Firm Investment, Labor Supply, and the Design of Social Insurance: Evidence from Accommodations for Workplace Disability*

Naoki Aizawa † Corina Mommaerts ‡ Stephanie Rennane §

August 30, 2021

Abstract

This paper studies the impact of firm accommodation decisions on labor market outcomes for individuals with workplace disabilities, and assesses the implications for optimal social insurance against workplace disability. We leverage detailed administrative data from a unique workers' compensation program in Oregon that provides wage subsidies to firms for workplace accommodation. Exploiting a policy change to the wage subsidy, we find that a five percentage point decrease in the wage subsidy rate led to a 5.5 percentage point decrease in accommodation and corresponding effects on employment and earnings through eight quarters after injury. We then develop and estimate a dynamic bargaining model between workers and firms in which labor market frictions, worker turnover, and imperfect experience rating can lead to under-accommodation and inefficient labor market outcomes after workplace disability. We use the quasi-experimental estimates to help identify key parameters of the model. Counterfactual analyses show that a wage subsidy of 40% maximizes overall worker welfare, with higher welfare gains for workers with low disutility of work during injury in labor markets with inefficiently low accommodation rates.

*__Preliminary. Comments welcome.__ We thank for Katsuhiro Komatsu for excellent research assistance, and Michael Dworsky, John Kennan, Rasmus Lentz, Amanda Michaud, Jeff Smith and Chris Taber, and seminar participants at the Barcelona GSE Summer Forum, Cowles Summer Conference on Labor Economics & Public Finance, Federal Reserve Bank of St. Louis/Washington University St. Louis, Household Dynamics at Older Ages Conference at the Federal Reserve Bank of Richmond, Montreal Ageing Conference, Retirement and Disability Research Consortium Annual Meeting, University of Michigan, University of Pennsylvania and University of Wisconsin-Madison for helpful comments and discussions. We are grateful to Don Gallogly, Gary Helmer and their colleagues in the Oregon Department of Business and Consumer Services and Oregon Employment Department for help with data access and patience answering our many questions. Funding from the Social Security Administration through Grant Number AAH3792 and the Wisconsin Alumni Research Foundation provided by the University of Wisconsin - Madison Office of the Vice Chancellor for Research and Graduate Education through Grant Number MSN237473 is gratefully acknowledged.

†University of Wisconsin-Madison and NBER. Email: naizawa@wisc.edu

‡University of Wisconsin-Madison and NBER. Email: cmommaerts@wisc.edu

§RAND Corporation. Email: srennane@rand.org

1 Introduction

Work-limiting disabilities and health shocks are some of the largest risks that workers face. These risks can not only have large consequences for health spending, but can also affect longer run labor market outcomes (Currie and Madrian, 1999). Large social insurance programs, including the Social Security Disability Insurance (SSDI) program and state workers' compensation programs, aim to protect workers against this risk, at a cost of $145 and $98 billion in 2018, respectively (Office of the Chief Actuary, 2020; Murphy et al., 2020). An important question in assessing the current design of these social insurance programs is whether they impede re-entry into the labor market after disability. Returning to work after disability is ultimately a decision that workers make based on their ability to perform their job as well as economic and institutional factors. However, the worker's choice may also heavily depend on decisions by employers to accommodate and retain workers with health limitations. While several studies have focused on *worker* decisions and incentives to return to work (Kostøl and Mogstad, 2014; O'Leary et al., 2011), little is known about firm accommodation decisions, how these decisions respond to policy incentives, and the extent to which accommodation affects labor market outcomes after disability.

In this paper, we study the role of firm accommodation incentives in the context of workplace injuries. Workplace injury is a major source of disability risk and labor force exit in the United States: in 2015, there were nearly three million non-fatal occupational injuries and illnesses (BLS, 2017), and around one third of SSDI recipients report disabilities originating from workplace injury (Reville and Schoeni, 2004). Many workplace injuries are covered by workers' compensation programs, which provide one of the earliest forms of intervention for disabled workers and thus provide a potential avenue for firm engagement. Given this backdrop, we have two main objectives in this paper. The first is to contribute quasi-experimental evidence on the effect of early-stage firm accommodation incentives on labor market outcomes for injured workers using detailed administrative claims and wage data. The second is to evaluate the welfare implications of firm accommodation incentives and optimal workers' compensation design within a dynamic bargaining model of workers and firms, using our empirical estimates to identify the model.

Our empirical context is the workers' compensation program in Oregon. A relatively unique feature of the Oregon program is the Employer at Injury Program (EAIP), which provides incentives for employers to accommodate injured workers as they return to work. EAIP provides funds for physical accommodations as well as wage subsidies for injured employees to help defray costs related to, for example, flexible work arrangements or retraining.[1] In 2013, almost 2,000

[1]These costs may be large: for example, Mas and Pallais (2020) find that the cost of offering flexible work

employers were provided EAIP benefits for accommodating over 8,000 workers, at a total cost of $19 million (ODBCS, 2016).

To examine the effect of accommodation incentives on both firm and worker behavior, we exploit a change in the EAIP wage subsidy rate from 50% to 45% that occurred in January 2013. We use detailed administrative data of the universe of Oregon workers' compensation claims from 2005 through 2015, linked to longitudinal quarterly wage records of claimants from 2000 through 2019 to conduct several empirical analyses. Our main analysis uses a difference-in-differences strategy to evaluate the policy change. To do this, we use machine learning techniques to assign individuals to "control" and "treatment" groups based on their predicted use of EAIP (the use of EAIP means that both the employer has offered accommodation, and the employee has accepted and decided to return to work). We predict EAIP use with data about worker demographics, occupation, earnings history, and firm and injury characteristics from the period prior to the policy change, and apply the resulting prediction algorithm to all claims. For claims that occurred after the policy change, this provides a counterfactual of what the take-up rate would have been in the absence of the subsidy change. We define the control group as workers who are unlikely to use accommodation, and thus unlikely to respond to any changes the firm makes in response to the policy change, due to their low observed and predicted likelihood of using EAIP. [2]

Comparing the treatment and control groups before and after 2013, we use difference-in-difference models to estimate the effect of the policy change on EAIP take-up, employment, retention, and earnings up to eight quarters after injury. We find that the subsidy change causes EAIP use to decline by 5.5 percentage points off a base of 28% in the treatment group, or a 20% decline. We find corresponding and persistent effects on labor market outcomes: a four percentage point decrease in employment; a decrease of over $1000 in earnings per quarter (approximately 15% off a base of $6,800); but no detectable changes in the probability of moving to a different firm.[3]

We then develop and estimate a model of workplace disability and workers' compensation to explore potential inefficiencies in accommodation decisions and assess the implications for optimal policy. The model is a dynamic bargaining model between workers and firms in an

scheduling must be high given the low prevalence of flexible work, yet high willingness to pay for it by workers.

[2]In our primary specification, the bottom 10% of predicted EAIP claims (claims whose predicted probability of EAIP take-up is lower than 7%) serve as the control group, and the remaining 90% of claims as the treatment group. There are two main assumptions to this approach. First, given the low observed and predicted EAIP take-up rate in the control group, we assume that they are unlikely to use accommodation regardless of the subsidy rate, so the policy change should not affect their take-up. Second, we assume that employment outcomes for this control group trend in parallel to the treatment group.

[3]Although we do not have linked data on other social programs, these persistent and negative labor market effects also suggest that EAIP subsidies can help reduce the take-up of longer run welfare and disability benefits.

environment with labor market frictions, worker turnover, and a workers' compensation program financed by firms. Workers are subject to injury risk, which potentially entails temporary disutility of work, a persistent loss of productivity, and a higher probability of exit from the labor force. Injuries are covered by workers' compensation, and injured workers either receive timeloss benefits or return to work early if accommodated. Wage and accommodation decisions are determined ex ante by Nash bargaining, in which accommodation may mitigate future employment and productivity losses of injured workers, but at a cost to the firm that depends on the severity of injury, the wage subsidy rate, and a match specific cost shock. Once the worker recovers from disability, they either continue to work at the firm, exogenously move to another firm, or exogenously leave the labor force. Firms differ by whether they self-insure their workers' compensation expenses or purchase workers' compensation insurance (which is imperfectly experience-rated).

The model highlights two main features that could generate socially inefficient accommodation decisions. First, worker turnover prevents firms from capturing future surplus from accommodation after paying the direct costs of accommodation. This externality in the labor market can lead to under-accommodation of injured workers.[4] Second, non-self insured firms that finance workers' compensation based on imperfect experience rating may also accommodate injured workers at inefficiently low rates because they are not fully exposed to the financial consequences of their accommodation decisions for workers' compensation program costs (i.e., a classic fiscal externality).

To quantify the importance of these channels and explore the optimal design of workers' compensation policy, we structurally estimate the parameters of the model. Some of the parameters have direct analogs in our data, while for others we match moments generated from the model to moments in the data to identify the parameters. In particular, we exploit our quasi-experimental estimate of the effect of the wage subsidy change on EAIP take-up to separately identify the cost of accommodation to firms from the utility cost of work for disabled workers. Because firm and worker incentives may differ along important margins such as experience rating and wage level, we build this heterogeneity into the model and parameter estimates. Our parameter estimates imply that net output is markedly lower during injury and workers incur a large disutility of working while disabled, but that accommodation increases future net output and labor force attachment, replicating our quasi-experimental findings.

Using our estimated model, we first show that worker turnover and the degree of experience rating are both important in explaining the observed levels of accommodation. Because

[4]This mechanism is the same as the dynamic inefficiency channel highlighted in Acemoglu and Pischke (1999). See Fang and Gavazza (2011) for evidence of this mechanism in the context of the U.S. health insurance market and the labor market.

both channels drive a wedge between the socially optimal and the firm's privately optimal level of accommodation, our results suggest that these features lead to socially inefficient levels of accommodation. At the same time, the disutility of work during injury is also an important determinant of accommodation rates, suggesting that across the board high rates of accommodation are not necessarily socially optimal.[5]

We then explore counterfactual workers' compensation policies to correct these inefficiencies. Holding constant the timeloss benefit, we find that increasing the subsidy rate to 40% maximizes overall welfare, but this overall figure masks significant heterogeneity across workers and firms. Higher wage subsidies provide the highest benefit for high-skilled workers in non-self-insured firms, while low-skilled workers prefer lower wage subsidies. This is in part because low-skilled workers have a much higher utility cost of working while disabled and thus do not necessarily benefit from accommodation, while high-skilled workers benefit from accommodation. Without sufficiently high wage subsidies, firms that are imperfectly experience rated (i.e., not self-insured) under-provide accommodation because they do not fully internalize the costs of paying timeloss benefits.

This paper contributes to a broad literature empirically estimating the behavioral responses by both workers and firms to disability insurance and workers' compensation policies. The majority of studies have focused on labor supply incentives for workers. In the context of disability insurance, most work has found that receipt of SSDI benefits has a strong negative effect on earnings and labor supply (Maestas et al., 2013; French and Song, 2014; Gelber et al., 2017). Studies estimating the effect of incentives to re-enter the labor market after receiving benefits find mixed results, ranging from large effects in the Norwegian context (Kostøl and Mogstad, 2014) to negligible effects in the US SSDI program (O'Leary et al., 2011). In workers' compensation, most of the evidence suggests that increased generosity in timeloss benefits leads to longer income benefit durations and higher medical expenditure, but little to no increase in the overall number of claims (Cabral and Dillender, 2020; Hansen et al., 2017; Neuhauser and Raphael, 2004; Meyer et al., 1995; Krueger, 1990).[6,7]

A smaller but growing literature studies the role of employers in disability and workers' compensation programs. This work has primarily focused on the effects of experience rating in

[5]The model assumes that accommodations are a joint ex-ante worker-firm decision that cannot be renegotiated post-injury, and thus it is possible that higher wage subsidies lead to higher accommodation that is welfare decreasing for workers.

[6]Mullen and Rennane (2017) find that unconditional cash transfers within workers' compensation also affect labor supply, suggesting an important role for income effects in addition to the standard labor supply incentives.

[7]Several studies place these benefit duration elasticities within a simple optimal social insurance framework that trades off moral hazard and insurance (or liquidity) a la Baily-Chetty, with some suggesting that optimal benefits should be slightly smaller (Bronchetti, 2012; Cabral and Dillender, 2020) and others suggesting optimal benefits should be slightly higher (Rennane, 2018).

disability programs, and typically finds that higher levels of experience rating lead to decreases in disability benefit receipt (Hawkins and Simola, 2020; Prinz and Ravesteijn, 2020; De Groot and Koning, 2016). Studies on employer accommodation document that the majority of disabled workers are not accommodated by their employers despite the ADA requirement to provide "reasonable accommodations" for workers with disabilities (Hill et al., 2016) yet a substantial fraction of these workers would benefit from accommodation (Maestas et al., 2019; Burkhauser et al., 1995). Accommodation provision also varies with firm characteristics and is more common at large, experience-rated employers (Bronchetti and McInerney, 2015).

Our paper contributes several advancements to these empirical literatures. While several policy proposals advocate for more employer responsibility in encouraging workers to return to work after injury and disability (Autor and Duggan, 2010; Burkhauser and Daly, 2011), few studies have identified or analyzed the impact of related employer-based programs in the U.S. setting, or considered the impact of policies affecting employer incentives to accommodate workers after injury, rather than ex ante. We study a unique return-to-work program that directly incentivizes employers to accommodate injured workers, and leverage quasi-experimental variation coupled with detailed administrative data to credibly identify some of the first estimates of the effects of these incentives. In addition, our welfare results suggest that accommodation incentives can be an important (and, until now, absent) input into an simple optimal social insurance framework. We show that accommodation subsidies can be complementary to the generosity of income benefits, suggesting more generous optimal income benefits in the presence of accommodation subsidies.

This paper also expands on theoretical and structural literatures that study firm incentives to invest in their workers and insure them against productivity-related shocks. Beginning with the classic theoretical result that firms do not invest in general training in a frictionless labor market because workers capture all of the surplus (Becker, 1962), Acemoglu and Pischke (1999) demonstrate that labor market frictions can overturn this result and lead to a positive level of firm investment in general training, and Fang and Gavazza (2011) show empirically that the presence of worker turnover leads to positive yet inefficiently low investment by firms in employee health.[8,9]

Our paper contributes to this literature by formalizing and quantifying the extent to which employer accommodation after disability can be considered a form of general human capital.

[8]In a similar vein, a lack of worker commitment in worker-firm relationships generates wage contracts with only partial insurance (Thomas and Worrall, 1988; Balke and Lamadon, 2020).

[9]Other work studies firm responses to policies aimed at correcting these inefficiencies, including wage subsidies to hire disadvantaged workers (Elvery et al., 2021; Giupponi and Landais, 2018), tax subsidies for health insurance (Aizawa and Fang, 2020), and disability accommodations (Acemoglu and Angrist, 2001; Aizawa et al., 2020).

From this standpoint, our empirical context, which offers policy variation and detailed data to identify our model, is well suited to quantify the mechanisms that lead to inefficiently low accommodation (or general human capital) and run counterfactual experiments to inform optimal policy.

The paper proceeds with an overview of return to work after disability, Workers' Compensation programs, and Oregon's EAIP program in Section 2. Section 3 describes our data and empirical strategy, and Section 4 presents the results. Section 5 presents our model of firm and worker behavior following a workplace injury, and Section 6 presents the estimation of the model. Counterfactual policies are discussed in Section 7, and Section 8 concludes.

2 Background

2.1 Workers' Compensation

Workers' compensation programs are designed to protect workers and employers against the risk of an injury or illness that occurs on the job. In all states except Wyoming and Texas, most employers are required to purchase workers' compensation insurance which covers both medical costs and timeloss benefits associated with workplace disabilities. Premiums are typically experience rated, meaning that an employer's past injury history factors into future premium rates relative to a base rate that varies by industry. Large employers in many states can also opt to self-insure, which is effectively perfect experience rating. A worker who experiences an illness or injury related to work must first file a workers' compensation claim. If deemed eligible, all related medical costs are covered by workers' compensation. Workers unable to work due to the illness or injury also receive disability benefits, typically after a short waiting period. Temporary benefits are provided as long as workers are still recovering, and in the event of permanent disability, workers are typically eligible for an additional benefit.

In Oregon, workers who miss work due to illness or injury are eligible to receive temporary total disability (TTD) benefits equal to 66-2/3 percent of wages (subject to a minimum and maximum) after a three-day waiting period from the date of injury. The worker may receive temporary benefits as long as a doctor verifies that she is unable to work and that her condition has not yet stabilized. Occasionally, workers may attempt work intermittently during their recovery and return to TTD benefits if they find they are still unable to work. Eventually, the worker is deemed to reach "maximum medical improvement", the point where no further recovery is expected. At this stage, if there is any residual incapacity due to the injury or

illness, the worker is assessed for permanent disability benefits and the claim is closed.[10]

2.2 Oregon's Employer at Injury Program

In addition to the mandatory medical and timeloss benefits, Oregon is one of only a few states whose workers' compensation program provides benefits to employers who accommodate workers with workers' compensation claims. The largest program, which is the focus of our analysis, is the Employer at Injury Program (EAIP), which is designed to help injured workers return to employment during their recovery.[11] The EAIP incentivizes firms to accommodate injured workers by offering subsidies for the cost associated with accommodation for transitional work. The accommodations are intended to support the worker during a temporary period where she may need to perform other job duties or learn new skills in order to begin transitioning back into employment. Workers must face restrictions or limitations that prevent them from returning to their full pre-injury job. Workers must also have an open claim during the time that they are accommodated in order for the accommodation expenses to be eligible for reimbursement. Eligible claims may either be disabling claims (e.g., claims where workers receive temporary or partial time loss benefits), or non-disabling claims (e.g., claims where workers only have medical expenses covered but do not receive time loss benefits).

In order to be eligible for these subsidies, the employer must be the employer at the firm where the worker was injured and must offer accommodation. The employer may receive a subsidy for wages during a transitional period when a worker returns as well as reimbursement for costs such as worksite modification (up to $5,000), tuition, books and fees associated with retraining and skill development (up to $1,000), or clothing costs (up to $400) (Oregon Department of Consumer and Business Services, 2020).[12] On average, approximately 20 percent of workers' compensation claims in Oregon have some costs reimbursed via EAIP, although there is variation across industries, firm size, insurer types and time, as discussed below.

The EAIP is funded via the Workers' Benefit Fund (WBF), which levies employer and employee-level taxes on all firms and the collected funds are dedicated to financing return-to-work programs. Unlike typical workers' compensation premiums, EAIP is funded through

[10] See Murphy et al. (2020) for a comprehensive overview of workers' compensation programs and https://www.oregon.gov/dcbs/reports/compensation/Pages/index.aspx for more details on workers' compensation in Oregon specifically.

[11] In addition to the EAIP, there are two other return-to-work programs in the Oregon workers' compensation program: the Preferred Worker Program (PWP), which offers premium reductions, claim cost reimbursement, as well as a wage subsidy for up to 6 months to employers who hire workers with permanent disabilities, and a vocational rehabilitation (VR) program. Participation in PWP and VR is much lower than in the EAIP (on the order of 2-3 percent of claims), and the share of claims who participate in both EAIP and one of the other programs is also small.

[12] See https://wcd.oregon.gov/rtw/Pages/eaip.aspx for more details about the EAIP.

a payroll tax on all firms that is not experience rated. Because the costs of EAIP use are not internalized in the same way that other workers' compensation costs are internalized via experience rating, this further increases the firm's incentive to have claim costs covered via EAIP.

The EAIP has been in place since the 1990s. In 2013, a change in policy reduced the wage subsidy from 50 percent to 45 percent of transitional earnings for up to 66 days during a 24-month period. Soon after, many employers began advocating for the 50 percent subsidy to be restored.[13] Based on this employer feedback, the subsidy was restored to 50 percent as of January 1, 2020 (SAIF, 2020). We use the 2013 policy change in our empirical strategy, to which we now turn.

3 Data and Empirical Strategy

3.1 Data

Our main data source is administrative workers' compensation claims from the state of Oregon, provided by the Oregon Department of Business and Consumer Services, Workers' Compensation Division. The sample includes all closed claims with a timeloss benefit or EAIP use from 1987 through 2019. The claims data include detailed information including the date of injury, payment dates, claim closure date, total workdays for which timeloss benefits were paid, total timeloss payments, and medical expenditures. Worker information includes information about the worker's injury, including ICD codes, the nature of the injury, the event causing the injury, and affected body part(s), and demographic characteristics including age, gender, occupation, industry, and pre-injury wage. All of this information is summarized over the life of the claim and included in one record for claim.

We link several separate data sources to the administrative claims. First, we link information from a separate database about use of EAIP, PWP, and VR. These data indicate whether the employer received any subsidies for the claim through return to work programs, the value of the subsidies received, and dates of first and last use of the program.

Next, we link these data to Unemployment Insurance earnings data from the Oregon Employment Department (OED). OED linked all workers' compensation claims in the dataset to quarterly earnings records and provided the matched records from 2000 through 2019. In other words, this linkage enables us to observe pre- and post-injury earnings history for all workers the claims database with injuries after 2000. The data include total earnings and hours for each

[13] Based on correspondence with Oregon Department of Consumer and Business Services.

employer where an individual worked during the quarter, as well as an employer ID enabling linkages between employers across individuals and over time.[14] Finally, we also link this data with industry-level and county-level labor demand information including labor force participation, employment rates, and job vacancies from the St. Louis Federal Reserve and Bureau of Labor Statistics (Bureau of Labor Statistics, 2020; Federal Reserve Bank of St. Louis, 2020).

Our primary sample for analysis focuses on claims from 2005-2015. After excluding a minority of open and pending claims which comprise less than one percent of the dataset, we have a primary sample size of just over 200,000 claims. Table 1 compares key characteristics of claims with costs that are subsidized via EAIP and those that are not. On average, workers whose claims have EAIP are slightly older and more likely to be female. Workers with EAIP claims also have higher pre-injury earnings and higher hours. Claims with EAIP have higher medical costs on average, and are more likely to be strains and less likely to be wounds.[15] Large firms and self-insured firms are over-represented among claims with EAIP. Over 50 percent of EAIP claims occur at large firms with more than 500 employees, compared to 28 percent of claims without EAIP, which could reflect both that larger firms may have more capacity to provide accommodation and/or have more knowledge of EAIP. Nearly one-third of EAIP claims occur at self-insured firms compared to 17 percent of non-EAIP claims. Self-insured firms are likely larger on average, consistent with the higher share at large firms. Because self-insured firms internalize all workers' compensation cost, they may also have a larger incentive to accommodate and have these costs offset via EAIP. EAIP is also over-represented in industries like trade, health and education services, and public administration, and under-represented in industries like transportation and accommodation services. Overall, one quarter of claims use EAIP.

Figure 1 plots the share of claims that have some costs reimbursed via EAIP by quarter of injury. The share steadily increases from 16 to nearly 27 percent by the end of 2012. There is a clear break after the subsidy change in 2013, and the share of claims using EAIP declines precipitously through 2015, returning to a level of approximately 24 percent.

3.2 Empirical Strategy

To examine the effect of accommodation incentives on both firm and worker behavior, we exploit a change in the EAIP wage subsidy rate from 50% to 45% that occurred in January 2013. We use two main empirical strategies: a before-after specification and a difference-in-difference specification. Our main outcome variables include: EAIP take-up, which is a

[14] Oregon is one of only a few states that records not only earnings but also hours, which allows us to construct a measure of wages.

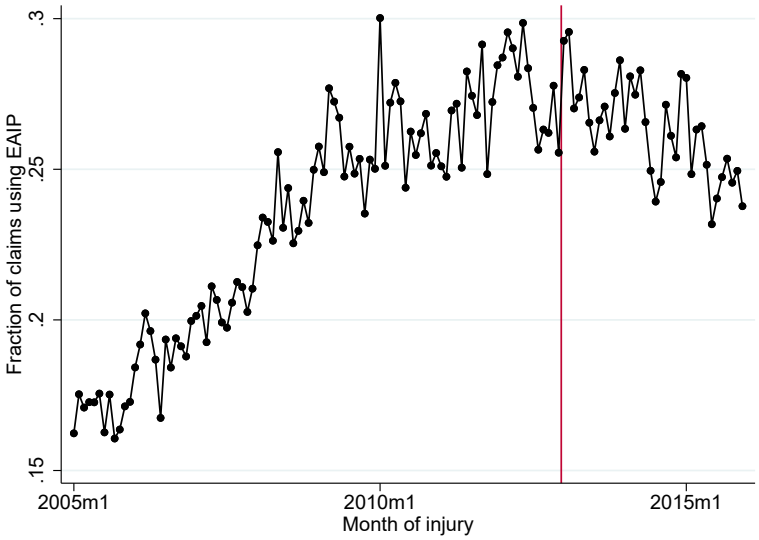
[15] Appendix Figure 1 shows that the EAIP use is highest for moderately severe injuries as measured by log medical spending and log medical spending per day of temporary disability.

Table 1: Summary statistics, sample of Oregon workers' compensation claims 2005-2015

	All claims	Claims with EAIP	Claims without EAIP
Worker characteristics			
Age	41.6	42.5	41.4
Female	0.35	0.40	0.34
Prior quarterly earnings	$7,534	$8,536	$7,213
	($6,227)	($5,351)	($6,449)
Prior quarterly hours	399	424	391
	(169)	(150)	(174)
Claim characteristics			
Claim medical costs	$9,245	$10,552	$8,849
	($17,295)	($17,475)	($17,221)
Claim days	129	165	117
	(217)	(238)	(208)
Claim days w/ timeloss paid	67	73	65
	(119)	(112)	(120)
Injury type: trauma	0.10	0.11	0.09
Injury type: fracture	0.14	0.14	0.13
Injury type: strain	0.55	0.58	0.54
Injury type: wound	0.13	0.08	0.14
Injury type: other	0.09	0.09	0.09
Firm characteristics			
Firm over 500+ employees	0.34	0.52	0.28
Self-insured firm	0.20	0.32	0.17
Industry: construction	0.06	0.06	0.06
Industry: manufacturing	0.14	0.14	0.14
Industry: trade	0.18	0.20	0.17
Industry: transportation	0.08	0.06	0.08
Industry: health and education	0.18	0.25	0.16
Industry: accommodation	0.06	0.03	0.07
Industry: public administration	0.07	0.11	0.05
Observations	212,846	50,686	162,160

Notes: Data provided by Oregon Department of Business and Consumer Services. Sample consists of disabling claims between 2005 and 2015. Prior quarterly earnings and hours are from the quarter prior to the quarter of injury. Claim days are calendar days, while claim days with timeloss paid are days in which timeloss benefits were paid. Reported values are means, or standard deviations in parentheses.

Figure 1: Fraction of claims that use EAIP, by month of injury



Notes: Data provided by Oregon Department of Business and Consumer Services. Sample consists of disabling claims. Red vertical line denotes the date of the policy change in January 2013.

binary variable indicating whether the workers' compensation claim included EAIP; whether the claimant is working in a particular quarter after injury, which is a binary variable indicating positive earnings; whether the claimant is working at a different firm than the firm-of-injury in a particular quarter after injury; and quarterly earnings in a particular quarter after injury.

The before-after analysis compares outcomes prior to the policy change to outcomes after the policy change in regressions of the following form:

$$Y_{it} = \beta \text{Post}_t + \gamma X_{it} + \varepsilon_{it} \tag{1}$$

where β is the coefficient of interest. Y_{it} is an outcome for individual claimant i with injury in quarter t, Post_t indicates that the injury occurred after the January 2013 policy change, and X_{it} are a host of controls, including worker demographics and work history, injury characteristics at the time of injury, industry fixed effects, firm characteristics, and county unemployment rates. Standard errors are clustered by firm because accommodation decisions may be correlated within firm. The main identifying assumption of the before-after specification is that any differences in EAIP or labor market outcomes after January 2013 are solely due to the policy change. In particular, it assumes that any aggregate time effects beyond the policy change are absorbed by the host of controls we include in X_{it}.

Our second specification relaxes this assumption by constructing a control group that consists of very low-probability EAIP users. We consider this set of claimants to be a reasonable

control group because they are unlikely to be affected by a small change in the wage subsidy rate, particularly a *decrease* in the wage subsidy. To identify low-probability EAIP users, we leverage the detailed administrative claims and wage data and run basic machine learning algorithms (primarily Lasso) to predict EAIP take-up. Importantly, we train our prediction algorithm using a 75% subsample of data from the period *prior* to the policy change, and then apply the resulting prediction algorithm to all claims. For claims that that occurred after the policy change, this provides a counterfactual EAIP take-up rate in the absence of the policy change. We then assign the bottom 10% of predicted EAIP claims to the control group, and all other claims to the treatment group.[16] In practice, the predicted probability of EAIP take-up in the control group is lower than 7%.

Using this classification of treatment and control groups, we run the following difference-in-differences regressions:

$$Y_{it} = \beta \text{Treat}_i \times \text{Post}_t + \alpha \text{Treat}_i + \delta_t + \gamma X_{it} + \varepsilon_{it} \tag{2}$$

where β is again the coefficient of interest but is now the coefficient on Post_t interacted with an indicator for whether the claimant is in the treatment group Treat_i. δ_t are quarter-year fixed effects, and X_{it} include the same controls as in Equation (1). Standard errors are clustered by firm.[17] The identifying assumptions of this difference-in-difference specification are that first, the employment outcomes of the control and treatment group would have trended in parallel in the absence of the policy change, and second, the control group take-up of EAIP is so low that the policy change does not meaningfully affect take-up. Fortunately, if EAIP take-up decreases in the control group in response to the policy change, this will bias our estimates toward finding a null effect.

The main advantage of the difference-in-difference specification is that it allows us to account for trends in the outcome variables over time using quarter-year fixed effects. These time fixed effects may be important in this context because our data spans the Great Recession, and while we do our best to control for macroeconomic changes to the labor market in the before-after analysis with county unemployment rates, the unemployment rate may not fully capture aggregate differences in labor market outcomes over time.

[16]This strategy, which uses machine learning to assign individuals to treatment and control groups, has also been used in other contexts, including college admissions probability (Black et al., 2020). More generally, machine learning has been used in the context of disability programs to show that information on healthcare spending in particular can help predict disability program disenrollment (Layton et al., 2019).

[17]We also run specifications that estimate the difference in outcomes between treatment and control claims by year to examine pre-trends: $Y_{it} = \beta \text{Treat}_i \times \text{Year}_t + \alpha \text{Treat}_i + \delta_t + \gamma X_{it} + \varepsilon_{it}$ where 2012 is the omitted year.

4 Empirical Results

In this section we first present results from the before-after specification, then discuss the results of the prediction algorithm, and finally present results from the difference-in-difference specification.

4.1 Before-After Analysis

Table 2 reports estimates of the effect of the wage subsidy policy change (the coefficient β in Equation 1) on EAIP take-up using the sample of over 200,000 disabling workers' compensation claims from 2005-2015 in Oregon. Column (1) only includes controls for treatment, post, and a linear time trend, while column (2) includes a more complete set of controls, including worker, firm, and injury characteristics. The coefficient in column (2) suggests that the change in the wage subsidy from 50% to 45% led to a 2.9 percentage point decrease in EAIP use, or a 12% decrease from a base of 25% take-up.

The remaining two columns show the effect broken down by the firm's insurance status (column 3) and worker wage (column 4). The policy change had no discernible effect for injuries at self-insured firms, but had a large effect on non-self-insured firms. Because firms that are not self-insured are typically only partially experience-rated, this finding is consistent with the theory that partial experience-rating creates a fiscal externality whereby firms are less likely to provide costly accommodations when they do not fully feel the consequences of their actions. The policy change decreased EAIP take-up for workers whose wages were both above and below the median, but moreso for lower wage workers.

While the findings in Table 2 show suggestive evidence that the decrease in the wage subsidy rate led to a marked decrease in EAIP use, the before-after analysis cannot control for aggregate time effects. We next turn to the results of our prediction algorithm and difference-in-difference specification, which allows us to control for aggregate time effects.

4.2 Predicting EAIP use

We next use standard regression and machine learning techniques to construct a control group of a subset of claimants whose predicted probability of using EAIP is so low that it is unlikely that the policy change would have an effect on their EAIP use.

Appendix Figures 4 and 5 show the relative importance of various predictors selected by the Lasso in the final prediction algorithm. Several firm characteristics are the strongest overall predictors, including insurance status (e.g., self-insured vs. not) and firm size. Important

Table 2: Before-After Analysis on EAIP Use

	EAIP take-up			
	(1)	(2)	(3)	(4)
Post policy change	-0.049***	-0.029***		
	(0.009)	(0.009)		
Post × Not self-insured			-0.039***	
			(0.008)	
Post × Self-insured			0.007	
			(0.020)	
Post × Lower wage				-0.039***
				(0.009)
Post × Higher wage				-0.020*
				(0.011)
Controls		Yes	Yes	Yes
Mean EAIP	0.238	0.255		
Mean EAIP, not self-insured			0.222	
Mean EAIP, self-insured			0.376	
Mean EAIP, lower wage				0.304
Mean EAIP, higher wage				0.208
Observations	212845	145001	140710	140895
R-squared	0.00597	0.132	0.106	0.136

Notes: Data provided by Oregon Department of Business and Consumer Services. Sample includes disabling claims in Oregon, 2005-2015. Controls include age, gender, nature of injury, body part injured, injury event, day of week, quarter of year, injury time, county, firm size, occupation, industry, county unemployment rate, and whether the claimant was working in the quarter of injury, the quarter prior, and two quarters prior to the injury and same for working at the firm of injury. Standard errors are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

worker characteristics include the nature, body part and type of injury, as well as the worker's pre-injury wage.

Figure 2 shows the comparison of predicted EAIP take-up between different samples (Figure 2a) and over time (Figure 2b). Figure 2a on the left reports a binscatter in which the x-axis is the predicted probability of EAIP use from the Lasso and the y-axis is the average observed EAIP use for claimants that fall in the bin of the predicted probability distribution. The gray circles show the training sample (which consists of a random 75% sample of claims prior to the policy change), the black hollow circles show the validation sample (the other 25% of claims prior to the policy change), and the red circles show the sample of claims following the policy change. There are three patterns of note: first, the close correlation between predicted EAIP and true EAIP for both the training and validation samples suggests that the Lasso prediction algorithm does a good job predicting EAIP take-up without overfitting. In addition, the red circles show that EAIP use is visibly lower than predicted following the policy change for the majority of the prediction distribution. Finally, all three samples show that the bottom of the predicted probability distribution has very low probabilities of taking up EAIP, suggesting that these low probabilities may be a suitable control group. We assign the lowest 10% of predicted probabilities to the "control" group and the remaining 90% of claims as the "treatment group". The claim at the margin of treatment-control assignment has a predicted probability of EAIP use of 8.2%, and thus we believe it is unlikely that the policy change would have had a dramatic effect on claims with lower probability of EAIP use.[18]

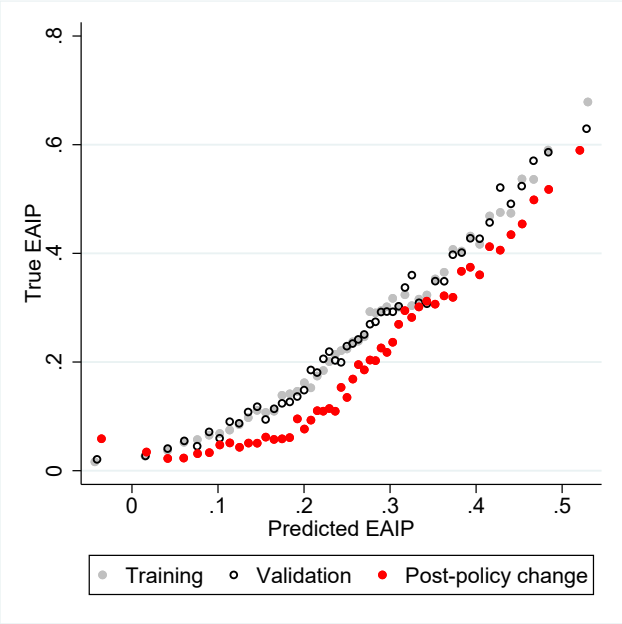
Figure 2b on the right shows the average predicted and true EAIP take-up rates over time in blue and black, respectively, with the vertical red line indicating the date of the policy change. This graph shows a similar story to the red circles in the left graph: EAIP use is visually lower than predicted following the policy change, controlling for a host of features related to the worker, firm, and injury, suggesting an important change in the use of EAIP around the time of the policy change.

4.3 Difference-in-Difference Analysis

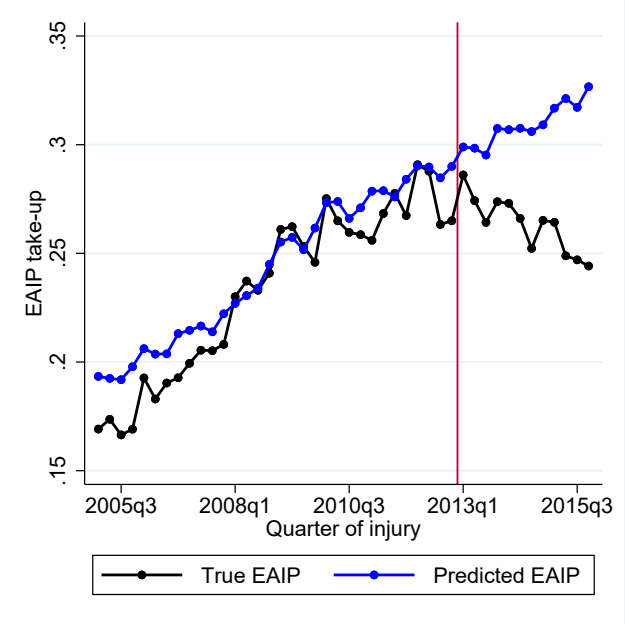
Using the treatment and control groups as defined above, we estimate difference-in-difference models on the treatment and control groups before and after the policy change on EAIP take-up, as well as employment, retention, and earnings up to eight quarters after injury. Table 3 shows the coefficient of interest (β in Equation 2) on EAIP take-up, beginning with no controls beyond a treatment indicator and an indicator that the claim occurred after the policy change in

[18]Note that because firm size and insurance type are such strong predictors of EAIP, relatively few workers with these characteristics end up in the control group.

Figure 2: Comparisons between true and predicted EAIP take-up



(a) Prediction distribution



(b) Average take-up, by quarter of injury

Notes: Figures show comparison between actual EAIP use and predicted EAIP use in our sample of workers' compensation claims from Oregon, 2005-2015. Predicted EAIP use is calculated using a Lasso regression on worker characteristics (age, gender, occupation, log weekly wage at time of injury, whether the worker worked in each of the four quarters prior to injury, and whether the worker worked at the same firm in each of the four quarters prior to injury), firm characteristics (industry, firm size, insurance type, ownership type), and injury characteristics (day of week, quarter of year, hour of day, nature, body part, event) as well as county unemployment rate, county fixed effects and a linear time trend.

column (1), to adding industry by year-quarter and county fixed effects as well as firm controls in column (2), additionally adding worker characteristics and work history controls in column (3), and finally adding injury controls in column (4).[19] With the addition of controls, the policy change had a strong negative effect on EAIP take-up. Specifically, the policy change induced a 5.5 percentage point decrease in EAIP take-up, or a 20% decrease off a base of 28% take-up among the treatment group.[20] The first graph in Appendix Figure 2 estimates the effect by year (including years prior to the policy change), and shows that there is no significant pre-trend.

Table 3: Difference-in-Difference Analysis on EAIP Use

	EAIP take-up			
	(1)	(2)	(3)	(4)
Treatment × Post	0.017	-0.027**	-0.047***	-0.055***
	(0.012)	(0.013)	(0.012)	(0.013)
Mean EAIP, treatment	0.264	0.264	0.268	0.278
Mean EAIP, control	0.0370	0.0370	0.0372	0.0404
Observations	188666	188660	177310	140889
R-squared	0.0255	0.119	0.133	0.148

Notes: Data provided by Oregon Department of Business and Consumer Services. Sample includes disabling claims in Oregon, 2005-2015. Column (1) only includes treat and post controls, column (2) adds industry by year-quarter fixed effects, firm size, and insurance type, column (3) adds gender, age, county, occupation, and work history going back four quarters, and column (4) adds injury characteristics. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

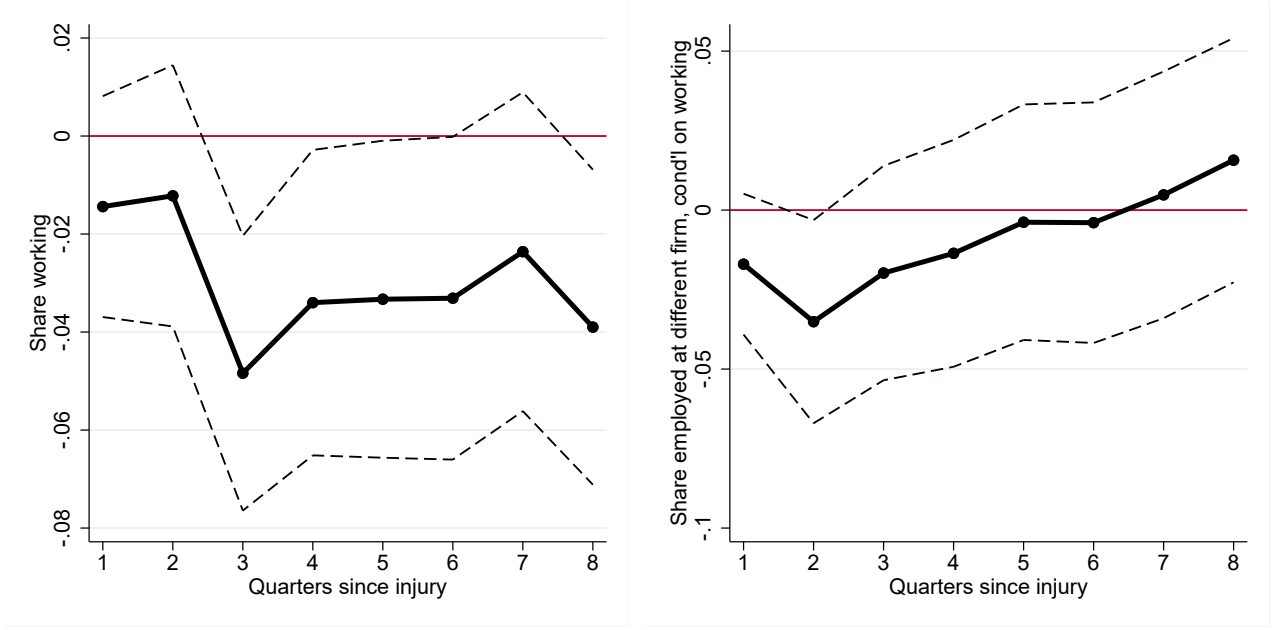
Turning to labor market outcomes, Figures 3 and 4 show the difference-in-difference estimates of the policy change on the probability of employment, the probability of working at a firm different from the firm of injury, conditional on working, log earnings conditional on working, and log wages conditional on working, separately for the first eight quarters following the quarter of injury (each coefficient represents a separate regression).[21]. By three quarters after injury, the difference-in-difference estimates in Figure 3 suggest that a decrease in wage subsidy from 50% to 45% induced a four percentage point decrease in the probability of working, which persists through at least eight quarters after injury. It is also notable that these effects only appear three quarters after injury, suggesting that measuring not only initial return-to-work outcomes but also longer run outcomes are crucial for understanding the effects of policy (as Butler et al. (1994) have discussed).

[19]Note that these standard errors do not take into account the error in the Lasso prediction that defines treatment status.

[20]Appendix Table 4 shows robustness to different prediction algorithms.

[21]See Appendix Tables 1-3 for the corresponding regression tables, Appendix Figure 2 for pre-trends, and Appendix Table 5 for alternative prediction algorithms.

Figure 3: Effect of EAIP policy change on employment outcomes



(a) Any employment in quarter

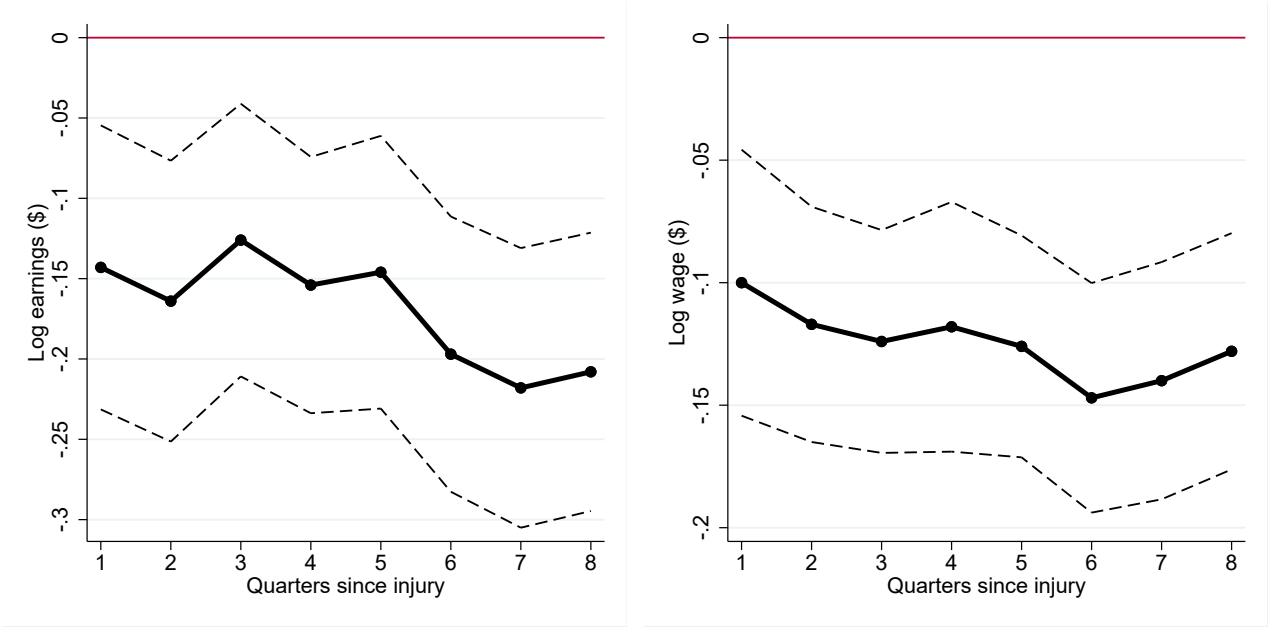
(b) Employment at different firm, cond.

Notes: Data provided by Oregon Department of Business and Consumer Services. Sample includes disabling claims in Oregon, 2005-2015. Dependent variable in (a) is whether the claimant is working in the quarter of interest (i.e., has positive quarterly earnings) and in (b) is whether the claimant is working in a new firm in the quarter of interest, conditional on working in that quarter. Solid dots denote the estimated coefficients on the interaction of treatment and post-period from regression equation (2) separately for each quarter since injury, and dashed lines report 95% confidence intervals. All regressions include the broad set of worker, firm, and injury controls.

While there are substantial effects of the policy on employment, Panel B of Figure 3 shows that there are no substantial changes in worker turnover conditional on working, with the possible exception of two quarters after injury. Thus our estimates suggest that the policy has sizeable impacts on employment overall, but not on retention or turnover to other firms; this finding has important implications for the mechanisms we model in the next section.

Finally, Figure 4 shows that the policy change had an immediate negative effect on earnings and wages conditional on working of around 15% per quarter, which persisted through at least eight quarters after injury. This suggests that the policy change had persistent effects not only on employment, but also on earnings and wages *conditional* on employment.

Figure 4: Effect of EAIP policy change on earnings and wage



(a) Log earnings, cond.

(b) Log wage, cond.

Notes: Data provided by Oregon Department of Business and Consumer Services. Sample includes disabling claims in Oregon, 2005-2015. Dependent variable in (a) is quarterly log earnings in the quarter of interest, conditional on working in that quarter and in (b) is quarterly log wage (earnings/hours) in the quarter of interest, conditional on working in that quarter. Solid dots denote the estimated coefficients on the interaction of treatment and post-period from regression equation (2) separately for each quarter since injury, and dashed lines report 95% confidence intervals. All regressions include the broad set of worker, firm, and injury controls.

In sum, our empirical analysis finds that a change in the EAIP wage subsidy to employers from 50% to 45% induced a substantial decrease in EAIP take-up among workers' compensation claims. Moreover, this decrease in EAIP take-up was also associated with a decrease in overall employment starting three quarters after injury and persisting at least two years and an immediate decrease in earnings even conditional on employment that persisted at least two

years. On the other hand, conditional on working, we found no differential outflow to new employers. We next turn to a model of workplace accommodation and labor market outcomes in order to understand the mechanisms behind these changes and conduct counterfactual policy experiments.

5 Dynamic Bargaining Model

To better understand the welfare impacts of EAIP and examine optimal policy, we develop and estimate a model of workplace injury and workers compensation that incorporates both employer decisions to accommodate and employee decisions to work.[22] The model has three key ingredients that capture the role of firm accommodation decisions in workers' compensation policy and labor market outcomes. First, the model incorporates the immediate costs and benefits of accommodation that accrue to the firm and worker: firms pay the direct cost of accommodation and may recoup some of that cost through increased worker productivity, and accommodated workers are able to work (with higher earnings than timeloss benefits) but incur a disutility of working while still injured. Second, the model incorporates longer run benefits of accommodation to account for our empirical finding that accommodation increases labor force attachment even after the worker has recovered from their injury. We operationalize this as a two stage model where the first period captures injury and accommodation decisions and the second period captures longer run labor market outcomes. Finally, the model incorporates labor market frictions and worker turnover to capture the risk to the firm that workers can leave the firm at any moment and thus the firm cannot necessarily recoup the cost of accommodation as future surplus. We next describe the model environment, the worker and firm value functions, and bargaining solution, and then return to a discussion of the model's key properties and assumptions.

5.1 The Environment

We consider a two period dynamic bargaining problem from time 0 to time T between a worker x and firm y that form a match $\mathbf{z} = (x, y)$ to produce output. Workers are heterogeneous in x to capture differences in skill and occupation, and firms are heterogeneous in y to capture differences in productivity and the type of workers' compensation contract they face.

Workers face risk of a workplace injury with probability p_j, where $j = 1, ..., N$ captures the severity of injury (i.e., more severe injuries are denoted by higher j), and $p_0 = 1 - \sum_{j=1}^{N} p_j$

[22] We restrict our attention to decisions taking the probability of injury as given, and abstract from decisions related to investment in workplace safety.

is the probability of no injury. The duration of injury is denoted by $d_j \in [0, T]$ where we assume that $d_j < d_{j'}$ for $j < j'$. Injured workers either receive timeloss benefits b from workers' compensation if they remain out of work for the duration of their injury, or return to work early if accommodated, where accommodation decisions ($a \in \{0, 1\}$) capture both transitionary work as well as physical workplace modifications.[23] Once recovered, workers spend their remaining time ($T - d_j$) working or unemployed.

We model four direct effects of working with accommodations. First, workers with accommodated injuries incur a disutility of work $\phi_{x,j}$ during the duration of injury (where the disutility of work for uninjured workers is normalized to zero).[24] Second, net output of workers with accommodated injuries ($f_{1,z,j,\xi}$) can differ from uninjured workers ($f_{1,z}$), due to both a difference in productivity as well as the financial cost of accommodation, which we model as a match-specific accommodation cost ξ with distribution Γ_j. Third, working with accommodation affects the probability of exogenously leaving the labor force after injury $q_{z,j,a}$. Finally, injury and accommodation can affect post-injury net output $f_{2,z,j,a}$ and wages $w_{2,z,j,a}$.

The timing of the model is as follows. First, workers and firms bargain ex-ante over the first period wage $w_{1,z}$ and accommodation decisions $a_{z,j}(\xi)$ for each possible injury j and accommodation cost ξ, prior to the injury realization j and accommodation cost ξ. Note that wages in the first period do not depend on injury j; this constraint is imposed to match the empirical context in which firms cannot legally pay lower wages to workers who experience disability and return to the same job. All workers who are accommodated and work receive wages $w_{1,z}$, and injured workers who do not work receive a timeloss benefit b_z from the workers' compensation program.[25]

After the duration of the injury (or straightaway for uninjured workers), each worker recovers and enters the second period of the model. The worker exits the labor market with probability $q_{z,j,a}$, and conditional on remaining in the labor market they either stay at the same firm or move to another firm with probability λ_z. Notably, injury and accommodation affects the probability of exiting the labor force, but not the probability of moving to a new firm, to match the empirical results in Section 4. If the worker remains with the same firm, the match produces output $f_{2,z,j,a}$ and the worker and firm bargain over the second period wage $w_{2,z,j,a}$, which depends on the match z, injury j, and the whether they were accommodated a (again, to match the empirical findings in Section 4 that accommodation affects wages conditional on

[23] Transitionary work includes reduced workloads to help injured workers slowly transition back to full time work as well as modified or different tasks to retrain injured workers.

[24] Implicitly we assume that injured workers without accommodations have infinite disutility of work, so in that sense accommodation mitigates the disutility of work while injured.

[25] Injured workers also incur medical expenditures, which we abstract from in the model but account for in the expenditure function.

working).

5.2 Worker and firm value functions

Workers derive utility from consumption (either wages or timeloss benefits) over the two periods and possible disutility from work when injured. Specifically, the worker's value function $V_z\left(w_{1,z}, \mathbf{a}_z\right)$ from match z given an employment contract defined by wage $w_{1,z}$ and a vector of state-contingent accommodation decisions $\mathbf{a}_z$ is given by:

$$V_z\left(w_{1,z}, \mathbf{a}_z\right) = p_0 V_{z,0} + \sum_{j=1}^{N} p_j \mathbb{E}_\xi \left[a_{z,j}\left(\xi\right) V_{z,j} + \left(1 - a_{z,j}\left(\xi\right)\right) \widetilde{V_{z,j}} \right] \tag{3}$$

where the first term in Equation (3) is the worker's value if uninjured, given by:

$$V_{z,0} = T\left(q_{z,0} u(c_u) + \left(1 - q_{z,0}\right)\left[\left(1 - \lambda_z\right) u(w_{1,z}) + \lambda_z u(w_{1,z,O})\right]\right) \tag{4}$$

where $d_0 = 0$ so they spend all of their time T in the second period.[26] With probability $q_{z,0}$, the worker becomes unemployed and receives an unemployment benefit c_u. If they remain employed, with probability $(1 - \lambda_z)$, they stay in the same firm and receive a wage of $w_{1,z}$, and with probability λ_z they exogenously move to another firm and receive an outside wage of $w_{1,z,O}$.

The terms within the summation of Equation (3) are the worker's values under injuries of different severity j for working ($V_{z,j}$) and not working ($\widetilde{V_{z,j}}$) during injury, given by:

$$V_{z,j} = d_j\left[u(w_{1,z}) - \phi_{x,j}\right] + \left(T - d_j\right)\left(\left(1 - q_{z,j,1}\right)\left(\left(1 - \lambda_z\right) u(w_{2,z,j,1}) + \lambda_z u(w_{2,z,j,1,O})\right) + q_{z,j,1} u(c_u)\right) \tag{5}$$

$$\widetilde{V_{z,j}} = d_j u(b_z) + \left(T - d_j\right)\left(\left(1 - q_{z,j,0}\right)\left(\left(1 - \lambda_z\right) u(w_{2,z,j,0}) + \lambda_z u(w_{2,z,j,0,O})\right) + q_{z,j,0} u(c_u)\right) \tag{6}$$

These values capture the weighted sum of the value during the injury period (first term) and the value in the post-injury period (second term). During the injury period, workers who work receive wage $w_{1,z}$ and incur a disutility of work $\phi_{x,j}$, while workers who decide not to work receive a timeloss benefit b_z. After the injury period, with probability $q_{z,j,a}$ the worker remains in the labor market, which depends on the accommodation choice a to capture our empirical finding that accommodation leads to higher long-run employment. Conditional on remaining employed, the worker stays with the current job with probability $(1 - \lambda_z)$ and receives a wage of $w_{2,j,z,a}$ and moves to a new employer with probability λ_z with wage $w_{2,z,j,a,O}$.

[26] Note, however, that their wage is $w_{1,z}$, which is the same wage that injured workers receive while accommodated.

Firms care about profits gained from the match over the two periods, which are equal to output net of wages and accommodation costs in each period. Specifically, a firm's value function J from match z with wage $w_{1,z}$ and accommodation decisions $\mathbf{a}_{z,j}(\xi)$ is given by:

$$J_z(w_{1,z}, \mathbf{a}_z) = p_0 J_{z,0} + \sum_{j=1}^{N} p_j \mathbb{E}_\xi \left[a_{z,j}(\xi) J_{z,j,\xi} + (1 - a_{z,j}(\xi)) \widetilde{J_{z,j}} \right] - P_{tot,z} \tag{7}$$

where the first term is firm profit if the worker is uninjured, given by:

$$J_{z,0} = T(1 - q_{z,0})(1 - \lambda_z)(f_{1,z} - w_{1,z}) \tag{8}$$

and the terms within the summation are profits under injuries of different severity j when the individual chooses to work while injured ($J_{z,j,\xi}$) or not work while injured ($\widetilde{J_{z,j}}$), given by:

$$J_{z,j,\xi} = d_j [f_{1,z,j,\xi} - (1 - \delta) w_{1,z}] + (T - d_j)(1 - q_{z,j,1})(1 - \lambda_z)(f_{2,z,j,1} - w_{2,z,j,1})$$
$$\widetilde{J_{z,j}} = (T - d_j)(1 - q_{z,j,0})(1 - \lambda_z)(f_{2,z,j,0} - w_{2,z,j,0})$$

where $f_{1,z,j,\xi}$ is output of the worker *net* of accommodation costs, which are paid during the injury period. In addition, δ denotes the wage subsidy provided by workers' compensation through the EAIP program if the firm accommodates the worker.

The final term in Equation (7) is the total premium paid for workers' compensation coverage, $P_{tot,z}$, defined as:

$$P_{tot,z} = \tau_y \sum_{j=1}^{N} p_j d_j \mathbb{E}_\xi [(1 - a_{z,j}(\xi)) b_z] + (1 - \tau_y) P_{z,b} + P_s \tag{9}$$

where τ_y is the firm-specific degree of experience rating for timeloss claim costs, $P_{z,b}$ is the average timeloss claim costs for non-self-insured firms, and P_s is the flat premium paid for wage subsidies. In estimation we distinguish between premium regimes for self-insured firms, for which the premium is fully experience-rated ($\tau_y = 1$), and non-self-insured firms, for which the premium is only partially experience-rated ($\tau_y < 1$).

5.3 Worker-firm bargaining problem and solution

Wages and accommodation choices are determined by Nash bargaining between the worker and firm in two stages: in the first stage, the first period wage and menu of accommodation decisions (by injury and accommodation cost realizations) are determined ex-ante (i.e., prior to the injury), and in the second stage post-injury wages are determined at the beginning of

the post-injury period. The outside option to the firm is zero and the worker's (exogenous) outside options are defined by $U_{2,x,j,a} = (1 - \lambda_{2,x,j,u})\, u(c_u) + \lambda_{2,x,j,u} u(w_{2,x,j,a,O)})$ in the post-injury period and ex-ante value $U_{1,x} = T\left(\lambda_{1,x,u} u(c_u) + (1 - \lambda_{1,x,u})\, u(w_{1,x,O})\right)$, both a weighted average of the value of unemployment and the value of finding a job with outside wage $w_{2,x,j,a,O}$ or $w_{1,x,O}$, respectively. Accommodation decisions are made contingent on injury severity j and the accommodation-specific cost ξ, i.e., $a_{z,j}(\xi)$. While wages in the injury period cannot differ by injury (by law), we allow post-injury wages to depend on all worker characteristics to capture effects such as promotions or hours changes.

We can solve this problem by backward induction. First, the post-injury wage for each injury severity j and accommodation decision a is determined by Nash bargaining at the beginning of the second period:

$$\max_{w_{2,z,j,a}} \left(u(w_{2,z,j,a}) - U_{2,x,j,a})\right)^{\beta} \left(f_{2,z,j,a} - w_{2,z,j,a}\right)^{1-\beta} \;\; \forall\; j, z, a \tag{10}$$

The first order conditions then define implicit solutions for post-injury wages for all z, j, a:

$$\beta u'(w_{2,z,j,a}) \left(f_{2,z,j,a} - w_{2,z,j,a}\right) - (1 - \beta) \left(u(w_{2,z,j,a}) - U_{2,x,j,a})\right) = 0 \tag{11}$$

Second, the accommodation choices and initial wage are determined by Nash bargaining at the beginning of the first period (prior to the realization of injury):

$$\max_{w_{1,z}, \mathbf{a}_z} \left(V_z(w_{1,z}, \mathbf{a}) - U_{1,x}\right)^{\beta} J_z(w_{1,z}, \mathbf{a})^{1-\beta} \tag{12}$$

To solve for accommodation choices, we posit that there are thresholds $\xi^*_{z,j}$ such that $a_j = 1$ for all $\xi_{z,j} < \xi^*_{z,j}$ and $a_j = 0$ otherwise. We solve for these thresholds and initial wage by solving first order conditions with respect to the initial wage and thresholds; see Appendix A for details.

5.4 Discussion

5.4.1 Mechanisms Behind Accommodation Decisions

Three key considerations determine the accommodation decision in our model: a static consideration, a dynamic consideration, and a fiscal externality consideration. First, there is a static trade-off during the injury period for both firms and workers. Firms pay the direct cost of accommodation ξ; whether accommodation is profitable thus depends on this direct cost, the productivity of the worker, and the wage cost. The static benefit of accommodation to

workers is higher wage compensation relative to timeloss benefits, but at the cost of disutility from working while injured. Therefore the relative static costs and benefits during the injury period can influence accommodation decisions.

Second, accommodation entails dynamic gains in the form of higher probability of employment and higher productivity in the second period for accommodated workers relative to unaccommodated workers (i.e., $q_{z,j,1} > q_{z,j,0}$ and $w_{2,z,j,1} > w_{2,z,j,0}$). An important feature of the employment channel is that these gains accrue to the worker regardless of whether they switch employers, and thus this channel has direct parallels to training decisions as in Becker (1962), Becker (1964), and Acemoglu and Pischke (1999). In a similar spirit to Acemoglu and Pischke (1999), if there is no static gain to accommodation and the labor market is frictionless, then firms have no incentive to accommodate because they cannot recoup the cost of accommodation. On the other hand, in a frictional labor market such as the bilateral monopoly we model, firms may have an incentive to accommodate injured workers even in the absence of static gains to accommodation because they can extract some of the surplus from accommodation. However, they may still under-accommodate workers (relative to the social optimum) due to the possibility that the worker may move to a new employer in the post-injury period. Therefore the economic environment in which dynamic gains take place is also an important factor in accommodation decisions.

Finally, the financing of workers' compensation benefits can also impact accommodation decisions through the impact of accommodation decisions on workers' compensation premiums, P_z. Accommodation can lower workers' compensation claim costs by decreasing the extent to which timeloss benefits are paid. For self-insured (or fully experience-rated) firms, these savings accrue directly to the firm, while partially experience-rated firms do not accrue the full savings of their actions. Firms that are not fully experience-rated thus have an incentive to under-accommodate as a result of this fiscal externality (similar to the static moral hazard channel in the context of Bailey-Chetty). This suggests that the efficiency of accommodation decisions may differ depending on the insurance contract that a firm faces.

5.4.2 Modeling Assumptions

We make a few important assumptions to make the analysis tractable. First, we assume that both the probability of injury and the duration of injury are exogenous. While we could in principle relax these assumptions by modeling effort as a function of future payoffs to avoiding or shortening injuries, we believe that these extensions are unlikely to change our main insights. In addition, Appendix Figure 3 shows that the number of claims did not respond to the wage subsidy policy change, and evidence from other contexts show that the number of claims also

does not respond to changes in the generosity of timeloss benefits (Cabral and Dillender, 2020). Thus, moral hazard on the margin of claiming is unlikely to be first-order in our policy environment. In addition, the duration of the majority of accommodated claims are a couple months long, so it is unlikely that moral hazard would have a large impact on the duration margin either.

Second, we assume that there is no heterogeneity in the duration of injury conditional on the realization of specific injury shock j. One can instead formulate that λ_j is the expected duration of injury from an ex-ante perspective, and we can consider that the realized claim duration in the data is drawn from the distribution of random injury outcomes. Such an extension does not change the essential feature of the model.[27]

6 Estimation

We estimate the model primarily using Oregon administrative workers' compensation claims data linked to longitudinal quarterly earnings records. Our sample is the same as in Section 3: closed disabling claims that originated between 2005-2015. We supplement this with publicly available data on overall rates of injury in Oregon during our sample period. We first estimate several parameters outside the model, and then structurally estimate the remaining parameters within the model using a combination of first-order conditions and indirect inference. For this version of the paper, our estimation assumes a binary injury state and four types of worker-firm pairs: two types of workers (high wage and low wage, where we define high and low wage as above and below the median wage in the quarter prior to injury) and two types of firms (self-insured and not self-insured).

6.1 Parameters Estimated Outside the Model

We estimate several parameters outside the model, summarized in Table 4. We set $p_j = 0.01$ to match the fact that 1% of workers file a disabling claim in Oregon annually.[28] We set the duration of injury to equal the mean claim duration for injury type j in our claims data, which is 60 days. We set the probability of unemployment in the post-injury period ($q_{z,0}$ and $q_{z,j,a}$), the job-to-job transition rate (λ_0 and $\lambda_{j,z}$), and the job-finding rate from unemployment ($\lambda_{u,z}$) using employment outcomes from the quarterly earnings records.[29] We also set the ex-ante

[27] Alternatively, one can formulate the model in the infinite-horizon continuous time with the hazard rate λ_j. Such an extension involves more complications without providing much newer insights.

[28] In future iterations with heterogeneous injury severity we will calibrate p_j by multiplying 1% with the proportion claims of injury type j in our claims data.

[29] We calibrate the job-finding rate from unemployment using job transitions prior to injury.

and post-injury outside wages ($w_{1,x,O}$ and $w_{2,x,j,a,O}$) to the mean earnings in a new job in the quarterly earnings data, and set the unemployment benefit (c_u) to 40% of the outside wage. We set the worker bargaining power parameter to $\beta = 0.5$, which is in the range of estimates in the labor search literature, and set the utility function to log utility.[30]

Table 4: Parameters estimated outside the model

Parameter	Description	Value
p_j	Probability of injury	1%
d_j	Duration of injury	60 days
$q_{z,j,0}$	Unemployment probability, post-injury, unacc.	0.30, 0.23, 0.12, 0.06
$q_{z,j,1}$	Unemployment probability, post-injury, acc.	0.15, 0.11, 0.05, 0.03
$q_{z,0}$	Unemployment probability, uninjured	0.10, 0.08, 0.01, 0.01
$\lambda_{j,z}$	Job-to-job transition rates, post-injury	0.22, 0.14, 0.07, 0.03
λ_0	Job-to-job transition rates, uninjured	0.06, 0.08, 0.14, 0.17
$\lambda_{u,z}$	Job-finding rate of unemployed	0.36, 0.35, 0.72, 0.66
$w_{1,x,O}$	Outside wage, first period	mean earning in a new job
$w_{2,x,j,a,O}$	Outside wage, second period	mean earning in a new job
c_u	Consumption during unemployment	40% replacement rate
β	Worker bargaining power	0.5
$u(c)$	Utility function	$\log(c)$
b	Timeloss cash benefit (replacement rate)	0.63
δ	Wage subsidy rate	0.5
$P_{b,z}$	Average claim cost	Public WC data
$P_{s,z}$	Premium to fund wage subsidies	Public WC data

Note: Rows with four values denote types of worker-firm matches: (1) Low skilled worker at a not-self-insured firm, (2) low skilled worker at a self-insured firm, (3) high skilled worker at a not-self-insured firm, and (4) high skilled worker at a self-insured firm.

Finally, we set the workers' compensation parameters to reflect Oregon's program during our sample period. Specifically, we set the replacement rate for the timeloss benefit to 63% of wages and the wage subsidy rate to 50%.

6.2 Structural Estimation: Identification and Estimation Procedure

For parameters structurally estimated within the model, our estimation proceeds in two steps. In the first step, we estimate the post-injury output parameters $f_{2,z,j,a}$ by solving the Nash bargaining solution in Equation (11), using the parameters in Table 4 and setting second period wages equal to the average earnings one year after injury. In the second step, we estimate

[30]For example, Flinn (2006) estimates that worker's bargaining power is about 0.4.

the remaining parameters by indirect inference, including parameters related to productivity during the injury period and the disutility of working while injured. We impose a functional form assumption on the net output for injured workers that $f_{1,z,j,\xi} = f_{1,z,j} + \xi$ where $f_{1,z,j}$ is the mean injury-match specific net output and ξ is random variable that follows a log-normal distribution with mean zero and standard deviation $\sigma_{\xi,y}$. Thus, the remaining parameters include $f_{1,z,0}, f_{1,z,j}, \sigma_{\xi,y}$, and $\phi_{x,j}$.

We use moments related to earnings and accommodation rates to help identify these parameters. A key identification challenge is that net output, the standard deviation of accommodation cost shocks, and worker disutility during the injury period all affect accommodation decisions. To separately identify net output from the disutility of work, we leverage the quasi-experimental estimates from Section 4 as well as accommodation rates by worker-firm type. First, a higher disutility of work should generate lower accommodation rates, so we use average accommodation rates by worker type to identify the disutility of work by worker type (low and high skill). Second, higher dispersion of firm accommodation costs should generate lower responsiveness of accommodation to a change in the wage subsidy, so we use the regression coefficient of the effect of the wage subsidy change on accommodation to identify the standard deviation of the cost shock by firm type.[31] Third, conditional on these parameters, the difference in accommodation rates by firm type within each worker type identifies the average net output for injured workers, given our functional form assumption of $f_{1,z,j} = \alpha \mathbb{1}_{\text{High}} + \beta \mathbb{1}_{\text{SI}}$. Finally, we identify net output for uninjured workers and recovered workers using their respective wages.[32]

6.3 Estimation Results

Tables 5 and 6 report the structurally estimated parameters and model fit, respectively, for each worker-firm type, where column (1) is low-skilled workers in non-self-insured firms, column (2) is low-skilled workers in self-insured firms, column (3) is high skilled workers in non-self-insured firms, and column (4) is high skilled workers in self-insured firms. The model is able to reproduce the main features of wage and accommodation patterns in the data, and there are a few noteworthy features of the estimates. First, net output during injury is significantly lower than net output for uninjured workers. This is may be a result of lower productivity of accommodated workers and/or high accommodation costs. Second, the distribution of accommodation cost shocks is very disperse, suggesting firms vary substantially in how costly it is to accommodate injured workers. This distribution is more disperse for self-insured firms, which helps explain the

[31] A more disperse distribution means that there is less mass in the range of accommodation cost shocks affected by the wage subsidy change.

[32] Note that we cannot use wages to identify net output of injured workers because they are constrained to be equal to wages of uninjured workers.

Table 5: Parameters estimated within the model

Param.	Description	Estimate			
		Low, NSI	Low, SI	High, NSI	High, SI
$f_{1,z,0}$	Net output, not injured	6.46	7.26	15.16	18.61
$f_{1,z,j}$	Net output (mean), injured ($= \alpha \mathbb{1}_{\text{High}} + \beta \mathbb{1}_{\text{SI}}$)	0	-0.29	-1.09	-1.38
$f_{2,z,j,1}$	Net output, recovered and acc.	7.39	7.52	12.56	15.42
$f_{2,z,j,0}$	Net output, recovered and not acc.	6.89	7.02	12.56	15.42
ϕ_x	Disutility of work	1.77	1.77	0.60	0.60
$\sigma_{\xi,y}$	SD of accommodation cost shock	5.16	11.15	5.16	11.15

Note: Output is quarterly and is expressed in units of $1,000. Columns denote types of worker-firm matches: (1) Low skilled worker at a not-self-insured firm, (2) low skilled worker at a self-insured firm, (3) high skilled worker at a not-self-insured firm, and (4) high skilled worker at a self-insured firm. Disutility of work parameters are estimated by worker type only, net output for recovered high skilled workers are not distinguished by accommodation, the standard deviation of the accommodation cost shock is estimated by firm type only, and net output for injured workers is parameterized as $\alpha \mathbb{1}_{\text{High}} + \beta \mathbb{1}_{\text{SI}}$.

lower responsiveness of accommodation to a change in the wage subsidy (as captured through the targeted regression coefficient).[33] Finally, low-skilled workers generate lower net output and have a higher disutility of work during injury than high-skilled workers, suggesting that on average it is less costly (to both firms and workers) to accommodate high-skilled workers. One possible reason is that it is more difficult for firms to provide alternative work arrangement for the low-skilled workers, making it very difficult for the low-skilled to adjust a new work environment during the injury.[34]

6.4 Mechanisms

We next use the estimated model to conduct comparative statics that shed light on key mechanisms that may affect the decision to accommodate. We focus on (i) the role of worker turnover, (ii) the role of experience rating, and (iii) the role of the utility cost of work while injured.

Table 7 reports the findings. The second row reports the effect of reducing the job-to-job transition rate to one quarter of its estimated value: $\tilde{\lambda}_z = 0.25\lambda_z$. As discussed in Section 5.4, worker turnover could generate under-provision of accommodation if firms cannot capture the surplus from future productivity gains brought about by accommodation, but it does not necessarily lead to under-provision if, for example, the static gains to accommodation are high

[33] A more disperse distribution means that there is less mass in the range of accommodation cost shocks affected by the wage subsidy change.

[34] Although it is beyond the scope of this paper, one interesting possibility is that firms may design the alternative arrangement to make it more costly for the low skilled to retain the current job. See Aizawa et al. (2020) for exploring such a mechanism in the labor market of disabled workers.

Table 6: Within-Sample Fit of Targeted Moments

	Type			
Moment	Low, NSI	Low, SI	High, NSI	High, SI
Accommodation (EAIP use, %)				
Data	19.88	36.28	27.67	46.62
Model	18.78	35.31	27.38	50.45
Wages, non-injured				
Data	4.48	4.61	11.13	12.91
Model	4.24	4.53	11.48	13.29
Wages, recovered and accommodated				
Data	4.54	4.58	9.96	11.74
Model	4.54	4.58	9.96	11.74
Wages, recovered and not accommodated				
Data	4.35	4.58	9.96	11.74
Model	4.35	4.58	9.96	11.74
	NSI		SI	
Regression coefficient of policy effect on EAIP				
Data	-0.04		0.00	
Model	-0.04		-0.02	

Note: Wages are quarterly and are expressed in units of $1,000. The regression coefficient of the policy effect on EAIP comes from Equation (1). Columns denote types of worker-firm matches: (1) Low skilled worker at a not-self-insured firm, (2) low skilled worker at a self-insured firm, (3) high skilled worker at a not-self-insured firm, and (4) high skilled worker at a self-insured firm.

enough. The simulations show, however, that lower turnover leads to higher accommodation rates for all worker-firm types. This suggests that accommodation is inefficiently low in labor markets with turnover. The simulations also show significant differences by type in the magnitude of the effect of turnover on accommodation. While some of this reflects differences in benchmark worker turnover rates, one important pattern is that the accommodation rate in non-self-insured firms is much more sensitive to the rate of worker turnover than the accommodation rate in self-insured firms, conditional on the worker's skill level. This difference mainly arises because self-insured firms have a greater incentive to accommodate injured workers to reduce their workers' compensation costs, even if the injured workers leave the firms later. In contrast, this incentive is weaker for non-self-insured firms because they are only partially experience rated. Thus, the dynamic inefficiency highlighted in this counterfactual is more stark for non-self-insured firms.

Table 7: Comparative Statics of Accommodation Decisions

	Accommodation Rate, by Type			
Model	Low, NSI	Low, SI	High, NSI	High, SI
Benchmark	18.78	35.31	27.38	50.45
$\tilde{\lambda}_z = 0.25\lambda_z$	37.25	46.27	31.89	50.96
All firms are self-insured	49.65	35.31	59.62	50.45
$\tilde{\phi}_{low} = \phi_{high}$	63.40	55.74	27.38	50.45

Note: Table shows accommodation rates from our benchmark model and from modifying the exogenous worker turnover rate λ_z to 25% of its estimated value. Columns denote types of worker-firm matches: (1) Low skilled worker at a not-self-insured firm, (2) low skilled worker at a self-insured firm, (3) high skilled worker at a not-self-insured firm, and (4) high skilled worker at a self-insured firm. The estimated values for each type (in order of how they appear in the columns) are reported in Table 4.

The third row reports the effect of experience rating on accommodation by forcing non-self-insured firms–which are only partially experience rated–to be self-insured (i.e., perfectly experience rated). As also discussed in Section 5.4, full experience rating makes firms more financially accountable for the costs they generate for the workers' compensation system, which encourages them to provide efficient levels of accommodation. The simulation results confirm this fiscal externality: fully experience-rating all firms (i.e., through self-insurance) increases accommodation rates substantially.

The final row reports the effect of the utility cost of work while injured by decreasing the disutility of work for low- skilled workers to be equal to the disutility of work for high-skilled workers (i.e., from 1.77 to 0.60). If workers have a very high disutility of work, then it may not be optimal to accommodate workers, even with low turnover, perfect experience rating,

and generous wage subsidies. The results show a substantial increase in accommodation among low-skilled workers.

In sum, we find that all three factors – worker turnover, experience rating, and the disutility of work – play an important role in explaining accommodation rates. We next turn to counterfactual policy experiments to explore the role of workers' compensation policy in influencing accommodation.

7 Counterfactual Workers' Compensation Policies

Using the estimated model, we conduct counterfactual experiments to quantitatively explore the optimal design of accommodation subsidies within the workers' compensation program. For each experiment, we impose budget neutrality for the workers' compensation system. Because claim costs are likely to differ in response to these experiments, budget neutrality requires solving for the equilibrium premia for workers' compensation. We first discuss the equilibrium of the insurance market, and then present counterfactual wage subsidies.

7.1 Equilibrium of the Workers' Compensation Insurance Market

In each of the counterfactual experiments, we impose budget neutrality for the workers' compensation system. Since changes in accommodation rates change the fraction of claims that use timeloss benefits, the counterfactual experiments are likely to generate changes in claim costs. In order to maintain budget neutrality, insurance premiums must also change, and thus we need to solve the insurance market equilibrium. As summarized in Equation (9), the premium for a non-self-insured firm is a weighted average of claim costs generated by the firm's worker and market-level claim costs t_{wb}. Both of these components might change in response to a change in the firm's and market's incentives to accommodate.

We solve for the equilibrium premium for each type ($P_{b,z}$) that satisfies the break even condition in the insurance market, i.e.,

$$\int (1-\tau_y)\, P_{b,z} dF_z(z|NSI) = \int (1-\tau_y) \sum_{j=1}^{N} p_j d_j \mathbb{E}_\xi \left[\left(1 - a_{j,z}\left(\xi\right)\right) b_z \right] dF_z(z|NSI) \tag{13}$$

where NSI is an indicator for non-self-insured firms. We then characterize the optimal combination of wage subsidies and worker compensation benefit, resolving this equilibrium for each

candidate policy.[35]

7.2 Optimal Wage Subsidies

In our experiment, we consider budget-neutral changes to the wage subsidy rate δ, holding timeloss benefits b constant.[36] This counterfactual is motivated by the possibility that firms under-accommodate injured workers, and thus the results will show the quantitative extent of under-accommodation, the welfare loss of such under-accommodation, and the effectiveness of wage subsidies as a tool to encourage efficient accommodation.

Figure 5: Worker Welfare Effects of Alternate Wage Subsidies



Note: Figures report ex-ante (left figure) and ex-post of injury (right figure) worker welfare for alternative wage subsidy rates relative to the benchmark model of $\delta = 0.5$. Low and High denote worker skill type and NSI and SI denote not-self-insured and self-insured firm type.

Figure 5 shows the impact of the wage subsidy on worker welfare ex-ante (left graph) and ex-post of injury (right graph) relative to the benchmark wage subsidy of 0.5. We measure welfare

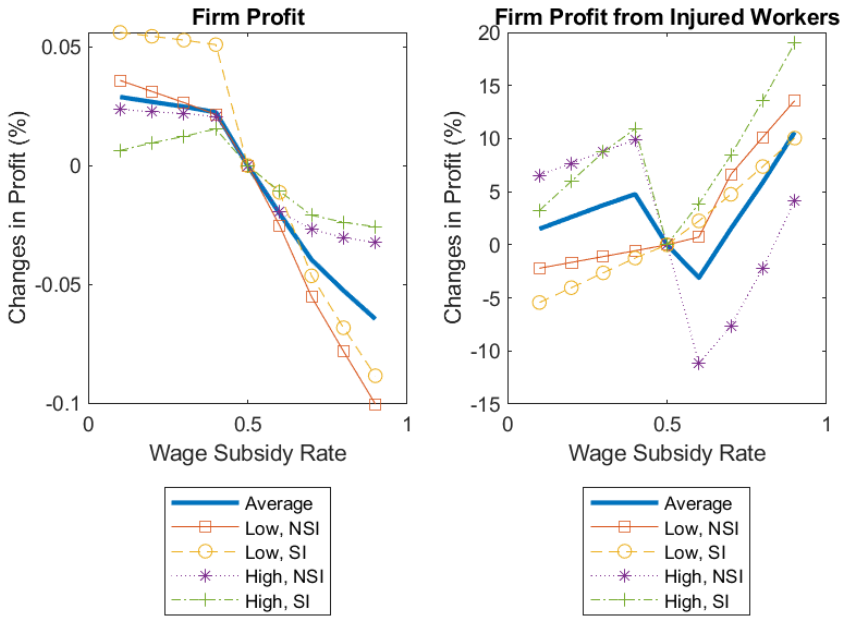
[35]Note that we assume that z is fixed for workers and firms, so they cannot change their insurance status in response to policy changes. We believe this is a reasonable assumption because there is very little variation in insurance status over time, perhaps in part because it is highly correlated with firm characteristics like firm size.

[36]Like timeloss benefits, we have to solve for the equilibrium $P_{s,z}$, but unlike timeloss benefits, wage subsidies are financed via a flat tax to employers so we simply solve for the change in $P_{s,z}$ for all firms to satisfy budget neutrality.

as the percent change in consumption in all states and periods of the counterfactual environment to be indifferent between the counterfactual wage subsidy and the benchmark wage subsidy. The thick blue lines report average welfare and the four thin lines report welfare by type z. Average ex-ante welfare is maximized at a 40% wage subsidy, though the magnitudes do not change substantially across wage subsidy rates. In contrast, there is significant heterogeneity across types, where high skilled workers and workers in non-self-insured firms prefer higher subsidies while low skilled workers and workers in self-insured firms prefer lower subsidies. There is very little change in ex-ante welfare and profit when the wage subsidy increases or decreases, likely because there is only a 1% chance of injury. However, conditional on being injured, worker welfare is maximized at a wage subsidy of 60% with a 0.2% welfare gain.

Figure 6 shows an analogous figure for firm profits under various wage subsidies. In general, higher wage subsidy rates *decrease* firm profits. The optimal wage subsidy thus weighs the opposing effects on workers and firms.

Figure 6: Firm Profit Effects of Alternate Wage Subsidies



Note: Figures report ex-ante (left figure) and ex-post of injury (right figure) firm profits for alternative wage subsidy rates relative to the benchmark model of $\delta = 0.5$. Low and High denote worker skill type and NSI and SI denote not-self-insured and self-insured firm type.

One implication from these findings is that optimal wage subsidies vary with worker characteristics. Because disutility of work during injury differs so much by skill, it may be more

desirable to set a low wage subsidy for low-skilled individuals and a higher subsidy for high-skilled individuals. Similarly, to correct fiscal externalities, it may be desirable to have higher subsidies for workers in non-self-insured firms.

8 Conclusion

In this paper, we examine the role of employer accommodations in return-to-work outcomes for workers who experience temporary disability shocks in the context of workers' compensation programs. We first leverage quasi-experimental variation and detailed administrative data on disabling claims from workplace injuries linked to quarterly earnings records in the state of Oregon to estimate the effect of firm investment incentives on accommodation and employment outcomes for injured workers. We show that accommodation is responsive to the wage subsidy incentives through the workers' compensation program, and that accommodation has positive effects on long-term labor market outcomes, including employment and earnings. We then develop and estimate a dynamic bargaining model between workers and firms. We use the model to first highlight that labor market frictions and worker turnover lead to firm under-accommodation and inefficient labor market outcomes after workplace injury, and then use the estimated model to quantitatively explore the optimal design of firm accommodation subsidies. Our finding suggests that a wage subsidy of 40% maximizes overall worker welfare, with higher welfare gains for workers with low disutility of work during injury in labor markets with inefficiently low accommodation rates.

This paper is an important first step to understanding the role of employers in returning to work after disability and in the design of social insurance programs to protect individuals after disability and work-related injury. Although our data and empirical application are specific to the workers' compensation context, we believe our analysis opens the door to further work on employer accommodation incentives in disability programs more broadly. An important insight from our analysis is that employer financial incentives are a key factor in encouraging accommodation; if employers do not have the proper incentives (e.g., workers' compensation is imperfectly experience rated, in our context), accommodation rates may suffer. A second broad insight is that while accommodation may be optimal for some workers, it can be too costly for other workers whose disabilities do not allow for safe or cost-effective accommodation. Future research is needed to explore these insights within other disability contexts.

References

Acemoglu, D. and J. D. Angrist (2001). Consequences of employment protection? the case of the Americans with Disability Act. *Journal of Political Economy 109*(5), 915–957.

Acemoglu, D. and J.-S. Pischke (1999). The structure of wages and investment in general training. *Journal of political economy 107*(3), 539–572.

Aizawa, N. and H. Fang (2020). Equilibrium labor market search and health insurance reform. *Journal of Political Economy 128*(11), 4258–4336.

Aizawa, N., S. Kim, and S. Rhee (2020). Labor market screening and social insurance program design for the disabled. Technical report, National Bureau of Economic Research.

Autor, D. H. and M. G. Duggan (2010). Supporting work: A proposal for modernizing the u.s. disability insurance system. *Center for American Progress and the Hamilton Project*.

Balke, N. and T. Lamadon (2020). Productivity shocks, long-term contracts and earnings dynamics. Technical report, National Bureau of Economic Research.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of political economy 70*(5, Part 2), 9–49.

Becker, G. S. (1964). *Human Capital*. The University of Chicago Press.

Black, S. E., J. T. Denning, and J. Rothstein (2020). Winners and losers? the effect of gaining and losing access to selective colleges on education and labor market outcomes. Technical report, National Bureau of Economic Research.

Bronchetti, E. T. (2012). Workers' compensation and consumption smoothing. *Journal of Public Economics 96*(5-6), 495–508.

Bronchetti, E. T. and M. P. McInerney (2015). What determines employer accommodation of injured workers? the influence of workers' compensation costs, state policies, and case characteristics. *ILR Review 68*(3), 558–583.

Bureau of Labor Statistics (2020). Local area unemployment statistics.

Burkhauser, R. V., J. Butler, and Y. W. Kim (1995). The importance of employer accommodation on the job duration of workers with disabilities: A hazard model approach. *Labour Economics 2*(2), 109–130.

Burkhauser, R. V. and M. Daly (2011). *The declining work and welfare of people with disabilities: What went wrong and a strategy for change*. AEI Press.

Butler, R. J., W. G. Johnson, and M. L. Baldwin (1994). Managing work disability: Why first return to work is not a measure of success. *Indus. & Lab. Rel. Rev. 48*, 452.

Cabral, M. and M. Dillender (2020). The impact of benefit generosity on workers' compensation claims: Evidence and implications. Technical report, National Bureau of Economic Research.

Currie, J. and B. Madrian (1999). Health, health insurance and the labor market. *Handbook of labor economics 3*, 3309–3416.

De Groot, N. and P. Koning (2016). Assessing the effects of disability insurance experience rating. the case of the netherlands. *Labour Economics 41*, 304–317.

Elvery, J., C. L. Reynolds, and S. M. Rohlin (2021). Employer wage subsidy caps and part-time work.

Fang, H. and A. Gavazza (2011). Dynamic inefficiencies in an employment-based health insurance system: Theory and evidence. *American Economic Review 101*(7), 3047–77.

Federal Reserve Bank of St. Louis (2020). Fred economic data: Unemployment rate.

Flinn, C. J. (2006). Minimum wage effects on labor market outcomes under search, matching, and endogenous contact rates. *Econometrica 74*(4), 1013–1062.

French, E. and J. Song (2014, May). The effect of disability insurance receipt on labor supply. *American Economic Journal: Economic Policy 6*(2), 291–337.

Gelber, A., T. J. Moore, and A. Strand (2017). The effect of disability insurance payments on beneficiaries' earnings. *American Economic Journal: Economic Policy 9*(3), 229–61.

Giupponi, G. and C. Landais (2018). Subsidizing labor hoarding in recessions: The employment & welfare effects of short time work.

Hansen, B., T. Nguyen, and G. R. Waddell (2017). Benefit generosity and injury duration: Quasi-experimental evidence from regression kinks.

Hawkins, A. and S. Simola (2020). Paying for disability insurance?: Firm cost sharing and its employment consequences. *Opublicerat manuskript https://www. dropbox. com/s/ksgkjkumdtz6ux0/ahss_disability_paper. pdf*.

Hill, M., N. Maestas, and K. J. Mullen (2016, August). Employer accommodation and labor supply of disabled workers. *Labour Economics 41*, 291–303.

Kostøl, A. R. and M. Mogstad (2014, February). How financial incentives induce disability insurance recipients to return to work. *American Economic Review 104*(2), 624–55.

Krueger, A. B. (1990). Workers' compensation insurance and the duration of workplace injuries. Technical report, National Bureau of Economic Research.

Layton, T. J., H. Liebert, N. Maestas, D. Prinz, and B. Vabson (2019). Predicting disability enrollment using machine learning.

Maestas, N., K. J. Mullen, and S. Rennane (2019). Unmet need for workplace accommodation. *Journal of Policy Analysis and Management 38*(4), 1004–1027.

Maestas, N., K. J. Mullen, and A. Strand (2013). Does disability insurance receipt discourage work? using examiner assignment to estimate causal effects of SSDI receipt. *American Economic Review 103*(5), 1797–1829.

Mas, A. and A. Pallais (2020). Alternative work arrangements. *Annual Review of Economics 12*, 631–658.

Meyer, B. D., W. K. Viscusi, and D. L. Durbin (1995). Workers' compensation and injury duration: evidence from a natural experiment. *The American economic review*, 322–340.

Mullen, K. J. and S. Rennane (2017). The effect of unconditional cash transfers on the return to work of permanently disabled workers. Technical report, National Bureau of Economic Research.

Murphy, G., J. Patel, E. Weiss, and L. I. Boden (2020). Workers' compensation: Benefits, costs, and coverage (2018 data). *National Academy of Social Insurance*.

Neuhauser, F. and S. Raphael (2004). The effect of an increase in worker's compensation benefits on the duration and frequency of benefit receipt. *Review of Economics and Statistics 86*(1), 288–302.

Office of the Chief Actuary (2020). The 2020 oasdi trustees report. Technical report, Social Security Administration, Baltimore MD.

O'Leary, P., G. A. Livermore, and D. C. Stapleton (2011). Employment of individuals in the social security disability programs. *Soc. Sec. Bull. 71*, 1.

Oregon Department of Consumer and Business Services (2020). Employer at injury program (eaip).

Prinz, D. and B. Ravesteijn (2020). Employer responsibility in disability insurance: Evidence from the netherlands.

Rennane, S. (2018). Buying time: The insurance value and distortionary effects of workers' compensation. *RAND Working Paper WR-1220*.

Reville, R. T. and R. F. Schoeni (2004). The fraction of disability caused at work. *SOCIAL SECURITY BULLETIN-WASHINGTON- 65*(4), 31.

SAIF (2020). Employer at injury program: Fast facts.

Thomas, J. and T. Worrall (1988). Self-enforcing wage contracts. *The Review of Economic Studies 55*(4), 541–554.

Appendix

A Worker-Firm Bargaining Solution Details

In this appendix we provide more details on the solution to the first stage bargaining problem in which accommodation decisions and the initial wage are determined:

$$\max_{w_{1,z},\mathbf{a}_z} \left(V_z(w_{1,z},\mathbf{a}) - U_{1,x}\right)^{\beta} J_z(w_{1,z},\mathbf{a})^{1-\beta} \tag{14}$$

To solve for accommodation choices, we posit that there are thresholds $\xi^*_{z,j}$ such that $a_j = 1$ for all $\xi_{z,j} < \xi^*_{z,j}$ and $a_j = 0$ otherwise. Given this threshold rule, we can re-express worker and firm value functions as

$$\overline{V}_z(w_{1,z},\boldsymbol{\xi}^*_{\mathbf{z}}) = V_z(w_{1,z},\mathbf{a}_z) = p_0 V_{z,0} + \sum_{j=1}^{N} p_j \left[\Gamma\left(\xi^*_{z,j}\right) V_{z,j} + \left(1-\Gamma\left(\xi^*_{z,j}\right)\right)\widetilde{V_{z,j}}\right] \tag{15}$$

and

$$\overline{J}_z(w_{1,z},\boldsymbol{\xi}^*_{\mathbf{z}}) = J_z(w_{1,z},\mathbf{a}_z) = p_0 J_{z,0} + \sum_{j=1}^{N} p_j \left[\Gamma\left(\xi^*_{z,j}\right) \bar{J}_{z,j}\left(\xi^*_{z,j}\right) + \left(1-\Gamma\left(\xi^*_{z,j}\right)\right)\widetilde{J_{z,j}}\right] - P_{tot,z} \tag{16}$$

where the value $\bar{J}_{z,j}$ is the conditional expectation of firm's profit of accommodating the injured,

$$\bar{J}_{z,j}\left(\xi^*_{z,j}\right) = d_j\left[\mathbb{E}_{\xi}\left[f_{1,z,j,\xi}|\xi < \xi^*_{z,j}\right] - (1-\delta)\, w_{1,z}\right] + (T-d_j)\,(1-q_{z,j,1})\,(1-\lambda_z)\,(f_{2,z,j,a} - w_{2,z,j,a}) \tag{17}$$

With this representation, the bargaining solution in the first stage is determined by:

$$\max_{w_{1,z},\boldsymbol{\xi}^*_{\mathbf{z}}} \left(\overline{V}_z(w_{1,z},\boldsymbol{\xi}^*_{\boldsymbol{z}}) - U_{1,x}\right)^{\beta} \overline{J}_z(w_{1,z},\boldsymbol{\xi}^*_{\boldsymbol{z}})^{1-\beta} \tag{18}$$

The first order condition with respect to the first period wage is:

$$\beta \overline{J}_z(w_{1,z},\boldsymbol{\xi}^*_{\boldsymbol{z}}) \frac{d\overline{V}_z}{dw_1} + (1-\beta)\left(\overline{V}_z(w_{1,z},\boldsymbol{\xi}^*_{\boldsymbol{z}}) - U_{1,x}\right)\frac{d\overline{J}_z}{dw_1} = 0. \tag{19}$$

where

$$\frac{d\overline{V}}{dw_1} = p_0 T u'(w_1) + \sum_{j=1}^{N} p_j d_j \Gamma\left(\xi^*_{z,j}\right) u'(w_1) \tag{20}$$

and

$$\frac{d\overline{J}_z}{dw_1} = -p_0 T - \sum_{j=1}^{N} p_j d_j \Gamma\left(\xi^*_{z,j}\right)(1-\delta) \tag{21}$$

Similarly, the first order conditions with respect to $\xi^*_{z,j}$ for each j are:

$$\beta \overline{J}_z(w_{1,z}, \boldsymbol{\xi}^*_{\boldsymbol{z}}) \frac{d\overline{V}_z}{d\xi^*_{z,j}} + (1-\beta)\left(\overline{V}_z(w_{1,z}, \boldsymbol{\xi}^*_{\boldsymbol{z}}) - U_{1,x}\right) \frac{dJ_z}{d\xi^*_{z,j}} = 0. \tag{22}$$

where

$$\frac{d\overline{V}_z}{d\xi^*_j} = p_j \gamma\left(\xi^*_{z,j}\right)\left[V_{z,j} - \widetilde{V_{z,j}}\right] \tag{23}$$

and

$$\frac{d\overline{J}_z}{d\xi^*_{z,j}} = p_j \gamma\left(\xi^*_{z,j}\right)\left(\ \bar{J}_{z,j}\ \left(\xi^*_{z,j}\right) - \widetilde{J_{z,j}}\right) - p_j\ \bar{J}'_{z,j}\ \left(\xi^*_{z,j}\right) \tag{24}$$

We can thus characterize $\left(w_{1,z}, \left\langle \xi^*_{z,j} \right\rangle_{j=1}^{J}\right)$ by solving these $J+1$ system of equations.

B Appendix Tables and Figures

Appendix Table 1: Difference-in-Difference Analysis on Working

	Work 1Q	Work 2Q	Work 3Q	Work 4Q	Work 5Q	Work 6Q	Work 7Q	Work 8Q
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post	-0.011	-0.014	-0.048***	-0.043***	-0.049***	-0.044***	-0.034**	-0.044***
	(0.011)	(0.013)	(0.013)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
Mean DV, treatment	0.912	0.852	0.821	0.797	0.769	0.747	0.734	0.722
Mean DV, control	0.861	0.771	0.732	0.707	0.675	0.648	0.631	0.616
Observations	148705	148705	148705	148705	148705	148705	148705	148705
R-squared	0.0850	0.107	0.0991	0.0876	0.0916	0.0930	0.0889	0.0843

Notes: Columns include all controls. Standard errors clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 2: Difference-in-Difference Analysis on Working at a Different Firm, Conditional on Working

	NewF 1Q	NewF 2Q	NewF 3Q	NewF 4Q	NewF 5Q	NewF 6Q	NewF 7Q	NewF 8Q
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post	-0.012	-0.030*	-0.014	-0.010	-0.005	-0.001	0.001	0.006
	(0.011)	(0.016)	(0.016)	(0.017)	(0.018)	(0.019)	(0.019)	(0.018)
Mean DV, treatment	0.0482	0.115	0.165	0.205	0.242	0.275	0.304	0.329
Mean DV, control	0.0966	0.233	0.315	0.382	0.440	0.484	0.516	0.548
Observations	134858	125496	120782	117174	113022	109694	107744	105797
R-squared	0.0716	0.159	0.191	0.204	0.218	0.226	0.228	0.229

Notes: Columns include all controls. Standard errors clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 3: Difference-in-Difference Analysis on Earnings, Conditional on Working

	Earn 1Q	Earn 2Q	Earn 3Q	Earn 4Q	Earn 5Q	Earn 6Q	Earn 7Q	Earn 8Q
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post	-1218***	-1345***	-1148***	-1121***	-1166***	-1410***	-1310***	-1207***
	(184)	(204)	(220)	(223)	(240)	(265)	(271)	(250)
Mean DV, treatment	7338.6	8012.6	8312.2	8510.8	8634.4	8718.4	8779.1	8883.9
Mean DV, control	4913.8	5472.2	5691.6	5838.3	5941.9	5982.6	6029.3	6023.9
Observations	134858	125496	120782	117174	113022	109694	107744	105797
R-squared	0.472	0.477	0.488	0.479	0.422	0.449	0.480	0.466

Notes: Columns include all controls. Standard errors clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 4: Difference-in-Difference Analysis on EAIP Use, Robustness

	Lasso	Lasso, 2005-2011	OLS	Logit
	(1)	(2)	(3)	(4)
Treatment × Post	-0.055***	-0.065***	-0.048***	-0.039***
	(0.013)	(0.014)	(0.011)	(0.011)
Mean EAIP, treatment	0.278	0.278	0.279	0.280
Mean EAIP, control	0.0404	0.0402	0.0357	0.0353
Observations	140889	140889	140889	140704
R-squared	0.148	0.148	0.149	0.149

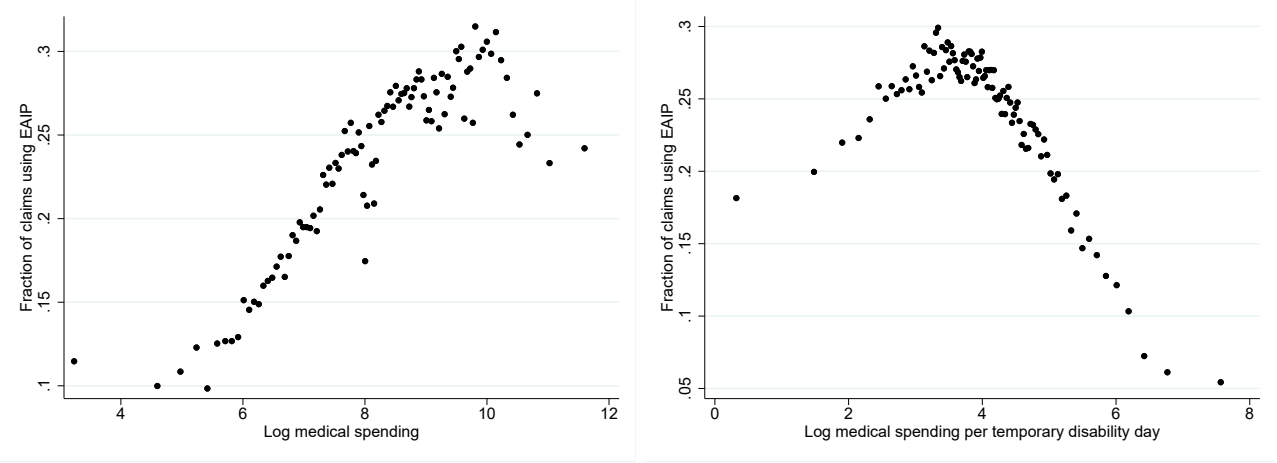
Notes: Columns include all controls. Standard errors clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 5: Difference-in-Difference Analysis on Working, Robustness

	Lasso	Lasso, 2005-2011	OLS	Logit
	(1)	(2)	(3)	(4)
Treatment × Post	-0.034**	-0.039**	-0.049***	-0.039***
	(0.016)	(0.018)	(0.013)	(0.013)
Mean working, treatment	0.799	0.799	0.799	0.798
Mean working, control	0.710	0.710	0.713	0.722
Observations	140889	140889	140889	140704
R-squared	0.0947	0.0947	0.0948	0.0945

Notes: Columns include all controls. Standard errors clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

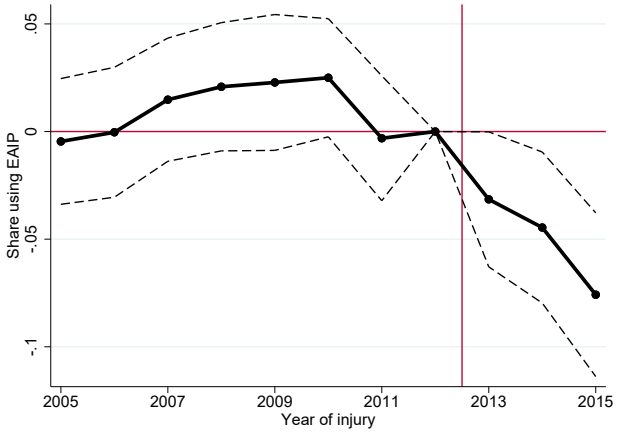
Appendix Figure 1: Fraction of claims using EAIP by medical spending

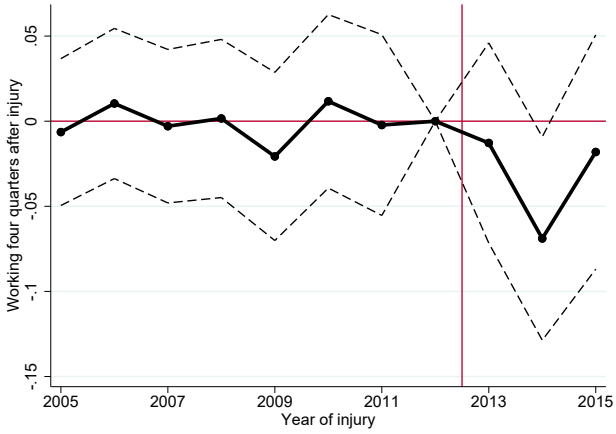


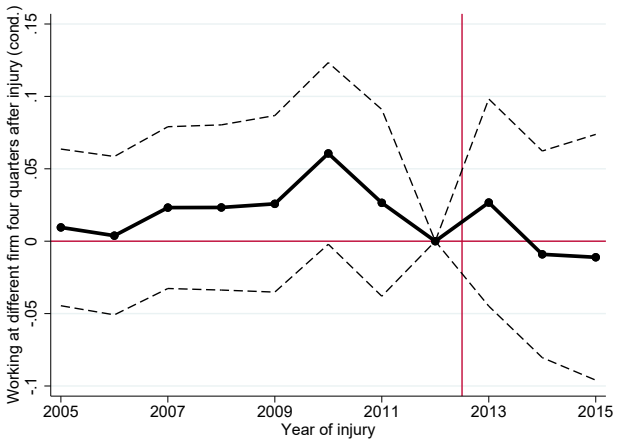
(a) Log medical spending

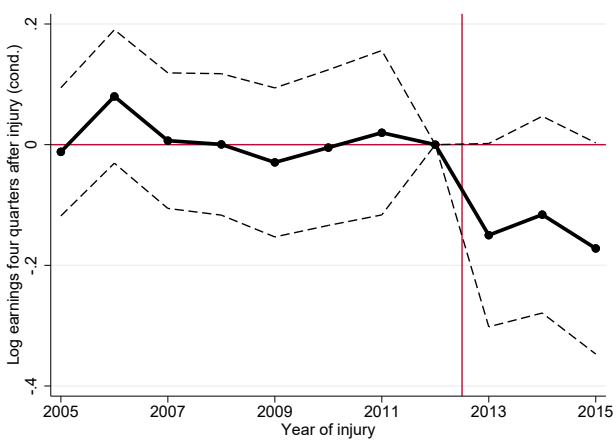
(b) Log medical spending per temp. disability day

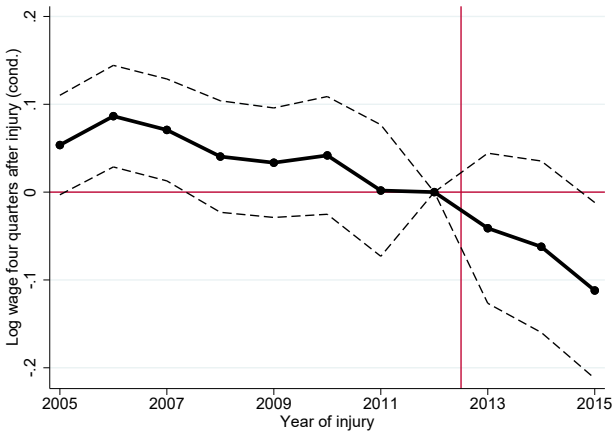
Appendix Figure 2: Regression-adjusted difference in outcomes between treatment and control, by year



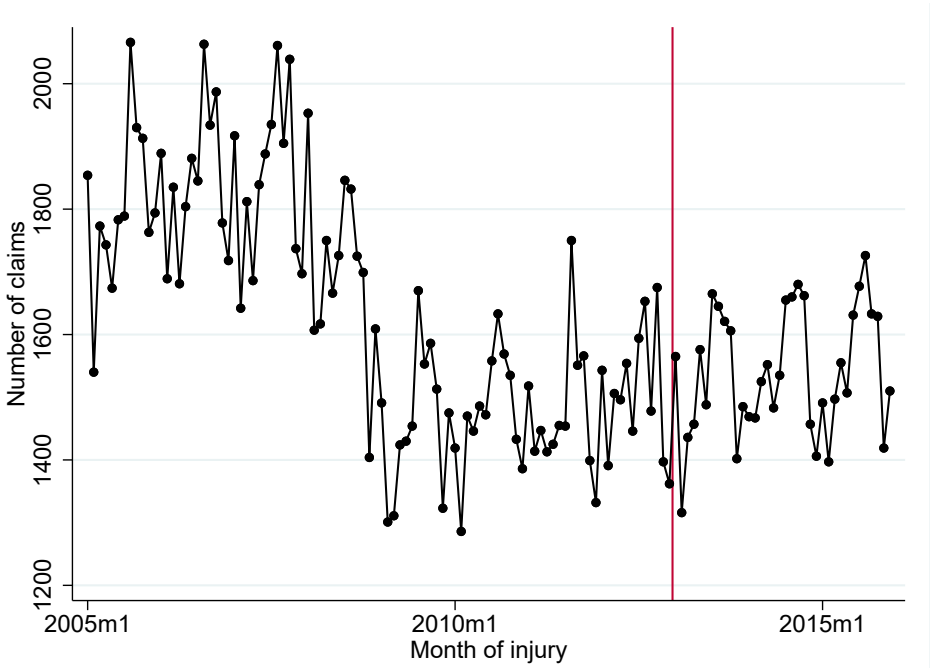




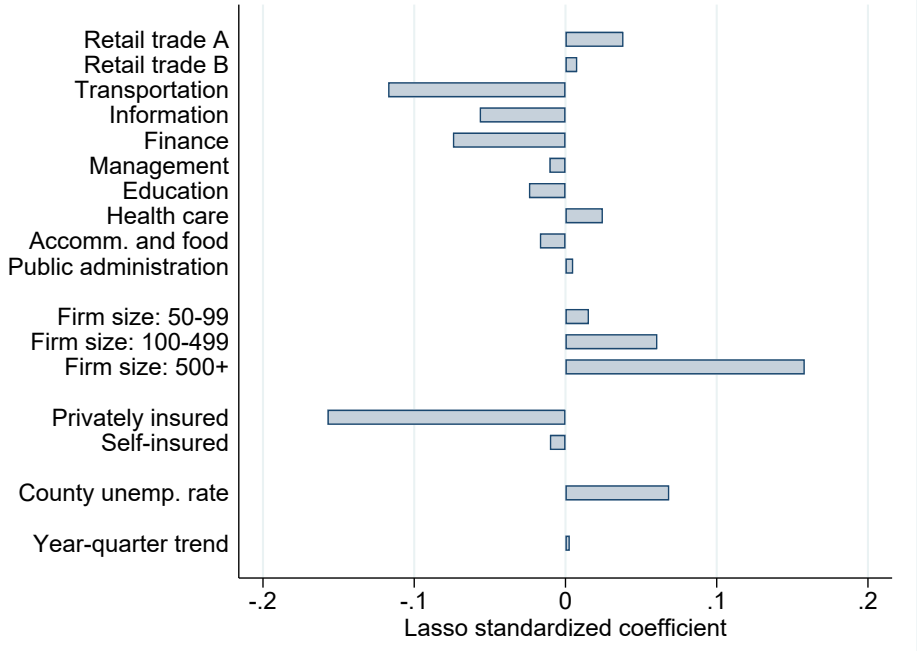




Appendix Figure 3: Number of claims, by month of injury



Appendix Figure 4: Importance of Lasso-selected firm characteristics in prediction algorithm



Appendix Figure 5: Importance of Lasso-selected worker characteristics in prediction algorithm

