Changing Tracks: Human Capital Investment after Loss of Earning Ability*

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Abstract

We provide the first evidence on how workers invest in human capital after losing ability. Studying quasi-random work accidents using Danish administrative data, we find that workers take up higher education after physical injuries. Workers enroll in bachelor's programs that build on their work experiences and provide pathways to cognitive occupations. Yet, most injured workers do not invest in human capital, and we cast light on the underlying causes. Exploiting differences in eligibility driven by prior vocational training, we find that human capital investment moves injured workers from disability benefits to full-time employment, earning 25 percent more than before their injuries. Higher education for injured workers can generate net social returns of 500 percent.

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1 Introduction

The transition of workers from physical to cognitive occupations is a core goal of modern reskilling programs. By providing the human capital necessary for such transitions, the programs promise to alleviate earnings shocks from automation, globalization, and physical injuries.[1]

We study these issues in the context of work accidents, a severe shock to the earning abilities of workers. We provide evidence on two fundamental questions: How do workers invest in human capital after losing physical abilities? And can human capital programs help workers switch from physical to cognitive occupations?

To answer these questions, we link micro data on the health shocks, human capital investments, and employment outcomes of workers in Denmark from 1995 to 2017. Our analysis proceeds in two parts.

In the first part of the paper, we study how workers invest in human capital after losing earning abilities. For this analysis, we first document that work accidents occur quasi-randomly within occupations, as affected and non-affected workers have similar health and earnings before accidents. Work accidents cause permanent damage to workers whose earnings suffer a persistent 40 percent loss.

Studying the work accidents, we establish three findings about how workers invest in human capital after losing ability. First, most injured workers do not invest in human capital. Ten years after the work accidents, about 13 percent of workers have enrolled in a degree at any level, and accumulated participation in non-degree courses is negligible. Second, workers who invest in human capital overwhelmingly enroll in four-year bachelor's degrees. Third, workers select degrees that build on their work experiences and provide pathways to jobs with lower physical demands.

Next, we investigate why more workers do not invest in human capital after losing earning ability. We highlight three critical factors. First, investment decreases steeply

[1] The World Economic Forum has called for a "Reskilling Revolution" to alleviate the automation of manual jobs (World Economic Forum, 2019). Trade Adjustment Assistance provides reskilling vouchers for workers displaced by import competition in the United States (U.S. Department of Labor, 2022). Workers' Compensation includes vouchers for reskilling injured workers (Department of Industrial Relations, 2022).

with age, such that workers older than 50 do not invest in education after work accidents. Yet, even among the youngest workers, only about 40 percent of workers pursue higher education after injuries. Second, human capital investments are made predominantly by workers whose prior vocational training gives direct access to higher education. Finally, we find that financial support is crucial, as workers only invest in human capital if offered extended unemployment benefits for their studies.

In the second part of the paper, we study how human capital investment affects the labor supply of injured workers. To identify causal effects, we exploit that only a subset of vocational degrees give direct access to post-secondary programs in Denmark. For example, prior vocational training in carpentry gives direct access to the bachelor's program in Construction Architecture. By contrast, welding (an otherwise similar vocational degree to carpentry) does not give access to post-secondary programs, and workers must complete three years of high school before any higher education.

We conduct a host of checks for whether workers with different access to higher education are otherwise comparable. First, we ensure that the workers are similar on observables before the accidents and validate that they experience comparable injuries. Second, we document that the workers have similar earnings profiles and human capital investments if not hit by a work accident. Third, we show that the oldest workers, who do not invest in human capital regardless of eligibility, fare similarly in the labor market after work accidents.

Comparing workers with different access to higher education, we estimate sizable earnings gains for workers who reskill after work accidents. Reskilled workers do not claim disability benefits and instead transition into cognitive occupations, earning 25 percent more than before their injuries. A back-of-the-envelope calculation implies a 500 percent net social return on higher education for injured workers.[2] These remarkable social returns reflect that higher education moves injured workers from disability insurance (a liability to the government budget) to taxable high-income employment (an asset to the budget). In total, the government reaps 60 percent of the social surplus from reskilling despite

[2]The internal rate of return (IRR, the annual interest rate that makes the investment break even) is 36.5 percent.

covering tuition and benefits.

We rationalize our empirical findings within a theoretical framework in which work accidents lower workers' physical abilities, and human capital investment helps workers switch to cognitive occupations. Additional empirical evidence validates this mechanism for the impact of work accidents on human capital investment. First, work accidents only induce human capital investment if they decrease workers' earning capacity. Second, workers do not invest in human capital after cognitive injuries. Finally, injured workers do not benefit from access to degrees with physical demands similar to their previous jobs.

Work accidents are costly to workers, firms, and the government, yet we have limited evidence on policies that alleviate these burdens (Nichols et al., 2020). In the United States, work injuries are a primary cause of disability insurance claims (Reville and Schoeni, 2004), and their total costs amount to 1.5 percent of the Gross Domestic Product (Leigh, 2011). Compared to mass layoffs, a shock to workers frequently studied in the labor literature (Jacobson et al., 1993), work accidents are both more prevalent and cause more persistent earnings losses.[3] Despite the high costs, we have limited knowledge of what helps injured workers reattach to the labor market. Aizawa et al. (2022) find an important role for wage subsidies in retaining injured workers at their original employers. We complement this work on retention by studying human capital policies to help workers change tracks in the labor market. In particular, workers' compensation often includes vouchers for reskilling (Department of Industrial Relations, 2022), yet no evaluation of human capital investment of injured workers exists.

Our study is inspired by human capital models featuring multidimensional ability (Adda and Dustmann, 2022; Lise and Postel-Vinay, 2020; Sanders and Taber, 2012; Yamaguchi, 2012). We provide direct evidence in support of the mechanisms in these structural models. First, by showing how loss of physical ability induces workers to invest in cognitive skills, our setting spotlights the importance of multidimensional ability for understanding human capital investment. Second, by documenting how human capital helps workers switch from physical to cognitive occupations, we highlight the role of multidimensional ability

[3]See Figures A.2 and A.3.

in workers' labor supply. Our findings are consistent with Gensowski et al. (2019), who show that physical disability from childhood makes individuals more likely to later obtain a university degree and work in white-collar jobs.

Our findings inform policies to help displaced workers (Jacobson et al., 2011). Reskilling programs are often motivated by structural changes, such as automation or globalization, forcing workers to switch out of manual occupations (Hyman, 2018).[4] Our theoretical framework clarifies how work accidents, automation, and globalization share implications for workers as they all lower the earning potential of manual work. Our empirical evidence spotlights the importance of four-year bachelor's degrees in helping workers switch from manual to cognitive occupations. The evidence suggests that policy discussions around reskilling may be reoriented toward post-secondary degrees instead of the traditional focus on shorter training courses (Humlum and Munch, 2019).

2 Institutional Setting and Data

In this section, we outline the Danish institutional setting, highlighting the features relevant to this study and describing our data sources.

2.1 Institutional Features

Denmark is known for its welfare state and flexicurity model. In brief, the government provides health care and education free of charge. Firms can hire and fire workers with relative ease, and displaced individuals are supported by generous transfers from the government. The income support requires individuals to adhere to an expansive set of active labor market policies. For a recent description and comparison to the US context, see Kreiner and Svarer (2022).

[4]In the United States, the Manpower Development and Training Act (MDTA) was enacted to alleviate industrial automation. Trade Adjustment Assistance (TAA) provides reskilling vouchers for workers displaced by import competition.

2.1.1 Work Accidents

Work accidents are sudden occurrences in the course of work, leading to occupational injury. The law mandates that employers report work accidents within 14 days of occurrence.[5]

Work accidents differ from *occupational diseases*, which are contracted slowly due to ongoing exposure during work. For example, a mining collapse is a work accident, whereas miner's lung is an occupational disease. Our empirical analysis focuses on work accidents, whose discrete and unexpected timing lends itself to event studies.

The Labor Market Insurance (Arbejdsmarkedets Erhvervssikring [AES]) assesses whether a work injury claim qualifies for compensation. The assessment is based on two metrics, *personal impairment* and *earning capacity loss*. Personal impairment is based solely on the injury diagnosis and does not consider the worker's occupation, age, or earnings. To determine the earning capacity loss caused by an injury, the AES employs a team of industry specialists to estimate the loss of work capacity in the worker's occupation. An injury qualifies for compensation if the personal impairment rate exceeds 5 percent or the earning capacity loss exceeds 15 percent. The compensations are paid as one-time transfers and do not depend on the receipt of other government transfers, including disability insurance.[6] Each year, AES pays between 3 and 5 billion DKK in compensation for work accidents, equivalent to 0.15-0.25 percent of GDP. Section 3.1 describes the prevalences of work accidents across occupations.

2.1.2 Health Care

Healthcare in Denmark is funded by the government and available free of charge to all residents, regardless of employment status. The universal and free healthcare system provides workers with the ideal conditions to seek care for injuries and alleviates a common concern in the literature that individuals select into healthcare based on socioeconomic conditions (Currie and Madrian, 1999).

[5]Workers, unions, or medical professionals may also report the accidents within one year of occurrence.

[6]For earning capacity losses above 50 percent, the additional compensations are paid in monthly installments.

2.1.3 Human Capital Investment

Upon completion of primary school (1st-9th grade), Danish students can enroll in high school or pursue a vocational degree, lasting three to four years. Vocational degrees target specific occupations, whereas high school is a stepping-stone to higher education. Higher education consists of three-year bachelor's degrees, many of which are extended by two-year master's programs. Individuals may also take non-degree courses at the primary, secondary, vocational, and higher levels.

Because work accidents happen in physical occupations, most injured workers have a vocational degree or primary school as their highest educational attainment (Table 2). While high school is the main track to higher education, a subset of vocational degrees provides access to specific higher degrees. For example, a vocational degree in carpentry gives access to the bachelor's program in Construction Architecture. We describe the vocational degrees and their access to higher education in Section 6.1 and Appendix D.1.

2.1.4 Government Transfers

Disability insurance is the most relevant transfer program for injured workers in Denmark. Disability benefits are set at 19,000 DKK (2,700 USD) per month, equivalent to 50-80 percent of injured workers' prior earnings. To receive disability benefits, workers must be medically disabled from work. Disability benefits are paid monthly until retirement age. In terms of eligibility criteria, replacement rates, and benefit duration, the Danish disability insurance matches the Social Security Disability Insurance (SSDI) in the United States (Autor and Duggan, 2003; Krueger and Meyer, 2002; Reno et al., 2003).[7]

Injured workers may receive *rehabilitation benefits* to participate in formal education or undergo retraining at a firm. The benefits are set at 19,000 DKK per month, identical to disability insurance. To claim rehabilitation benefits, a worker must be limited in his ability to work at his current skill set and have a realistic chance that reskilling could lead to sustainable employment. (Ramboll, 2015). We use the term *reskilling benefits* to

[7]One difference is that there is no offset for workers' compensation in Denmark. SSDI caps the total wage replacement at 80 percent (Khan et al., 2017).

refer to rehabilitation benefits for formal education.[8]

If not offered rehabilitation benefits, students are eligible for *State Education Support* (SU) set at 6,400 DKK (900 USD) per month, equivalent to 15-30 percent of injured workers' prior earnings (one third of disability or rehabilitation benefits).[9] Full-time students opt out of other transfers, including disability insurance, unemployment benefits, or cash assistance.

Unemployed workers may claim *unemployment benefits* (if members of a unemployment insurance fund, which most injured workers are) or *cash assistance*. Unemployment benefits are set at a maximum of 19,000 DKK per month, identical to disability and rehabilitation benefits. To claim the benefits, the workers must meet with a caseworker, who monitors job search and assigns training programs. Individuals who are temporarily ill may claim *sickness benefits* instead of unemployment benefits.

2.2 Data Sources

This section describes our sources of data. Our starting point is an administrative register of work injury claims in Denmark. We link the injuries to a host of registers at Statistics Denmark, providing detailed information about the health, human capital investments, government transfers, and employment of individuals from 1996 to 2017.

2.2.1 Work Accidents

Our data on work accidents come from the administrative registers of the AES, the entity responsible for handling injury claims under the Workers' Compensation Act of Denmark.

In evaluating the injury claims, the AES records detailed information on the accidents, including the injury type (e.g., bone fracture), placement on the body (e.g., arm), and cause of the accident (e.g., collision with a machine). The *Industrial Injury Register* (Arbejdsskaderegisteret) collects this information, together with the timing, assessed

[8] Reskilling benefits mirrors policies in the US, such as the vocational rehabilitation benefits of Workers' Compensation or the transfer component of Trade Adjustment Assistance.

[9] Disabled workers may apply for an additional Special Education Support of 5,000-9,000 DKK per month, equivalent to 15-30 percent prior earnings of injured workers, although these transfers are rarely granted in practice (Ramboll, 2015).

earning capacity loss, personal impairment, and compensations, of all work injuries.[10]

2.2.2 Health Care

We link three administrative registers of the healthcare utilization of individuals in Denmark.

The *National Patient Registry* (Landspatientregisteret) covers all hospitalizations (inpatient and outpatient), in both private and public hospitals, with detailed diagnosis codes. The *Health Insurance Registry* (Sygesikringsstatistik) covers all individual contacts with primary-care physicians and medical-care specialists outside of hospitals. The *Prescription Drug Database* (LMDB) covers all prescribed drugs that were purchased in Denmark.[11]

Combining the three registers, we observe the universe of transactions for every person within the Danish healthcare system, including hospitalizations, doctor's visits, and prescription drug purchases from 1996 to 2017.[12]

2.2.3 Human Capital Investment

We measure human capital investments using administrative registers that cover all participations in formal degrees and courses in Denmark.

The *Education Register* (UDDA) records enrollment in and completion of formal degrees. The register contains six-digit program codes covering basic education (primary and secondary school), vocational programs (e.g., a vocational degree in carpentry), and post-secondary programs (e.g., a bachelor's degree in Construction Architecture).

The *Course Participant Register* (VEUV) records enrollment in and completion of training courses at the basic (e.g., a Danish language course), vocational (e.g., a certificate course in crane operations), and post-secondary (e.g., a master's course in computer programming) levels. The courses are classified according to five-digit codes. The register covers courses eligible for government subsidies and records all attendees regardless of

[10] Leth-Petersen and Rotger (2009) use the register to study whiplash claims.

[11] In Denmark, 90 percent of medications are subject to prescriptions (Fadlon and Nielsen, 2019). Prescription drugs include, for example, painkillers and opioids.

[12] Fadlon and Nielsen (2019) use the registers to study how family networks shape health behaviors.

their funding source.[13]

2.2.4 Government Transfers

The *Danish Register for Evaluation of Marginalization* (DREAM) records social transfers to individuals, including benefits for unemployment, rehabilitation, disability, and public pensions.

2.2.5 Matched Employer-Employee Data

Our data on workers and employers come from the *Integrated Database for Labor Market Research* (IDA). The database records the earnings, hours, wage rates, and occupations of workers in Denmark. Workers are linked to establishments and firms in week 48 of each year. Occupations are classified according to a six-digit version of the ISCO nomenclature, which we link to the Occupational Information Network (O*NET) on the task contents of occupations.

2.2.6 Sociodemographics

The *Population Register* (POP) records the age, gender, and family relations of all individuals in Denmark.

3 Work Accidents

This section studies the incidence of work accidents. We start with a bird's-eye view of work accidents, documenting their prevalence across occupations. Next, we zoom in at the worker level, examining the outcomes of workers before and after accidents.

In brief, we find that work accidents are common in physically demanding occupations. We also document that work accidents occur quasi-randomly within occupations and cause persistent damage to the health and earnings of workers.

[13] In 2010, about 642,000 Danes (out of a labor force of 2.7 million) participated in courses recorded in the Course Participant Register.

3.1 Incidence across Occupations

Every year, about 0.6 percent of workers in Denmark are injured in a work accident. For comparison, this number is slightly higher than the risk of being displaced in a mass layoff, a shock to workers frequently studied in the labor literature (Jacobson et al., 1993).[14]

Table 1 lists the five occupations with the highest rate of work accidents. The ranking shows that accidents predominantly occur in physically demanding jobs, such as building and construction. For example, measuring the physical requirements of occupations using the O*NET index of *"Physical Ability Requirements"*, we find that 84 percent of all work injuries occur in the 50 percent most physical occupations.[15]

Table 1: Occupations with Highest Accident Rates

Occupation	Injuries/ 1000 FTEs	Most Common Injury	
		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.

3.2 Impact on Workers

This section examines the outcomes of workers before and after they experience a work accident. We make a series of sample cuts to hone in on a set of well-defined injury events.

First, we use the AES data to focus on work accidents that caused a loss to workers' earning capacities. Second, we focus on work accidents with a physical impact on workers,

[14] Appendix Figure A.2 shows the time series of work accidents and mass layoffs in Denmark.

[15] *Physical Ability* is defined as the average importance of Static Strength, Explosive Strength, Dynamic Strength, Trunk Strength, and Stamina, as measured by O*NET.

and thus exclude psychological shocks. Third, we focus on workers with stable employment before the injury, defined as full-time employment in the three years leading up to the accident. Finally, we exclude military workers because they represent a distinct set of work accidents and labor market prospects. Appendix Table A.1 shows how the restrictions shrink our analysis sample of work accidents.

Table 2 shows characteristics of workers in the year before experiencing an accident ("Injury" column). The typical injured worker is a 44-year-old man who has completed a vocational degree. Before the accident, the worker was employed in a physically demanding occupation with lower cognitive requirements.

The next columns report characteristics of workers who do not experience an accident in the event year ("No Injury"). The "Match" column matches the workers to characteristics of the "Injury" workers. That is, for each injured worker, we find a control worker with the same occupation (three-digit ISCO), industry (two-digit NACE), education level, age, and gender in the year before the work accident.

The "Employment" panel shows that the "Injury" and "Match" workers are similar on outcomes that we do not match on, including their earnings, work hours, and amount of sick leave. The similarity supports the notion that the workers are indeed comparable.[16]

In Appendix Figure A.1, we plot the incidence of work accidents for the "Injury" and "Match" workers. The figure shows that the workers have a minimal risk of work accidents before and after the event year, alleviating identification concerns when treatments are staggered (De Chaisemartin and d'Haultfoeuille, 2020).

[16](Altonji et al., 2005) and Oster (2019) provide conditions under which the similarity of workers on observable outcomes is informative about the quasi-exogeneity of work accidents.

Table 2: Worker Outcomes before Accident

	Injury	No Injury		Mean Difference
		Random	Match	Injury - Match
Demographics				
Age	43.32	43.11	43.32	0.00
	(10.14)	(10.89)	(10.14)	(10.14)
Female	0.39	0.45	0.39	0.00
	(0.49)	(0.50)	(0.49)	(0.49)
Education				
Years of Schooling	12.85	14.12	12.91	-0.06
	(2.63)	(2.55)	(2.56)	(2.59)
Primary	0.32	0.18	0.32	0.00
	(0.46)	(0.38)	(0.46)	(0.46)
Vocational	0.51	0.42	0.51	0.00
	(0.50)	(0.49)	(0.50)	(0.50)
High School	0.02	0.05	0.02	0.00
	(0.13)	(0.22)	(0.13)	(0.13)
Post-Secondary	0.16	0.35	0.16	0.00
	(0.36)	(0.48)	(0.36)	(0.36)
Employment				
Hours Worked	1,691.64	1,735.67	1,724.33	-32.69
	(551.49)	(430.04)	(862.41)	(723.84)
Labor Income (1000 DKK)	314.19	386.91	317.27	-3.07
	(116.03)	(278.36)	(128.91)	(122.64)
Sick Leave	0.05	0.02	0.03	0.02
	(0.12)	(0.10)	(0.10)	(0.11)
Occupation				
Cognitive Ability Requirement	-0.39	0.11	-0.37	-0.03
	(0.84)	(0.95)	(0.86)	(0.85)
Physical Ability Requirement	0.75	-0.07	0.71	0.03
	(0.93)	(1.11)	(0.92)	(0.92)
Injury Rate (x 1000)	10.35	6.06	10.08	0.27
	(5.03)	(4.86)	(4.94)	(4.99)
Injury				
Earnings Capacity Loss	36.58	0.00	0.00	-
	(22.20)	(0.00)	(0.00)	
Personal Impairment	12.44	0.00	0.00	-
	(10.03)	(0.00)	(0.00)	
Year of Injury	2,004.9	2,006.7	2,004.9	0.00
	(4.84)	(5.60)	(4.84)	(4.84)
Observations	14481	14481	14481	

Notes: The "Injury" column shows the average outcomes of workers in the year before a work accident. Standard deviations are reported in parentheses. The "No Injury" columns show workers who satisfy the pre-event employment requirements but do not experience work accident in the event year. The "Random" subcolumn shows averages for randomly chosen workers (one-to-one). The "Match" subcolumn shows averages for workers with the age, gender, education level, occupation, and industry as the "Injury" workers in the year before the injury (one-to-one random match within cells). The "Mean Difference" column reports the mean difference between the "Injury" and "Match" workers with mean standard deviations in parentheses.

In Figure 1, we study the outcomes of workers around the work accidents. The plots are simple differences-in-differences in outcomes Y between the injured workers ($I = 1$) and their matches ($I = 0$), indexed to the year before the accident:

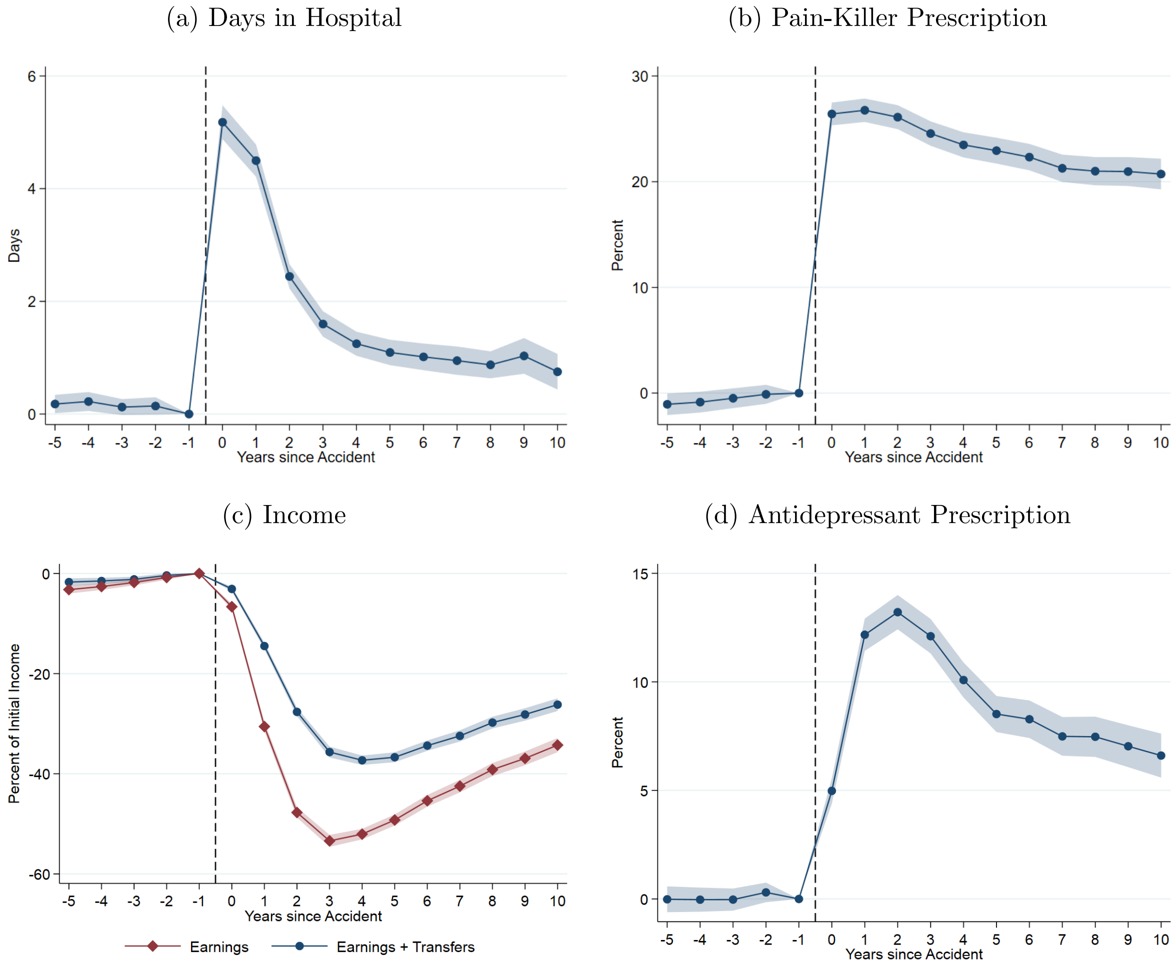
$$Y_{it} = \beta_1^Y I_{ie} + \sum_k \beta_{0k}^Y \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -1} \beta_{1k}^Y I_{ie} \mathbf{1}_{\{t=e+k\}}, \tag{1}$$

where $\mathbf{1}_{\{t=e+k\}}$ are event-time dummies that switch on if year e occurred k ago, and β_{1k}^Y are our coefficients of interest. We estimate Equation (1) by OLS and cluster standard errors at the match-cell level.

Figure 1 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, whose days spent in the hospital spike after injuries (Panels (a) and (b)). Third, work accidents cause persistent damage to workers. Workers' use of painkiller prescriptions jumps after the injury (Panel (b)), and their labor earnings suffer a persistent loss of about 40 percent (Panel (c)). For comparison, Appendix Figure A.3 shows that work accidents cause more persistent losses of earnings than mass layoffs. 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 about 30 percent (Panel (c)) and the share of workers who use antidepressants increases about 10 percentage points (Panel (d)).[17]

[17] Our focus on mental and physical health complement studies of the health effects of job displacement. Sullivan and Von Wachter (2009) find that job loss increases mortality among workers in the US. Kuhn et al. (2009) show that displacement is associated with increased use of antidepressants among workers in Austria. Browning and Heinesen (2012) find that displacement increases mortality due to suicide, alcohol-related disease, and mental illness in Denmark.

Figure 1: Worker Outcomes around Accident



Notes: This figure shows the differences-in-differences in outcomes (measured relative to year -1) between the "Injury" and "Match" workers from Table 2. Shaded areas represent 95 percent confidence bands, estimated using the regression equation (1). Panel (a) shows the days spent in the hospital, Panel (b) shows the share of workers with a prescription for pain-relieving medications, and Panel (c) shows the labor income measured in percent of the average level in year -1. Panel (d) shows the share of workers with a prescription for antidepressant medications.

4 Human Capital Investment

In this section, we use work accidents to study how workers invest in human capital after losing earning ability. Our goal is twofold. First, we document which types of human capital programs appeal to workers who have lost ability. Second, we study the extent to which workers invest in these programs.

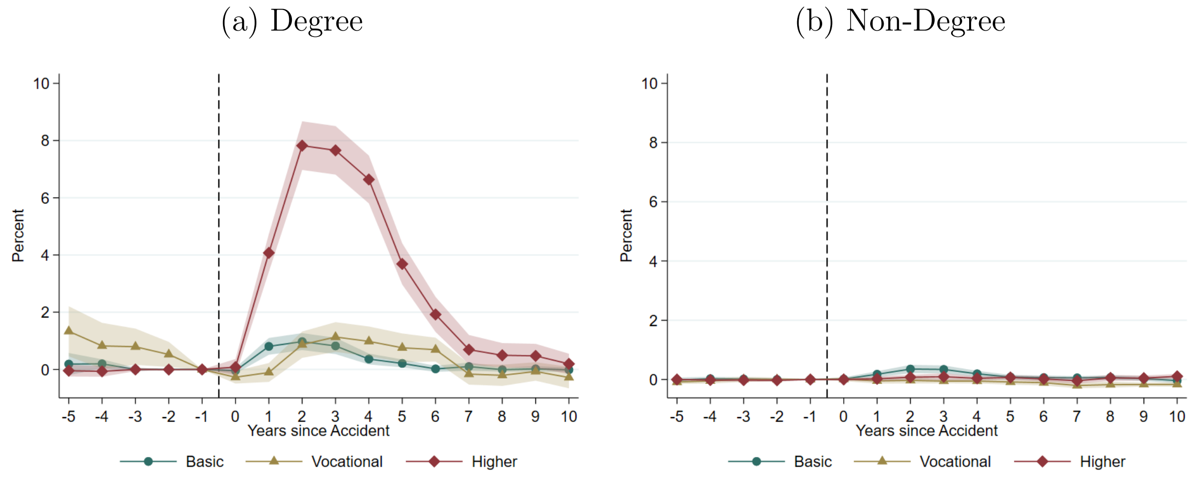
Figure 2 plots the participation of workers in degree and non-degree courses. For example, *higher non-degree* include university courses in computer programming, and *higher degree* include bachelor's programs in construction engineering. The activity is measured in full-time equivalents. For example, the *higher degree* line shows that, two years after the accident, eight percent of injured workers are enrolled in a post-secondary degree. The figure focuses on workers whose initial education provides access to higher degrees because these workers are better positioned to invest in human capital upon injury. Appendix Figure B.1 shows the plots separately for each initial level of education.[18]

Figure 2 reveals two findings. First, most workers do not invest in human capital after losing work abilities. Ten years after work accidents, only about 13 percent of workers have enrolled in a degree at any level, and the workers have participated in around a percent of a full-year's worth of non-degree courses. Second, workers who invest overwhelmingly enroll in higher degrees, lasting about four years. In particular, higher degrees constitute 83 percent of total human capital investment after work accidents.

In summary, Figure 2 shows that workers make long-term and advanced investments in human capital after losing abilities. By contrast, shorter training courses, including those targeting high-skill jobs, are not attractive for injured workers. The results indicate that switching from physical to cognitive jobs may require ambitious investment in human capital, lasting multiple years at the post-secondary level.

[18]Workers with access to higher education consist of high school graduates and workers whose vocational training provides access to specific higher degrees. Because work accidents happen in physical occupations (and most high school graduates continue to earn a post-secondary degree), 95 percent of injured workers with access to higher education have a vocational degree as their highest educational attainment (Table B.1). Section 2.1.3 describes the Danish educational system, and Appendix D.1 lists the vocational degrees and their access to higher education. Sections 5.2 and further analyze the importance of access to education.

Figure 2: Enrollment in Courses



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 workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95 percent confidence bands estimated using the regression equation (1).

In Appendix B.1, we cast light on the types of higher degrees injured workers invest in. To do so, we link each degree to its target occupations, allowing us to compare characteristics of the degrees to workers' initial jobs.[19] The classification of degrees delivers two insights. First, workers invest in degrees that target occupations that are less physically demanding than their initial job (Figure B.2.(a)). Second, when investing in human capital, workers target degrees that build on their work experiences (Figure B.2.(b)). For example, many carpenters obtain a bachelor's degree in Construction Architecture after work accidents.[20]

[19]For example, we link the bachelor's degree "4087 Construction Architecture" to the target occupation "2142 Construction Architects." Appendix B.1.1 explains the linking methodology.

[20]Workers 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"* (O*NET). The career clusters are 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*.

4.1 Mechanisms

In this paper, we interpret work accidents as shocks to workers' physical abilities. The interpretation allows us to tie our reduced-form evidence to theories of human capital investment that feature multidimensional ability (Sanders and Taber, 2012).[21] In Appendix B.2, we provide empirical evidence on this mechanism for the impact of work accidents on human capital investment.

To assess the importance of lost earning *ability* for human capital investment, we exploit that the AES assesses the loss of earnings capacity caused by each work accident.[22] Figure B.3 shows that work accidents *only* generate human capital investment if they cause a loss of earnings capacity.

To examine whether human capital investment differs for *cognitive* versus *physical* injuries, we use diagnosis codes to identify permanent brain damage. First, cognitive injuries are rare among work accidents. Second, zooming in on these rare events, Figure B.4 shows that workers do not invest in human capital after cognitive injuries.

5 Determinants of Investment

A takeaway from Section 4 is that most workers do not invest in human capital after losing physical ability. In this section, we shed light on the underlying causes of the modest responses. In Section 6, we exploit one of the determinants (eligibility for higher education) to identify the causal effect of reskilling injured workers.

5.1 Worker Age

In Figure 3, we plot the enrollment rate in higher degrees by the age at which workers experience a work accident. The plot delivers two insights.

First, human capital investment decreases steeply with age. In particular, workers older than 50 do not invest in higher education after work accidents.[23] The pattern is

[21] Appendix E develops such a model, which we use to derive empirical predictions and discuss theoretical implications.

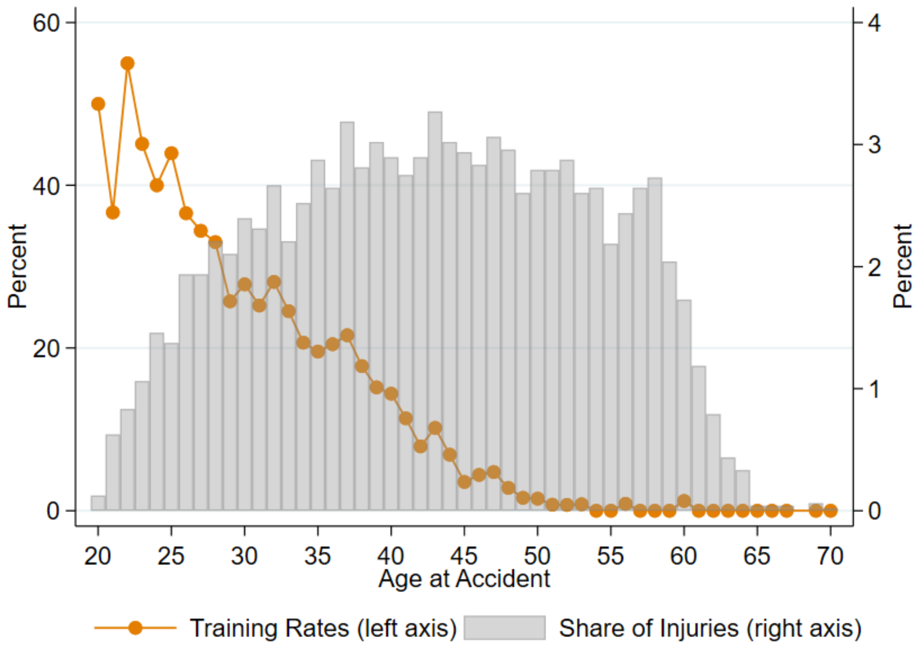
[22] Section 2.2 details the assessment process.

[23] Jacobson et al. (2005) document a similar age gradient in the retraining decisions of displaced workers.

consistent with a lifecycle model in which forward-looking workers consider if they have enough remaining working years to recoup an educational investment.[24] The pattern suggests that workers invest in human capital based on the expected returns and that the modest responses to injuries could be rational from a cost-benefit perspective. We return to the cost-benefit considerations in Section 6.4.

Second, even among the youngest workers, only about 40 percent of eligible workers enroll in higher education. Hence, factors other than age must discourage injured workers from investing in human capital. We explore two of these factors below.

Figure 3: 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 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.

[24]We formalize this mechanism in the theoretical framework in Appendix E; see discussions in Section E.2.3.

5.2 Access to Higher Education

Section 4 highlights the importance of admission eligibility for human capital investment after work accidents. In particular, Figure B.1 shows that human capital investments are made overwhelmingly by workers whose initial educational backgrounds give eligibility for higher education. For example, ten years after the work accidents, two-thirds of the total impact on the completion of higher degrees are driven by the one-third of workers who initially had direct access to higher education (Table B.1).

The importance of access to higher education suggests that relaxing admission criteria could be a way to reskill more injured workers. In Section 6, we explore this idea further by comparing the outcomes of injured workers who differ in their eligibility for higher education.

5.3 Financial Support

Policy discussions on reskilling often emphasize income support for participating workers. For example, TAA extends UI benefits to workers who participate in formal education, and Jacobson et al. (2011) emphasize covering living expenses for incentivizing displaced workers to reskill.

To investigate the role of financial support, we exploit that local job centers may offer *reskilling benefits* to injured workers who reskill. Reskilling benefits extend UI benefits to injured workers who enroll in full-time studies. The transfers represent around 65 percent of the prior earnings of injured workers, equivalent to three times the default stipend paid to students in Denmark (SU).[25] To receive reskilling benefits, a worker should (*i*) be limited in his ability to work at his current skill set, and (*ii*) have a realistic chance that reskilling could lead to sustainable employment (Ramboll, 2015). Appendix Figure C.2 shows that about 17 percent of workers receive reskilling benefits after work accidents.

Appendix Figure C.1 splits the take-up of higher degrees by whether the workers receive reskilling benefits after the work accidents. Strikingly, the figure shows that it is *only* workers who receive reskilling benefits enroll in higher education after work accidents.

[25] Section 2 describes the government transfers relevant for injured workers.

To be clear, the remaining 83 percent of injured workers who do not receive reskilling benefits could still study free of charge and even receive the default stipend (SU). The fact that none of these workers choose to do so highlights the crucial importance of financial support for incentivizing workers to reskill.[26]

6 Returns to Investment

In this section, we ask how human capital investment affects the labor supply of injured workers. Identifying the causal effects of these investments is challenging because, as we have documented, workers reskill based on the severity of their injuries (Section 4.1), their expected payoffs from education (Section 5.1), and other factors related to their counterfactual job opportunities without reskilling.

To identify the causal effect of human capital investment, we exploit that some initial vocational degrees give direct access to post-secondary programs in Denmark, but others do not.[27] The differences in admission criteria allow us to compare otherwise similar workers who differ in their access to higher education upon injury.

In Section 6.1.1, we identify similar workers who differ in their eligibility for higher education. We conduct several placebo checks of the comparability of these workers. In Section 6.2, we use the workers to estimate the reduced-form impacts of access to higher education for injured workers. Section 6.3 estimates the potential outcomes of workers who reskill after a work accident. Finally, in Section 6.4, we conduct a cost-benefit analysis of providing higher education for injured workers.

[26]To appreciate the importance of financial support, it is key to realize the life situation of most injured workers. The typical worker is about 45 years old, has a family with kids to support, and was the breadwinner in the household before the accident. The default stipend (SU) does not cover the living expenses of these workers. Hence, to make financial ends meet, the workers may be forced to stay on unemployment benefits or take up disability benefits if eligible. In Section 6.3, we study the outside options of injured workers who invest in human capital.

[27]The identification strategy is motivated by the finding in Section 5.2 that initial eligibility for higher education is crucial for the human capital investment of workers.

6.1 Access to Higher Education

In Denmark, some initial vocational degrees give direct access to higher education programs, but others do not. For example, vocational training in carpentry gives direct access to the bachelor's program in Construction Architecture. By contrast, landscape gardening (an otherwise similar vocational degree to carpentry) does not give access to post-secondary degrees, and workers must complete three years of high school before any higher education.

In Appendix Table D.3, we provide a list of vocational degrees and their access to higher-education programs. The injured workers whose vocational training provides access to higher education are about 70 percent craft workers (e.g., carpenters), 10 percent care workers (e.g., nurse assistants), 10 percent retail workers (e.g., sales assistants), and 10 percent food service workers (e.g., chefs).

In Section 6.1.1, we first identify comparable workers who differ in their initial eligibility for higher education. We show that the workers are similar before the work accidents and suffer similar injuries after the work accident. In Section 6.1.2, we verify that the workers with access to higher education indeed invest more in human capital after work accidents. In Section 6.1.3, we conduct placebo checks of the comparability of the worker groups.

6.1.1 Identification Strategy

To find similar workers who differ in their eligibility for higher education, we implement an inverse probability weighing (IPW) of workers (Abadie, 2005). The reweighing strategy, which we detail in Appendix D.1, allows us to compare workers of similar health, age, gender, years of schooling, and occupation, who differ in their access to higher education. Table 3 shows that the "Access" and "No Access, IPW" workers balance on these covariates.

Table 3: Worker Outcomes before Accident

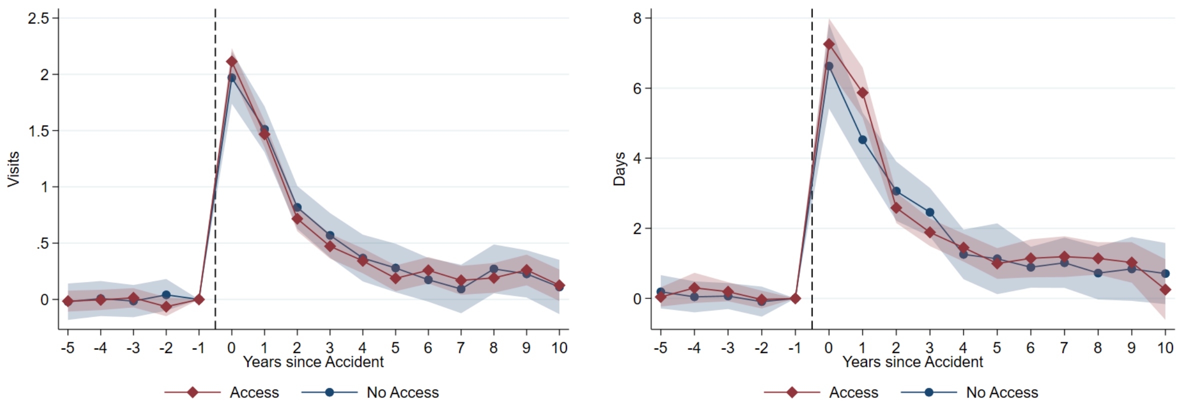
	Access	No Access		Mean Difference
		Raw	IPW	Access - IPW
Age	41.83	43.96	42.32	-0.49
	(10.80)	(9.97)	(10.04)	(10.42)
Female	0.19	0.42	0.24	-0.04
	(0.40)	(0.49)	(0.35)	(0.37)
Years of Schooling	14.26	10.98	14.18	0.08
	(0.33)	(2.25)	(0.70)	(0.54)
Post-Secondary Degree	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Parent with Post-Secondary Degree	0.08	0.05	0.07	0.01
	(0.27)	(0.22)	(0.25)	(0.26)
Sickness Benefits	0.05	0.05	0.04	0.00
	(0.11)	(0.12)	(0.12)	(0.11)
Hours Worked	1673.35	1683.27	1684.97	-11.61
	(0.60)	(0.45)	(486.52)	(344.02)
Labor Income (1000 DKK)	387.44	357.70	389.40	-1.96
	(123.19)	(115.72)	(124.68)	(123.94)
Physical Ability Requirement	0.98	0.80	0.74	0.24
	(0.89)	(0.83)	(0.82)	(0.86)
Cognitive Ability Requirement	-0.41	-0.65	-0.53	0.12
	(0.73)	(0.74)	(0.72)	(0.73)
Earnings Cap. Loss	34.31	37.60	36.14	-1.83
	(22.13)	(22.13)	(22.03)	(22.08)
Injury Severity	12.82	12.32	12.89	-0.07
	(11.14)	(9.66)	(10.49)	(10.82)
Injury Rate (x 1000)	11.06	10.13	10.40	0.66
	(4.72)	(4.99)	(5.01)	(4.86)
Year of Injury	2005.27	2004.48	2005.49	-0.22
	(4.85)	(4.76)	(4.83)	(4.84)
Observations	4568	7412		

Notes: This table shows the characteristics of workers in the year before work accidents. 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. Section D.1 details the IPW procedure. The "Mean Diffifference" column shows the mean difference between the "Access" and "IPW" workers with mean standard deviations in parentheses.

To validate the comparability of the two groups, Figure 4 shows that the work accidents cause similar health impacts for the groups immediately after the injury. In the year of the work accidents, the "Access" and "No Access" workers spend about six days in the hospital. The hospitalization rates then decline similarly in the years after the work accidents.

Figure 4: 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 groups correspond to the "Access" and "No Access, IPW" columns of Table 3. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. This figure focuses on workers with a vocational degree within craft work. Shaded areas represent 95 percent confidence bands, estimated using the regression equation (1).

As mentioned earlier, workers whose initial vocational training provides access to higher education are predominantly craft and care workers, representing about 70 and 10 percent of the "Access" group. Appendix Table D.2 reports the characteristics of workers in each educational group. Care workers are different from craft workers along multiple dimensions: They are predominantly female and employed in the public sector. Yet, one critical difference is that the degrees available for care workers target jobs with physical demands similar to their original jobs. For example, nursing assistants are eligible for the bachelor's program in nursing. However, because most nurses end up in physically demanding hospital jobs, these educational opportunities may not provide a better way back to work.

Motivated by the critical importance of physical intensity for human capital investment (Figure B.2.(a)), we divide our analysis into two parts. In the main text, we focus on the craft workers, who all have access to degrees with lower physical intensity. In Appendix D.2.1, we study the care workers. We find that care workers invest significantly less in human capital after accidents and that their access to education does not help their employment prospects after injuries. The findings for care workers underscore that higher education only helps injured workers if the programs target jobs that are less physically demanding.

6.1.2 Relevance for Human Capital Investment

Figure 5 shows the pursuit of higher degrees around work accidents by workers' eligibility for higher education. The plots are the differences-in-differences in outcomes Y between the access groups $A \in \{0, 1\}$, indexed to year before the accident:

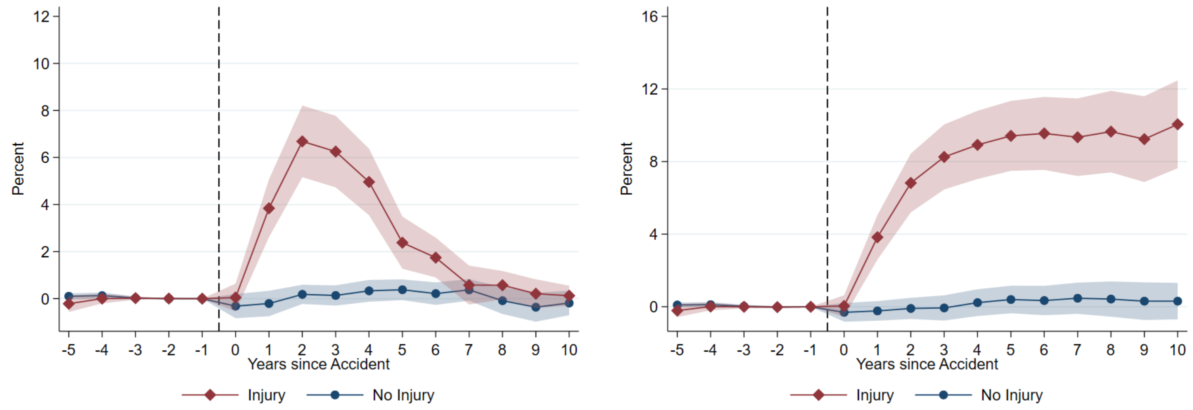
$$Y_{it} = \theta_1^Y A_{ie} + \sum_k \theta_{0k}^Y \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -1} \theta_{1k}^Y A_{ie} \mathbf{1}_{\{t=e+k\}}, \tag{2}$$

where θ_{1k}^Y is our coefficients of interest. We estimate Equation (2) by OLS, weighing the workers as in the "IPW" column of Table 3.

Figure 5 shows that access to higher education is crucial for injured workers' investments in human capital. The "Access" group invests more in human capital, but only if pushed by a work injury. Ten years after work accidents, the workers with access to higher education are 10 percent more likely to have pursued a higher degree.

Figure 5: Investment in Higher Degrees
("Access" – "No Access")

(a) Participation (Flow) (b) Participated (Stock)



Notes: This figure shows the differences in the pursuit of higher degrees according to workers' access to higher education. The figure focuses on craft workers. Panel (a) shows enrollment in the given year, and Panel (b) shows the accumulated enrollment. The plots are differences-in-differences between the "Access" and "No Access, IPW" workers from Table 3, indexed to year -1. Shaded areas represent 95 percent confidence bands, estimated using Equation (2).

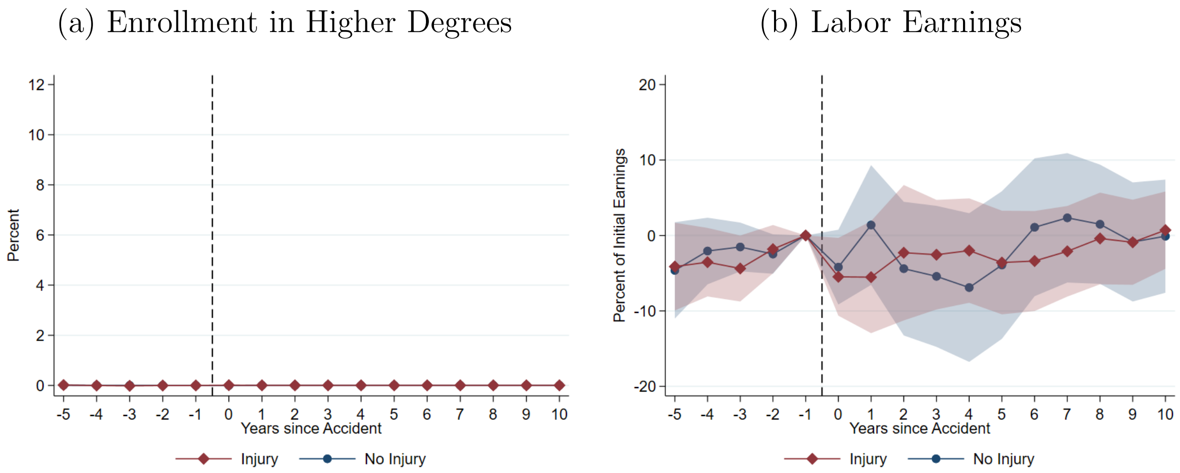
6.1.3 Placebo Checks

In using the "Access" and "No Access" groups to identify the causal impact of human capital investment, our identifying assumption is that the two groups would have fared similarly after work accidents if not for their different access to higher education. In this section, we conduct placebo checks of this identifying assumption.

First, in all figures, we report the outcomes of the match workers around their "placebo" accident events. The "No Injury" lines of Figures 5 and 7.(a) show that the "Access" and "No Access" workers have similar human capital investments and labor earnings if not injured by a work accident.

In Figure 6, we focus on workers older than 55 who do not invest in human capital despite being eligible for higher education (Figure 3). The figure shows that these older workers, who do not take advantage of higher education, fare similarly after work accidents.

Figure 6: Outcomes around Work Accidents of Workers Age 55+
("Access" – "No Access")



Notes: The figure restricts to workers above age 55. The plots show differences-in-differences between the "Access" and "No Access, IPW" workers from Table 3, 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 percent confidence bands, estimated using Equation (2).

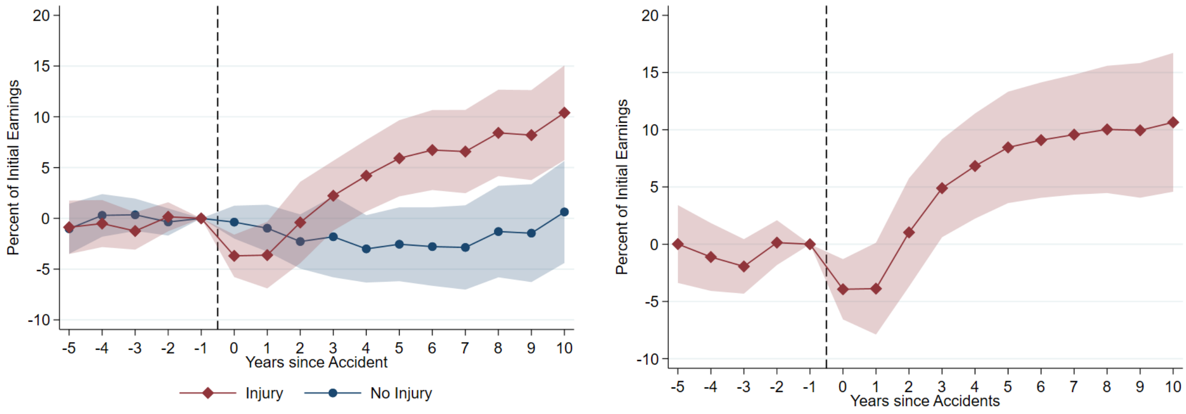
6.2 Reduced-Form Effects

In this section, we use the "Access" and "No Access" groups to study the impact of access to higher education for the labor supply of injured workers.

Figure 7 compares the workers' labor earnings around work accidents. After an initial lock-in period, workers with access to higher education have permanently higher earnings. The differences in earnings represent around 10 percent of the workers' earnings before the accident.

Figure 7: Labor Earnings around Work Accident

(a) "Access" – "No Access" (b) Triple Difference



Notes: This figure shows the differences in labor earnings of workers according to their access to higher education. Labor earnings are measured in percent of workers' average earnings in year -1. The figure focuses on craft workers. Panel (a) shows the difference-in-differences in outcomes between the "Access" and "No Access, IPW" workers from Table 3, estimated using Equation (2). Panel (b) shows the difference between the two differences-in-differences (a "triple difference" estimator). Shaded areas represent 95 percent confidence bands.

In Appendix Figure D.2, we investigate the labor-supply choices that generate the earnings differences. The figure shows that access to education helps injured workers move from disability benefits to formal employment. Ten years after work accidents, workers with access to higher education are ten percent less likely to receive disability benefits (Panel (a)) and ten percent more likely to be employed (Panel (b)). By contrast, we do not find that access to education influences workers' take-up of non-means tested pensions (Appendix Figure D.3).

6.3 Potential Outcomes

In this section, we estimate the potential outcomes of injured workers with and without human capital investment. We identify these counterfactuals for the workers who comply with access to education by pursuing a higher degree after work accidents.

We convert the reduced-form effects into potential outcomes by assuming that *access* to education affects workers only if they complete the programs.[28,29] Hence, our treatment variable D is equal to 1 if the worker completes a higher degree within ten years after the accident.

Let D_{Ai} denote the potential education of worker i depending on his access to higher education $A \in \{0, 1\}$. Following Abadie (2002), the average potential outcomes of compliers are given by the Wald estimates:

$$\mathbb{E}[Y_{ik}(0)|D_{1i} > D_{0i}] = \frac{\theta_{1k}^{Y(1-D)}}{\theta_{1,10}^{(1-D)}} \tag{3}$$

$$\mathbb{E}[Y_{ik}(1)|D_{1i} > D_{0i}] = \frac{\theta_{1k}^{YD}}{\theta_{1,10}^{D}}, \tag{4}$$

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

$$Y_{it} = \sum_k \theta_{0k}^{Y} \mathbf{1}_{\{t=e+k\}} + \sum_k \theta_{1k}^{Y} A_{ie} \mathbf{1}_{\{t=e+k\}} \tag{5}$$

For example, θ_{1k}^{D} is our first-stage estimate in Figure 5.(b), whereas θ_{1k}^{YD} and $\theta_{1k}^{Y(1-D)}$ decompose our reduced-form effects (e.g., Figures 7 and D.2) according to whether workers complete a higher education after the accidents.[30]

We estimate Equations (3)-(5) using two-stage least squares (TSLS) and follow Imbens and Rubin (1997) in imposing non-negativity constraints on the potential outcomes.[31]

Figure 8 shows the labor supply of injured workers with and without human capital investment. The figure delivers three insights. First, human capital investment keeps workers in school during the first six years after work injuries. Second, about 85 percent of injured workers who reskill end up finding employment. Third, if these workers do not reskill, they end up exclusively on disability benefits.

[28] Appendix Figure D.1 supports this exclusion restriction by showing that the "Access" and "No Access" workers invest similarly in degrees and courses both groups have access to.

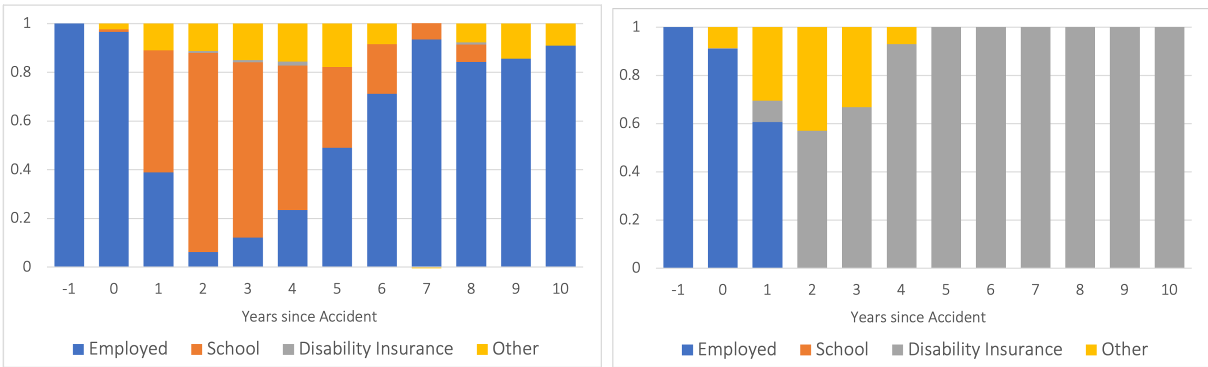
[29] Mountjoy (2022) imposes a similar exclusion restriction in using commuting distance to estimate the returns to colleges. The exclusion restriction is violated if, for example, the *option value* of higher education makes workers stay in the labor force.

[30] We estimate θ_{1k}^{Y} as simple differences in between the access groups to recover the levels of workers' potential outcomes. Note that the simple differences (Equation (5)) and the difference-in-differences (Equation (2)) give similar point estimates of θ_{1k}^{Y} for our reduced-form outcomes (e.g., Figures 7 and D.2) because the access groups are similar on the outcomes before the injury (Table 3).

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

Figure 8: Labor Supply

(a) Injury & Reskill (b) Injury & No Reskill



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. *School* is enrollment in a higher degree. *Other* is mainly unemployment and non-participation. Panels (a) and (b) report treated and control complier means, estimated using Equations (3)-(5).

Table 4: Job Characteristics (Injury & Reskill)

	Standard Deviations from Economy Average		Change in Percent
	Year -1	Year +10	Year -1 to +10
Physical Ability Requirements	1.547	-0.264	
	(0.123)	(0.203)	
Cognitive Ability Requirements	-0.054	0.694	
	(0.098)	(0.211)	
Earnings	-0.016	0.323	24.7
	(0.056)	(0.063)	(4.6)

Notes: This table shows the job characteristics of complier workers who are employed ten years after a work accident if they reskill. *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. Column 1 and 2 are measured in standard deviations from the "No Injury, Random" workers in Table 2. Column 3 reports the percent change in the worker's outcome.

Table 4 reports the job characteristics of the injured workers who find employment after human capital investment.[32] The table shows that higher education allows workers to reallocate from physically demanding occupations to more cognitively intense jobs. Ten

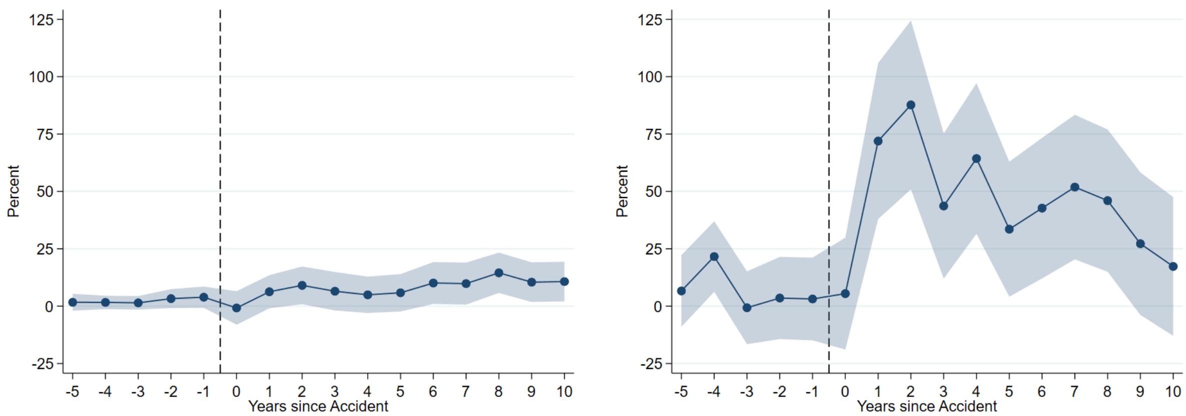
[32]Because job characteristics are measured for employed workers only, we define the treatment variable as $D \times E$, where E equals 1 if the worker is employed ten years after the accident (blue area in Figure 8.(a)).

years after the work accident, these reskilled workers earn about 25 percent more than before their injuries.

Figure 1.(d) showed that work accidents are a severe shock to the mental well-being of workers, whose use of antidepressants spike after injuries. Does reskilling alleviate these mental burdens of injuries? To assess this question, Figure 9 plots workers' potential use of antidepressants with and without reskilling. Strikingly, the figure shows that work accidents *only* make workers depressed if they cannot reskill. The results highlight that it is the lack of career prospects – and not the injuries per se – that makes injured workers depressed.

Figure 9: Antidepressant Prescription

(a) Injury & Reskill (b) Injury & No Reskill



Notes: This figure shows the prescriptions of antidepressants of workers who comply with access to higher education by pursuing a higher degree after work accidents. Panels (a) and (b) report treated and control complier means, estimated using Equations (3)-(5).

In summary, we find injured workers who reskill get back to work, earn more than before their injuries, and do not get depressed. The positive results probe the question: Are these workers, in fact, made *better* off by experiencing a work accident? To answer this question, Appendix D.3 compares the complier workers to their match workers (who are not injured in the event year). Table D.4 shows that the reskilled workers end up in very different types of jobs (less physically demanding and more cognitively intense), compared to the scenario without injury. However, in terms of earnings and mental well-being, the difference in scenarios is less stark. Ten years after the accidents, the workers are slightly more employed (Figure D.5), earning about five percent more (Table D.4), than if they had not been injured. However, the differences are not statistically significant. The use of antidepressants is flat for both groups (Figure D.6).

6.4 Cost-Benefit Analysis

In this section, we use the causal estimates from Section 6.2 to conduct a back-of-the-envelope evaluation of the costs and benefits of investing in human capital for injured workers. To be precise, we calculate the present discounted values of providing higher education for workers who suffer a work injury at age 40. Our calculations combine the dynamic paths estimated in Section 6.2 with government tax and transfer rates to estimate the costs and benefits for injured workers and the government. Appendix D.4 details our approach to the cost-benefit calculations.

Table 5 summarizes the costs and benefits for workers and the government.

Table 5: Costs and Benefits of Higher Education for Injured Workers

	Per Retrained Worker ($)	Per Dollar of Education	Percent of Total
Workers	**192,543**	**1.9**	**38.4**
Earnings	369,610	3.6	73.6
Transfers	-236,962	-2.3	-47.2
Educ. Transfers	59,896	0.6	11.9
Government	**309,357**	**3.0**	**61.6**
Education	-103,324	-1.0	-20.6
Transfers	236,962	2.3	47.2
Taxes	175,718	1.7	35.0
Total	**501,900**	**4.9**	**100.0**

Notes: This table shows the present discounted values of providing higher degrees for an injured worker of age 40. *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), *Education* expenses include tuition and education transfers, and *Taxes* refer to labor income taxes. Appendix D.4 details our approach to the cost-benefit calculations.

The cost-benefit analysis delivers three takeaways. First, providing post-secondary education for an injured worker generates a social surplus of about a half million USD, equivalent to a 500 percent return on the education expenses.[33] The investment generates an internal rate of return (IRR) of 36.5 percent per year, about three times higher than conventional estimates for young or displaced workers (Heckman et al., 2003; Jacobson et al., 2005; Kane and Rouse, 1995).[34] Second, the remarkable social returns reflect that higher education moves injured workers from disability insurance (a liability to the government budget) to taxable high-income employment (an asset to the budget). The combination of lower transfer payments and higher tax receipts means that the government expense on education "pays for itself".[35] Finally, the table shows how a generous transfer system weakens the private incentives for workers to invest in human capital. In particular, about half of the higher earnings from reskilling are countered by lower transfer payments for workers.

7 Conclusion

This paper provides the first evidence on how workers invest in human capital after losing physical abilities.

Our analysis delivers two takeaways. First, the transition of workers from physical to cognitive jobs requires ambitious investments in human capital, lasting multiple years at the higher education level. Second, higher education of injured workers yields large social returns, yet individual workers have weak incentives to make the investments.

Our findings suggest that policymakers may want to expand the access of manual workers to higher education. These policies could alleviate other displacement shocks to manual occupations, such as automation or globalization.

[33] Cost-benefit analyses sometimes inflate the direct cost to the government (*Education* in Table 5) with a "marginal cost of public funds", reflecting deadweight loss of taxation to finance the program (Kleven and Kreiner, 2006). However, since the education cost pays for itself in Table 5, the government would not need to collect more taxes to finance the program. That said, applying a deadweight loss of 50 percent to the direct costs, as in Heckman et al. (2010), would deliver a net social return of 330 percent, and the total public cost (program cost and deadweight loss) would still pay for itself.

[34] The internal rate of return is the annual interest rate that makes an investment break even.

[35] In the terminology of Hendren and Sprung-Keyser (2020), higher education for injured workers has an infinite "marginal value of public funds".

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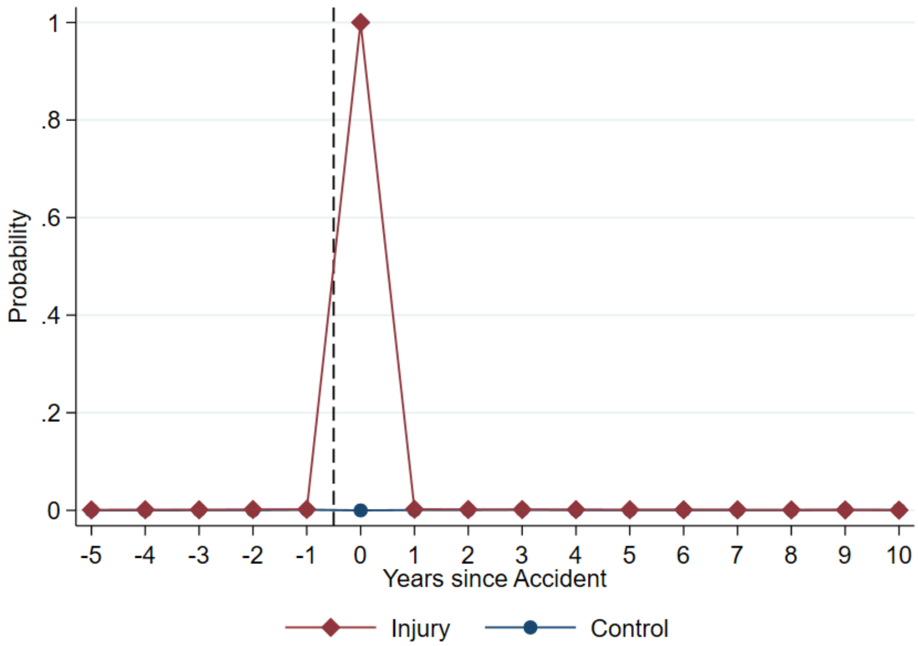
A Work Accidents

Table A.1: Work Accident Sample Reduction

Sample Step		Injury Events	Distinct Individuals	Personal Impairment	Earnings Cap. Loss
1.	All work injury and illness claims	749,775	562,778	2.51	2.22
2.	Accidents	395,897	332,421	2.91	2.95
3.	Accepted	274,625	240,416	4.19	4.23
4.	Accepted with compensation	130,910	121,964	8.70	8.78
5.	Accepted with ECL >0	31,129	30,693	12.84	36.18
6.	Exclude psychological shock	29,875	29,482	12.77	35.86
7.	Collapse to person-year	29,853	29,482	12.78	35.89
8.	Person exists in register data	29,783	29,413	12.75	35.88
9.	Full time employed before injury	14,623	14,510	12.52	36.57
10.	Exclude Military Workers	14,481	14,369	12.45	36.63
11.	Vocational and secondary degrees with access to higher education	4,799	4,758	12.77	34.30

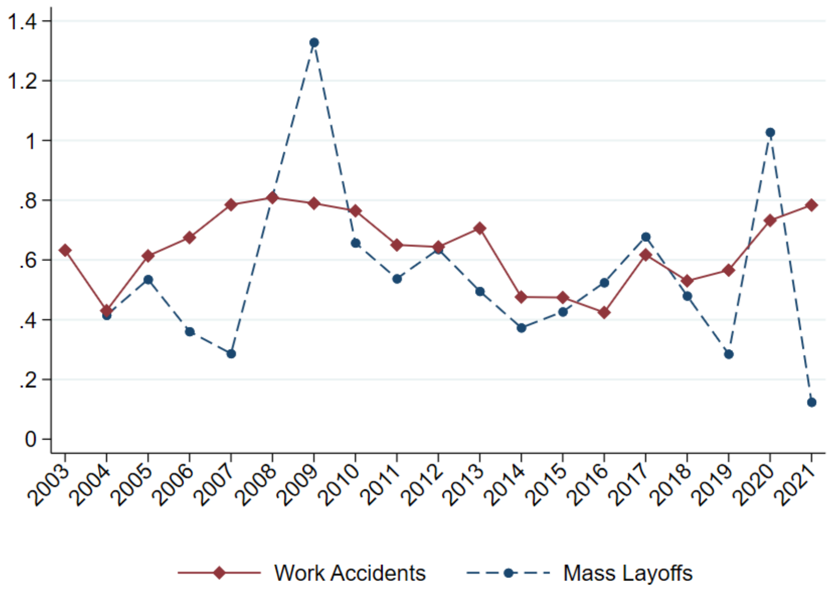
Notes: This table shows how our sample restrictions shrink the analysis data, starting from the universe of workers' compensation claims from 1998 to 2017. See Section 2.1 for definitions of *earning capacity loss* and *personal impairment*. Step 3 corresponds to the injury rates in Table 1 and Figure A.2. Step 10 corresponds to the "Injury" column of Table 2. Step 11 corresponds to the "Access" column of Table 3.

Figure A.1: Probability of Work Accident



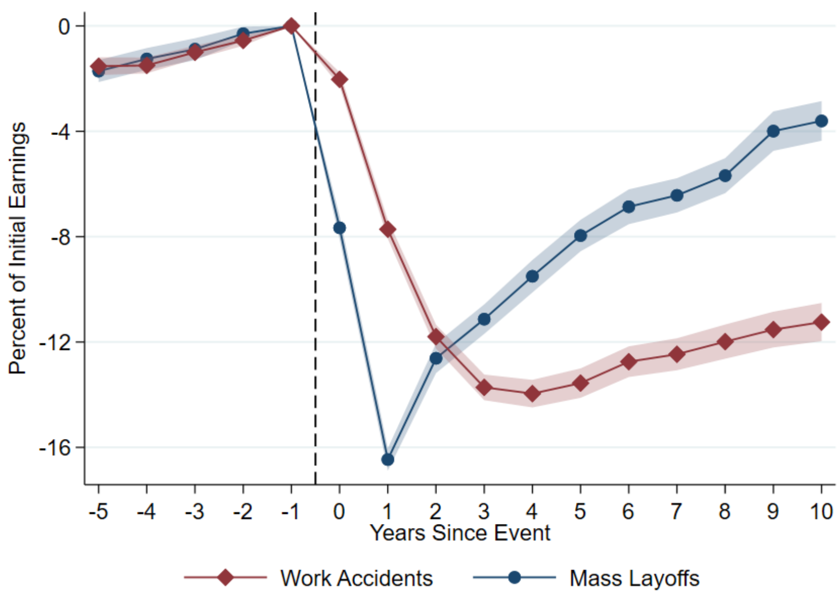
Notes: This figure shows the probability of work accidents in event time. The "Control" workers correspond to the "Match" column in Table 2.

Figure A.2: Work Injuries 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 A.3: 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 work accidents accepted with compensation. We match each displaced (injured) worker to a control worker, following the procedure in Table 2. The graphs show the differences-in-differences in outcomes between the displaced (injured) workers and their matches. Shaded areas represent 95 percent confidence bands, estimated using the regression equation (1).

B Human Capital Investment

Table B.1: Human Capital Investment by Educational Background of Workers

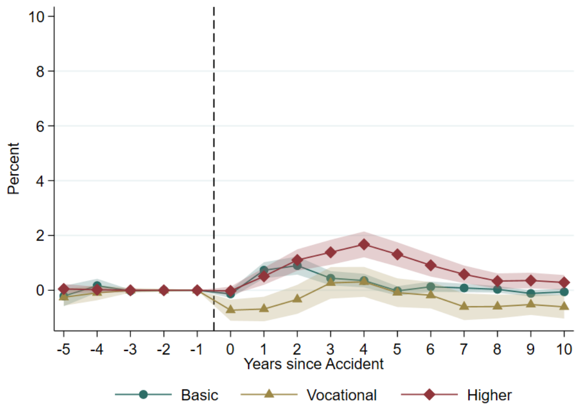
		Completion Rates (FTE, Diff-in-Diff, Year +10)					
		Degrees			Courses		
	Percent of Injuries	Basic	Vocational	Higher	Basic	Vocational	Higher
Primary	31.5	0.021	-0.009	0.019	0.009	-0.002	0.000
		(0.003)	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)
Vocational							
w/o Access	19.6	0.038	0.012	0.031	0.012	0.001	0.011
		(0.005)	(0.008)	(0.006)	(0.003)	(0.002)	(0.006)
w/ 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 2, estimated using the regression equation (1). Standard errors are reported in parentheses.

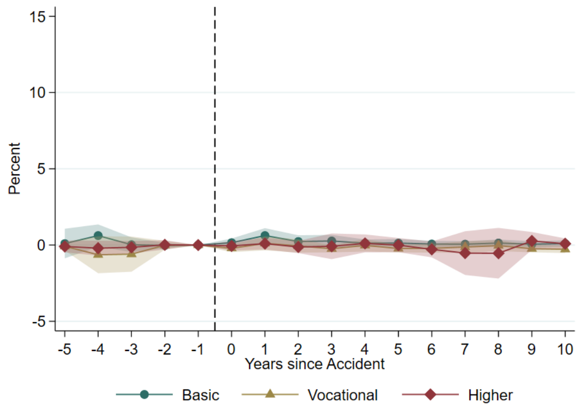
Figure B.1: Human Capital Investment by Educational Background of Workers

(a) Initial Attainment: Primary School

Degrees

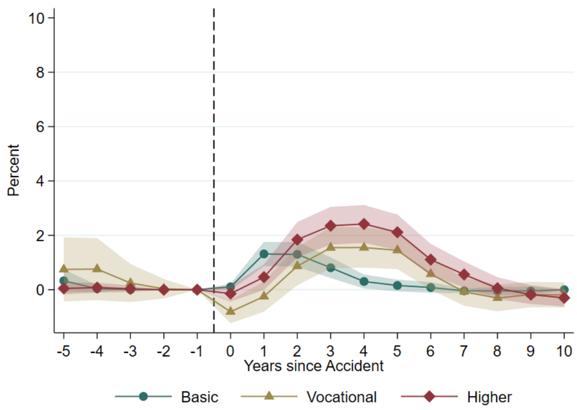


Courses

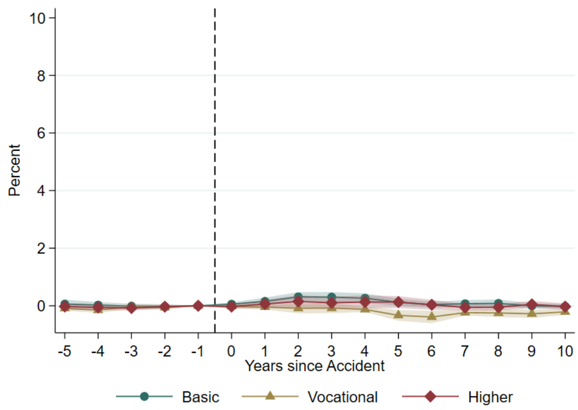


(b) Initial Attainment: Vocational Degree without Access to Higher Education

Degrees

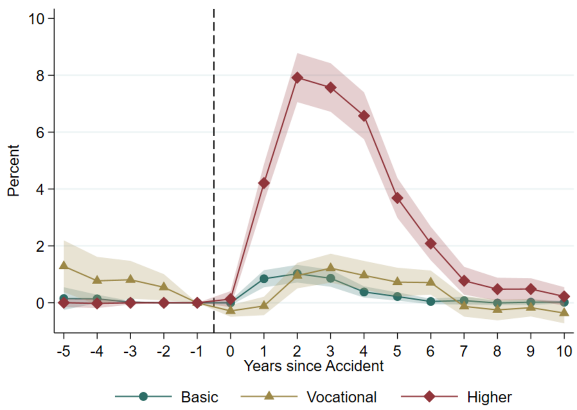


Courses

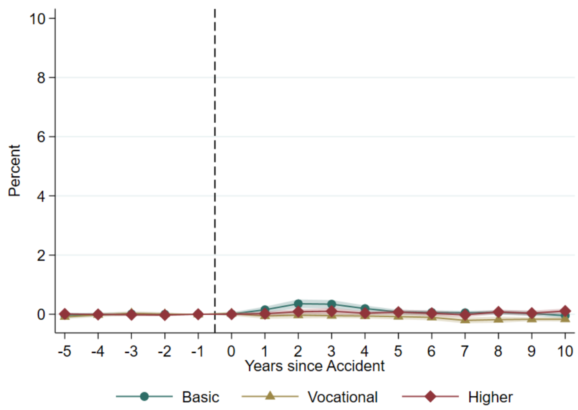


(c) Initial Attainment: Vocational Degree with Access to Higher Education

Degrees



Courses

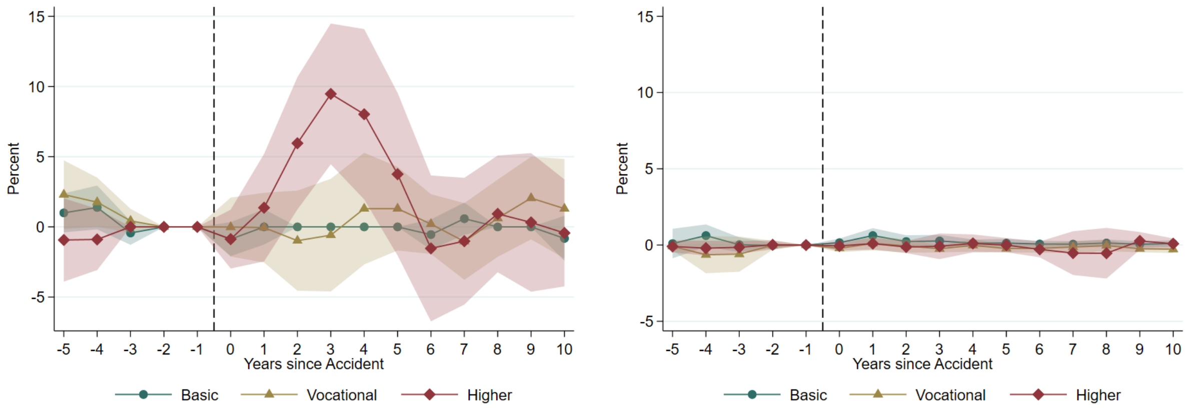


Notes: This table continues on the next page.

Figure B.1 (Cont.): Human Capital Investment by Educational Background of Workers

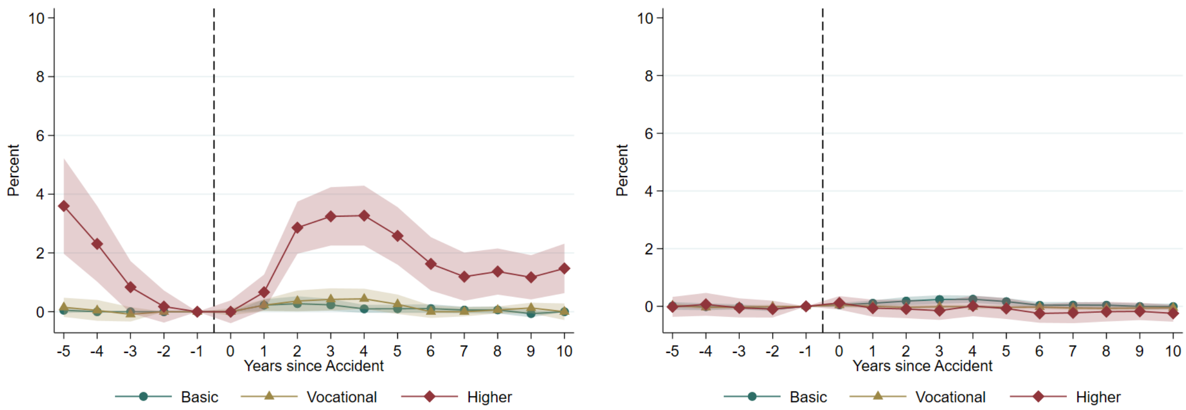
(a) Initial Attainment: High School

Degrees Courses



(b) Initial Attainment: Post-Secondary Degree

Degrees Courses



Notes: This figure shows participation (measured in full-time equivalents) in degrees and 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 2, indexed to year -1. Shaded areas represent 95 percent confidence bands.

B.1 Targeted Investment

B.1.1 Linking Degrees to Target Jobs

This section describes how we link degrees to their target occupations and sectors. These links form the basis of Figure B.2.

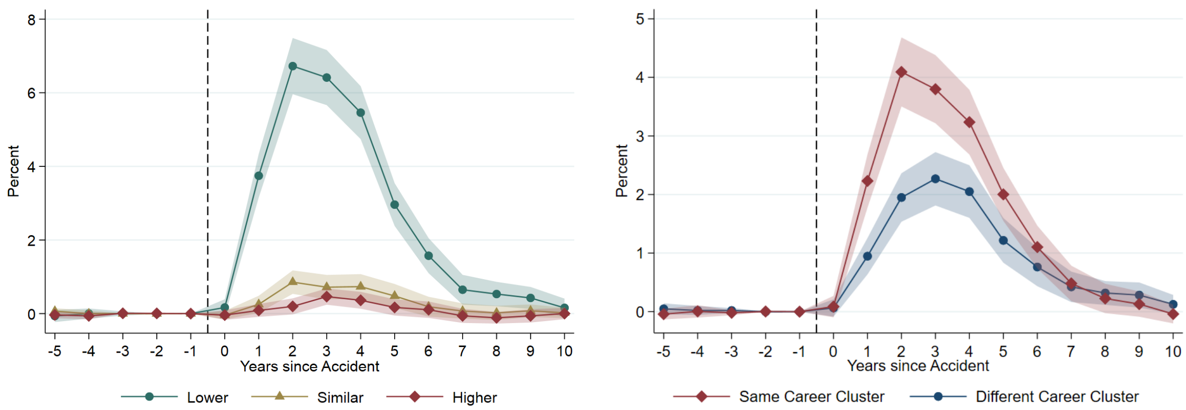
To guide the creation of the links, we exploit the correlations between workers' attained degrees and their occupations in the administrative data. For example, most workers with a bachelor's degree in "4087 Construction Architecture" are employed as "2142 Construction Architects."

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 links from degrees to occupations. We implement a similar strategy for linking degrees to sectors.

B.1.2 Evidence

Figure B.2: Investment in Higher Degrees by Similarity of Target vs. Initial Occupation

(a) Physical Intensity (b) Career Cluster

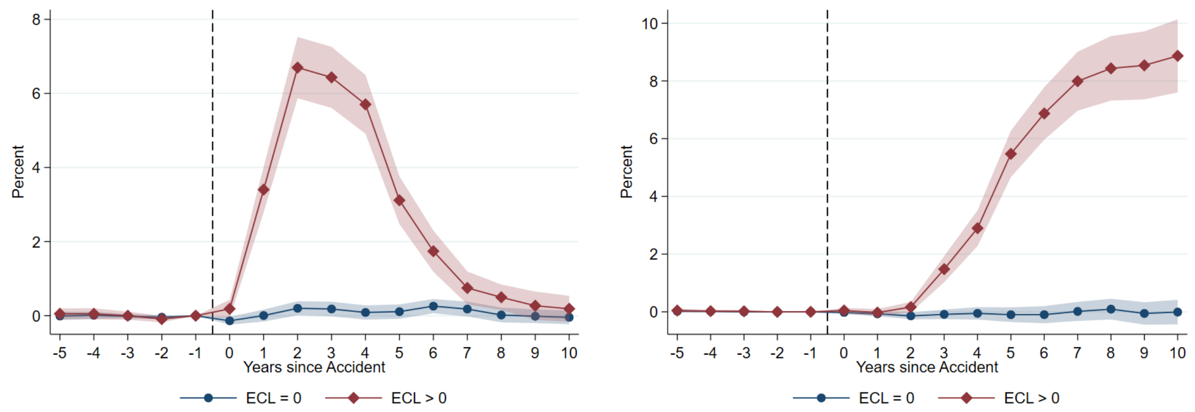


Notes: This figure shows participation in higher degrees according to the similarity between the worker's initial job and the higher degree's target occupation. *Physical Intensity* is *"performing general physical activities"* (O*NET). "Similar" degrees target occupations with physical intensities within ± 1/2 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 differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95 percent confidence bands, estimated using the regression equation (1).

B.2 Mechanisms

Figure B.3: Investment in Higher Degrees by Earning Capacity Loss

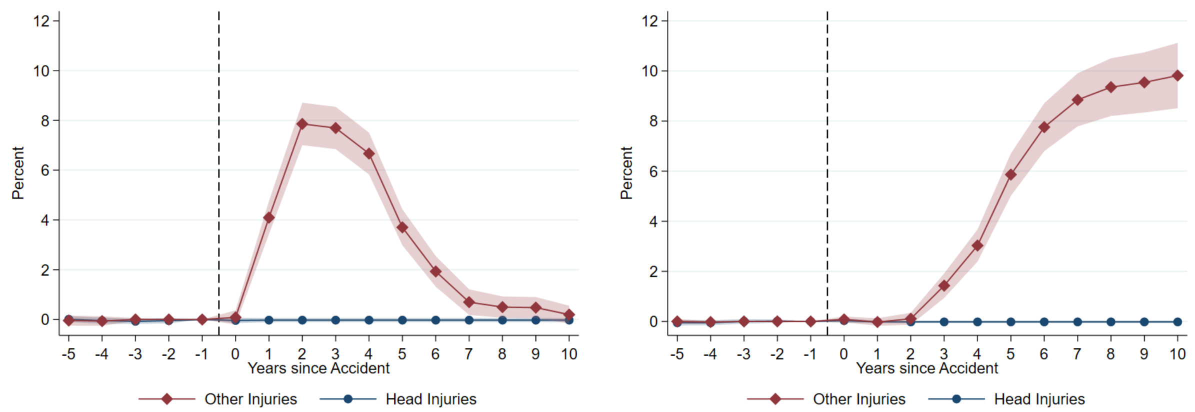
(a) Participation (b) Completion



Notes: The figure shows pursuit 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 differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95 percent confidence bands, estimated using the regression equation (1).

Figure B.4: Investment in Higher Degrees by Injured Body Part

(a) Participation (b) Completion



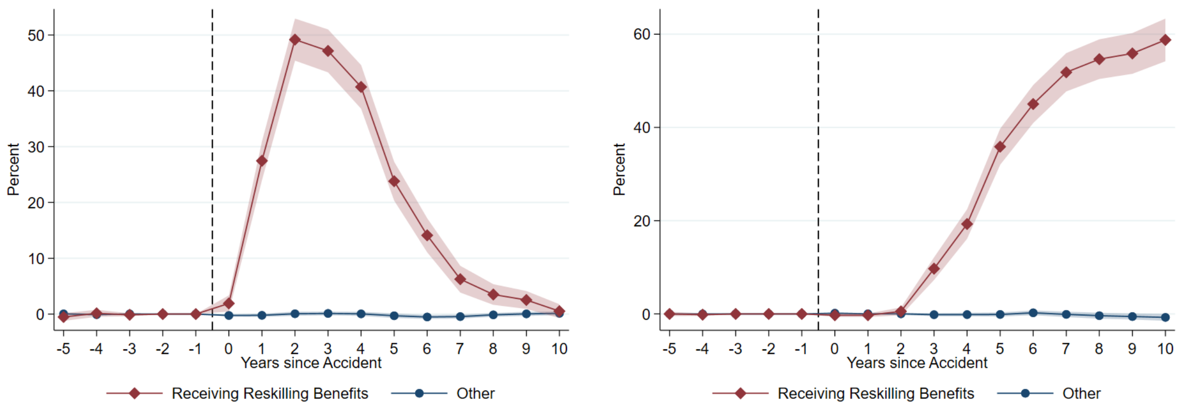
Notes: The figure shows pursuit and completion of higher degrees around work accidents, split by whether the injury caused Post Concussion Syndrome (PCS). Post Concussion Syndrome (PCS) is a typical brain damage diagnosis after accidents with symptoms that include persistent headaches, dizziness, and problems with concentration and memory, continuing after the normal recovery period of concussion. Head injuries constitute 6 percent of accidents and 0.4 percent of accidents cause PCS. See Figure B.3 for notes on the regression specification.

C Determinants of Investment

C.1 Financial Support

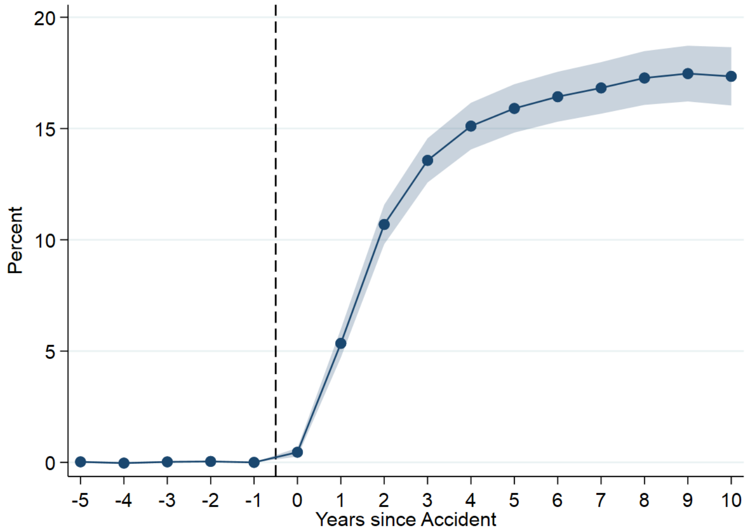
Figure C.1: Investment in Higher Degrees by Receipt of Reskilling Benefits

(a) Participation (b) Completion



Notes: This figure shows the pursuit and completion of higher degrees, split by whether the injured worker receives reskilling benefits within six years of the work accident. 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 differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95 percent confidence bands, estimated using the regression equation (1).

Figure C.2: Received Reskilling Benefits (Stock)



Notes: This figure shows whether the worker has received reskilling benefits. 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 differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95 percent confidence bands, estimated using the regression equation (1).

D Returns to Investment

D.1 Access to Higher Education

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 give access to higher education. See Table for D.3 for the top-3 vocational degrees in each education group.

Table D.2: Characteristics of Workers by Education Groups

	Care Workers	Craft Workers	Other Workers
Age	41	42	42
	(9.7)	(11)	(10)
Female	.93	.024	.49
	(.25)	(.15)	(.5)
Public Sector	.96	.087	.31
	(.2)	(.28)	(.46)
Years of Schooling	14	14	14
	(.41)	(.16)	(.28)
Injury Severity			
Earnings Capacity Loss	31	35	34
	(22)	(22)	(22)
Personal Impairment	11	13	12
	(6.9)	(12)	(9.7)
Physical Intensity			
Initial Occupation	-.25	1.1	.18
	(.17)	(.76)	(.7)
Target Occupation	-.52	-.68	-.47
	(.79)	(.69)	(.67)
Year of Injury	2,006	2,005	2,005
	(4.3)	(4.9)	(4.7)
Observations	367	3,243	958

Notes: This table shows the characteristics of injured workers whose vocational education give access to higher education. The characteristics are measured in the year before the work accident. See Table for D.3 for the top-3 vocational degrees in each education group.

Table D.3: Vocational Degrees with Access to Higher Education

Group	Vocational Degree	Share of Injuries (%)	Share of Reskilling (%)	Vocational Occupation	Access Degree	Access Occupation
Craft Workers	Carpentry	14.4	26.3	7124 Carpenters and Joiners	Construction Architecture (BA)	3112 Civil Engineering Technicians
	Electrician	6.0	6.9	7137 Electrician Work	Service Engineering (AP)	3113 Electrical Engineering Technicians
	Welder	5.6	5.7	7222 Tool-makers and related workers	Production Technology (AP)	3000 Technicians, n.e.c.
Care Workers	Social-Health Assistant	7.5	8.2	5132 Care Work at Institutions	Social Worker (BA)	3460 Social Work Associates
	Pedagogical Assistant	0.4	0.3	5131 Childcare Work	Social Education (BA)	3320 Pre-Primary Education Teachers
Other Workers	Retail, Groceries	4.8	2.3	5220 Salespersons and Demonstrators	Commerce Management (AP)	3140 Sales and Finance Work
	Cook	1.6	1.8	5122 Cooks	Nutrition & Technology (AP)	3000 Technicians, n.e.c.
	Nutrition Assistant	1.0	1.5	5122 Cooks	Nutrition & Technology (AP)	3000 Technicians, n.e.c.

Notes: This table lists the top-3 vocational degrees among education groups that give access to higher education.

D.1.1 Identification Strategy

This section describes our inverse probability weighing (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:

$$\text{Access} = p(X_{ie-1}), \tag{6}$$

where p is a logistic link function, and X include first- and second order terms of age, injury severity, hours worked, hourly wages, labor market income, physical- and cognitive ability requirements, labor market experience, and occupational injury rate, first order terms of years of schooling, personal impairment, sickness benefits, as well as indicators for working in the public sector, living alone, having children of school age, and owning property. 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

$$w_i = \frac{\hat{p}(X_{ie-1})}{1 - \hat{p}(X_{ie-1})}. \tag{7}$$

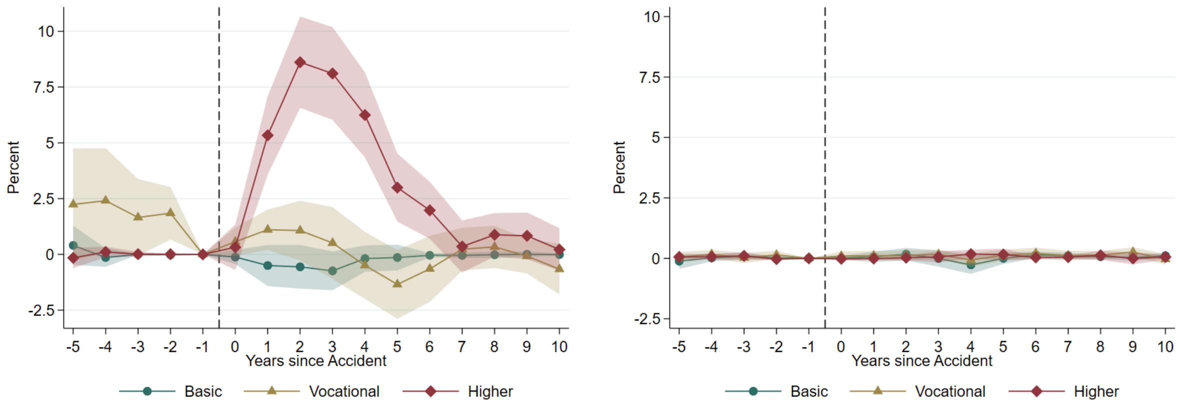
We estimate the propensity scores separately by the education groups (craft, care, and other workers) defined in Table D.3. Table 3 validates that the IPW-weighted "No Access" workers are comparable to the "Access" group on the observables X.

D.2 Reduced-Form Effects

Figure D.1: Enrollment in Courses (Triple Difference)

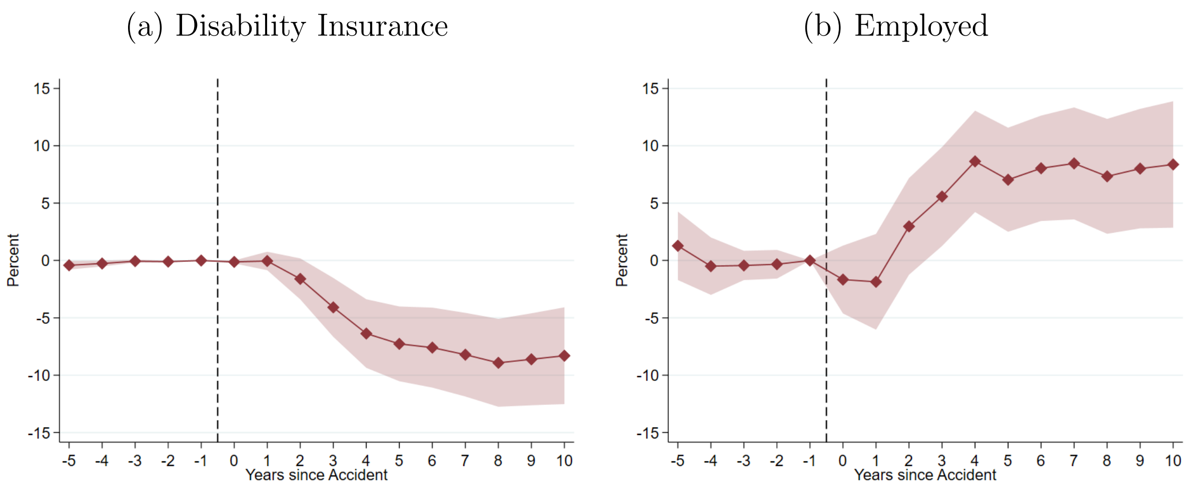
(a) Degree

(b) Non-Degree



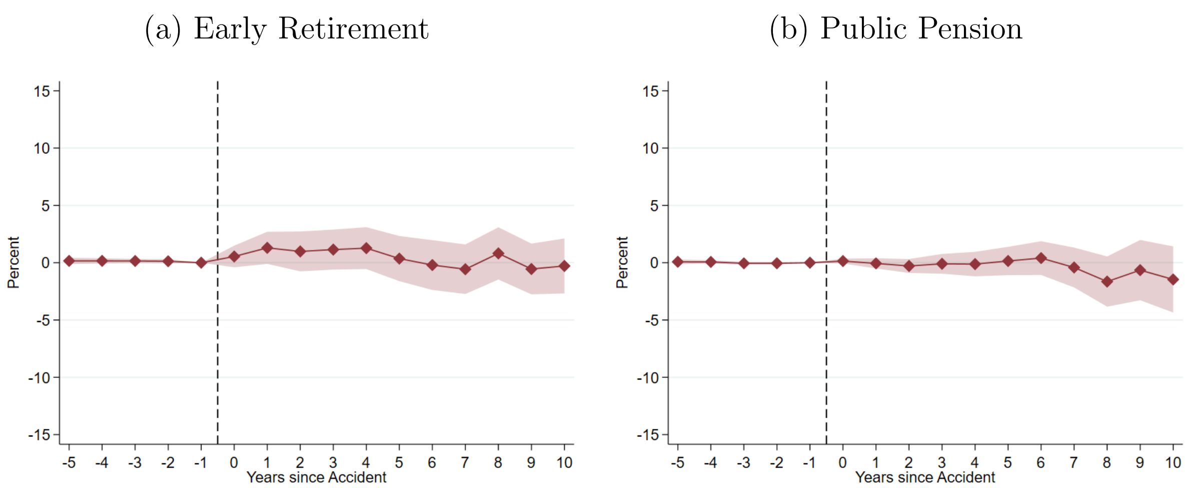
Notes: This figure shows the participation in degrees and courses at the *basic* (primary and high school), *vocational*, and *higher* (all post-secondary) levels. Participation is measured in full-time equivalents. This figure focuses on craft workers. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 3), each measured relative to their "No Injury" matches, and indexed to year -1. The "No Injury" workers correspond to the "Match" column in Table 2. Shaded areas represent 95 percent confidence bands.

Figure D.2: Labor Supply around Work Accident (Triple Difference)



Notes: This figure shows the extensive-margin labor supply of workers. The figure focuses on craft workers. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 3), each measured relative to their "No Injury" matches, and indexed to year −1. The "No Injury" workers correspond to the "Match" column in Table 2. Shaded areas represent 95 percent confidence bands.

Figure D.3: 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 3), each measured relative to their "No Injury" matches, and indexed to year −1. The "No Injury" workers correspond to the "Match" column in Table 2. Shaded areas represent 95 percent confidence bands.

D.2.1 Care Workers

The main analysis in Section 6 focuses on craft workers who all have access to higher degrees that target occupations with lower physical intensity than their previous jobs. In this section, we study care workers whose higher degrees have similar physical intensity. An example is nursing assistants who may enroll in the bachelor's program in nursing.

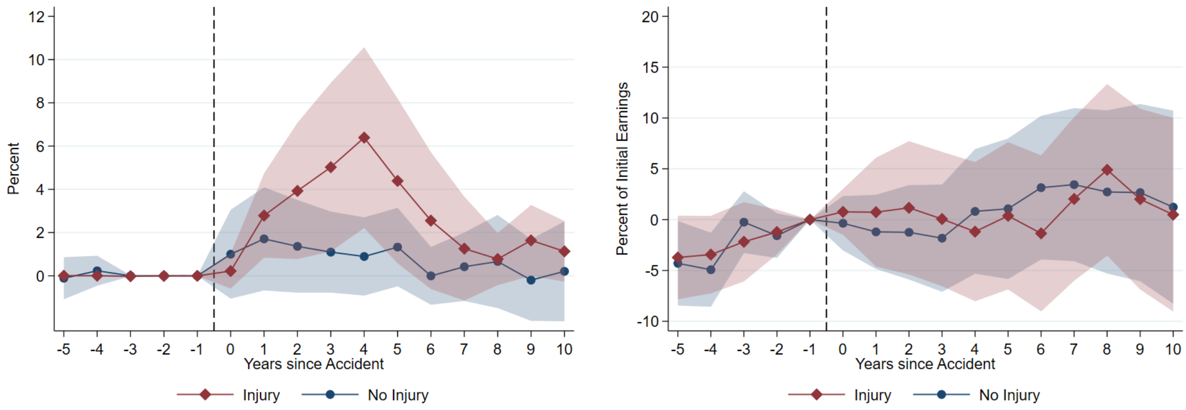
Figure D.4 shows the care workers' pursuit of higher degrees around work accidents. Comparing the responses to our main Figure 5 delivers two insights. First, care workers invest less in human capital after work accidents. Ten years after the accident, only three percent of care workers have enrolled in a higher degree due to the injury (Figure D.4.(a)), which is significantly less than the 10 percent effect in our main sample (Figure 5.(b)). Second, because care workers constitute a smaller share of work injuries, we have less precision in estimating the effects in Figure D.4. Combined, these two effects (lower point estimates and less precision) imply that we cannot detect a statistically significant first-stage relationship between access to higher education and subsequent pursuit of higher degrees.

Figure D.4.(b) shows that 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.

Taken together, the null effects in Figure D.4 suggest that access to higher degrees only helps workers if the programs target jobs that are less physically demanding.

Figure D.4: Outcomes around Work Accidents (Care Workers)
("Access" – "No Access")

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



Notes: The plots show differences-in-differences between the "Access" and "No Access, IPW" workers from Table 3, indexed to year -1. The figure focuses on care 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 percent confidence bands, estimated using the Equation (2).

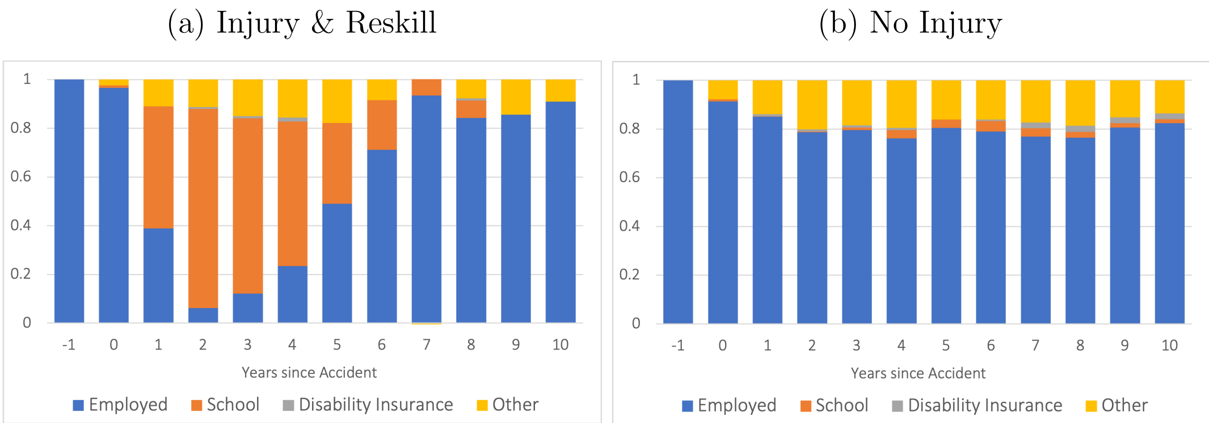
D.3 Potential Outcomes

Table D.4: Job Characteristics of Compliers

	Standard Deviations from Economy Average		Change in Percent
	Year -1	Year +10	Year -1 to +10
Injury & Reskill			
Physical Ability Requirements	1.547	-0.264	
	(0.123)	(0.203)	
Cognitive Ability Requirements	-0.054	0.694	
	(0.098)	(0.211)	
Earnings	-0.016	0.323	24.7
	(0.056)	(0.063)	(4.6)
No Injury			
Physical Ability Requirements	1.683	0.873	
	(0.145)	(0.173)	
Cognitive Ability Requirements	-0.040	0.025	
	(0.120)	(0.152)	
Earnings	-0.028	0.262	21.4
	(0.056)	(0.069)	(5.1)

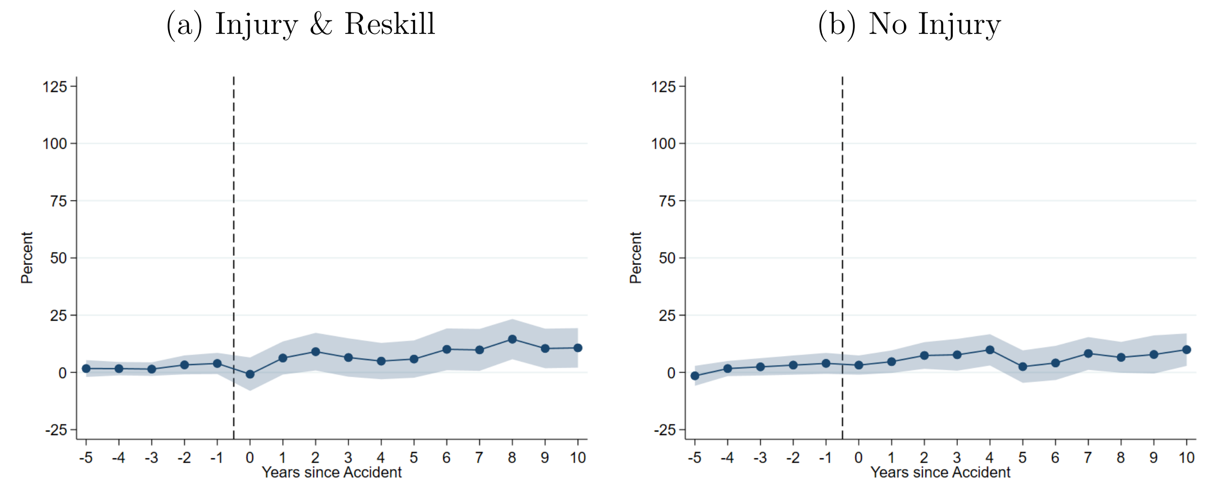
Notes: This table shows the job characteristics of workers who are employed ten years after a work accident. The "Injury & Reskill" panel reports treated complier means, estimated using Equation (4). The "No Injury" panel reports the outcomes of their match workers (who do not experience a work injury 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. Column 1 and 2 are measured in standard deviations from the "No Injury, Random" workers in Table 2. Column 3 reports the percent change in the worker's outcome.

Figure D.5: 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. *School* is enrollment in a higher degree. *Other* is mainly unemployment and non-participation. Panel (a) reports treated complier means, estimated using Equation (4). Panel (b) reports the outcomes of their match workers (who do not experience a work injury in the event year).

Figure D.6: Antidepressant Prescription



Notes: This figure shows the prescriptions of antidepressants of workers who comply with access to higher education by pursuing a higher degree after work accidents. Panel (a) reports treated complier means, estimated using Equation (4). Panel (b) reports the outcomes of their match workers (who do not experience a work injury in the event year).

D.4 Cost-Benefit Analysis

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 40 and retires at age 65.[36,37] 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 median tax rate in the year prior to injury (32.2 percent) to the labor income effects estimated in Figure 7.

For public transfers, we first estimate the effect of higher education on receiving different transfers, including disability benefits (shown in Figure D.2) and unemployment benefits. Section 2 describes the transfers. We then scale these effects with the transfer rates collected from the government budget.[38]

Education expenses include tuition and school-related transfers. Tuition costs amounts to approximately 16,500 US dollars a year per full time student. We collect the tuition costs from the government budget.[39] The transfers include the default 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 six percent per year. The internal rate of return (IRR) is the discount rate that makes the total net present value equal to zero.

We do not include health expenditures, e.g., the lower antidepressants in Figure 9, in the cost-benefit analysis. Hence, in this regard, Table 5 likely constitutes a lower bound on the benefits of providing higher education for injured workers.

[36] Figure D.3 supports the assumption that human capital investment does not affect the age of public pension retirement of injured workers.

[37] The average *complier* is only 32 at the time of injury, which means that evaluating the costs and benefits at age 42 actually serves as a lower bound of the true benefits for compliers.

[38] The transfer rates, linked to the transfer codes of the DREAM register, are available upon request.

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

E Theoretical Framework

This section develops a theoretical framework for how loss of work ability impacts human capital investment. In Section E.1.1, we present a lifecycle model of workers' schooling and career choices. In Section E.2, we confront predictions of the model with the empirical evidence in Sections 3 to 6. Finally, in Section E.3.1, we discuss implications of the theory, including how work accidents compare with ability demand shocks such as automation and globalization.

E.1 Model

E.1.1 Setup

In the model, workers start their careers at age $\underline{a}$ and retire at age $\bar{a}$. In each year of their careers, they choose between enrollment in school S, employment in occupations $o \in \mathcal{O}$, or non-employment N.

Workers differ in their physical and cognitive abilities (θ^P, θ^C). A worker's earnings potential in occupation o is

$$E_o(\theta) = \omega_o^P \theta^P + \omega_o^C \theta^C, \tag{8}$$

where ω_o^P measures the physical demands of occupation o. We focus our analysis on two occupations, manual (M) and analytical (A), with $\omega_M^P > \omega_A^P$.

Work accidents occur randomly in the manual occupation, lowering workers' physical abilities by severity δ:

$$\theta_{ia}^P = \theta_{ia-1}^P - \delta_{ia}, \quad \delta_{ia} \overset{iid}{\sim} F_\delta, \tag{9}$$

Workers' compensation (WC) covers lost earnings from injuries such that the risk of work accidents does not affect career choices.[40]

Schooling provides access to the analytical occupation at the cost of tuition T. Denoting

[40]Using the value function defined in Equation (15), WC is set to equalize

$$\mathrm{WC}(a, \theta, \delta) = -\omega_P^M \delta + \beta \left[V(a+1, 0, \theta^P, \theta^C) - V(a+1, 0, \theta^P - \delta, \theta^C) \right]. \tag{10}$$

the accumulated years of schooling by $s_{ia} = \sum_{t=\underline{a}}^{a_i} S_{it}$, the set of accessible occupations satisfies

$$A \in \mathcal{O}(s) \quad \text{iff} \quad s = \textstyle\sum_{t=\underline{a}}^{a} S_t \geq \bar{s}, \tag{11}$$

where $\bar{s}$ denotes the duration of school.[41] Non-employment pays benefits B.[42]

A worker's realized income is

$$W(\theta, L, \delta) = \begin{cases} \omega_M^P(\theta^P - \delta) + \omega_M^C \theta^C + \mathrm{WC}(a, \theta, \delta) & \text{if } L = M \\ \omega_A^P \theta^P + \omega_A^C \theta^C & \text{if } L = A \\ -T & \text{if } L = S \\ B & \text{if } L = N \end{cases}. \tag{13}$$

Workers make career decisions to maximize the expected present discounted value of income, choosing over their set of accessible occupations:

$$V(a, s, \theta) = \max_{L \in \{\mathcal{O}(s), S, N\}} V_L(a, s, \theta) \tag{14}$$

$$V_L(a, s, \theta) = \mathbb{E}_\delta W(\theta, L, \delta) + \mathbf{1}_{[a<\bar{a}]} \beta \mathbb{E}_\delta V(a+1, s+\mathbf{1}_{[L=S]}, \theta^P - \delta, \theta^C), \tag{15}$$

Schooling is an investment decision, trading off tuition and foregone earnings while studying with future earnings gains in the analytical occupation after graduation.

E.1.2 Career Choices

The optimal career decisions of workers can be solved by backward induction. In the year before retirement, workers face a static choice of maximizing their current income in Equation (13). In each preceding year, $a = \bar{a} - 1, ..., \underline{a}$, the value of each career choice is given recursively by Equations (14)-(15).

Panel (a) of Figure E.1 illustrates the optimal decisions of workers without prior

[41] To keep the theory, we conceptualize schooling only to lower switching costs. All predictions and implications extend to the case where schooling also enhances workers' cognitive productivity within occupations:

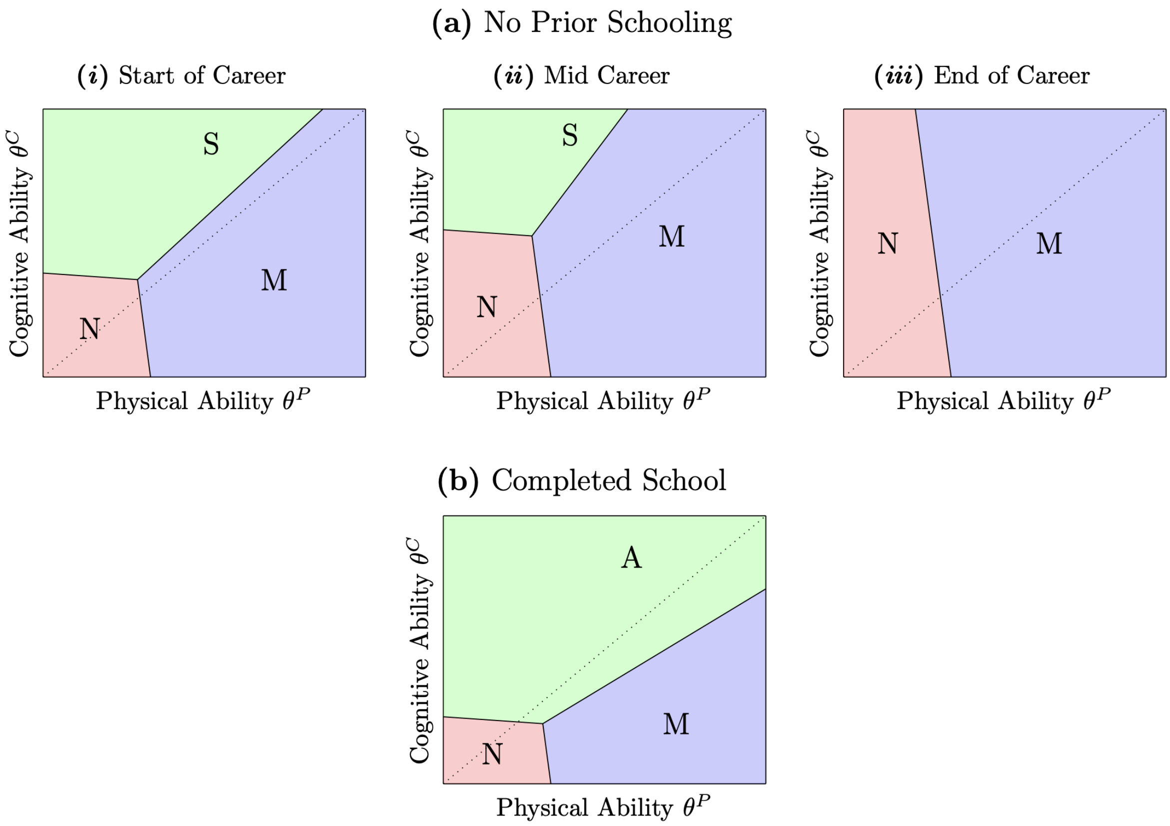
$$\theta_{it}^C = \theta_{it-1}^C + \delta_S S_{it-1}, \quad \delta_S \geq 0. \tag{12}$$

The derivations for this model extension are available upon request.

[42] In Section E.3.2, we allow non-employment benefits to depend on workers' abilities $B(\theta)$ through disability insurance.

schooling at different stages of their careers. At each age level, the optimal decisions are characterized by three indifference lines, separating the workers who prefer to work in the manual occupation, enroll in school, and exit the labor force. Appendix E.4 solves the analytical expressions of these indifference lines.

Figure E.1: Career Choices by the Education, Age, and Ability of Workers



Notes: The figure shows the optimal career choices by the education, age, and ability of workers. S denotes "School", N denotes "Non-Employment", M denotes "Manual Work", and A denotes "Analytical Work". The figure is based on the following parameter values $\omega_M^P = 0.9, \omega_M^C = 0.1, \omega_A^P = 0.1, \omega_A^C = 1.2, \theta \in [0,1]^2, \underline{a} = 18, \bar{a} = 63, \bar{s} = 6, T = 0.1, B = 0.3, \beta = 0.95$. The "Start of Career", "Mid Career", and "End of Career" subplots set the worker's age to 18, 48, and 61, respectively.

First, because schooling is a fixed investment with constant annual returns, workers enroll in school at the start of their careers, all else equal. Second, no workers older than $\bar{a} - \bar{s}$ enroll in school, because the remainder of their careers is too short to reap the benefits of a degree through analytical work. Third, during a worker's career (between the age of $\underline{a}$ and $\bar{a} - \bar{s}$), workers only enroll in school if an injury makes it unprofitable for them to continue in the manual occupation.[43] Work injuries move workers horizontally in ability space by the injury severity δ.

Panel (b) of Figure E.1 depicts the optimal decisions of workers who have completed school and gained access to the analytical occupation. The optimal decisions are characterized by three indifference lines, separating the workers who prefer analytical work, manual work, and non-employment. If pushed to schooling by an injury, workers will transition into the analytical occupation after completing their degree.

E.2 Confronting Theory and Evidence

In this section, we show that the model developed in Section E.1.1 rationalizes a series of the empirical findings in Sections 3 to 6.

E.2.1 Earnings Capacity

Figure B.3 shows that work accidents *only* generate human capital investment if they cause a loss of earnings capacity. This finding supports the theoretical interpretation of work accidents as shifters to the abilities of workers.

E.2.2 Cognitive Injuries

Figure B.4 shows that cognitive injuries do not induce human capital investment. From the viewpoint of our theory, cognitive injuries correspond to a downward shift in ability space. As Figure E.1.(a) makes clear, such downward shifts do not push workers toward more schooling.

E.2.3 Worker Age

Figure 3 documents an age gradient in human capital investment after work injuries. The empirical plot is consistent with our theory in two ways. First, comparing across the panels of Figure E.1.(a), younger workers invest more in human capital after work injuries. In particular, for all combinations of initial abilities θ and injury severity δ, younger

[43] In a similar vein, (McCall et al., 2016, Section 2.2) propose a dynamic model of human capital in which skill-depreciation shocks can push mid-career workers back into school. We extend the theoretical analysis to multidimensional skills and occupational choice, and analytically characterize the optimal career choices in terms of separating hyperplanes.

workers are more likely to invest in human capital after an injury. Second, as depicted in Figure E.1.(a).(*iii*), an age cutoff exists above which no worker invests in human capital after injuries.

E.2.4 Occupational Switching after Work Accident

Table 4 shows that workers who invest in human capital that transition out of physically demanding jobs and into cognitively intense occupations after work injuries. This finding is consistent with our model in which schooling constitutes a gateway to analytical work.

E.2.5 Substitution between Schooling and Disability Insurance

Figure D.2 shows that access to education substitutes for disability insurance after work accidents. This finding is consistent with the theoretical analysis in Section E.3.2 in which disability insurance is the next-best option of most workers who reskill.

E.3 Implications

In this section, we discuss implications of our theoretical framework.

E.3.1 Ability Demand Shocks

Reskilling programs are often motivated by automation or globalization, lowering the demand for manual abilities in the labor market. What can we learn about reskilling responses to automation or globalization from evidence on work injuries? The model developed in Section E.1.1 highlights an interesting equivalence but also omits important differences.

In the model, automation and globalization shock the *demand* for physical abilities ω^P.[44] By contrast, work injuries lower workers' *supply* of physical abilities θ^P. Interestingly, shocks to ω^P and θ^P have equivalent implications for the career choices of workers, because both shocks work by lowering workers' earnings potential in physical tasks.[45] Put differently, taking our theory at face value, we can extend our findings for work injuries to learn about

[44]In the theoretical frameworks of Acemoglu and Restrepo (2018) and Grossman and Rossi-Hansberg (2008), ω^P can be microfounded as the set of physical work tasks that have not been automated or offshored.

[45]Mathematically, θ^P and ω^P enter Equations (13)-(15) through $E^P = \omega^P \times \theta^P$.

responses to ability demand shocks, such as automation or globalization. Furthermore, injury events are econometrically appealing to study because they occur at the worker level (δ_{ia} has an i-subscript), whereas automation or globalization often affect a whole labor market simultaneously (ω^P are shared by all workers).

However, with this theoretical equivalence in mind, the model omits important features that set ability supply and demand shocks apart in their implications for workers and the economy. First, injuries often qualify workers for disability benefits and other government transfers.[46] As Section E.3.2 below shows, disability insurance tilts injured workers away from investing in human capital and toward non-employment. Put differently, the pressures on workers to reskill caused by automation or offshoring should be even stronger than the pressures caused by work injuries. The clear investment responses documented in Sections 4 to 6 are striking in this light. Second, because work injuries occur at the individual level, the empirical evidence presented in Section 4 to 6 is not informative about any general-equilibrium implications of reskilling a large set of workers at single time, as may be required if, for example, robots make a whole profession obsolete. These general-equilibrium effects include constraints on the supply of effective reskilling programs and changing wages when aggregate labor supply shifts from manual to analytical work.

E.3.2 Disability Insurance

In this section, we let non-employment benefits depend on workers' physical abilities via disability insurance:

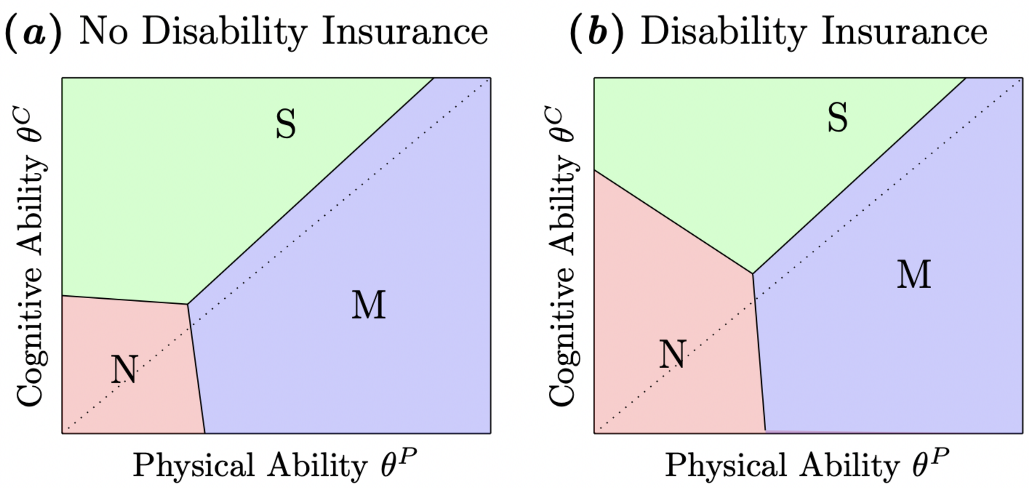
$$B(\theta) = b_0 - b_1\theta^P, \tag{16}$$

Figure E.2 shows that disability insurance ($b_1 > 0$) rotates the indifference curves with respect to non-employment benefits counterclockwise. Section E.4.3 solves the indifference curves analytically. As the figure shows, disability insurance mainly crowds out human capital investments. The reason is that disability insurance targets workers with low

[46] Despite this theoretical distinction, David et al. (2013) find that import competition from China mainly shifted workers toward disability insurance instead of Trade Adjustment Assistance (TAA), a reskilling program designed for workers displaced by import competition.

physical abilities, who are the same workers who have the most to gain from switching to analytical work through schooling.

Figure E.2: Start of Career



Notes: The figure shows the optimal career choices by the skill, age, and ability of workers. S denotes "School", N denotes "Non-Employment", and M denotes "Manual Work". Panel (a) is based on the following parameter values $\omega_M^P = 0.9, \omega_M^C = 0.1, \omega_A^P = 0.1, \omega_A^C = 1.2, \theta \in [0,1]^2, \underline{a} = 18, \bar{a} = 63, a = 18, \bar{s} = 6, T = 0.1, b_0 = 0.3, b_1 = 0, \beta = 0.95$. Panel (b) changes the benefit parameters to $b_0 = 0.6, b_1 = -0.6$.

E.4 Solving Career Choices

This section solves the dynamic career problem of workers stated in Equations (13)-(15) of Section E.1.1. At each level of age and skill, the optimal decisions are characterized by three indifference curves, delineating workers who prefer one feasible option to another.

E.4.1 Indifference Curves of Workers without Prior Schooling

The feasible career choices of a worker who has not completed school are school, manual work, and non-employment.

School vs. Manual Work. The decision to enroll in school or work in a manual occupation trades off tuition and foregone earnings while studying with future earnings in the cognitive occupation after graduation:

$$V_S(a,0,\theta) \geq V_M(a,0,\theta) \iff \tag{17}$$

$$-(1+...+\beta^{\bar{s}-1})T + (\beta^{\bar{s}}+...+\beta^{\bar{a}-a})(\omega_A^P\theta^P+\omega_A^C\theta^C) \geq (1+...+\beta^{\bar{a}-a})(\omega_M^P\theta^P+\omega_M^C\theta^C). \tag{18}$$

At a given age a, Equation (18) identifies a line of indifference in ability space, delineating workers who prefer school to manual work:

$$\theta^C \geq \gamma_0^{SM} + \gamma_1^{SM} \times \theta^P, \quad \text{where} \tag{19}$$

$$\gamma_0^{SM} = \frac{(1-\beta^{\bar{s}})T}{(\beta^{\bar{s}}-\beta^{\bar{a}-a+1})\omega_A^C - (1-\beta^{\bar{a}-a+1})\omega_M^C} \tag{20}$$

$$\gamma_1^{SM} = \frac{(1-\beta^{\bar{a}-a+1})\omega_M^P - (\beta^{\bar{s}}-\beta^{\bar{a}-a+1})\omega_A^P}{(\beta^{\bar{s}}-\beta^{\bar{a}-a+1})\omega_A^C - (1-\beta^{\bar{a}-a+1})\omega_M^C}. \tag{21}$$

School vs. Non-Employment. The decision between school and non-employment compares tuition and foregone benefits while studying with future earnings in the cognitive occupation after graduation:

$$V_S(a,0,\theta) \geq V_N(a,0,\theta) \iff \tag{22}$$

$$-(1+...+\beta^{\bar{s}-1})T + (\beta^{\bar{s}}+...+\beta^{\bar{a}-a})(\omega_A^P\theta^P+\omega_A^C\theta^C) = (1+...+\beta^{\bar{a}-a})B. \tag{23}$$

At a given age a, Equation (23) identifies a curve of indifference in ability space, delineating workers who prefer school to non-employment

$$\theta^C \geq \gamma_0^{SN} + \gamma_1^{SN} \times \theta^P, \quad \text{where} \tag{24}$$

$$\gamma_0^{SN} = \frac{(1-\beta^{\bar{s}})T + (1-\beta^{\bar{a}-a+1})B}{(\beta^{\bar{s}}-\beta^{\bar{a}-a+1})\omega_A^C} \tag{25}$$

$$\gamma_1^{SN} = -\frac{\omega_A^P}{\omega_A^C}. \tag{26}$$

Work vs. Non-Employment. The decision to work in a feasible occupation $o \in \mathcal{O}(s)$ or exit the labor force compares earnings in the occupation with benefits if not employed.

$$V_o(a,0,\theta) \geq V_N(a,0,\theta) \iff \tag{27}$$

$$\omega_o^P\theta^P + \omega_o^C\theta^C \geq B. \tag{28}$$

Equation (28) identifies a line of indifference in ability space, delineating workers who prefer working in occupation o to non-employment:

$$\theta^C \geq \gamma_0^{oN} + \gamma_1^{oN} \times \theta^P, \quad \text{where} \tag{29}$$

$$\gamma_0^{oN} = \frac{B}{\omega_o^C}, \quad \gamma_1^{oN} = -\frac{\omega_o^P}{\omega_o^C} \tag{30}$$

E.4.2 Indifference Curves of Workers Who Have Completed School

The feasible career choices of a worker who has completed school are manual work, analytical work, and non-employment.

Analytical Work vs. Manual Work. After graduation, the decision between manual and analytical work compares the earnings in each occupation:

$$V_A(a, \bar{s}, \theta) \geq V_M(a, \bar{s}, \theta) \iff \tag{31}$$

$$\omega_A^P \theta^P + \omega_A^C \theta^C \geq \omega_M^P \theta^P + \omega_M^C \theta^C. \tag{32}$$

Equation (34) identifies a line of indifference in ability space, delineating workers who prefer analytical work to manual work:

$$\theta^C \geq \gamma_0^{AM} + \gamma_1^{AM} \times \theta^P, \quad \text{where} \tag{33}$$

$$\gamma_0^{AM} = 0, \quad \gamma_1^{AM} = \frac{\omega_M^P - \omega_A^P}{\omega_A^C - \omega_M^C}. \tag{34}$$

Work vs. Non-Employment. See Section E.4.1.

E.4.3 Disability Insurance

In this section, we solve for the career decisions of workers when non-employment benefits depend on workers' physical abilities via disability insurance. Inserting Equation (16) for the non-employment benefits into the conditions for optimal career decisions in Equations

(23) and (28), the indifference curves are

$$\gamma_0^{oN} = \frac{b_0}{\omega_o^C} \tag{35}$$

$$\gamma_1^{oN} = -\left[\frac{\omega_o^P + b_1}{\omega_o^C}\right] \tag{36}$$

$$\gamma_0^{SN} = \frac{(1-\beta^{\bar{s}})T + (1-\beta^{\bar{a}-a+1})b_0}{(\beta^{\bar{s}} - \beta^{\bar{a}-a+1})\omega_A^C} \tag{37}$$

$$\gamma_1^{SN} = -\left[\frac{\omega_A^P + b_1\frac{1-\beta^{\bar{a}-a+1}}{\beta^{\bar{s}}-\beta^{\bar{a}-a+1}}}{\omega_A^C}\right]. \tag{38}$$

Disability insurance increases b_0 and b_1, rotating the indifference curves in Equations (35)-(38) counterclockwise in ability space.