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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 workers with workplace disabilities. Leveraging 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 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. Broadly, accommodation adjusts the work environment or task composition (and possibly provides skill investment opportunities) to enable an individual to continue working after experiencing a shock, whether due to disability, caregiving, or other disruptions. By doing so, firm accommodation may not only mitigate productivity shocks in the short run by allowing the worker to continue to work, but may also mitigate productivity loss in the long run by serving as human capital investment. Policies to encourage, or even mandate, firms to provide accommodations are becoming more common and are often a component of social insurance and safety net policy, in addition to labor market policy.[1] However, little is known about firm decisions to provide (optional) accommodations or the impact of accommodation on workers and firms.

In this paper, we study the decision of firms to accommodate workers experiencing 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 incentives (mainly wage subsidies), we first provide quasi-experimental evidence of the effect of these subsidies on firm accommodation decisions and long-run employment and earnings outcomes.[2] We then examine the

[1]See, for example, "reasonable accommodation" provisions under the Americans with Disabilities Act (Acemoglu and Angrist, 2001) for disabled workers, broader work-from-home allowances (Bloom et al., 2024), and even leave flexibility policies like paid sick leave, paid parental leave, and the Family and Medical Leave Act (e.g., Rossin-Slater et al., 2013).

[2]We note that wage subsidies may generate different implications than reimbursements for particular monetary costs, like worksite modifications. Our results primarily speak to the effects of wage subsidies.

welfare implications of wage subsidies for accommodation by developing and estimating a frictional labor market model with firm accommodation decisions following workplace disability. Our model highlights potential inefficiencies in accommodation decisions and the role for corrective policy. We use our empirical estimates to tightly discipline the structural estimates of our model.

Our empirical context is 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 disabilities are a major source of disability risk and labor force exit in the U.S., and workers' compensation programs are the predominant source of social 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 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 workers with temporary disabilities as they return to work to help defray costs (explicit or implicit) related to, for example, flexible work arrangements or retraining.[3] 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 workers with workplace disabilities, 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

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

define exposure as a firm's rate of accommodation during a baseline period.[4] Firms with no use of accommodation during the baseline period are unlikely to respond to a *reduction* in the subsidy as a result of the policy change, while firms with higher baseline accommodation are more "exposed" 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 continuous difference-in-difference specification (similar to those reviewed in Dube and Lindner, 2024), and then use the predicted change in accommodation generated by the subsidy across firm exposure as an instrument to examine the impact of accommodation on labor market outcomes.

We find that the reduction in the wage subsidy decreased accommodation rates by 2.9 percentage points (or 9.3 percent) for claims in firms with average exposure. We find corresponding effects on labor market outcomes: the policy change led to a 0.95 percentage point decrease in employment and $120 decrease in quarterly earnings among average-exposure firms (roughly a 1.3-1.5 percent decline relative to the means, respectively).[5] We further explore heterogeneous treatment effects through a marginal treatment effect (MTE) framework, and find evidence of negative selection on gains: workers with workplace disabilities who would have benefited most from accommodation were the least likely to receive it. Finally, we also show several pieces of suggestive evidence that accommodation in this context is largely a form of general human capital investment.

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 disability, a workers' compensation program, and firm accommodation. In the model, workers are subject to workplace disability 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 workers with workplace disabilities, which can improve their future general human capital through both avoiding depreciation from non-employment and enhancing productive capacity. Workplace disabilities are covered by workers' compensation, and workers either receive time loss benefits or return to work early if accommodated. Workers and firms bargain over wages, and firms decide

[4]This instrument is motivated in part by Aizawa et al. (2022), which finds that time-invariant firm factors are a major driver of accommodation. Such firm heterogeneity in the relative benefits and costs of accommodation means that the same proportional change can differentially affect similar workers across firms.

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

whether to accommodate workers in the event of a workplace disability.[6] Firms fund the workers' compensation program through a premium that is imperfectly experience-rated.

The model highlights two main features that could generate socially inefficient accommodation decisions. First, worker turnover prevents firms from capturing future surplus from accommodation. This externality in the labor market can lead to under-accommodation of workers with workplace disabilities.[7] Second, firms whose workers' compensation premiums are imperfectly experience-rated may also accommodate workers with workplace disabilities 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 key 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 wage subsidy rate for accommodation to understand the welfare and distributional impacts. While subsidies benefit workers with disabilities by increasing the probability of accommodation and therefore mitigating the negative labor market consequences of workplace disability, 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 wage subsidies for accommodation from the current level (50% wage subsidy rate) decreases accommodation rates from 33% to 11%, leading to a decline in post-disability employment and earnings of 7% and 15%, respectively. From a welfare perspective, a revenue-neutral reform that eliminates wage subsidies reduces average welfare as well as welfare of more than 90% of workers. The welfare gains from wage subsidies are much larger for low-skilled workers. 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 experiencing work-related disability

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

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

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) studies 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 literature studying the labor market and welfare impacts of workers' compensation programs and social insurance programs for individuals with disabilities more generally. 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; Cabral and Dillender, 2024; Mullen and Rennane, 2024 for workers' compensation and Maestas et al., 2013; Kostøl and Mogstad, 2014; Low and Pistaferri, 2015 for Social Security Disability Insurance or analogous programs).[8] Previous research on the role of employers in these programs is much smaller, and mainly focuses on the effects of employer experience rating in European 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., 2025).[9] We add to this literature by providing new quasi-experimental evidence that firm accommodation within the context of workplace disability and workers' compensation programs has positive impacts on a worker's subsequent return to work and welfare, as well as quantifying sources of inefficiency in firm accommodation decisions.

Finally, positing firm accommodation as a form of investment in workers, this paper is also related to the literature on firm-provided training. Moving beyond the classic theoret-

[8] In addition, Humlum et al. (2023) studies incentives for human capital investment after physical injury.

[9] A related literature on wage subsidies for hiring disadvantaged workers, including disabled individuals, finds no to modest effects (Katz, 1996; Aizawa et al., 2025; Jain et al., 2025), suggesting differential success by whether a policy encourages retention of workers versus new hires.

ical 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) shows 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 are an important input into optimal social insurance and labor market policy.

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 (Murphy and Wolf, 2022). While a majority of workers may return to work immediately after such an event, approximately two-thirds of workers with a workplace injury or illness experience temporary disability (meaning they are unable to perform their job during a recovery period).[10] Even temporary disabilities present a significant shock, leading to earnings losses several years after the disabling event (Dworsky et al., 2022).

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 claim 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

[10] Though our context focuses exclusively on workplace disabilities, we adopt the broader terms "workers with disabilities", "disability" or "disabling event" throughout the paper for ease of discussion. Some terms, such as "date of injury" have specific meaning in workers' compensation policy, but encompass the broader set of all workers' compensation disabilities.

benefit. In Oregon, temporary benefits equal 66-2/3 percent of wages (subject to a minimum and maximum). Most employers in Oregon with at least 20 employees must return a worker to the same or similar job at the end of a workers' compensation claim.

In addition to the mandatory medical and time loss benefits, Oregon's workers' compensation program provides financial incentives to employers who accommodate workers with workers' compensation claims. Our analysis focuses on the Employer at Injury Program (EAIP), which is designed to help workers with temporary disabilities return to employment during their recovery. The EAIP incentivizes firms to accommodate workers with disabilities by offering subsidies (primarily in the form of wage subsidies) for the costs associated with accommodation for transitional work. The accommodations are intended to support workers during a temporary period during which they may need to perform other job duties or learn new skills in order to begin transitioning back into employment, and thus is not only a mechanism to return to work earlier but also a form of human capital investment.[11] Participating workers must face restrictions or limitations that prevent them from returning to their full pre-disability job. For example, a warehouse worker with a restriction on lifting heavy objects may instead be tasked with administrative tasks during their transitional work period. Workers cannot receive time loss 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 which the workplace disability occurred and must offer accommodation. The employer may receive a subsidy for wages during the transitional period when a worker returns. Firms may also receive reimbursement for costs such as worksite modifications up to \$5,000, tuition, books, and fees associated with retraining and skill development up to \$1,000, and clothing costs up to \$400 (ODCBS, 2020). However, the wage subsidy component is by far the most commonly used component of EAIP, accounting for over 96 percent of EAIP expenses.[12] On average, approximately 25 percent of workers' compensation claims in Oregon have some costs reimbursed via EAIP. According to a 2017 review, 13 states offer a partial return to work option similar to EAIP, while only three provide direct financial incentives to employers for offering these options to their employees (Ashley et al., 2017).

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

[11] See: https://wcd.oregon.gov/Publications/3525.pdf.

[12] See Appendix Table 1 for details on other types of EAIP expenses.

the same way that other workers' compensation costs are internalized via experience rating, this further increases the firm's incentive to accommodate workers.

EAIP has been in place since the 1990s. In 2013, a policy change reduced the wage subsidy from 50 to 45 percent of transitional earnings for up to 66 days during a 24-month period. The subsidy change was made to ensure compliance with a law requiring that the Workers' Benefit Fund (WBF, which finances EAIP and other employment-related programs) maintains a 12-month fund balance (see Aranda et al. (2018) for more details). Soon after, many employers began advocating for the 50 percent subsidy to be restored,[13] and based in part on this feedback, it returned to 50 percent in January 2020 (SAIF, 2020).

2.2 Data

We use a rich data linkage of workplace disability characteristics, longitudinal accommodation decisions of firms, and long-run labor market outcomes of workers who experience workplace disability. Our main data source is administrative workers' compensation claims from the state of Oregon, provided by the Oregon Department of Consumer and Business Services (ODCBS) 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 event and payment dates, total benefit payments and durations, and medical expenditures. Worker information includes 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.[14]

We then 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 1999 through 2019, enabling us to observe pre- and post-disability earnings history for all workers in the claims database with disabilities in or after 1999.[15] The data include total earnings and hours for

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

[14] Note that "nature of injury" and "cause of injury" are common terms in workers' compensation and so we use them in this instance to describe the details of our administrative data. However they refer to the broader set of events (e.g., illness or injury) that could result from a workplace event.

[15] Unfortunately, we do not observe earnings of workers who never have a workplace disability claim, so

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 Federal Reserve Bank of St. Louis, Bureau of 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 workers with disabilities that receive accommodations. Second, we estimate the effect of wage subsidies for accommodation 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. 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-disability earnings. Claims with EAIP have higher medical costs on average, and are more likely to be strains and less likely to be wounds. 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 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 2).

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 more likely to provide accommodation could reflect both that larger firms may have more capacity to

we cannot examine other firm-level outcomes, such as spillovers to other workers or replacement hiring.

Table 1: Summary statistics, Oregon workers' compensation claims 2011-2017

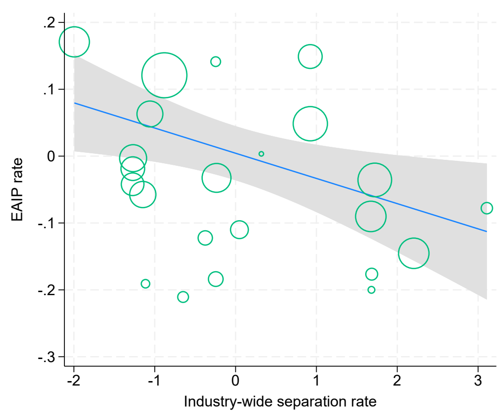
	Full sample			Analysis sample		
	All	EAIP	No EAIP	All	High exp	Low exp
	(1)	(2)	(3)	(4)	(5)	(6)
Worker characteristics						
Age	42.3	42.8	42.1	43.6	43.8	43.4
Female	0.37	0.42	0.35	0.37	0.40	0.33
Prior quarterly earnings ($)	7,601	8,607	7,250	8,857	9,710	8,003
	(5,914)	(5,663)	(5,959)	(6,077)	(6,1701)	(5,858)
Claim characteristics						
Accommodated	0.25	1.00	0.00	0.31	0.46	0.16
Claim medical costs ($)	8,166	9,442	7,746	8,145	7,566	8,719
	(14,247)	(14,965)	(13,977)	(14,212)	(13,505)	(14,857)
Claim days	111	145	99	114	110	117
	(168)	(183)	(160)	(172)	(167)	(177)
Claim days w/ timeloss	61	69	59	60	56	64
	(101)	(99)	(102)	(100)	(94)	(106)
Disability type: trauma	0.11	0.12	0.11	0.11	0.11	0.12
Disability type: fracture	0.11	0.12	0.11	0.11	0.10	0.12
Disability type: strain	0.58	0.63	0.56	0.60	0.62	0.58
Disability type: wound	0.13	0.08	0.15	0.12	0.11	0.12
Disability 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	33,412	97,807	71,527	35,785	35,742

Notes: Data provided by ODCBS. Column 1 consists of disabling claims between 2011 and 2017. Columns 2 and 3 distinguish claims that were accommodated and not accommodated, respectively. The analysis sample (Column 4) consists of the subset of claims for which the firm had at least one claim between 2005-2009 and one claim between 2011-2017 (excluding claims in the first two quarters of 2013), and workers who worked at least 250 hours in the quarter prior to disability. Columns 5 and 6 distinguish claims in the analysis sample 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 disability. 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.

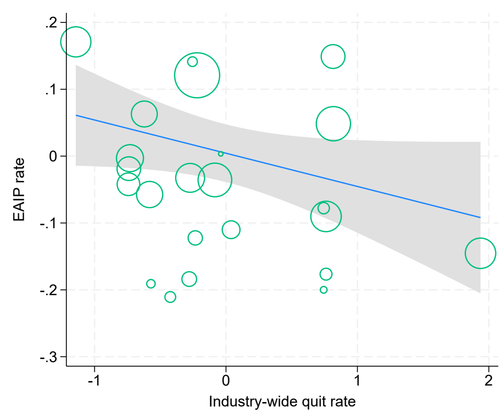
provide accommodation and/or have more knowledge of EAIP, or that self-insured firms fully internalize workers' compensation costs and thus may have a greater incentive to accommodate and offset these costs via EAIP. Appendix Table 3, which regresses EAIP on a host of characteristics, shows that the relationship between insurance status and EAIP remains after controlling for firm size, suggesting a role for the experience-rating channel. Thus, 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 ODCBS 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 leverage a change in the EAIP wage subsidy rate from 50 percent to 45 percent. The subsidy change was effective for wage subsidy periods beginning on or after July 1, 2013.[16] 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 this change, 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

[16] See WCD 3-2013 f. & cert. ef. 07-01-2013.

EAIP, which captures firm-level permanent heterogeneity in the relative benefits and costs of accommodation. If this heterogeneity drives differences in accommodation decisions,[17] then firms with historically low - or zero - 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.[18] Therefore, workers in different firms experience different changes in the likelihood of receiving accommodation. We estimate the relationship between accommodation and exposure before and after 2013 (in a difference-in-difference style specification with a continuous treatment), and then use the predicted change in accommodation 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 a continuous measure of 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.[19] Our approach thus requires firms to have at least two workers' compensation 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 250 hours in the quarter prior to disability to focus on workers attached to the labor market. Finally, we drop the first two quarters of 2013 because claims that originated during those quarters may have been treated for a couple reasons.[20] Specifically, the beginning of

[17]In Aizawa et al. (2022), we show that the specifics of the firm, rather than the worker or disability, is the strongest predictor of accommodation through EAIP. Worker and disability characteristics explain 1 and 3 percent of the variation in accommodation, 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.

[18]Similar exposure-style instruments have been used in many other settings, including studies of the introduction of Medicare, minimum wage policy, minimum legal working hours policy, and payroll tax policy (e.g., Finkelstein, 2007; Harasztosi and Lindner, 2019; Saez et al., 2019; Carry, 2022).

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

[20]We also show robustness to keeping the first two quarters of 2013.

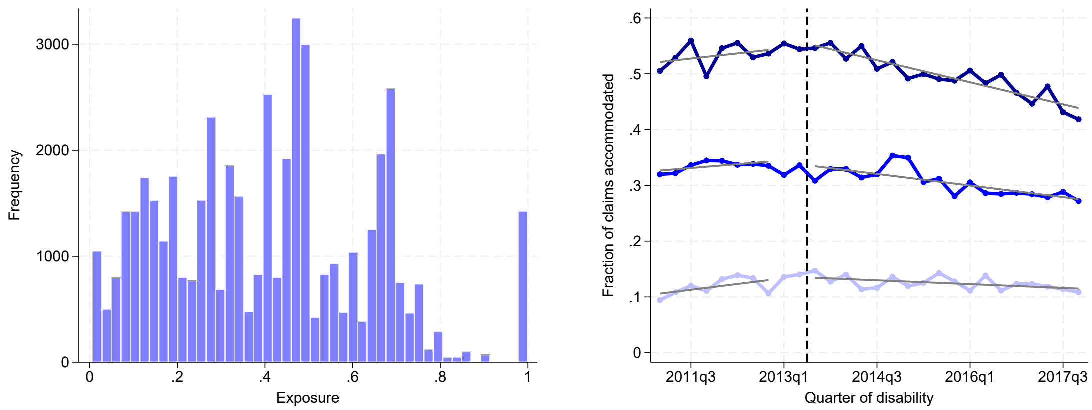
a claim's wage subsidy period (i.e., the beginning of accommodations) is usually after the date of disability, and the firm has some degree of discretion over when the wage subsidy period begins. The proposed policy change was announced during the first quarter of 2013, meaning that firms could have sped up wage subsidy period start dates in anticipation of the policy change for early 2013 claims that otherwise would have begun accommodations after July. At the same time, claims with disabilities that occurred just prior to July 2013 could still have been subject to the lower subsidy rate if their wage subsidy start date fell after the policy change.

These restrictions result in a final analysis sample of roughly 71,500 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, and mean exposure is 0.27 with a standard deviation of 0.27. 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 by tercile of exposure (collapsed from our continuous measure of exposure). Each tercile has a similar slight upward slope in EAIP use prior to the policy change in 2013. After the policy change, accommodation rates decreased, particularly for claims in more highly exposed firms (dark blue line). For firms in the lowest tercile of exposure (light blue line), however, there was little change in accommodation rates after the policy change.[21]

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-disability earnings. High exposure claims are more likely to be accommodated, 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. In-

[21] There are several reasons why firms' response to the policy change may have not been immediate. First, according to program rules, firms are allowed to submit reimbursement for EAIP up to 13 months after the claim has closed (Helmer, 2018). If information frictions prevented firms from learning about the change at implementation, it could have taken months or even years before firms realized it on their own as they submit claims. Second, given adjustment costs in hiring replacement workers (Dube et al., 2010; Ginja et al., 2023), firms may want to gradually test out the relative profitability of replacement hiring versus accommodation for these temporary absences. Finally, as noted above, policymakers stated that if WBF balance was achieved, the subsidy rate could potentially revert back to the prior level. Some employers may have delayed in changing their accommodation behavior due to this uncertainty, particularly in the presence of adjustment costs.

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



(a) Distribution of exposure

(b) Accommodation rate by exposure tercile

Notes: Data provided by ODCBS. Panel (a) reports the number of claims by exposure bin in our analysis sample, 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 quarter from 2011-2017, by exposure tercile (darkest blue is highest exposure tercile, lightest blue is lowest exposure tercile), each with fitted lines before and after the policy change in gray. Terciles are constructed from the continuous exposure measure. Dashed vertical line denotes the date of the policy change in July 2013. For the sake of completeness, we also include claims from the first two quarters of 2013 claims in Panel (b) even though they are excluded from the analytic sample.

terestingly, disability 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 this exposure-based difference-in-differences (DID) regression:

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

where β is the coefficient of interest: the effect of claim i occurring after July 2013 (Post_t) interacted with our continuous 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, disability characteristics, firm characteristics, and county unemployment rates. Standard errors are clustered by firm.

As discussed in other work using exposure-based designs that leverage continuous "treatments" (Sun and Shapiro, 2022; Dube and Lindner, 2024), the key identification assumption for the causal interpretation of β is the strong parallel trends assumption (Callaway et al., 2024).[22] Specifically, this assumption requires that if claims in all firms were given exposure $E = e'$, their average response to the policy change would have been equal to the response of claims in firms that actually experienced exposure $E = e'$.[23] This rules out selection into each exposure level e resulting from (unobserved) factors that are correlated with $\text{Exposure}_{f(i)} \times \text{Post}_{t(i)}$.

We provide several pieces of evidence to support this assumption. First, we show an analogue to the standard test of parallel pre-trends: Figure 2b shows that accommodation rates trended in parallel across exposure terciles prior to the policy change, and Figure 3 further shows parallel trends prior to the policy change by reporting annual estimates of β relative to 2012 and adjusted for a host of controls. Second, we verify that our results are not sensitive to interacting observable characteristics (insurance type, occupation, and the nature of injury) with an indicator for the post-period (see Appendix Table 5).

Next, we use Equation (1) to predict EAIP usage as a first stage, and use predicted EAIP to instrument for accommodation 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 $\text{Exposure}_f \times \text{Post}_t$:

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

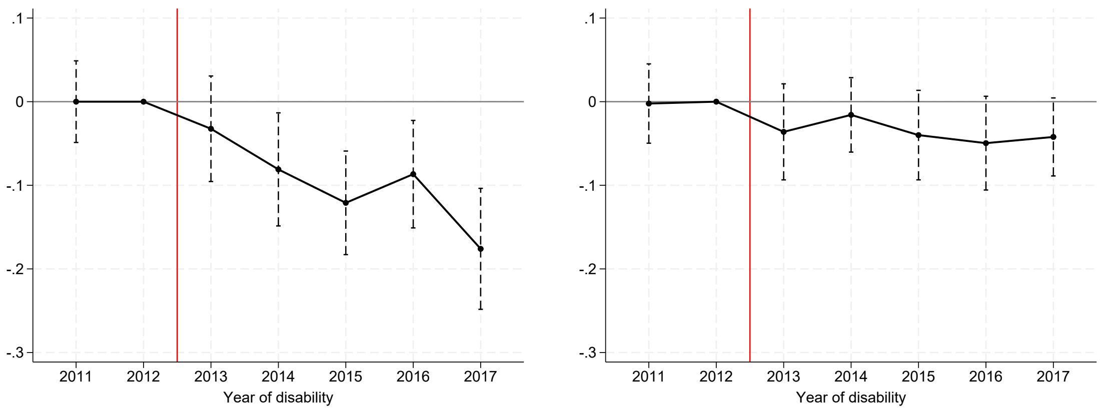
$$Y_i = \psi \widehat{EAIP}_i + \rho \text{Exposure}_{f(i)} + \pi_{j(i),t(i)} + \lambda X_i + \upsilon_i \quad (3)$$

where Equation (2) is the first stage prediction of EAIP (the DID-style specification as in Equation (1)), and Equation (3) is the IV equation regressing employment outcomes Y_i on

[22] Alternatively, under the assumptions of standard parallel trends and the presence of a control group (in lieu of the assumption of strong parallel trends), β captures the weighted average of average treatment effects on the treated across exposure groups. In our setting, a natural assumption is that claims in firms with zero exposure are unaffected by the policy change and thus can serve as a control group, as supported by Figure 2b, which shows that accommodation rates of the lowest tercile of the exposure distribution did not change with the policy. As discussed by Callaway et al. (2024), however, interpretation of estimates under these assumptions can be difficult due to negative weighting issues.

[23] To be precise, if all claims are given exposure $E = e'$, their average response to the policy change must satisfy: $\mathbb{E}[Y_{i,post}(e') - Y_{i,pre}(e')] = \mathbb{E}[Y_{i,post}(e') - Y_{i,pre}(e')|E = e']$ where $Y_{i,t}(e')$ is an outcome for claim i in period t with exposure $E = e'$. Technically, this identifies a weighted average of average causal responses, which is subject to the standard interpretation critique that the underlying weights do not necessarily align with the distribution of exposure. However, we test the sensitivity of this weighting issue by estimating a non-parametric specification which allows flexible interactions between exposure and the post-reform dummy and then constructing an average causal response that weights these estimates based on the distribution of exposure (as suggested in Callaway et al., 2024). We can alternatively impose an additional assumption that potential outcomes are linear in exposure to resolve this issue.

Figure 3: Event Study Analysis of Policy Change on Accommodation and Employment



(a) Accommodation

(b) Employment four quarters later

Notes: Data provided by ODCBS. Solid dots denote the estimated coefficients on the interaction of exposure and year from a regression of the outcome variable on exposure, quarter, and the interaction between exposure and year (2012 is omitted), along with a broad set of worker, firm, and disability controls. Estimate for 2013 excludes claims from the first two quarters of the year. Dashed vertical lines report 95% confidence intervals. Vertical red line distinguishes time periods before and after the policy change.

our instrumented prediction of $EAIP_i$ from the first stage. Along with the identifying assumptions needed for the DID-style specification, we require an assumption of monotonicity: essentially, that the reduction in subsidy did not make any firms *more* likely to offer accommodations; and an exclusion restriction: that the policy change impacted subsequent labor market outcomes for claims from more highly exposed firms relative to claims from less exposed firms only through higher accommodation rates at those firms. 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 was stable over time (Appendix Figure 1), as was the classification of firms as either high or low exposure firms over time (Appendix Figure 2).

Because accommodation decisions are made at the worker-firm level, there may be substantial heterogeneity in the effect of accommodation on labor market outcomes, even among workers in the same firm. To explore this and to shed light on the complier population identified in the IV estimates, we apply a marginal treatment effects (MTE) framework following Heckman and Vytlacil (2005) (see Appendix B for derivation of the MTE from the potential outcomes framework). 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 DID-style regressions from Equation (1), with EAIP and each of our labor market outcomes (employment, defined as working at least 250 hours in the quarter, quarterly earnings, and employment at a firm other than the firm at which the disability occurred) four quarters after disability 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 2.9 percentage points moving from no exposure to average firm exposure, corresponding to a 9.3% change relative to average accommodation rates and thus a subsidy elasticity of 0.9).

For labor market outcomes, the results show that the reduction in the subsidy reduced the probability of working four quarters after disability by 0.35 percentage points and decreased quarterly earnings by $45 for every ten percentage point increase in firm exposure (or 0.95 percentage points and $120 for moving from no exposure to average firm exposure - a change of approximately 1.3-1.5 percent relative to average employment rates and earnings and corresponding to subsidy elasticities of 0.13-0.15, respectively), but that there were no substantial changes in worker turnover (defined as moving to a new firm or a new industry).[24]

The results are robust to several other specifications and sample restrictions, as further discussed in Appendix A. We perform several sensitivity checks to rule out mean reversion, including placebo regressions assigning the policy change to earlier years, reducing the baseline historical period over which exposure is defined, and a Bayesian shrinkage

[24] We also estimate a non-parametric specification allowing for flexible interactions between exposure types and the post-reform dummy, and use the estimates to reweight the resulting average causal responses by the distribution of exposure in the sample (as proposed in Callaway et al. (2024)). The resulting average causal response estimates are very similar to those in Table 2: -0.126 for EAIP, -0.032 for employment four quarters later, -$438 for earnings four quarters later, and -0.001 for employment in a new firm four quarters later.

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

		Four quarters after disability		
	EAIP	Employment	Earnings	New firm
	(1)	(2)	(3)	(4)
Exposure × Post	-0.107***	-0.035**	-446.516***	0.001
	(0.024)	(0.016)	(151.754)	(0.012)
Mean DV	0.312	0.721	7806.8	0.106
Observations	71525	71525	71525	71525

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1). Dependent variables are whether the claim is accommodated through EAIP (column 1) and, four quarters after disability: whether the claimant is employed (column 2), the claimant's quarterly earnings (column 3), and whether the claimant is employed in a new firm (column 4). All regressions include a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

estimator, excluding firms with 10 or fewer workers, and excluding firms with 100% exposure (Appendix Tables 6 - 8). In addition, Appendix Tables 9 and 10 show robustness to alternative definitions of exposure, including a binary measure of any exposure and a measure of exposure defined at the firm-occupation level.[25] Finally, Appendix Table 13 shows robustness to dropping only the second quarter of 2013 (Panel a) and keeping all quarters of 2013 in the sample (Panel b). Panel c shows that when we look at longer-run effects by dropping all claims occurring in 2013, the estimate on EAIP slightly increases, but overall estimates are broadly similar to our main estimates.

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 33 percentage point increase in the probability of working four quarters after the disability and to an increase in quarterly earnings of $4,100. There is no effect of accommodation on the probability of moving to a new firm, though this effect is noisy.

[25] We also test whether the overall composition of claims has changed over time. Appendix Tables 11 and 12 report average characteristics of claims by year and DID estimates with pre-disability characteristics as outcomes, respectively. There are no obvious compositional changes, and the few DID estimates that are statistically significant push in the opposite direction of our main findings, suggesting that our main results are not driven by compositional changes.

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

	Four quarters after disability		
	Employment	Earnings	New firm
	(1)	(2)	(3)
EAIP	0.329**	4177.9**	-0.0107
	(0.160)	(1624.1)	(0.108)
Mean DV	0.721	7806.8	0.106
Observations	71525	71525	71525

Notes: Data provided by ODCBS. Table reports IV coefficients ψ and standard errors (clustered by firm) from Equation (3). Dependent variables are, four quarters after disability: whether the claimant is employed (column 1), the claimant's quarterly earnings (column 2), and whether the claimant is employed in a new firm (column 3). All regressions include a broad set of worker, firm, and disability controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

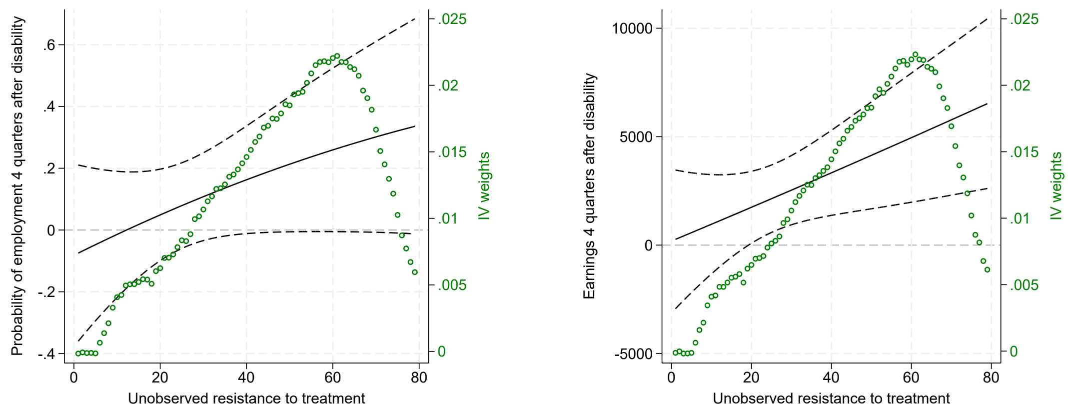
Figure 4 shows MTE curves in black for employment (Panel a) and earnings (Panel b) along the distribution of unobserved resistance to treatment (accommodation) for which we have common support. We find that workers with disabilities who are least likely to receive accommodation (i.e., workers with the highest unobserved resistance to treatment) have the highest potential employment and earnings gains from accommodation. These larger treatment effects are in part driven by the fact that these workers have significantly worse employment outcomes in the absence of accommodation (see Appendix Figure 4 for the estimated outcomes for treated and untreated states – i.e., the marginal treatment response curves), suggesting that these workers' workplace disabilities are more severe and thus the cost of accommodating such disabilities is high. This mechanism generates negative selection on gains.[26] We also find negative selection on gains for observable characteristics, including workers in self-insured firms, healthcare support occupations, women, and injuries involving wounds, cuts, and burns (see Appendix Table 14).[27]

[26] 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 has higher employment effects for individuals who are the least likely to be employed without the program.

[27] Appendix Table 14 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 -0.11 in column 1 of Table 2.

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, 2005). 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 instrument. 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 disability

(b) Earnings four quarters after disability

Notes: Data provided by ODCBS. 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. Corresponding marginal treatment response curves are in Appendix Figure 4.

Interpretation: firm accommodation as human capital investment. Overall, our estimates show that firm accommodation improves labor market outcomes after disability. One potential mechanism through which this operates is that accommodation allows for earlier return to work after disability, which prevents the decay of human capital.[28] A

[28]Recent work on this topic shows that human capital depreciates when younger workers do not use their skills (Dinerstein et al., 2022; Arellano-Bover, 2022), but Cohen et al. (2023) finds no such effect for older workers. In our sample, Appendix Table 15 shows sizeable labor market effects for all age groups. Relative

second potential mechanism is through skill accumulation: by providing alternative work arrangements during the disability 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 more specific human capital, such as firm-specific human capital (Becker, 1964). Although accommodation can have both components, if it mainly provides firm-specific human capital then it 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 disability, though the standard errors are large.[29] Moreover, given these null findings, we run a modified version of 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 17 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.

Given these findings, we proceed with a model that characterizes firm accommodation as a form of general human capital investment, but also consider a model with industry-specific human capital (Neal, 1995) as a robustness exercise in Online Appendix E.1.

to the literature, our effects for older workers could be driven by changes in work capacity as a result of their injury, in addition to human capital decay more generally.

[29] Additionally, using claim information on whether a claim uses additional EAIP benefits such as reimbursements for worksite modifications, tuition, or clothing, Appendix Table 16 shows that accommodated workers with claims that receive these other benefits are significantly less likely to move to a new firm than accommodated workers with claims that did not receive these other benefits, controlling for other firm, worker, and disability characteristics. This exercise suggests that our measures of job-to-job mobility pick up evidence of firm- or industry-specific investment in cases in which firms use additional accommodation benefits beyond wage subsidies, but very few claims receive accommodation benefits of that sort (less than 5% of the sample), suggesting the predominant form of investment in our context is general.

4 Dynamic Bargaining Model

To better understand the welfare impacts of accommodation and wage subsidies, we develop and estimate a frictional labor market model of workplace disability, 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 $z \in \mathscr{Z}$ in which injuries are realized and accommodation decisions are made in the first period, and the second period represents the labor market after disability. A workers' compensation program pays timeloss benefits for workers with disabilities, funded by firm premiums. The premiums are imperfectly experienced-rated, and the extent of experience rating differs across firms.

The model begins with risk-averse workers and risk-neutral firms bargaining ex-ante over the first-period wage $w_{1,z}$.[30] In the first period, workers incur a workplace disability with probability p, which results in a disability duration of $d \in [0,T]$. [31] Workers with disabilities either receive time loss benefits b_z from workers' compensation if they remain out of work for the duration of their disability, 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 disability that results in net output $f_{1,z,\xi}$.[32]

In the second period, workers who experienced disability 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

[30]The assumption of risk neutral firms assumes away a potential downside of experience rating, which is that it can exacerbate labor demand shocks by raising tax rates on struggling firms (Johnston, 2021). While beyond the scope of this paper, an interesting avenue for future work would be to study optimal experience-rating in workers' compensation that incorporates such trade-offs (Spaziani, 2024).

[31]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 1 shows that the number of claims did not respond to the wage subsidy policy change. Thus, moral hazard on the margin of disability (or claiming) rates are unlikely to be first-order in our policy environment.

[32]We do not explicitly model the possibility of firms engaging in replacement hiring because our earnings data only includes workers with workplace disability claims. However, as long as the value of posting a new vacancy for replacement hiring is zero in equilibrium —- a property commonly satisfied in standard search and matching models -— this simplification does not affect our main analysis.

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.

Workers without disabilities 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.[33] If they move to a new firm, they receive an outside wage $w_{1,z,O}$.

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 they do not have a disability, 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. 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 worker's value of being accom-

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

modated and working (V_z^a) and not being accommodated and not working (V_z^{na}) given by:

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

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

These values capture the weighted sum of the value during the disability period (first term) and the value in the post-disability period (second term). During the disability period, workers who are accommodated receive wage $w_{1,z}$ while workers who are not accommodated receive a time loss benefit b_z.[34] After the disability 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 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:

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

where the first term is firm profit if the worker does not have a disability, given by:

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

and the terms within the expectation are profits from accommodating a worker with a disability ($J_{z,\xi}^a$) and from not accommodating a worker with a disability (J_z^{na}), given by:

$$J_{z,\xi}^a = d\left[f_{1,z,\xi} - (1-\delta_z)w_{1,z}\right] + (T-d)(1-q_{z,1})(1-\lambda_z)(f_{2,z,1} - w_{2,z,1}) \quad (10)$$

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

[34]Note that their wage $w_{1,z}$ is the same wage that workers without disabilities receive to capture the wage-setting constraints of our empirical context. Because of identification challenges that arise from this constraint, we assume that disabled workers do not incur disutility from working while accommodated. In Online Appendix E.2, we show that our main findings are robust to assuming a disutility of work equivalent to 30% of wages.

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:

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

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 disability, the first-period wage $w_{1,z}$ is determined by Nash bargaining between the worker and firm. Second, after the realization of disability 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-disability 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 $U_{1,z} = T\left(\lambda_{1,z}^{ue}u(c_b) + \left(1-\lambda_{1,z}^{ue}\right)u(w_{1,z,O})\right)$ and $U_{2,z,a} = \left(1-\lambda_{2,z}^{ue}\right)u(c_b) + \lambda_{2,z}^{ue}u(w_{2,z,a,O})$ for the ex-ante and post-disability 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-disability 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-disability wages for all z,a:

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

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 worker with a disability 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 workers with disabilities 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 disability 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 workers with disabilities 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 ($f_{2,z,a,O} > w_{2,z,a,O}$), creating a dynamic inefficiency in accommodation. This inefficiency is larger when worker turnover rates are higher.[35]

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.

[35]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).

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 $z \in \mathscr{Z}$, which include both observable and unobservable characteristics that capture the economic mechanisms driving the empirical patterns. In terms of observables, the model incorporates the firm's insurance status (self-insured or not), which generates differential effects due to their different implications for fiscal externalities, worker skill type (high or low, measured by pre-disability wages), along which output and labor market parameters are allowed to vary, the firm's baseline accommodation rate (i.e., our measure of exposure defined in Section 3), and whether the disability took place before or after the policy change in 2013. In addition, we incorporate unobserved heterogeneity that corresponds to the unobserved resistance to treatment (accommodation) as defined in our MTE analysis, and we introduce it to capture additional heterogeneity in the labor market return from accommodation that stems from hard-to-observe characteristics like disability severity. The distribution of observables is directly measurable from our data and the unobserved component is independent from the observable variables and uniformly distributed.

We estimate or set several parameters outside the model, summarized in Appendix Table 18. We set the probability of disability to $p = 0.022$, the annual disabling claim rate in Oregon, and set the duration of disability 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 workers with disabilities, $q_{z,a}$, vary by accommodation status and match characteristics (except disability year) and are given by the estimates from the marginal treatment responses in Appendix Figure 4. Other transition rates are assumed to only vary by worker skill type and firm insurance type. E-E transition rates of workers with disabilities (λ_z) are measured by the percent of individuals who are not at the firm of disability four quarters after disability, conditional on having positive earnings. For E-U transition rates for workers without disabilities ($q_{z,u}$), we measure, among individuals who were employed seven quarters prior to disability, the percent who were unemployed four quarters later, at three quarters prior to disability. For E-E transition rates $\lambda_{z,u}$, we measure the percent of individuals who were not at the firm of disability four quarters prior to disability, 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 disability, the percent who were employed four quarters later, at three quarters prior to the disability.

We set the ex-ante and post-disability outside wages ($w_{1,z,O}$ and $w_{2,z,a,O}$) equal to 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.[36] 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.

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-disability output parameters $f_{2,z,a}$ by solving the Nash bargaining problem in Equation (13). Using the parameters in Appendix Table 18, we solve for $f_{2,z,a}$ by matching the model-implied post-disability 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 4).

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

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 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 (Exposure $\in \{1,2,...,5\}$) and 10 unobservable deciles (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 workers without disabilities 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 workers with disabilities because their earnings are constrained to be equal to the earnings of workers without disabilities. Instead, cross-sectional variation in accommodation rates of workers with disabilities 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 DID 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 $\alpha_{\sigma,0}$. If this parameter is large, variation in idiosyncratic accommodation cost shocks become more influential in accommodation decisions, reducing firms' sensitivity to wage subsidies. Thus the DID 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 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 workers without disabilities by worker skill (high or low), firm insurance status (self-insured or not), exposure type (above median or below), and whether the disability occurred prior to the policy change in 2013;[37] (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 DID regression in Equation (1) for accommodation (EAIP), post-disability employment, and post-disability earnings; and (4) average post-disability 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 $\overline{\beta}$.[38,39] Standard errors are based on the asymptotic variance.

5.3 Estimation Results

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

[37]These earnings are calculated in the quarter prior to disability.

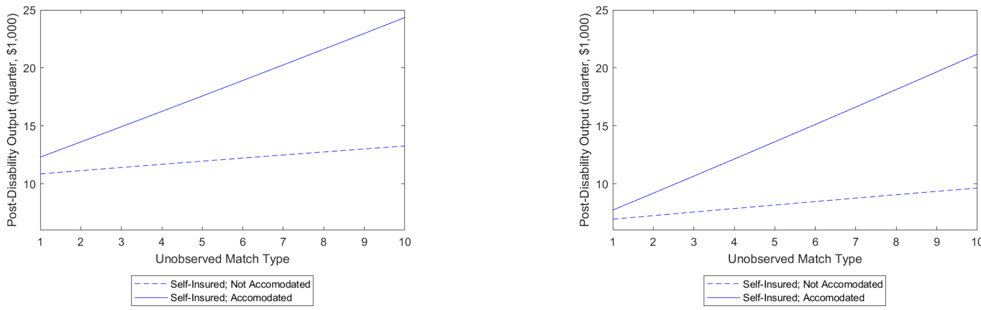
[38]To construct the simulated DID estimates, we run the following regression for each of the three outcomes for claim i:

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

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

[39]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.

Figure 5: Post-disability Output of Workers in Self-insured and Median Exposure Firms



(a) High-skilled workers (b) Low-skilled workers

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

Figure 5 shows post-disability output for workers in self-insured and median exposure firms, by worker's skill type 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-disability earnings are an increasing function of unobserved type for accommodated workers. Second, low-skilled workers experience higher productivity gains from accommodation than high-skilled workers.

Table 4: Parameters estimated within the model

Net output, without disability: $f_{1,z,0}$				Net output, with disability: $f_{1,z,\xi}$			
Param.	Description	Estimate	SE	Param.	Description	Estimate	SE
$\alpha^0_{f,0}$	Baseline	14.14	(0.03)	$\alpha^0_{f,1}$	Baseline	-17.21	(0.05)
$\alpha^1_{f,0}$	Self-insured	1.84	(0.02)	$\alpha^1_{f,1}$	Self-insured	-1.48	(0.01)
$\alpha^2_{f,0}$	High skilled	0.10	(0.02)	$\alpha^2_{f,1}$	High skilled	1.17	(0.01)
$\alpha^3_{f,0}$	Exposure	0.02	(0.01)	$\alpha^3_{f,1}$	Exposure	1.27	(0.002)
				$\alpha^4_{f,1}$	Unobs. type	-0.01	(0.01)
Accommodation cost shock std. dev.: $\sigma_{\xi,z}$							
Param.	Description	Estimate	SE				
$\alpha_{\sigma,0}$	Baseline	4.76	(0.03)				
$\alpha_{\sigma,1}$	Unobs. type	-0.63	(0.01)				

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.

Estimates of the first-stage parameters. Table 4 reports parameter estimates. First, we find that the output produced by workers without disabilities 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 disability period is negative, suggesting that accommodation is a costly investment, at least in a static sense. In the post-disability 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 workers with disabilities are accommodated, net output must be negative during the disability period.

Third, we find that, in addition to observed heterogeneity, unobserved heterogeneity also affects the parameters. We 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. Moreover, we also find that the accommodation cost shock variance is lower for higher unobserved types ($\alpha_{\sigma,1}$), meaning accommodation decisions for these claims respond more to changes in the environment (e.g., subsidies) compared to lower unobserved types. Because higher unobserved types also tend to have higher labor market returns to accommodation, their large response to the wage subsidies is consistent with the large IV estimates of accommodation on the post-disability 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 DID coefficients for accommodation rates and post-disability employment and wages reasonably well, suggesting that the model captures the large local effects of accommodation on subsequent labor market outcomes.

Sensitivity of estimates. In Online Appendix D, we provide further evidence of our identification argument by quantifying the relative importance of each auxiliary moment for each parameter of interest. Specifically, we 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 DID regression coefficients relative to other moments.

Table 5: Within-Sample Fit of Targeted Moments

	Accommodation rate		Wages in period 1	
	Data	Model	Data	Model
DID coefficient	-0.11	-0.07		
Levels by subsample:				
Self-insured	0.43	0.50	11.24	11.20
Not self-insured	0.27	0.23	9.22	9.80
High skilled	0.34	0.38	13.46	12.19
Low skilled	0.28	0.23	6.36	8.22
High exposure	0.46	0.39	10.63	10.47
Low exposure	0.16	0.17	8.97	9.81
Pre-policy change	0.32	0.33	9.64	10.15
	Post-disability employment		**Post-disability wages**	
	Data	Model	Data	Model
DID coefficient	-0.04	-0.03	-0.45	-0.56
Overall level	0.72	0.77	9.19	8.70

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

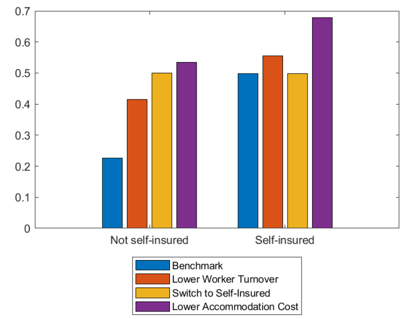
5.4 Mechanisms

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 left-most blue bar in each set reports the accommodation rate under the benchmark economy.

The orange bars second from left report the effect of reducing the job-to-job transition rate of workers with disabilities 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 workers with disabilities 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

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 workers with disabilities by 25% of the absolute value of $a^0_{f,1}$.

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 disability period. To do this, we increase the net output of workers with disabilities by 25% of the absolute value of the baseline parameter $a^0_{f,1}$. We find that accommodation rates increase for workers in both imperfectly experience-rated firms and 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 Experiments

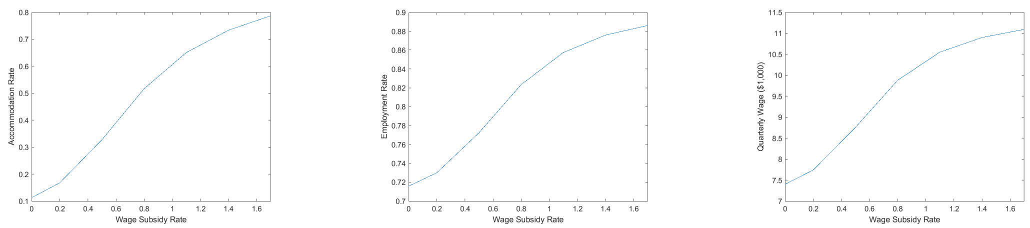
Using the estimated model, we conduct counterfactual policy experiments that change the wage subsidy rate δ to quantitatively explore their labor market, welfare and distributional effects. This counterfactual is motivated by potential inefficiencies in the model that may lead firms to under-accommodate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

We impose budget neutrality for the workers' compensation program. By changing accommodation rates, the counterfactual experiments 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.[40] The wage subsidy program is also budget neutral, so we also solve for a new flat tax P_s on all employers.

6.1 Labor Market Impacts

Figure 7: Labor Market Impacts of Wage Subsidies for Accommodation



(a) Accommodation rate (b) Post-disability employment (c) Post-disability 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%.

Figure 7 reports the labor market impacts of wage subsidies for accommodation ranging from a 0% to a 170% 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 33% to 11%. Such a large response is consistent with our empirical findings, in which firm accommodation responds significantly to financial incentives.

Second, Panels (b) and (c) show that more generous wage subsidies increase post-disability employment and wages: if we set the wage subsidy to zero, post-disability employment decreases by 7% (or 6 percentage points) and post-disability quarterly wages decrease by 15% (or $1,358). 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.

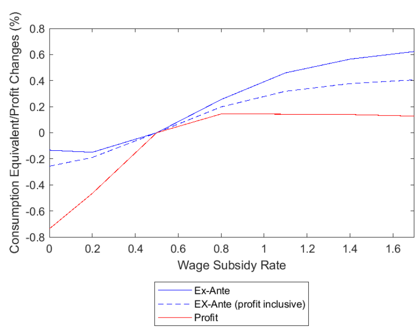
[40] Formally, the break even condition is defined as

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

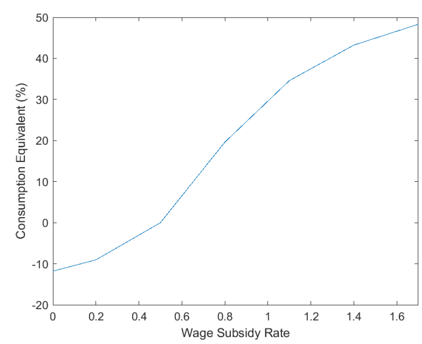
6.2 Average Welfare Impacts

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 disability. Second and relatedly, accommodation leads to higher earnings during both the disability period and post-disability period, which lowers the consumption risk from experiencing an disability. Welfare gains thus have both an insurance component as well as a labor market efficiency component. 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: Average Welfare Impacts of Wage Subsidies for Accommodation



(a) Ex-ante welfare (profit)



(b) Welfare at the time of disability

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 workers at the time of disability.

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 worker welfare at the time of disability. 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.

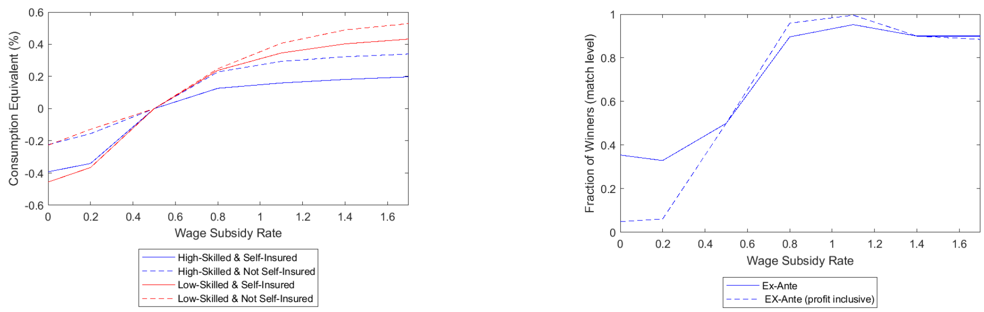
Panel (a) shows that there are modest effects on ex-ante worker welfare and firm profit. Regardless of whether firm profits are included in worker welfare, the welfare gain of wage subsidies is at most a 0.6% increase in consumption, and the welfare loss of eliminating wage subsidies is only 0.3%. A 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 diminishes because more generous subsidies generate higher taxes to firms. Taken together, higher wage subsidies increase average welfare (inclusive of profits), but these gains diminish as subsidies approach 100%. This occurs because subsidies beyond this level have less impact on accommodation rates (see Figure 7), while their cost is offset by higher taxes on firms, effectively neutralizing their welfare effects. Moreover, even a 100% wage subsidy only partially offsets accommodation costs, as net output during accommodation periods is typically substantially negative (Table 4).

Panel (b) shows that wage subsidies have a significant effect on welfare for workers with disabilities. Conditional on experiencing disability, 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 disability period and better labor market outcomes after the disability period for most workers with disabilities.

Overall, wage subsidies significantly increase the welfare of workers with disabilities and moderately increase average ex-ante welfare by mitigating inefficiently low rates of accommodation. Because the probability of disability is small (2.2%), the welfare gain from additional accommodation has a relatively limited impact on the ex-ante average welfare. Moreover, wage subsidies do not generate much consumption smoothing benefit partly because during the disability period workers with disabilities that are not accommodated still receive two-thirds of the wage they would have received if they worked. 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 Implications

Figure 9: Distributional Implications of Wage Subsidies for Accommodation



(a) Ex-ante Welfare by Worker-Firm Match

(b) Fraction of Winners

Notes: The left subfigure shows the welfare impact of wage subsidies by the type of worker-firm match, measured by the change in average ex-ante worker welfare inclusive of firm profit as an ex-post transfer to workers relative to a 50% wage subsidy. The right subfigure 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.

Although we find that higher wage subsidies increase average welfare, the distributional implications are less obvious.[41] For one, there is substantial heterogeneity in the labor market return from accommodation (Section 3.3). Moreover, the degree of under-accommodation varies by the type of worker-firm match (Section 5.4). For example, accommodation rates for disabilities 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(a) presents welfare impacts of alternative wage subsidies by worker-firm type. We find that welfare gains from higher wage subsidies are larger for low-skilled workers than high-skilled workers, suggesting that larger subsidies not only improve efficiency, but also redistribute across workers with different skills. Moreover, welfare gains are typically larger for imperfectly experience-rated firms, suggesting a corrective role of subsi-

[41] Note that all of the welfare results we present are *ex ante* welfare. Ex post, there are also distributional consequences due to spillovers from injured workers to uninjured workers. These spillovers arise from the impact of subsidies on workers' compensation premiums, which flow into wages of all workers, and because wages are constrained (by law) to be equal between accommodated and uninjured workers (at w_{1z}), which can implicitly lower the equilibrium wage for all workers.

dies against moral hazard in accommodation decisions. Figure 9(b) reports 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. If we instead eliminate wage subsidies, more than 90% of 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 implications of firm accommodation decisions for the design of workers' compensation programs. Leveraging quasi-experimental variation and detailed administrative data on disabling claims from workplace injuries and illnesses linked to quarterly earnings records in the state of Oregon, we show that accommodation responds 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. Counterfactual experiments show that wage subsidies for accommodation significantly increase firm accommodation rates, improve post-disability 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. One can also extend our framework to answer other interesting questions, including the optimal combination of wage subsidies to firms for accommodation and timeloss benefits to workers within the workers' compensation program. 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 Robustness of DID Analysis

We conduct several robustness checks to rule out mean reversion. First, we run placebo regressions around several artificial reform cutoff dates, assigning placebo policy changes in years 2006 through 2009. If mean reversion were an issue, we would expect to find a negative effect of the artificial reform on EAIP; however, the placebo results show no evidence of an effect of the artificial reform(s) on EAIP take-up.

Specifically, for each placebo policy year, we shift the historical period and analysis period back to maintain a five year historical baseline period to determine exposure and a seven year analysis period. For example, when assigning a placebo policy year of 2008, we used a historical baseline of 2000-2004 and analysis period of 2006-2012. Our choice of assigning placebo policy years from 2006-2009 provides the cleanest comparison because the post-policy placebo period occurs prior to the actual policy change (the one exception is when assigning a placebo year of 2009, the final post-analysis year is 2013, which includes two treated quarters). Our employment data begins in 1999, so 1998 is the earliest year we can use in the historical baseline where we still observe employment outcomes one year after injury (this corresponds to a placebo policy year of 2006).

Columns (1) through (4) of Appendix Table 6 show the DID estimates on accommodation rates for these placebo regressions. In all cases, the coefficients are positive (reverse signed from what we would anticipate in the presence of mean reversion), at least an order of magnitude smaller than our main results in the paper, and statistically insignificant.

Second, we shorten the historical baseline period while holding the policy year at the implementation date of July 2013. The logic underlying this exercise is that exposure measures using a shorter baseline period are more likely to capture random noise in firms (e.g., having one year of high or low EAIP use rather than a sustained pattern), which increases the likelihood of mean reversion. In this case, we might expect *larger* coefficients when shorter baseline periods are used. Instead, columns (5) through (7) of Appendix Table 6 shows that the results are similar to our main results, suggesting that random variation in EAIP use is not resulting in mean reversion in our analysis.

Finally, we conduct a Bayesian shrinkage exercise (similar to what is done in the school value-added literature, e.g., Angrist et al., 2017). Specifically, we re-define exposure as a weighted average of the sample (firm-level) and population accommodation rates, giving relatively more weight to population accommodation rates for firms with relatively fewer observations, and relatively more weight to sample accommodation rates for firms with relatively more observations. The final column of Appendix Table 6 shows that the DID estimates using the shrunken exposure measure are still very similar to our main results.

Appendix Tables 7 and 8 show additional robustness checks, including excluding very small firms (fewer than 11 workers) whose exposure measure may be more subject to mean reversion, and excluding firms whose exposure measure is 100%.

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 (2005). Using a potential outcomes framework, denote a binary variable $D = \{0,1\}$ if a worker with a disability receives accommodation and denote Y and Y_j for $j = \{0,1\}$ as the observed outcome and potential outcomes, respectively. Define:

$$Y_j = X\beta_j + U_j \tag{19}$$

$$Y = DY_1 + (1-D)Y_0 \tag{20}$$

$$D = \mathbb{1}\{\mu_D(X,Z) > V\} \tag{21}$$

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:

$$MTE(x,u) = E(Y_1 - Y_0|X = x, U_D = u) \tag{22}$$

$$= x(\beta_1 - \beta_0) + E(U_1 - U_0|U_D = u) \tag{23}$$

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

$$MTR_0(x,u) = E(Y_0|X = x, U_D = u) \tag{24}$$

$$MTR_1(x,u) = E(Y_1|X = x, U_D = u) \tag{25}$$

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 14 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 4 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 15th 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 only slightly increasing. These curves do not intersect, resulting in positive MTEs at 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

$$J^a_{z,\xi_z^*} = J_z^{na} - \tau_z d b_z. \tag{26}$$

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:

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

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:

$$\max_{w_{1,z}} \left(V_z(w_{1,z}, \mathbf{a}_\mathbf{z}^*) - U_{1,z}\right)^\beta J_z(w_{1,z}, \mathbf{a}_\mathbf{z}^*)^{1-\beta} \tag{27}$$

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^*:

$$\overline{V}_z(w_{1,z}, \xi_z^*) = (1-p)V_{z,u} + p\left[\Gamma\left(\xi_z^*\right) V_z^a + \left(1 - \Gamma\left(\xi_z^*\right)\right) V_z^{na}\right] \tag{28}$$

and

$$\overline{J}_z(w_{1,z}, \xi_z^*) = (1-p)J_{z,u} + p\left[\Gamma\left(\xi_z^*\right) J^a_{z,\xi_z^*} + \left(1 - \Gamma\left(\xi_z^*\right)\right) J_z^{na}\right] - P_{tot,z} \tag{29}$$

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

$$J^a_{z,\xi_z^*} = d\left[f_{1,z} - \mathbb{E}\left[\xi_z | \xi_z < \xi_z^*\right] - (1-\delta_z)\, w_{1,z}\right] + (T-d)\,(1-q_{z,1})\,(1-\lambda_z)\,(f_{2,z,a} - w_{2,z,a}) \tag{30}$$

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

$$\max_{w_{1,z}, \xi_\mathbf{z}^*} \left(\overline{V}_z(w_{1,z}, \xi_z^*) - U_{1,z}\right)^\beta \overline{J}_z(w_{1,z}, \xi_z^*)^{1-\beta} \tag{31}$$

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

$$\beta \bar{J}_z(w_{1,z},\xi_z^*)\frac{d\bar{V}_z}{dw_{1,z}} + (1-\beta)\left(\bar{V}_z(w_{1,z},\xi_z^*) - U_{1,z}\right)\frac{d\bar{J}_z}{dw_{1,z}} = 0 \tag{32}$$

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

D Sensitivity Analysis

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. Following Einav et al. (2018), we provide 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 $\left\{\widehat{\Theta}_1,\ldots,\widehat{\Theta}_n+\widehat{\sigma}_{\beta_n},\ldots,\widehat{\Theta}_N\right\}$, 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 DID 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 workers without disabilities; cross-sectional accommodation rates; DID coefficients, and average employment and wages in the post-disability period.

Appendix Table 19 reports the main finding. First, while changes in parameters associated with output for workers without disabilities have modest impacts on most of the auxiliary models compared with other parameters, changes in cross-sectional wage moments for workers without disabilities are relatively larger than other auxiliary models. Second, changes in parameters associated with net output for workers with disabilities lead to significant responses in accommodation rates and the DID coefficients and modest responses in post-disability outcomes, but lead to little response to the wages of workers without disabilities. Finally, changes in parameters associated with the accommodation shock distribution lead to significant responses in the DID coefficients, but they have little effect on wages for workers without disabilities and post-disability worker outcomes.

These patterns suggest that wage moments for workers without disabilities are especially informative for parameters associated with output for workers without disabilities. Moreover, cross-sectional accommodation rates and average post-disability outcomes are informative in identifying parameters associated with the net output for workers with disabilities. Then, the DID coefficients provide identifying information for parameters associated with the accommodation cost shock distribution.

E Model Extensions

E.1 Industry-specific Human Capital

We consider the case where accommodation provides industry-specific human capital. Unlike general human capital, if workers transition to jobs in other sectors, they lose the industry-specific human capital acquired through accommodation. Specifically, with probability $\lambda_z \lambda_{ind,switch}$, workers' job-to-job transitions involve moving to a different industry, while with probability $\lambda_z(1-\lambda_{ind,switch})$, they remain within the same industry. If workers switch industries, they receive wages $w_{2,z,s,O}$, independent of their accommodation status. If they stay within the same industry, they receive wages $w_{2,z,a,O}$, as specified in our main model. Similarly, uninjured workers experience job-to-job transitions to a different industry with probability $\lambda_{z,u}\lambda_{ind,switch}$, resulting in wage $w_{1,z,s,O}$.

Using our data, we calibrate $\lambda_{ind,switch} = 0.64$, $w_{2,z,s,O} = 0.73 * w_{2,z,1,O}$, and $w_{1,z,s,O} = w_{1,z,O}$ to reflect that 61% of job-to-job transitions involve industry switches that come with a 30% wage decline on average. We then re-estimate the model parameters and conduct the same set of counterfactual experiments.

Appendix Figure 5 presents our primary findings. Consistent with the baseline model, we find that higher subsidies enhance welfare. However, the welfare gains are smaller than in the main model, reflecting the limited human capital benefits for accommodated workers when switching industries.

E.2 Disutility during Accommodated Jobs

We relax the model's assumption that accommodated workers experience no disutility while on the job. Specifically, we modify Equation (6) as

$$V_z^a = d\left[u(w_{1,z}) - \psi_d\right] + (T-d)\left[(1-q_{z,1})\left((1-\lambda_z)\,u(w_{2,z,1}) + \lambda_z u(w_{2,z,1,O})\right) + q_{z,1}u(c_b)\right] \tag{33}$$

where ψ_d represents the disutility experienced by the workers in accommodated jobs. As before, the accommodation decision remains employer-driven, and we assume this disutility is not large enough to deter workers from staying employed rather than opting for unemployment. Specifically, we set ψ_d to match the utility value of 30% of wages during the injury period for each worker, such that $u(w) - u(0.7w) = \psi_d$. Then, we re-estimate the model parameters and conduct the same set of counterfactual experiments.

Appendix Figure 6 presents our primary findings. As in the baseline model, we find that higher subsidies enhance welfare. However, the magnitude of welfare gains is smaller compared to the main model, reflecting the disutility of accommodated jobs. This occurs because disutility is incurred only during the relatively short disability period, whereas workers still benefit from surplus after being accommodated. Consequently, the latter effect quantitatively outweighs the former.

F Appendix Tables and Figures

Appendix Table 1: Share of EAIP claims with detailed expenses

	Any use	Fraction of total amount
Wage subsidy	0.896	96.5
Worksite modification	0.021	1.4
Equipment	0.029	2.0
Clothing	0.001	0.0
Tuition	0.002	0.1

Notes: Data provided by ODCBS. Sample consists of the subset of our analysis sample which received payment from EAIP via wage subsidies or other accommodation benefits. Any use is calculated as the share of EAIP claims receiving the benefit denoted in the row; Fraction of total $ amount is calculated as the average share of EAIP expenditures spent on the benefit denoted in the row.

Appendix Table 2: Occupation and industry 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)
Occupation: transportation	0.18	0.16	0.19	0.19	0.17	0.21
Occupation: production	0.12	0.11	0.12	0.12	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	0.07	0.07	0.08
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	0.06
Industry: manufacturing	0.13	0.12	0.13	0.15	0.14	0.16
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	0.23	0.28	0.17
Industry: accommodation	0.07	0.03	0.08	0.04	0.01	0.07
Industry: public administration	0.07	0.11	0.05	0.10	0.16	0.04
Observations	131,219	33,412	97,807	71,527	35,785	35,742

Notes: Data provided by ODCBS. Column 1 consists of disabling claims between 2011 and 2017. Columns 2 and 3 distinguish claims that were accommodated and not accommodated, respectively. The analysis sample (column 4) consists of the subset of claims for which the firm had at least one claim between 2005-2009 and one claim between 2011-2017 (excluding the first two quarters of 2013), and workers who worked at least 250 hours in the quarter prior to disability. Columns 5 and 6 distinguish claims in the analysis sample 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 3: Association between EAIP and experience rating

	Accommodation rate				
	(1)	(2)	(3)	(4)	(5)
Perfect experience rating	0.189***	0.169***	0.170***	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	102964	102963	102963
R-squared	0.0310	0.0510	0.0818	0.121	0.122

Notes: Data provided by ODCBS. Table reports coefficients and standard errors (clustered by firm) from a regression of whether a claim is accommodated on whether the firm is perfectly experience-rated (self-insured), along with controls denoted by "X". Sample consists of all disabling claims between 2011 and 2017 (the "full sample"). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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	0.00871	0.0107	0.0285

Notes: Data provided by ODCBS. Table reports coefficients and standard errors (clustered by industry) from a regression of whether a claim is accommodated on the industry-wide separation rate (columns 1-3) or industry-wide quit-rate (columns 4-6), along with controls denoted by "Yes". Sample consists of all disabling claims between 2011 and 2017. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 5: Difference-in-Differences Analysis of Policy Change on Accommodation and Labor Market Outcomes Four Quarters after Disability, Robustness to $X_i \times Post_t$ Controls

		Four quarters after disability		
	EAIP	Employment	Earnings	New firm
	(1)	(2)	(3)	(4)
Exposure × Post	-0.120***	-0.031*	-425.456***	-0.000
	(0.026)	(0.016)	(154.874)	(0.012)
Mean DV	0.312	0.721	7806.8	0.106
Observations	71525	71525	71525	71525

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1). Dependent variables are whether the claim is accommodated through EAIP (column 1) and, four quarters after disability: whether the claimant is employed (column 2), the claimant's quarterly earnings (column 3), and whether the claimant is employed in a new firm (column 4). All regressions include a broad set of worker, firm, and disability controls, including interactions between a post indicator and insurance type, occupation, and the nature of injury. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 6: Difference-in-Differences Analysis of Accommodation Rates: Placebo Policy Change Years, Alternative Historical Periods, and Shrunken Exposure

	Placebo policy year				Alternative historical period			Shrunken
	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 4 years	(6) 3 years	(7) 2 years	(8)
Exposure × Post	0.015	0.019	0.017	-0.000	-0.114***	-0.109***	-0.117***	-0.128***
	(0.031)	(0.034)	(0.029)	(0.027)	(0.025)	(0.022)	(0.021)	(0.033)
Mean DV	0.271	0.282	0.297	0.308	0.315	0.317	0.321	0.312
Observations	80875	81766	81719	75029	70471	68329	65228	71525

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1). Dependent variable is whether the claim is accommodated through EAIP. Columns (1)-(4) are assigned a placebo policy change year as stated in the column header, and the historical period is analogously shifted back. Columns (5)-(7) shorten the historical period to the number of years stated in the column header. Column (8) shrinks a claims measure of exposure toward the population average. 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 and Labor Market Outcomes Four Quarters after Disability, No Tiny Firms

		Four quarters after disability		
	EAIP	Employment	Earnings	New firm
	(1)	(2)	(3)	(4)
Exposure × Post	-0.115***	-0.026*	-396.491**	0.004
	(0.026)	(0.016)	(157.948)	(0.012)
Mean DV	0.320	0.724	7881.6	0.103
Observations	68279	68279	68279	68279

Notes: Data provided by ODCBS. Sample excludes firms with 10 or fewer workers. Table reports β coefficients and standard errors (clustered by firm) from Equation (1). Dependent variables are whether the claim is accommodated through EAIP (column 1) and, four quarters after disability: whether the claimant is employed (column 2), the claimant's quarterly earnings (column 3), and whether the claimant is employed in a new firm (column 4). All regressions include a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 8: Difference-in-Differences Analysis of Policy Change on Accommodation and Labor Market Outcomes Four Quarters after Disability, Exposure < 100%

		Four quarters after disability		
	EAIP	Employment	Earnings	New firm
	(1)	(2)	(3)	(4)
Exposure × Post	-0.113***	-0.044**	-514.946***	0.005
	(0.028)	(0.017)	(169.137)	(0.013)
Mean DV	0.312	0.721	7829.0	0.105
Observations	70097	70097	70097	70097

Notes: Data provided by ODCBS. Sample excludes firms with 100% exposure. Table reports β coefficients and standard errors (clustered by firm) from Equation (1). Dependent variables are whether the claim is accommodated through EAIP (column 1) and, four quarters after disability: whether the claimant is employed (column 2), the claimant's quarterly earnings (column 3), and whether the claimant is employed in a new firm (column 4). All regressions include a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 9: Difference-in-Differences Analysis of Policy Change on Accommodation and Labor Market Outcomes Four Quarters after Disability, Binary Exposure Measure

		Four quarters after disability		
	EAIP	Employment	Earnings	New firm
	(1)	(2)	(3)	(4)
Any exposure $\times$ Post	-0.050***	-0.028***	-307.893***	-0.005
	(0.014)	(0.009)	(97.228)	(0.007)
Mean DV	0.312	0.721	7806.8	0.106
Observations	71525	71525	71525	71525

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1), but with a binary measure of any exposure. Dependent variables are whether the claim is accommodated through EAIP (column 1) and, four quarters after disability: whether the claimant is employed (column 2), the claimant's quarterly earnings (column 3), and whether the claimant is employed in a new firm (column 4). All regressions include a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 10: Difference-in-Differences Analysis of Policy Change on Accommodation and Labor Market Outcomes Four Quarters after Disability, Firm-Occupation Exposure Measure

		Four quarters after disability		
	EAIP	Employment	Earnings	New firm
	(1)	(2)	(3)	(4)
Exposure $\times$ Post	-0.106***	-0.033**	-451.064***	0.002
	(0.024)	(0.015)	(150.287)	(0.012)
Mean DV	0.312	0.721	7806.8	0.106
Observations	71525	71525	71525	71525

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1), but with exposure defined at the firm-occupation level (or firm for firm-occupation cells with 5 or fewer observations). Dependent variables are whether the claim is accommodated through EAIP (column 1) and, four quarters after disability: whether the claimant is employed (column 2), the claimant's quarterly earnings (column 3), and whether the claimant is employed in a new firm (column 4). All regressions include a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 11: Mean Claim Characteristics by Year

	(1) 2011	(2) 2012	(3) 2013	(4) 2014	(5) 2015	(6) 2016	(7) 2017
Worker characteristics							
Age at injury	43.5	43.4	43.6	43.6	43.6	44.0	43.7
Female	0.37	0.37	0.37	0.36	0.36	0.37	0.36
Earnings (pre-disability qtr)	8,760	8,5876	8,686	8,815	9,100	9,004	9,019
Hours worked (pre-disability qtr)	430	432	437	436	443	429	429
Claim characteristics							
Disability type: trauma	0.10	0.11	0.12	0.13	0.13	0.11	0.10
Disability type: fractures	0.13	0.11	0.09	0.10	0.10	0.10	0.11
Disability type: strains	0.58	0.60	0.61	0.60	0.61	0.61	0.60
Disability type: wounds	0.10	0.12	0.11	0.11	0.11	0.12	0.13
Disability type: other	0.08	0.06	0.06	0.06	0.06	0.06	0.06
Firm characteristics							
Self-insured	0.29	0.29	0.28	0.28	0.29	0.28	0.29
Large firms	0.44	0.45	0.45	0.45	0.46	0.47	0.48
Industry							
Construction	0.07	0.07	0.06	0.06	0.06	0.06	0.06
Manufacturing	0.15	0.15	0.14	0.15	0.15	0.15	0.15
Transportation	0.20	0.20	0.20	0.19	0.19	0.19	0.21
Trade	0.08	0.08	0.09	0.08	0.08	0.09	0.09
Health care	0.23	0.23	0.23	0.22	0.23	0.23	0.22
Accommodation	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Public administration	0.09	0.10	0.10	0.10	0.10	0.10	0.10
Occupation							
Transportation	0.19	0.17	0.18	0.19	0.19	0.19	0.21
Production	0.13	0.12	0.12	0.13	0.13	0.13	0.12
Manufacturing	0.08	0.07	0.07	0.08	0.07	0.07	0.08
Construction	0.05	0.06	0.06	0.07	0.06	0.07	0.06
Health care	0.13	0.13	0.13	0.12	0.13	0.12	0.11
Observations	11,620	11,649	5,793	11,229	10,787	9,569	10,880

Notes: Data provided by ODCBS. Table reports mean claim characteristics by year in the analysis sample.

Appendix Table 12: Difference-in-Differences Analysis with Demographic Characteristics as Dependent Variable

	(1) Age	(2) Female	(3) Pre-dis earnings	(4) Strains	(5) Self Ins	(6) Large firms
Exposure × Post	0.018	-0.009	505***	0.044***	-0.014	0.006
	(0.301)	(0.014)	(178)	(0.011)	(0.021)	(0.018)
Mean DV	43.61	0.366	8857.4	0.600	0.286	0.456
Observations	71401	71527	71137	71527	71527	71527
	(7) Ind: trans	(8) Ind: Cons	(9) Ind: Manuf	(10) Occ: Trans	(11) Occ: Prod	(12) Occ: Health
Exposure × Post	-0.004	-0.030*	-0.020	0.025**	-0.011	0.003
	(0.017)	(0.016)	(0.017)	(0.011)	(0.012)	(0.011)
Mean DV	0.198	0.0626	0.152	0.190	0.124	0.122
Observations	71527	71527	71527	71527	71527	71527

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1). Dependent variables are denoted in column header. All regressions include a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 13: Difference-in-Differences Analysis of Policy Change on Accommodation and Labor Market Outcomes Four Quarters after Disability, Alternative Sample Restrictions on 2013

		Four quarters after disability		
	EAIP	Employment	Earnings	New firm
	(1)	(2)	(3)	(4)
A. Dropping only 2013 Q2 claims				
Exposure × Post	-0.106***	-0.031**	-400.155***	0.007
	(0.024)	(0.015)	(149.600)	(0.011)
Mean DV	0.313	0.721	7793.4	0.105
Observations	74382	74382	74382	74382
B. Dropping no 2013 claims				
Exposure × Post	-0.100***	-0.027*	-339.007**	0.009
	(0.023)	(0.015)	(144.487)	(0.011)
Mean DV	0.314	0.721	7796.1	0.105
Observations	77194	77194	77194	77194
C. Dropping all 2013 claims				
Exposure × Post	-0.129***	-0.031*	-407.162***	0.004
	(0.027)	(0.016)	(157.548)	(0.012)
Mean DV	0.311	0.720	7805.2	0.105
Observations	65732	65732	65732	65732

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1), only dropping claims that occurred in the second quarter of 2013 (Panel a), not dropping any claims that occurred in 2013 (Panel b), and dropping claims that occurred in any quarter of 2013 (Panel c). Dependent variables are whether the claim is accommodated through EAIP (column 1) and, four quarters after disability: whether the claimant is employed (column 2), the claimant's quarterly earnings (column 3), and whether the claimant is employed in a new firm (column 4). All regressions include a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 14: Selection Equation and Employment Outcome Equation

	Selection Eq. (Accomm)	Outcome Eq. (Employment)	
		Not Accomm (β_0)	Treat Eff ($\beta_1 - \beta_0$)
	(1)	(2)	(3)
Exposure x post	-0.0862***		
	(0.0130)		
Female	0.0258***	-0.0320***	-0.0154
	(0.00425)	(0.00550)	(0.0105)
Log pre-injury earnings	0.0361***	0.107***	-0.0136
	(0.00411)	(0.00518)	(0.0118)
Self-insured	0.169***	0.0182	-0.0742*
	(0.00501)	(0.0132)	(0.0382)
Occupation			
Healthcare practitioners	-0.0187	0.00150	-0.0307
	(0.0117)	(0.0162)	(0.0267)
Healthcare support	-0.0252**	-0.0392**	0.0233
	(0.0120)	(0.0163)	(0.0277)
Maintenance/repair	-0.0220**	0.0476***	-0.00504
	(0.0099)	(0.0127)	(0.0228)
Production	0.00504	0.0217*	-0.0184
	(0.0101)	(0.0127)	(0.0226)
Transportation	-0.0187*	0.0249**	-0.0208
	(0.0097)	(0.0124)	(0.0221)
Nature of injury			
Wounds/cuts/burns	-0.113***	0.0655***	0.0231
	(0.0068)	(0.0111)	(0.0287)
Fractures/breaks	0.0242***	0.0718***	0.00269
	(0.00717)	(0.00901)	(0.0161)
Strains, back pain	-0.0245***	0.0467***	-0.0182
	(0.00543)	(0.00705)	(0.0128)
Propensity score		0.696	
		(0.602)	
Propensity score squared		-0.212	
		(0.420)	
Observations	70419	70419	

Notes: Data provided by ODCBS. Table shows selection equation and employment outcome of the MTE specification detailed in Appendix B. Not shown are coefficients for other disability characteristics (event, body part). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 15: Difference-in-Differences Analysis of Policy Change on Accommodation and Labor Market Outcomes Four Quarters after Disability, by Age Group

		Four quarters after disability		
	EAIP	Employment	Earnings	New firm
	(1)	(2)	(3)	(4)
Exposure $\times$ Post, age 20-34	-0.148***	-0.063**	-421.251*	-0.019
	(0.031)	(0.028)	(252.128)	(0.022)
Exposure $\times$ Post, age 35-49	-0.097***	-0.014	-254.284	0.004
	(0.030)	(0.022)	(250.495)	(0.016)
Exposure $\times$ Post, age 50-64	-0.082**	-0.029	-668.528***	0.018
	(0.033)	(0.025)	(255.441)	(0.014)
Mean DV, age 20-34	0.309	0.701	6464.8	0.176
Mean DV, age 35-49	0.322	0.748	8581.3	0.0983
Mean DV, age 50-64	0.312	0.722	8284.5	0.0614
Observations	69273	69273	69273	69273

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1), but with exposure defined at the firm-occupation level. Dependent variables are whether the claim is accommodated through EAIP (column 1) and, four quarters after disability: whether the claimant is employed (column 2), the claimant's quarterly earnings (column 3), and whether the claimant is employed in a new firm (column 4). All regressions include a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 16: Descriptive Regression Analysis of Additional Accommodation Benefits on Job Mobility, Among Accommodated Claims

	(1) New firm	(2) New firm	(3) New industry	(4) New industry
Worksite modification benefits	-0.018*		-0.010**	
	(0.010)		(0.004)	
Any other benefits		-0.012		-0.008*
		(0.008)		(0.004)
Mean DV without other benefits	0.082	0.082	0.040	0.041
Observations	22301	22301	21342	21342

Notes: Data provided by ODCBS. Sample is the subset of claims in the analysis sample that received EAIP benefits. Table reports coefficients and standard errors (clustered by firm) of a regression of whether, four quarters after disability, the claimant is employed in a new firm (columns 1-2) and employed in a new industry (columns 3-4). All regressions include a broad set of worker, firm, and disability controls. "Any other benefits" includes worksite modifications, clothing, equipment, and tuition benefits. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 17: Difference-in-Differences Analysis of Policy Change on Earnings For Quarters after Disability, by Worker Turnover

	(1) Earnings
Exposure × Post	-397.6**
	(165.1)
Exposure × Post × New firm	-209.7
	(386.1)
Mean DV	7806.8
Observations	71525

Notes: Data provided by ODCBS. Table reports β coefficients and standard errors (clustered by firm) from Equation (1), but also interacted with whether the claimant works at a new firm four quarters after disability. Dependent variable is quarterly earnings four quarters after disability. Regression includes a broad set of worker, firm, and disability controls. Mean (SD) of exposure is 0.27 (0.27). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 18: Parameters estimated outside the model

Parameter	Description	Value	Source
p	Probability of disability	2.2%	ODCBS (2013)
d	Duration of disability	60 days	See Table 1
$q_{z,a}$	E-U transition rate, post-disability	MTR est., AF 4a	Our sample
$q_{z,u}$	E-U transition rate, no disability	0.13, 0.13, 0.06, 0.05	Our sample
λ_z	E-E transition rate, post-disability	0.29, 0.19, 0.13, 0.06	Our sample
$\lambda_{z,u}$	E-E transition rate, no disability	0.24, 0.17, 0.11, 0.06	Our sample
λ_z^{ue}	U-E transition rate	0.49, 0.49, 0.63, 0.66	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	ODCBS (2007)
δ_z	Wage subsidy rate	{0.5, 0.45}	Oregon policy

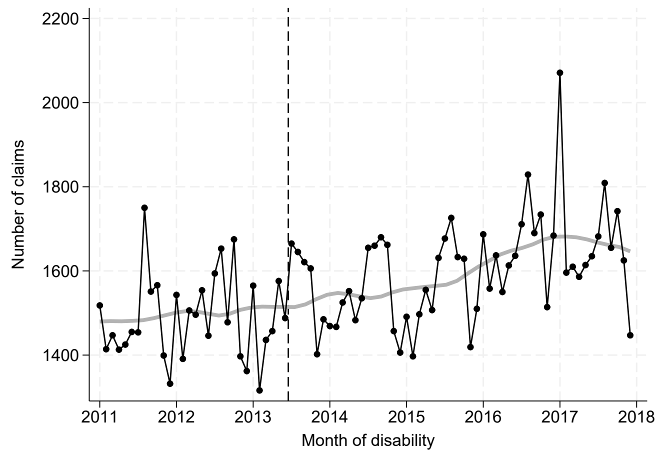
Note: Rows with four values denote types of worker-firm matches: (1) Low skilled worker at a not-self-insured firm, (2) low skilled worker at a self-insured firm, (3) high skilled worker at a not-self-insured firm, and (4) high skilled worker at a self-insured firm.

Appendix Table 19: Impact of Changes in Parameter Values on Auxiliary Models

Parameters	Wage	Accommodation rate	DID coefficient	Post-disability outcome
		Net output, no disability: $f_{1,z,0}$		
$\alpha_{f,0}^0$	5.57	2.69	5.06	0.28
$\alpha_{f,0}^1$	3.78	0.69	1.82	0.05
$\alpha_{f,0}^2$	3.32	1.76	5.06	0.19
$\alpha_{f,0}^3$	12.08	5.28	6.08	0.52
		Net output, with disability: $f_{1,z,\xi}$		
$\alpha_{f,1}^1$	0.15	31.38	56.60	3.29
$\alpha_{f,1}^2$	0.03	1.95	1.58	0.16
$\alpha_{f,1}^3$	0.01	3.31	5.16	0.36
$\alpha_{f,1}^4$	0.02	2.67	11.13	0.27
$\alpha_{f,1}^5$	0.13	30.41	67.00	3.45
		Accommodation cost shock (Std Dev): $\sigma_{\xi,z}$		
$\alpha_{\sigma,0}$	0.04	23.33	17.72	1.02
$\alpha_{\sigma,1}$	0.06	24.75	23.13	1.18

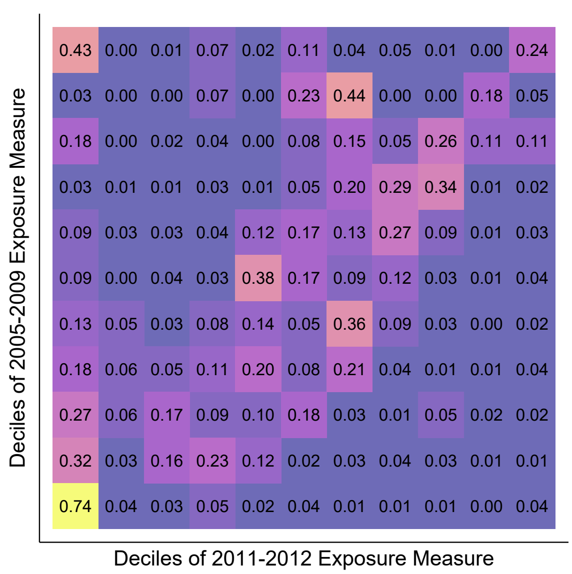
Notes: Each cell shows, as the parameter estimate in the row increases by one standard error of its estimate, the associated average % change (in absolute terms) in auxiliary models within each group in the column. Wages are quarterly and are expressed in units of $1,000.

Appendix Figure 1: Number of claims, by month of disability



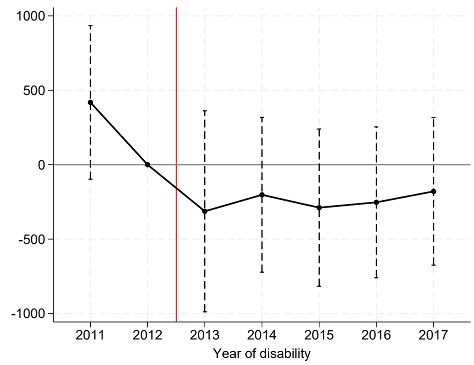
Notes: Data provided by ODCBS. Sample consists of 2011-2017 disabling claims. Figure reports number of claims by month of disability. The gray curve denotes a fitted polynomial, and the dashed vertical line denotes date of policy change.

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

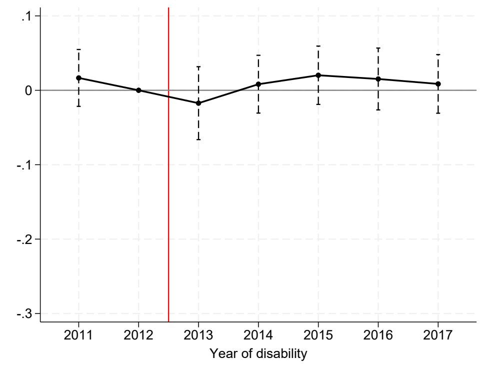


Notes: Data provided by ODCBS. Sample consists of 2011-2017 disabling claims. Figure reports, for each decile of 2005-2009 exposure on the y-axis, the fraction of claims in the decile of 2011-2013 exposure, as reported numerically and in color (warmer colors denote higher fractions).

Appendix Figure 3: Event Study Analysis of Policy Change on Earnings and Job Mobility



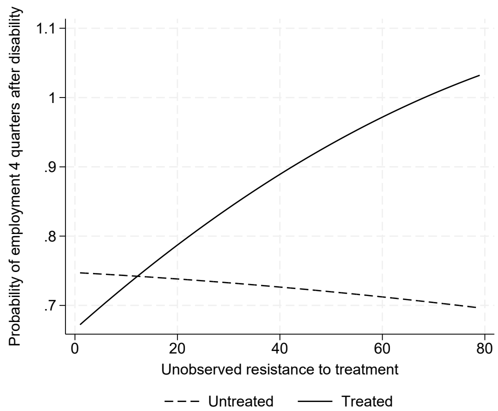
(a) Earnings



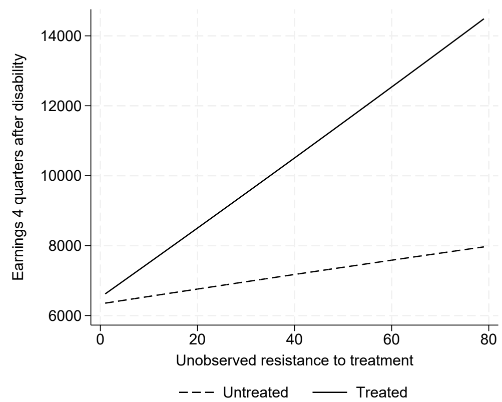
(b) New firm

Notes: Data provided by ODCBS. Solid dots denote the estimated coefficients on the interaction of exposure and year from a regression of the outcome variable on exposure, quarter, and the interaction between exposure and year (2012 is omitted), along with a broad set of worker, firm, and disability controls. Estimate for 2013 excludes claims from the first two quarters of the year. Dashed vertical lines report 95% confidence intervals. Vertical red line distinguishes time periods before and after the policy change. All dependent variables are four quarters after disability.

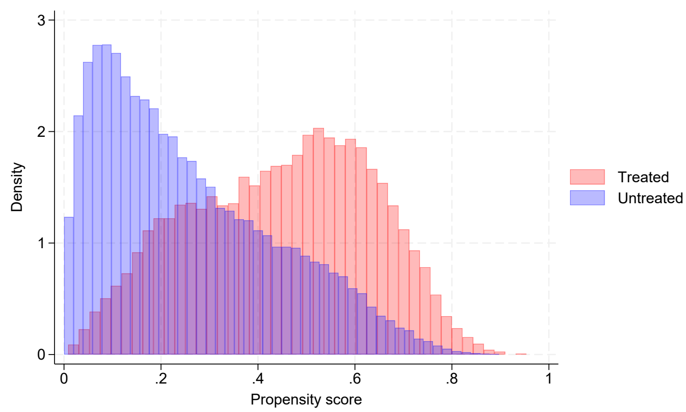
Appendix Figure 4: Marginal Treatment Responses for Employment and Earnings and Distribution of Propensity Score



(a) Employment four quarters after disability



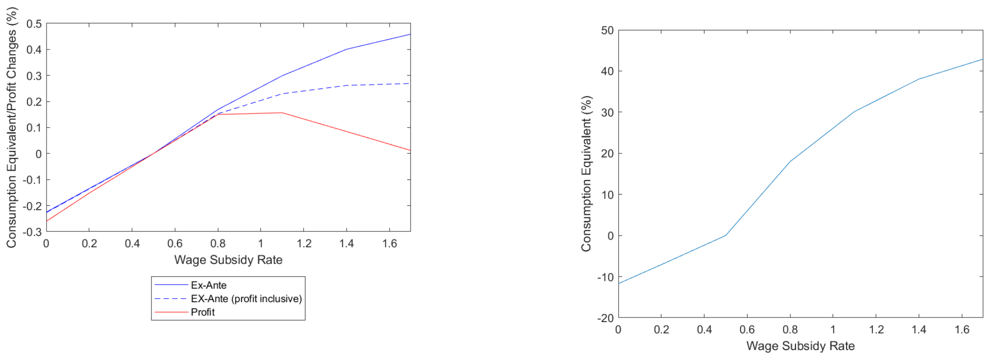
(b) Earnings four quarters after disability



(c) Distribution of Propensity Score

Notes: Data provided by ODCBS. Panels (a) and (b) report marginal treatment response curves for accommodated (solid lines) and not accommodated (dashed lines) claims for employment and earnings four quarters after disability, respectively. Effects of observables (for employment) are reported in Appendix Table 14. Corresponding marginal treatment effects are in Figure 4. Panel (c) shows the distribution of the propensity score by accommodation status.

Appendix Figure 5: Welfare Impacts of Wage Subsidies for Accommodation in a Model of Industry-Specific Human Capital

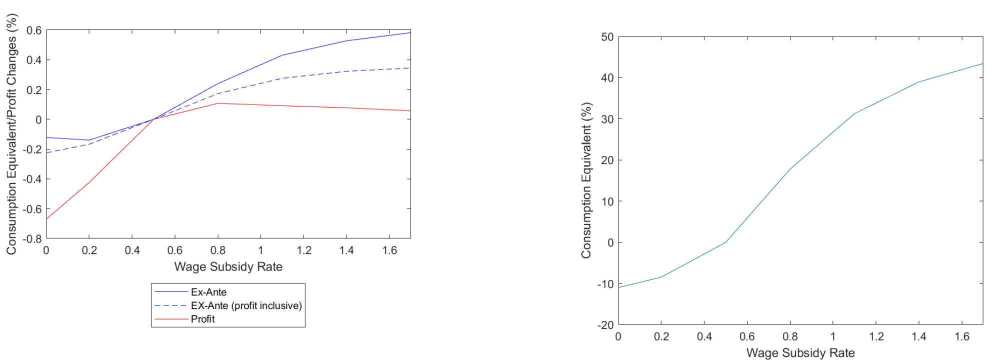


(a) Ex-ante welfare (profit)

(b) Welfare at the time of disability

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 disabled workers at the time of disability.

Appendix Figure 6: Welfare Impacts of Wage Subsidies for Accommodation in a Model With Disutility of Work



(a) Ex-ante welfare (profit)

(b) Welfare at the time of disability

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 disabled workers at the time of disability.

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