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ABSTRACT

This paper studies the labor market impacts of firm accommodation decisions and assesses implications for the design of social insurance for workplace disability. We leverage a unique workers' compensation (WC) program in Oregon that provides wage subsidies to firms for accommodating injured workers. Exploiting rich administrative data and a policy change to the wage subsidy, we show that accommodation rates respond to the subsidy rate and that receipt of accommodation leads to a significant increase in employment and earnings a year later. To explore welfare implications, we develop and estimate a frictional labor market model of accommodation as a form of human capital investment. Worker turnover and imperfect experience rating in WC lead to under-accommodation and inefficient labor market outcomes after workplace disability. Counterfactual simulations show that subsidizing accommodation not only improves long-run labor market outcomes of workers experiencing work-related disability but also leads to welfare gains for most workers.

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1 Introduction

Households face a number of shocks that may adversely affect their labor market outcomes, including work-limiting health and disability shocks, unemployment and employer productivity shocks, and caregiving shocks. Protection against the negative consequences of these shocks is a major rationale for various social insurance and welfare programs. Given the intimate link between workers and employers in determining labor market outcomes, a key input in the design of such programs is firm behavior. Firms can affect the underlying risk (e.g., through decisions about how quickly to lay off a worker or through investments in workplace safety) as well as the impact of shocks (e.g., by offering health insurance or paid leave).

A potentially important but under-explored channel is firm accommodation. By adjusting the work environment or task composition (and possibly providing skill investment opportunities), firm accommodation may not only mitigate productivity shocks in the short run by allowing the worker to continue to work, but may also serve as human capital investment in the long run. The potentially beneficial role of firm accommodation has led to serious policy reform proposals to incentivize firms to more actively provide accommodation (e.g., Autor and Duggan, 2010 and OECD, 2010 in the case of disability insurance).

In this paper, we study the decision of firms to accommodate workers after workplace disability and assess the implications for the design of social insurance policies. Using rich administrative data on workplace disabilities from a unique workers' compensation program that provides accommodation subsidies, we first provide quasi-experimental evidence on the effect of accommodation subsidies on firm accommodation decisions and long-run employment and earnings outcomes. We then examine the welfare implications of accommodation subsidies by developing and estimating a frictional labor market model with firm accommodation decisions following workplace injury. Our model highlights potential inefficiencies in accommodation decisions and the role for corrective policy, and uses our empirical estimates to tightly discipline the structural estimates of our model.

Our empirical context is workplace disability within the workers' compensation program in the state of Oregon. This context naturally lends itself to the study of employer accommodation for a few main reasons. First, workplace disability is a major source of disability risk and labor force exit in the US and workers' compensation programs are the predominant source of insurance against this risk. In 2015, there were nearly three million non-fatal occupational injuries and illnesses (BLS, 2017), and workers' compensation programs provided $63 billion in aggregate wage replacement benefits in 2019 (Murphy and Wolf, 2022). Furthermore, because all disabilities covered by workers' compensation occur as a result of employment, the program provides a natural avenue for firm engagement. Second, Oregon's workers' compensation program includes a relatively unique accommodation subsidy program that offers a window into firm accommodation decisions. The program is the Employer at Injury Program (EAIP), which provides wage subsidies to employers to accommodate injured workers as they return to work to help defray costs related to, for example, flexible work arrangements or retraining.[1] Finally, the administrative data collected in this context allows us to observe extremely rich information about the specifics of a worker's disability, accommodation decisions, and labor market outcomes.

We use detailed administrative data on the universe of Oregon workers' compensation claims from 2005 through 2017, linked to their longitudinal quarterly earnings records. We start by showing descriptive patterns about accommodation, which we measure as a claim using EAIP. On average, around one quarter of claims are accommodated, though this masks important heterogeneity across workers and particularly firm characteristics. For example, large, self-insured firms are more likely to accommodate injured workers, as are firms in industries with low turnover rates of workers.

We then estimate the effect of accommodation on labor market outcomes. To do this, we develop an instrument for accommodation that leverages variation in firm exposure to a policy change in 2013 that decreased the EAIP wage subsidy rate from 50% to 45%. We define exposure as a firm's rate of accommodation during a baseline period.[2] Firms with very low baseline accommodation are unlikely to respond to the policy change, while firms with higher baseline accommodation are more "exposed"

[1]These costs may be large: for example, Mas and Pallais (2020) find that the cost of offering flexible work scheduling must be high given the low prevalence of flexible work, yet high willingness to pay for it by workers.

[2]This instrument is motivated in part by Aizawa et al. (2022), which finds that time-invariant firm factors are a major driver of accommodation.

and thus more likely to respond to the reduced incentive to accommodate after 2013. We estimate the differential relationship between accommodation and exposure before and after 2013 (in a difference-in-difference style specification), and then use the predicted change in accommodation use generated by the subsidy across firm exposure as an instrument to examine the impact of accommodation on labor market outcomes.

We find that the subsidy change reduced accommodation by one percentage point for every ten percentage point increase in exposure. We find corresponding effects on labor market outcomes: a ten percentage point increase in exposure led to a 0.3 percentage point decrease in employment and a $41 decrease in quarterly earnings.[3] We further explore heterogeneous treatment effects through a marginal treatment effect (MTE) framework, and find evidence of negative selection on gains: injured workers who would benefit most from accommodation are the least likely to receive it.

We also find suggestive evidence that accommodation is a form of general human capital investment rather than firm-specific investment in that the investment is transferable to new firms. We show that accommodation does not lower subsequent transitions of workers to new firms. Moreover, accommodated workers who move to new firms do not experience earnings decreases relative to workers who remain in the firm that provided accommodation.

To examine potential inefficiencies in accommodation decisions and assess the implications for optimal policy, we develop and estimate a frictional labor market model that incorporates workplace injury, a workers' compensation program, and firm accommodation. In the model, workers are subject to injury risk, which potentially entails a persistent loss of productivity and a higher probability of exit from the labor force. Firms can potentially mitigate these effects by accommodating injured workers, which improves their future general human capital. Injuries are covered by workers' compensation, and injured workers either receive time loss benefits or return to work early if accommodated. Workers and firms bargain over wages, and firms decide whether to accommodate workers in the event of injury.[4] Firms fund the workers' compensation program through a premium that is imperfectly experience-rated.

[3] Although we do not have linked data on other social programs, these findings also suggest that accommodation subsidies may help reduce the take-up of longer run welfare and disability benefits.

[4] We use the terms "earnings" and "wages" interchangeably; likewise for "firm" and "employer".

The model highlights two main features that could generate socially inefficient accommodation decisions. First, worker turnover prevents firms from capturing future surplus from accommodation. This externality in the labor market can lead to under-accommodation of injured workers.[5] Second, firms whose workers' compensation premiums are imperfectly experience-rated 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.

To structurally estimate the model, we allow for both observed and unobserved heterogeneity in the labor market effects of accommodation and the cost of accommodation, and use the quasi-experimental estimates to identify key parameters. A novelty of our approach is to incorporate heterogeneity in the return to accommodation guided by our MTE framework and estimate the model to account for our IV estimates. We find important differences in both the cost of accommodation and the gains from accommodation along both observable and unobservable dimensions, pointing to the importance of modeling such heterogeneity.

We then conduct counterfactual policy experiments that vary the accommodation subsidy rate to understand their welfare and distributional impacts. While subsidies benefit injured workers by increasing the probability of accommodation and therefore mitigating the negative labor market consequences of injury, their costs are paid by employers in the form of higher payroll taxes which are partially passed through to wages. We find large effects of the subsidy rate on accommodation and labor market outcomes: for example, eliminating accommodation subsidies from the current level (50% wage subsidy rate) decreases accommodation rates from 32% to 6%, leading to a decline in post-injury employment and earnings of 8% and 13%, respectively. From a welfare perspective, we find that an 80% wage subsidy generates welfare gains to the greatest percent of workers, while an even larger subsidy maximizes average welfare. Such large subsidies assist firms by partially covering the loss of human capital during the injury period and sizable accommodation costs. Overall, our findings suggest that policies that subsidize firm accommodation, such as Oregon's wage subsidy program, improve not only long-run labor market outcomes of workers

[5] This mechanism is the accommodation analogue of the dynamic inefficiency channel highlighted in Acemoglu and Pischke (1999) and Fang and Gavazza (2011).

experiencing work-related disability but also overall welfare.

This paper contributes to several strands of literature. First, it is related to the growing literature that studies firm responses to social insurance and the role of such behavior in the design of social insurance programs. Many papers in this literature focus on how wage contracts respond to and affect the value of social insurance. For example, Acemoglu and Shimer (1999), Golosov et al. (2013), and Giupponi and Landais (2022) study how unemployment insurance and short time work policies affect employment contracts and welfare. Aizawa and Fang (2020) study how health insurance reforms affect labor market equilibrium and firm provision of health insurance. More recently, Bana et al. (2022) and Lachowska et al. (2021) emphasize the role of firms in determining workers' access to and use of social insurance programs. We contribute to this literature by studying a new channel through which firms respond to social insurance: firm accommodation.

Second, the paper is related to a large literature studying the labor market and welfare impacts of social insurance programs for individuals with disabilities. Much of this work focuses on worker-side incentives, documenting that higher benefit generosity in these programs often reduces labor supply and delays return to work, but increases welfare (e.g., Meyer et al., 1995; Maestas et al., 2013; French and Song, 2014; Kostøl and Mogstad, 2014; Low and Pistaferri, 2015; Rennane, 2018; Cabral and Dillender, 2020; Mullen and Rennane, 2022).[6] Previous research on the role of employers in these programs is much smaller, and mainly focus on the effects of employer experience rating in disability programs (e.g., De Groot and Koning, 2016) and employer incentives to recruit workers with disabilities (e.g., Acemoglu and Angrist, 2001; Aizawa et al., 2023). We add to this literature by providing new quasi-experimental evidence that firm accommodation has positive impacts on a worker's subsequent return to work and welfare, as well as quantifying sources of inefficiency in firm accommodation decisions.[7]

Finally, positing firm accommodation as a form of investment in workers, this

[6] In addition, a few papers study incentives for human capital investment in this context (Deshpande and Dizon-Ross, 2023; Humlum et al., 2023).

[7] There are a few descriptive analyses that suggest that a substantial fraction of disabled workers would benefit from additional accommodation (Burkhauser et al., 1995; Bronchetti and McInerney, 2015; Maestas et al., 2019).

paper is also related to the literature on firm-provided training. Moving beyond 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, 1964), 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 its empirical relevance to firm investment in employee health. Alfonsi et al. (2020) and Caicedo et al. (2022) also assess whether to subsidize firm-sponsored training. We contribute to this literature by showing that appropriate incentives for firm investment in workers is an important input into optimal social insurance design.

2 Background and Data

2.1 Workers' Compensation and Oregon's EAIP

Workers' compensation programs are designed to protect workers and employers against the risk of an injury or illness that occurs on the job. In nearly all states, most employers are required to purchase workers' compensation insurance which covers both medical costs and time loss benefits associated with workplace disabilities. Premiums are typically experience-rated, meaning that an employer's past injury history adjusts 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 as these firms fully internalize the cost of workers' compensation insurance. 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. 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, temporary benefits equal 66-2/3 percent of wages (subject to a minimum and maximum). The mean workers' compensation spell in Oregon lasts approximately nine weeks, and approximately 20% percent of claims ultimately receive a permanent disability payment. Most employers in Oregon with at least 20 employees are required to return a worker to the same or similarly suitable job at the end of a workers' compensation claim.[8]

In addition to the mandatory medical and time loss benefits, Oregon is one of only a few states whose workers' compensation program provides benefits to employers who accommodate workers with workers' compensation claims. Our analysis focuses on the Employer at Injury Program (EAIP), which is designed to help injured workers return to employment during their recovery. 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. Participating workers must face restrictions or limitations that prevent them from returning to their full pre-injury job. Workers cannot receive timeloss benefits and work in a transitional capacity at the same time.

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) (ODBCS, 2020). The wage subsidy component is by far the most commonly used component of EAIP, accounting for over 90% of EAIP expenses.[9] On average, approximately 25 percent of workers' compensation claims in Oregon have some costs reimbursed via EAIP.

Unlike typical workers' compensation premiums, EAIP is funded through a payroll tax on all firms that is not experience-rated. Because the costs of EAIP 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 accommodate workers.

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

[8]See Murphy and Wolf (2022) for a comprehensive overview of workers' compensation programs.
[9]See Appendix Table 2 for details on other types of EAIP expenses.

the 50 percent subsidy to be restored.[10] Based on this employer feedback, the subsidy was restored to 50 percent as of January 1, 2020 (SAIF, 2020).

2.2 Data

We utilize a rich data linkage of workplace injury characteristics, longitudinal accommodation decisions of firms, and long run labor market outcomes of workers who experience workplace injury. Our main data source is administrative workers' compensation claims from the state of Oregon, provided by the Oregon Department of Business and Consumer Services (ODBCS), Workers' Compensation Division. The sample includes all closed, disabling claims with a time loss 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 time loss benefits were paid, total time loss payments, and medical expenditures. Worker information includes details 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.

We link several separate data sources to the administrative claims. First, we link information from a separate database about use of EAIP. 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. This linkage enables us to observe pre- and post-injury earnings history for all workers in the claims database with injuries in or after 2000. The data include total earnings and hours for each employer where an individual worked during the quarter, as well as an employer ID enabling linkages between employers across individuals and over time. Finally, we also link this data with industry-level and county-level labor demand information including labor force participation, employment rates, and separation rates from the St. Louis Federal Reserve, Bureau of

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

Labor Statistics, and Job Openings and Labor Turnover Survey (Bureau of Labor Statistics, 2020; Federal Reserve Bank of St. Louis, 2020).

3 Empirical Patterns

We use this rich data to document empirical patterns of accommodation and to motivate the model in Section 4. First, we characterize the types of firms that accommodate and the types of injured workers that receive accommodations. Second, we estimate the effect of accommodation incentives on firm accommodation decisions and subsequent worker labor market outcomes.

3.1 Patterns of Firm Accommodation Decisions

We focus our analysis on disabling claims from 2011-2017. The first column in Table 1 reports summary statistics for this full sample, which comprises over 131,000 claims. On average, workers are in their early forties, are more likely to be male, and make around $8,000 per quarter. Their claims on average last around four months, with around 60 days of paid time loss benefits. The majority of injuries are strains, and the top industries are health and education, trade, and manufacturing (see Appendix Table 3 for occupation and industry summary statistics). One-third of claims are in very large firms, and over one-fifth are in self-insured firms. Around one-quarter of claims are accommodated via EAIP.

Columns 2 and 3 of Table 1 compare key characteristics of claims with costs that are subsidized via EAIP and those that are not. On average, workers who are accommodated through EAIP are slightly older, more likely to be female, and have higher pre-injury earnings. Claims with EAIP have higher medical costs on average, and are more likely to be strains and less likely to be wounds.[11] Large firms and self-insured firms are over-represented among claims with EAIP: over half of EAIP claims occur at large firms with more than 500 employees, compared to 29 percent of claims without EAIP, and one-third of EAIP claims occur at self-insured firms compared

[11] 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, Oregon workers' compensation claims 2011-2017

	Full sample			Analysis sample		
	All (1)	EAIP (2)	No EAIP (3)	All (4)	High exp (5)	Low exp (6)
Worker characteristics						
Age	42.3	42.8	42.1	43.7	43.9	43.6
Female	0.37	0.42	0.35	0.36	0.39	0.33
Prior quarterly earnings ($)	7,601	8,607	7,250	9,016	9,838	8,179
	(5,914)	(5,663)	(5,959)	(6,081)	(6,151)	(5,892)
Claim characteristics						
Accommodated	0.25	1.00	0.00	0.32	0.46	0.17
Claim medical costs ($)	8,166	9,447	7,745	8,204	7,623	8,789
	(14,245)	(14,971)	(13,970)	(14,226)	(13,775)	(14,643)
Claim days	111	145	99	115	111	119
	(167)	(183)	(160)	(175)	(168)	(181)
Claim days w/ timeloss	61	69	59	60	56	64
	(101)	(99)	(102)	(100)	(94)	(107)
Injury type: trauma	0.11	0.12	0.11	0.12	0.11	0.12
Injury type: fracture	0.11	0.12	0.11	0.11	0.10	0.12
Injury type: strain	0.58	0.63	0.56	0.60	0.62	0.59
Injury type: wound	0.13	0.08	0.15	0.11	0.11	0.12
Injury type: other	0.06	0.06	0.06	0.06	0.07	0.06
Firm characteristics						
Firm size 500+	0.35	0.53	0.29	0.46	0.60	0.31
Self-insured firm	0.21	0.33	0.17	0.29	0.39	0.19
Observations	131,219	33,415	97,804	73,205	36,897	36,308

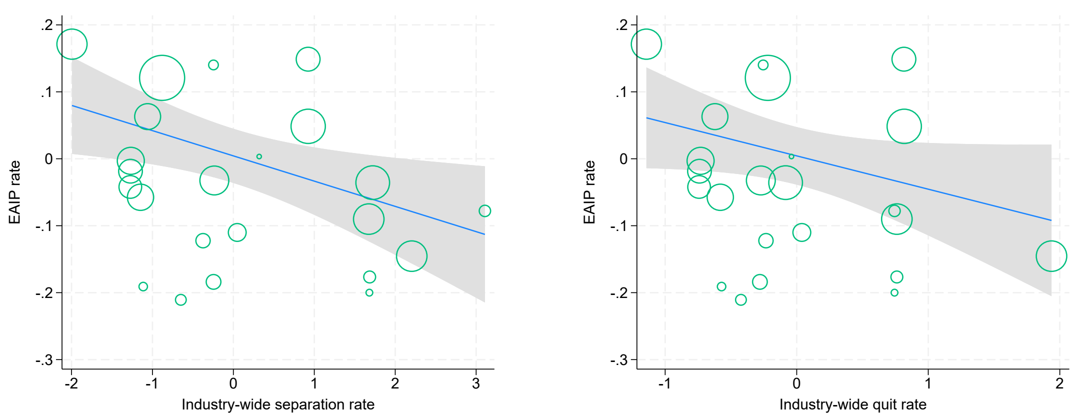
Notes: Data provided by ODBCS. The full sample consists of disabling claims between 2011 and 2017. The EAIP and no EAIP columns distinguish claims that were accommodated and not accommodated, respectively. The analysis sample consists of the subset of claims for which the firm had at least one claim between 2005-2009 and one claim between 2011-2017, and workers who worked at least 300 hours in the quarter prior to injury and the high exposure (High exp) and low exposure (Low exp) columns are claims for which the firm's accommodation rate in 2005-2009 was above or below the median accommodation rate, respectively. Prior quarterly earnings are from the quarter prior to the quarter of injury. Claim days are calendar days, while claim days with time loss paid are days in which time loss benefits were paid. Reported values are means, and standard deviations in parentheses.

to 17 percent of non-EAIP claims. 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 (Appendix Table 3).

The differences in accommodation rates by firm characteristics point to the important role that firms play in accommodation decisions (as also shown in Aizawa et al. (2022) using decomposition methods). The fact that large, self-insured firms are much more likely to provide accommodation could reflect both that larger firms may have more capacity to provide accommodation and/or have more knowledge of EAIP, or that self-insured firms fully internalize workers' compensation costs and thus may have a greater incentive to accommodate and have these costs offset via EAIP. Appendix Table 1, which regresses EAIP on a host of characteristics, shows that the relationship between insurance status and EAIP remains after controlling for firm size, suggesting a role for the experience-rating channel. As such, partially experience-rated firms might under-provide accommodation because they do not fully internalize the workers' compensation costs that they generate. We return to this channel in Section 4 where we evaluate the welfare loss due to such underprovision.

Figure 1 shows that rates of accommodation are strongly associated with worker turnover rates (Appendix Table 4 reports the underlying regression estimates). Specifically, there is a strong negative association between EAIP use and separation rates, suggesting that firms that retain workers longer tend to offer accommodation at higher rates. We also return to this channel in Section 4.

Figure 1: Fraction of claims that use EAIP, by industry-wide separation rates



(a) Separation Rate

(b) Quit Rate

Notes: Data from the ODBCS merged to two-digit industry-month separation and quit rates from the Job Openings and Labor Turnover Survey. Sample consists of disabling claims between 2011 and 2017, aggregated to the two-digit industry level. Circles are proportional to the number of claims within that industry in the sample. Lines represent fitted regression lines through the aggregate data, taking out year-month effects, and shaded areas are 95% confidence intervals.

3.2 Estimating the Effects of Accommodation Incentives

We next establish evidence on the effect of accommodation incentives and the effect of accommodation on worker labor market outcomes. To do this, we exploit a change in the EAIP wage subsidy rate from 50 percent to 45 percent that occurred in January 2013. We use this variation in accommodation generated by the subsidy change to examine the effect of accommodation on subsequent labor market outcomes. Simply comparing labor market outcomes before and after 2013, however, would conflate any impact of EAIP on these outcomes with broader, contemporaneous trends in the labor market. Given this, we construct a firm-level measure of "exposure" to the policy change based on the firm's average historical use of EAIP. If time-invariant firm factors are a major driver of accommodation use,[12] then firms with historically low use of EAIP (i.e., low exposure) are unlikely to respond to the reduction in the subsidy, while firms with high exposure are more likely to respond.[13] We estimate the differential relationship between accommodation use and exposure before and after 2013 (in a difference-in-difference specification), and then use the predicted change in accommodation use generated by the subsidy across firm exposure as an instrument to examine the impact of accommodation on labor market outcomes.

More specifically, our measure of firm-level exposure is the percent of claims that used EAIP in a given firm over a five year period prior to our analysis period. Our primary sample for the empirical analysis includes claims from 2011-2017, and we use claims from 2005-2009 to estimate baseline EAIP "exposure" which ranges from 0 to 1.[14] Our approach requires firms to have at least two workers' compensation

[12]In Aizawa et al. (2022), we show that the specifics of the firm, rather than the worker or injury, is the strongest predictor of accommodation through EAIP. Worker and injury characteristics explain 1 and 3 percent of the variation in accommodation use, respectively, while firm characteristics such as firm size and insurance type account for 5 percent of the variation and firm fixed effects account for nearly 25 percent of the variation in accommodation. This finding suggests that inherent characteristics of the firm - e.g., firm culture or management structure - are an important driving factor in use of EAIP.

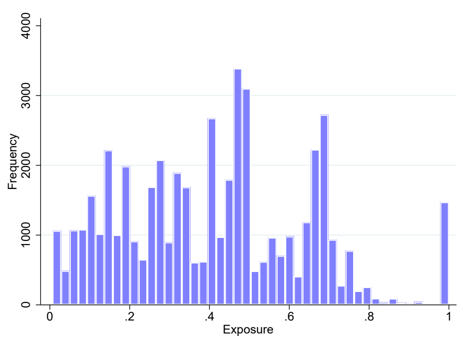
[13]Similar exposure-style instruments have been used in many other settings, including studies of minimum wage policy, minimum legal working hours policy, and payroll tax policy (e.g., Harasztosi and Lindner, 2019; Carry, 2022; Saez et al., 2019).

[14]We use a separate "historical" period of five years to reduce the volatility of the measure and thus avoid potential mean reversion issues. We also exclude 2010 from the historical period to reduce the potential impact of mean reversion. We later report robustness to subsamples that are likely less prone to measurement error, mean reversion, and small sample issues, and Appendix Figure 2

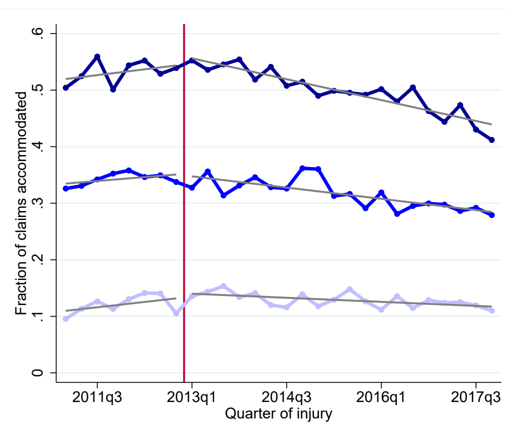
claims in our dataset: one between 2005 and 2009 to calculate exposure, and another during or after 2011 to be included in the analysis sample. This restriction excludes approximately 26 percent of observations from firms with claims between 2011 and 2017, most of whom tend to be smaller or newer firms. We also restrict our sample to workers who worked at least 300 hours in the quarter prior to injury to focus on workers attached to the labor market. These sample restrictions result in a final analysis sample of roughly 73,000 claims. As shown in Column 4 of Table 1, worker and claim characteristics in the analysis sample are very similar to the full sample, but firms in the analysis sample are more likely to be large and self-insured. Almost one-third of claims in the analysis sample are accommodated.

Figure 2: Distribution of exposure and accommodation rates by exposure tercile

(a) Distribution of exposure



(b) Accommodation rate by exposure tercile



Notes: Panel (a) reports the number of claims by exposure bin, among claims in firms with positive exposure. 33% of the sample has zero exposure. Panel (b) reports the fraction of claims that are accommodated, by exposure tercile (darkest blue is highest exposure tercile, lightest blue is lowest exposure tercile). Red vertical line denotes the date of the policy change in January 2013.

In our analysis sample, mean exposure is 0.275 with a standard deviation of 0.270. One third of the sample has zero exposure (i.e., no use of EAIP during the baseline period). Figure 2a plots the distribution of (positive) exposure in our sample and shows that firms cover nearly the full distribution between 0 and 100 percent exposure. Figure 2b plots the raw trends in EAIP use separately by tercile of exposure. Each tercile has a similar slight upward slope in EAIP use prior to the policy change in

shows that exposure rates are relatively consistent between the historical period and 2011-2012.

2013. After the policy change, there was a trend break in EAIP use, which was more pronounced for claims in more highly exposed firms (dark blue line) and less pronounced for claims in less exposed firms (light blue line).

Columns 5 and 6 of Table 1 collapse our (continuous) exposure variable into above-median and below-median exposure to investigate potential differences in observables by exposure. Workers in firms with above-median EAIP exposure are slightly older, more likely to be female, and have higher pre-injury earnings. High exposure claims are more likely to be accommodated (mostly by construction), and have slightly lower medical costs and slightly shorter claim duration. They are also more likely to come from large firms and self-insured firms. Interestingly, injury type does not differ dramatically by exposure, though there are some differences in industry make-up. We directly control for these observable characteristics in our regressions below.

We first estimate the following difference-in-differences regressions:

$$Y_i = \beta \text{Exposure}_{f(i)} \times \text{Post}_{t(i)} + \alpha \text{Exposure}_{f(i)} + \delta_{j(i),t(i)} + \gamma X_i + \varepsilon_i \tag{1}$$

where β is the coefficient of interest: the effect of claim i occurring after 2013 (Post_t) interacted with our measure of firm-level exposure (Exposure_f). The δ_{jt} parameters are industry j by quarter-year t fixed effects, and X_i include a host of controls, including worker demographics and work history, injury characteristics, firm characteristics, and county unemployment rates. Standard errors are clustered by firm.

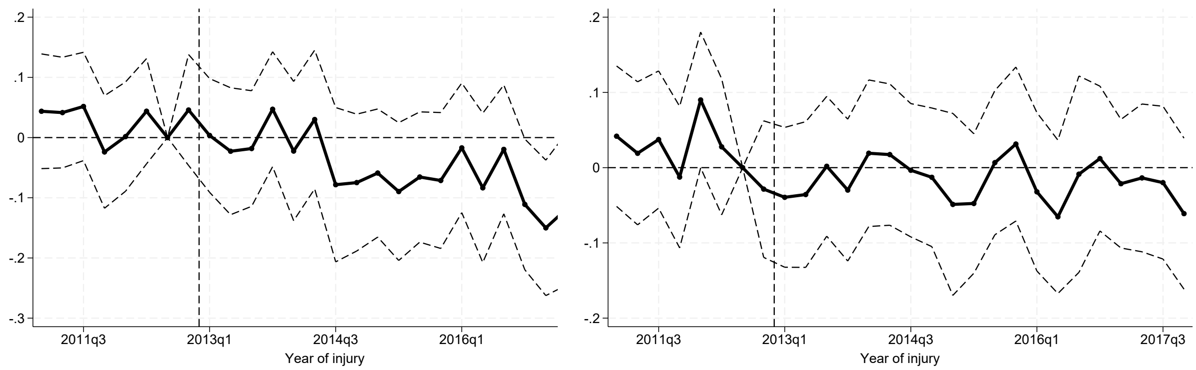
There are two important identifying assumptions in this specification. First, we assume the employment outcomes for workers with claims in firms with different exposure levels would have trended in parallel in the absence of the policy change. Figure 3 shows parallel trends in EAIP and employment outcomes prior to the policy change (coefficients reported are unadjusted linear effects of exposure by quarter, relative to the difference in the third quarter of 2012).[15] Second, we assume that EAIP take-up among firms with very low exposure is not meaningfully impacted by the policy change. If instead EAIP take-up among low-exposure firms responded to the policy change, this will bias our estimates toward finding a null effect.

Next, we use Equation (1) to predict EAIP use as a first stage, and use predicted

[15] Appendix Figure 4 includes the full set of control variables and shows similar trends.

Figure 3: Differences in outcomes over time by treatment status

(a) EAIP use (b) Working four quarters later



Notes: Solid dots denote the estimated coefficients on the interaction of exposure and quarter from a regression of the outcome variable on exposure, quarter, and their interaction (the third quarter of 2012 is omitted), and dashed lines report 95% confidence intervals. Vertical line denotes the date of the policy change.

EAIP to instrument for accommodation use in a two-stage least squares analysis of the impact of accommodation on labor market outcomes. In particular, we estimate the following two-stage least squares equations in which the excluded variable is $\text{Exposure}_f \times \text{Post}_t$:

$$EAIP_i = \beta \text{Exposure}_{f(i)} \times \text{Post}_{t(i)} + \alpha \text{Exposure}_{f(i)} + \delta_{j(i),t(i)} + \gamma X_i + \varepsilon_i \tag{2}$$

$$Y_i = \psi \widehat{EAIP}_i + \rho \text{Exposure}_{f(i)} + \pi_{j(i),t(i)} + \lambda X_i + \upsilon_i \tag{3}$$

where Equation (2) is the first stage prediction of EAIP (the difference-in-differences specification as in Equation (1)), and Equation (3) is the IV equation regressing employment outcomes Y_i on our instrumented prediction of $EAIP_i$ from the first stage. Along with the identifying assumptions needed for the difference-in-differences specification, the IV specification requires that the policy change impacts subsequent labor market outcomes for claims from more highly exposed firms relative to claims from less exposed firms only through the higher EAIP take-up rate at those firms (i.e., the exclusion restriction). In support of this assumption, we note that there were no coincident policy changes affecting accommodation or other workers' compensation policies for employees during the analysis period. Moreover, the total number of claims filed is stable over time (see Appendix Figure 3), as is the classification of firms as either high or low exposure firms over time (see Appendix Figure 2).

Finally, to explore treatment effect heterogeneity and to shed light on the complier population of the IV estimates, we apply a marginal treatment effects (MTE) framework following Heckman and Vytlacil (2007) (see Appendix B for more details). Specifically, we estimate a continuum of treatment effects along a distribution of unobserved "resistance to treatment". Following standard practice in this literature, we estimate a propensity score as a function of observable characteristics, including the instrument defined above. We set an individual's unobserved "resistance to treatment" to be their propensity score value, reflecting the point at which they are indifferent to treatment (i.e., where their unobserved resistance is equal to their propensity for accommodation). We also recover marginal treatment response estimates for treated and untreated claims, as introduced by Mogstad et al. (2018).

3.3 Results

Table 2 shows the results for the difference-in-differences regressions from Equation (1), with EAIP and each of our labor market outcomes four quarters after injury as the dependent variables. The coefficient in column (1) shows that the policy change induced a one percentage point decrease in EAIP take-up for every ten percentage point increase in firm exposure (or 2.8 percentage points for every one standard deviation increase in firm exposure). For labor market outcomes, the results show that the reduction in the subsidy reduced the probability of working four quarters after injury by 0.32 percentage points and decreased quarterly earnings by $41 for every ten percentage point increase in firm exposure (or 0.9 and $111 for every one standard deviation increase in firm exposure), but that there were no substantial changes in worker turnover (defined as moving to a new firm). Appendix Figure 5 reports analogous estimates for quarters one through eight after the injury, and shows that employment and earnings had immediate effects that slowly dissipated over time.

These results are robust to several other specifications and sample restrictions. Appendix Tables 5 and 6 show that the effects are robust to a binary measure of any exposure and a measure of exposure defined as days of wages subsidized by EAIP. The

Table 2: Difference-in-Differences Analysis of Policy Change on Accommodation Use and Labor Market Outcomes Four Quarters after Injury

		Four quarters after injury		
	EAIP	Employment	New firm	Earnings
	(1)	(2)	(3)	(4)
Exposure × Post	-0.102***	-0.032**	0.000	-411.755***
	(0.024)	(0.015)	(0.011)	(147.671)
Mean DV	0.318	0.702	0.0961	7961.3
Observations	73201	73201	73201	73201

Notes: Dependent variable shown in column header. All regressions include a broad set of worker, firm, and injury controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

effects are also robust to defining exposure at the firm-occupation level when there are over five observations for a particular occupation in a firm (and otherwise use the firm level exposure measure), as shown in Appendix Table 7. To check concerns about mean reversion, Appendix Tables 8 and 9 show robustness to samples that excludes firms with fewer than 11 workers (whose measure of exposure may be more subject to mean reversion) and firms whose exposure measure is 100%, respectively.

Under the assumption that the labor market effects of the policy change only operate through accommodation, the instrumental variable analysis yields the estimated effect of accommodation (through EAIP) on employment outcomes. Table 3 reports the IV coefficients from Equation (3) for employment, worker turnover, and earnings. Receipt of accommodation has large effects on labor market outcomes: it leads to a 32 percentage point increase in the probability of working four quarters after the injury and to an increase in quarterly earnings of $4,000. There is no effect of accommodation on the probability of moving to a new firm.

We interpret the large effects as treatment effects of accommodation among claims whose receipt of EAIP changes as a result of the change in the subsidy. Given that our IV estimates potentially mask considerable heterogeneity in treatment effects, we next explore heterogeneity in treatment effects using an MTE framework.

Figure 4 shows MTE curves in black for employment (Panel a) and earnings (Panel b) along the distribution of unobserved resistance to treatment (accommodation) for

Table 3: IV Analysis on Labor Market Outcomes Four Quarters after Injury

	Four quarters after injury		
	Employment	New firm	Earnings
	(1)	(2)	(3)
EAIP	0.315**	-0.00359	4023.3**
	(0.159)	(0.112)	(1625.7)
Mean DV	0.702	0.0961	7961.3
Observations	73201	73201	73201

Notes: Dependent variable shown in column header. All regressions include a broad set of worker, firm, and injury controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

which we have common support. We find that injured workers who are least likely to receive accommodation (i.e., workers with the highest unobserved resistance to treatment) have the highest potential employment and earnings gains from accommodation, suggesting negative selection on gains.[16] The larger treatment effects for workers who are less likely to receive accommodation is in part driven by the fact that they have significantly worse employment outcomes in the absence of accommodation (see Appendix Figure 7 for the estimated outcomes for treated and untreated states – i.e., the marginal treatment response curves). We also find negative selection on gains for observable characteristics, including workers in self-insured firms, health-care support occupations, women, and injuries involving wounds, cuts, and burns (see Appendix Table 10).[17]

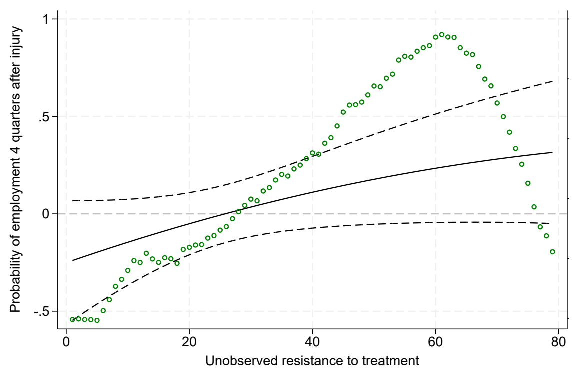
The MTE analysis also sheds light on the complier population of the IV estimates, as our IV estimates can be expressed as a weighted average of MTE estimates (Heckman and Vytlacil, 2007). The green circles in Figure 4 represent these weights, and show that individuals with higher unobserved resistance have higher IV weights, meaning their accommodation status is more likely to be influenced by the instru-

[16]Negative selection on gains has also been found for other labor market programs targeted towards disabled populations. For example, Aakvik et al. (2005) finds that a vocational rehabilitation program for disabled workers has higher employment effects for individuals who are the least likely to be employed without the program.

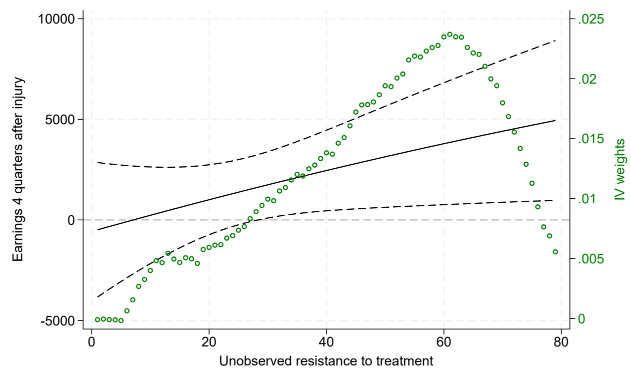
[17]Appendix Table 10 also reports the marginal effect of the instrument on accommodation in the probit selection equation (column 1) of -0.09, and shows that it is similar to the linear probability estimate of -0.10 in column 1 of Table 2.

ment. The fact that these large weights are concentrated among the individuals with the largest potential gains from accommodation explains the large estimate obtained from the IV analysis. In other words, these findings suggest that there are potentially large labor market returns to the subgroup of workers whose accommodation status is influenced by the wage subsidies offered through EAIP, though the smaller (and negative) MTEs at other points in the distribution suggest that not all workers would benefit as much (or at all) from accommodation.

Figure 4: Marginal Treatment Effects on Employment and Earnings



(a) Employment four quarters after injury



(b) Earnings four quarters after injury

Notes: Figures report marginal treatment effects (solid line) and 95% confidence intervals (dashed lines) on the left axis and the IV weights in green circles on the right axis.

Interpretation: firm accommodation as human capital investment. Overall, our estimates show that firm accommodation improves labor market outcomes after injury. One potential mechanism through which this operates is that accommodation allows for earlier return to work after injury, which prevents the decay of human capital. A second potential mechanism is through skill accumulation: by providing alternative work arrangements during the injury period, firm accommodation can provide training for new skills. In that sense, accommodation operates as a form of human capital investment by firms in its workers.

One natural question is whether firm accommodation provides general human capital or firm-specific human capital (Becker, 1964). Although accommodation can have both components, if it mainly provides firm-specific human capital then human capital acquired from accommodation is not transferable across firms. As such, we would expect to find that (i) accommodated workers are more likely to remain with the firm that provided accommodation, and (ii) workers who move to a new firm experience lower earnings gain from accommodation than workers who remain at the firm that provided accommodation. If accommodation mainly provides general human capital, neither (i) nor (ii) hold.

We find that accommodation is consistent with general human capital training. Our IV analysis in Table 3 shows that accommodation does not affect the probability of being in a new firm four quarters after injury. Moreover, given these null findings, we run a modified version of the difference-in-differences regression (Equation (1)) in which we include an interaction term $\text{Exposure}_{f(i)} \times \text{Post}_{t(i)} \times \text{NewFirm}_i$ (as well as corresponding lower level interaction terms) to examine whether the effect of the policy change differs between individuals who move to a new firm and individuals who remain with the firm that provided accommodation. The results in Appendix Table 11 are suggestive of even larger earnings gains from accommodation for individuals who move to a new firm, although the estimate is not statistically significant. This is at odds with firm-specific human capital investment. We thus proceed with a model that characterizes firm accommodation as a form of general human capital investment.

4 Dynamic Bargaining Model

To better understand the welfare impacts of accommodation and accommodation subsidies, we develop and estimate a frictional labor market model of workplace injury, firm accommodation, and workers' compensation that closely mirrors the institutional setup of Section 2 and the empirical findings of Section 3.

4.1 The Environment

We consider a two-period bargaining problem between a worker-firm match with type $z \in \mathcal{Z}$ in which injuries are realized and accommodation decisions are made in the first period, and the second period represents the labor market after injury. A workers' compensation program pays timeloss benefits for injured workers, funded by firm premiums. The premiums are imperfectly experienced-rated, and the extent of experience rating differs across firms.

Consider that workers are risk averse and firms are risk neutral. The model begins with workers and firms bargaining ex-ante over the first-period wage $w_{1,z}$. In the first period, workers are injured with probability p, which results in an injury duration of $d \in [0, T]$.[18] Injured workers either receive time loss benefits b_z from workers' compensation if they remain out of work for the duration of their injury, or return to work early and receive wage $w_{1,z}$ if accommodated ($a \in \{0, 1\}$). Firms make accommodation decisions after observing the accommodation cost shock ξ_z associated with the injury that results in net output $f_{1,z,\xi}$.

In the second period, workers previously injured spend their remaining time $(T - d)$ working or unemployed. They exit the labor market with probability $q_{z,a}$ 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, accommodation decisions affect the probability of exiting the labor force but not the probability of moving to a new firm, to match the empirical results in Section 3. If the worker remains with the same firm, the match produces output $f_{2,z,a}$ and the worker and firm bargain over the second-period wage $w_{2,z,a}$, which again depends on the accommodation decision to match the empirical findings in Section 3 that accommodation affects wages conditional on working. If the worker moves to a new firm, they receive an outside wage of $w_{2,z,a,O}$ and produce output $f_{2,z,a,O}$. Motivated by our empirical evidence, we assume that accommodation provides general human capital and affects both the outside wage and output at new firms.

Uninjured workers spend all of their time T in the second-period labor market with analogous transition probabilities $q_{z,u}$ and $\lambda_{z,u}$. If they remain with the firm, they produce output $f_{1,z}$ and earn a wage $w_{1,z}$ equal to that of accommodated workers as constrained by law.[19] If they move to a new firm, they receive an outside wage $w_{1,z,O}$.

[18]We abstract from endogenous injury probabilities. While we could, in principle, relax this assumption by modeling firm effort to avoid (or lessen the severity of) injury, we believe these extensions are unlikely to change our main insights. Moreover, Appendix Figure 3 shows that the number of claims did not respond to the wage subsidy policy change. Thus, moral hazard on the margin of injury (or claiming) rates are unlikely to be first-order in our policy environment.

[19]ORS § 659A.040 - 046, OAR § 839-006-0100 - 0150.

4.2 Worker and Firm Value Functions

The worker's value function $V_z(w_{1,z}, \mathbf{a}_z)$ 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:

$$V_z(w_{1,z}, \mathbf{a}_z) = (1-p) V_{z,u} + p\mathbb{E}_\xi \left[a_z(\xi_z) V_z^a + (1 - a_z(\xi_z)) V_z^{na}\right] \tag{4}$$

where the first term in Equation (4) is the worker's value if uninjured, given by:

$$V_{z,u} = T\left(q_{z,u}u(c_b) + (1-q_{z,u})\left[(1-\lambda_{z,u}) u(w_{1,z}) + \lambda_{z,u}u(w_{1,z,O})\right]\right) \tag{5}$$

where $d = 0$ so they spend all of their time T in the second period.[20] With probability $q_{z,u}$, the worker becomes unemployed and receives an unemployment benefit c_b. If they remain employed, with probability $(1-\lambda_{z,u})$, they stay in the same firm and receive a wage of $w_{1,z}$, and with probability $\lambda_{z,u}$ they move to another firm and receive an outside wage of $w_{1,z,O}$.

The terms within the expectation of Equation (4) are the injured worker's value of being accommodated and working (V_z^a) and not being accommodated and not working (V_z^{na}) given by:

$$V_z^a = du(w_{1,z}) + (T-d)\left[(1-q_{z,1})\left((1-\lambda_z) u(w_{2,z,1}) + \lambda_z u(w_{2,z,1,O})\right) + q_{z,1}u(c_b)\right] \tag{6}$$

$$V_z^{na} = du(b_z) + (T-d)\left[(1-q_{z,0})\left((1-\lambda_z) u(w_{2,z,0}) + \lambda_z u(w_{2,z,0,O})\right) + q_{z,0}u(c_b)\right] \tag{7}$$

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 are accommodated receive wage $w_{1,z}$ while workers who are not accommodated receive a time loss benefit b_z. After the injury period, with probability $q_{z,a}$ 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 firm with probability $(1-\lambda_z)$ and receives a wage of $w_{2,z,a}$ and moves to a new firm

[20]Note that their wage $w_{1,z}$ is the same wage that injured workers receive when accommodated.

with probability λ_z and receives a wage of $w_{2,z,a,O}$.

Next, a firm's value function J from match z with wage $w_{1,z}$ and accommodation decisions $\mathbf{a}_z$ is given by:

$$J_z(w_{1,z}, \mathbf{a}_z) = (1-p)\, J_{z,u} + p\mathbb{E}_\xi \left[a_z\,(\xi_z)\, J^a_{z,\xi} + (1 - a_z\,(\xi_z))\, J^{na}_z\right] - P_{tot,z} \tag{8}$$

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

$$J_{z,u} = T\,(1 - q_{z,u})\,(1 - \lambda_{z,u})\,(f_{1,z} - w_{1,z}) \tag{9}$$

and the terms within the expectation are profits from accommodating an injured worker ($J^a_{z,\xi}$) and from not accommodating an injured (J^{na}_z), given by:

$$J^a_{z,\xi} = d\,[f_{1,z,\xi} - (1-\delta_z)\,w_{1,z}] + (T-d)\,(1-q_{z,1})\,(1-\lambda_z)\,(f_{2,z,1} - w_{2,z,1}) \tag{10}$$

$$J^{na}_z = (T-d)\,(1-q_{z,0})\,(1-\lambda_z)\,(f_{2,z,0} - w_{2,z,0}) \tag{11}$$

where $f_{1,z,\xi}$ is output of the worker *net* of the match-specific accommodation cost, and δ_z denotes the wage subsidy provided by workers' compensation through the EAIP program if the firm accommodates the worker.

The final term in Equation (8) is the total premium paid for workers' compensation coverage, $P_{tot,z}$, defined as:

$$P_{tot,z} = \tau_z pd\mathbb{E}_{\xi_z}\,[(1 - a_z\,(\xi_z))\,b_z] + (1-\tau_z)\,P_{z,b} + P_s \tag{12}$$

where τ_z is the firm-specific degree of experience rating, $P_{z,b}$ is average timeloss costs for firms of type z, and P_s is the flat premium paid for wage subsidies.

4.3 Worker-Firm Bargaining Problem and Solution

Wages and accommodation choices are determined at three points in time: first, prior to the injury, the first-period wage $w_{1,z}$ is determined by Nash bargaining between the worker and firm. Second, after the realization of injury and its associated accommodation cost ξ_z, the firm makes an accommodation decision $a_z(\xi_z)$. Finally, at the beginning of the second period, the post-injury wage is again determined by Nash bargaining. For the Nash bargaining problems, the firm's outside options are zero and the worker's outside options are defined by $U_{1,z} = T\left(\lambda^{ue}_{1,z} u(c_b) + \left(1 - \lambda^{ue}_{1,z}\right) u(w_{1,z,O})\right)$ and $U_{2,z,a} = \left(1 - \lambda^{ue}_{2,z}\right) u(c_b) + \lambda^{ue}_{2,z} u(w_{2,z,a,O})$ for the ex-ante and post-injury periods, respectively, both a weighted average of the value of unemployment and the value of finding a job with outside wage $w_{1,z,O}$ or $w_{2,z,a,O}$, respectively.

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

$$\max_{w_{2,z,a}} \left(u(w_{2,z,a}) - U_{2,z,a}\right)^{\beta} \left(f_{2,z,a} - w_{2,z,a}\right)^{1-\beta} \tag{13}$$

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

$$\beta u'(w_{2,z,a}) \left(f_{2,z,a} - w_{2,z,a}\right) - (1-\beta)\left(u(w_{2,z,a}) - U_{2,z,a}\right) = 0 \tag{14}$$

Second, the accommodation choices and initial wage are determined in the first period. Given a wage $w_{1,z}$ and accommodation cost realization ξ_z, a firm decides whether to accommodate their injured worker by maximizing its conditional profit:

$$a^*(w_{1,z}, \xi_z) = \begin{cases} 1 & \text{if } J^a_{z,\xi} > J^{na}_z - \tau_z db_z \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

Note that the conditional profit from not accommodating the worker includes the term $\tau_z db_z$, which reflects the impact of non-accommodation on workers' compensation costs (db_z), which impacts the firm's premium due to experience rating (τ_z). We posit that the solution to Equation (15) is a threshold ξ^*_z such that $a = 1$ for all $\xi_z < \xi^*_z$ and $a = 0$ otherwise.

Finally, the first-period wage $w_{1,z}$ is determined ex-ante by Nash bargaining:

$$\max_{w_{1,z}} \left(V_z(w_{1,z}, \mathbf{a}^*_{\mathbf{z}}) - U_{1,z}\right)^{\beta} J_z(w_{1,z}, \mathbf{a}^*_{\mathbf{z}})^{1-\beta} \tag{16}$$

where $\mathbf{a}^*_{\mathbf{z}}$ is the solution to Equation (15). We solve the initial wage by solving the first-order condition; see Appendix C for details.

Note that our bargaining structure closely follows the theoretical analysis by Acemoglu and Pischke (1999) and Fang and Gavazza (2011), except for the fact that these papers assume that the initial wage is determined competitively from a firm zero profit condition. We replace such an assumption with Nash bargaining for the initial wage to be consistent with the bargaining structure in the second period.

4.4 Discussion: Inefficiency in Accommodation Decisions

There are two key sources of inefficiency in accommodation rates in our model that arise from the fact that firms choose whether to accommodate workers based on their profit motive rather than the social surplus of accommodation. The first is a human capital externality. In the model, firm accommodation provides general human capital in that the earnings gains from accommodation accrue to workers even if they switch employers, captured by the term $w_{2,z,a,O}$. As shown in Acemoglu and Shimer (1999), the extent to which firms efficiently accommodate injured workers crucially depends on whether the surplus from accommodation remains with the match. Even if there is (social) surplus from accommodation due to future productivity gains, if the net profit from accommodation during the injury period is negative 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 Nash bargaining framework we assume, 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 future surplus from accommodation. However, because of a lack of commitment (the worker and firm re-bargain over wages in the second period), part of the surplus generated within a match is captured by future employers in the event of separation ($f_{2,z,a,O} > w_{2,z,a,O}$), thus creating a dynamic inefficiency in accommodation. This inefficiency is larger when worker turnover rates are higher.[21]

[21] Note that this efficiency result is sensitive to the framework of bargaining and lack of commitment (Moen and Rosén, 2004; Lentz and Roys, 2015). We chose this framework to match descriptive evidence presented in Figure 1 and Appendix Table 4 that higher labor market-wide or industry-wide turnover rates are negatively associated with accommodation rates, which is consistent with bargaining models as opposed to other models (e.g., directed search or offer-matching models).

The second source of potential inefficiency is a fiscal externality from the design of the workers' compensation program. Firms fund the workers' compensation program through premiums $P_{tot,z}$ that do not necessarily fully reflect the (expected) claim costs that they generate for the program. Accommodation lowers workers' compensation claim costs by decreasing the amount of timeloss benefits paid. For fully experience-rated firms, whose premiums are directly related to the claim costs that they generate, the claim cost savings from accommodation accrue directly to the firm. For partially experience-rated firms, on the other hand, their premiums are not directly related to their own claim costs, and thus their incentive to accommodate for the purposes of lowering claim cost is muted, potentially resulting in under-accommodation as a result of this fiscal externality.

The above channels can lead to inefficiencies in accommodation choices, calling for government intervention. There are at least two ways that the government can restore inefficiency. First, the government can subsidize firms to induce the efficient level of accommodation. Second, the government can provide accommodation directly, e.g., through government training programs. In our context, subsidies to firms are a more natural policy lever because firms are likely to quickly observe their workers' disabilities and resulting need for accommodation and thus are more readily able to experiment with accommodations such as providing new work arrangements, providing flexibility in work schedules, or temporarily assigning workers new job duties.

5 Estimation

We estimate the model primarily using Oregon administrative claims data linked to longitudinal quarterly earnings records. We first estimate or set parameters outside the model and then structurally estimate parameters related to net output and the accommodation cost shock distribution within the model.

5.1 Parameters Estimated or Set Outside the Model

We first specify the components of the match type $z \in \mathcal{Z}$. We allow rich heterogeneity based on observable and unobservable characteristics: $\mathcal{Z}$ consists of a combination of the worker's skill type (high or low, measured by pre-injury wages), the firm's insurance status (self-insured or not), the firm's baseline accommodation rate (i.e., our measure of exposure defined in Section 3), *unobserved* match types defined in our MTE analysis, and whether the injury took place before or after the policy change in 2013.[22] The unobserved component corresponds to the unobserved resistance to treatment (accommodation), and we introduce it to capture additional heterogeneity in the labor market return from accommodation. The distribution of observable variables is directly measurable from our data and the unobserved component is independent from the observable variables and uniformly distributed. We allow these types (except injury year) to affect the primitives in the model, and allow injury year to affect the wage subsidy rate.

We estimate or set several parameters outside the model, summarized in Appendix Table 12. We set the probability of injury to $p = 0.022$, the annual disabling claim rate in Oregon, and set the duration of injury d to equal the mean claim duration in our analysis sample of claims, which is 60 days.

Employment-to-unemployment (E-U) transition rates for injured workers, $q_{z,a}$, vary by accommodation status and match characteristics (except injury year) and are given by the estimates from the marginal treatment responses in Appendix Figure 7. Other transition rates are assumed to only vary by worker skill type and firm insurance type. E-E transition rates of injured workers (λ_z) are measured by the percent of individuals who are not at the firm of injury four quarters after injury, conditional on having positive earnings. For E-U transition rates for uninjured workers ($q_{z,u}$), we measure, among individuals who were employed seven quarters prior to injury, the percent who were unemployed four quarters later, at three quarters prior to injury. For E-E transition rates $\lambda_{z,u}$, we measure the percent of individuals who were not at the firm of injury four quarters prior to injury, conditional on having positive earnings. Finally, for U-E transition rates, we assume that $\lambda_z^{ue} = \lambda_{1,z}^{ue}$ and then measure, among individuals who were unemployed seven quarters prior to the injury, the percent who were employed four quarters later, at three quarters prior to the injury.

We set the ex-ante and post-injury outside wages ($w_{1,z,O}$ and $w_{2,z,a,O}$) equal to

[22] We do not explicitly model heterogeneity in injuries beyond heterogeneity in accommodation cost shocks because we do not believe it would affect the main conclusions from the model.

their respective internal wage, reflecting that some job-to-job transitions lead to wage gains and others lead to wage losses in our context and that the estimated effects of accommodation are not significantly different between new jobs and current jobs.[23] We set the unemployment benefit (c_b) to 40% of the outside wage and the worker bargaining power parameter to $\beta = 0.5$; the latter is in the range of estimates in the labor search literature. We set the utility function as $u(c) = \log(c)$.

Finally, we set workers' compensation parameters to reflect Oregon's program during our sample period. Specifically, we set the replacement rate for the time loss benefit to 66.7% of wages (ORS § 656.210-211) and the wage subsidy rate prior to and following the policy change in 2013 to 50% and 45%, respectively. The experience rating weight for firms that are not self-insured is set as one minus the fraction of firms that are not experience rated, or 0.38 (see Appendix A for more details).

5.2 Structural Estimation

For parameters structurally estimated within the model (net output, the accommodation cost shock distribution), estimation proceeds in two steps.

Step 1: estimating the second-stage parameters. In the first step, we estimate the post-injury output parameters $f_{2,z,a}$ by solving the Nash bargaining problem in Equation (13). Using the parameters in Appendix Table 12, we solve for $f_{2,z,a}$ by matching the model-implied post-injury wage $w_{2,z,a}$ (the solution from the first order condition of the Nash bargaining problem defined in Equation (14)) to its data analogue (the marginal treatment response estimates reported in Appendix Figure 7).

Step 2: estimating the first-stage parameters. In the second step, we estimate the remaining parameters by indirect inference, including parameters related to net output and the distribution of accommodation cost shocks. We impose the following

[23] This choice also implies that $f_{2,z,a} = f_{2,z,a,O}$.

functional form assumptions on the heterogeneity of net output:

$$f_{1,z,0} = \alpha^0_{f,0} + \alpha^1_{f,0}\mathbb{1}_{\text{SelfInsured}} + \alpha^2_{f,0}\mathbb{1}_{\text{HighSkilled}} + \alpha^3_{f,0}\text{Exposure} \tag{17}$$

$$f_{1,z,\xi_z} = \alpha^0_{f,1} + \alpha^1_{f,1}\mathbb{1}_{\text{SelfInsured}} + \alpha^2_{f,1}\mathbb{1}_{\text{HighSkilled}} + \alpha^3_{f,1}\text{Exposure} + \alpha^4_{f,1}\text{Unobs} - \xi_z \tag{18}$$

and impose that the distribution of the accommodation cost shock ξ_z is normally distributed with mean zero and standard deviation $\sigma_{z,\xi_z} = \exp(\alpha_{\sigma,0}+\alpha_{\sigma,1}\text{Unobs})$. $\mathbb{1}$ is an indicator function, Exposure is firm exposure, and Unobs is the worker-firm match's unobservable. In our quantitative specification, we impose five exposure quintiles ($\text{Exposure} \in \{1, 2, ..., 5\}$) and 10 unobservable deciles ($\text{Unobs} \in \{1, 2, ..., 10\}$).

Identification. Our identification strategy relies on moments related to earnings and accommodation rates. First, cross-sectional variation in earnings of uninjured workers by observable type (high skilled, self-insure, exposure) identifies the $\alpha^n_{f,0}$ terms for $n = 0, 1, 2, 3$. We do not have analogous moments to identify the $\alpha^n_{f,1}$ terms for injured workers because their earnings are constrained to be equal to the earnings of uninjured workers. Instead, cross-sectional variation in accommodation rates of injured works by observable type identifies the $\alpha^n_{f,1}$ terms because higher output leads to higher accommodation (see Equations (10), (11), and (15)).

To identify the parameters of the accommodation cost shock distribution ($\alpha_{\sigma,0}$ and $\alpha_{\sigma,1}$) and the parameter that shifts net output by unobserved type $\left(\alpha^4_{f,1}\right)$, we exploit our difference-in-differences estimates of the effect of the change in the wage subsidy rate on accommodation rates, employment, and earnings. First, a change in the wage subsidy rate directly affects the profitability of accommodation, but the extent to which this pushes firms across the accommodation threshold in Equation (15) is governed by the variance parameter $\alpha_{\sigma,0}$. Thus the difference-in-differences estimate for accommodation identifies $\alpha_{\sigma,0}$. Next, as our MTE estimates show, the treatment effects of accommodation are very heterogeneous across unobserved types. Our difference-in-differences estimates for post-injury outcomes (which, divided by the difference-in-differences estimates for accommodation, generate our IV estimates) are a weighted average of our MTE estimates, and thus they are informative in identifying the parameters associated with unobserved types $\left(\alpha^4_{f,1}, \alpha_{\sigma,1}\right)$.

Auxiliary model. Given these identification arguments, our auxiliary models are: (1) cross-sectional average earnings of uninjured workers by worker skill (high or low), firm insurance status (self-insured or not), exposure type (above median or below), and whether the injury occurred prior to the policy change in 2013;[24] (2) cross-sectional average accommodation rates by worker skill (high or low), firm insurance status (self-insured or not), exposure type (above median or below), and pre-reform; (3) coefficient β of the difference-in-differences regression in Equation (1) for accommodation (EAIP), post-injury employment, and post-injury earnings; and (4) average post-injury employment and earnings prior to the policy change in 2013.

We implement our indirect inference approach as follows: (i) construct the auxiliary models (1)-(4), denoted by $\overline{\beta}$, from the data, (ii) solve and simulate the structural model for a given guess of model parameters Θ and compute corresponding auxiliary models from the simulated data, denoted by $\hat{\beta}(\Theta)$, and (iii) repeat step (ii) by searching over the parameter space to minimize the following objective:

$$\hat{\Theta} = \arg\min_{\Theta} \left[\hat{\beta}(\Theta) - \overline{\beta}\right]' W \left[\hat{\beta}(\Theta) - \overline{\beta}\right]$$

where W is a weighting matrix, which is based on the inverse of the variance of $\overline{\beta}$.[25,26] Standard errors are based on the asymptotic variance (Gourieroux et al., 1993).

5.3 Estimation Results

Estimates of the second-stage parameters. We first report our second-stage parameter estimates of post-injury output, $f_{2,z,a}$. We back out each parameter for each state and accommodation status respectively, where a state is a combination

[24] These earnings are calculated in the quarter prior to injury.

[25] To construct the simulated difference-in-differences estimates, we run the following regression for each of the three outcomes for claim i in injury year t:

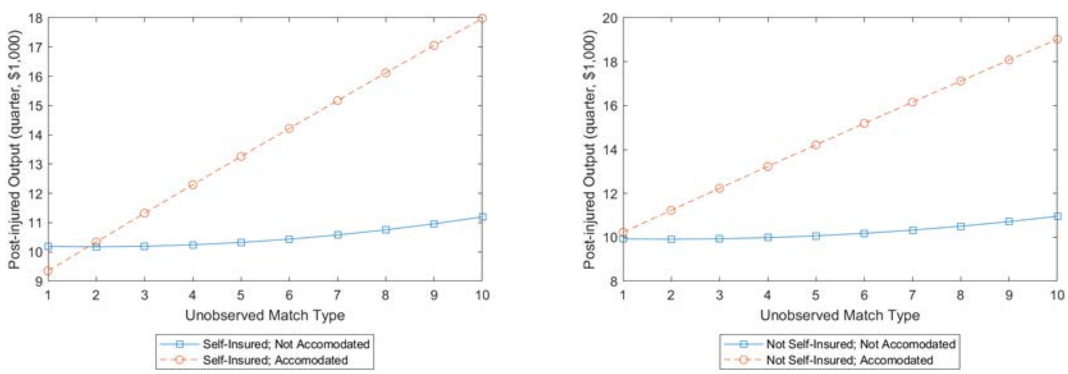
$$Y_i = \beta_0 + \beta_1 \text{Exposure value}_{f(i)} \times \text{Post}_{t(i)} + \beta_2 \text{Exposure value}_{f(i)} + \beta_3 \text{Post}_{t(i)} + \gamma X_i + \varepsilon_i$$

where Exposure value$_{f(i)}$ is discretized into five values representing the five quantiles of the distribution of exposure: $\{0.00, 0.07, 0.23, 0.45, 0.69\}$.

[26] Because of substantial differences between the weights on auxiliary models from the regression coefficients and weights on cross-sectional moments, we put additional weight on cross-sectional moments of accommodation rates to ensure similarity in magnitudes.

of the worker's skill type, the firm's insurance status, the firm's exposure, and the unobserved match type. Because the number of parameters recovered at this stage is large, we describe some of the important patterns.

Figure 5: Post-Injury Output, High-Skilled Workers in Median Exposure Firms



(a) Self-insured firms

(b) Imperfectly experience-rated firms

Notes: The left (right) figures report the post-injury output of high-skilled workers in self-insured (imperfectly experience-rated) firms with median exposure, by accommodation status. The x-axis in each figure denotes the worker-firm match's unobserved type decile.

Figure 5 shows post-injury output for high skilled workers in firms with median exposure, by firm insurance status and accommodation status. Output is an increasing function of unobserved type for accommodated workers, which is consistent with our MTE results in Section 3 that find that post-injury earnings are an increasing function of unobserved type for accommodated workers. Moreover, for low unobserved types, the return from accommodation to output is actually negative, which is also consistent with our MTE findings. Finally, the figures reveal interesting heterogeneity by firm insurance status: the return from accommodation can be negative for self-insured firms, but is always positive for firms that are not self-insured.

Estimates of the first-stage parameters. Table 4 reports parameter estimates. First, we find that the output produced by uninjured workers is larger for jobs filled by high skilled workers, jobs in self-insured firms, and jobs in high-exposure firms. Second, we find that net output during the injury period is negative, suggesting that accommodation is a costly investment, at least in a static sense. In the post-injury

Table 4: Parameters estimated within the model

Net output, uninjured: $f_{1,z,0}$				Net output, injured: $f_{1,z,\xi}$			
Param.	Description	Estimate	SE	Param.	Description	Estimate	SE
$\alpha^0_{f,0}$	Baseline	13.73	(0.05)	$\alpha^0_{f,1}$	Baseline	-14.74	(0.004)
$\alpha^1_{f,0}$	Self-insured	3.59	(0.06)	$\alpha^1_{f,1}$	Self-insured	1.50	(0.01)
$\alpha^2_{f,0}$	High skilled	0.50	(0.01)	$\alpha^2_{f,1}$	High skilled	1.27	(0.004)
$\alpha^3_{f,0}$	Exposure	0.01	(0.01)	$\alpha^3_{f,1}$	Exposure	1.38	(0.01)
				$\alpha^4_{f,1}$	Unobs. type	-0.01	(0.002)
Accommodation cost shock std. dev.: $\sigma_{\xi,z}$							
Param.	Description	Estimate	SE				
$\alpha_{\sigma,0}$	Baseline	4.14	(0.01)				
$\alpha_{\sigma,1}$	Unobs. type	-0.64	(0.004)				

Note: Output is quarterly and is expressed in units of \$1,000. The parameters and their functional forms are introduced in Equations (17) and (18). Standard errors of estimates are in parentheses.

period, however, accommodation tends to generate positive returns due to higher employment and productivity of accommodated workers relative to unaccommodated workers. Moreover, accommodation lowers the firm's future workers' compensation insurance premium. Thus, to rationalize the fact that fewer than half of injured workers are accommodated, net output must be negative during the injury period.

Third, we find that heterogeneity in net output for injured workers is similar to the heterogeneity in output for uninjured workers. We also find a small but negative correlation between unobserved type and net output. Because our model maps higher unobservable types to higher unobserved resistance to treatment – which have higher returns to accommodation, as shown in our MTE analysis – this pattern is consistent with our findings of negative selection on gains. Finally, we find that the accommodation cost shock variance is lower for higher unobserved types ($\alpha_{\sigma,1}$), meaning accommodation decisions for these claims respond much more significantly to changes in the environment (e.g., subsidies) compared to lower unobserved types. Because higher unobserved types also tend to have higher labor market return from accommodation, their large response to the wage subsidies is consistent with the large IV estimates of accommodation on the post-injury labor market outcomes.

Table 5 presents the model fit given our estimates. The model is able to account for the data patterns well both qualitatively and quantitatively. In particular, the model is able to match the difference-in-differences coefficients for accommodation rates and post-injury employment and wages quite well, suggesting that the model captures the large local effects of accommodation on subsequent labor market outcomes.

Table 5: Within-Sample Fit of Targeted Moments

	Accommodation rate		Wages in period 1	
	Data	Model	Data	Model
DID coefficient	-0.10	-0.10		
Levels by subsample:				
Self-insured	0.43	0.51	11.47	12.07
Not self-insured	0.27	0.21	9.44	10.03
High skilled	0.34	0.30	12.61	12.13
Low skilled	0.29	0.28	6.23	8.20
High exposure	0.46	0.39	10.82	10.94
Low exposure	0.17	0.16	9.22	10.15
Pre-policy change	0.33	0.32	9.88	10.58
	Post-injury employment		**Post-injury wages**	
	Data	Model	Data	Model
DID coefficient	-0.03	-0.01	-0.41	-0.50
Overall level	0.70	0.78	9.35	8.95

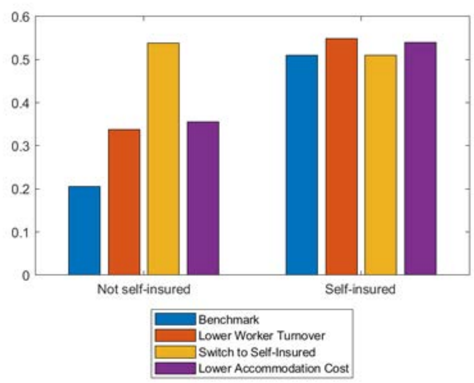
Note: Wages are quarterly and are expressed in units of $1,000.

Sensitivity of estimates. In the spirit of Andrews et al. (2017), we provide further evidence of our identification argument by quantifying the relative importance of each auxiliary moment for each parameter of interest. In Online Appendix D, we follow Einav et al. (2018) and perturb structural parameters one by one and measure the responses of the predicted auxiliary moments. We confirm patterns that are consistent with our identification arguments: e.g., changes in parameters associated with accommodation shocks σ_{z,ξ_z} lead to large changes in auxiliary moments associated with the difference-in-differences regression coefficients relative to other moments.

5.4 Mechanisms

We next use the estimated model to conduct comparative statics that shed light on key mechanisms that may affect the decision to accommodate. Figure 6 reports how accommodation rates are influenced by (i) worker turnover, (ii) the extent of experience rating, and (iii) the magnitude of the accommodation cost, separately by firms that are imperfectly experience rated (left set of bars) and firms that are self-insured (right set of bars). The leftmost blue bar in each set reports the accommodation rate under the benchmark economy.

Figure 6: Comparative Statics of Accommodation Decisions



Notes: The figure shows changes in accommodation rates in four scenarios: (i) the benchmark (i.e., the outcome under the estimated samples; (ii) the effect of lowering worker's job-to-job transition rate λ_z to 25% of its estimated value; (iii) the effect of switching to the self-insured contract; (iv) and the effect of increasing the net output of injured workers in low-skilled jobs by $a^2_{f,1}$ and increasing the net output of injured workers in a non-self insured job by $a^1_{f,1}$.

The orange bars second from left report the effect of reducing the job-to-job transition rate of injured workers to one-quarter of its estimated value: $\tilde{\lambda}_z = 0.25\lambda_z$. The simulations show that lower turnover leads to higher accommodation rates, consistent with the discussion in Section 4.4. The simulations also show that the accommodation rate in imperfectly experience-rated firms is much more sensitive to the rate of worker turnover than the accommodation rate in self-insured firms. This difference mainly arises because self-insured firms have a greater incentive to accommodate injured workers to reduce their workers' compensation premiums than imperfectly experience-rated firms. Thus, the dynamic inefficiency from worker turnover is more stark for non-self-insured firms.

The yellow bars third from the left report 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), holding other model parameters fixed. This exercise confirms the intuition discussed in Section 4.4: fully experience-rating all firms (i.e., through self-insurance) increases accommodation rates substantially. The purple rightmost bars report the effect of lowering the accommodation cost during the injury period. To do this, we increase the net output of low skilled injured workers to that of high-skilled injured workers and increase the net output of imperfectly experience-rated firms to that of self-insured firms. This has a significant impact on accommodation rates for workers in imperfectly experience-rated firms, but less so in self-insured firms.

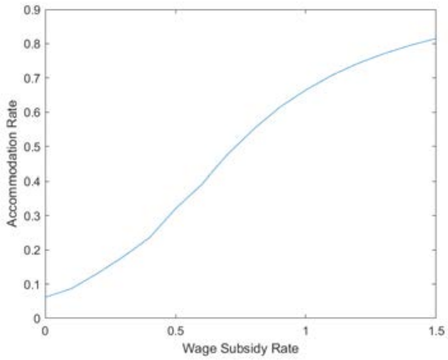
In sum, we find that all three factors – worker turnover, experience rating, and the static accommodation cost – play an important role in explaining accommodation rates. We next turn to counterfactual policy experiments to explore the role of workers' compensation policy in influencing accommodation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

6 Counterfactual Experiment

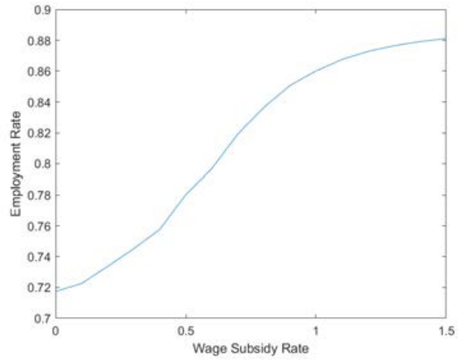
Using the estimated model, we conduct counterfactual policy experiments that change the wage subsidy rate δ to quantitatively explore their labor market, welfare and distributional effects. This counterfactual is motivated by potential inefficiencies in the model that may lead firms to under-accommodate injured workers.

We impose budget neutrality for the workers' compensation program. By changing accommodation rates, the counterfactual experiments we conduct may generate changes in claim costs, which require us to solve for equilibrium premiums for imperfectly experience-rated firms ($P_{z,b}$) that satisfy the break-even conditions in the insurance market.[27] The wage subsidy program (EAIP) is also budget neutral, so we also solve for a new flat tax P_s on all employers.

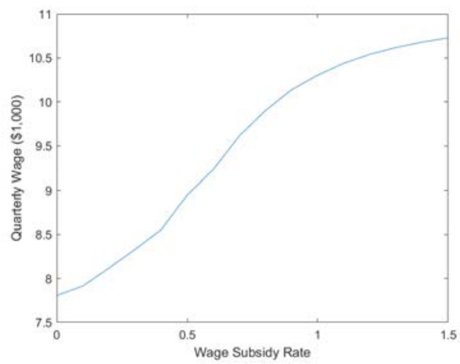
Figure 7: Labor Market Impacts of Accommodation Subsidies



(a) Accommodation rate



(b) Post-injury employment



(c) Post-injury wage

Notes: Each subfigure reports outcomes from counterfactual experiments in which we vary the wage subsidy rate for accommodation. The benchmark case is a wage subsidy rate of 50%.

6.1 Labor Market Impacts

Figure 7 reports the labor market impacts of wage subsidies for accommodation ranging from a 0% subsidy to a 150% subsidy. There are two important findings. First, Panel (a) shows that a generous subsidy rate is crucial for incentivizing firm accommodation: for example, if we set the wage subsidy to zero (thereby eliminating EAIP), the accommodation rate decreases from 32% to 6%. Such a large response is

[27] Formally, the break even condition is defined as

$$\int (1-\tau_z)\, P_{z,b} dF_z(z|\mathbb{1}_{\text{SelfInsured}}=0) = \int (1-\tau_z)\, pd\mathbb{E}_{\xi_z}\left[(1-a_z(\xi_z))\, b_z\right] dF_z(z|\mathbb{1}_{\text{SelfInsured}}=0).$$

consistent with our finding from the empirical section, in which firm accommodation responds significantly to financial incentives.

Second, Panels (b) and (c) show that more generous wage subsidies increase post-injury employment and wages: if we set the wage subsidy to zero, post-injury employment decreases by 8% (or 6 percentage points) and post-injury quarterly wages decrease by 13% (or $1,140). Note that these magnitudes differ from our IV estimates in Section 3 because they are average effects (of very heterogeneous treatment effects, as our MTE estimates imply), while the IV estimates are local to workers whose accommodation changed as a result of the instrument.

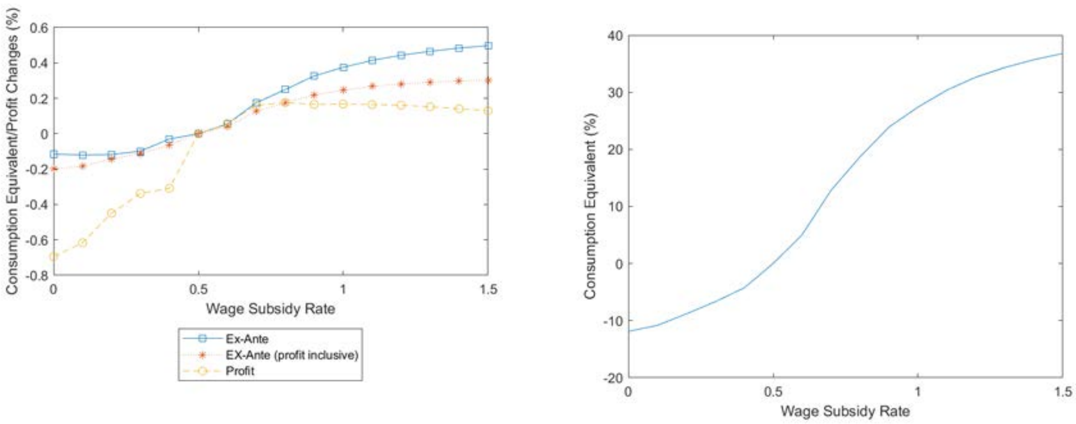
6.2 Average Welfare Impacts

Next, we examine the welfare impacts of these counterfactual wage subsidies. In practice, the welfare impacts on worker's ex-ante welfare are ambiguous. On the one hand, more generous subsidies have two sources of potential welfare benefits. First, because the subsidy increases accommodation and accommodation has positive impacts on post-labor market outcomes, subsidies increase welfare for workers who experience injury. Second and relatedly, accommodation leads to higher earnings during both the injury period and post-injury period, which lowers the consumption risk from experiencing an injury. On the other hand, these effects are attenuated by a higher EAIP tax (P_s) from higher accommodation rates. Although this tax is paid by firms, some of the incidence of the tax falls on workers through a reduction in wages in the first period.

Figure 8 presents the average welfare impacts of alternative wage subsidy rates relative to the benchmark rate of 50%. We report four relevant metrics: changes in worker ex-ante welfare, changes in firm ex-ante profit, changes in worker ex-ante welfare inclusive of firm profit as an ex-post transfer (i.e., not affecting workers' decisions), and changes in injured worker welfare at the time of injury. Worker welfare changes are measured by consumption equivalent variation, i.e., 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 50% wage subsidy.

Panel (a) shows that there are modest effects on ex-ante worker welfare and firm profit. Regardless of whether firm profits are included in worker welfare, the welfare

Figure 8: Average Welfare Impacts of Wage Subsidies for Accommodation



(a) Ex-ante welfare (profit)

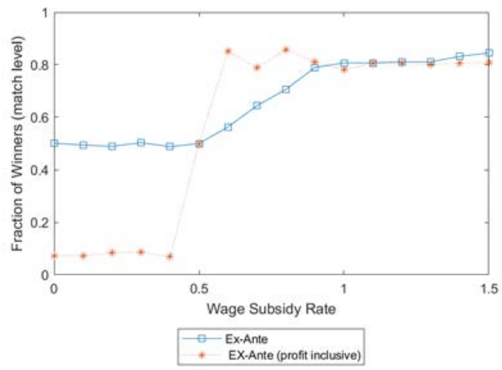
(b) Welfare at the time of injury

Notes: The figure shows the welfare and profit impacts of counterfactual wage subsidy rates relative to a 50% wage subsidy. The left subfigure includes three measures: (i) the change in average ex-ante worker welfare; (ii) the change in average ex-ante worker welfare inclusive of firm profit as an ex-post transfer to workers; and (iii) the change in average ex-ante firm profit. The right subfigure reports the change in average welfare for injured workers at the time of injury.

gain of wage subsidies is at most a 0.5% increase in consumption, and the welfare loss of eliminating wage subsidies is only 0.2%. A similar observation can be made with firm profit. Firm profit is increasing in the wage subsidy rate up to a rate of 80% because the wage subsidy helps correct inefficiently low levels of accommodation, but then decreases for wage subsidy rates over 80% because more generous subsidies generate higher taxes to firms. Taken together, we find that ex-ante welfare inclusive of firm profit is maximized at 0.3% of consumption with a wage subsidy rate of 140%. Given the large differences between uninjured workers and accommodated workers in net output (stemming from productivity differences and accommodation costs), even a 100% wage subsidy covers only a fraction of these differences.

On the other hand, Panel (b) shows that wage subsidies have a significant effect on welfare for injured workers. Conditional on experiencing injury, eliminating wage subsidies decreases welfare by about 10%, while increasing the wage subsidy rate to 100% increases welfare by around 30%. These large welfare effects are induced by large responses in accommodation rates documented in Figure 7, which generate higher earning during the injury period and better labor market outcomes after the

Figure 9: Distributional Impacts of Wage Subsidies for Accommodation



Notes: The figure shows distributional outcomes from counterfactual wage subsidy rates relative to a 50% wage subsidy. We report the fraction of matches that experience strictly positive welfare gains relative to the benchmark based on two welfare measures: ex-ante worker welfare and ex-ante worker welfare inclusive of firm profit as an ex-post transfer to workers.

injury period for most injured workers.

Overall, wage subsidies significantly increase the welfare of injured workers and moderately increase average ex-ante welfare by mitigating inefficiently low rates of accommodation. Because the probability of injury is small (2.2%), the welfare gain from additional accommodation has a relatively limited impact on the ex-ante average welfare. Moreover, accommodation subsidies do not generate much consumption smoothing benefit partly because during the injury period injured workers that are not accommodated still receive two-thirds of the wage they would have received if they worked (regardless of injury status). Although these factors limit the welfare gain from wage subsidies, the ex-ante welfare benefits still outweigh the welfare costs associated with financing wage subsidies through higher payroll tax rates.

6.3 Distributional Impacts

Although we find that higher wage subsidies increase average welfare, their distributional effects are less obvious. For one, there is substantial heterogeneity in the labor market return from accommodation, as documented in Section 3.3. Moreover, as documented in Section 5.4, the degree of under-accommodation varies by the type of worker-firm match. For example, accommodation rates for injuries in self-insured firms are closer to optimal than accommodation rates for injuries in imperfectly experience-rated firms. Because higher wage subsidies require higher payroll tax rates, they tend to hurt matches whose accommodation rates are close to optimal even in the absence of wage subsidies.

Figure 9 presents distributional impacts of accommodation subsidies by reporting the fraction of workers experiencing a welfare gain from a counterfactual wage subsidy relative to the benchmark subsidy of 50% using the ex-ante worker welfare (inclusive and exclusive of firm profit) as the welfare metric. For both welfare metrics, the majority of workers prefer higher wage subsidies. Inclusive of firm profit, a wage subsidy rate of 80% generates welfare gains for the highest percent of workers: more than 80% of workers prefer a wage subsidy rate of 80% relative to the benchmark economy. If we instead eliminate wage subsidies, almost all workers experience a welfare loss. These findings suggest that positive wage subsidies lead to welfare gains for a broad population of workers.

7 Conclusion

In this paper, we examine the labor market impacts of firm accommodation and assess the implications of firm accommodation decisions for the design of social insurance in the context of workers' compensation programs. Leveraging quasi-experimental variation and detailed administrative data on disabling claims from workplace injuries linked to quarterly earnings records in the state of Oregon, we show that accommodation is responsive to wage subsidy incentives, and that accommodation has positive effects on long-term employment and earnings. We then develop and estimate a frictional labor market model with workplace disability and firm accommodation. The model highlights that worker turnover and imperfect experience rating in workers' compensation programs lead to under-accommodation. In counterfactual experiments, we find that accommodation subsidies significantly increase firm accommodation rates, improve post-injury labor market outcomes, and increase overall welfare.

This paper is an important first step to understanding the role of employer accommodation in the labor market and in the design of social insurance programs. 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 social insurance programs and labor market policies more broadly.

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Online Appendix (Not For Publication)

A Experience Rating in Workers' Compensation

In nearly all states, most employers are required to obtain workers' compensation coverage for their employers. This coverage can be obtained through a private insurance market (which may contain a public option), self-insurance, or a residual market for employers that are deemed uninsurable on the private market. In many states, including Oregon, the National Council on Compensation Insurance (NCCI) is designated as the licensed rating and statistical organization, as well as the Plan Administrator for the state's residual market.[28] NCCI thus determines loss-based factors that enter into premium calculations.

Premiums for firm j at a particular insurer i are calculated as a function of expected losses of similarly classified firms c ("Loss Cost"), multiplied by the firm's differential loss risk (experience rating modification factor) and the insurer's overhead expenses ("Loss Cost Multiplier"):

$$\text{Premium}_{ij} = \text{Loss Cost}_{c(j)} \times \text{LCM}_{ij} \times \text{ER Mod}_j \tag{19}$$

The goal of the experience rating modification factor ("mod" from now on) is to modify the premium to better reflect a particular firm's own loss experience rather than the average loss experience of similarly classified firms. Firms with better-than-average loss experiences typically have a mod of < 1, while firms with worse-than-average loss experiences typically have a mod of > 1, and firms with average loss experiences have a mod of 1. A firm's loss experience is usually calculated from the previous three years of firm loss data, but if it does not have enough history (e.g., a new firm) or the premium is low enough (e.g., a small firm), the firm does not qualify for experience rating.

Most mods are not simply calculated as the total amount of losses generated in the previous three years, as some aspects of accidents provide more signal about the

[28] See https://www.ncci.com/pages/au_nccistatemap.aspx (accessed June 11, 2023) for a map of the role of NCCI for each state.

risk of future accidents than other aspects. In practice, the mod is a function of both frequency and cost. The mod function in most states (including Oregon) uses a "split rating approach" in which individual losses are split and differentially weighted, along with other modifications as follows:

- The amount of the loss up to a particular dollar amount (the split point, e.g., \$10,000) is known as primary loss, which is meant to reflect the expected *frequency* of loss events.
- The amount in excess of the split point is known as excess loss, which is meant to reflect the expected *severity* of loss events.
- Excess losses are often capped (e.g., so that primary plus excess losses do not exceed \$250,000).
- Finally, a "ballast" factor is added that is calculated as a function of expected losses based on previous years to prevent the experience rating factor from going too high or low.

The primary loss and excess loss are given different weights in calculating the mod. These weights typically place more weight on primary losses, and can vary by the size of the employer.[29] In other words, the NCCI mod puts more weight on accident frequency rather than severity. This means that employers have an incentive to reduce the number of injuries as well as an incentive to encourage workers to return to work because of the excess loss.[30]

In our model, we distinguish perfectly experience-rated firms and imperfectly experience-rated firms. We assign self-insured firms as perfectly experience-rated, and give all other firms an experience rating weight that is equal to the fraction of firms that have at least some experience rating.

[29] Moreover, for medical-only claims only 30% of the primary and excess losses are included.

[30] NCCI states: "Since experience rating gives individual employers some influence over the premium they pay, it provides an incentive for employers to [...] to have the injured employees return to work as soon as reasonably possible." (https://www.ncci.com/articles/documents/uw_abc_exp_rating.pdf)

B Details on Marginal Treatment Effect Estimates

In this appendix we describe the details for estimating the Marginal Treatment Effects (MTEs) in Section 3.2, following the notation of Heckman and Vytlacil (1999, 2005). Using a potential outcomes framework, denote a binary variable $D = \{0, 1\}$ if an injured worker receives accommodation and denote Y and Y_j for $j = \{0, 1\}$ as the observed outcome and potential outcomes, respectively. Define:

$$Y_j = X\beta_j + U_j \tag{20}$$

$$Y = DY_1 + (1 - D)Y_0 \tag{21}$$

$$D = \mathbb{1}\{\mu_D(X, Z) > V\} \tag{22}$$

where X are observables, Z are instruments that affect selection into treatment D but not potential outcomes, and V is the unobserved resistance to treatment. Assuming V is continuously distributed, we can rewrite the third equation above as $P(Z) > U_D$ in which U_D is distributed uniform and $P(Z)$ is the propensity score.

Before defining the MTE, we make two important assumptions. First, we assume conditional independence: $(U_0, U_1, V) \perp Z|X$, which implies and is implied by standard IV assumptions. Second, we make a separability assumption: $E(U_j|V, X) = E(U_j|V)$ for $j = 0, 1$. This implies that the shape of MTE curve will not depend on X.

The MTE is then defined as:

$$MTE(x, u) = E(Y_1 - Y_0|X = x, U_D = u) \tag{23}$$

$$= x(\beta_1 - \beta_0) + E(U_1 - U_0|U_D = u) \tag{24}$$

We also report estimates of Marginal Treatment Responses (MTRs) for treated and untreated claims, as introduced by Mogstad et al. (2018) and defined as:

$$MTR_0(x, u) = E(Y_0|X = x, U_D = u) \tag{25}$$

$$MTR_1(x, u) = E(Y_1|X = x, U_D = u) \tag{26}$$

We estimate the MTRs and construct the MTE from the MTRs using the "separate approach" (Heckman and Vytlacil, 2007) with polynomial of degree 2 using Stata's `mtefe` command (Andresen, 2018). Appendix Table 10 reports the estimates from the selection equation and differences in the treatment effect of accommodation by observable characteristics, which show consistent findings of negative selection on gains. For example, women and claims at self-insured firms are more likely to be treated (as shown in column 1), but have lower treatment effects (column 3), while claims in health care support and wounds/cuts/and burns are both less likely treated, but the treatment effects are larger (though not precise).

Appendix Figure 7 shows the MTR curves for employment and earnings at the average values of observable characteristics (the inputs for the estimated model in Section 5 add back in the effects of observables that correspond to each type in the model). In both figures, the difference between the curves for treated and untreated claims yields the MTEs shown in Figure 4. For employment, the MTR curve for treated claims is increasing in unobserved resistance to treatment, while the MTR curve for untreated claims is decreasing in unobserved resistance to treatment, resulting in negative selection on gains. The treated curve exceeds the untreated curve once unobserved resistance to treatment exceeds the 25th percentile, resulting in the positive MTEs shown in Figure 4. For earnings, the curve for treated claims is again increasing, while the curve for untreated claims is quite flat. The curves intersect much lower in the distribution of unobserved resistance to treatment, resulting in positive MTEs at nearly all points for earnings.

C Worker-Firm Bargaining Solution Details

In this appendix we provide more details on the solutions to the first stage bargaining problem and accommodation decision problem. As explained in Section 4 of the main text, the accommodation decision is determined by the threshold condition ξ_z^*, given by

$$J^a_{z,\xi_z^*} = J_z^{na} - \tau_z db_z. \tag{27}$$

Given the linear functional form for net output, i.e., $f_{1,z,\xi_z} = f_{1,z} - \xi_z$, the threshold condition is equivalent to:

$$\begin{aligned} d\left[\xi_z^* + (1-\delta_z)\, w_{1,z} - f_{1,z} - \tau_z p b_z\right] = \\ (T-d)\,(1-\lambda_z)\left[(1-q_{z,1})\,(f_{2,z,1} - w_{2,z,1}) - (1-q_{z,0})\,(f_{2,z,0} - w_{2,z,0})\right] \end{aligned}$$

Note that the threshold condition ξ_z^* is determined given the wage $w_{1,z}$; and the wage is determined by the following Nash bargaining problem:

$$\max_{w_{1,z}} \left(V_z(w_{1,z}, \mathbf{a}^*_{\mathbf{z}}) - U_{1,z}\right)^{\beta} J_z(w_{1,z}, \mathbf{a}^*_{\mathbf{z}})^{1-\beta} \tag{28}$$

where $\mathbf{a}^*_{\mathbf{z}}$ is the continuum of $a^*(w_{1,z}, \xi_z)$ for each ξ_z. To solve the bargaining problem, we re-express the value functions by replacing $a^*(w_{1,z}, \xi_z)$ with ξ_z^*:

$$\overline{V}_z(w_{1,z}, \boldsymbol{\xi}^*_{\boldsymbol{z}}) = (1-p)V_{z,u} + p\left[\mathit{\Gamma}\left(\xi_z^*\right) V_z^a + \left(1 - \mathit{\Gamma}\left(\xi_z^*\right)\right) V_z^{na}\right] \tag{29}$$

and

$$\overline{J}_z(w_{1,z}, \boldsymbol{\xi}^*_{\boldsymbol{z}}) = (1-p)J_{z,u} + p\left[\mathit{\Gamma}\left(\xi_z^*\right) J^a_{z,\xi_z^*} + \left(1 - \mathit{\Gamma}\left(\xi_z^*\right)\right) J_z^{na}\right] - P_{tot,z} \tag{30}$$

where the value J^a_{z,ξ_z^*} is the conditional expectation of firm's profit of accommodating the injured,

$$J^a_{z,\xi_z^*} = d\left[f_{1,z} - \mathbb{E}\left[\xi_z | \xi_z < \xi_z^*\right] - (1-\delta_z)\, w_{1,z}\right] + (T-d)\,(1-q_{z,1})\,(1-\lambda_z)\,(f_{2,z,a} - w_{2,z,a}) \tag{31}$$

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

$$\max_{w_{1,z},\boldsymbol{\xi}_{\mathbf{z}}^{*}} \left(\overline{V}_z(w_{1,z},\boldsymbol{\xi}_{\boldsymbol{z}}^{*}) - U_{1,z}\right)^{\beta} \overline{J}_z(w_{1,z},\boldsymbol{\xi}_{\boldsymbol{z}}^{*})^{1-\beta} \tag{32}$$

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

$$\beta \overline{J}_z(w_{1,z},\boldsymbol{\xi}_{\boldsymbol{z}}^{*})\frac{d\overline{V}_z}{dw_{1,z}} + (1-\beta)\left(\overline{V}_z(w_{1,z},\boldsymbol{\xi}_{\boldsymbol{z}}^{*}) - U_{1,z}\right)\frac{d\overline{J}_z}{dw_{1,z}} = 0 \tag{33}$$

where

$$\frac{d\overline{V}}{dw_{1,z}} = (1-p)T(1-q_{z,0})(1-\lambda_z)u'(w_{1,z}) + pd\mathit{\Gamma}\left(\xi_z^*\right)u'(w_{1,z}) + p\gamma\left(\xi_z^*\right)\frac{\partial \xi_z^*}{\partial w_{1,z}}\left(V_z^a - V_z^{na}\right),$$

$$\begin{aligned}\frac{d\overline{J}_z}{dw_{1,z}} =& -(1-p)T(1-q_{z,0})(1-\lambda_z) - pd\mathit{\Gamma}\left(\xi_z^*\right)(1-\delta_z) - pd\mathit{\Gamma}\left(\xi_z^*\right)\frac{\partial \mathbb{E}\left[\xi_z|\xi_z<\xi_z^*\right]}{\partial w_{1,z}} \\ &+ p\gamma\left(\xi_z^*\right)\frac{\partial \xi_z^*}{\partial w_{1,z}}\left(J_{z,\xi_z^*}^a - J_z^{na}\right) - \frac{\partial P_{tot,z}}{\partial w_{1,z}},\end{aligned}$$

$$\frac{\partial \xi_z^*}{\partial w_{1,z}} = -(1-\delta_z),$$

and

$$\frac{\partial P_{tot,z}}{\partial w_{1,z}} = \tau_z p d b_z \frac{\partial\left(1-\mathit{\Gamma}\left(\xi_z^*\right)\right)}{\partial w_{1,z}} = \tau_z p d b_z \gamma\left(\xi_z^*\right)(1-\delta_z)$$

By solving the first order condition, we obtain $w_{1,z}$ and then characterize ξ_z^* sequentially.

D Sensitivity Analysis

Following Einav et al. (2018), we provide additional diagnosis of the mapping between data and parameters via a perturbation exercise. We adjust each parameter one at a time and measure responses of the predicted auxiliary models we use for estimation. Let $\left\{\widehat{\Theta}_n\right\}_{n=1}^{N}$ be the vector of estimated structural parameters and $\{\widehat{\sigma}_{\Theta_n}\}_{n=1}^{N}$ be the vector of their standard errors. We re-simulate our model N times by adjusting one parameter in each simulation. In the n^{th} simulation, we use the parameter vector $\left\{\widehat{\Theta}_1, ..., \widehat{\Theta}_n + \widehat{\sigma}_{\beta_n}, ..., \widehat{\Theta}_N\right\}$, where the n^{th} parameter is perturbed by its standard error, and obtain new estimates of the auxiliary models. We then compute the percent change in absolute terms for each auxiliary model (cross-sectional moments or difference-in-differences coefficients). This exercise produces a matrix of dimension (number of auxiliary models $\times$ number of estimated parameters). To ease exhibition, we group auxiliary models into 4 groups as described in Section 5.2: cross-sectional average wages among uninjured workers; cross-sectional accommodation rates; difference-in-differences coefficients, and average employment and wages in the post-injury period.

Appendix Table 13 reports the main finding. First, while changes in parameters associated with output for uninjured workers have modest impacts on most of the auxiliary models compared with other parameters, changes in cross-sectional wage moments for uninjured workers are relatively larger than other auxiliary models. Second, changes in parameters associated with net output for injured workers lead to significant responses in accommodation rates and the difference-in-differences coefficients and modest responses in post-injury outcomes, but lead to little response to the wages of uninjured workers. Finally, changes in parameters associated with the accommodation shock distribution lead to significant responses in the difference-in-differences coefficients, but they have little effect on wages for uninjured workers and post-injury worker outcomes.

These patterns suggest that wage moments for uninjured workers are especially informative for parameters associated with output for uninjured workers. Moreover, cross-sectional accommodation rates and average post-injury outcomes are informative in identifying parameters associated with the net output for injured workers.

Then, the difference-in-differences coefficients provide identifying information for parameters associated with the accommodation cost shock distribution.

E Appendix Tables and Figures

Appendix Table 1: Association between EAIP and experience rating

	Accommodation rate				
	(1)	(2)	(3)	(4)	(5)
Perfect experience rating	0.188***	0.169***	0.169***	0.061**	0.060**
	(0.032)	(0.032)	(0.032)	(0.030)	(0.030)
Demographic controls		X	X	X	X
Injury controls			X	X	X
Firm controls				X	X
Time, county controls					X
Mean Accommodation	0.255	0.264	0.261	0.261	0.261
Observations	131219	118493	102965	102964	102964
R-squared	0.0309	0.0510	0.0817	0.121	0.122

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 2: Share of EAIP claims with detailed expenses

	Mean
Wage subsidy	0.903
Worksite modification	0.021
Equipment	0.028
Clothing	0.001
Tuition	0.002
Any detailed use	0.955

Appendix Table 3: Summary statistics, Oregon workers' compensation claims 2011-2017

	Full sample			Analysis sample		
	All	EAIP	No EAIP	All	High exp	Low exp
	(1)	(2)	(3)	(4)	(5)	(6)
Occupation: transportation	0.18	0.16	0.19	0.19	0.17	0.21
Occupation: production	0.12	0.11	0.12	0.13	0.12	0.13
Occupation: healthcare	0.11	0.17	0.09	0.12	0.17	0.07
Occupation: manufacturing	0.07	0.06	0.07	0.08	0.07	0.09
Occupation: construction	0.08	0.08	0.08	0.06	0.06	0.06
Industry: construction	0.05	0.05	0.05	0.06	0.06	0.07
Industry: manufacturing	0.13	0.12	0.13	0.16	0.14	0.17
Industry: trade	0.18	0.21	0.17	0.20	0.21	0.19
Industry: transportation	0.08	0.06	0.08	0.08	0.07	0.10
Industry: health and education	0.20	0.28	0.17	0.22	0.27	0.17
Industry: accommodation	0.07	0.03	0.08	0.03	0.01	0.06
Industry: public administration	0.07	0.11	0.05	0.10	0.16	0.04
Observations	131,219	33,415	97,804	73,205	36,897	36,308

Notes: Data provided by ODBCS. The full sample consists of disabling claims between 2011 and 2017. The EAIP and no EAIP columns distinguish claims that were accommodated and not accommodated, respectively. The analysis sample consists of the subset of claims for which the firm had at least one claim between 2005-2009 and one claim between 2011-2017, and workers who worked at least 300 hours in the quarter prior to injury and the high exposure and low exposure columns are claims for which the firm's accommodation rate in 2005-2009 was above or below the median accommodation rate, respectively. Reported values are means.

Appendix Table 4: Association between EAIP and industry-wide separation and quit rates

	Accommodation rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Industry-wide separation rate	-0.032**	-0.032**	-0.028**			
	(0.012)	(0.013)	(0.011)			
Industry-wide quit rate				-0.045**	-0.046*	-0.042*
				(0.021)	(0.024)	(0.021)
Year-month fixed effects		Yes	Yes		Yes	Yes
Occupation fixed effects			Yes			Yes
Observations	124395	124395	124395	124395	124395	124395
R-squared	0.0120	0.0146	0.0304	0.00873	0.0107	0.0286

Notes: Standard errors clustered by industry. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 5: Difference-in-Differences Analysis of Policy Change on Accommodation Use and Labor Market Outcomes Four Quarters after Injury, Binary Exposure Measure

		Four quarters after injury		
	EAIP	Employment	New firm	Earnings
	(1)	(2)	(3)	(4)
Any exposure × Post	-0.046***	-0.023***	-0.005	-303.617***
	(0.013)	(0.009)	(0.007)	(96.922)
Mean DV	0.318	0.702	0.0961	7961.3
Observations	73201	73201	73201	73201

Notes: Dependent variable shown in column header. All regressions include a broad set of worker, firm, and injury controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 6: Difference-in-Differences Analysis of Policy Change on Accommodation Use and Labor Market Outcomes Four Quarters after Injury, Days of Exposure Measure

		Four quarters after injury		
	EAIP	Employment	New firm	Earnings
	(1)	(2)	(3)	(4)
Exposure × Post	-0.00235***	-0.00069*	0.00021	-8.40853**
	(0.00059)	(0.00040)	(0.00029)	(3.92724)
Mean DV	0.318	0.702	0.0961	7961.3
Observations	73201	73201	73201	73201

Notes: Dependent variable shown in column header. All regressions include a broad set of worker, firm, and injury controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 7: Difference-in-Differences Analysis of Policy Change on Accommodation Use and Labor Market Outcomes Four Quarters after Injury, Firm-Occupation Exposure Measure

		Four quarters after injury		
	EAIP	Employment	New firm	Earnings
	(1)	(2)	(3)	(4)
Exposure × Post	-0.101***	-0.031**	0.002	-423.877***
	(0.023)	(0.015)	(0.011)	(146.142)
Mean DV	0.318	0.702	0.0961	7961.3
Observations	73201	73201	73201	73201

Notes: Dependent variable shown in column header. All regressions include a broad set of worker, firm, and injury controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 8: Difference-in-Differences Analysis of Policy Change on Accommodation Use and Labor Market Outcomes Four Quarters after Injury, No Tiny Firms

		Four quarters after injury		
	EAIP	Employment	New firm	Earnings
	(1)	(2)	(3)	(4)
Exposure × Post	-0.110***	-0.025	0.001	-364.230**
	(0.025)	(0.015)	(0.012)	(153.288)
Mean DV	0.325	0.705	0.0941	8034.9
Observations	69947	69947	69947	69947

Notes: Dependent variable shown in column header. All regressions include a broad set of worker, firm, and injury controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 9: Difference-in-Differences Analysis of Policy Change on Accommodation Use and Labor Market Outcomes Four Quarters after Injury, Exposure < 100%

		Four quarters after injury		
	EAIP	Employment	New firm	Earnings
	(1)	(2)	(3)	(4)
Exposure × Post	-0.110***	-0.036**	0.003	-447.045***
	(0.027)	(0.016)	(0.013)	(164.621)
Mean DV	0.317	0.702	0.0953	7986.2
Observations	71728	71728	71728	71728

Notes: Dependent variable shown in column header. All regressions include a broad set of worker, firm, and injury controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 10: Selection Equation and Employment Outcome Equation

	Selection Eq. (Accomm)	Outcome Eq. (Empl)	
		Not Accomm (β_0)	Treat Eff ($\beta_1 - \beta_0$)
	(1)	(2)	(3)
Exposure x post	-0.0901***		
	(0.0134)		
Female	0.0277***	-0.0334***	-0.0185*
	(0.00418)	(0.00574)	(0.0111)
Above median wages	0.00340	0.0363***	0.0150
	(0.00529)	(0.00664)	(0.0122)
Self-insured	0.170***	0.0299**	-0.0862**
	(0.00505)	(0.0142)	(0.0403)
Occupation			
Healthcare practitioners	-0.0168	-0.0234	-0.0275
	(0.0119)	(0.0166)	(0.0271)
Healthcare support	-0.0262**	-0.0427**	0.0334
	(0.0122)	(0.0168)	(0.0282)
Maintenance/repair	-0.0221**	0.0469***	-0.00377
	(0.00997)	(0.0130)	(0.0230)
Production	0.00248	0.0182	-0.0147
	(0.0101)	(0.0130)	(0.0228)
Transportation	-0.0191*	0.0234*	-0.00892
	(0.00977)	(0.0127)	(0.0225)
Nature of injury			
Wounds/cuts/burns	-0.115***	0.0616***	0.0375
	(0.00689)	(0.0117)	(0.0302)
Fractures/breaks	0.0274***	0.0820***	0.00272
	(0.00727)	(0.00932)	(0.0167)
Strains, back pain	-0.0267***	0.0501***	-0.0140
	(0.00547)	(0.00727)	(0.0132)
Propensity score		1.087*	
		(0.642)	
Propensity score squared		-0.476	
		(0.444)	
Observations	69724	69724	

Notes: Table shows selection equation and employment outcome of the MTE specification detailed in Appendix B. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 11: Difference-in-Differences Analysis of Policy Change on Earnings For Quarters after Injury, by Worker Turnover

	(1)
	Earnings
Exposure × Post	-351.8**
	(158.4)
Exposure × Post × New firm	-414.6
	(396.7)
Mean DV	7961.3
Observations	73201
R-squared	0.416

Notes: Dependent variable is earnings four quarters after injury. Regression includes broad set of worker, firm, and injury controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 12: Parameters estimated outside the model

Parameter	Description	Value	Source
p	Probability of injury	2.2%	ODBCS (2013)
d	Duration of injury	60 days	See Table 1
$q_{z,a}$	E-U transition rate, post-injury	MTR est., AF 7a	Our sample
$q_{z,u}$	E-U transition rate, uninjured	0.11, 0.10, 0.06, 0.05	Our sample
λ_z	E-E transition rate, post-injury	0.28, 0.19, 0.13, 0.06	Our sample
$\lambda_{z,u}$	E-E transition rate, uninjured	0.23, 0.17, 0.10, 0.06	Our sample
λ_z^{ue}	U-E transition rate	0.52, 0.52, 0.64, 0.67	Our sample
c_b	Consumption during unemployment	40% replacement rate	Shimer (2005)
β	Worker bargaining power	0.5	
$u(c)$	Utility function	$\log(c)$	
b	Time loss cash benefit (replacement rate)	0.667	ORS § 656.210-211
τ_z	Experience rating weight	0.38	ODBCS (2007)
δ_z	Wage subsidy rate	{0.5, 0.45}	Oregon policy

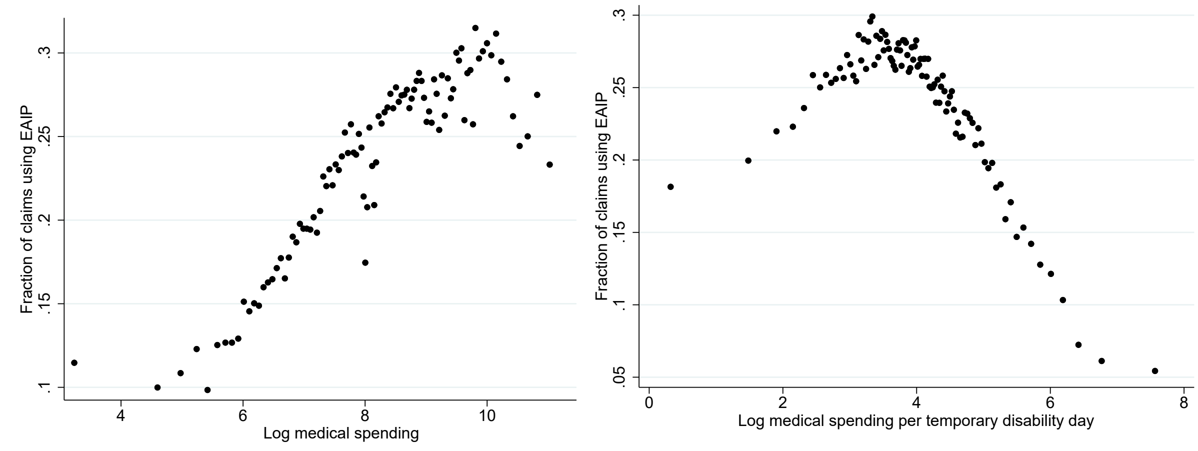
Note: Rows with four values denote types of worker-firm matches: (1) Low skilled worker at a not-self-insured firm, (2) low skilled worker at a self-insured firm, (3) high skilled worker at a not-self-insured firm, and (4) high skilled worker at a self-insured firm.

Appendix Table 13: Impact of Changes in Parameter Values on Auxiliary Models

Parameters	Wage	Accommodation rate	DD coefficient	Post-injury outcome
		Net output, uninjured: $f_{1,z,0}$		
$\alpha^0_{f,0}$	4.66	3.11	8.09	0.41
$\alpha^1_{f,0}$	2.06	1.18	8.09	0.09
$\alpha^2_{f,0}$	0.61	0.33	20.36	0.08
$\alpha^3_{f,0}$	3.85	2.36	20.36	0.32
		Net output, injured: $f_{1,z,\xi}$		
$\alpha^1_{f,1}$	0.01	1.37	31.07	0.14
$\alpha^2_{f,1}$	0.00	1.69	6.12	0.13
$\alpha^3_{f,1}$	0.00	0.52	31.07	0.09
$\alpha^4_{f,1}$	0.02	6.07	127.29	0.79
$\alpha^5_{f,1}$	0.06	4.48	58.03	0.63
		Accommodation cost shock (Std Dev): $\sigma_{\xi,z}$		
$\alpha_{\sigma,0}$	0.01	4.51	30.65	0.11
$\alpha_{\sigma,1}$	0.01	4.67	60.10	0.06

Notes: Each cell shows, as the parameter estimate in the row increases by one standard error of its estimate, the associated average % change (in absolute terms) in auxiliary models within each group in the column.

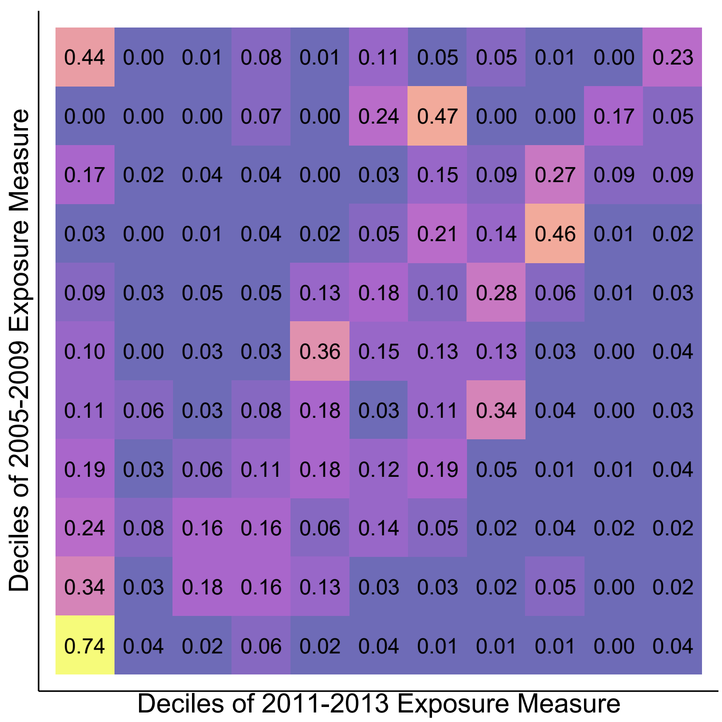
Appendix Figure 1: Fraction of claims using EAIP by medical spending



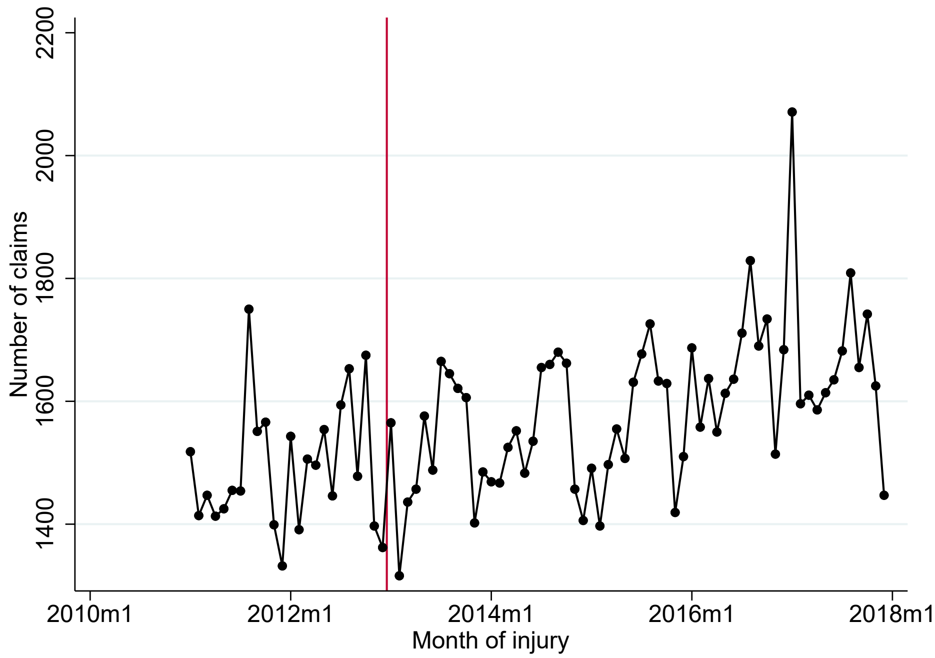
(a) Log medical spending

(b) Log medical spending per temp. disability day

Appendix Figure 2: Correlation of exposure measures, 2005-2009 vs 2011-2012

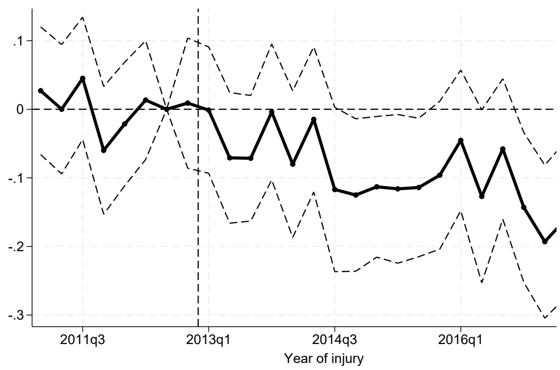


Appendix Figure 3: Number of claims, by month of injury

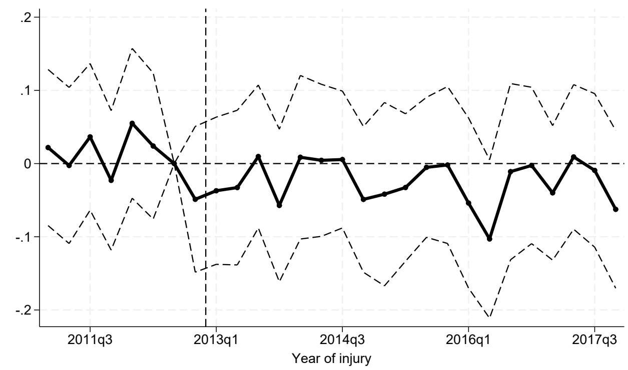


Appendix Figure 4: Regression-adjusted differences in outcomes by treatment status

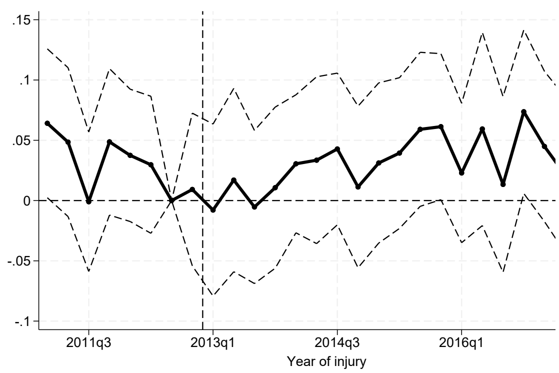
(a) EAIP use



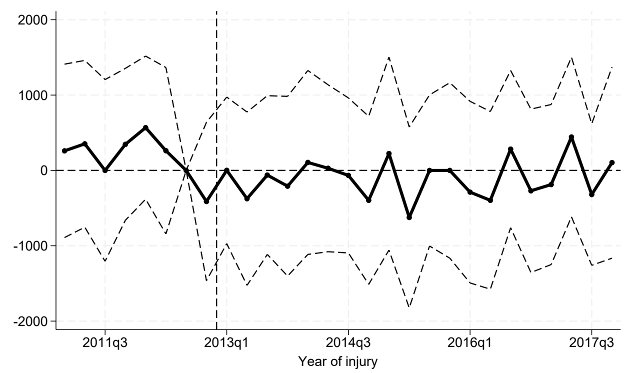
(b) Working four quarters later



(c) New firm four quarters later



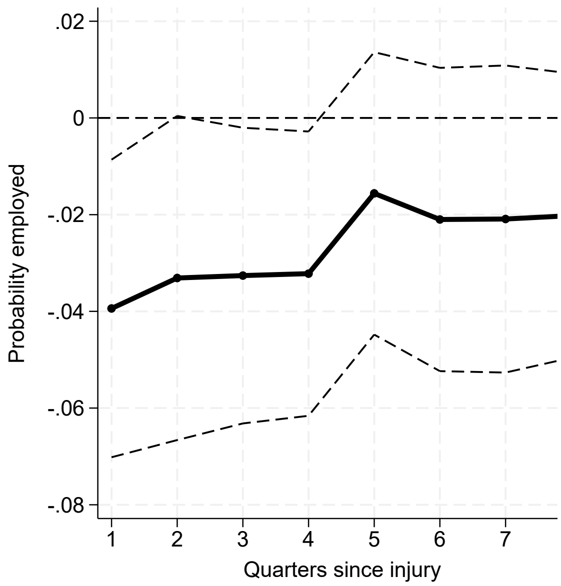
(d) Earnings four quarters later



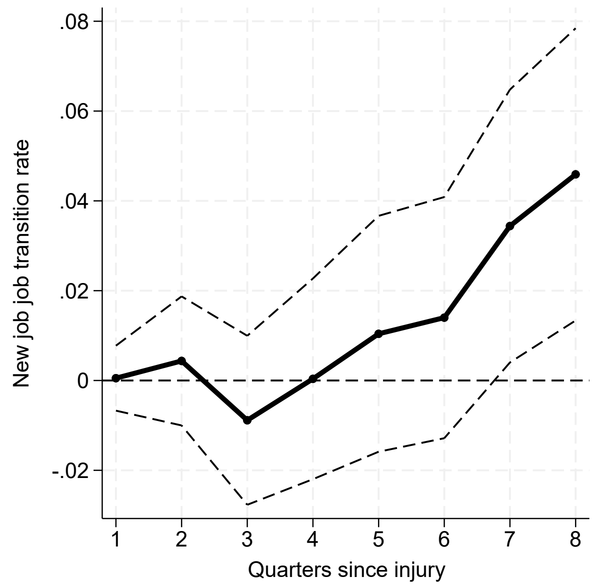
Notes: All regressions include a broad set of worker, firm, and injury controls. Solid dots denote the estimated coefficients on the interaction of treatment and quarter (the third quarter of 2012 is omitted), and dashed lines report 95% confidence intervals. Vertical line denotes the date of the policy change.

Appendix Figure 5: Difference-in-Differences Estimates on Labor Market Outcomes, by Quarter after Injury

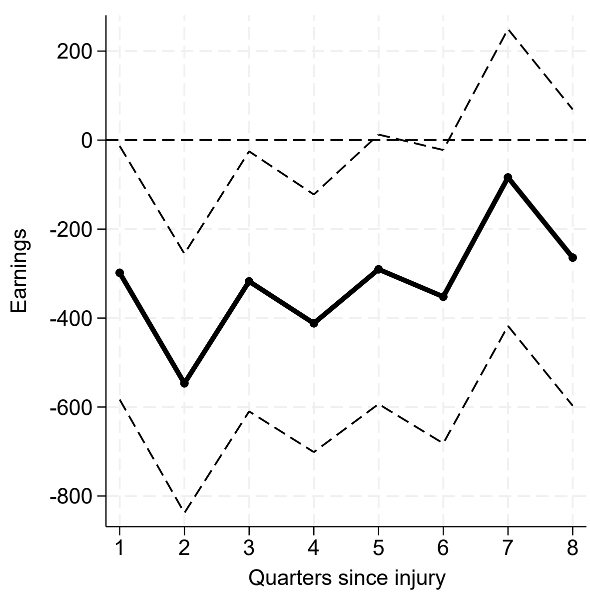
(a) Working



(b) Working in a new firm

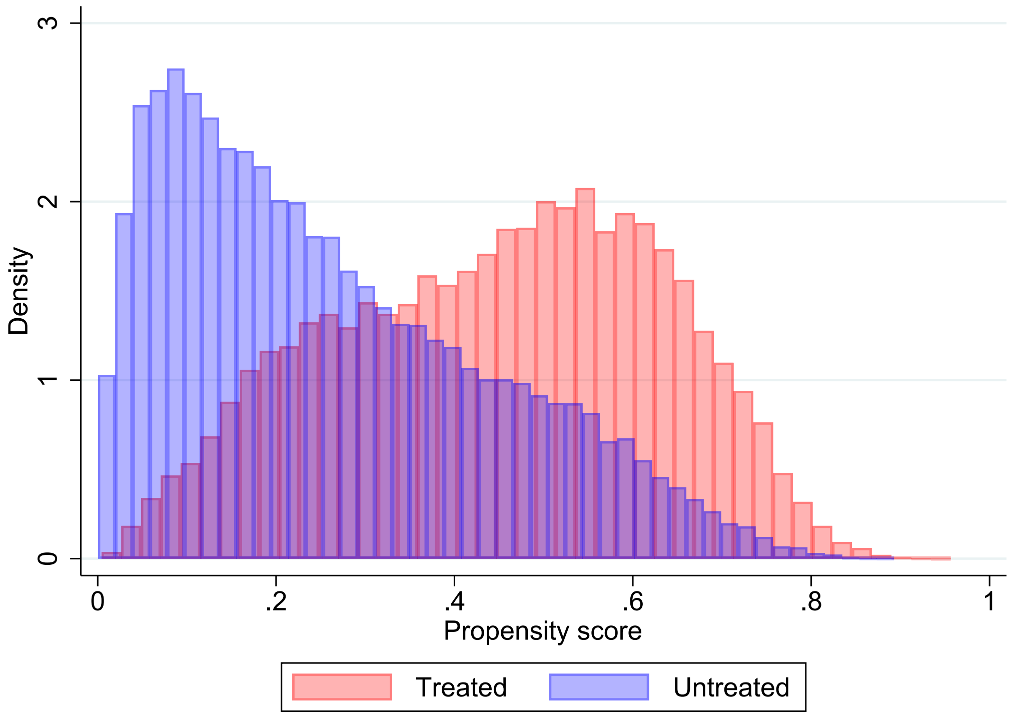


(c) Earnings ($)

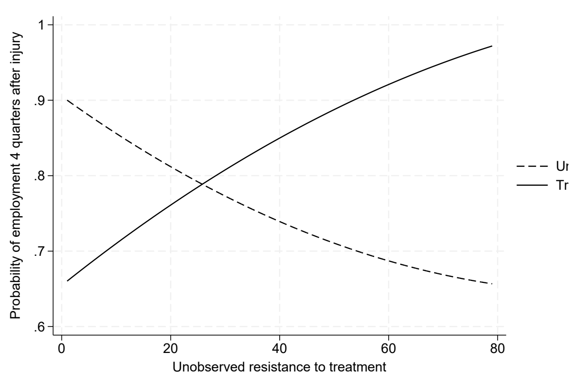


Notes: Dependent variable in (a) is whether the claimant is employed in the quarter of interest (i.e., has positive quarterly earnings); in (b) is whether the claimant is working in a new firm in the quarter of interest; and in (c) is earnings in the quarter of interest. Solid dots denote the estimated coefficients on the interaction of exposure and post-period from Equation (1) separately for each quarter since injury, and dashed lines report 95% confidence intervals. All regressions include a broad set of worker, firm, and injury controls.

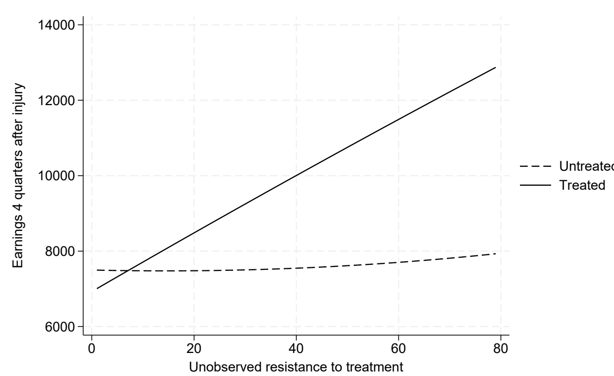
Appendix Figure 6: Distribution of Propensity Score by Treatment Status



Appendix Figure 7: Marginal Treatment Responses for Employment and Earnings



(a) Employment four quarters after injury



(b) Earnings four quarters after injury

Notes: Effects of observables (for employment) are reported in Appendix Table 10.

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