CHANGING TRACKS: HUMAN CAPITAL INVESTMENT AFTER LOSS OF ABILITY*

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Abstract

We provide the first evidence on how workers invest in human capital after losing ability. Using quasi-random work accidents in Danish administrative data, we find that workers enroll in bachelor's programs after physical injuries, pursuing degrees that build on their work experiences and provide pathways to cognitive occupations. Exploiting differences in eligibility driven by prior vocational training, we find that higher education moves injured workers from disability benefits to full-time employment. Reskilled workers earn 25% more than before their injuries and do not end up on antidepressants. Without higher education, by contrast, these workers end up entirely on disability benefits and often resort to taking antidepressants. Reskilling subsidies for injured workers pay for themselves four times over, and current rates of reskilling are substantially below the social optimum, especially for middle-aged workers. *JEL Codes*: I26, J24, J62.

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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] Human capital investment may also help lift exposed workers out of disability insurance programs, which consume a substantial and growing proportion of government budgets in advanced countries (Autor and Duggan, 2006; OECD, 2023).

We study reskilling and occupational transitions in the context of work accidents, a severe shock to the ability of workers. We answer three questions: Do workers invest in human capital after losing physical ability? Do human capital programs help workers switch from physical to cognitive occupations? What are the returns on these investments for workers and society?

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 three parts.

First, we study how workers invest in human capital after losing physical ability. For this analysis, we 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 the livelihoods of workers whose labor earnings suffer a persistent 40% loss while antidepressant prescriptions increase by 10 percentage points. We establish four 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, only about 13% of workers have enrolled in a degree at any level,

[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).

and participation in non-degree courses is negligible. Second, workers who invest in human capital overwhelmingly enroll in four-year bachelor's programs, suggesting that a substantial human capital investment is needed to change tracks. Third, workers select degrees that build on their work experiences and provide pathways to jobs with lower physical demands. Finally, investment decreases steeply with age; workers older than 50 do not invest in education after work accidents. By contrast, about half of the workers aged 20 to 25 pursue higher education after injuries.

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 grants direct entry into post-secondary programs in Denmark. For example, prior vocational training in carpentry provides direct admission into the bachelor's program in Construction Architecture. By contrast, landscape gardening (an otherwise similar vocational degree to carpentry) does not offer entry to any post-secondary program, so a worker would have to complete an additional three years of high school to become eligible for 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 from reskilling for injured workers. Reskilled workers do not claim disability benefits and instead transition into cognitive occupations, earning 25% more than before their injuries. Without access to higher education, by contrast, these workers end up

entirely on disability benefits and often resort to taking antidepressants. Combining the effects on earnings, taxes, and transfers in a cost-benefit framework, we calculate a 600% social surplus on higher education for injured workers. These remarkable social returns reflect that higher education moves injured workers from disability benefits (a liability to the government budget) to taxable high-income employment (an asset to the budget). In total, the government reaps 60% of the social surplus from reskilling despite covering tuition and generous benefits.

In the final part of the paper, we evaluate the counterfactual effects of reskilling more injured workers. To do so, we estimate marginal treatment effects (MTE) of reskilling by interacting our "access to higher education" instrument with the age-based differences in reskilling. We identify the private, public, and social returns to reskilling for workers at the margin of participation at different levels of program expansion. We incorporate general equilibrium effects by embedding the treatment effects into a calibrated model of the labor market.

We find that the marginal surplus of reskilling declines in workers' age and in the share of each age cohort induced to reskill. We use these marginal surplus estimates to determine the optimal rates of reskilling for injured workers. Averaging across age cohorts, we find a socially optimal rate of 33%, more than twice the current level. The current rates are especially sub-optimal for middle-aged workers between the ages of 40 and 50. In particular, only 6% of middle-aged workers reskill after injuries, yet reskilling subsidies covering tuition and benefits pay for themselves for 36% of these workers. A rate of reskilling of around 36% also maximizes the workers' private surplus, measured as present-discounted lifetime income. The fact that so few of the workers reskill points to substantial barriers to investing in human capital. In particular, the marginal middle-aged worker currently leaves $110,000 on the table by not reskilling. By contrast, the current reskilling rates among the youngest and oldest workers are close to optimal, socially and

privately.

1.1 Related Literature

Work accidents are costly to workers, firms, and the government, yet we have limited knowledge of what helps injured workers reattach to the labor market (Autor and Duggan (2010); Nichols et al. (2020)). In the United States, work injuries are a major cause of disability insurance claims, and their total costs amount to 1.3% of the Gross Domestic Product (Reville and Schoeni (2004); Leigh (2011)). Compared to mass layoffs, a shock to workers frequently studied in the labor literature (Jacobson, LaLonde and Sullivan (1993); Sullivan and Von Wachter (2009)), work accidents are both more prevalent and cause more persistent earnings losses.[2] Existing studies have mostly focused on disability benefits in discouraging workers from returning to work (Maestas, Mullen and Strand (2013); Kostøl and Mogstad (2014); Low and Pistaferri (2015); Autor et al. (2016)). More recently, Aizawa, Mommaerts and Rennane (2022) study the role of 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 cost-benefit calculations show large returns to reskilling middle-aged workers. These findings contrast with the conventional wisdom that investing in older workers generates lower returns (Hendren and Sprung-Keyser, 2020). Our setting showcases how substantial social returns can arise when programs alleviate existing distortions in the economy – in this case, the fiscal externality of disability insurance.

In addition to the fiscal benefits, we find that reskilling shields injured workers from

[2]See Figures A.3 and A.4.

depression. These findings relate to the "deaths of despair" crisis documented by Case and Deaton (2015), in which midlife economic hardship has led to rising drug overdoses and mortality. Sullivan and Von Wachter (2009) find that job displacement from a mass layoff increases mortality, which Browning and Heinesen (2012) link to drug abuse and mental illness. Our findings for injuries and reskilling highlight that it is the lack of career prospects – and not the injuries per se – that makes workers depressed.

Our study is inspired by human capital models featuring multidimensional ability (Sanders and Taber (2012); Traiberman (2019); Lise and Postel-Vinay (2020); Adda and Dustmann (2023)). In particular, we interpret work accidents as shocks to workers' physical abilities that induce them to invest in cognitive skills. 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. Third, injured workers do not benefit from access to degrees with physical demands similar to their previous jobs. Finally, human capital investments help workers switch from physical to cognitive occupations. Our evidence is 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, LaLonde and Sullivan, 2011). Reskilling programs are often motivated by structural changes, such as automation or globalization, forcing workers to switch out of manual occupations (Hyman, 2018).[3] Interestingly, 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

[3]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.

cognitive occupations. These findings complement recent evidence on sectoral training programs in placing marginalized workers in high-wage jobs (Katz et al., 2022). By reorienting workers toward in-demand occupations, reskilling policies may have smaller displacement effects in the labor market than pure job-search assistance (Crépon et al., 2013). In particular, we show that the optimal rates of reskilling for injured workers are robust to general equilibrium considerations.

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).

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.[4]

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.

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

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% or the earning capacity loss exceeds 15%. The compensations are paid as one-time transfers and do not depend on the receipt of other government transfers, including disability insurance.[5] Each year, AES pays between 3 and 5 billion DKK in compensation for work accidents, equivalent to 0.15%-0.25% of GDP. Section 3 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).

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,

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

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 4.1.

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% 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 (Krueger and Meyer (2002); Autor and Duggan (2003); Reno, Thompson Williams and Sengupta (2003)).[6]

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 refer to rehabilitation benefits for formal education.[7]

If not offered rehabilitation benefits, students are eligible for *State Education Support*

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

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

(SU) set at 6,400 DKK (900 USD) per month, equivalent to 15-30% of injured workers' prior earnings (one third of disability or rehabilitation benefits).[8] 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 an 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 1995 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] Disabled workers may apply for an additional Special Education Support of 5,000-9,000 DKK per month, equivalent to 15-30% 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.[9]

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.[10]

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 1995 to 2017.[11]

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 non-degree 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

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

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

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

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 their funding source.[12]

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.

[12] 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 Work Accidents

Every year, about 0.6% 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, LaLonde and Sullivan, 1993).[13]

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% of all work injuries occur in the 50% most physical occupations.[14]

In this section, we use work accidents to document which types of human capital programs appeal to workers who have lost ability. We establish three findings that set the stage for our main analysis in Sections 4 and 5. First, work accidents occur quasi-randomly within occupations and cause persistent damage to the health and earnings of workers. Second, injured workers who invest in human capital overwhelmingly enroll in higher degrees. Finally, human capital investment decreases steeply with age.

[Table 1 around here]

3.1 Impacts 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, and thus exclude psychological shocks. Third, we focus on workers with stable employment

[13] Appendix Figure A.3 shows the time series of work accidents and mass layoffs in Denmark.

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

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 43-year-old man who has completed a vocational degree. Before the accident, the worker was employed in a physically demanding occupation with low 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 the 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 and work hours. The similarity supports the notion that the workers are indeed comparable.[15] The "Injury" panel shows the severity of the injuries, as assessed by AES.[16] The average injury in our sample reduces workers' earning capacity by 37% and causes a personal impairment of 12%.

[Table 2 around here]

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

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

[16] Section 2.2.1 describes the severity metrics.

before the accident:

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

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

Three connections to the recent literature on differences-in-differences designs deserve notice (Callaway and Sant'Anna (2021); Roth et al. (2022)). First, by matching treated and control workers before each event year e, we ensure Equation (1) identifies positively-weighted averages of causal effects under parallel trends. Second, recent estimators often use later-treated or never-treated units as the control group. However, because treatment in our case happens at the workplace, later-treated and never-treated workers are implicitly selected on their post-event employment outcomes. For this reason, we prefer to match workers before the accidents and not condition the control group on post-event outcomes. That said, because workers have minimal risk of work accidents before and after the event year, our control workers are overwhelmingly never-treated units.[17] Appendix Figure A.2 verifies that our baseline estimates are virtually identical to the estimators of Callaway and Sant'Anna (2021), Sun and Abraham (2021), and De Chaisemartin and d'Haultfoeuille (2022*a*) implemented on never-treated units. Finally, in our main analysis of human capital investment (Sections 4 and 5), we compare injured workers who differ in their access to education, where the non-injured match workers merely serve as placebo checks.

[17] Appendix Figure A.1 plots the incidence of work accidents for the treated and control workers.

3.1.1 Health and Income

Figure 1 shows the impact of work accidents on the health and income of workers. The figure delivers four insights. First, before experiencing a work accident, workers have a similar evolution of health and earnings as other workers in their occupations. The flat pre-trends support the assumption that work accidents happen quasi-randomly within occupations. Second, work accidents severely shock workers' health, with days spent in the hospital spiking after injuries (Panel (a)). 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% (Panel (c)). For comparison, Appendix Figure A.4 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 by about 30% (Panel (c)) and the share of workers who use antidepressants increases by about 10 percentage points (Panel (d)).

[Figure 1 around here]

3.1.2 Human Capital Investment

Figure 2 plots the participation of workers in degree and non-degree courses. For example, *higher non-degree* includes university courses in computer programming, and *higher degree* includes bachelor's programs in construction engineering. The activity is measured in full-time equivalents. The *higher degree* line shows that, two years after the accident, 8% 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.[18]

[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% of injured workers with

Appendix Figure A.5 shows the plots separately for each initial level of education, confirming that human capital investments are made overwhelmingly by workers with access to higher education.[19] In Section 4.1, we investigate the causal role of access to education in the reskilling of injured workers.

Figure 2 reveals two findings. First, most workers do not invest in human capital after losing work abilities. Ten years after work accidents, about 13% of the workers have enrolled in a degree at any level, and the workers have participated in 1% 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% of total human capital investment after work accidents. Appendix Figure A.6 shows that over 80% of injured workers who pursue higher education also complete their degrees.

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.

In Appendix B, 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.[20] 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.1.(a)). Second, when investing in human capital, workers target degrees that build on their work experiences (Figure B.1.(b)). For example, many

access to higher education have a vocational degree as their highest educational attainment (Table A.2). Section 2.1.3 describes the Danish educational system, and Appendix Table A.3 lists the vocational degrees and their access to higher education.

[19] 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 A.2).

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

carpenters obtain a bachelor's degree in Construction Architecture after work accidents.[21]

[Figure 2 around here]

In Figure 3, we split the enrollment rates in higher degrees by the age at which workers experience a work accident. The plot shows that human capital investment decreases steeply with age. In particular, workers older than 50 do not invest in higher education after work accidents.[22] By contrast, almost half of the youngest workers aged 20 to 25 take up higher education after injuries. The pattern is consistent with a lifecycle model in which forward-looking workers consider if they have enough remaining working years to recoup an educational investment. We return to these cost-benefit considerations in Section 5.3.

[Figure 3 around here]

3.2 Mechanisms

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). Appendix Figures A.7 and A.8 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.[23]

[21]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.*

[22]Jacobson, LaLonde and Sullivan (2005) document a similar age gradient in the retraining decisions of displaced workers.

[23]Section 2.2 details the assessment process.

Figure A.7 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 A.8 shows that workers do not invest in human capital after cognitive injuries.

4 Human Capital 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 (Figure A.7), their expected payoffs from education (Figures 3 and A.8), 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. The differences in admission criteria allow us to compare otherwise similar workers who differ in their access to higher education upon injury.

In Section 4.1, 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 4.2, we use the workers to estimate the reduced-form impacts of access to higher education for injured workers. Section 4.3 estimates the potential outcomes of workers who reskill after a work accident. Finally, in Section 4.4, we conduct a cost-benefit analysis of providing access to higher education for injured workers.

4.1 Identification Strategy

In Denmark, some initial vocational degrees provide 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 A.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% craft workers (e.g., carpenters), 10% care workers (e.g., nurse assistants), 10% retail workers (e.g., sales assistants), and 10% food service workers (e.g., chefs); see Appendix Table A.4 for an overview.[24]

These institutional rigidities in the Danish educational system allow us to identify comparable workers in similar occupations and with similar amounts of schooling who differ in their access to higher education.[25] To find these workers, we implement an inverse probability weighting (IPW) strategy detailed in Appendix C. The reweighing 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. Importantly, while the IPW ensures that the worker groups are comparable before the injuries, Appendix C.1 shows our main difference-in-differences estimates in Sections 4.1.1 and 4.2 are robust to the IPW method.

The idea behind our identification strategy is that workers' initial vocational specializa-

[24]The fact that vocational degrees differ in their access to higher education is not specific to Denmark. For example, the International Standard Classification of Education (ISCED) subcategories 353 and 354 distinguish between vocational degrees without and with direct access to higher education.

[25]The institutional differences in access to higher education are widely believed to reflect rigidities of the current Danish educational system (Regeringen, 2014). For example, a stated goal of the Danish government is to *"make it easier for vocationally-trained workers to take a relevant higher education without first going through high school"* (Regeringen, 2022). Our reduced-form evidence in Section 4.2 informs this policy proposal.

tions may not anticipate the need for reskilling after severe injuries later in life. Four facts substantiate this idea. First, individuals decide on their vocational training at age 16, on average 27 years before injuries occur. Second, workers with access to higher education do not have better-educated parents (reported in Table 3 but excluded from the IPW estimation). Third, physical injuries that cause loss of earning capacity are low-probability events, as workers have a 4% risk of such accidents throughout their careers. Finally, Section 4.1.2 conducts a host of placebo checks of the comparability of the "Access" and "No Access" workers.

[Table 3 around here]

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 around here]

As mentioned earlier, workers whose initial vocational training provides access to higher education are predominantly craft and care workers, representing 70% and 10% of the "Access" group, respectively. Appendix Table A.5 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.1.(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, 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.

4.1.1 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:

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

where θ_{1k} are our coefficients of interest, identifying the causal effects of access to higher education around work accidents. 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% more likely to have pursued a higher degree.

[Figure 5 around here]

4.1.2 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 fare similarly after work accidents.

[Figure 6 around here]

4.2 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% of the workers' earnings before the accident.

In Appendix Figure A.10, 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 10% less likely to receive disability benefits (Panel (a) of Figure A.10) and 10% more likely to be employed (Panel (b) of Figure A.10). By contrast, we do not find that access to education influences workers' take-up of non-means-tested pensions (Appendix Figure A.11).

[Figure 7 around here]

4.3 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 pursue the programs.[26,27] Hence, our treatment variable D is equal to 1 if the worker pursues a higher degree within ten years after the accident.

Let $Y_i(D_i)$ denote the potential outcome of worker i with and without higher education, and D_{Ai} denote his potential education 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:

$$Y_{it} = \theta_{0k}^{Y} + \theta_{1k}^{Y} A_{ie} + \varepsilon_{it}^{Y} \quad \text{if} \quad t = e + k. \tag{5}$$

We estimate Equation (5) on a balanced sample, weighing the workers as in the "IPW" column of Table 3. 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 A.10) according to whether workers complete a higher education after the accidents.[28]

[26]Figure 6 supports this exclusion restriction by showing that the oldest workers, who do not invest in human capital regardless of eligibility, fare similarly in the labor market after work accidents.

[27]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 access to education makes workers stay in the labor force.

[28]We estimate θ_{1k}^{Y} as simple differences in between the access groups to recover the levels of workers'

The idea behind Equations (3)-(4) is that access to education affects labor market outcomes exclusively by shifting compliers into higher education. Hence, by interacting the outcome variable (Y) with the higher-education treatment status (D and $1 - D$), we identify the average potential outcomes of compliers with and without higher education.

We estimate Equations (3)-(5) using two-stage least squares (TSLS) and follow Imbens and Rubin (1997) in imposing non-negativity constraints on the potential outcomes.[29]

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 80% of injured workers who reskill end up finding employment. Third, if these workers do not reskill, they end up entirely on disability benefits.

[Figure 8 around here]

Table 4 reports the job characteristics of the injured workers who find employment after reskilling.[30] The table shows that higher education allows workers to reallocate from physically demanding occupations to more cognitively intense jobs. Ten years after the work accident, these reskilled workers earn 25% more than before their injuries. These earnings effects are especially remarkable given that the workers were not marginalized before the injuries but earned slightly more than the median in Denmark.

[Table 4 around here]

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

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 A.10) because the "Access" and "No Access, IPW" groups are similar on the outcomes before the injury (Table 3).

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

[30]Because job characteristics are measured for employed workers only, Table 4 define the treatment variable as $D \times E$, where E equals 1 if the worker has completed his degree and is employed ten years after the accident (blue area in Figure 8.(a)).

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 around here]

In summary, we find that 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, we compare the complier workers to their match workers (who are not injured in the event year). Appendix Table A.6 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 about 10 percentage points more likely to be employed (Appendix Figure A.12) and earn about 5% more in their jobs (Appendix Table A.6) than if they had not been injured. However, the differences are not statistically significant. The use of antidepressants is flat for both groups (Appendix Figure A.13).

4.4 Cost-Benefit Evaluation

In this section, we use the causal estimates from Section 4.2 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 estimates from Section 4.2 with government tax and transfer rates to estimate

the costs and benefits for injured workers and the government. Appendix E details our approach to the cost-benefit calculations.

Table 5 summarizes the costs and benefits for workers and the government. 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 600% return on the education expenses.[31] The investment generates an internal rate of return (IRR) of 54.0% per year, about four times higher than conventional estimates for young or displaced workers (Kane and Rouse (1995); Heckman, Lochner and Todd (2003); Jacobson, LaLonde and Sullivan (2005)).[32] 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 expenditure on education pays for itself four times over.[33] Finally, the table shows how a generous transfer system weakens the private incentives for workers to invest in human capital. In particular, about 40% of the higher earnings from reskilling are countered by lower transfer payments for workers.

[Table 5 around here]

Our main cost-benefit analysis focuses on earnings, taxes, and transfers, whose monetary values are straightforward to evaluate. In particular, Table 5 does not include the health benefits of reskilling, such as preventing depression (Figure 9). In Appendix E.1, we assess the mental health benefits using expenditures on treatment (medication and

[31] Cost-benefit analyses sometimes inflate the direct gross 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). Applying a deadweight loss of 50% to the direct costs, as in Heckman et al. (2010), would deliver a net social return of 360%, and the total government cost (program cost and deadweight loss) would pay for itself three times over. Reskilling subsidies for injured workers pay for themselves as long as the deadweight factor is below 340%.

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

[33] In the terminology of Hendren and Sprung-Keyser (2020), subsidizing higher education for injured workers has an infinite Marginal Value of Public Funds (MVPF).

counseling) and existing estimates of the value of mental health in terms of life quality. In total, we estimate a lower bound on the added social surplus from mental health of $47,000 per reskilled worker, which is split $27,000 for workers and $20,000 for the government.

By construction of our access IV, the reduced-form evidence presented in this section is relevant for policies that provide access from vocational degrees to higher education. Indeed, a stated goal of the Danish government is to *"make it easier for vocationally-trained workers to take a relevant higher education without first going through high school"* (Regeringen, 2022). Table 5 directly informs the costs and benefits of such a policy. The large surpluses in Table 5 beg the question of whether reskilling should be rolled out to more injured workers. In Section 5, we evaluate expansions of the reskilling program.

5 Policy Counterfactuals

In this section, we assess the counterfactual effects of reskilling more injured workers. Expanding reskilling programs could face decreasing returns for at least three reasons. First, within a cohort, workers may self-select into reskilling based on their idiosyncratic returns to the program. For example, at the current level of the policy, individuals may only reskill if they cannot find jobs otherwise. Hence, expanding reskilling to more workers could entail lower returns. Second, expanding the program could imply rolling it out to older workers with fewer working years left to reap the labor market returns to new skills. Finally, large expansions of the reskilling programs could have equilibrium impacts on labor markets.

In Sections 5.1 and 5.2, we assess the first two sources of decreasing returns by estimating how marginal treatment effects (MTEs) of reskilling vary within and across cohorts of injured workers. In Section 5.3, we use these estimates to evaluate the partial-equilibrium effects of changing the rates of reskilling for injured workers. Finally, in Appendix F, we show that the optimal rates of reskilling are robust to general equilibrium

considerations.

5.1 Marginal Treatment Effects

In this section, we estimate the returns to reskilling for workers at the margin of participation at different levels of program expansion (p).

Following Heckman and Vytlacil (2007), we aim to estimate a continuum of treatment effects according to the "encouragement" (based on an observable propensity score) needed for workers to take up the treatment:

$$p(\text{Reskill}_i = 1) = \mu(Z_i) \tag{6}$$

$$\text{MTE}(p) = \frac{\partial \mathbb{E}[Y_i | \hat{p}_i = p]}{\partial p}, \tag{7}$$

where Y is an outcome and $\hat{p}$ is a propensity score based on an instrument Z. That is, the estimated propensity score measures the extent of the program, and the MTE is the change in the outcome generated by an expansion in the program.

With a continuous instrument, obtaining a continuous distribution of propensity scores is straightforward. Because our access instrument is binary, however, we combine our instrument with a continuous covariate X to trace out a distribution of propensity scores with continuous support. Kline and Walters (2016) and Walters (2018) follow similar strategies, combining an access instrument with covariates to estimate marginal treatment effects.

Our strategy is to interact our access IV with the age pattern in reskilling (Figure 3) to estimate the propensity scores:

$$p(D_i = 1) = \mu(X_i, Z_i) = \mu(\text{Age}_i, \text{Access}_i), \tag{8}$$

where D_i is an indicator for enrolling in a post-secondary degree within ten years after the accident.

To obtain the MTEs, we regress the outcome variable on the propensity score and age controls and calculate the MTE in a second step:

$$\mathbb{E}[Y_i] = g(\text{Age}_i) + f(\hat{p}_i) \tag{9}$$

$$\text{MTE}(p) = \frac{\partial f(p)}{\partial p}, \tag{10}$$

where $g(\cdot)$ and $f(\cdot)$ are flexible functions we specify in Section 5.1.1. As outcomes Y, we use annual earnings, public transfers, and tuition costs at different time horizons after injury, allowing us to compute the social, private, and public returns to reskilling.

The outcome equation (9) assumes a crucial separability in the effects of age and the propensity score. The separability embodies the identifying assumption that the schedule of MTEs on annual outcomes before retirement is the same across age cohorts. The separability allows us to use the interaction between access and age to trace out the MTE function.[34]

5.1.1 Estimation

We estimate the propensity score and outcome equation for injured workers below age 50, who all have at least ten years left until retirement age. We use the IPW weights defined earlier to account for differences between workers with and without access to education.

Propensity scores. We estimate the propensity scores using a flexible logit specification in age and access:

$$p(D_i = 1) = \mu(\text{Age}_{ie}, \text{Access}_{ie}) \tag{11}$$

$$= \mu\left(g(\text{Age}_{ie}) + \beta_1 \text{Access}_{ie} + \beta_2 \text{Age}_{ie} \times \text{Access}_{ie} + \beta_3 \text{Age}_{ie}^2 \times \text{Access}_{ie}\right), \tag{12}$$

[34]Two factors could account for the variation in reskilling (more precisely, compliance with access) based on age under the assumption of a shared MTE schedule. First, younger workers may reskill at a higher rate because they have more working years left to reap the annual returns to new skills. Second, older workers may find schooling more costly (due to personal preferences, lack of information, time constraints, etc.).

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

$$g(\text{Age}_{ie}) = \pi_{0e} + \pi_1 \text{Age}_{ie} + \pi_2 \text{Age}_{ie}^2. \tag{13}$$

Appendix Figure A.14 plots the propensity scores by age and access status (Panel (a)), showing significant interactions between the two determinants.[35] Panel (b) plots the distribution of propensity scores by treatment status, showing continuous overlap from 0 to 0.5.

Outcome equation. We use a quadratic polynomial in the propensity score for the outcome equation, corresponding to a linear MTE function.[36] We estimate the effects for different horizons k after injury:

$$Y_{it} = g_k(\text{Age}_{ie}) + f_k(\hat{p}_{ie}) + \varepsilon_{it} \tag{14}$$

$$= g_k(\text{Age}_{ie}) + \alpha_{1k}\hat{p}_{ie} + \frac{\alpha_{2k}}{2}\hat{p}_{ie}^2 + \varepsilon_{it} \tag{15}$$

$$\text{if} \quad t = e + k \quad \text{for} \quad k \in [0, 10], \tag{16}$$

where we control for age using the flexible specification $g(\cdot)$ in Equation (13). We calculate standard errors using a Bayesian bootstrap (Shao and Tu, 2012) over the propensity score and outcome equations (12) and (15).

Appendix Tables A.7-A.10 report the estimation results for the outcome variables that capture the benefits and costs for workers, government, and society.

5.2 Marginal Surplus

We use the marginal treatment effects to calculate the surplus of increasing reskilling for workers of age a from a reskilling level p. In particular, let S denote a measure of annual

[35] The null hypothesis of no interaction effects ($H_0 : \beta_2 = \beta_3 = 0$) has an F-stat of 14.8.

[36] Cornelissen et al. (2018) also use a quadratic polynomial in the outcome equation.

surplus (benefits minus costs), the present-discounted marginal surplus is:

$$\mathrm{MS}(a,p) = \sum_{k=0}^{\bar{A}-a} \beta^k \left(\alpha_{1k}^S + \alpha_{2k}^S p\right), \tag{17}$$

where α_k^S are the marginal treatment effects estimated in Equation (15) and β is a discount factor. As in Section 4.4, we assume treatment effects are constant after year $k = 10$ and until retirement age $\bar{A}$.

Figure 10 depicts the marginal social, private, and public surplus (corresponding to the Total, Workers, and Government rows in Table 5) of reskilling for different age cohorts.[37] To read the figure, consider a policy that induces 8% of workers aged 40 to reskill, which is close to the current program. A marginal expansion of the program for these workers generates a social surplus of \$400,000, which is split into \$120,000 for workers and \$280,000 for the government. Reassuringly, the levels of surplus align with the cost-benefit estimates for compliers in Table 5.

More generally, Figure 10 shows that the marginal surplus of reskilling is decreasing in worker age (between-cohort effect) and the share of each age cohort induced to reskill (within-cohort effect). The within-cohort effect captures that workers with higher returns to reskilling are less resistant to the programs. The between-cohort effect stems from older workers having fewer working years left.

[Figure 10 around here]

5.3 Optimal Policy

In Figure 11, we calculate the rates of reskilling that maximize the social, private, and public surplus for each worker age. Figure 12 shows that surplus attained by each of the policies. A comparison to the current rates of reskilling reveals three insights.

[37] Appendix Figure A.15 reports confidence bands calculated using a Bayesian bootstrap. Figure 10 suppresses these confidence bands to enhance the readability of the marginal surplus curves.

First, the current reskilling rates are substantially below the social optimum. Averaging across age cohorts, the optimal and current rates of reskilling are 33% and 11%, respectively. The current rates capture 60% of the potential social surplus, leaving an unrealized surplus of $30,000 per injured worker.

Second, the current rates of reskilling are especially sub-optimal for workers in the middle of their careers (age 40 to 50). In particular, the current rates realize only 34% of the potential surplus for middle-aged workers, implying a missed social surplus of $50,000 per injured worker in this age category. By contrast, the reskilling rates among the youngest and oldest workers (age 20-30 and 55-65, respectively) are close to the social optimum.

Third, reskilling rates among middle-aged workers appear sub-optimal for both the government and workers. In particular, government subsidies for reskilling (covering tuition and benefits) pay for themselves for about 36% of middle-aged workers. From the viewpoint of middle-aged workers, a reskilling share of around 36% would also maximize their present-discounted lifetime income. The fact that only 6% of these workers opt into the program points to substantial barriers to reskilling for this group of workers. In particular, the marginal middle-aged worker currently leaves $110,000 of private surplus on the table by not reskilling (Figure 10.(b)).

[Figures 11 and 12 around here]

5.3.1 General Equilibrium Effects

A takeaway from Figures 11 and 12 is that reskilling programs may be expanded for injured workers. Yet, large increases in reskilling could have general equilibrium effects. For example, reskilled workers could bid down wages (Heckman, Lochner and Taber, 1998). In Appendix F, we incorporate such equilibrium effects by embedding our estimated treatment effects into a calibrated model of the labor market. In particular, we show

that the surplus from reskilling lost due to general equilibrium effects depends on the elasticity of labor demand and the share of injured workers in aggregate labor supply. Our calibration shows that the optimal reskilling rates are robust to labor market equilibrium effects, which partly reflects that injured workers constitute a minor share of aggregate labor supply.

6 Conclusion

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

Our analysis delivers three 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 returns, especially for the government, by saving on disability benefits. Finally, current rates of reskilling are substantially below the social optimum, especially for mid-aged workers.

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.

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Main Tables

Table 1: Occupations with the 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.

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)
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	2,004.92	2,006.73	2,004.92	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.

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)
Personal Impairment	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. Appendix C details the IPW procedure. The "Mean Difference" column shows the mean difference between the "Access" and "IPW" workers with mean standard deviations in parentheses.

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.

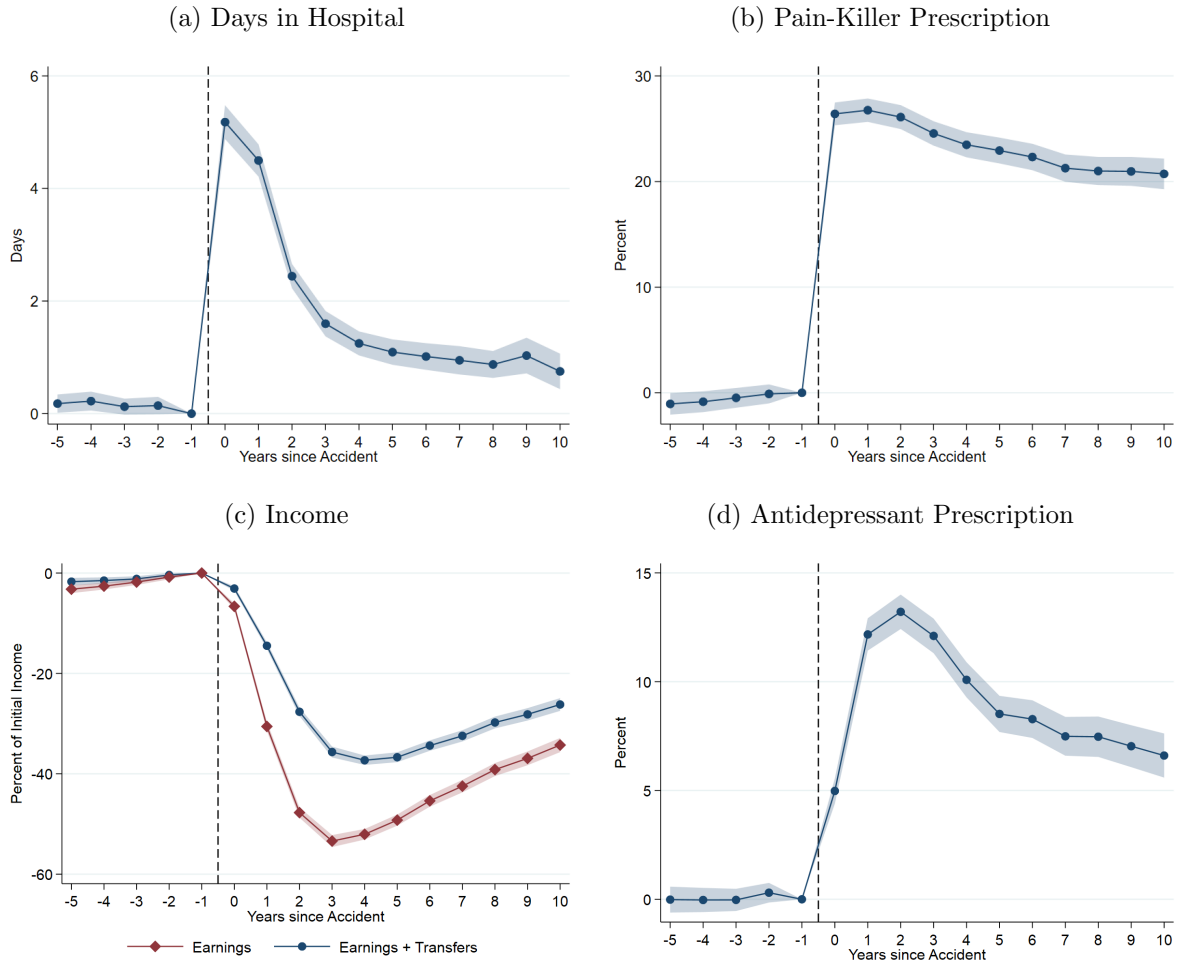
Table 5: Costs and Benefits of Higher Education for Injured Workers

		Per Reskilled Worker ($)	Per Dollar of Education	Percent of Total
Workers		**187,820**	**2.5**	**42.6**
	Earnings	320,102	4.3	72.7
	Transfers	-173,565	-2.3	-39.4
	Educ. Transfers	41,282	0.6	9.4
Government		**252,708**	**3.4**	**57.4**
	Education	-74,526	-1.0	-16.9
	Transfers	173,565	2.3	39.4
	Taxes	153,670	2.1	34.9
Total		**440,528**	**5.9**	**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 E details our approach to the cost-benefit calculations.

Main Figures

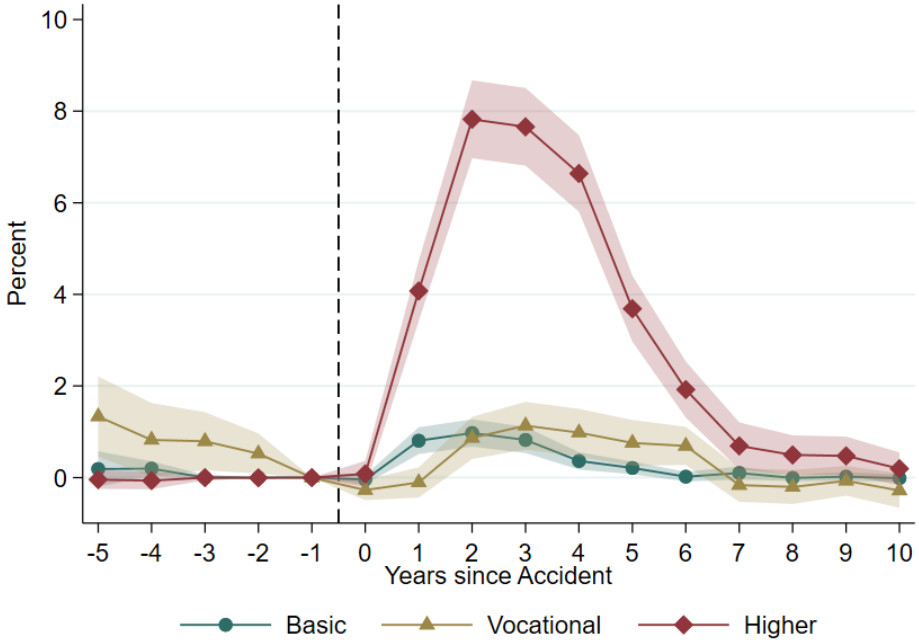
Figure 1: Worker Outcomes around Accident



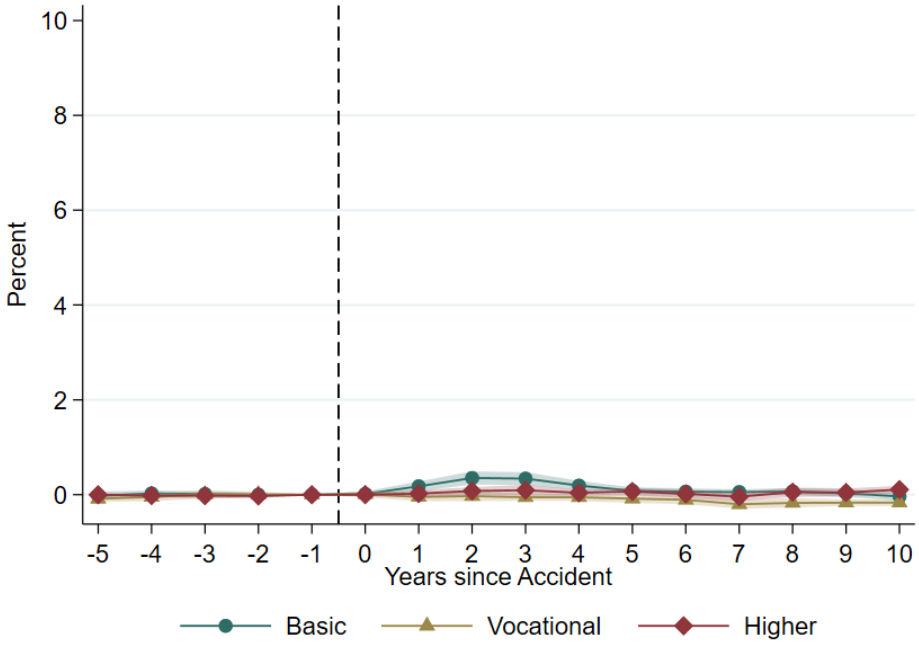
Notes: This figure shows the differences-in-differences in outcomes (measured relative to year -1) between the "Injury" and "Match" workers from Table 2. Shaded areas represent 95% confidence bands, estimated using the regression equation (1). Panel (a) shows the days spent in the hospital, Panel (b)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

Figure 2: Participation in Courses around Accident

(a) Degree

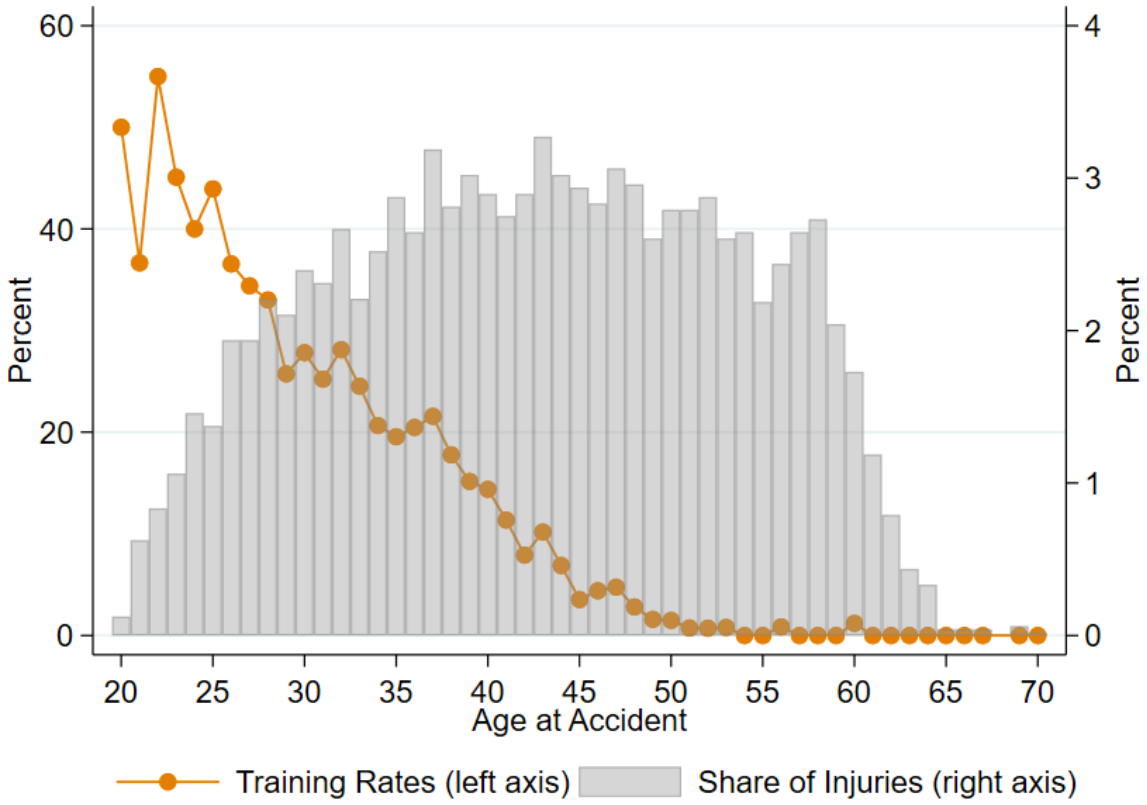


(b) Non-Degree



Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses by level of education. *Basic* is primary and high school (academic track), and *Higher* is all post-secondary education. 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% confidence bands estimated using the regression equation (1).

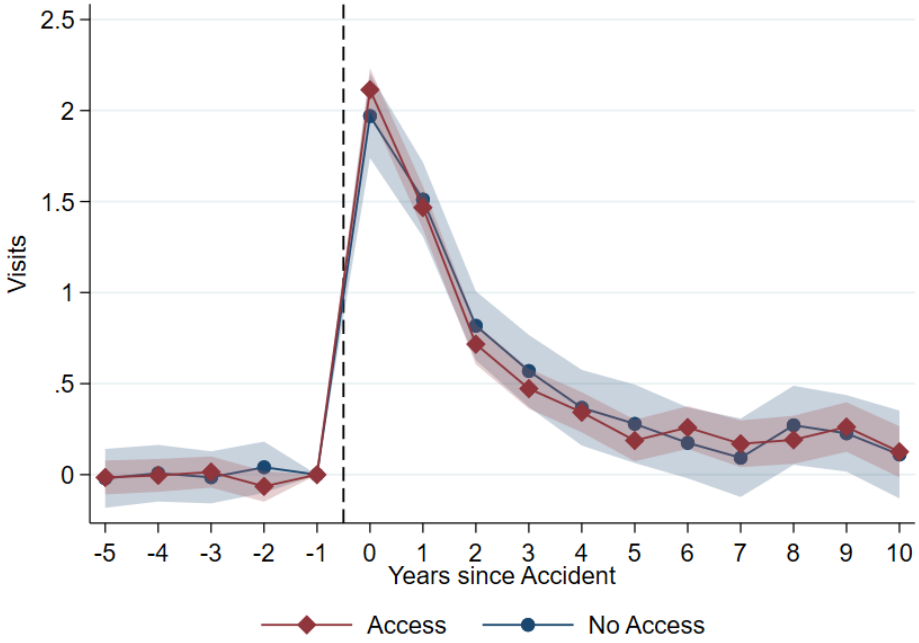
Figure 3: Enrollment in Higher Degrees after Work Accident by Worker Age at Accident



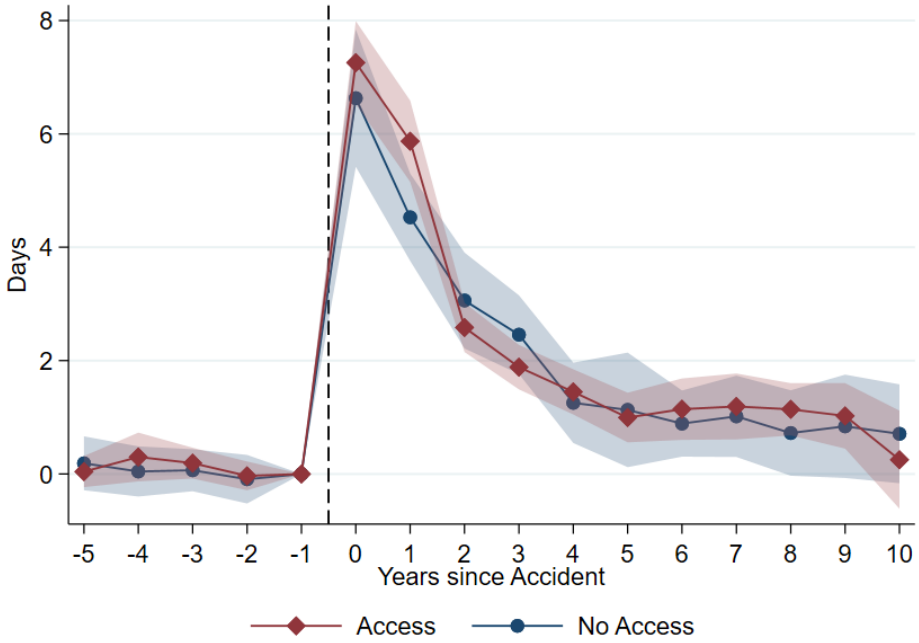
Notes: The line shows the enrollment of workers in higher degrees (measured within six years after a work accident) according to each worker's age at the time of the accident. The histogram shows the distribution of work accidents by each worker's age at the the time of the accident. The figure focuses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

Figure 4: Hospitalization around Accident

(a) Number of Hospital Visits



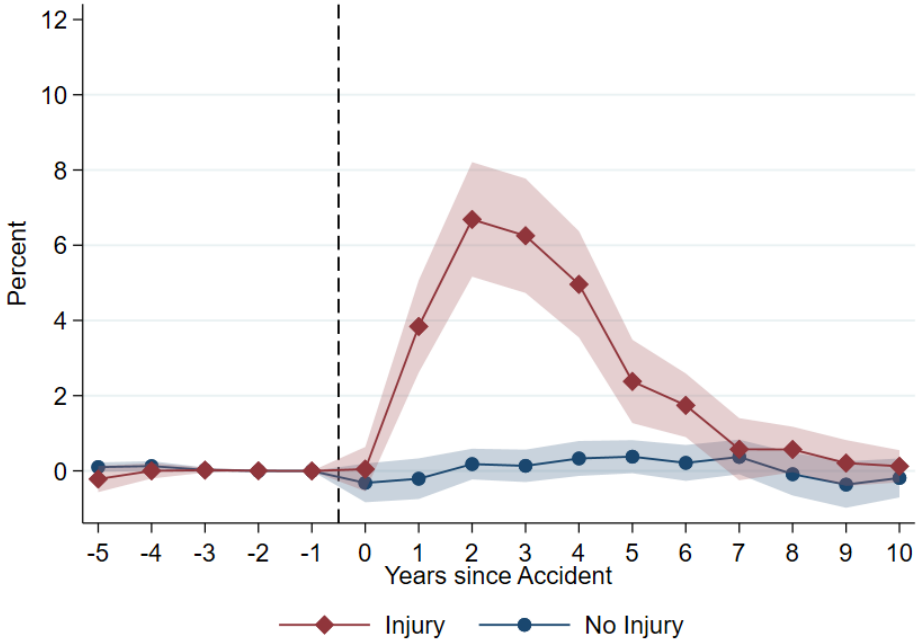
(b) Days in Hospital



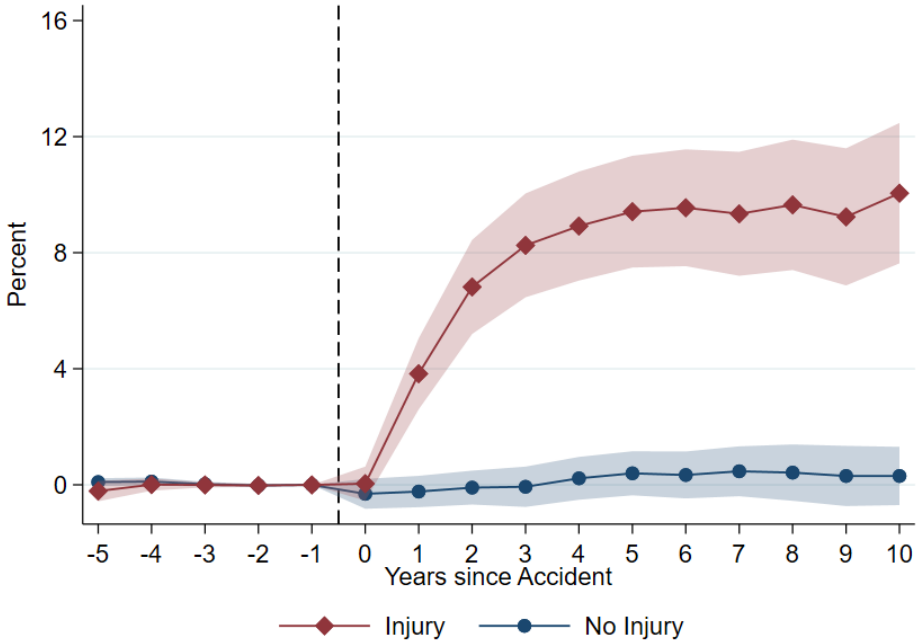
Notes: This figure shows the hospitalization of workers, split by whether the workers have access to higher education upon injury. The groups correspond to the "Access" and "No Access, IPW" columns of Table 3. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. This figure focuses on workers with a vocational degree within craft work. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

Figure 5: Pursuit of Higher Degrees ("Access" − "No Access")

(a) Participation (Flow)



(b) Participated (Stock)

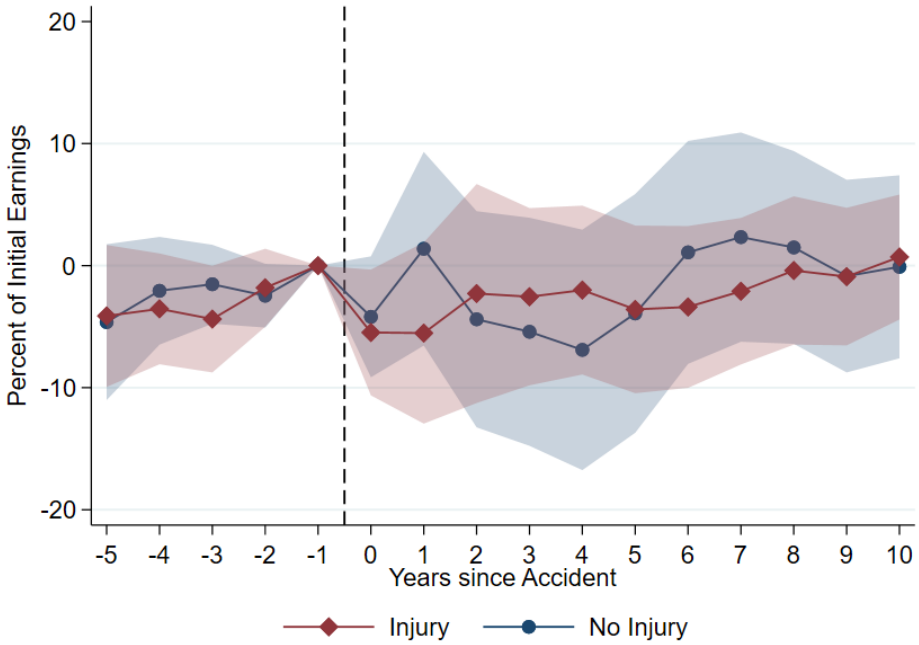


Notes: This figure shows the differences in the pursuit of higher degrees according to workers' access to higher education. The figure focuses on craft workers. Panel (a) shows enrollment in the given year, and Panel (b) shows the accumulated enrollment. The plots are differences-in-differences between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

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

(a) Enrollment in Higher Degrees

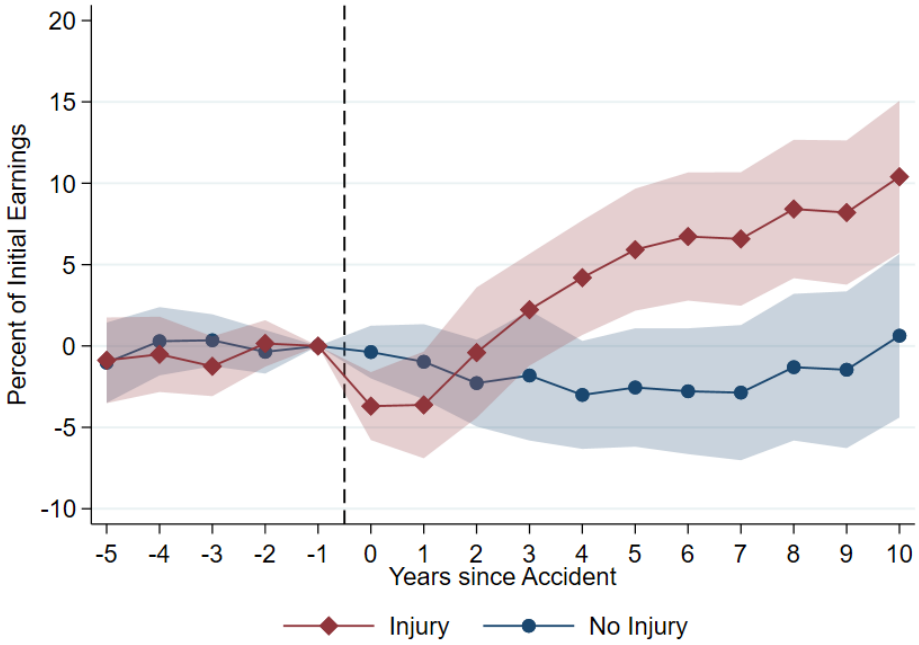
(b) Labor Earnings



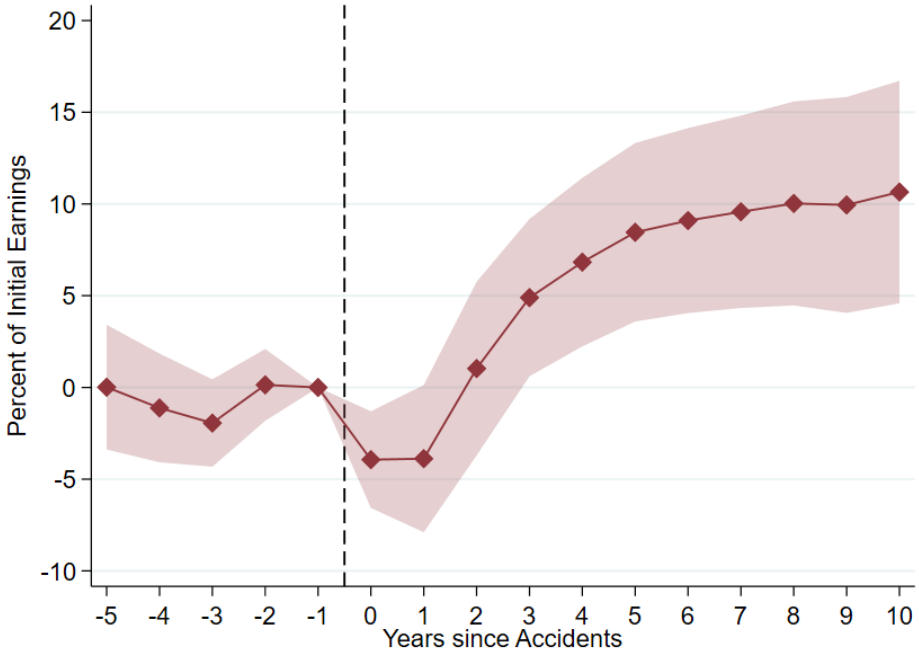
Notes: The figure restricts to workers above age 55. The plots show differences-in-differences between the "Access" and "No Access, IPW" workers from Table 3, indexed to year -1. The figure focuses on craft workers. Panel (a) shows enrollment in higher degrees measured in full-time equivalents. Panel (b) shows labor earnings measured in percent of average earnings in year -1. Shaded areas represent 95% confidence bands, estimated using Equation (2).

Figure 7: Labor Earnings around Work Accident

(a) "Access" – "No Access"



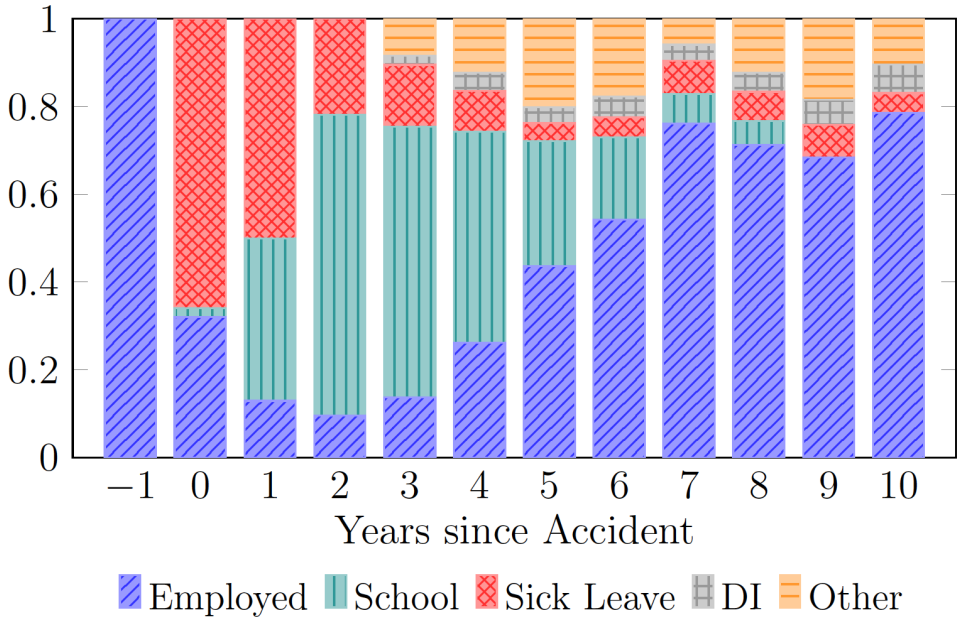
(b) Triple Difference



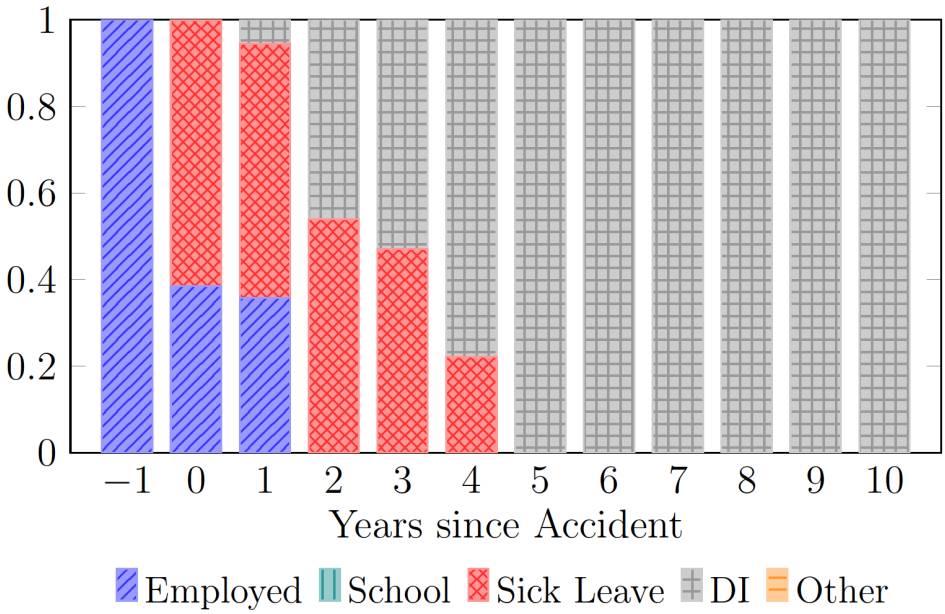
Notes: This figure shows the differences in labor earnings of workers according to their access to higher education. Labor earnings are measured in percent of workers' average earnings in year -1. The figure focuses on craft workers. Panel (a) shows the difference-in-differences in outcomes between the "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% confidence bands.

Figure 8: Labor Supply

(a) Injury & Reskill



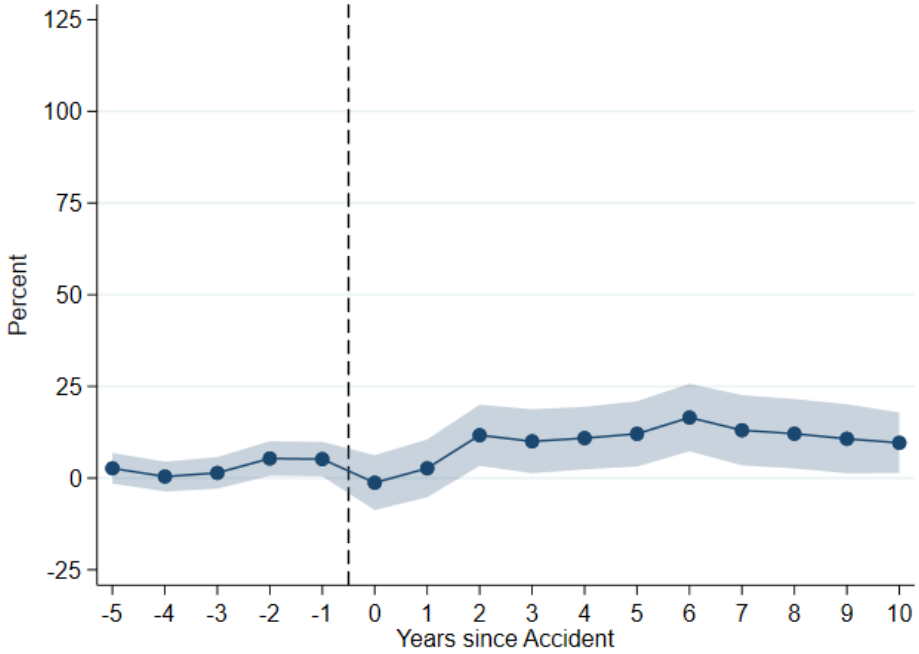
(b) Injury & No Reskill



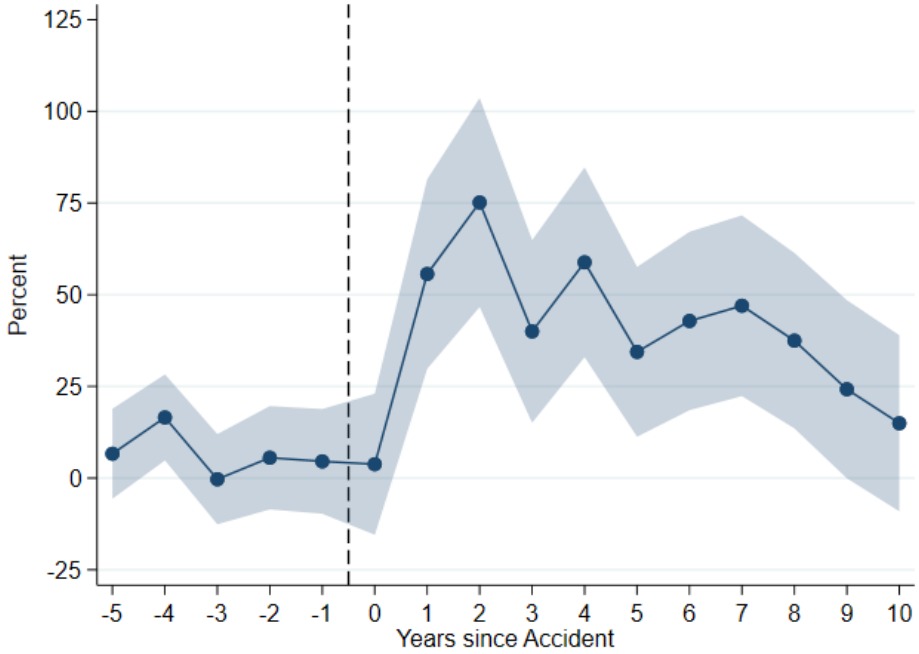
Notes: This figure shows the labor supply of complier workers who comply with access to higher education by pursuing a higher degree after work accidents.*Employed* is fulltime employment. *School* is enrollment in a higher degree. *Sick Leave* refers to receiving sickness benefits. *DI* is disability insurance. *Other* is mainly unemployment and non-participation. Panels (a) and (b) report treated and control complier means, estimated using Equations (3)-(5).

Figure 9: Antidepressant Prescription

(a) Injury & Reskill



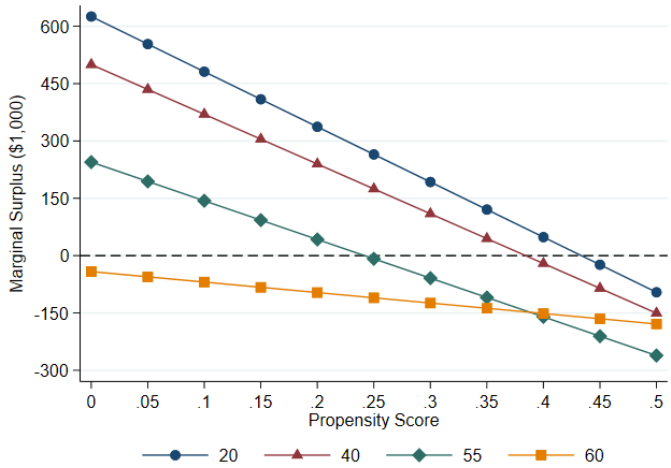
(b) Injury & No Reskill



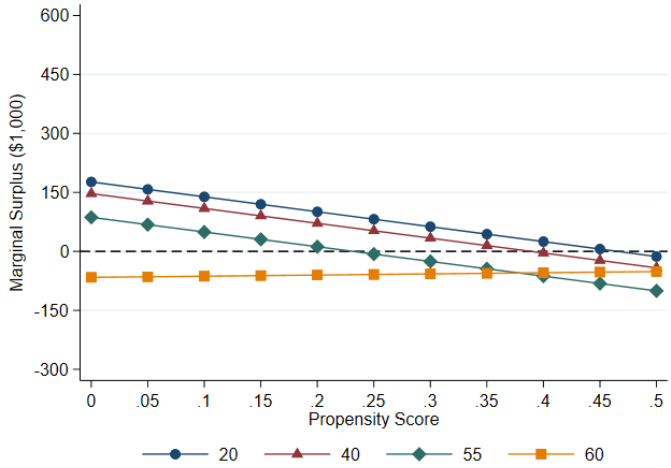
Notes: This figure shows the prescriptions of antidepressants for workers who comply with access to higher education by pursuing a higher degree after work accidents. Panels (a) and (b) report treated and control complier means, estimated using Equations (3)-(5).

Figure 10: Marginal Surplus of Reskilling Workers of Different Ages ($1,000)

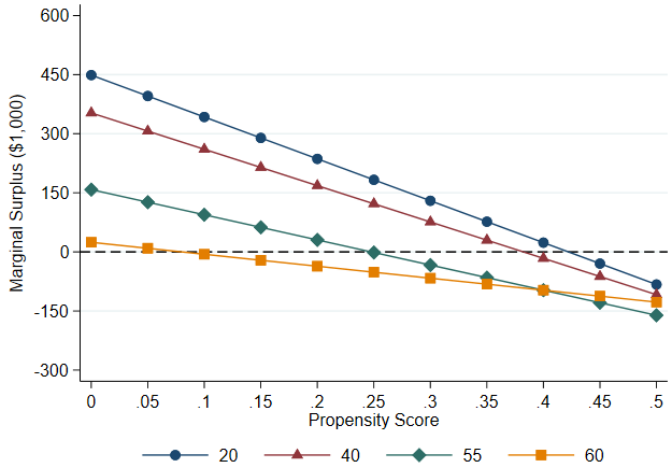
(a) Total (Social Surplus)



(b) Workers (Private Surplus)

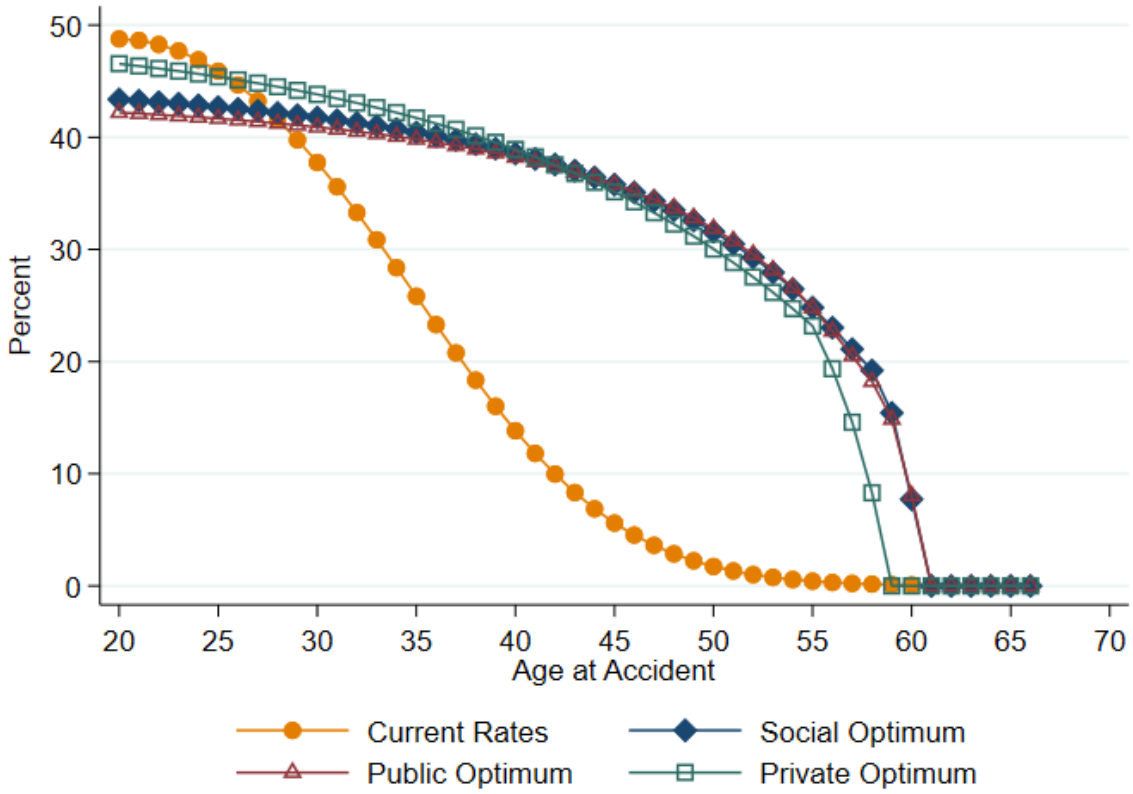


(c) Government (Public Surplus)



Notes: This figure shows the marginal surplus of reskilling workers of different ages (Equation (17)). Social surplus (Panel (a)) is the sum of surplus for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 5.

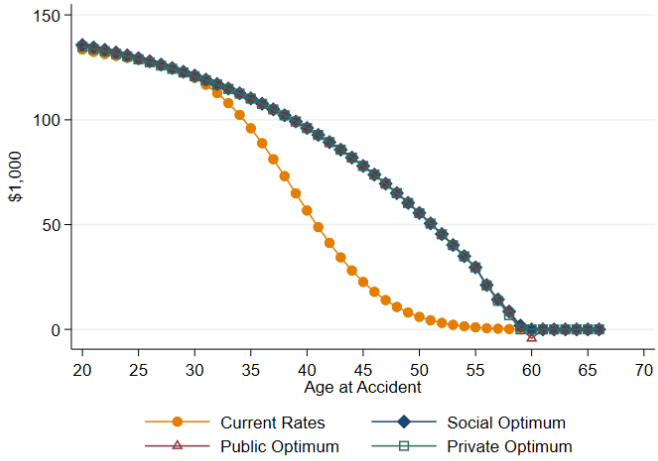
Figure 11: Optimal vs. Current Rates of Reskilling



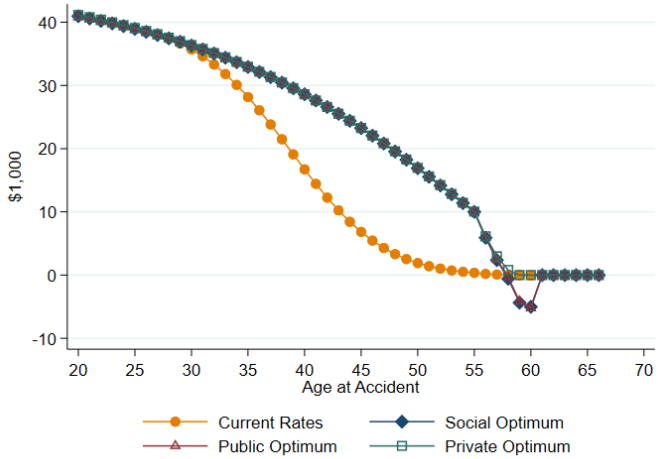
Notes: This figure compares the current rates of reskilling across worker ages with the optimal rates from the perspective of society (social optimum), injured workers (private optimum), and the government (public optimum). The optimal rates maximize the surpluses from Figure 10 (Panels (a), (b), and (c), respectively).

Figure 12: Surplus of Reskilling Policies ($1,000 Per Injured Worker)

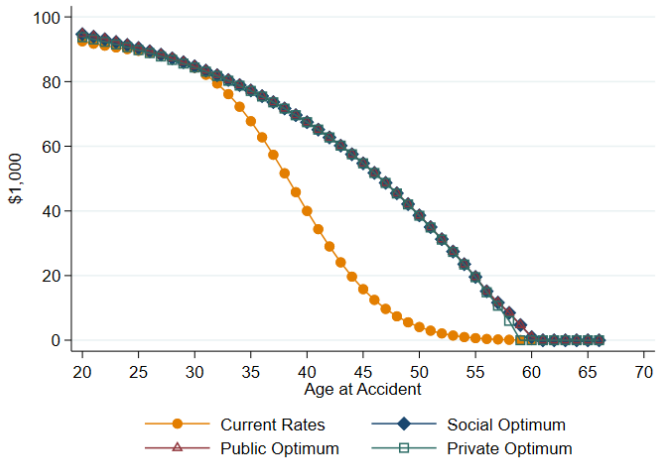
(a) Total (Social Surplus)



(b) Workers (Private Surplus)



(c) Government (Public Surplus)



Notes: This figure shows the total surplus of reskilling policies. Social surplus (Panel (a)) is the sum of surplus for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 5.

Appendix

A Appendix Figures and Tables

A.1 Tables

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 degrees with access to higher education	4,568	4,528	12.85	34.37

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

Table A.2: Human Capital Investment by Educational Background of Workers

		Accumulated Participation (FTE, Diff-in-Diff, Year +10)					
		Degrees			Courses		
	Percent of Injuries	Basic	Vocational	Higher	Basic	Vocational	Higher
Primary	31.5	0.021	-0.009	0.019	0.009	-0.002	0.000
		(0.003)	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)
Vocational							
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.

Table A.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. The full list of vocational degrees with access to higher education is available at `www.andershumlum.com/s/access_list.xlsx`.

Table A.4: Share of Injuries and Reskilling by Educational Group (Vocational Degrees with Access to Higher Education)

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

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

Table A.5: 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 gives access to higher education. The characteristics are measured in the year before the work accident. See Table for A.3 for the top-3 vocational degrees in each education group.

Table A.6: 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.

Table A.7: Estimation of Private Benefits

Dep. var.: Private Benefits: After-tax labor market earnings + education transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-17.22**	15.69*	13.02	22.99***	40.11***	63.40***	54.06***	31.90***	36.0***9	39.75***	29.28**
	(7.37)	(9.17)	(10.32)	(7.97)	(8.79)	(10.45)	(10.56)	(10.70)	(12.10)	(13.23)	(13.27)
$\hat{p}^2/2$	38.34	-94.36***	-30.92	-69.92**	-127.98***	-204.42***	-156.15***	-67.64*	-77.01*	-80.72	-32.68
	(28.99)	(34.95)	(35.73)	(30.10)	(32.73)	(39.02)	(39.75)	(39.24)	(46.35)	(50.60)	(50.36)
Observations	6,506	6,471	6,389	6,297	6,189	6,038	5,856	5,642	5,322	5,019	4,604

Notes: This table shows the reduced-form estimation results (Equation (15)) for the private benefits of reskilling (post-tax labor earnings and reskilling benefits). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu, 2012) of 1000 iterations over the propensity score and outcome equations (12) and (15) with weights drawn from a uniform distribution, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.8: Estimation of Private Costs

Dep. var.: Private Costs: Lost public transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-4.70	12.04***	21.73***	16.32***	18.60***	24.12***	15.01***	14.82***	14.31***	22.56***	19.93***
	(2.96)	(3.55)	(4.74)	(4.19)	(4.54)	(4.64)	(4.63)	(4.57)	(4.98)	(5.29)	(5.36)
$\hat{p}^2/2$	21.02*	-37.72***	-53.60***	-32.39**	-40.28**	-67.42***	-33.70*	-23.51	-16.58	-46.31**	-33.98*
	(11.68)	(13.81)	(19.34)	(16.14)	(17.36)	(18.00)	(17.30)	(16.73)	(18.75)	(19.90)	(19.78)
Observations	6,506	6,471	6,389	6,297	6,189	6,038	5,856	5,642	5,322	5,019	4,604

Notes: This table shows the reduced-form estimation results (Equation (15)) for the private costs of reskilling (lost public benefits). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu, 2012) of 1000 iterations over the propensity score and outcome equations (12) and (15) with weights drawn from a uniform distribution, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.9: Estimation of Public Benefits

Dep. var.: Public Benefits: Tax income + avoided public transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	-12.98**	18.18**	23.96***	25.85***	36.48***	52.50***	42.29***	30.49***	31.52***	41.51***	33.88***
	(5.76)	(7.05)	(7.44)	(7.18)	(8.03)	(8.91)	(9.20)	(9.18)	(9.85)	(10.82)	(10.72)
$\hat{p}^2/2$	39.53*	-84.77***	-70.00**	-75.68***	-108.38***	-167.07***	-119.58***	-62.45*	-53.28	-84.78**	-49.56
	(22.52)	(27.12)	(27.40)	(27.42)	(30.16)	(33.86)	(34.99)	(33.87)	(37.11)	(41.05)	(39.94)
Observations	6,506	6,471	6,389	6,297	6,189	6,038	5,856	5,642	5,322	5,019	4,604

Notes: This table shows the reduced-form estimation results (Equation (15)) for the public benefits of reskilling (tax income and lost public transfers). Control variables are not displayed. Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu, 2012) of 1000 iterations over the propensity score and outcome equations (12) and (15) with weights drawn from a uniform distribution, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

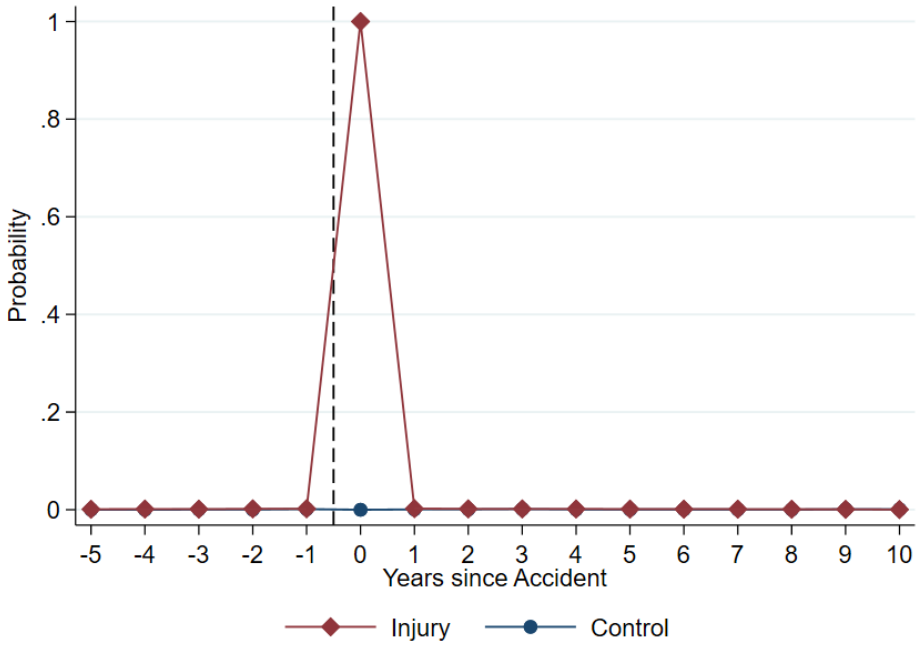
Table A.10: Estimation of Public Costs

Dep. var.: Public Costs: Education cost + educational transfers ($1,000)											
Years since Accident	0	1	2	3	4	5	6	7	8	9	10
$\hat{p}$	1.16	12.10**	21.76***	9.98	9.18	8.54	-3.48	0.18	0.00	0.00	0.00
	(1.20)	(4.71)	(7.44)	(6.71)	(6.63)	(5.65)	(4.34)	(3.26)	(0.00)	(0.00)	(0.00)
$\hat{p}^2/2$	-6.40	-10.53	-13.87	34.85	19.91	-0.22	38.63**	12.38	0.00	0.00	0.00
	(5.00)	(20.42)	(32.80)	(28.73)	(28.48)	(24.17)	(18.36)	(15.05)	(0.00)	(0.00)	(0.00)
Observations	6,506	6,471	6,389	6,297	6,189	6,038	5,856	5,642	5,322	5,019	4,604

Notes: This table shows the reduced-form estimation results (Equation (15)) for the public costs of reskilling (tuition and reskilling benefits). We set the estimates to zero after year 8 since workers do not participate in education after that point (Figure 5.(a)). Standard errors in parentheses are estimated with a Bayesian bootstrap (Shao and Tu, 2012) of 1000 iterations over the propensity score and outcome equations (12) and (15) with weights drawn from a uniform distribution, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

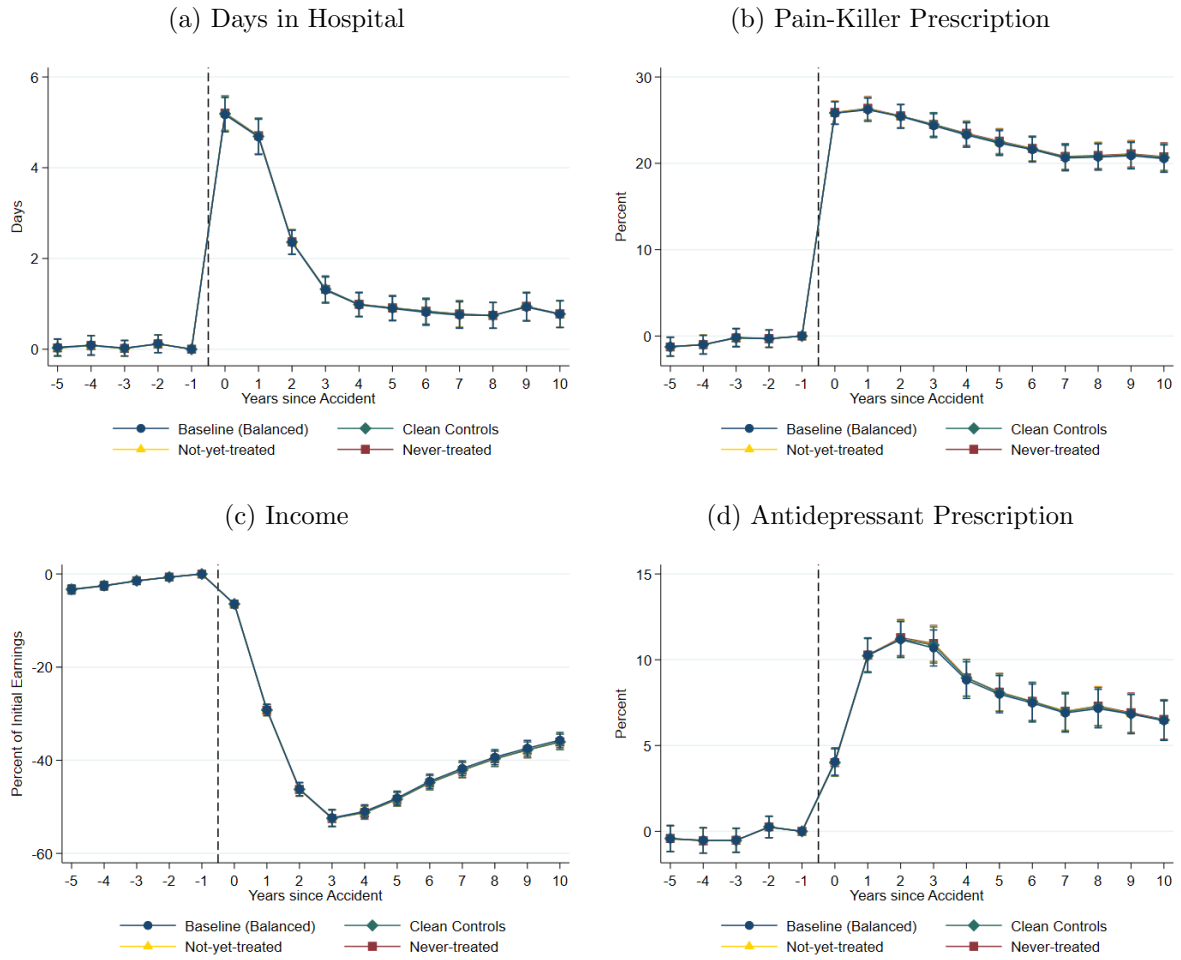
A.2 Figures

Figure A.1: Probability of Work Accident



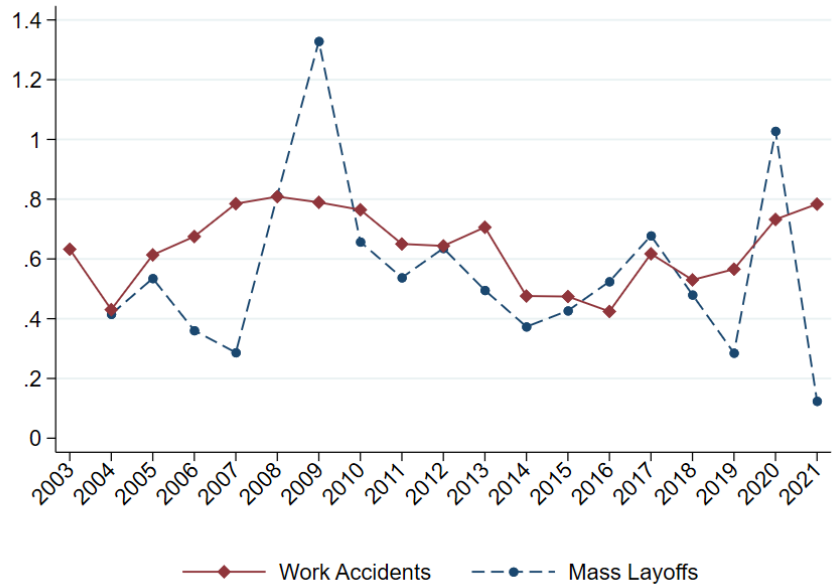
Notes: This figure shows the probability of work accidents (causing loss of physical earning capacity) in event time. The "Control" workers correspond to the "Match" column in Table 2.

Figure A.2: Worker Outcomes around Accident (Comparison of Estimators)



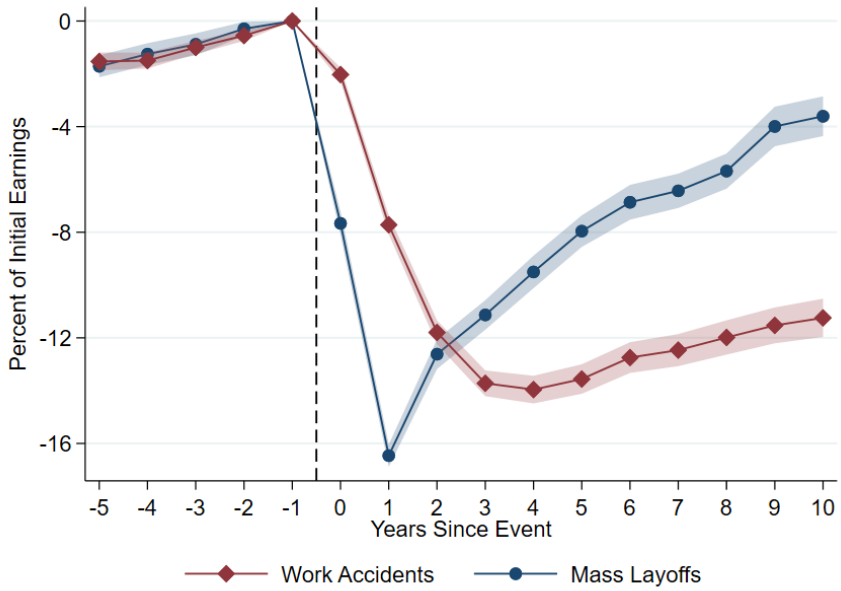
Notes: This figure compares our baseline estimates (Figure 1) with estimators that address identification issues that may arise in difference-in-differences designs when treatments are staggered (De Chaisemartin and d'Haultfoeuille, 2022*b*; Gardner, 2022; Roth et al., 2022). The estimators impose successively stricter requirements on the treatment and control groups. "Baseline (Balanced)" plots our baseline estimates on a balanced sample from years -5 to 10 (the event window). "Clean Controls" requires that control workers are not treated in the event window, corresponding to the specification in Cengiz et al. (2019). "Not-yet-treated" focuses on the first events of our treatment group and further requires that control workers are not treated before or during the event window, corresponding to the estimators developed in (Callaway and Sant'Anna (2021); De Chaisemartin and d'Haultfoeuille (2022*a*)). "Never-treated" further requires that control workers are not treated throughout our data period, corresponding to the estimators developed in Callaway and Sant'Anna (2021) Sun and Abraham (2021), and De Chaisemartin and d'Haultfoeuille (2022*a*).

Figure A.3: Work Accidents and Mass Layoffs per 100 Workers



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

Figure A.4: Labor Earnings around Work Accident vs. Mass Layoff

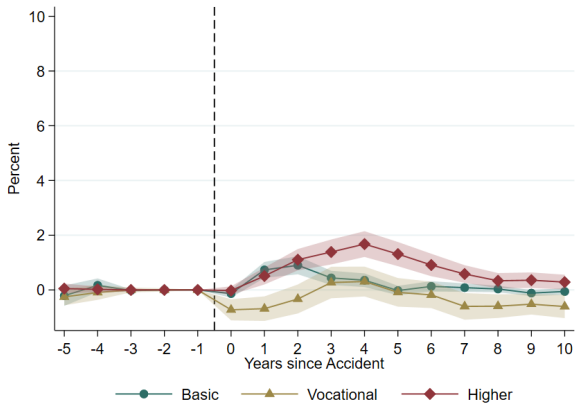


Notes: This figure compares the labor earnings of workers around work accidents and mass layoffs. Mass layoffs are defined as in Davis and Von Wachter (2011). We include all work accidents accepted with compensation. We match each injured/displaced worker to a control worker, following the procedure in Table 2. The graphs show the differences-in-differences in outcomes between the injured/displaced workers and their matches. Shaded areas represent 95% confidence bands, estimated using the regression equation (1).

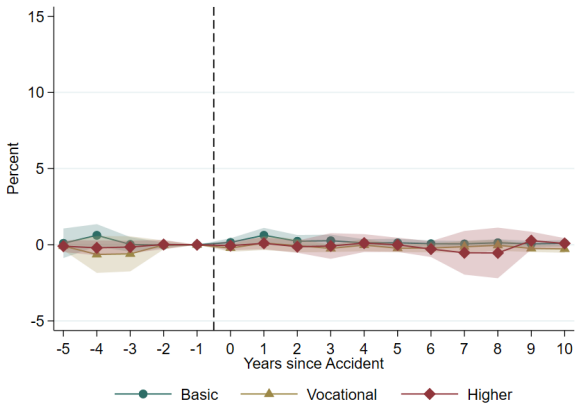
Figure A.5: Human Capital Investment by Educational Background of Workers

(a) Initial Attainment: Primary School

Degree

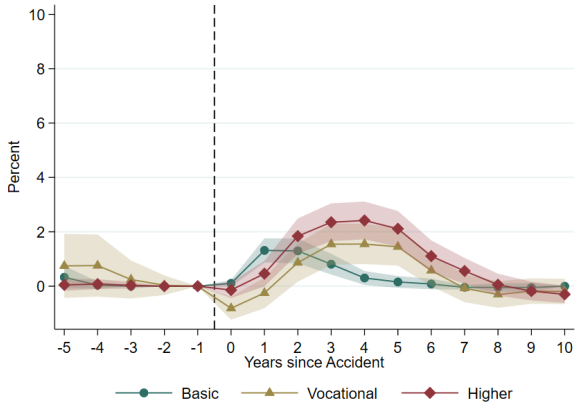


Non-Degree

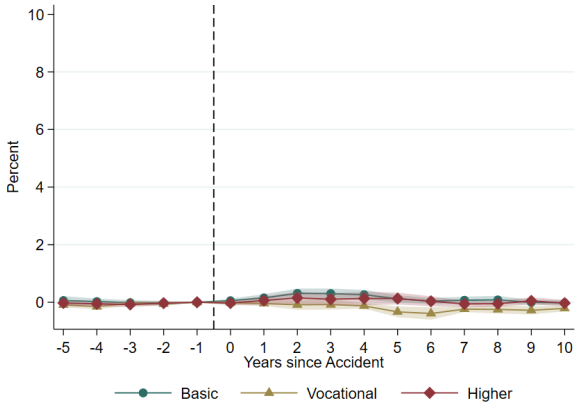


(b) Initial Attainment: Vocational Degree without Access to Higher Education

Degree

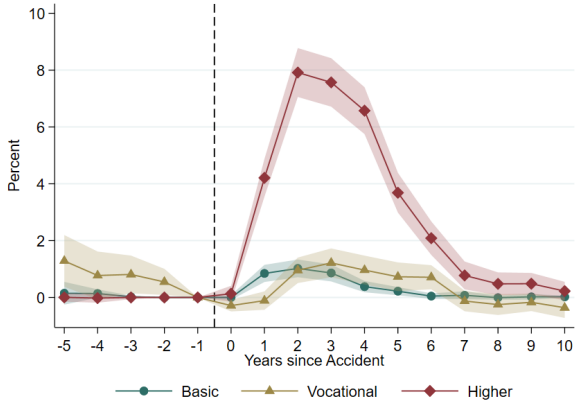


Non-Degree

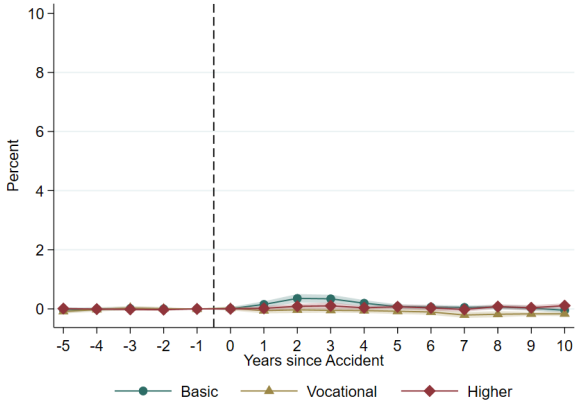


(c) Initial Attainment: Vocational Degree with Access to Higher Education

Degree



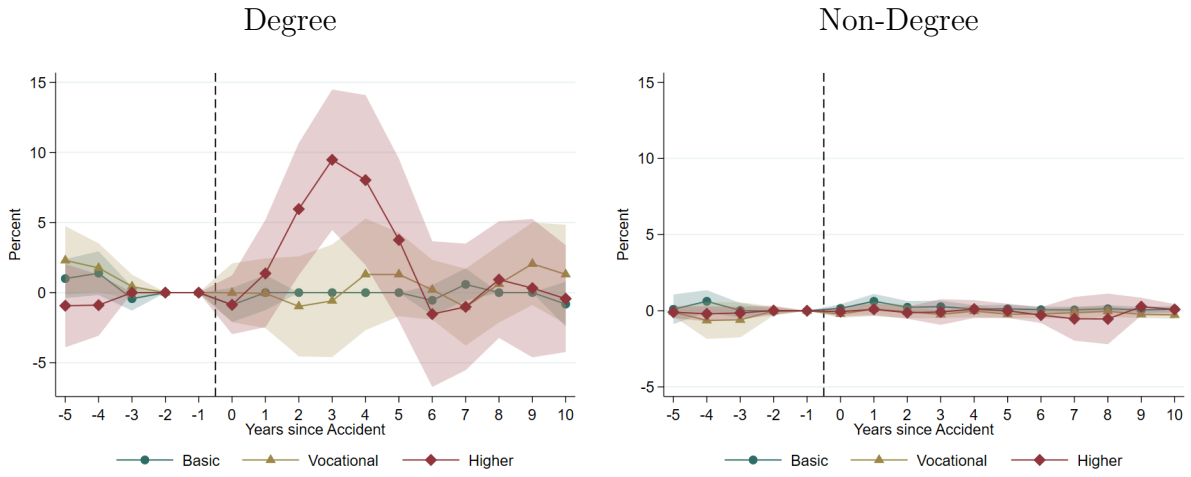
Non-Degree



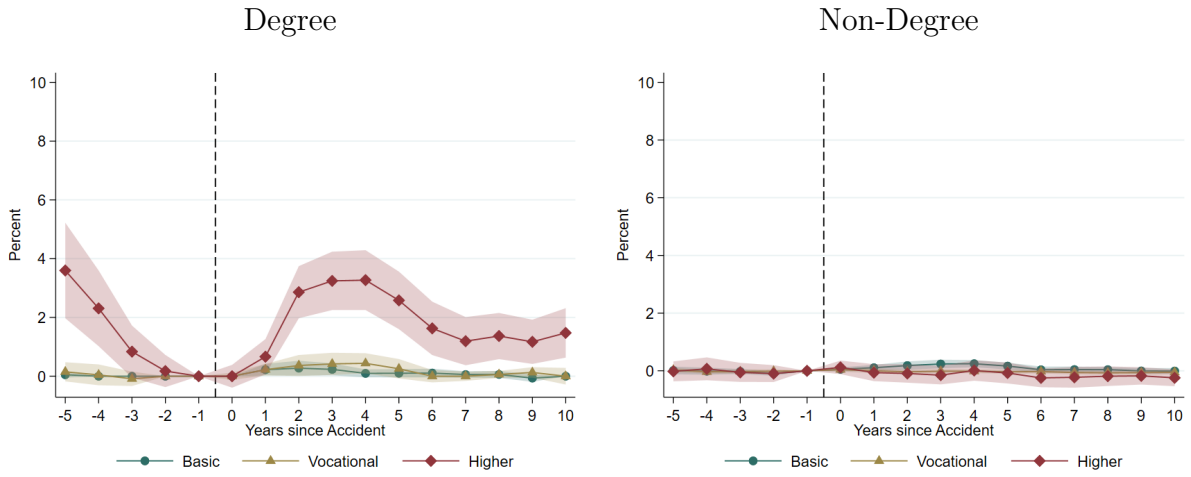
Notes: This table continues on the next page.

Figure A.5 (Cont.): Human Capital Investment by Educational Background of Workers

(a) Initial Attainment: High School

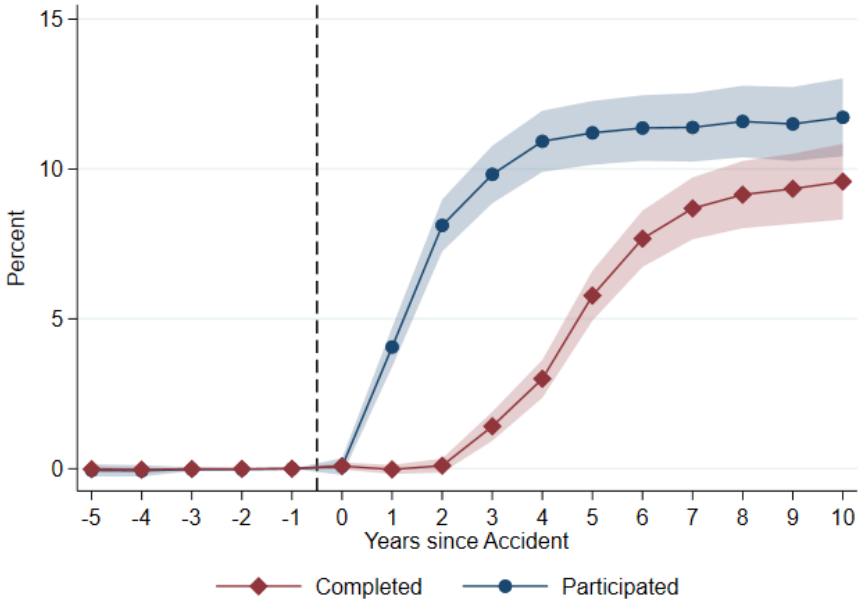


(b) Initial Attainment: Post-Secondary Degree



Notes: This figure shows participation (measured in full-time equivalents) in degree and non-degree courses, split by the worker's initial educational attainment. *Basic* is primary and high school, and *Higher* is all post-secondary education. The graphs show the difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95% confidence bands.

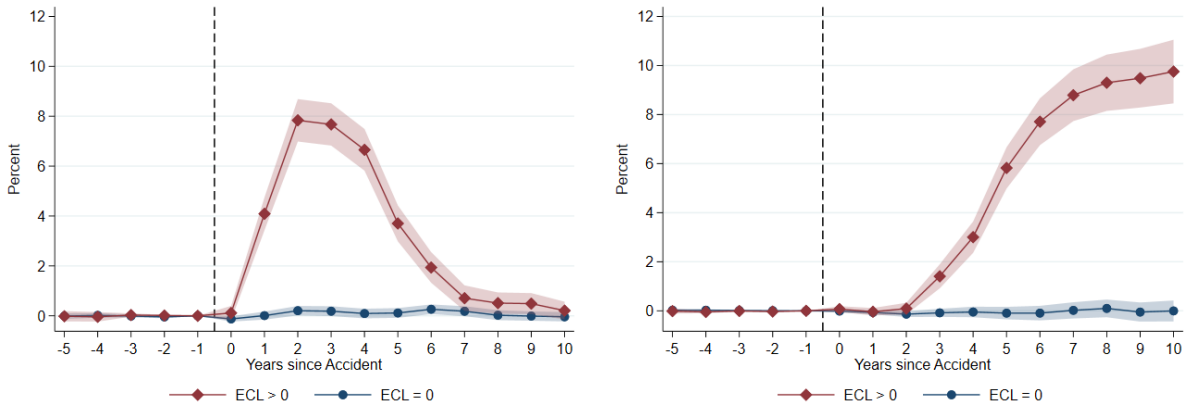
Figure A.6: Pursuit of Higher Degrees around Work Accident



Notes: This figure shows the participation and completion of higher degrees around work accidents. The figure focuses on workers who, before the work accident, had a secondary or vocational degree that gives access to higher education. The graphs show the difference-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas represent 95% confidence bands.

Figure A.7: Investment in Higher Degrees by Earning Capacity Loss

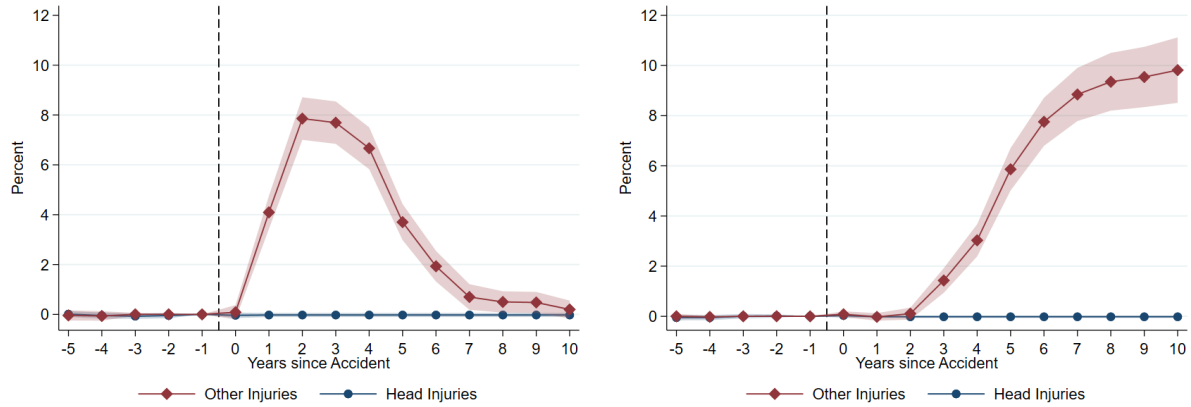
(a) Participation (b) Completion



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% confidence bands, estimated using the regression equation (1).

Figure A.8: Investment in Higher Degrees by Injured Body Part

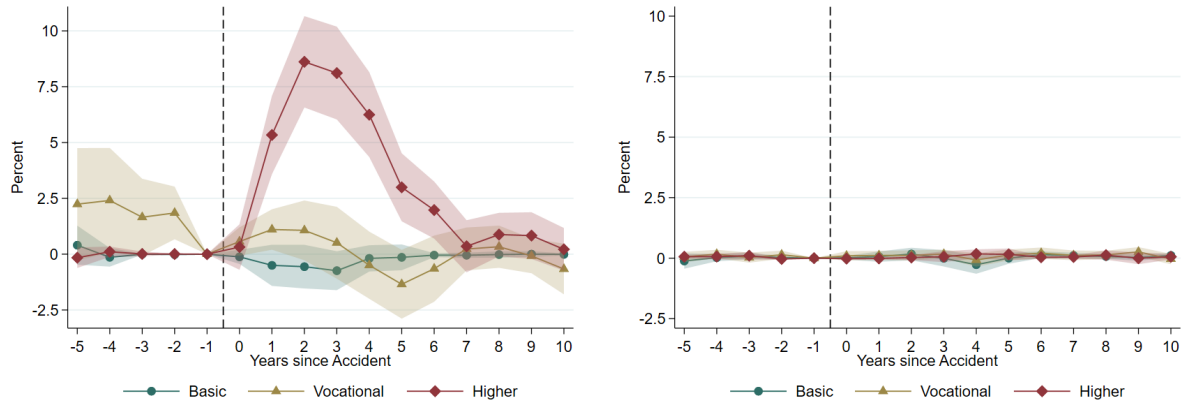
(a) Participation (b) Completion



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% of accidents and 0.4% of accidents cause PCS. See Figure A.7 for notes on the regression specification.

Figure A.9: Enrollment in Courses (Triple Difference)

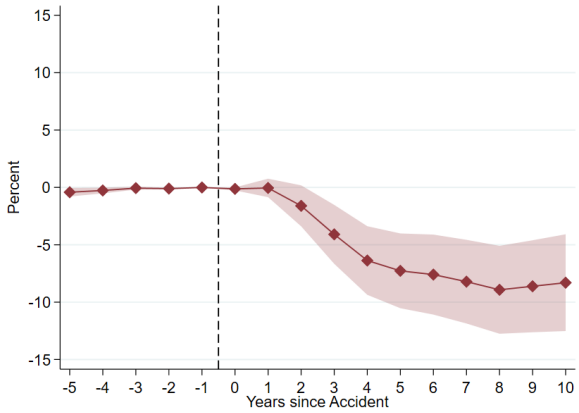
(a) Degree (b) Non-Degree



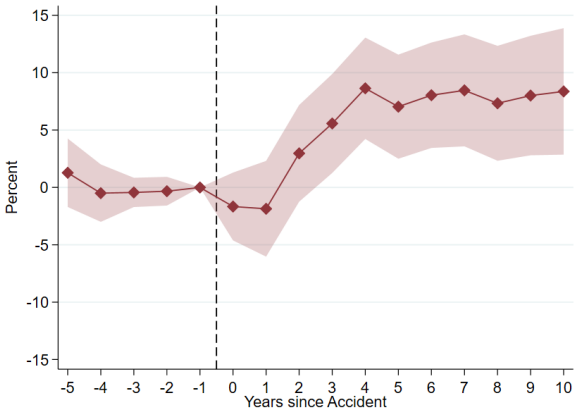
Notes: This figure shows the participation in degrees and courses at the *basic* (primary and high school), *vocational*, and *higher* (all post-secondary) levels. Participation is measured in full-time equivalents. This figure focuses on craft workers. The graphs show triple-differences in outcomes 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% confidence bands.

Figure A.10: Labor Supply around Work Accident (Triple Difference)

(a) Disability Insurance



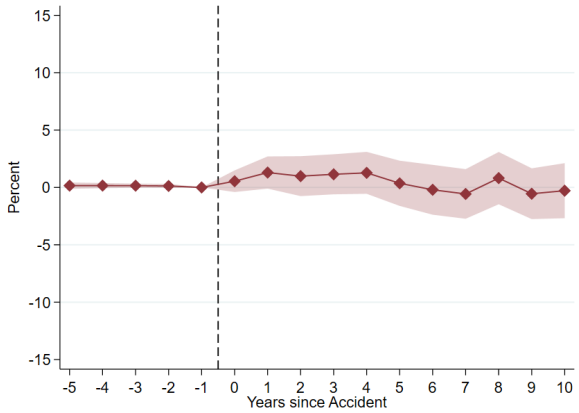
(b) Employed



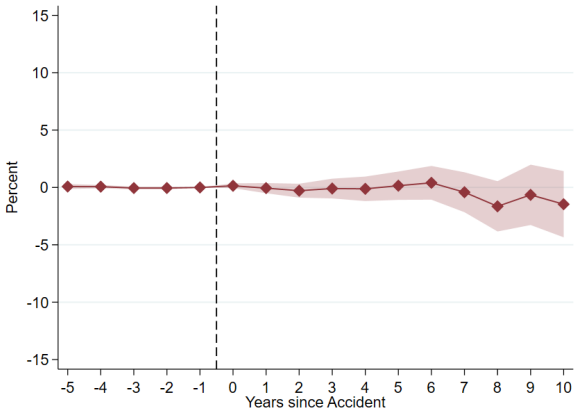
Notes: This figure shows the extensive-margin labor supply of workers. The figure focuses on craft workers. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 3), each measured relative to their "No Injury" matches, and indexed to year -1.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

Figure A.11: Non-Means-Tested Pensions (Triple Difference)

(a) Early Retirement

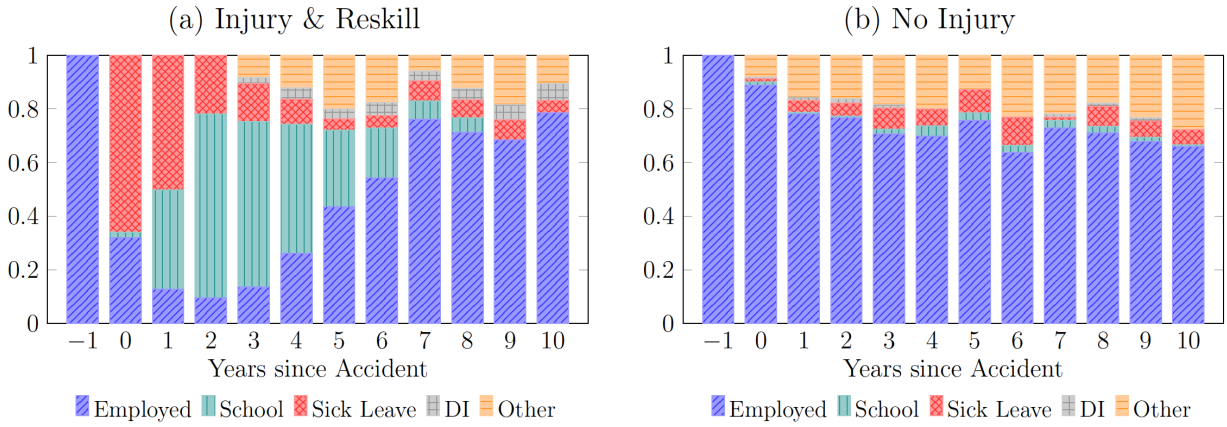


(b) Public Pension



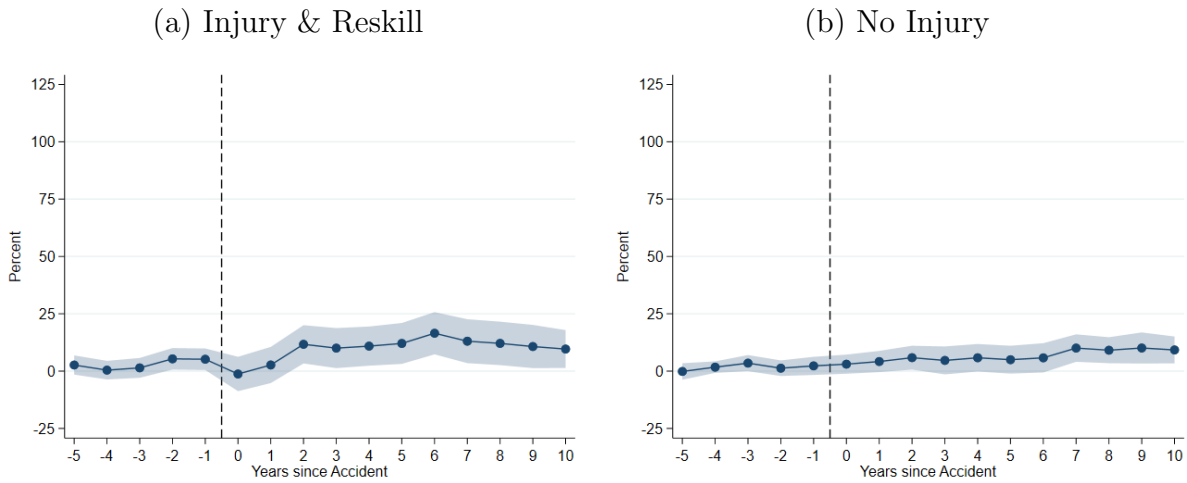
Notes: This figure shows the receipt of pensions that are not means tested. The graphs show triple-differences in outcomes between the "Access" and "No Access, IPW" workers (defined in Table 3), each measured relative to their "No Injury" matches, and indexed to year -1. The "No Injury" workers correspond to the "Match" column in Table 2. Shaded areas represent 95% confidence bands.

Figure A.12: Potential Labor Supply of Compliers



Notes: This figure shows the labor supply of workers who comply with access to higher education by pursuing a higher degree after work accidents. *Employed* is fulltime employment. *School* is enrollment in a higher degree. *Sick Leave* refers to receiving sickness benefits. *DI* is disability insurance. *Other* is mainly unemployment and non-participation. Panel (a) reports treated complier means, estimated using Equation (4). Panel (b) reports the outcomes of their match workers (who do not experience a work injury in the event year).

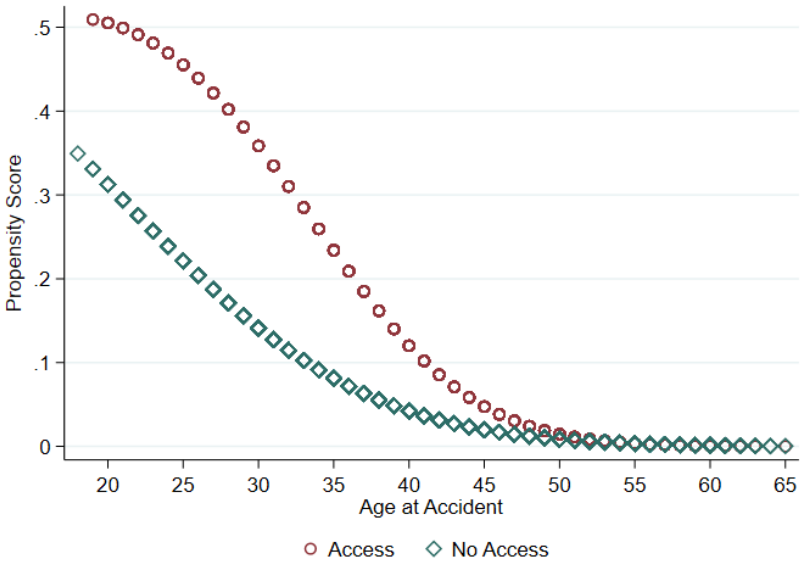
Figure A.13: Antidepressant Prescription



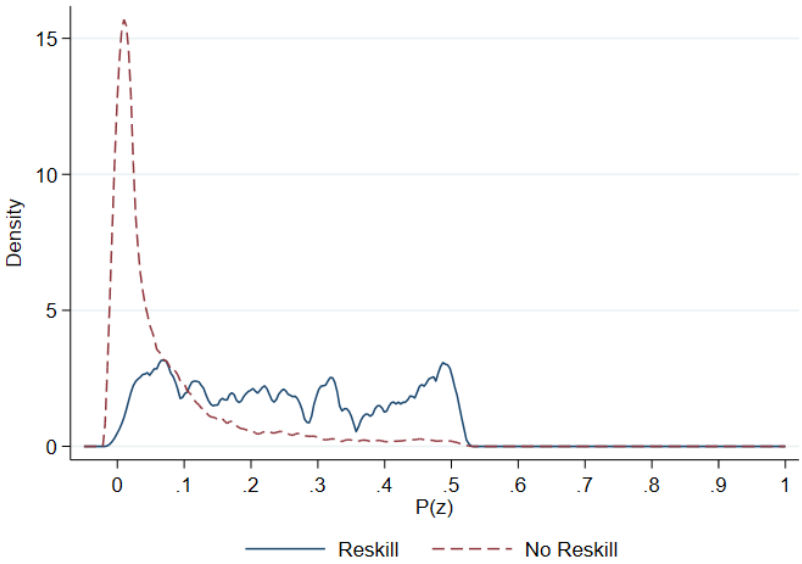
Notes: This figure shows the prescriptions of antidepressants of workers who comply with access to higher education by pursuing a higher degree after work accidents. Panel (a) reports treated complier means, estimated using Equation (4). Panel (b) reports the outcomes of their match workers (who do not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

Figure A.14: Propensity Scores

(a) By Age and Access Status



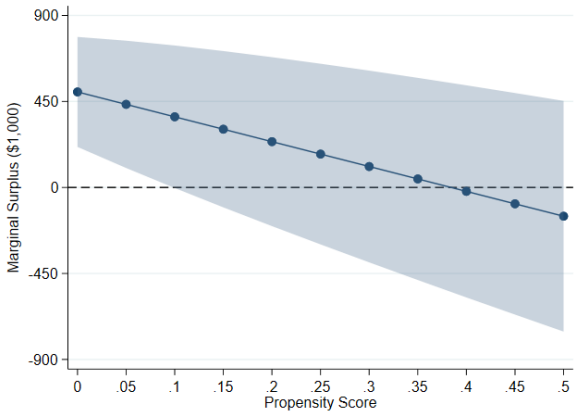
(b) Density by Treatment Status



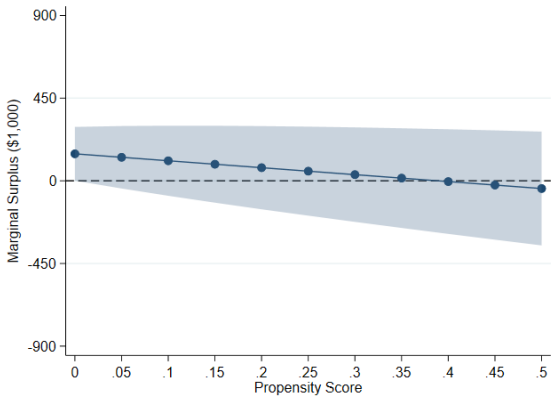
Notes: Panel (a) shows the estimated propensity scores for reskilling (Equation (12)) of workers of different ages and access to higher education. Panel (b) plots the distribution of propensity scores for treated ("Reskill") and nontreated ("No Reskill") workers.

Figure A.15: Marginal Surplus of Reskilling Workers of Age 40 ($1,000)

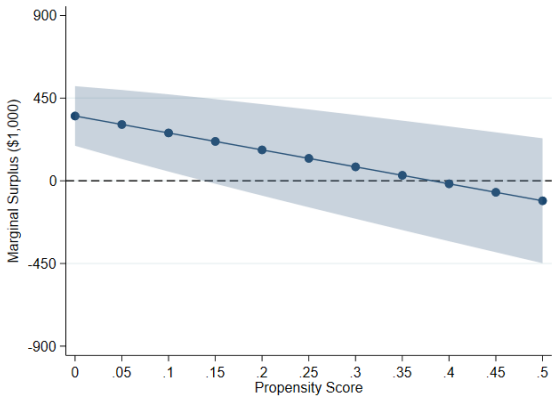
(a) Total (Social Surplus)



(b) Workers (Private Surplus)



(c) Government (Public Surplus)



Notes: This figure shows the marginal surplus of reskilling workers of age 40. Social surplus (Panel (a)) is the sum of surplus for workers (Panel (b)) and the government (Panel (c)), each defined as in Table 5. The shaded areas represent 90% confidence bands, estimated with a Bayesian bootstrap (Shao and Tu, 2012) of 1000 iterations over the propensity score and outcome equations (12) and (15) with weights drawn from a uniform distribution.

B Targeted Investment

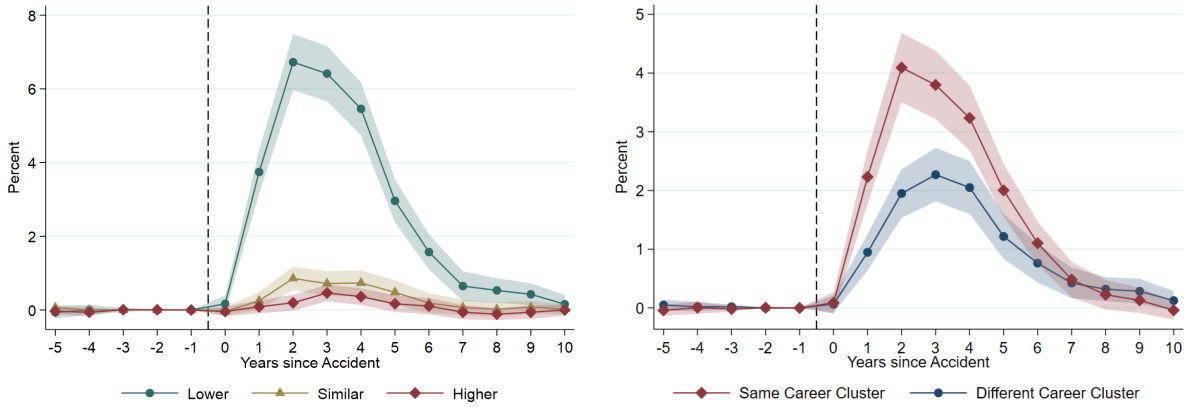
This section describes how we link degrees to their target occupations and sectors. These links form the basis of Figure B.1.

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. The list of degrees and target occupations is available at `www.andershumlum.com/s/target_occupations.xlsx`.

Figure B.1: 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 $\pm$ 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% confidence bands, estimated using the regression equation (1).

C Inverse Probability Weighting

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

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

$$p(\text{Access}_{ie-1} = 1) = \mu(X_{ie-1}), \tag{18}$$

where μ 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

$$w_i = \frac{\hat{p}(X_{ie-1})}{1 - \hat{p}(X_{ie-1})}. \tag{19}$$

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

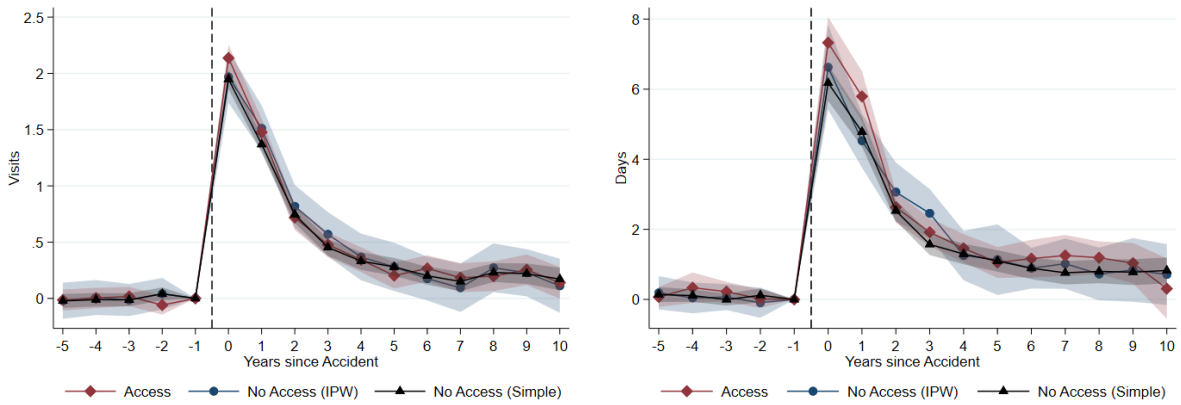
C.1 Robustness Analysis

This section shows that our difference-in-difference estimates from Section 4 are robust to the inverse probability weighting (IPW) of the control group. To do so, we reproduce our first-stage and reduced-form estimates, only balancing on the immediate severity of the

injuries.[38] That is, we reweigh the "No Access" workers based only on the hospitalization (number and days of visits) in the year of the accident (X in Equation (18)). We call this specification "No Access (Simple)". Figure C.1 confirms that the worker groups experience similar hospitalizations following their injuries.

Figure C.1: Hospitalization around Accident

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



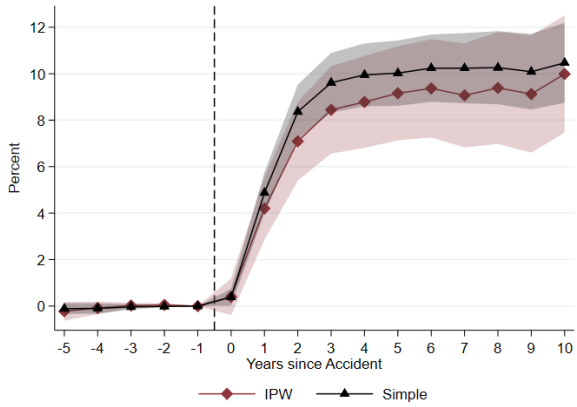
Notes: This figure shows the hospitalization of workers, split by whether the workers have access to higher education upon injury. The first two lines correspond to the "Access" and "No Access, IPW" columns of Table 3. The last lines reweigh the "No Access" workers only based on the hospitalization (number and days of visits) in the year of the accident. The graphs show differences-in-differences in outcomes between the "Injury" and "Match" workers from Table 2, indexed to year -1. Shaded areas are 95% confidence bands.

Figure C.2 shows our main triple-difference estimates using either "No Access (IPW)" or "No Access (Simple)" as the control group. The figure shows that the first-stage and reduced-form results are robust to the IPW method.

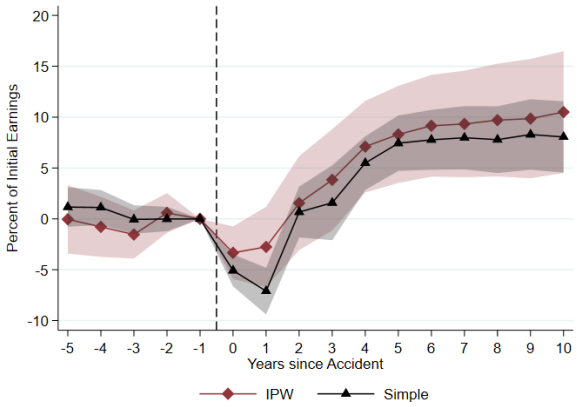
[38]The "No Access (Raw)" group experiences milder injuries than the "Access" workers, spending on average five days instead of seven in the hospital in the year of the accident. So, to ensure we compare similar injuries, "No Access (Simple)" reweigh the control group based on the hospitalization in the year of the accident.

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

(a) Participated in Higher Degree



(b) Labor Earnings



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

D Care Workers

The main analysis in Section 4 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.1 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 3% of care workers have enrolled in a higher degree due to the injury (Figure D.1.(a)), which is significantly less than the 10% 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.1. Combined, these two effects (lower point estimates and less precision) imply that we cannot detect a statistically significant first-stage relationship

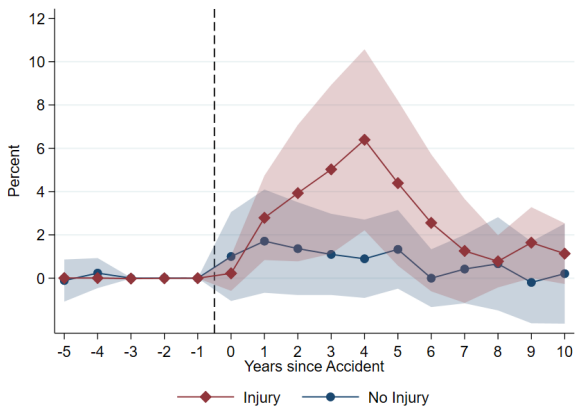
between access to higher education and subsequent pursuit of higher degrees.

Figure D.1.(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.

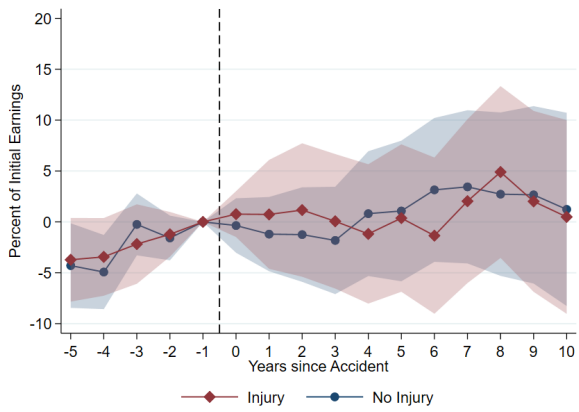
Taken together, the null effects in Figure D.1 suggest that access to higher degrees only helps workers if the programs target jobs that are less physically demanding.

Figure D.1: 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% confidence bands, estimated using the Equation (2).

E Cost-Benefit Evaluation

This section describes our approach to estimating the costs and benefits of higher education for injured workers. We evaluate the incidence for a worker who suffers an injury at age 40 and retires at age 65.[39,40] 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%) 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 A.10) and unemployment benefits. Section 2 describes the transfers. We then scale these effects with the transfer rates collected from the government budget.[41]

Education expenses include tuition and school-related transfers. Tuition costs amounts to approximately $16,500 a year per full-time student. We collect the tuition costs from the government budget.[42] The transfers include the State Education Support (SU) and reskilling benefits.

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

[39]Figure A.11 supports the assumption that human capital investment does not affect the age of public pension retirement of injured workers.

[40]The average *complier* is only 32 at the time of injury, which means that evaluating the costs and benefits at age 40 serves as a lower bound of the true benefits for compliers.

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

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

E.1 Mental Health

This section describes how we include the effects on mental health in the cost-benefit calculations. We include expenditures related to mental health in the form of co-pay and reimbursements related to treatment (medication, counseling) and the effect on quality-adjusted life years (QALYs).

First, we calculate the average yearly costs of medication for three categories of prescription drugs related to mental health: antidepressants (ATC-codes N06A), sleep medication (ATC-codes N05C), and painkillers, including opioids (ATC-codes N02). We use the average price per Defined Daily Dose (DDD)[43] within each category and multiply by 365 days to get the yearly cost of each type of medication. We split this cost into co-pay for workers and subsidies from the government using the reimbursement thresholds provided by the Danish Medicines Agency.[44]

In addition to medication costs, we include the costs of counseling offered by registered psychologists and psychiatrists using standard rates of co-pay and reimbursement agreed to by the state and unions.[45]

The monetary value of mental health in terms of life quality is the most difficult component to assess. Therefore, we take a conservative approach and apply the lower bounds of existing estimates. In particular, the literature has estimated depression to lower QALYs by 20% to 40% (Fryback et al. (1993); Lave et al. (1998); Jia et al. (2015); Williams et al. (2023)) and the monetary value of a QALY to range between $20,000 and $75,000 (Huang et al. (2018); Chilton et al. (2020); Himmler (2021)).[46] Combining the two lower bounds implies a burden of depression of at least $4,000 per year. We multiply

[43]The DDD is defined by WHO and adapted by the Danish Medicines Agency to provide prices per DDD for each drug. A full list of prescription drug prices is available at `www.medicinpriser.dk`.

[44]The reimbursement thresholds are available at `https://laegemiddelstyrelsen.dk/en/reimbursement/calculate-reimbursement/reimbursement-thresholds/`.

[45]The rates are available at `https://www.dp.dk/raadgivning/selvstaendig/psykolog-med-ydernummer/honorarer-afregning-og-omsaetning/praksishonorarer/`.

[46]Institute for Clinical and Economic Review (2020) uses a range between $50,000 and $200,000.

this burden with the effect of reskilling on antidepressant use (the outcome in Figure 9) to quantify the impact on life quality.

Table E.1 shows the benefits (avoided costs) of reskilling on mental health. Reskilling generates a social surplus from mental health of $47,000 per reskilled worker. Workers reap 57% of the surplus, driven mainly by the effect on QALYs, while the government avoids covering costly treatments.

Table E.1: Benefits (Avoided Costs) of Higher Education on Mental Health

	Per Reskilled Worker ($)	Percent of Total
Workers	**26,825**	**57.2**
Co-pay (medication, counseling)	6,631	14.1
Quality-adjusted life years (QALYs)	20,193	43.1
Government	**20,099**	**42.8**
Reimbursements (medication, counseling)	20,099	42.8
Total	**46,923**	**100.0**

F General Equilibrium Effects

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

F.1 Model

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

$$E_i = w \times H_i. \tag{20}$$

Wages equalize the demand and supply of human capital:

$$H^D = w^{-\epsilon} \tag{21}$$

$$H^S = H^N + H^I(p), \tag{22}$$

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

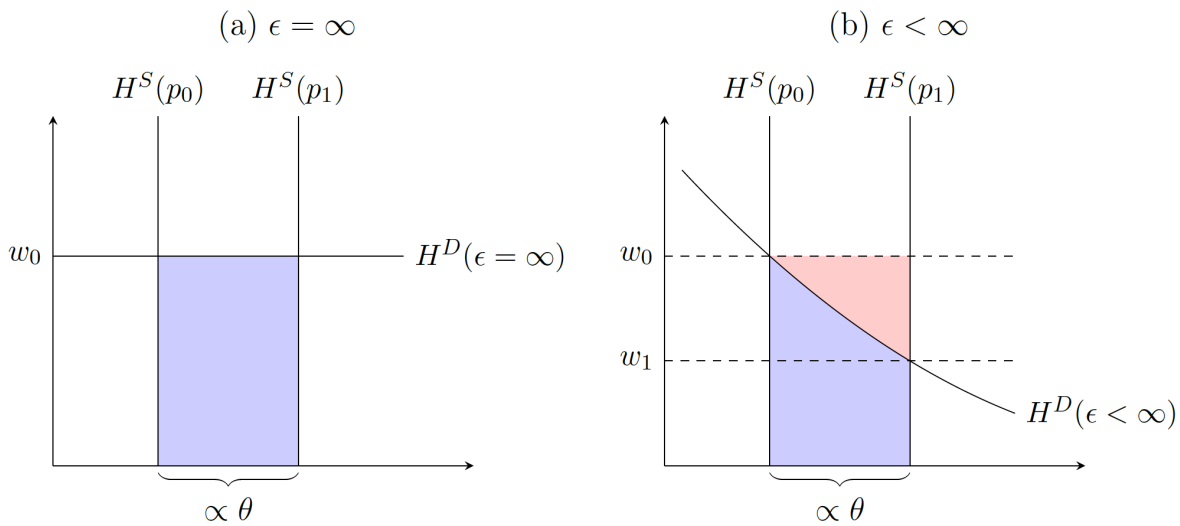
Section 5.1 estimates the impact of reskilling p on individual earnings, keeping market wages fixed at their current levels w_0. As Panel (a) of Figure F.1 shows, these earnings effects correspond to the labor market surplus when labor demand is perfectly elastic. However, when labor demand is finitely elastic, as in Panel (b), the reskilled workers face decreasing marginal returns, dampening the surplus from reskilling.

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

$$\theta = \frac{H^I(p_0)}{H^N + H^I(p_0)}. \tag{23}$$

Consequently, when injured workers constitute a small fraction of the aggregate labor supply, the labor market surplus from reskilling remains closer to the estimates from Section 5.1.

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



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

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

F.2 Calibration

Elasticity of labor demand ϵ

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

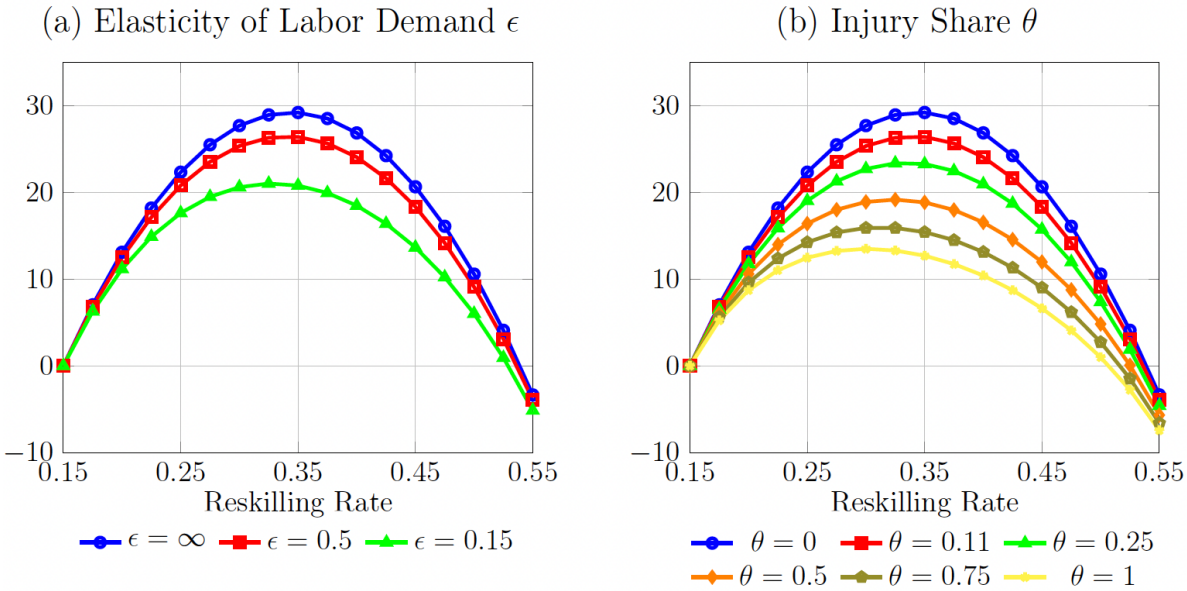
Injury share θ

Appendix F.3.2 calibrates the share of injured workers in aggregate labor supply. We first estimate the labor supply of injured workers $H^I(p)$ by scaling the treatment effects on earnings $f^E(p)$ with the number of injured workers per year. Next, we estimate the aggregate labor supply $H^S(p_0)$ as the total annual labor earnings in the occupations of reskilled workers. Combining the estimates, we obtain a share of $\hat{\theta} = \frac{\hat{H}^I(p_0)}{\hat{H}^S(p_0)} = 0.11$.

F.2.1 Simulations

Figure F.2 simulates the social surplus of increasing the reskilling rate from its current level. We simulate the surplus under various values of the elasticity of labor demand (Panel (a)) and the share of injured workers in aggregate human capital (Panel (b)). The cases of perfectly elastic labor demand ($\epsilon = \infty$) or infinitesimal injury share ($\theta = 0$) correspond to the counterfactuals from Section 5.3.

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



Notes: This figure shows the social surplus of increasing reskilling from its current rate of 15% under various values of (*a*) the elasticity of labor demand ϵ (fixing the current injury share θ at 0.11) and (*b*) the current share of injured workers in aggregate human capital θ (fixing the elasticity of demand ϵ at 0.5).

Figure F.2 shows that the optimal reskilling rates are fairly robust to labor market equilibrium effects. For example, by lowering the labor demand elasticity to 0.5 (the focal estimate in the literature) and setting the injury share to 0.11 (the actual share), the optimal rate of reskilling decreases from 34.5% to 34.0%, and the maximum social surplus falls by 10%. Lowering the elasticity of labor demand even further to 0.15 (the lower bound in the literature), the optimal rate of reskilling drops to 32.8%, and the potential surplus decreases by 28%. The robustness of the optimal reskilling rates to labor market equilibrium effects partly reflects that injured workers constitute a minor fraction of aggregate labor supply $\theta = 11\%$. That said, by raising the injury share to 50%, the optimal rate of reskilling only falls to 32%.

F.3 Technical Details

F.3.1 Labor Market Equilibrium

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

$$H^D = w^{-\epsilon} \tag{24}$$

$$H^S(p) = H^N + H^I(p). \tag{25}$$

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

$$H^S(p) = 1 + \theta h(p), \tag{26}$$

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

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

$$S(p) = \frac{f(p_0)}{\theta} \int_{1-\theta}^{1+\theta h(p)} H^{-1/\epsilon} dH \tag{27}$$

$$= \frac{f(p_0)}{\theta} \left(\frac{\epsilon}{\epsilon - 1} \right) \left[(1 + \theta h(p))^{\frac{\epsilon-1}{\epsilon}} - (1 - \theta)^{\frac{\epsilon-1}{\epsilon}} \right], \tag{28}$$

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

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

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

is increasing in ϵ and decreasing in θ.

F.3.2 Calibration

Injury share θ

The share of injured workers in aggregate human capital is

$$\theta = \frac{H^I(p_0)}{H^S(p_0)} = \frac{I \times f^E(p_0)}{E_0}, \tag{30}$$

where I is the number of injured workers, f^E is the treatment effects of reskilling on earnings from Equation (9), and E_0 is the total annual earnings in the occupation.[47] For I, we use the number of workers per year who lose earning capacity from a physical work accident (the population of workers for the causal estimates in Section 5.1), corresponding to row 8 of Table A.1. For E_0, we assume that labor markets are segregated by four-digit occupations and use Equation (4) to estimate the total annual labor earnings in the four-digit occupations of reskilled workers. For $f^E(p)$, we convert the annual estimates from Tables A.7 and A.9 into lifetime values of workers aged 40 using Equation (17).[48,49] Combining the estimates, we obtain a share of $\hat{\theta} = 0.11$.

[47]We set $H^I(0) = 0$ following the result in Table 4 that injured workers only transition into cognitive occupations if they are reskilled.

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

[49]The effect of reskilling p depends on its distribution across worker ages. We use, for simplicity, the estimates for workers of age 40.