases by about 30%.

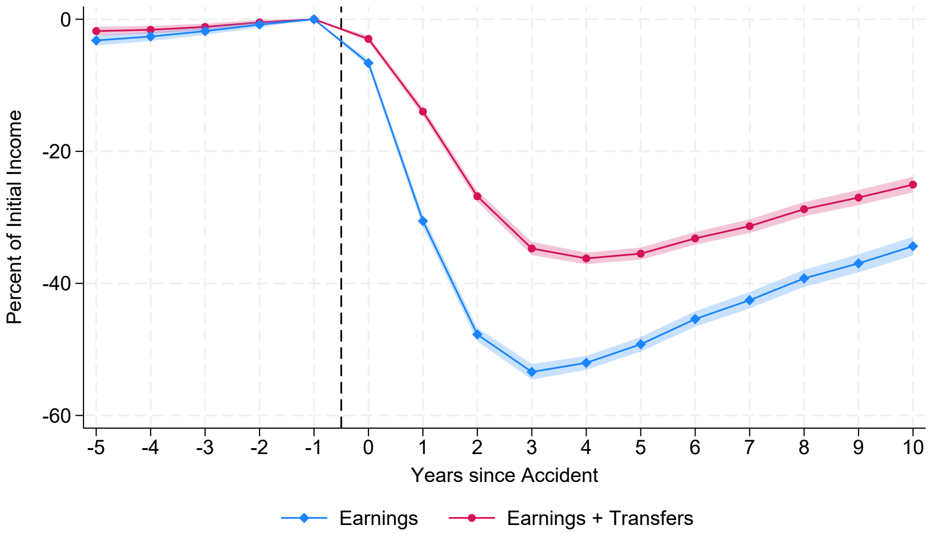
Figure C.5 splits the transfers by program. The figure shows that sickness benefits spike right after the injury, then rehabilitation benefits become relevant in an intermediate period, before DI becomes the dominant program over time.

Figure C.4: Worker Outcomes around Accident

(a) Days in Hospital

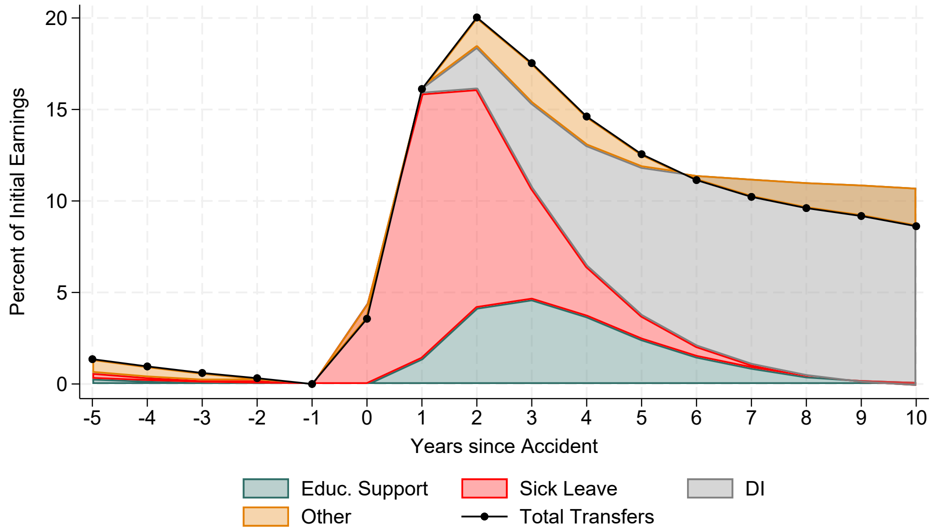


(b) Income



Notes: This figure shows the difference-in-differences in outcomes (measured relative to year -1) between the "Injury" and "Match" workers from Table 1. Shaded areas represent 95% confidence bands, estimated using the regression equation (1). Panel (a) shows the days spent in the hospital, and Panel (c) shows the labor income measured in percent of the average level in year -1.

Figure C.5: Receipt of Public Transfers around Accident

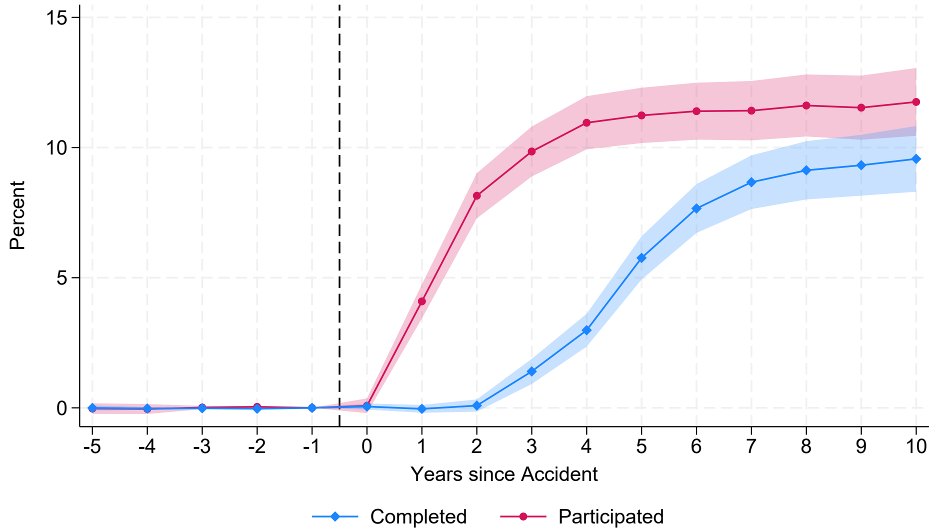


Notes: This figure splits the effect of work accidents on the receipt of transfers by public programs. *Educ. Support* is reskilling benefits and SU, *Sick Leave* is sickness benefits, *DI* is disability insurance, and *Other* only includes transfers and is mostly unemployment insurance. The figure shows the difference-in-differences in outcomes (measured relative to year -1) between the "Injury" and "Match" workers from Table 1.

C.3 Results

Figure C.6 shows the participation and completion of higher degrees around work accidents. More than 80% of injured workers who pursue higher education also complete their degrees. The completion rate among injured workers is similar to the average rate in the student population. In particular, the average completion rate of full-time students in bachelor's degrees is 81% in Denmark and 78% in the United States OECD (2023, Table A9.1).

Figure C.6: Pursuit of Higher Degrees around Work Accident



Notes: This figure shows the participation and completion of higher degrees around work accidents. The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show the difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 1, indexed to year -1. Shaded areas represent 95% confidence bands.

Table C.3 and Figure C.7 show that the slight imbalances for job tenure (in Table 1) and pre-trends for vocational degrees (in Figure 1) disappear if we exclude recent vocational graduates.

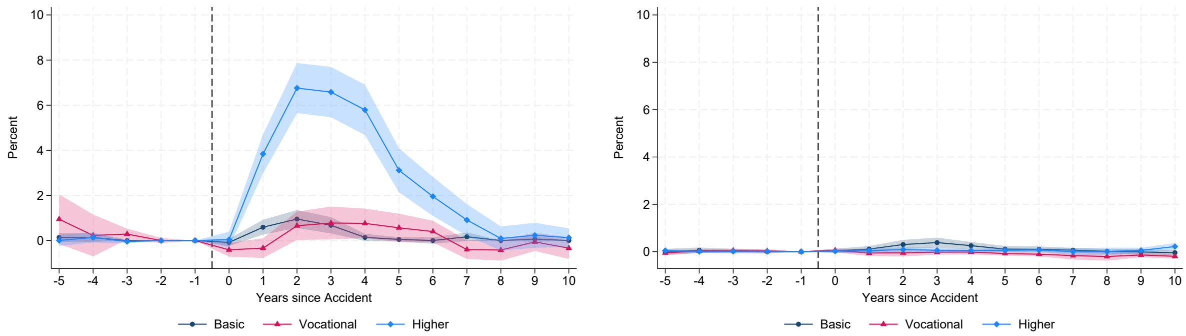
Table C.3: Worker Outcomes before Accident (Excluding Recent Vocational Graduates)

	No Injury	Injury	
	Match	Baseline	Fulltime with pre-degree
Panel A. Demographics			
Age	43.32	43.32	44.98
	(10.14)	(10.14)	(9.59)
Female (%)	39.16	39.16	47.59
	(48.81)	(48.81)	(49.94)
Cohabiting (%)	71.74	70.62	72.03
	(45.03)	(45.55)	(44.89)
School-aged Children (%)	32.17	33.47	33.40
	(46.72)	(47.19)	(47.17)
Property Owner (%)	61.63	58.57	59.35
	(48.63)	(49.26)	(49.12)
Panel B. Education			
Years of Schooling	12.91	12.85	12.91
	(2.56)	(2.63)	(2.66)
Primary (%)	31.54	31.54	29.64
	(46.47)	(46.47)	(45.67)
Vocational (%)	51.18	51.18	50.53
	(49.99)	(49.99)	(50.00)
High School (%)	1.60	1.60	1.57
	(12.53)	(12.53)	(12.42)
Post-Secondary (%)	15.68	15.68	18.27
	(36.36)	(36.36)	(38.64)
Panel C. Employment			
Hours Worked (Yearly)	1739.58	1705.78	1729.03
	(850.76)	(531.57)	(494.55)
Labor Income (1000 DKK)	380.96	377.40	379.76
	(142.02)	(126.45)	(126.19)
Hourly Wage (DKK)	229.71	236.80	230.30
	(125.28)	(171.44)	(177.34)
Job Tenure (Years)	4.02	3.62	4.08
	(3.45)	(3.22)	(3.47)
Labor Market Experience (Years)	20.76	19.53	20.63
	(9.37)	(9.33)	(9.14)
Public Sector (%)	30.07	30.07	40.41
	(45.86)	(45.86)	(49.08)
Union Membership (%)	89.77	91.11	92.17
	(30.31)	(28.46)	(26.87)
Panel D. Wealth			
Debt-to-Income Ratio (%)	23.71	28.49	26.81
	(25.44)	(27.35)	(27.00)
Savings-to-Income Ratio (%)	16.31	14.02	15.00
	(25.43)	(23.64)	(24.42)
Panel E. Occupation			
Physical Ability Requirement (Std.)	0.71	0.75	0.86
	(0.92)	(0.93)	(0.94)
Cognitive Ability Requirement (Std.)	-0.37	-0.39	-0.32
	(0.86)	(0.84)	(0.85)
Injury Rate (x 1000)	10.08	10.35	10.38
	(4.94)	(5.03)	(4.87)
Panel F. Reskilling			
Access to Higher Education (%)	48.82	48.82	49.40
	(49.99)	(49.99)	(50.00)
Travel Time to Higher Education (Min.)	33.49	34.08	32.89
	(24.84)	(24.29)	(24.82)
Panel G. Injury			
Earnings Capacity Loss (%)	0.00	36.58	37.08
	(0.00)	(22.20)	(21.90)
Personal Impairment (%)	0.00	12.44	12.14
	(0.00)	(10.03)	(9.57)
Year of Injury	2004.92	2004.92	2005.30
	(4.84)	(4.84)	(5.06)
Observations	14481	14481	7790

Notes: This table shows how the sample of injured workers changes as we exclude recent vocational graduates. "No Injury - Match" column corresponds to the "No Injury - Match" column from Table 1, while the "Baseline" corrsponds to the "Injury" column of Table 1. "Fulltime with pre-degree" refers to injured workers who had the same 3-digit occupational code and the same highest completed degree in $year_k = -1, -2, -3$. Standard deviations are reported in parentheses.

Figure C.7: Participation in Courses around Accident (Excluding Recent Vocational Graduates)

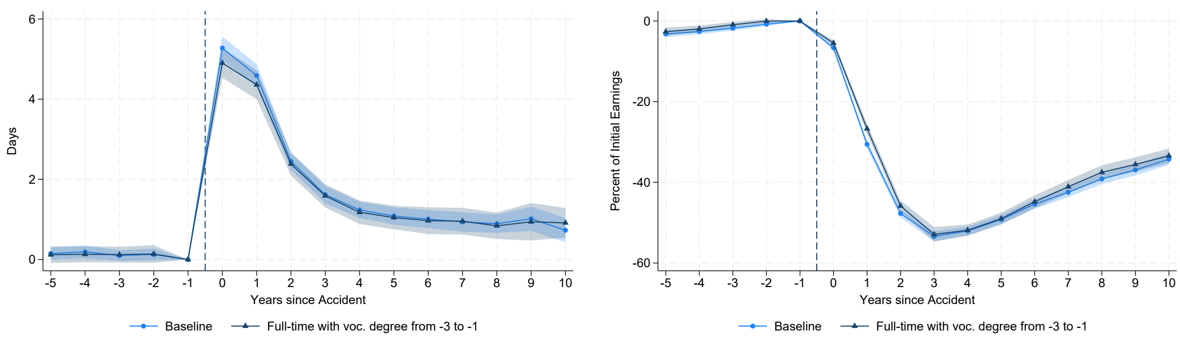
(a) Degree (b) Non-Degree



Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses by level of education. *Basic* is primary and high school (academic track), and *Higher* is all post-secondary education. The graphs show difference-in-differences in outcomes between the "Fulltime with pre-degree" and their "Match" workers from Table C.3, indexed to year -1. "Fulltime with pre-degree" refers to injured workers who had the same 3-digit occupational code and the same highest completed degree in $year_k = -1, -2, -3$. This figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. Shaded areas represent 95% confidence bands.

Figure C.8: Worker Outcomes around Accident (Excluding Recent Vocational Graduates)

(a) Days in Hospital (b) Income



Notes: This figure shows the difference-in-differences in outcomes (measured relative to year 1) between the "Baseline" and "Match" workers from Table C.3, and between the "Fulltime with pre-degree" and their "Match" workers from Table C.3. "Fulltime with pre-degree" refers to injured workers who had the same 3-digit occupational code and the same highest completed degree in $year_k = -1, -2, -3$. Panel (a) shows the days spent in the hospital, and Panel (c) shows the labor income measured in percent of the average level in year 1. Shaded areas represent 95% confidence bands.

C.3.1 Causal Effects of Reskilling

This section describes how we estimate the causal effects of reskilling in Figure 6.

We define reskilling $D_i \in \{0,1\}$ as pursuing a higher degree within ten years after the accident. We instrument reskilling with workers' access to higher education $A_i \in \{0,1\}$ upon injury. The second-stage regression relates the outcomes Y_{it} of workers after injuries to their reskilling choices. The two-stage least squares (2SLS) specification reads

$$D_i = \beta_{10} + \beta_{11} A_i + \varepsilon_i \tag{1}$$

$$Y_{it} = \beta_{0k}^Y + \beta_{1k}^Y \widehat{D}_i + \varepsilon_{it}^Y \quad \text{if} \quad t = e + k, \tag{2}$$

where β_{1k}^Y identifies the causal effect of reskilling on the outcomes of compliers in year k after their injuries. We estimate Equations (1)-(2) on a balanced sample, weighing the workers as in the "IPW" column of Table 2. Finally, we impose non-negativity constraints on the underlying potential outcomes (following Imbens and Rubin (1997)), which also ensures that Figure 6 corresponds to the exact difference between Panels (a) and (b) of Figure F.1.

C.4 Heterogeneity

C.4.1 Initial Education

This section studies the human capital responses to work accidents by workers' initial levels of education. Figure C.9 shows the plots separately for each initial level of education, and Table C.4 provides an overview of the accumulated effects.

Human capital investments are made overwhelmingly by workers with direct access to higher education. For example, ten years after the work accidents, two-thirds of the total impact on the completion of higher degrees is driven by the one-third of workers who initially had direct access to higher education.

Table C.4: Human Capital Investment by Educational Background of Workers

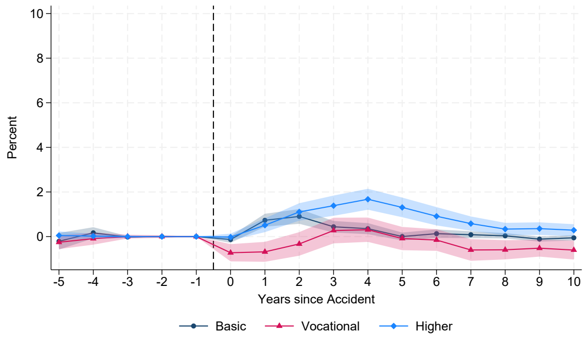
		Accumulated Participation (FTE, Diff-in-Diff, Year +10)					
		Degrees			Courses		
	Percent of Injuries	Basic	Vocational	Higher	Basic	Vocational	Higher
Primary	31.5	0.021	-0.009	0.019	0.009	-0.002	0.000
		(0.003)	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)
Vocational							
without Access	19.6	0.038	0.012	0.031	0.012	0.001	0.011
		(0.005)	(0.008)	(0.006)	(0.003)	(0.002)	(0.006)
with Access	31.5	0.024	0.018	0.107	0.010	-0.001	0.002
		(0.003)	(0.005)	(0.007)	(0.002)	(0.002)	(0.002)
Secondary	1.6	-0.018	0.006	0.099	0.024	0.003	-0.006
		(0.018)	(0.034)	(0.040)	(0.010)	(0.006)	(0.008)
Post-Secondary	15.6	0.005	0.005	0.037	0.012	0.001	-0.004
		(0.003)	(0.004)	(0.008)	(0.003)	(0.001)	(0.006)

Notes: This table shows the completion of education (measured in full-year equivalents) ten years after work accidents. The estimates are the difference-in-differences in outcomes (measured relative to year -1) between the "Injury" and "Match" workers from Table 1, estimated using the regression equation (1). Standard errors are reported in parentheses.

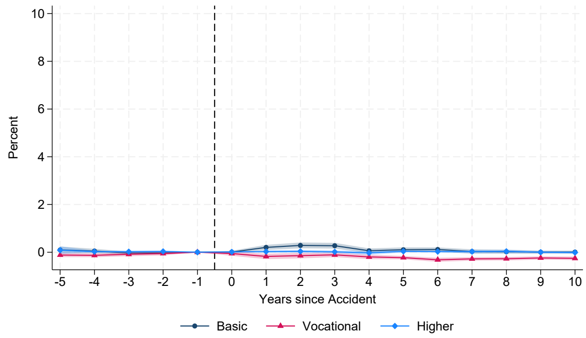
Figure C.9: Human Capital Investment by Educational Background of Workers

(a) Initial Attainment: Primary School

Degree

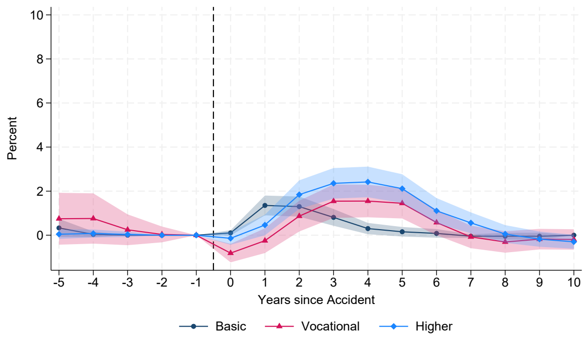


Non-Degree

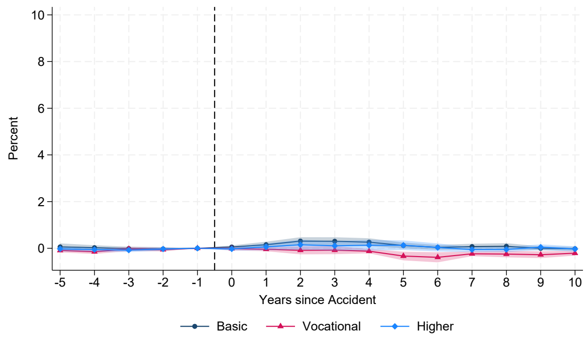


(b) Initial Attainment: Vocational Degree without Access to Higher Education

Degree

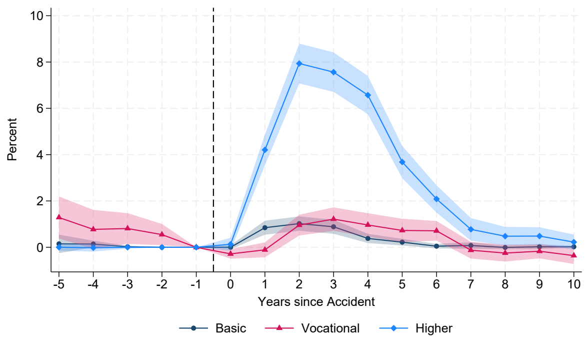


Non-Degree

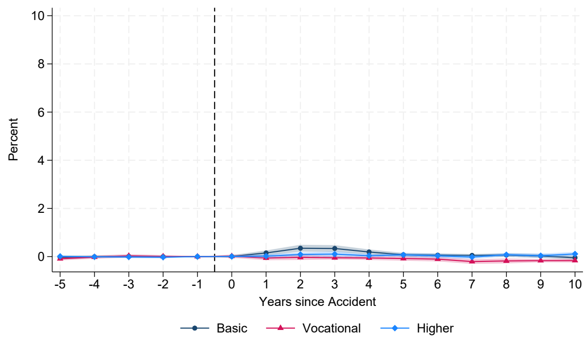


(c) Initial Attainment: Vocational Degree with Access to Higher Education

Degree



Non-Degree

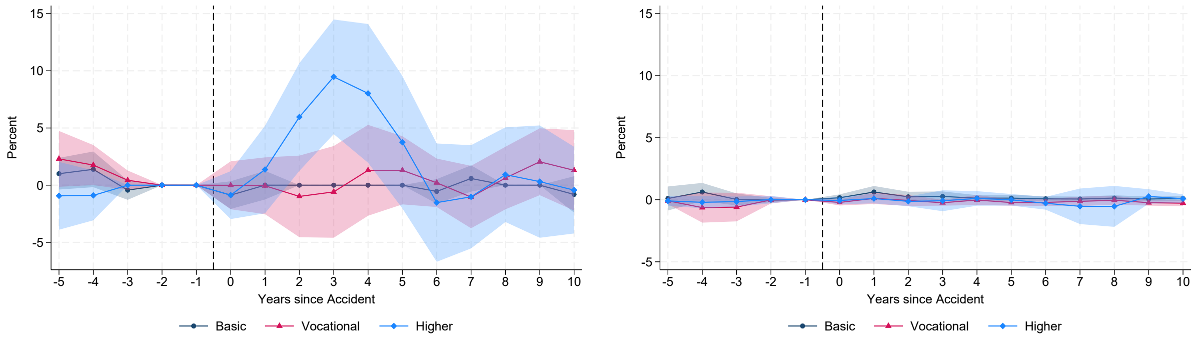


Notes: This table continues on the next page.

Figure C.9 (Cont.): Human Capital Investment by Educational Background of Workers

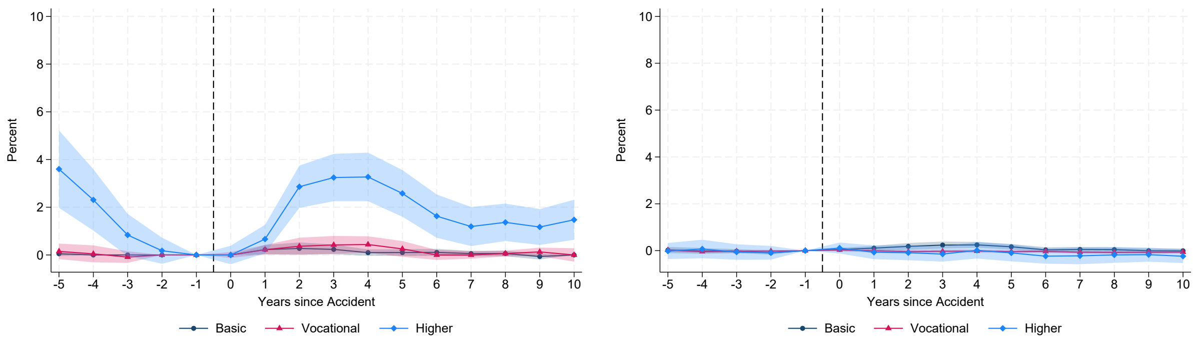
(a) Initial Attainment: High School

Degree | Non-Degree



(b) Initial Attainment: Post-Secondary Degree

Degree | Non-Degree



Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses, split by the worker's initial educational attainment. *Basic* is primary and high school, and *Higher* is all post-secondary education. The graphs show the difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 1, indexed to year -1. Shaded areas represent 95% confidence bands.

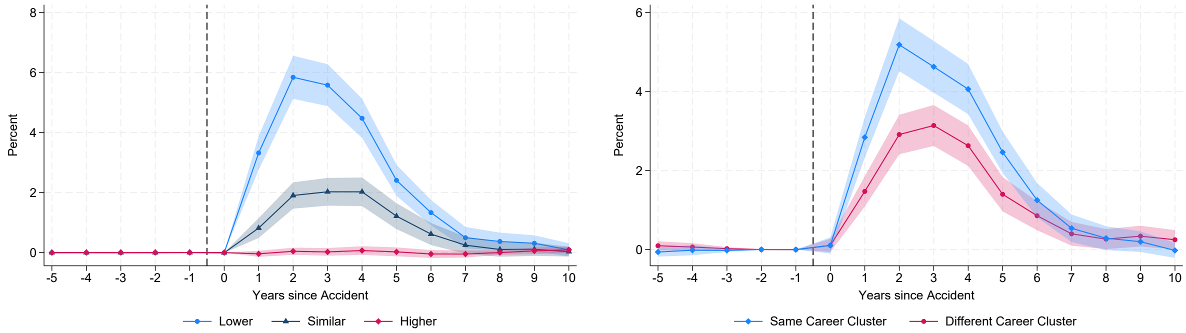
C.4.2 Program Types

Figure C.10 characterizes the types of higher degrees injured workers invest in. To do so, we link each degree to its target occupations, allowing us to compare the characteristics of the degrees to workers' initial jobs. Appendix I.1 explains the linking methodology.

Figure C.10.(a) shows workers invest in degrees that target occupations that are less physically demanding than their initial job. Figure C.10.(b) shows workers' investments target degrees that belong to the same *career cluster* as their original jobs. Career clusters are defined as *"occupations in the same field of work that require similar skills"* and developed by O*NET to help *"focus education plans towards obtaining the necessary knowledge, competencies, and training for success in a particular career pathway."* For example, carpentry and construction architecture belong to the career cluster *Architecture & Construction*. In particular, 65.7% of the human capital investments happen within these career clusters. For comparison, if the investments were unrelated to workers' career clusters, only 5.9% of them would occur within clusters.

Figure C.10: Investment in Higher Degrees by Similarity of Target vs. Initial Occupation

(a) Physical Intensity (b) Career Cluster

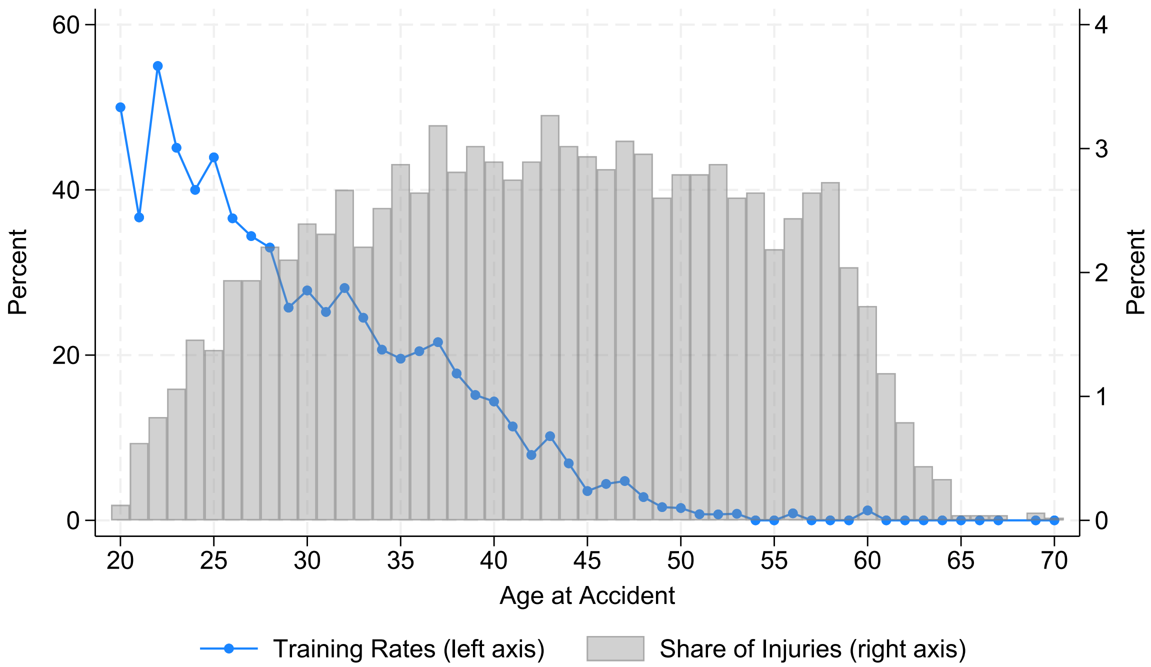


Notes: This figure shows participation in higher degrees according to the similarity between the worker's initial job and the higher degree's target occupation. *Physical Intensity* is *"performing general physical activities"* (O*NET). "Similar" degrees target occupations with physical intensities within ± 1 standard deviations of the worker's initial job. *Career Clusters* are *"occupations in the same field of work that require similar skills"* (O*NET). The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 1, indexed to year -1. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

C.4.3 Worker Characteristics

Figure C.11 studies how human capital investments vary by the age of the injured worker. Enrollment rates in higher degrees decrease steeply with age. In particular, workers older than 50 do not invest in higher education after work accidents. Jacobson, LaLonde, and Sullivan (2005) document a similar age gradient in the retraining decisions of displaced workers.

Figure C.11: Enrollment in Higher Degrees after Work Accident by Worker Age at Accident



Notes: The line shows the enrollment of workers in higher degrees (measured within six years after a work accident) according to each worker's age at the time of the accident. The histogram shows the distribution of work accidents by each worker's age at the time of the accident. The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education.

C.4.4 Nature of Accident

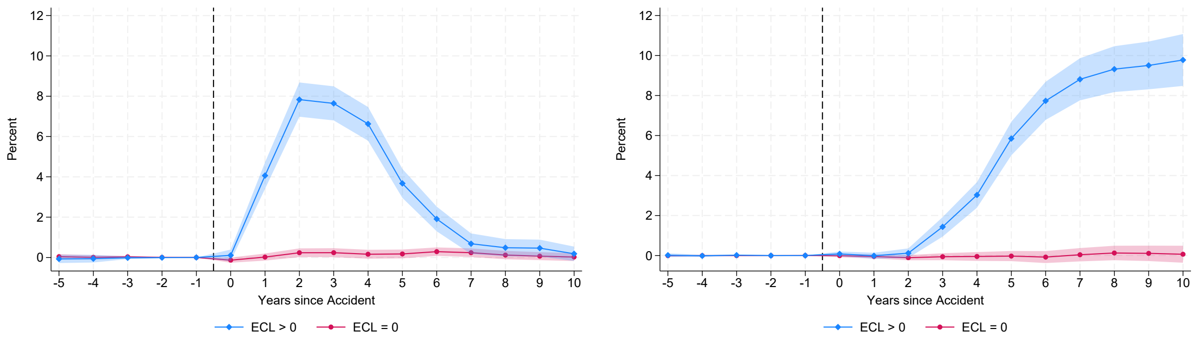
This section studies which accidents induce workers to reskill.

Figure C.12 splits the accidents by whether they cause an earning capacity loss (ECL). Work accidents *only* induce workers to reskill if they cause a loss of earnings capacity. Figure C.13 splits the work accidents by whether they cause *physical* or *cognitive* injuries (using diagnosis codes to identify permanent brain damage). Cognitive injuries are rare among work accidents.[3] Yet, zooming in on these rare events, Figure C.13 shows that workers do not invest in human capital after cognitive injuries.

[3]Head injuries constitute 6% of accidents, and 0.4% of accidents cause Post Concussion Syndrome (PCS), a typical brain damage diagnosis after accidents with symptoms that include persistent headaches, dizziness, and problems with concentration and memory, continuing after the normal recovery period of concussion.

Figure C.12: Pursuit of Higher Degrees by Earning Capacity Loss

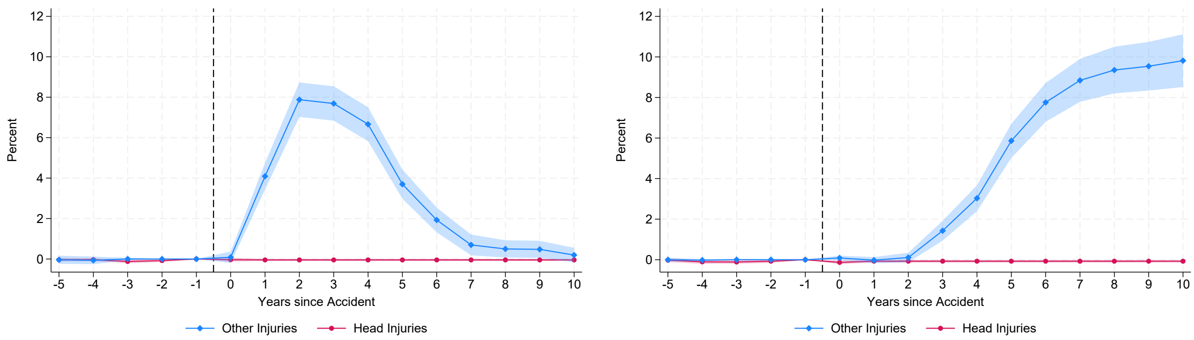
(a) Participation (b) Completion



Notes: The figure shows the participation in and completion of higher degrees around work accidents, split by whether the accidents generated an earning capacity loss (ECL). The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 1, indexed to year -1. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

Figure C.13: Pursuit of Higher Degrees by Injured Body Part

(a) Participation (b) Completion



Notes: The figure shows the participation in and completion of higher degrees around work accidents, split by whether the injury caused Post Concussion Syndrome (PCS). See Figure C.12 for notes on the regression specification.

D Effects of Reskilling

D.1 Access to Higher Education

This section characterizes vocational degrees and their access to higher education.

Table D.1 shows that injured workers whose vocational training provides access to higher education are about 70% craft workers (e.g., carpenters), 10% care workers (e.g., nurse assistants), 10% retail workers (e.g., sales assistants), and 10% food service workers (e.g., chefs).

For each of these occupational groups, Table D.2 lists the top vocational degrees with and without access to higher education. Column (2) shows that the degrees have similar injury rates, while Column (3) shows that the ones with access to higher education have substantially higher reskilling rates, especially among craft workers.

Table D.1: Share of Injuries and Reskilling by Educational Group (Vocational Degrees with Access to Higher Education)

	Share of Injuries (%)	Share of Reskilling (%)
Craft Workers	71.0	78.0
Care Workers	8.0	8.5
Other Workers	21.0	13.5
Retail	13.1	5.4
Food & Agriculture	7.9	8.0

Notes: This table shows the share of education groups among injured workers whose vocational education gives access to higher education. See Table for D.2 for the top-3 vocational degrees in each education group.

Table D.2: Reskilling Patterns by Vocational Degrees with and without Access to Higher Education

Group	Vocational Degree	Injury Rate (x1000)	Reskilling Rate (%)	Vocational Occupation	Top Reskilling Degree	Reskilling Occupation
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Craft Workers						
With Direct Access	Carpentry	13.5	24.4	7124 Carpenters and Joiners	Construction Architecture (BA)	3112 Civil Engineering Technicians
	Electrician	7.9	15.3	7137 Electrician Work	Service Engineering (AP)	3113 Electrical Engineering Technicians
	Welder	11.6	13.7	7222 Tool-makers and Related Workers	Production Technology (AP)	3000 Technicians, n.e.c.
Without Direct Access	Blacksmith	9.9	0.0	7221 Blacksmiths	-	-
	Technics and Mft.	10.4	2.2	9320 Mft. Labourers	Production Technology (AP)	3000 Technicians, n.e.c.
	Iron and Metal	13.3	0.0	9310 Mining and Construction Labourers	-	-
Panel B. Care Workers						
With Direct Access	Social-Health Assistant	11.4	14.5	5132 Care Work at Institutions	Social Worker (BA)	3460 Social Work Associates
	Pedagogical Assistant	10.5	10.5	5131 Childcare Work	Social Education (BA)	3320 Pre-Primary Education Teachers
Without Direct Access	Social-Health Helper	12.1	6.2	5132 Care Work at Institutions	Social Education (BA)	3321 Pre-Primary Education Teachers
	Carework	10.4	3.0	5132 Care Work at Institutions	Social Education (BA)	3322 Pre-Primary Education Teachers
Panel C. Other Workers						
With Direct Access	Retail, Groceries	6.3	6.4	5220 Salespersons and Demonstrators	Commerce Management (AP)	3140 Sales and Finance Work
	Chef	7.0	14.9	5122 Cooks	Nutrition & Technology (AP)	3000 Technicians, n.e.c.
	Nutrition Assistant	5.1	9.5	5122 Cooks	Nutrition & Technology (AP)	3000 Technicians, n.e.c.
Without Direct Access	Office "All Around"	2.6	1.7	4115 Secretary Work	Social Worker (BA)	3460 Social Work Associates
	Hairdresser	5.3	4.1	5141 Hairdressers, Barbers, etc.	Social Worker (BA)	3460 Social Work Associates
	Banking	2.1	5.4	4212 Tellers and Other Counter Clerks	Administrative Management (AP)	4115 Secretary Work

Notes: This table lists the top vocational degrees *with direct access* according to their share of total reskilling activity, and the top vocational degrees *without direct access* according to their share of total injuries. This table is based on injured workers with a vocational degree (w/wo direct access) as their highest completed degree prior to the work accident. Workers with direct access constitute 62% of all accidents and 81% of all reskilling activity. Injury rates are calculated as the yearly average of accepted workplace accidents reported by workers holding each vocational degree divided by the yearly average of full-time equivalent employees with the same vocational degree. Reskilling rates are calculated as the number of injured workers who reskill after injury divided by the total number of injured workers holding each degree. There exist short 1-year secondary education (high-school) programs tailored specifically for some post-secondary welfare degrees. This includes Social Worker (BA) and Social Education (BA), and this is likely the reason we find these as the top-most choices for workers without direct access to post-secondary programmes initially. The full list of vocational degrees with access to higher education is available at `www.andershumlum.com/s/access_list.xlsx`.

D.2 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:

$$p(\text{Access}_{ie-1} = 1) = \mu(X_{ie-1}), \tag{3}$$

where μ is a logistic link function, and X include first- and second-order terms of the variables listed in the "*Demographics*", "*Employment*", "*Education*", "*Occupation*", and "*Injury*" panel of Table 2. To be specific, X includes first- and second-order terms of age, hours worked, labor market income, hourly wages, job tenure, labor market experience, sickness benefits, physical- and cognitive ability requirements, occupational injury rates, earnings capacity loss, personal impairment, year of injury, and first-order terms of gender, cohabiting, having children of school age, owning property, working in the public sector (all of which are binary outcomes), and years of schooling.

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

$$w_i = \frac{\hat{p}(X_{ie-1})}{1 - \hat{p}(X_{ie-1})}. \tag{4}$$

We estimate the propensity scores separately by injury status and the education groups (craft, care, and other workers) defined in Table D.2. Table 2 validates that the IPW-weighted "No Access" workers are comparable to the "Access" group on the observables X.

D.3 Robustness Analysis

This section shows that our difference-in-difference estimates from Section 4 are robust to the inverse probability weighting (IPW) of the control group.

The key explanation for the robustness of the estimates is that we interact the access variation with the workplace accident events. In particular, although gender, years of schooling, etc., are correlated with the *levels* of outcomes before injuries, the key determinant of the *changes* in outcomes after injuries is workers' access to higher education.

D.3.1 Relaxing the Matching Variables

We first show that our estimates are robust to relaxing the set of covariates used in the IPW method. To do so, we reproduce our first-stage and reduced-form estimates, only balancing on the immediate severity of the injuries and whether the workers are employed in the public sector.[4]

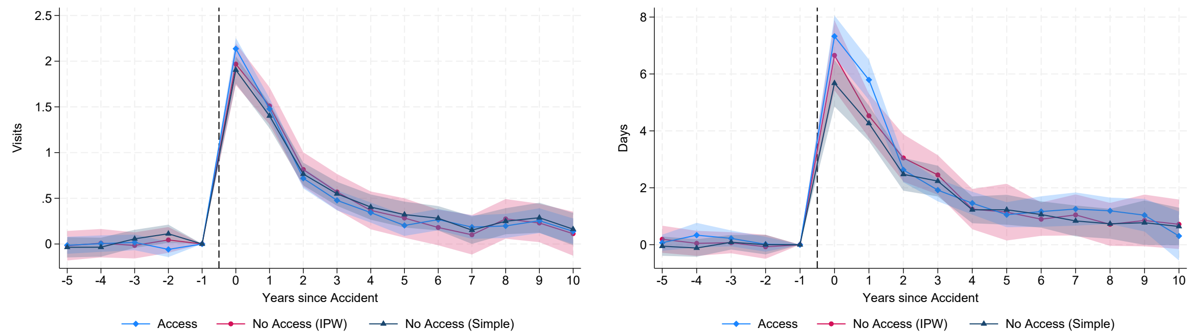
That is, we reweigh the "No Access" workers based only on the hospitalization (number and days of visits) in the year of the accident and an indicator for working in the public sector in the year before the accident (X in Equation (3)). We call this specification "No Access (Simple)". Figure D.1 confirms that the worker groups experience similar hospitalizations following their injuries.

Figure D.2 shows our main triple-difference estimates using either "No Access (IPW)" or "No Access (Simple)" as the control group. The figure shows that the first-stage and reduced-form results are robust to the IPW method. These results highlight our main conclusions for the effects of reskilling do not hinge on the specific reweighing of the "No Access" control group.

[4] The "No Access (Raw)" group experiences milder injuries than the "Access" workers, spending on average 4.5 additional days in the hospital in the year of the accident (instead of 7.5 additional days). So, to ensure we compare similar injuries, "No Access (Simple)" reweigh the control group based on the hospitalization in the year of the accident. In addition, our "Access" group of craft workers is more likely to be employed in the private sector. Hence, because public sector employees face better job security immediately following work accidents, we also reweigh the control group based on whether workers were employed in the public sector.

Figure D.1: Hospitalization around Accident

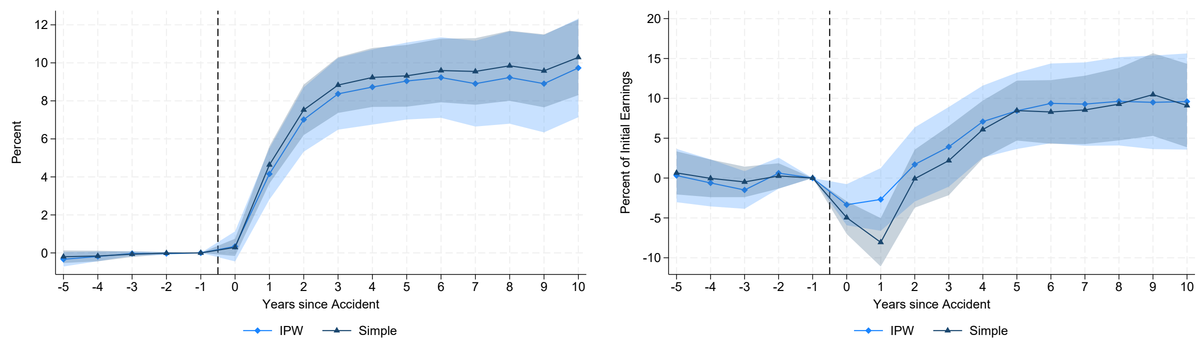
(a) Number of Hospital Visits | (b) Days in Hospital



Notes: This figure shows the hospitalization of workers split by whether the workers have access to higher education upon injury. The first two lines correspond to the "Access" and "No Access, IPW" columns of Table 2. The last lines reweigh the "No Access" workers only based on the hospitalization (number and days of visits) in the year of the accident and an indicator for working in the public sector in the year before the accident. The graphs show difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 1, indexed to year -1. Shaded areas are 95% confidence bands.

Figure D.2: Outcomes around Work Accident (Triple Differences)

(a) Participated in Higher Degree | (b) Labor Earnings



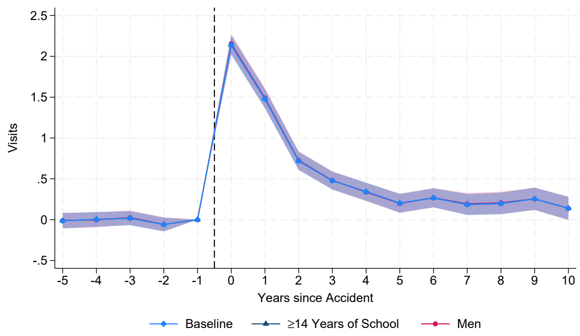
Notes: This figure shows the outcomes of workers around work accidents according to workers' initial access to higher education. The plots are triple differences, where the first difference is between the "Access" and "No Access" workers ("IPW" and "Simple", respectively), the second difference is between the "Injury" and "No Injury" workers, and the third difference is indexed to year -1. Shaded areas represent 95% confidence bands.

D.3.2 Stratification

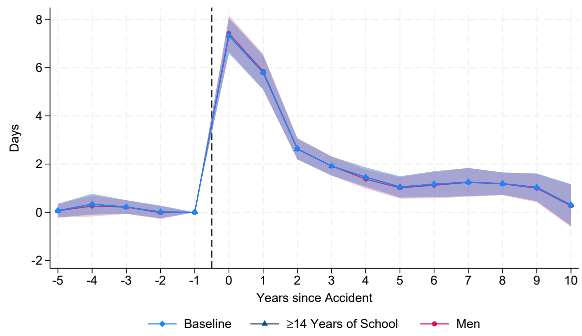
Figures D.3-D.4 show that our results hold when we restrict to our main strata in terms of gender and years of schooling. Put differently, our results are not driven by having women or less-educated workers in the "No Access" group.

Figure D.3: Hospitalization around Accident

(a) Number of Hospital Visits



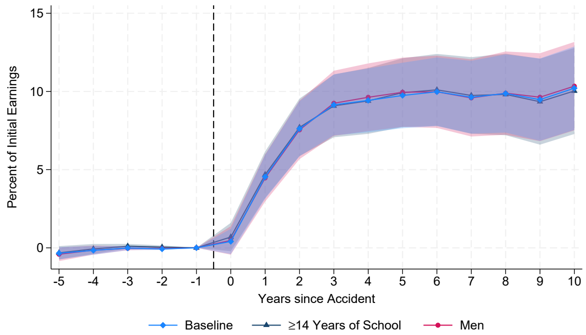
(b) Days in Hospital



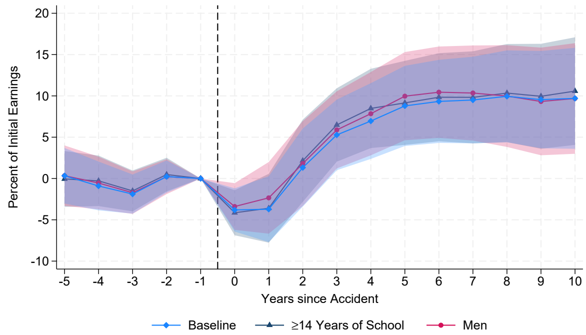
Notes: This figure shows the hospitalization of workers around work accidents. *Baseline* corresponds to the "Access" line in Figure 3.(a). The next two lines focus the sample on our main strata. The line $\geq$ *14 Years of School* focuses on the workers with at least 14 years of prior schooling. The line *Men* focuses on male workers. The graphs show difference-in-differences in outcomes between the "Injury" and "No Injury, Match" workers from Table 1, indexed to year -1. Shaded areas are 95% confidence bands.

Figure D.4: Outcomes around Work Accident (Triple Differences)

(a) Participated in Higher Degree



(b) Labor Earnings



Notes: This figure shows the difference in outcomes of workers around work accidents according to workers' initial access to higher education. *Baseline* corresponds to our main specification in Figure 5.(b). The next two lines focus the sample on our main strata. The line $\geq$ *14 Years of School* focuses on the workers with at least 14 years of prior schooling. The line *Men* focuses on male workers. The plots are triple differences, where the first difference is between the "Access" and "No Access (IPW)" workers, the second difference is between the "Injury" and "No Injury, Match" workers (from Table 1), and the third difference is indexed to year -1. Shaded areas represent 95% confidence bands.

D.4 Placebo Checks

This section provides placebo checks of whether workers with and without access to higher education are valid comparison groups.

Table D.3 shows that workers with and without access to higher education were similar at age 16, the time at which they decided on their vocational specializations.

Table D.4 shows that workers with and without access to higher education experience similar types of detailed injuries.

Figure D.5 shows that workers with and without access to higher education experience had similar earnings-experience profiles before the accidents.[5]

Figure D.6 shows that workers with and without access to higher education experience fare similarly in the labor market after temporary injuries that do not induce them to reskill.

Figure D.7 shows that older workers (who do not invest in human capital despite being eligible) with and without access to higher education experience fare similarly after work accidents.

[5] The "No Access (Raw)" workers have lower earnings, as documented in Table 2.

Table D.3: Worker Outcomes at Age 16

	Access	No Access		Std. Diff
		Raw	IPW	Access - IPW
Panel A. Primary school grades				
Overall GPA (0-100)	50.76	50.77	51.77	-10.6%
	(8.95)	(10.57)	(9.93)	
Math GPA (0-100)	54.57	49.64	53.92	5.3%
	(10.14)	(12.83)	(14.03)	
Panel B. Employment				
Employed (%)	76.86	68.87	73.43	8.0%
	(41.37)	(46.37)	(44.18)	
Labor Income (1000 DKK)	38.12	29.56	33.58	15.3%
	(30.17)	(27.19)	(29.04)	
Panel C. Parental Education				
Years of Schooling	11.54	11.31	11.54	-0.2%
	(2.69)	(2.82)	(2.77)	
Primary (%)	27.55	31.58	27.89	-0.8%
	(44.68)	(46.54)	(44.87)	
Vocational (%)	54.58	50.53	54.60	0.0%
	(49.77)	(50.06)	(49.82)	
High School (%)	0.75	0.53	0.50	3.4%
	(8.20)	(7.25)	(6.83)	
Post-Secondary (%)	16.26	16.32	16.49	-0.6%
	(36.95)	(37.00)	(37.11)	
Panel D. Parental Employment				
Labor Income (1000 DKK)	366.20	353.00	362.40	1.9%
	(212.88)	(186.89)	(185.60)	
Both Employed (%)	67.08	62.89	66.94	0.3%
	(46.95)	(48.37)	(47.07)	
At Least One Employed (%)	92.93	89.47	94.57	-6.9%
	(25.28)	(30.73)	(22.58)	
Panel E. Parental Wealth				
Debt-to-Income Ratio (%)	35.27	36.09	35.67	-1.1%
	(35.98)	(34.24)	(34.89)	
Savings-to-Income Ratio (%)	17.37	17.74	17.01	1.0%
	(36.89)	(37.29)	(36.80)	
Observations	1079	436	436	

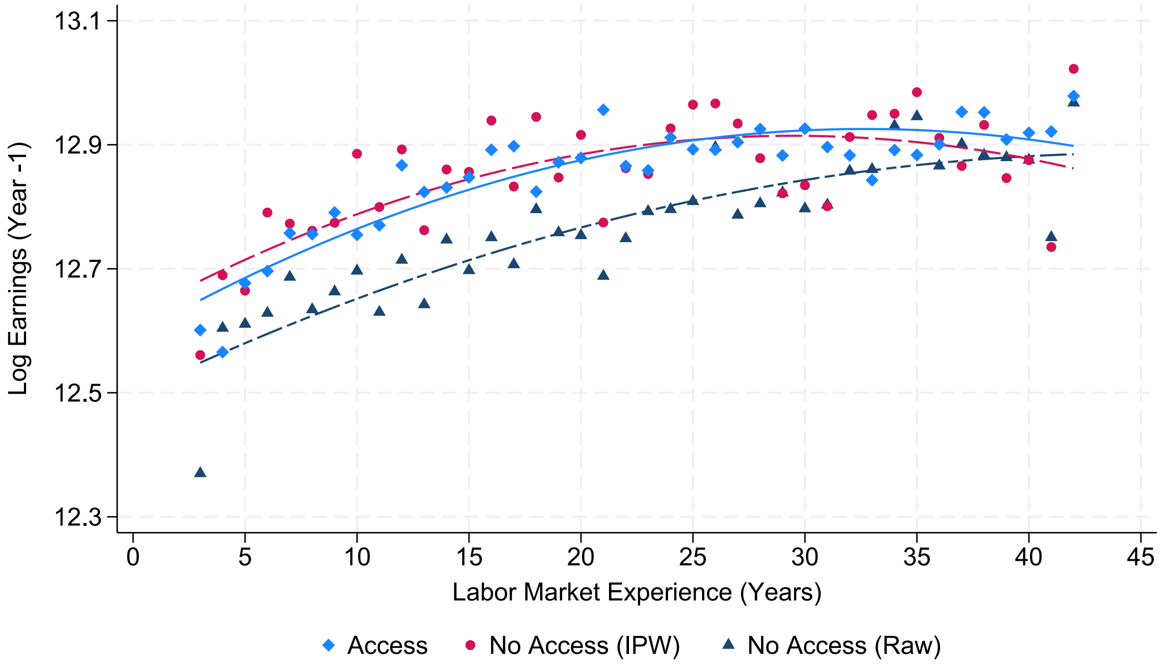
Notes: This table shows the characteristics of workers at age 16, the time at which they decided on their vocational training. The table has fewer observations than Table 2 because primary school grades are only observed for workers who graduated after 2002. Standard deviations are in parentheses. The "Access" column shows workers eligible for a higher degree (but have not attained one). 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 D.2 details the IPW procedure. The "Std. Mean Diff" column shows the standardized mean difference between the "Access" and "IPW" workers with absolute values above 25% indicative of imbalance (Stuart and Rubin (2008)).

Table D.4: Injury Characteristics by Access Group

	Access	No Access		Std. Diff.
		Raw	IPW	Access - IPW
Panel A. Body Part (%)				
Head	5.60	6.47	6.54	-3.9%
	(22.97)	(24.60)	(24.70)	
Neck	5.87	6.50	6.18	-1.3%
	(23.39)	(24.67)	(24.07)	
Back	33.49	36.81	33.84	-0.7%
	(47.08)	(48.24)	(47.20)	
Torso	3.66	2.99	2.71	5.4%
	(18.73)	(17.03)	(16.25)	
Upper Extremities	25.55	24.37	23.30	5.2%
	(43.60)	(42.94)	(42.28)	
Lower Extremities	17.32	14.24	17.36	-0.1%
	(37.49)	(34.95)	(37.77)	
Multiple Body Parts	6.33	7.21	7.95	-6.3%
	(24.31)	(25.87)	(27.06)	
Other/Unknown	2.19	1.41	2.12	0.5%
	(14.60)	(11.78)	(14.36)	
Panel B. Injury Event (%)				
Contact with Dangerous Matter	0.96	0.63	0.96	0.0%
	(9.57)	(7.93)	(9.62)	
Suffocation	0.02	0.04	0.01	1.6%
	(1.25)	(1.88)	(0.50)	
Falling	36.84	29.61	32.73	8.7%
	(47.65)	(45.66)	(46.64)	
Collision	12.81	12.73	15.22	-7.0%
	(33.29)	(33.34)	(35.86)	
Cutting	4.23	3.41	4.15	0.4%
	(19.83)	(18.15)	(19.75)	
Crushing	2.04	1.69	2.94	-5.8%
	(14.04)	(12.88)	(16.72)	
Acute Physical Strain	29.55	37.13	30.91	-3.0%
	(44.60)	(48.32)	(45.71)	
Violence (from humans or animals)	1.12	2.18	1.36	-2.3%
	(9.34)	(14.61)	(11.03)	
Other/Unknown	12.43	12.59	11.72	2.2%
	(32.97)	(33.18)	(32.17)	
Observations	4568	2844	2844	

Notes: This table shows the characteristics of accidents (affected body part and cause of injury events, as assessed by AES) by workers' access to higher education. Standard deviations are in parentheses. 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)).

Figure D.5: Earnings-Experience Profiles before Injury by Access to Higher Education

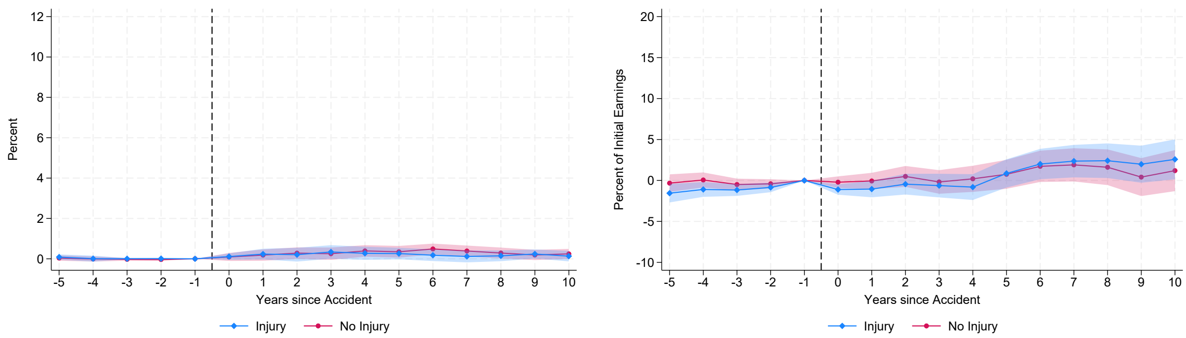


Notes: This figure shows the earnings-experience profiles of injured workers in the year prior to the accident, split by whether the workers have access to higher education upon injury. The plots correspond to the "Access", "No Access, IPW" and "No Access, Raw" columns of Table 2. The graph shows log labor market earnings as a function of log labor market experience with a corresponding quadratic fit for each group. The null hypothesis that the earnings-experience profiles are the same for the "Access" and "No Access, IPW" workers cannot be rejected (F-stat of 0.88, $p = 0.46$).

Figure D.6: Outcomes around Temporary Work Injuries (Placebo Check): "Access" – "No Access"

(a) Enrollment in Higher Degrees

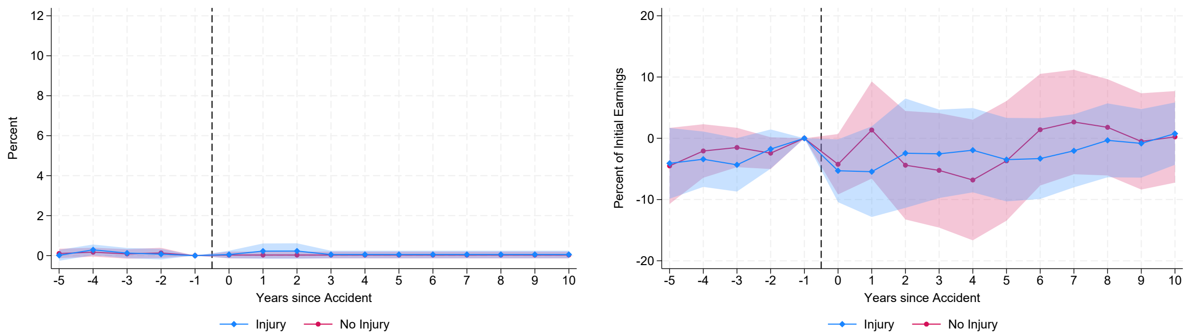
(b) Labor Earnings



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 plots show difference-in-differences between the "Access" and "No Access, IPW" workers, indexed to year -1. The figure focuses on craft workers. Panel (a) shows enrollment in higher degrees measured in full-time equivalents. Panel (b) shows labor earnings measured in percent of average earnings in year -1. Shaded areas represent 95% confidence bands, estimated using Equation (2).

Figure D.7: Outcomes around Work Accidents of Workers Age 55+ (Placebo Check): "Access" – "No Access"

(a) Enrollment in Higher Degrees (b) Labor Earnings



Notes: The figure restricts to workers above age 55. The plots show difference-in-differences between the "Access" and "No Access, IPW" workers from Table 2, indexed to year -1. The figure focuses on craft workers. Panel (a) shows enrollment in higher degrees measured in full-time equivalents. Panel (b) shows labor earnings measured in percent of average earnings in year -1. Shaded areas represent 95% confidence bands, estimated using Equation (2).

D.5 Results

This section shows additional results for the reduced-form effect of access to higher education on the outcomes after work accidents.

Figure D.8 shows that the access policy does not affect workers' take-up of other education. This motivates using enrollment in higher degrees as the treatment variable in Sections 4.2 and 5.

Figure D.9 shows that access to higher education does not influence workers' take-up of non-means-tested pensions.

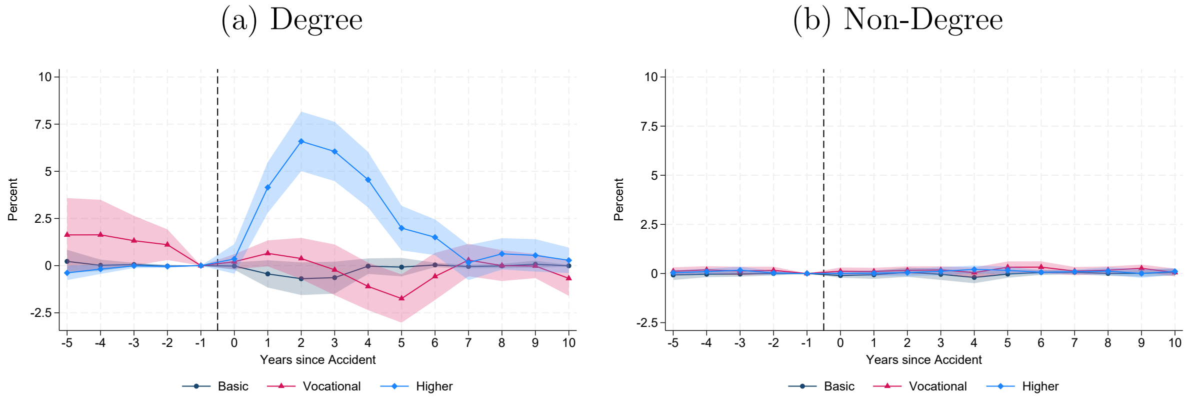
Figure D.10 shows that access to higher education does not influence school-related employment.

Figure D.11 shows that access to higher education does not affect future injury risk.

Figure D.12 shows that the positive effects of access to higher education on earnings are driven by workers who complete their degrees.

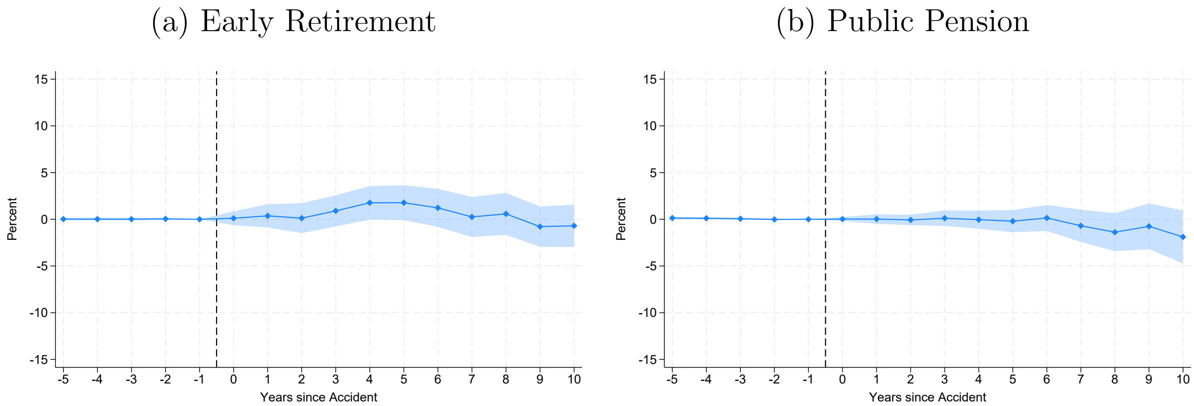
Table D.5 shows that injured reskilled workers earn similar amounts to recent graduates, despite being older and having accumulated more labor market experience outside their new occupation.

Figure D.8: Participation in Courses around Accident



Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses by level of education. *Basic* is primary and high school (academic track), and *Higher* is all post-secondary education. This figure focuses on craft workers. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 2), each measured relative to their "No Injury" matches, and indexed to year -1. The "No Injury" workers correspond to the "Match" column in Table 1. Shaded areas represent 95% confidence bands.

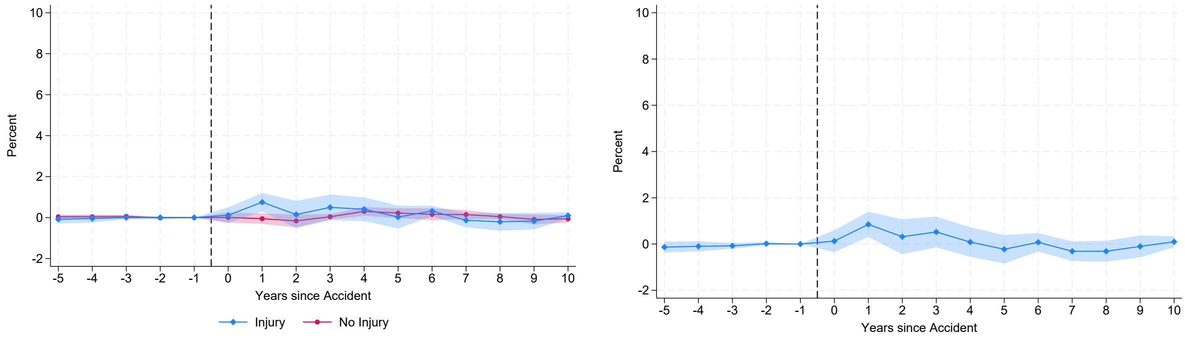
Figure D.9: Non-Means-Tested Pensions (Triple Difference)



Notes: This figure shows the receipt of pensions that are not means tested. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 2), each measured relative to their "No Injury" matches, and indexed to year -1. The "No Injury" workers correspond to the "Match" column in Table 1. Shaded areas represent 95% confidence bands.

Figure D.10: School-Related Employment around Work Accident

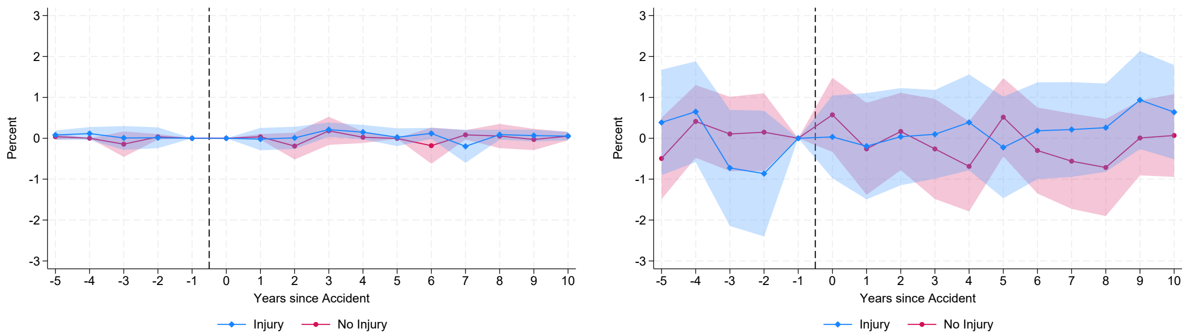
(a) “Access” – “No Access” (b) Triple Difference



Notes: This figure shows school-related employment around work accidents. School-related employment is defined as being simultaneously enrolled in a higher degree and working in the labor market. Panel (a) plots show difference-in-differences between the “Access” and “No Access, IPW” workers from Table 2, indexed to year -1. Panel (b) shows the difference between the two difference-in-differences (the “triple-differences” estimator). The “No Injury” workers correspond to the “Match” column in Table 1. Shaded areas represent 95% confidence bands.

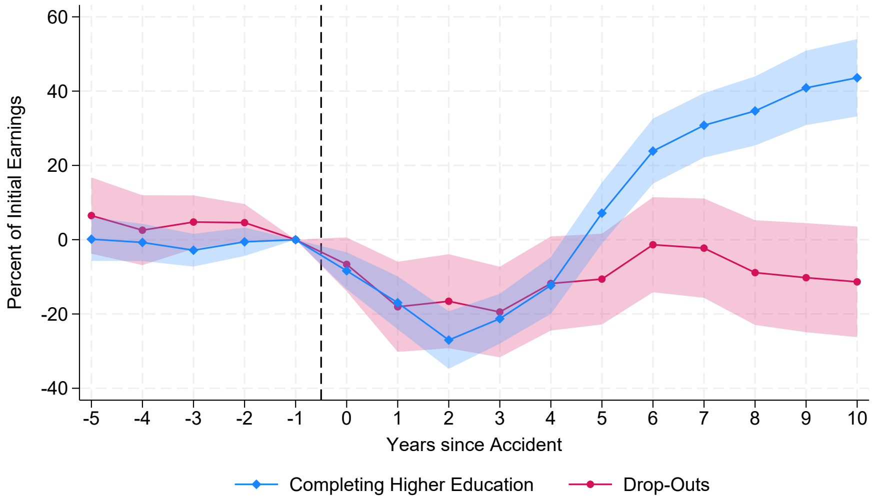
Figure D.11: Effects of Access on Work Accidents (“Access” – “No Access”)

(a) Severe Accidents (ECL > 0) (b) All Accepted Accidents



Notes: This figure shows the reduced-form effects on work accidents around the main work accidents. The graphs show difference-in-differences between the “Access” and “No Access, IPW” workers from Table 2, indexed to year -1. Panel (a) focuses on severe work accidents that cause loss of earnings capacity, while Panel (b) illustrates the effects on all accepted work accidents. The “No Injury” workers correspond to the “Match” column in Table 1. Shaded areas represent 95% confidence bands.

Figure D.12: Effects of Access on Labor Earnings By Completion of Degrees



Notes: This figure decomposes the effect of access to higher education on earnings (Figure 5.(b)) into those who complete versus drop out of higher education. *Completing Higher Education* indicates workers with direct access to higher education who enroll in and complete higher education within the first ten years post-injury, while *Drop-Outs* are defined as workers with direct access to higher education who enroll but does not finish higher education within the first ten years post-injury. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 2), each measured relative to their "No Injury" matches, and indexed to year -1. The "No Injury" workers correspond to the "Match" column in Table 1. Shaded areas represent 95% confidence bands.

Table D.5: Comparing Reskilled Injured Workers to Non-Injured Workers with Similar Occupational Tenure

	Injury & Reskill	No Injury
Labor Market Income (1000DKK)	347.61	341.96
	(136.77)	(142.52)
Age (Years)	37.67	30.24
	(6.94)	(7.17)
Labor Market Experience (Years)	16.12	6.80
	(7.59)	(6.46)
Occupational Experience (Years)	2.31	2.45
	(2.37)	(2.13)
Years since Graduation	1.99	2.00
	(0.80)	(0.80)
Observations	657	41,969

Notes: This table compares injured workers with direct access to higher education who reskill after injury (and complete their degrees) with a random sample of non-injured workers within the same occupation with the same amount of years since completing their higher degree. We only consider full-time workers with non-missing DISCO codes within the first 4 years of graduation (0,1,2,3) in order to mitigate noise associated with the transition from studying to entering the labor market. The table reports average outcomes and standard deviations in parentheses. We consider a random sub-sample of a maximum of 100 non-injured workers per injured worker within each full-time-completed degree-disco-years since graduation-year cell. That is, we match on having completed the higher degree, working full-time in the same (non-missing) DISCO code, and being the same amount of years away from graduation in the same calendar year. Occupational experience is measured by the number of years working in the same 4-digit DISCO code.

D.6 Heterogeneity

The main analysis in Section 4 focuses on craft workers, our by-far largest group with 78% of all reskilling activity after injuries (Table D.1). This section studies the effects of reskilling in other occupational groups.

In Section D.6.1, we first study care workers, our second largest group with 8.5% of the reskilling activity. Care workers are peculiar because their higher-education programs target jobs with physical demands similar to their original jobs. We find that care workers invest significantly less in human capital after accidents and that their access to higher education does not help their employment prospects after injuries.

In Section D.6.2, we consider all occupations with access to higher education and split the effects of reskilling by whether or not workers come from physical jobs. The analysis confirms that reskilling only helps injured workers if the programs facilitate transitions away from physically demanding jobs.

D.6.1 Care Workers

In this section, we study care workers whose higher degrees have similar physical intensity. An example is nursing assistants who are eligible for the bachelor's program in nursing.

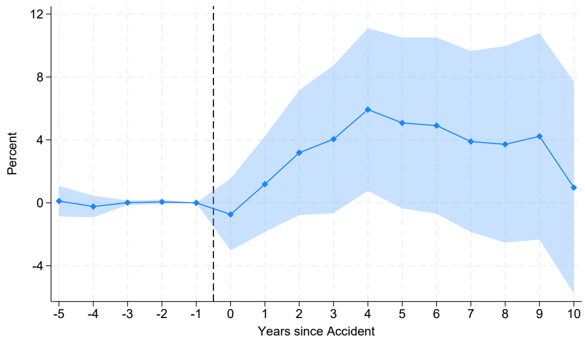
Yet, because most nurses end up in physically demanding hospital jobs, these educational opportunities may not provide a better way back to work.

Figure D.13.(a) shows that care workers invest less in human capital after work accidents. Ten years after the accident, only around 3% of care workers have enrolled in a higher degree due to the injury, markedly less than the 10% effect in our main sample (Figure 4.(b)). Furthermore, because care workers constitute a smaller share of work injuries, we have less precision in estimating the effects in Figure D.13.

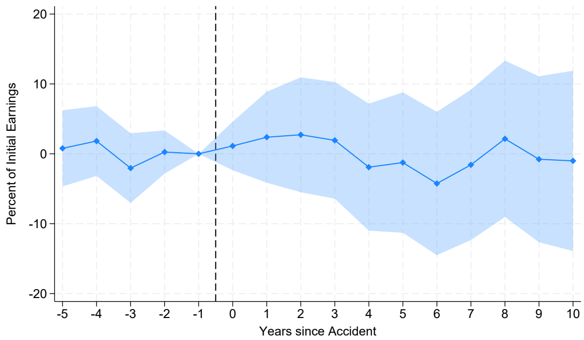
Figure D.13.(b) shows that care workers who have access to higher degrees with similar or higher physical demands do not fare better in the labor market after experiencing a work injury.[6]

Figure D.13: Outcomes around Work Accidents: Care Workers (Triple Differences)

(a) Participated in Higher Degrees (Stock)



(b) Labor Earnings



Notes: This figure shows outcomes of workers around work accidents according to workers' initial access to higher education. The figure focuses on care workers. The plots are triple differences, where the first difference is between the "Access" and "No Access" workers ("IPW" and "Simple", respectively), the second difference is between the "Injury" and "No Injury" workers, and the third difference is indexed to year -1. Panel (a) shows enrollment in higher degrees measured in full-time equivalents. Panel (b) shows labor earnings measured in percent of average earnings in year -1. Shaded areas represent 95% confidence bands, estimated using the Equation (2).

D.6.2 Physical Jobs

This section splits the effects of access to higher education by whether workers come from physically demanding jobs. In total, 76.9% of injured workers come from physical jobs. These are 83.2% craft workers, 0.6% care workers, and 16.2% from other occupations. In comparison, workers from non-physical jobs are 30.3% craft workers, 32.7% care workers, and 37.0% from other occupations.

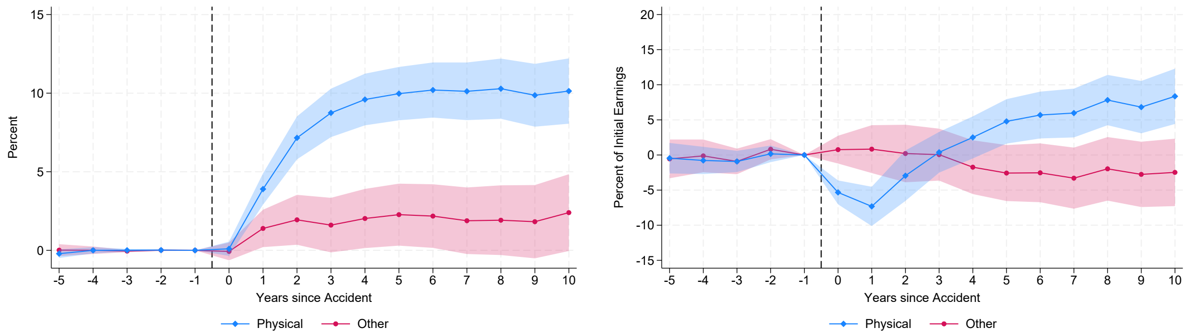
Figures D.14 and D.15 show that access to higher education increases reskilling and labor earnings by around 10% for workers from physical jobs. These effects are similar

[6]Because care workers are predominantly female, the smaller impact of the access policy could also reflect gender differences in reskilling behaviors. However, two pieces of evidence counter this hypothesis. First, zooming in on the *male* care workers, we find similar insignificant effects of the access policy on their human capital investment and labor earnings. Second, studying the craft workers, Table E.2 shows that *women* are more likely to reskill after injuries.

to our main estimates from Section 4.2. By contrast, the effects on other workers are not statistically different from zero. These findings confirm that access to higher education only helps injured workers if the programs facilitate transitions away from physically demanding jobs.

Figure D.14: Worker Outcomes around Work Accidents ("Access" - "No Access")

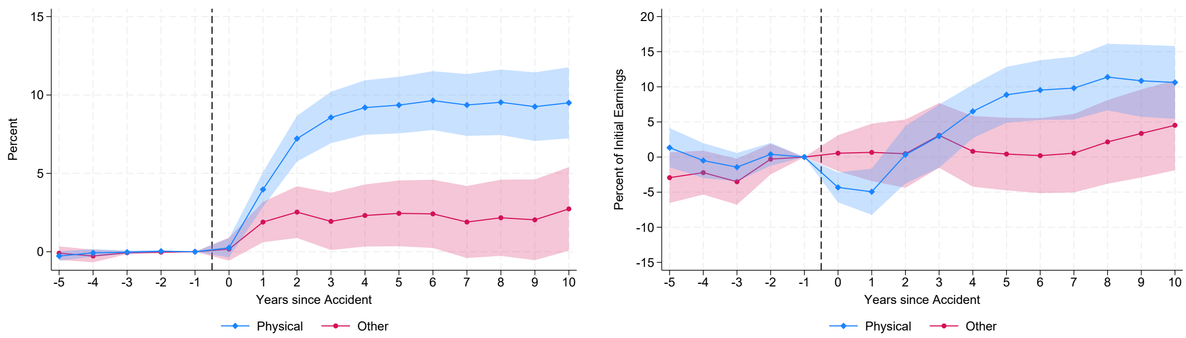
(a) Participated in Higher Degree (b) Labor Earnings



Notes: This figure shows the effects of access to higher education around work accidents, split by whether the workers' initial occupation was a physical job. *Physical jobs* are occupations with physical requirements greater than 0.5 standard deviations above the mean. The graphs show difference-in-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 2), and indexed to year -1. Shaded areas represent 95% confidence bands.

Figure D.15: Worker Outcomes around Work Accidents (Triple Differences)

(a) Participated in Higher Degree (b) Labor Earnings



Notes: This figure shows the effects of access to higher education around work accidents, split by whether the workers' initial occupation was a physical job. *Physical jobs* are occupations with physical requirements greater than 0.5 standard deviations above the mean. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 2), each measured relative to their "No Injury" matches, and indexed to year -1. The "No Injury" workers correspond to the "Match" column in Table 1. Shaded areas represent 95% confidence bands.

E Profiling Instrument Compliers

This section characterizes the compliers, always-takers, and never-takers of our access instrument. Instrument compliers are workers who reskill after injuries if they have direct access.

E.1 Method

We use the method of Marbach and Hangartner (2020) to profile the compliers, always-takers, and never-takers of our access instrument. Because "access to higher education" can only be considered "conditional random" (after the IPW reweighing on the propensity score $\hat{p}$), we require some modified assumptions. This section states these assumptions and provides evidence of their plausibility.

First, we require a "conditional monotonicity" assumption that our access instrument Z monotonously induces reskilling at each value of the propensity score $\hat{p}$. Blandhol et al. (2022) call this "monotonicity-correctness". In Table E.1, we examine this assumption by running our first-stage regression in each separate quartile of the propensity score. Supporting the "conditional monotonicity" assumption, Table E.1 shows that our access instrument induces reskilling in all quartiles of the propensity score.

Table E.1: Testing for Conditional Monotonicity

	Quartile of propensity for access			
	Q4	Q3	Q2	Q1
Access	8.4	10.5	12.9	11.0
	(3.0)	(2.9)	(2.9)	(2.3)
F-stat	8.0	12.7	19.8	23.1
Observations (weighted)	2,277	2,277	2,278	2,277

Notes: This table shows our first stage regression coefficients of access on the probability of reskilling where we split the "No Access" control workers into (weighted) quartiles depending on their IPW weights. Q1 represents the quartile with the lowest IPW weights, while Q4 represents the quartile with the highest weights.

Second, we require that the covariates X we profile are "conditional independent" of our access instrument Z. That is, conditional on the propensity score for access to higher education $\hat{p}$, the covariates X are independent of Z. Supporting this "conditional independence" assumption, Table 2 shows that the "Access" ($Z = 1$) and "No Access (IPW)" ($Z = 0$) groups are similar on each separate covariate X.

Given these assumptions, we use the formulas of Marbach and Hangartner (2020) to profile the mean characteristics of the always-takers (AT), never-takers (NT), and compliers (C) of our instrument as follows:

$$
\begin{aligned}
\mathbb{E}[X|AT] &= \mathbb{E}_w[X|Z=0, D=1] && (5)\\
\mathbb{E}[X|NT] &= \mathbb{E}_w[X|Z=1, D=0] && (6)\\
\mathbb{E}[X|C] &= \frac{\mathbb{E}_w[X] - \mathbb{E}_w[X|D=1, Z=0]\mathbb{E}_w[D|Z=0] - \mathbb{E}_w[X|D=0, Z=1]\mathbb{E}_w[D|Z=1]}{\mathbb{E}_w[D|Z=1] - \mathbb{E}_w[D|Z=0]}, && (7)
\end{aligned}
$$

where $\mathbb{E}_w$ denotes IPW-weighted averages.

E.2 Results

Table E.2 shows that compliers are younger, more likely female, and live closer to reskilling facilities.

Table E.3 shows that the compliers received better grades in primary school and had higher-educated parents.

Table E.2: Profiling Workers by Their Reskilling after Injuries

	Average	Compliers	Always-takers	Never-takers
Panel A. Demographics				
Age	42.03	31.31	32.15	43.84
	(0.10)	(0.69)	(0.53)	(0.12)
Female (%)	3.63	10.48	11.90	2.35
	(0.14)	(1.25)	(1.76)	(0.16)
Cohabiting (%)	73.01	64.25	74.10	73.88
	(0.39)	(2.89)	(3.40)	(0.48)
School-aged Children (%)	30.78	30.82	34.38	30.54
	(0.41)	(3.03)	(3.80)	(0.50)
Property Owner (%)	70.32	56.24	58.95	72.58
	(0.41)	(3.13)	(3.88)	(0.49)
Panel B. Education				
Years of Schooling	14.40	14.37	14.31	14.41
	(0.00)	(0.02)	(0.02)	(0.00)
Primary (%)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Vocational (%)	100.00	100.00	100.00	100.00
	(0.00)	(0.00)	(0.00)	(0.00)
High School (%)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Post-Secondary (%)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Panel C. Employment				
Hours Worked (Yearly)	1674.95	1543.02	1589.96	1694.69
	(5.80)	(30.91)	(33.88)	(7.55)
Labor Income (1000 DKK)	401.16	379.19	374.51	405.28
	(1.07)	(7.52)	(9.08)	(1.32)
Hourly Wage (DKK)	256.20	307.31	225.81	252.74
	(2.21)	(20.33)	(6.17)	(1.76)
Job Tenure (Years)	4.10	3.36	2.66	4.27
	(0.03)	(0.19)	(0.17)	(0.04)
Labor Market Experience (Years)	20.92	11.04	14.25	22.42
	(0.09)	(0.60)	(0.56)	(0.10)
Public Sector (%)	4.56	6.30	9.35	4.05
	(0.18)	(1.28)	(1.67)	(0.22)
Sick Leave (% of weeks)	4.35	4.53	2.56	4.45
	(0.10)	(0.61)	(0.51)	(0.13)
Panel D. Wealth				
Debt-to-Income Ratio (%)	45.89	24.36	63.41	47.03
	(0.76)	(4.77)	(6.98)	(0.99)
Savings-to-Income Ratio (%)	22.05	10.53	13.36	23.86
	(0.65)	(2.56)	(1.93)	(0.87)
Panel E. Occupation				
Physical Ability Requirement (Std.)	0.99	1.10	0.84	0.99
	(0.01)	(0.06)	(0.06)	(0.01)
Cognitive Ability Requirement (Std.)	-0.37	-0.27	-0.38	-0.38
	(0.01)	(0.05)	(0.06)	(0.01)
Injury Rate (x 1000)	11.39	12.00	10.41	11.39
	(0.04)	(0.31)	(0.34)	(0.05)
Panel F. Reskilling				
Access to Higher Education (%)	84.16	100.00	0.00	100.00
	(0.28)	(0.00)	(0.00)	(0.00)
Travel Time to Higher Education (Min.)	36.08	29.01	36.66	36.80
	(0.23)	(1.47)	(1.41)	(0.29)
Panel G. Injury				
Earnings Capacity Loss (%)	35.17	17.13	20.60	38.07
	(0.20)	(1.49)	(1.53)	(0.23)
Personal Impairment (%)	13.30	11.04	11.49	13.66
	(0.11)	(0.61)	(0.63)	(0.14)
Year of Injury	2005.36	2004.62	2005.45	2005.44
	(0.04)	(0.30)	(0.35)	(0.05)
Share of Injuries	100.0%	9.1%	5.7%	85.2%

Notes: This table characterizes injured workers according to their potential decisions after injuries. Reskilling is defined as enrolling in a higher degree within ten years after the accident. *Compliers* reskill only if they have direct access to higher education. *Always-takers* reskill regardless of their access to higher education. *Never-takers* do not reskill regardless of their access to higher education. Section E.1 provides details on the profiling method. Standard errors in parentheses are calculated using a Bayesian bootstrap with 5,000 replications.

Table E.3: Profiling Workers by Their Reskilling after Injuries

	Average	Compliers	Always-takers	Never-takers
Panel A. Primary school grades				
Overall GPA (0-100)	51.03	64.82	64.82	48.64
	(0.67)	(6.33)	(1.39)	(1.05)
Math GPA (0-100)	55.42	62.73	71.58	53.56
	(0.65)	(2.56)	(1.93)	(0.87)
Panel B. Employment				
Employed (%)	80.25	63.98	80.08	82.00
	(0.76)	(6.38)	(4.15)	(0.99)
Labor Income (1000 DKK)	40.81	22.65	44.91	42.48
	(0.57)	(5.08)	(4.13)	(0.76)
Panel C. Parental Education				
Years of Schooling	11.57	11.72	12.35	11.51
	(0.05)	(0.44)	(0.30)	(0.07)
Primary (%)	26.51	27.86	26.05	26.40
	(0.86)	(7.07)	(5.18)	(1.15)
Vocational (%)	56.15	51.36	48.11	57.20
	(0.96)	(7.95)	(5.49)	(1.29)
High School (%)	0.86	2.29	2.44	0.60
	(0.18)	(1.65)	(1.43)	(0.20)
Post-Secondary (%)	15.90	21.57	23.39	14.80
	(0.70)	(5.94)	(4.79)	(0.91)
Panel D. Parental Employment				
Labor Income (1000 DKK)	374.89	473.12	450.97	359.34
	(4.30)	(36.84)	(21.91)	(5.54)
Both Employed (%)	68.74	61.72	70.19	69.40
	(0.88)	(7.36)	(5.11)	(1.18)
At Least One Employed (%)	94.19	93.17	95.75	94.20
	(0.45)	(3.65)	(2.42)	(0.62)
Panel E. Parental Wealth				
Debt-to-Income Ratio (%)	34.69	47.79	31.02	33.53
	(0.78)	(6.37)	(4.56)	(1.03)
Savings-to-Income Ratio (%)	17.56	30.27	10.67	16.66
	(0.73)	(5.88)	(1.18)	(1.02)
Share of Injuries	100.0%	9.1%	5.7%	85.2%

Notes: This table characterizes injured workers according to their reskilling decisions after injuries. Reskilling is defined as enrolling in a higher degree within ten years after the accident. *Compliers* reskill only if they have direct access to higher education. *Always-takers* reskill regardless of their access to higher education. *Never-takers* do not reskill regardless of their access to higher education. Section E.1 provides details on the profiling method. Standard errors in parentheses are calculated using a Bayesian bootstrap with 5,000 replications.

F Potential Outcomes

This section estimates the potential outcomes of injured workers with and without reskilling. We identify these counterfactuals for the workers who comply with the access policy by reskilling after injuries.

F.1 Method

Let $D_{Ai} \in \{0, 1\}$ denote the reskilling of worker i depending on his access to higher education $A \in \{0, 1\}$. His potential outcome with and without reskilling is $Y_i(D_i)$.

Following Abadie (2002), the average potential outcomes of compliers are given by the Wald estimates:

$$\mathbb{E}[Y_{ik}(0)|D_{1i} > D_{0i}] = \frac{\theta_{1k}^{Y(1-D)}}{\theta_{1,10}^{(1-D)}} \tag{8}$$

$$\mathbb{E}[Y_{ik}(1)|D_{1i} > D_{0i}] = \frac{\theta_{1k}^{YD}}{\theta_{1,10}^{D}}, \tag{9}$$

where θ_{1k}^{Y} is the difference in outcomes between the access groups k years after the injury:

$$Y_{it} = \theta_{0k}^{Y} + \theta_{1k}^{Y} A_{ie} + \varepsilon_{it}^{Y} \quad \text{if} \quad t = e + k. \tag{10}$$

For example, θ_{1k}^{D} is our first-stage estimate in Figure 4.(b), whereas θ_{1k}^{YD} and $\theta_{1k}^{Y(1-D)}$ decompose our reduced-form effects (e.g., Figure 5) according to whether workers complete a higher education after the accidents.[7] The idea behind Equations (8)-(10) is that access to education affects labor market outcomes exclusively by shifting compliers into higher education. Hence, by interacting the outcome variable (Y) with the higher-education treatment status (D and $1 - D$), we identify the average potential outcomes of compliers with and without higher education.

We estimate Equations (8)-(10) using two-stage least squares (2SLS) on a balanced sample, weighing the workers as in the "IPW" column of Table 2, and impose non-negativity constraints on the potential outcomes following Imbens and Rubin (1997).[8] The difference in potential outcome estimates (Figure F.1, Panels (a) vs. (b)) corresponds exactly to the causal effect estimates in Figure 6.

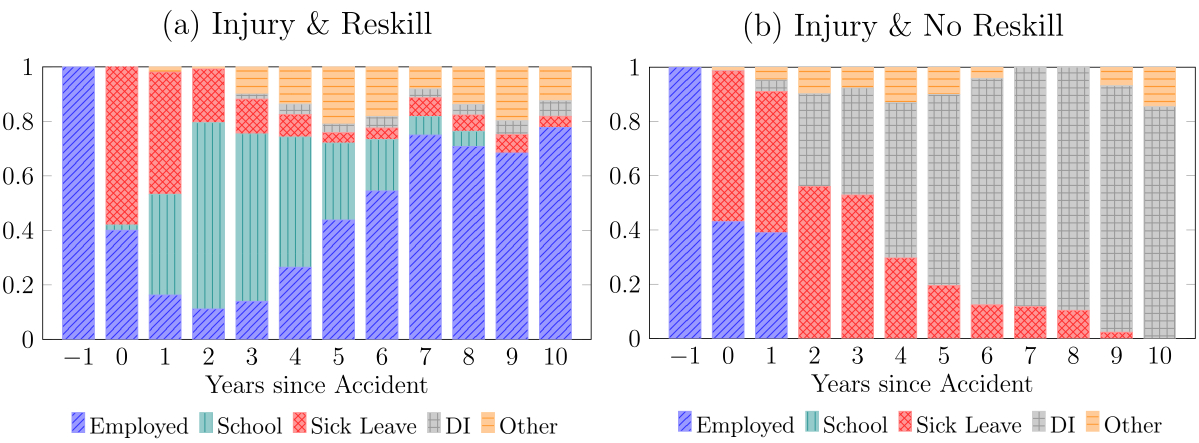
[7] We estimate θ_{1k}^{Y} as simple differences between the access groups to recover the levels of workers' potential outcomes. Note that the simple differences (Equation (10)) and the difference-in-differences (Equation (2)) give similar point estimates of θ_{1k}^{Y} for our reduced-form outcomes (e.g., Figure 5) because the "Access" and "No Access, IPW" groups are similar on the outcomes before the injury (Table 2).

[8] The constrained outcomes are within the confidence bands of the unconstrained estimates for all outcomes and time periods.

F.2 Results

Figure F.1 shows the labor supply of injured workers with and without reskilling. The figure delivers three insights. First, reskilling keeps workers in school during the first six years after work injuries. Second, about 80% of injured workers who reskill end up finding employment. Third, if these workers do not reskill, they end up entirely on disability benefits.

Figure F.1: Labor Supply



Notes: This figure shows the labor supply of complier workers who comply with access to higher education by pursuing a higher degree after work accidents. *Employed* is fulltime employment. *School* is enrollment in a higher degree. *Sick Leave* refers to receiving sickness benefits. *DI* is disability insurance. *Other* is mainly unemployment and non-participation. Panels (a) and (b) report treated and control complier means, estimated using Equations (8)-(10).

F.2.1 Potential Outcomes without Injuries

Are workers made better off by experiencing a work accident? To answer this question, we compare the complier workers to the outcomes of their match workers (who are not injured in the event year). That is, we rerun Equations (9)-(10), using outcomes of the match workers as the dependent variable. Appendix Table F.1 shows that the reskilled workers end up in very different types of occupations (less physically demanding, more cognitively intense, and with higher average pay), compared to the scenario without injury. However, in terms of lifetime income, the difference in scenarios is less stark. Ten years after the accidents, the workers are about 10 percentage points more likely to be employed (Figure F.2) and earn about 3% more in their jobs (Table F.1) than if they had not been injured. Importantly, before arriving at these higher earnings, the workers undergo a period of lower income while in school. In present-discounted terms, the reskilled workers have similar lifetime income (1% lower) compared to the scenario without injury (Appendix Table F.2).[9] Furthermore, as Figure C.4 showed, the

[9]If workers are constrained in smoothing their consumption over time (e.g., due to liquidity constraints, as in Chetty (2008)), the reskilling scenario with lower income while in school is less attractive

injuries cause physical pain, hospitalizations, and other suffering not reflected in lifetime income. From a public perspective, the injuries are also not desirable, as the government forgoes taxes and pays tuition and benefits while the injured workers are in school (Table F.2).

Should workers have been reskilled before the accidents? To assess this question, we make two adjustments to the "Injury & Reskill" scenario.[10] First, without the injuries, workers would avoid the immediate spike in sick leave and gradual increase in disability benefits following the accidents.[11] Second, the workers would not be eligible for reskilling benefits while in school.[12] Appendix Table F.2 incorporates these adjustments, showing that workers' lifetime income in the "No Injury & Reskill" scenario is very close to (0.7% higher in present-discounted values) the "No Injury" counterfactual.[13,14] The reskilling of non-injured workers is also not desirable from a public perspective, as the government forgoes taxes and pays tuition and benefits while the workers are in school. In total, the government loses an additional 60 cents on each dollar spent reskilling non-injured workers (Table F.2).

for workers.

[10]See the note of Appendix Table F.2 for a detailed explanation of these adjustments.

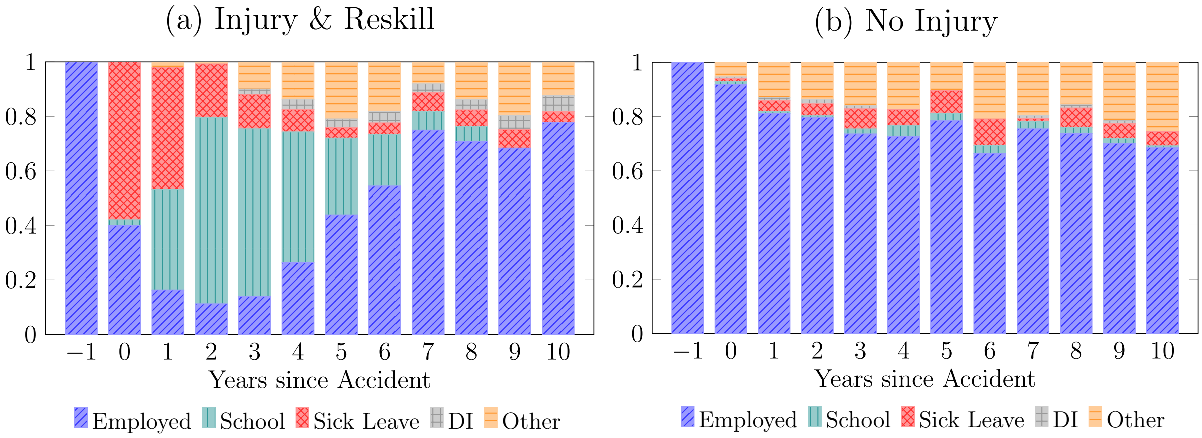
[11]This adjustment likely overstates the lifetime income in the "No Injury & Reskill" scenario. The calculations namely make the extreme assumption that injured workers who go on sick leave (in years 0-3) or DI (in years 3 and onwards) would have experienced their match workers' outcomes without the initial work injury. By contrast, Figure F.2 shows that a smaller fraction of workers do take sick leave and DI even without the initial work accidents. We adopt the extreme assumption to clarify the robustness of our conclusion that workers should not have been reskilled before the accidents.

[12]The workers would instead receive the standard stipend (SU); see Section I.A for a description of these government transfers.

[13]The difference would increase to 5.5% if non-injured workers could access reskilling benefits.

[14]Again, if workers are constrained in smoothing consumption, the lower income while in school is less attractive for workers. Access to reskilling benefits would partly alleviate this disadvantage of reskilling for non-injured workers.

Figure F.2: Potential Labor Supply of Compliers



Notes: This figure shows the labor supply of workers who comply with access to higher education by pursuing a higher degree after work accidents. *Employed* is fulltime employment. *School* is enrollment in a higher degree. *Sick Leave* refers to receiving sickness benefits. *DI* is disability insurance. *Other* is mainly unemployment and non-participation. Panel (a) reports treated complier means, estimated using Equation (9). Panel (b) reports the outcomes of their match workers (who do not experience a work injury in the event year).

Table F.1: Job Characteristics of Compliers

	Standard deviations from Economy Average		Change in Percent
	Year -1	Year +10	Year -1 to +10
	Panel A. Injury + Reskill		
Physical Ability Requirements	1.677	-0.254	
	(0.266)	(0.312)	
Cognitive Ability Requirements	0.003	0.711	
	(0.208)	(0.322)	
Earnings	-0.189	0.408	25.1
	(0.202)	(0.231)	(9.7)
Occupational Earnings Premium	-0.251	1.527	76.9
	(0.095)	(0.336)	(14.5)
	Panel B. No Injury		
Physical Ability Requirements	1.701	0.875	
	(0.197)	(0.228)	
Cognitive Ability Requirements	-0.034	0.016	
	(0.163)	(0.201)	
Earnings	-0.265	0.226	21.4
	(0.130)	(0.160)	(7.0)
Occupational Earnings Premium	-0.385	0.206	27.1
	(0.085)	(0.099)	(4.5)

Notes: This table shows the job characteristics of workers who are employed ten years after a work accident. The "Injury & Reskill" panel reports treated complier means, estimated using Equation (9). The "No Injury" panel reports the outcomes of their match workers (who do not experience a work injury in the event year). *Physical Ability* is defined as the average importance of Static Strength, Explosive Strength, Dynamic Strength, Trunk Strength, and Stamina, as measured by O*NET. *Cognitive Ability* is 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. We calculate "Occupational Earnings Premium" as the average labor market earnings within each "Match" (Year-Occupation-Industry-Education-Age-Gender) cell in the full population of non-injured workers with at least three years of full-time work leading up to year -1. Columns 1 and 2 are measured in standard deviations from the average occupational earnings premium of the "No Injury" workers matched on the calendar year in Table C.2 (Column (1)). Column 3 reports the percent change in the worker's outcome.

Table F.2: Scenarios for Compliers: Present-Discounted Values

	Injury & Reskill (Complier)	No Injury	No Injury & Reskill
Panel A. Workers	434,007	438,093	418,624
Earnings	344,580	419,656	385,419
Transfers	51,490	16,402	22,091
Educ. Transfers	37,937	2,036	11,115
Panel B. Government	200,973	360,995	317,965
Educ. Transfers + Tuition	-74,989	-5,552	-41,460
Transfers	-51,490	-16,402	-22,091
Taxes	327,452	382,949	381,516
Panel C. Total	634,979	799,088	736,589

Notes: This table shows the present-discounted values generated by compliers (i.e., workers who respond to the access policy by reskilling after injuries) in different scenarios. The present-discounted values assume a real discount rate of 6% per year. *Earnings* are labor earnings after tax, *Transfers* include disability benefits, unemployment benefits, sickness benefits, and cash assistance, *Educ. Transfers* include reskilling benefits and State Education Support (SU), *Educ. Transfers + Tuition* expenses include tuition and education transfers, and *Taxes* refer to labor income taxes. The "Injury & Reskill" column reports treated complier means, estimated using Equation (9). The "No Injury" column reports the outcomes of their match workers (who do not experience a work injury in the event year). The "No Injury & Reskill" is based on the "Injury & Reskill" column with two adjustments: (1) injured workers who are on sick leave in years 0-3 or disability insurance in years 3 and onward after the accidents are assigned the outcomes of their match workers (for income, transfers, and educ. transfers), and (2) workers in school receive the standard SU stipend (instead of the higher reskilling benefits which are only available for injured workers).

G Marginal Treatment Effects

This section provides details on our estimation of Marginal Treatment Effects (MTEs). Our estimation strategy combines our access IV with workers' age and distances to education facilities. We pursue two complementary approaches. In Section G.1, we adopt a non-parametric approach to the estimation, binning workers by their propensities to reskill and estimating our access IV specification within each of the bins. In Section G.2, we pursue a parametric approach, estimating a linear MTE curve on the continuum of propensity scores.

The non-parametric approach offers the benefit of avoiding assumptions about the functional form of the MTE curve, enabling a transparent evaluation of potential non-linearities. In contrast, the parametric approach leverages the entire distribution of propensity scores to estimate a single MTE curve, a common strategy in the literature; see, e.g., Cornelissen et al. (2018) and Carneiro, Heckman, and Vytlacil (2011). Reassuringly, both approaches yield similar results, as shown in Figure 8. In Section G.3, we extend the analysis by estimating age-specific MTE curves, taking into account how many years workers have left until retirement.

Across all approaches, we focus on injured workers under age 50, ensuring they have at least ten years remaining before retirement. To control for differences between workers with and without access to education, we apply IPW weights, as defined in Table 2 to account for differences between workers with and without access to education.

G.1 Estimation by Propensity Score Bins

G.1.1 Propensity Scores

We first estimate a logit model for reskilling after injuries based on workers' age and commuting distance to education facilities:

$$p(D_i = 1) = \mu(\pi_e + \pi_1 \text{Age}_i + \pi_2 \text{Distance}_i + \pi_3 \text{Age}_i^2 + \pi_4 \text{Distance}_i^2), \tag{11}$$

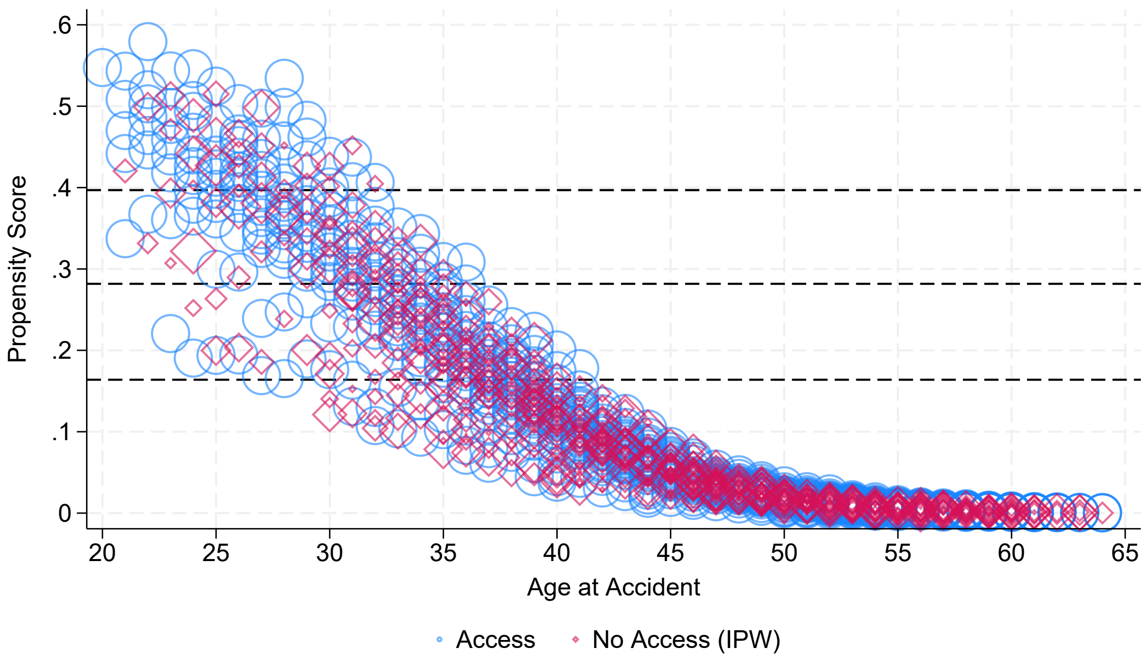
where $\mu(\cdot)$ is a logit link function, and π_e are event-year fixed effects. Table G.1 reports the propensity score estimates, and Figure G.1 visualizes the results in a binned scatter plot. Younger workers are more likely to reskill, and commuting distances generate variation in propensity scores among workers of the same age.

Table G.1: Propensity Score Estimation

	Dependent var.: Reskilling in year $\in$ [0,10]
Age	0.082
	(0.015)
Distance	-0.006
	(0.001)
Age^2	-0.003
	(0.000)
Distance^2	0.000
	(0.000)
Constant	-0.894
	(0.281)
Event-year FEs	✓

Notes: This table reports propensity score estimation results (Equation (11)). Robust standard errors are in parentheses.

Figure G.1: Propensity Scores by Age and Commuting Distances

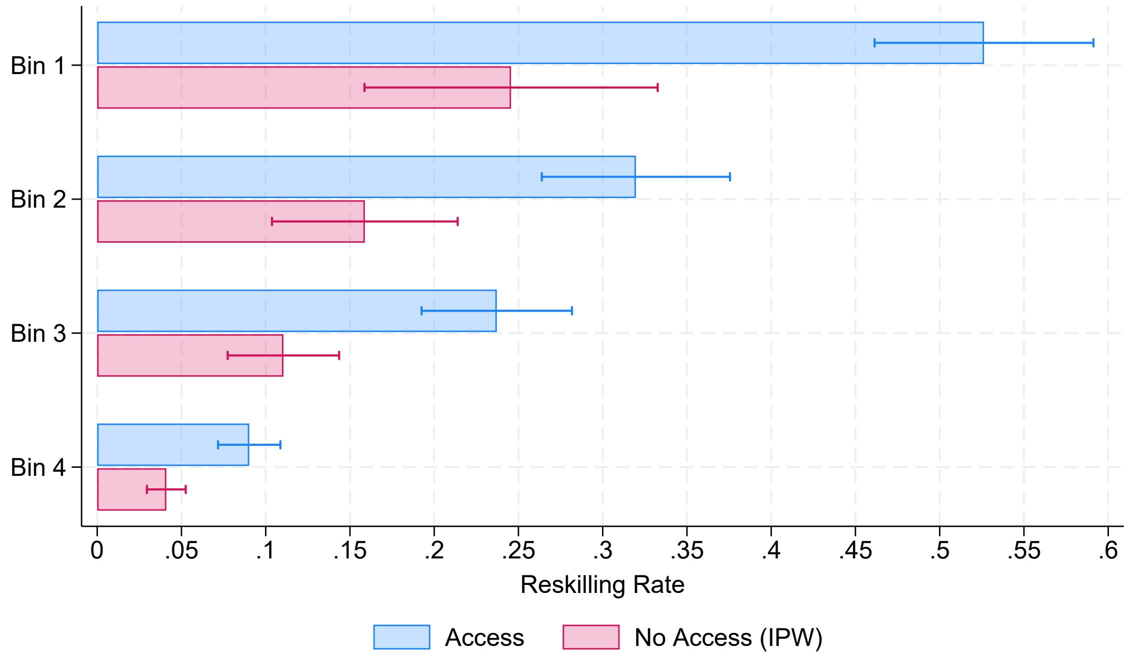


Notes: This figure shows a binned scatter plot of estimated propensity scores for reskilling (Equation (11)) of workers of different ages and access to higher education. Each dot contains exactly 4 observations. Marker size reflects the sum of IPW weights within each dot.

We divide workers into four equal-sized bins based on their propensity scores. Since workers are less likely to reskill in bins with lower propensity scores, the statistical power of our access IV is reduced in these bins. Hence, to maintain balanced statistical power across all four bins, we adjust the bin sizes by weighting workers according to their propensity scores. The horizontal dashed lines in Figure G.1 show the cutoff points of the propensity score bins.

Figure G.2 displays the reskilling rates of workers with and without direct access to higher education in each bin. The differences between the rates yield first-stage F-statistics of 9.5, 7.3, 10.3, and 11.0 for bins 1 to 4.

Figure G.2: Reskilling Rates by Propensity Score Bin and Access to Higher Education



Notes: This figure shows the average reskilling rates by propensity score bins and workers' access to higher education. Whiskers represent 95% confidence bands.

G.1.2 Bin-Specific IV Estimation

Finally, we run our main 2SLS estimation from Section C.3.1 within each propensity score bin:

$$D_i = \beta_{10} + \beta_{11} A_i + \varepsilon_i \tag{12}$$

$$Y_i = \beta_0 + \beta_1 \widehat{D}_i + \varepsilon_i. \tag{13}$$

where β_1 identifies the causal effect of reskilling on the outcomes of compliers in the bin. Figure 8 of the main text shows the results for the social, private, and public returns on reskilling (corresponding to the Total, Workers, and Government rows in Table 4).

G.2 Parametric Estimation

G.2.1 Propensity Scores

We first estimate a flexible logit model for reskilling after injuries based on workers' age, distance to education facilities, and access to higher education:

$$
\begin{aligned}
p(D_i = 1) = \mu(g(\text{Age}_i, \text{Distance}_i) &+ \beta_1 \text{Access}_i \\
&+ \beta_2 \text{Age}_i \times \text{Access}_i + \beta_3 \text{Age}_i^2 \times \text{Access}_i \\
&+ \beta_4 \text{Distance}_i \times \text{Access}_i + \beta_5 \text{Distance}_i^2 \times \text{Access}_i)),
\end{aligned} \tag{14}
$$

where $\mu(\cdot)$ is a logit link function, and $g(\cdot)$ includes a quadratic in age and commuting distance, and event-year fixed effects:

$$
g(\text{Age}_i, \text{Distance}_i) = \pi_e + \pi_1 \text{Age}_i + \pi_2 \text{Age}_i^2 + \pi_3 \text{Distance}_i + \pi_4 \text{Distance}_i^2 \tag{15}
$$

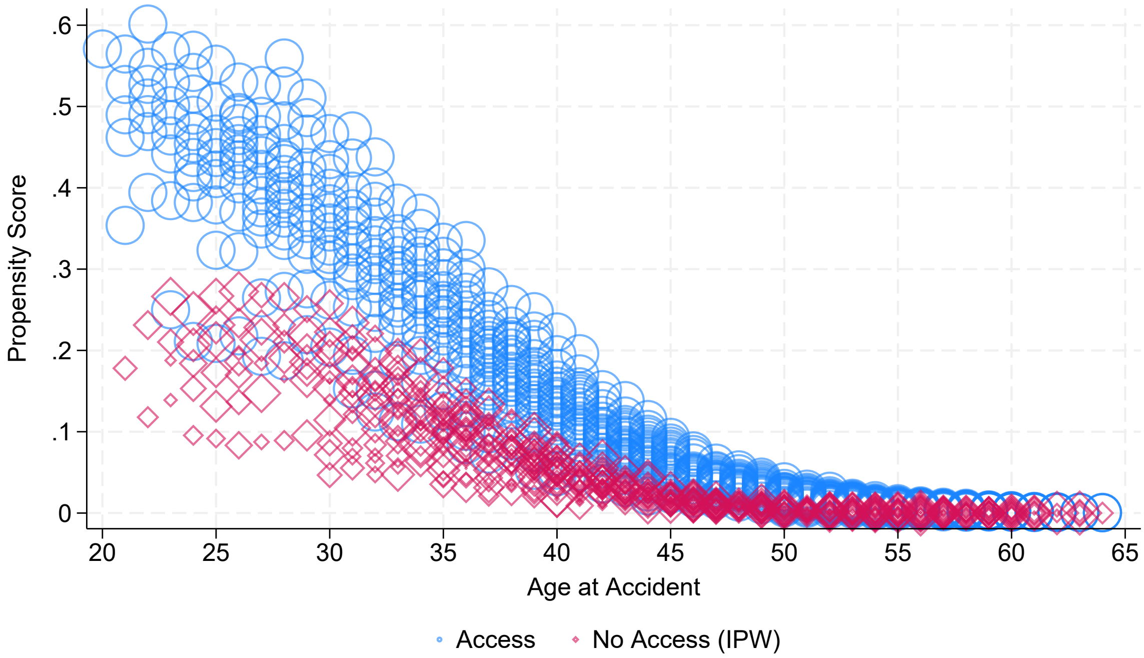
Table G.2 reports the propensity score estimation results, showing significant interaction terms between the access instrument and workers' age and distance to education facilities (F-stat of 15.29), with stronger responses to the access policy for younger workers living closer to education facilities. Figure G.3 provides a graphical representation of the first stage, showing that younger workers respond more strongly to the access policy and that commuting distances generate variation in reskilling among workers with the same age and eligibility for education.

Table G.2: Propensity Score Estimation

	Dependent var.: Reskilling in year $\in$ [0,10]
Access	4.727
	(0.916)
Age	0.281
	(0.049)
Access $\times$ Age	-0.190
	(0.051)
Age^2	-0.006
	(0.001)
Access $\times$ Age^2	0.003
	(0.001)
Distance	0.017
	(0.003)
Access $\times$ Distance	-0.024
	(0.004)
Distance^2	-0.000
	(0.000)
Access $\times$ Distance^2	0.000
	(0.000)
Constant	-5.552
	(0.878)
Event-year FEs	✓
F-stat on 'Access' interaction terms	15.29

Notes: This table reports the propensity score estimation results (Equation (14)). Robust standard errors are in parentheses.

Figure G.3: Propensity Scores by Age, Commuting Distances, and Access Status



Notes: This figure shows a binned scatter plot of estimated propensity scores for reskilling (Equation (14)) of workers of different ages and access to higher education. Each dot contains exactly 4 observations. Marker size reflects the sum of IPW weights within each dot.

G.2.2 Outcome Equation

In a second step, we relate our outcome Y to a parametric function of the propensity scores $f(\cdot)$, while controlling for workers' age and commuting distances:

$$Y_i = g(\text{Age}_i, \text{Distance}_i) + f(\hat{p}_i) + \varepsilon_i, \tag{16}$$

where $g(\cdot)$ is the flexible function in Equation (15).

The identifying assumption in Equation (16) is that the interaction terms between workers' access to higher education (Access_i) and their age (Age_i) or commuting distances to education facilities (Distance_i) only affect annual outcomes before retirement (Y_i) through the propensity to retrain ($f(\hat{p}_i)$). This exclusion restriction allows us to control for worker commuting distances and age separately (through $g(\cdot)$) and only use their interactions with our access instrument to trace out the MTE function. In Section G.4, we show our estimates are robust to using either of the two interactions separately.

As in Cornelissen et al. (2018), we use a quadratic polynomial for $f(\cdot)$, which yields a linear MTE function in the propensity score:

$$Y_i = g(\text{Age}_i, \text{Distance}_i) + \alpha_1 \hat{p}_i + \frac{\alpha_2}{2}\hat{p}_i^2 + \varepsilon_i \implies \tag{17}$$

$$\text{MTE}(p) \equiv \frac{\partial \mathbb{E}[Y_i|\hat{p}_i = p]}{\partial p} = \hat{\alpha}_1 + \hat{\alpha}_2 p. \tag{18}$$

Figure 8 of the main text plots the estimated MTE curve from Equation (18).

G.3 Marginal Returns by Age Cohorts

In this section, we estimate age-specific marginal returns to reskilling, taking into account how many years workers have left until retirement. To do so, we first estimate our outcome equation (17) in each year k after the injury event year e:

$$Y_{it} = g_k(\text{Age}_i, \text{Distance}_i) + \alpha_{1k}\hat{p}_i + \frac{\alpha_{2k}}{2}\hat{p}_i^2 + \varepsilon_{it} \tag{19}$$
$$\text{if} \quad t = e + k \quad \text{for} \quad k \in [0, 10].$$

We then use the marginal treatment effects to calculate the present-discounted incomes generated by reskilling workers of age a from a rate of p. In particular, let Y denote a measure of annual net income (benefits minus costs), the present-discounted marginal return is:

$$\text{MR}(a, p) = \sum_{k=0}^{\bar{A}-a} \beta^k \left(\hat{\alpha}_{1k} + \hat{\alpha}_{2k} p\right), \tag{20}$$

where $\hat{\alpha}_k$ are the marginal treatment effects estimated in Equation (19) and β is a discount factor. As in Section III.B, we assume treatment effects are constant after year $k = 10$ and until retirement age $\bar{A}$. Section G.3.2 computes standard errors for the marginal returns using a Bayesian bootstrap.

G.3.1 Results

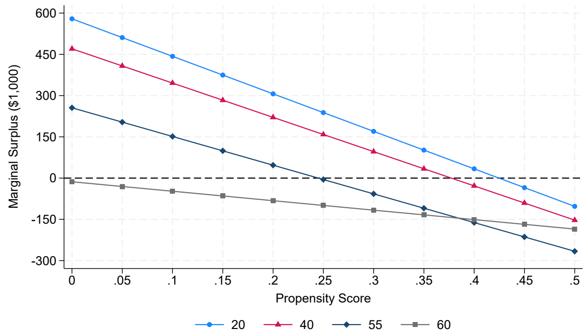
Tables G.3-G.6 reports the marginal costs and benefits of reskilling (Equation (19)) for workers and the government.

Figure G.4 depicts the marginal social, private, and public returns (corresponding to the Total, Workers, and Government rows in Table 4) on reskilling for different age cohorts.

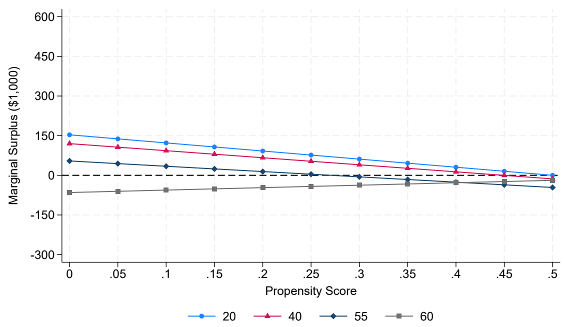
Figure G.5 uses the marginal returns to calculate the total returns attained by the reskilling policies that maximize the social, private, and public returns for each worker age.

Figure G.4: Marginal Returns on Reskilling Workers of Different Ages ($1,000)

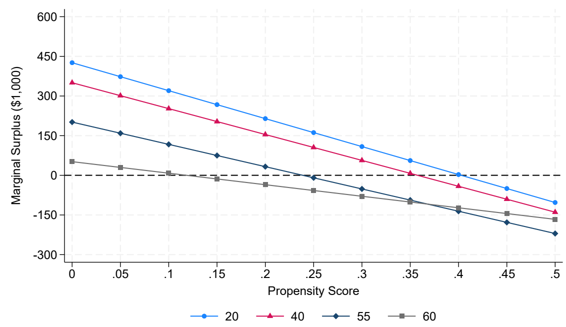
(a) Total (Social Returns)



(b) Workers (Private Returns)



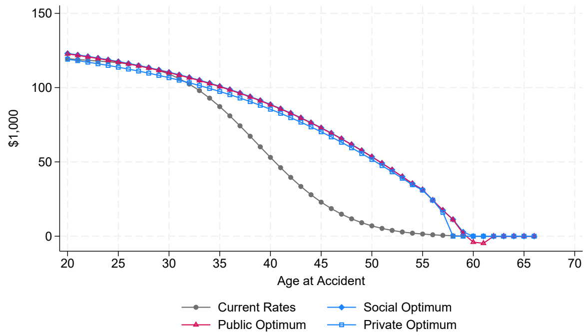
(c) Government (Public Returns)



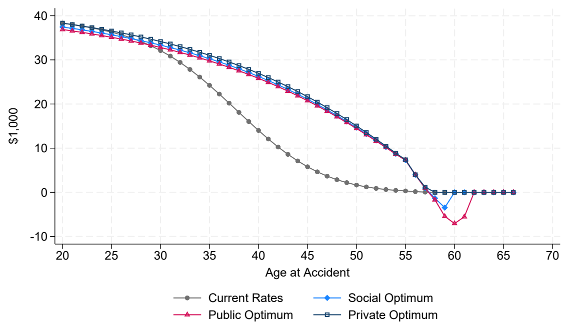
Notes: This figure shows the marginal returns of reskilling workers of different ages (Equation (20)). Social returns (Panel (a)) is the sum of returns for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 4.

Figure G.5: Returns on Reskilling Policies ($1,000 Per Injured Worker)

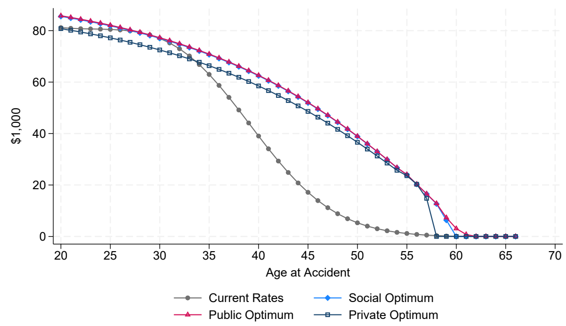
(a) Total (Social Returns)



(b) Workers (Private Returns)



(c) Government (Public Returns)



Notes: This figure shows the total returns of reskilling policies. Social returns (Panel (a)) is the sum of returns for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 4.

Table G.3: Estimation of Private Benefits

Dep. var.: Private Benefits: After-tax labor market earnings + educational transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-6.83	-2.38	9.27	22.52	27.83	37.51	43.87	24.78	29.06	29.32	23.30
	(4.41)	(6.88)	(6.53)	(6.18)	(7.08)	(7.94)	(8.21)	(8.57)	(9.62)	(10.73)	(11.43)
$\hat{p}^2/2$	13.21	-16.81	-2.75	-52.09	-66.22	-97.24	-119.73	-44.53	-64.74	-58.61	-13.97
	(15.21)	(23.11)	(21.34)	(19.74)	(23.38)	(28.06)	(28.51)	(29.14)	(33.23)	(37.90)	(39.47)
Observations	3518	3518	3466	3401	3327	3230	3119	2984	2791	2608	2335

Notes: This table shows the reduced-form estimation results (Equation (19)) for the private benefits of reskilling (post-tax labor earnings and reskilling benefits). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (14) and (19) with weights drawn from a uniform distribution.

Table G.4: Estimation of Private Costs

Dep. var.: Private Costs: Lost public transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-2.46	7.17	14.83	16.75	17.62	16.47	13.19	11.79	12.28	15.63	14.20
	(2.74)	(3.48)	(3.93)	(3.71)	(3.70)	(3.99)	(4.25)	(4.26)	(4.85)	(4.95)	(5.31)
$\hat{p}^2/2$	13.63	-17.87	-24.70	-31.40	-33.83	-41.28	-29.84	-19.60	-18.80	-27.75	-17.66
	(9.20)	(11.95)	(13.37)	(12.40)	(12.10)	(13.78)	(14.46)	(13.88)	(16.30)	(16.70)	(17.63)
Observations	3518	3518	3466	3401	3327	3230	3119	2984	2791	2608	2335

Notes: This table shows the reduced-form estimation results (Equation (19)) for the private costs of reskilling (lost public benefits). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (14) and (19) with weights drawn from a uniform distribution.

Table G.5: Estimation of Public Benefits

Dep. var.: Public Benefits: Tax income + avoided public transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-8.47	7.49	4.98	27.82	32.03	45.95	53.60	34.66	33.35	32.40	18.40
	(10.10)	(11.59)	(13.75)	(9.42)	(9.80)	(11.06)	(12.12)	(12.30)	(13.41)	(15.54)	(16.17)
$\hat{p}^2/2$	10.77	-52.54	6.55	-83.89	-91.38	-145.76	-158.46	-84.47	-70.06	-58.66	9.70
	(31.09)	(36.41)	(40.01)	(29.92)	(31.58)	(37.01)	(40.70)	(38.91)	(44.25)	(51.54)	(53.81)
Observations	3518	3518	3466	3401	3327	3230	3119	2984	2791	2608	2335

Notes: This table shows the reduced-form estimation results (Equation (19)) for the public benefits of reskilling (tax income and lost public transfers). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (14) and (19) with weights drawn from a uniform distribution.

Table G.6: Estimation of Public Costs

Dep. var.: Public Costs: Education cost + education transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-0.52	9.23	17.30	9.15	1.14	-4.07	-9.20	-8.28	0.00	0.00	0.00
	(1.17)	(3.71)	(5.75)	(5.83)	(5.78)	(5.20)	(4.75)	(3.58)	(0.00)	(0.00)	(0.00)
$\hat{p}^2/2$	1.10	-3.27	3.34	43.77	58.57	47.58	65.29	45.01	0.00	0.00	0.00
	(4.07)	(13.84)	(21.50)	(22.43)	(22.01)	(19.20)	(17.63)	(14.20)	(0.00)	(0.00)	(0.00)
Observations	3518	3518	3466	3401	3327	3230	3119	2984	2791	2608	2335

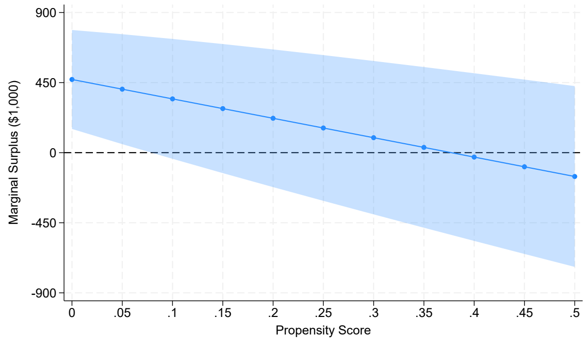
Notes: This table shows the reduced-form estimation results (Equation (19)) for the public costs of reskilling (tuition and reskilling benefits). We set the estimates to zero after year 8 since workers do not participate in education after that point (Figure 4.(a)). Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (14) and (19) with weights drawn from a uniform distribution.

G.3.2 Confidence Bands

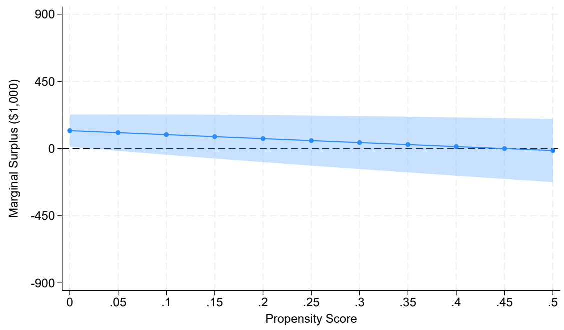
Figure G.6 reports confidence bands for the marginal returns curves calculated using a Bayesian bootstrap (Shao and Tu (2012)) over the propensity score and outcome equations (14) and (19)-(20). The figure focuses on the marginal returns on reskilling workers of age 40.

Figure G.6: Marginal Returns of Reskilling Workers of Age 40 ($1,000)

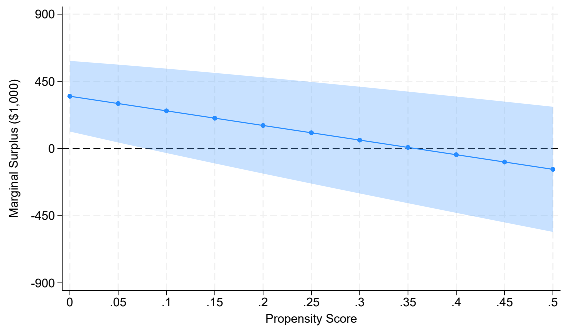
(a) Total (Social Returns)



(b) Workers (Private Returns)



(c) Government (Public Returns)



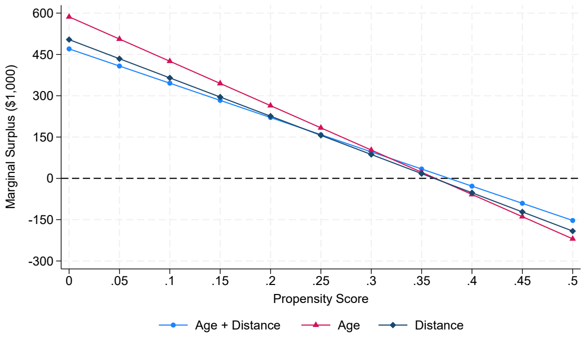
Notes: This figure shows the marginal returns on reskilling workers of age 40. Social returns (Panel (a)) is the sum of returns for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 4. The shaded areas represent 90% confidence bands, estimated with a Bayesian bootstrap (Shao and Tu (2012)) of 1000 iterations over the propensity score and outcome equations (14) and (19) with weights drawn from a uniform distribution.

G.4 Robustness Analysis

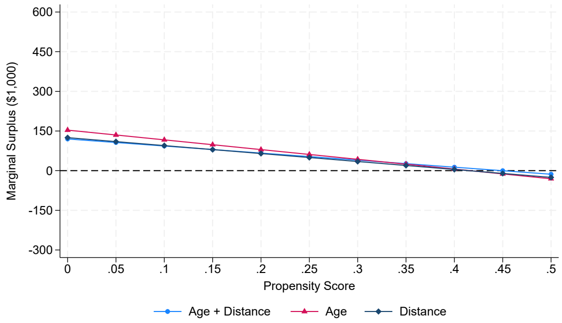
To assess the robustness of our marginal returns analysis, Figure G.7 repeats the MTE estimation in Section G.3, focusing on either workers' age or distances to training facilities as the interacting covariate in the propensity score equations (14). The marginal return estimates across specifications are very similar and not significantly different. Reassuringly, the optimal rates of reskilling (that set the marginal returns to zero) presented in Section IV.D are robust to the choice of interacting covariates in the MTE estimation. The robustness of the estimates to different instrumental variables mitigates concerns about the excludability of each instrument and also suggests that our MTEs are generalizable across policy instruments.

Figure G.7: Robustness of Marginal Returns Estimates

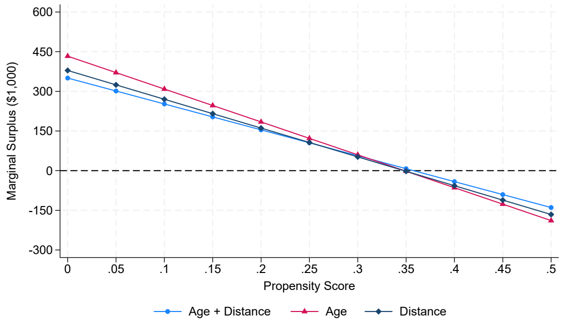
(a) Total (Social Returns)



(b) Workers (Private Returns)



(c) Government (Public Returns)



Notes: This figure shows the robustness of our marginal returns estimates to the choice of interacting covariate in the propensity score estimation. Social returns (Panel (a)) is the sum of returns for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 4. The estimates represent the marginal returns of reskilling workers of age 40. The *Age + Distance* lines refer to our main specification described in Section G.3. The Age lines only use worker age as the interacting covariate in the propensity score estimation, thus setting $\beta_4 = \beta_5 = 0$ in Equations (14). The *Distance* lines only use workers' distance to education facilities as the interacting covariate, thus setting $\beta_2 = \beta_3 = 0$ in Equations (14).

H The Broader Potential for Reskilling

H.1 Nature of Displacement

Our evidence indicates that reskilling primarily works for *long-term displacements* from *manual jobs*. While the AES determines which accidents cause long-term loss of physical ability, we do not have such an external assessment for mass layoffs. For mass layoffs, we instead infer the nature of the displacements from labor market outcomes and show sensitivity to our baseline specification.

First, we say that a worker is *long-term displaced* if he falls into long-term unemployment within the first two years of the mass layoff. We use the official definition of long-term unemployment, set at 52 consecutive weeks (Statistics Denmark (2024)).

Second, we define *manual jobs* as occupations with manual ability requirements (defined by Autor, Levy, and Murnane (2003)) greater than 0.5 standard deviations above the mean. This cutoff mirrors our definition of physical jobs in Section D.6.2.

Table H.1 shows the sensitivity of our conclusions in Section V to varying the cutoffs for *long-term displacements* and *manual jobs*. For example, increasing the cutoff for what we call a long-term displacement from 52 weeks (our baseline) to 65 weeks decreases the share of budget costs of mass layoffs that can be mitigated by reskilling from 15.8% to 12.6%. Similarly, increasing the cutoff for what we call a manual job from 0.5 (our baseline) to 1 standard deviation above the mean decreases the share of budget costs from mass layoffs that can be mitigated by reskilling from 15.8% to 12.9%. To help interpret these choices, Table H.2 lists the occupations around different cutoffs for the manual ability requirements.

Table H.1: Sensitivity Analysis for the Broader Potential of Reskilling after Mass Layoffs: Percent of Budget Cost

Cutoff for long-term displacement: Weeks of benefits in years 0–1	Cutoff for Manual Jobs: SD Deviation from Mean				
	-0.5	0	0.5	1	1.5
26	21.6%	21.1%	19.9%	16.4%	9.6%
39	19.9%	19.4%	18.3%	14.9%	8.7%
52	17.2%	16.8%	15.8%	12.9%	7.4%
65	13.7%	13.4%	12.6%	10.4%	5.9%
78	9.1%	8.9%	8.4%	6.9%	4.0%

Notes: This table investigates the sensitivity of our results for the broader potential of reskilling among displaced workers. The percentages in the table show the shares of total budget costs that workers with positive returns from reskilling constitute. The cutoff for what we call *manual jobs* (measured as standard deviations from the population mean) is varied along the columns, while the cutoff for what we call *long-term displaced* (measured as weeks receiving public benefits in years 0 and 1 after the mass layoffs) is varied along the rows.

Table H.2: Occupations around Cutoffs for Manual Requirements

Cutoff	Occupation	Manual Requirements
	2441 Economists	-1.736
Lowest	2445 Psychologists	-1.656
	2421 Lawyers	-1.629
	3432 Legal and related business associate professionals	-1.044
-1	3413 Estate agents	-1.007
	3415 Technical and commercial sales representatives	-0.996
	3320 Pre-primary education teaching associate professionals	-0.518
-0.5	5220 Shop, stall and market salespersons and demonstrators	-0.502
	2140 Architects, engineers and related professionals	-0.432
	2460 Religious professionals	-0.072
0	3224 Optometrists and opticians	-0.049
	9132 Helpers and cleaners in offices, hotels and other establishments	0.042
	5132 Institution-based personal care workers	0.456
0.5	3226 Physiotherapists and related associate professionals	0.490
	5133 Home-based personal care workers	0.527
	8271 Meat- and fish-processing-machine operators	0.926
1	7141 Painters and related workers	0.933
	9330 Transport labourers and freight handlers	1.217
	7143 Building structure cleaners	2.273
Highest	8324 Heavy truck and lorry drivers	2.321
	7214 Structural-metal preparers and erectors	2.750

Notes: This table lists the occupations with manual ability requirements (defined as in Autor, Levy, and Murnane (2003)) around different cutoffs.

To be clear, the precise cutoffs are somewhat arbitrary, and we see Section V as a first step toward evaluating the relevance of reskilling among displaced workers. Ideally, a government agency would assess case-by-case whether mass layoffs cause long-term displacements from manual jobs. For example, the U.S. Department of Labor takes this role for Trade Adjustment Assistance (assessing whether a displacement was caused by offshoring or import competition) and Workers' Compensation (assessing whether an injury was caused by a work accident). However, our evidence in Sections II.C, III.C, and IV.C shows that workers self-select into reskilling only if they benefit from it, reducing the need for agencies to judge individual cases.

H.1.1 Relation to Automation and Offshoring

In this section, we examine whether workers employed in manual occupations (studied in Table 5) are also exposed to the structural challenges caused by automation and offshoring.

We measure automation using the "exposure to robots" index of Webb (2019). To measure offshoring, we follow Autor and Dorn (2013) and Firpo, Fortin, and Lemieux (2011), and define a "non-offshorability" index as the simple average of the "decision-making" and "face-to-face" characteristics in O*NET. As for manual jobs in Table 5, we say that a worker is exposed to automation if their "exposure to robots" index is 0.5 standard deviations above the average. Similarly, we say that a worker is exposed to offshoring if their "non-offshorability" index is 0.5 standard deviations below the average.

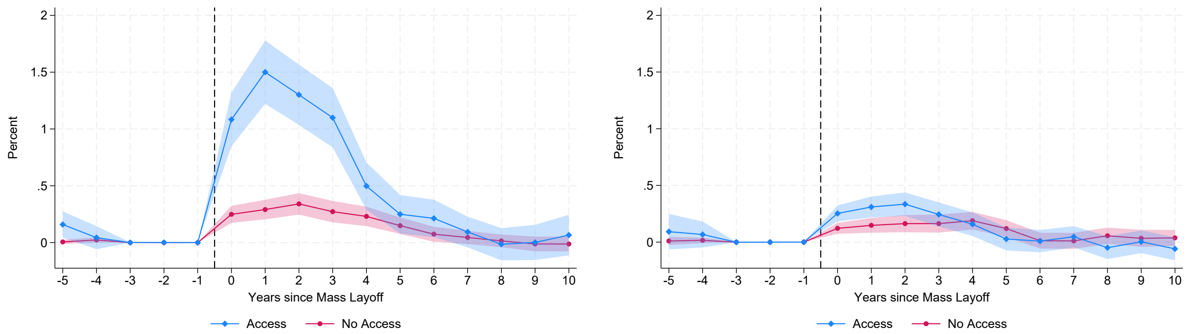
Using these definitions, we find that workers exposed to automation and offshoring are 275% and 114%, respectively, more likely to come from the manual occupations used in Table 5.

H.2 Reskilling after Mass Layoffs

Figure H.1 shows workers' pursuit of higher degrees around mass layoffs. Reskilling activities are multiple times higher among workers who could be advantageously reskilled (Panel (a)), especially if the workers have direct access to higher education in the Danish system. Still, reskilling activity is substantially lower among displaced workers than injured workers (Figure 1.(a)). This could point to the potential importance of rehabilitation benefits for workers to reskill.

Figure H.1: Participation in Higher Degrees around Mass Layoff

(a) Relevant Workers (b) All Workers



Notes: This figure shows the participation (measured in full-time equivalent) in higher degrees around mass layoffs. Panel (a) focuses on workers who could be advantageously reskilled (i.e., workers in Row 5 of Table 5, Panel B). Panel (b) shows all workers (i.e., Row 1 of Table 5, Panel B). The figures are split by whether the workers have direct access to higher education. The graphs show difference-in-differences in outcomes between the "Displaced" and "Match" workers (using the matching strategy of Table 1), indexed to year -1. Shaded areas represent 95% confidence bands estimated using the regression equation (1).

I Linking Occupations and Degrees

I.1 Linking Degrees to Target Occupations

This section describes how we link degrees to their target occupations and sectors. These links form the basis of Figure C.10 and the links from relevant degrees to target occupations in Table 5 and Appendix Table I.1.

To guide the creation of the links, we exploit the correlations between workers' degrees and their occupations in the administrative data. For example, most workers with a bachelor's degree in 4087 Construction Architecture are employed as 3112 Civil Engineering Technicians.

For workers who have completed degree d, we rank occupations o by their shares in total employment of the workers. We also rank occupations by the share of their employees who have completed degree d. Based on these rankings, we manually verify the plausibility of the links from degrees to occupations. The list of degrees and target occupations is available at `www.andershumlum.com/s/target_occupations.xlsx`.

I.2 Linking Origin Occupations to Relevant Degrees

This section describes how we link origin occupations to potential stackable higher degrees. We use these links between occupations and target degrees in Table 5 and Appendix Table I.1.

We utilize the fact that most workers enroll in higher degrees within the same *career cluster* as their origin occupation when creating the links between origin occupations and potential stackable higher degrees (Figure C.10).[15] That is, for each origin occupation o we list the higher degrees d, that belongs to the same career cluster c. We only include vocational bachelor's degrees and academy profession degrees as potential stackable higher degrees.

Many career clusters have several higher degrees that could plausibly be stacked on top of the workers' existing experiences. In Table 5, Row 4, we include all physical (manual) origin occupations that have at least one degree in their career clusters targeted less physical (manual) jobs.

In Table I.1, we manually select the single most relevant degree for each occupation, considering both workers' specific prior experience *and* whether the degree targets jobs with less manual and physical requirements.[16] The table shows the selected links for the largest origin occupations (in terms of workplace injuries and mass layoff events) in each career cluster. Notably, for most physical and manual origin occupations (e.g., construction), their selected degree also has lower physical and manual ability requirements.

[15] See Section II.C and the note of Figure C.10 for a definition of career clusters.

[16] We perform the classification for occupations with at least 5 injured (displaced) workers in physically (manual) jobs (corresponding to the samples in Row 3 of Table 5), as these are the occupations that stackable degrees are relevant for.

Hence, because we already restrict to physical (manual) origin occupations in Table 5, our conclusions are also largely robust to using only the selected most relevant degree for each occupation.

The full list of occupation-degree pairs (including the selected ones) is available at `www.andershumlum.com/s/linking_origin_target_occ.xlsx`.

Table I.1: Linking Origin Occupations, Relevant Degrees and Target Jobs

Top Origin Occupations	Relevant Degree in Career Cluster	Target Occupation	Requirements	
			Physical	Manual
Agriculture, Food & Natural Resources				
Injuries				
7233 Agricultural- or industrial-machinery mechanics	Mechanical Engineering (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
9141 Building caretakers	Automation Engineering (AP)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
6112 Gardeners	Agro Business and Landscape Management (AP)	3212 Agronomy and forestry technicians	Lower	Similar
9211 Farm-hands and laborers	Agricultural Technician (AP)	3212 Agronomy and forestry technicians	Lower	Similar
9161 Garbage collectors	Environmental Energy Technology (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
Mass Layoffs				
7233 Agricultural- or industrial-machinery mechanics	Mechanical Engineer (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
3211 Life science technicians	Production Engineer (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
6112 Gardeners	Agro Business and Landscape Management (AP)	3212 Agronomy and forestry technicians	Lower	Similar
Architecture & Construction				
Injuries				
7124 Carpenters and joiners	Construction Architecture (VBA)	3112 Civil Engineering Technicians	Lower	Lower
9312 Construction and maintenance laborers	Plant Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower
7000 Craft workers, n.e.c.	Building Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower
7233 Agricultural- or industrial-machinery mechanics	Mechanical Engineering (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
9313 Building construction laborers	Building Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower
Mass Layoffs				
9313 Building construction laborers	Building Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower
8284 Metal-, rubber- and plastic-product assemblers	Production Engineer (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
7000 Craft workers, n.e.c.	Building Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower
7233 Agricultural- or industrial-machinery mechanics	Mechanical Engineering (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
7124 Carpenters and joiners	Construction Architecture (VBA)	3112 Civil Engineering Technicians	Lower	Lower
Arts, Audio/Video Technology & Communic				
Injuries				
8251 Printing machine operators	Product Development (AP)	3471 Decorators and commercial designers	Lower	Lower
7244 Telegraph and telephone installers	Product Development (AP)	3471 Decorators and commercial designers	Lower	Lower
8252 Book-binding-machine operators	Product Development (AP)	3471 Decorators and commercial designers	Lower	Lower
Mass Layoffs				
8251 Printing machine operators	Product Development (AP)	3471 Decorators and commercial designers	Lower	Lower
8252 Book-binding-machine operators	Product Development (AP)	3471 Decorators and commercial designers	Lower	Lower
2452 Sculptors, painters and related workers	Industrial Designer (VBA)	3471 Decorators and commercial designers	Lower	Lower
7345 Bookbinders	Industrial Designer (VBA)	3471 Decorators and commercial designers	Lower	Lower
Business Management & Administration				
Injuries				
4142 Mail carriers and sorting clerks	Logistic Management (VBA)	4115 Secretary work	Lower	Lower
Mass Layoffs				
4142 Mail carriers and sorting clerks	Logistic Management (VBA)	4115 Secretary work	Lower	Lower
Education & Training				
Injuries				
3340 Other teaching ass. prof.	Education (VBA)	2331 Primary education teaching prof.	Lower	Similar
Mass Layoffs				
-				
Finance				
Injuries				
-				
Mass Layoffs				
-				
Government & Public Administration				
Injuries				
9152 Doorkeepers, watchpersons and related	Emergency and Risk Management (VBA)	3152 Safety, health and quality inspectors	Similar	Similar
Mass Layoffs				
-				
Health Science				
Injuries				
3330 Special education teaching ass. prof.	Social- and Special Education (VBA)	3330 Special education teaching ass. prof.	Similar	Similar
3231 Nursing ass. prof.	Health Informatics and Technology (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
2230 Nursing and midwifery prof.	Health Informatics and Technology (VBA)	2150 Architects, engineers and related, n.e.c.	Lower	Lower
3226 Physiotherapists and related	Nutrition and Health (AP)	3224 Dieticians and nutritionists	Lower	Lower
Mass Layoffs				
3231 Nursing ass. prof.	Health Informatics and Technology (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower

Notes: This table continues on the next page.

Table I.1 (Cont.): Linking Origin Occupations, Relevant Degrees and Target Jobs

Top Origin Occupations	Relevant Degree in Career Cluster	Target Occupation	Requirements	
			Physical	Manual
Hospitality & Tourism				
Injuries				
9132 Helpers and cleaners in establishments	Service, Hospitality and Tourism Management (AP)	4222 Receptionists and information clerks	Lower	Similar
9141 Building caretakers	International Hospitality Management (VBA)	4222 Receptionists and information clerks	Lower	Lower
5122 Cooks	Nutrition and Technology (AP)	5122 Cooks	Similar	Similar
5123 Waiters and bartenders	Service, Hospitality and Tourism Management (AP)	4222 Receptionists and information clerks	Lower	Similar
5112 Transport conducters	International Hospitality Management (VBA)	4222 Receptionists and information clerks	Lower	Similar
Mass Layoffs				
7143 Buildning structure cleaners	Service, Hospitality and Tourism Management (AP)	4222 Receptionists and information clerks	Lower	Lower
Human Services				
Injuries				
5131 Child-care workers	Social Education (VBA)	3320 Pre-primary education teaching ass. prof.	Similar	Similar
3320 Pre-primary education teaching ass. prof.	Social Work (VBA)	3460 Social work ass. prof.	Lower	Similar
9133 Hand-launderers and pressers	Environmental Engineering (VBA)	3222 Hygienists, health and environmental officers	Similar	Similar
Mass Layoffs				
-				
Information Technology				
Injuries				
-				
Mass Layoffs				
3123 Industrial robot controllers	Economics and Information Technology (VBA)	2139 Computing professionals, n.e.c.	SImilar	Lower
Law, Public Safety, Corrections & Secur				
Injuries				
5162 Police officers	Emergency and Risk Management (VBA)	3152 Safety, health and quality inspectors	Lower	Lower
5163 Prison guards	Emergency and Risk Management (VBA)	3152 Safety, health and quality inspectors	Lower	Similar
5161 Fire-fighters	Emergency and Risk Management (VBA)	3152 Safety, health and quality inspectors	Lower	Lower
5160 Protective service workers	Emergency and Risk Management (VBA)	3152 Safety, health and quality inspectors	Lower	Similar
Mass Layoffs				
-				
Manufacturing				
Injuries				
8271 Meat- and fish-processing-machine operators	Plant Technician (AP)	3111 Chemical and physical science technicians	Lower	Lower
7000 Craft workers, n.e.c.	Building Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower
9320 Manufacturing laborers	Plant Technician (AP)	3111 Chemical and physical science technicians	Lower	Lower
7233 Agricultural- or industrial-machinery mechanics	Mechanical Engineering (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
8000 Plant and machine operators	Management Technology Offshore (AP)	3119 Physical and engineering technicians, n.e.c	Lower	Lower
Mass Layoffs				
9320 Manufacturing laborers	Plant Technician (AP)	3111 Chemical and physical science technicians	Lower	Lower
8211 Machine-tool operators	Mechanical Engineering (VBA)	3115 Mechanical engineering technicians	SImilar	Lower
8284 Metal-, rubber- and plastic-product assemblers	Production Engineer (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
8271 Meat- and fish-processing-machine operators	Plant Technician (AP)	3111 Chemical and physical science technicians	Lower	Lower
7000 Craft workers, n.e.c.	Building Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower
Marketing				
Injuries				
-				
Mass Layoffs				
-				
Science, Technology, Engineering & Math				
Injuries				
-				
Mass Layoffs				
3141 Ships' engineers	Electrical Engineering (VBA)	2143 Electrical engineers	Lower	Lower
Transportation, Distribution & Logistic				
Injuries				
8324 Heavy truck and lorry drivers	Automotive Technology (AP)	7231 Motor vehicle mechanics and fitters	Similar	Similar
9312 Construction and maintenance laborers	Plant Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower
9330 Transport laborers and freight handlers	Automotive Technology (AP)	7231 Motor vehicle mechanics and fitters	Similar	Similar
4142 Mail carriers and sorting clerks	Logistic Management (VBA)	4115 Secretary work	Lower	Lower
7233 Agricultural- or industrial-machinery mechanics	Mechanical Engineer (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
Mass Layoffs				
9330 Transport laborers and freight handlers	Automotive Technology (AP)	7231 Motor vehicle mechanics and fitters	Similar	Similar
7233 Agricultural- or industrial-machinery mechanics	Mechanical Engineer (VBA)	2149 Architects, engineers and related, n.e.c.	Lower	Lower
8000 Plant and machine operators	Management Technology Offshore (AP)	3119 Physical and engineering technicians, n.e.c	Lower	Lower
8324 Heavy truck and lorry drivers	Automotive Technology (AP)	7231 Motor vehicle mechanics and fitters	Similar	Similar
9312 Construction and maintenance laborers	Plant Technician (AP)	3112 Civil Engineering Technicians	Lower	Lower

Notes: This table shows links between origin occupations, relevant degrees, and target occupations for the top-exposed occupations in terms of workplace injuries and mass layoff events in each career cluster (in bold). The pair has lower (higher) requirements if the ability requirements of the target occupation are at least one standard deviation lower (higher) than the origin occupation. The full list of occupation-degree pairs is available at `www.andershumlum.com/s/linking_origin_target_occ.xlsx`.

J Cost-Benefit Evaluation

This section describes our approach to estimating the costs and benefits of higher education for injured workers. We evaluate the incidence for a worker who suffers an injury at age 32 (the average among our compliers, cf. Table E.2) and retires at age 65.[17] We base our calculations on the reduced-form estimates in Equation (2), assuming the estimates are stable after year 10. All nominal values are deflated to their 2015 US dollar value.

The benefits include post-tax earnings for workers and labor income taxes for the government, which we calculate by applying the marginal tax rate (including tax brackets for middle- and top-income earners) to the labor income effects estimated in Figure 5.[18]

For public transfers, we first estimate the effect of higher education on receiving different transfers, including disability benefits and unemployment benefits. Section I describes the transfers. We then scale these effects with the transfer rates collected from the government budget.[19]

Education expenses include tuition and school-related transfers. Tuition costs amount to approximately $16,500 a year per full-time student. We collect the tuition costs from the government budget.[20] The transfers include the State Education Support (SU) and reskilling benefits.

We then calculate the present-discounted value of each stream of costs and benefits, assuming a real discount rate of 6% per year. The internal rate of return (IRR) is the discount rate that makes the total net present value equal to zero.

[17] Figure D.9 supports the assumption that human capital investment does not affect the age of public pension retirement of injured workers.

[18] The marginal tax rates changes over time, as does the cutoffs for being in the middle- and top tax bracket. We apply the following function for the total taxes paid, τ, by each individual i in year t: $\tau_{it} = \mathbb{1}(I_{it} < c_t^{mid}) * I_{it} * r_t^{low} + \mathbb{1}(c_t^{mid} < I_{it} < c_t^{top}) * \left[c_t^{mid} * r_t^{low} + (I_{it} - c_t^{mid}) * r_t^{mid}\right] + \mathbb{1}(I_{it} > c_t^{top}) * \left[c_t^{mid} * r_t^{low} + (c_t^{top} - c_t^{mid}) * r_t^{mid} + (I_{it} - c_t^{top}) * r_t^{top}\right]$, where I_{it} refers to taxable income for worker i in year t and c_t^x and r_t^x for $x = \{low, mid, top\}$ refers to cutoffs and marginal tax rates for the lowest, middle and top tax brackets in year t, respectively. The applied marginal tax rates vary from 39.7% for taxpayers in the lowest tax bracket in 2013-2017 to 61.4% for taxpayers in the top tax bracket in 1996. See the full overview of historical marginal tax rates and tax brackets here `https://skm.dk/tal-og-metode/satser/tidsserier` (in Danish).

[19] The transfer rates, linked to the transfer codes of the DREAM register, are available at `www.andershumlum.com/s/dream_transfer_rates.xlsx`.

[20] The "rate catalogs" (Takstkataloger, in Danish) list the cost per full-time student by detailed degrees.

K General Equilibrium Effects

Reskilling programs could affect the labor market equilibrium. For example, a large expansion of reskilled workers could bid down wages (Heckman, Lochner, and Taber (1998)). In this section, we assess how sensitive the optimal rates of reskilling are to incorporating such equilibrium effects. To do so, we embed our estimated treatment effects into a calibrated model of the labor market.

K.1 Model

The labor earnings of a worker i are the product of the market wage and his human capital:

$$E_i = w \times H_i. \tag{21}$$

Wages equalize the demand and supply of human capital:

$$H^D = w^{-\epsilon} \tag{22}$$
$$H^S = H^N + H^I(p), \tag{23}$$

where ϵ is the wage elasticity of labor demand, and aggregate labor supply is the sum of human capital supplied by non-injured (N) and injured (I) workers. The human capital of injured workers depends on the reskilling rate p. We assume that labor supply is inelastic to wages to focus on the role of labor demand in absorbing the reskilled workers.

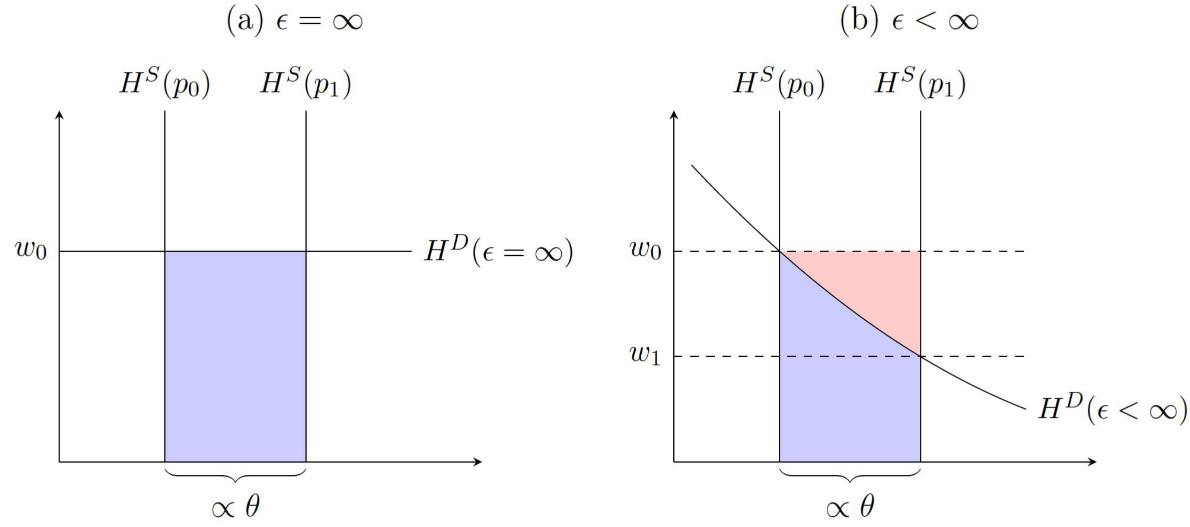
Section IV estimates the impact of reskilling p on individual earnings, keeping market wages fixed at their current levels w_0. As Panel (a) of Figure K.1 shows, these earnings effects correspond to the labor market surplus when labor demand is perfectly elastic. However, when labor demand is finitely elastic, as in Panel (b), the reskilled workers face decreasing marginal returns, dampening the surplus from reskilling.

The share of lost surplus in general equilibrium (the red triangle in Panel (b) as a fraction of the blue rectangle in Panel (a)) grows in the size of the labor supply shock. The size of the shock, in turn, depends on the share of injured workers in labor supply:

$$\theta = \frac{H^I(p_0)}{H^N + H^I(p_0)}. \tag{24}$$

Consequently, when injured workers constitute a small fraction of the aggregate labor supply, the labor market surplus from reskilling remains closer to the estimates from Section IV.

Figure K.1: Labor Market Surplus from Reskilling by Elasticities of Labor Demand ϵ



Notes: This figure illustrates how the labor market surplus from increasing the reskilling rate (from p_0 to p_1) depends positively on the elasticity of labor demand ϵ (flatness of the labor demand curve) and negatively on the fraction of injured workers in labor supply θ (scaling the horizontal shift in the labor supply curve).

In Appendix K.3.1, we formalize the graphical intuitions from Figure K.1 by solving for the labor market equilibrium as a function of the reskilling rate p. In particular, we show that the labor market surplus from increasing reskilling is (i) increasing in the elasticity of demand ϵ, and (ii) decreasing in the share of injured workers in aggregate labor supply θ.

K.2 Calibration

Elasticity of labor demand ϵ

Hamermesh (1996) and Lichter, Peichl, and Siegloch (2015) survey existing estimates of labor demand elasticities to lie between 0.15 and 0.75 with a focal estimate of 0.5.

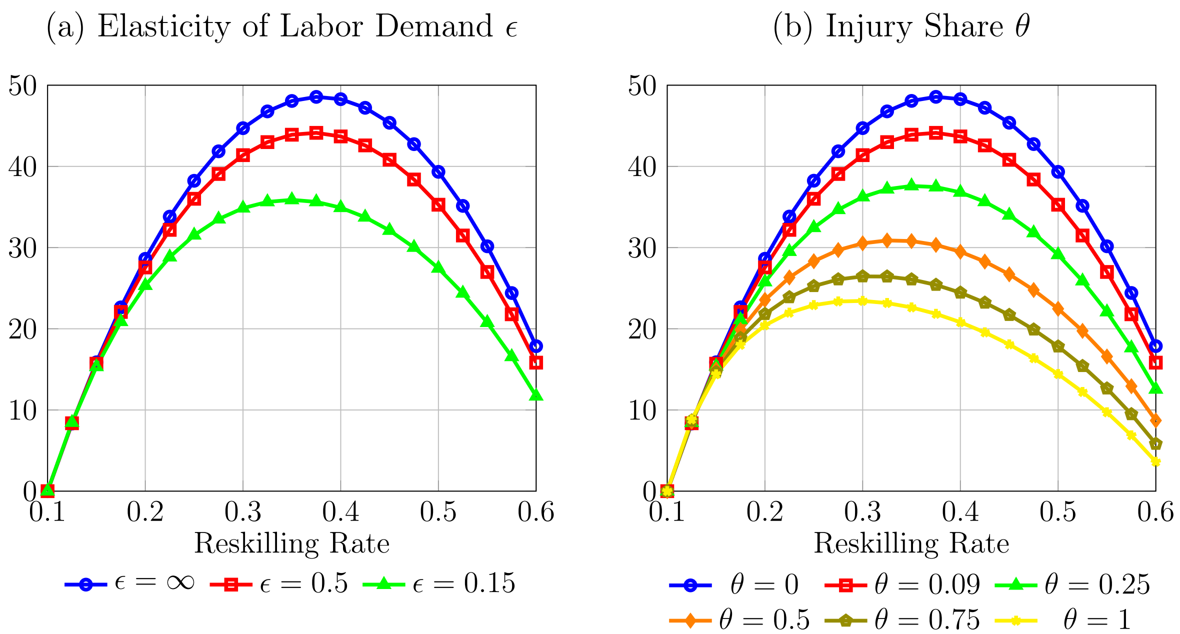
Injury share θ

Appendix K.3.2 calibrates the share of injured workers in aggregate labor supply. We first estimate the labor supply of injured workers $H^I(p)$ by scaling the treatment effects on earnings $f^E(p)$ with the number of injured workers per year. Next, we estimate the aggregate labor supply $H^S(p_0)$ as the total annual labor earnings in the occupations of reskilled workers. Combining the estimates, we obtain a share of $\hat{\theta} = \frac{\hat{H}^I(p_0)}{\hat{H}^S(p_0)} = 0.09$.

K.2.1 Simulations

Figure K.2 simulates the social surplus of increasing the reskilling rate from its current level. We simulate the surplus under various values of the elasticity of labor demand (Panel (a)) and the share of injured workers in aggregate human capital (Panel (b)). The cases of perfectly elastic labor demand ($\epsilon = \infty$) or infinitesimal injury share ($\theta = 0$) correspond to the counterfactuals from Section IV.D.

Figure K.2: Social Surplus of Increasing Reskilling at Different Parameter Values



Notes: This figure shows the social surplus of increasing reskilling from its current rate of 15% under various values of (a) the elasticity of labor demand ϵ (fixing the current injury share θ at 0.09) and (b) the current share of injured workers in aggregate human capital θ (fixing the elasticity of demand ϵ at 0.5).

Figure K.2 shows that the optimal reskilling rates are fairly robust to labor market equilibrium effects. For example, by lowering the labor demand elasticity to 0.5 (the focal estimate in the literature) and setting the injury share to 0.09 (the actual share), the optimal rate of reskilling decreases from 38% to 37%, and the maximum social surplus falls by 9%. Lowering the elasticity of labor demand even further to 0.15 (the lower bound in the literature), the optimal rate of reskilling drops to 35%, and the potential surplus decreases by 26%. The robustness of the optimal reskilling rates to labor market equilibrium effects partly reflects that injured workers constitute a minor fraction of aggregate labor supply $\theta = 9\%$. That said, by raising the injury share to 50%, the optimal rate of reskilling only falls to 33%.

K.3 Technical Details

K.3.1 Labor Market Equilibrium

The labor market clears the demand and supply of human capital:

$$H^D = w^{-\epsilon} \tag{25}$$

$$H^S(p) = H^N + H^I(p). \tag{26}$$

We normalize the current level of aggregate human capital $H^S(p_0)$ to 1 and define $h(p) = \frac{f^E(p)}{f^E(p_0)} - 1$. The aggregate human capital is then

$$H^S(p) = 1 + \theta h(p), \tag{27}$$

where $\theta = \frac{H^I(p_0)}{H^N + H^I(p_0)}$ is the current share of injured workers in aggregate human capital.

The labor market surplus is the area under the labor demand curve. The surplus per injured worker is

$$S(p) = \frac{f(p_0)}{\theta} \int_{1-\theta}^{1+\theta h(p)} H^{-1/\epsilon} dH \tag{28}$$

$$= \frac{f(p_0)}{\theta} \left(\frac{\epsilon}{\epsilon - 1}\right) \left[(1 + \theta h(p))^{\frac{\epsilon-1}{\epsilon}} - (1 - \theta)^{\frac{\epsilon-1}{\epsilon}}\right], \tag{29}$$

which reduces to the partial-equilibrium expression $f(p)$ when labor demand is infinitely elastic ($\epsilon \to \infty$), or injured workers constitute a vanishing of aggregate labor supply ($\theta \to 0$).

The general-equilibrium surplus from increasing the reskilling rate to $p > p_0$,

$$S(p) - S(p_0) = \frac{f(p_0)}{\theta} \left(\frac{\epsilon}{\epsilon - 1}\right) \left[(1 + \theta h(p))^{\frac{\epsilon-1}{\epsilon}} - (1 + \theta h(p_0))^{\frac{\epsilon-1}{\epsilon}}\right], \tag{30}$$

is increasing in ϵ and decreasing in θ.

K.3.2 Calibration

Injury share θ

The share of injured workers in aggregate human capital is

$$\theta = \frac{H^I(p_0)}{H^S(p_0)} = \frac{I \times f^E(p_0)}{E_0}, \tag{31}$$

where I is the number of injured workers, f^E is the treatment effects of reskilling on earnings from Equation (17), and E_0 is the total annual earnings in the occupation.[21] For I, we use the number of workers per year who lose earning capacity from a physical work accident (the population of workers for the causal estimates in Section IV), corresponding to row 4 of Table C.1. For E_0, we assume that labor markets are segregated by four-digit occupations and estimate the total annual labor earnings in the four-digit occupations of reskilled workers. For $f^E(p)$, we convert the annual estimates from Tables G.3 and G.5

[21] We set $H^I(0) = 0$ following the result in Table 3 that injured workers only transition into cognitive occupations if they are reskilled.

into lifetime values of workers aged 40 using Equation (20).[22,23] Combining the estimates, we obtain a share of $\hat{\theta} = 0.09$.

[22] By using lifetime earnings for injured workers f but annual earnings for aggregate labor supply H_0^S, we take into account that reskilling affects the stock of human capital.

[23] The effect of reskilling p depends on its distribution across worker ages. For simplicity, we use the estimates for workers aged 40.

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