Unemployment Insurance Benefits and Worker Reallocation

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This version: January, 2022

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Abstract:
Does Unemployment Insurance (UI) affect employed workers' propensity to find new and different jobs? If so, how do these responses influence the costs of providing UI? To answer these questions, I combine a regression kink design (RKD) with predicted unemployment risk using rich Norwegian administrative data. My data covers the universe of workers in Norway, their tax filings, and detailed information on their employers, including corporate bankruptcy filings. I find that a one percent increase in benefits lowers the annual probability of a job-to-job transition by 0.2 percent. This average effect is driven by workers with high predicted unemployment risk, and the reduction in job mobility increases the inflow of workers into unemployment. Despite this adverse effect on employment, the negative earnings effect is modest, and I find no effects on other measures of job quality. I rationalize these findings by showing how the effect on job quality can be decomposed into two opposing forces in a standard on-the-job search framework: (i) UI leads workers to seek better jobs, but (ii) increases the likelihood of future unemployment. I propose a new method to quantify the relative importance of these two forces from reduced-form estimates. Finally, I estimate how the changes in mobility and job outcomes affect net costs of providing UI. Using data on benefits received and taxes paid, I find that for each dollar increase in benefits, the government must pay an additional 50 cents because of these behavioral changes. About 80 percent of this cost stems from the increased flow from employment to unemployment – a margin typically omitted in the empirical literature on optimal UI.

Keywords: On the job search; Unemployment Insurance; Regression kink design; Unemployment Risk
JEL codes: H31, H55, G33, G52, J31, J65

*BI Norwegian Business School. E-mail: morten.grindaker@bi.no. I am indebted to my advisors, Gisle Natvik and Andreas Kostøl as well as Plamen Nenov for their continuous guidance and support. I would like to direct a special thanks to Espen Moen, Maria Olsson, Jon Fiva, Karl Harmenberg, and Itzik Fadlon for detailed and constructive early feedback on the paper. Moreover, I thank participants at the 14th Nordic Summer Symposium in Macroeconomics, 6th Annual Empirical Microeconomics Conference at Arizona State University, BI Macro Group for their comments and suggestions. This helped to greatly improve this work. All remaining errors are my own.

1 Introduction

The level of unemployment insurance (UI) affects both the duration of unemployment spells and how good jobs unemployed workers find (e.g. Card et al., 2007; Schmieder et al., 2016, and Nekoei and Weber, 2017). However, little is known about how UI affects *employed* workers' efforts to avoid unemployment in the first place. In this paper, I seek to bridge this gap with novel empirical evidence from Norway.

The risk of job loss is a salient feature of workers' careers, and it is well-documented that workers can mitigate this risk by searching for new and safer jobs.[1] The level of unemployment insurance has the potential to shape how these workers search for new jobs. While the magnitude of these behavioral responses matters for the reallocation effects (Giupponi et al., 2022) and optimal design of UI (Baily, 1978 and Chetty, 2006), there is scarce empirical evidence on how UI affects the job-search behavior and job outcomes of workers at risk of job loss.[2] This lack of empirical evidence reflects the challenge of measuring and identifying individual responses to higher benefits.[3] Even if a generous UI schedule can impede worker reallocation, the responses are likely to be highly heterogeneous across workers with different levels of job security.

This paper aims to address this challenge and provide credible estimates on the effect of UI benefits on job mobility and job outcomes of employed workers at risk of job loss. To this end, I combine rich administrative data on Norwegian workers with a regression kink design (RKD) and a predictive model of unemployment risk. This strategy allows me to identify the reallocation effects of a marginal increase in UI benefits for workers with different levels of job security. In Norway, as in most western countries, the UI replacement rate (ratio of benefits to pre-earnings) is constant up to a maximum benefit amount. This creates a kink in the replacement rate as workers do not receive higher benefits for earnings above this threshold. Following Card et al. (2015b) and Kolsrud et al. (2018), I exploit this variation to identify the effects of UI benefits with a regression kink design. To measure unemployment risk, I identify firms with high predicted layoff risk using detailed data on firm characteristics, including corporate bankruptcy petitions from the Norwegian Court Administration (NCA). I use this data to predict workers' future unemployment risk following Landais et al. (2021). By focusing on firm-level predictors of unemployment risk, I aim to capture risk factors that a worker can avoid by changing firm.

Using this design, I find evidence of strong reallocation responses among employed workers. Higher UI benefits lead to a significant decline in job mobility, driven by workers in firms with high average layoff risk. A one percent increase in benefits lowers the annual probability of a job-to-job transition by 0.2 percent

[1] Several empirical studies documents that workers are searching for new jobs to avoid future layoffs (see, e.g., Burgess and Low 1992, Baghai et al. 2021, and Simmons, 2022). Knowledge of future layoffs affects workers' job outcomes (Cederlöf et al., 2021), savings behavior (Hendren, 2017), and insurance choices (Landais et al., 2021). Moreover, in a large class of search models, workers subject to job loss risk are searching on the job for new matches. The level of UI benefits features as a critical component in these models, as it partly determines workers' outside options (see, e.g., Lise 2013 or Jarosch 2021)

[2] The literature on optimal UI has mainly focused on the moral hazard costs through increased unemployment duration. However, as displayed in Chetty (2009), the general framework accounts for the moral hazard effects of workers' efforts to avoid unemployment. Giupponi et al. (2022) argues that UI generosity can impede reallocation because workers remain longer unemployed with higher UI benefits. The same distortions to workers' search behavior apply when workers risk job loss and can search on the job for new matches.

[3] Only a few empirical studies look at how UI affects the search behavior of employed workers see, e.g., Burgess and Low (1998), Light and Omori (2004), Lalive et al. 2011, Gutierrez (2016), Britto (2016), and Doornik et al. (2021). Most of these studies use a control function approach to account for potential endogeneity, and none of these studies investigate how UI affects job outcomes or how the responses vary with unemployment risk.

overall and 0.6 percent for the workers in the upper quintiles of the risk distribution. In contrast, there is no evidence of an effect on workers in firms with low average layoff risk. The reduction in mobility leads to an increased inflow of workers into unemployment. On average, the probability that a worker makes an employment-to-unemployment (E-U) transition increases by between 0.2 and 0.4 percent per percentage change in benefits. Despite this increased inflow of workers to unemployment, I only estimate a modest negative earnings effect and find no clear effect on other measures of average job quality and productivity. [4]

I rationalize these findings in a model of on-the-job search where workers face layoff risk and workers choose their level of search effort and job selectivity. In this model, higher benefits induce workers to become more selective. This lowers job-finding rates and increases the likelihood of unemployment but can improve the quality of jobs for workers who find new employment. The earnings effect of higher benefits depends on the relative strength of these two opposing forces. On the one hand, higher benefits increase the probability that a worker will enter unemployment and have zero wage earnings. On the other hand, higher benefits can improve wages for workers who move to new positions.

I show that my empirical findings are qualitatively and quantitatively consistent with this framework. First, the model offers a precise, testable prediction. For workers subject to future job-destruction risk, job-finding rates will be a kinked function of their earnings if the benefit schedule features a maximum benefit threshold, but will be smooth for workers who face no job loss risk. In the data, I find a clear kink in the job-finding probability at the maximum benefit threshold for workers at risk of job loss and no kink for my placebo sample of public sector workers. The magnitude of this kink also matches well with the predicted kink from a calibrated version of the framework. Second, I find that the reduction in job mobility caused by higher benefits is driven by a reduction in job moves where the worker experiences a wage decline. This suggests that higher benefits also make workers more selective when searching for a new job.

Building on this framework, I develop a method to isolate the quantitative importance of the selectivity effects as a residual in a simple wage decomposition. This decomposition shows how the selectivity effects attenuate the negative effect of higher benefits for all measures of job quality. Without these selectivity effects, the negative impact on job mobility would translate into larger earnings losses. I am not the first to highlight these selectivity effects of higher benefits (see, e.g., Acemoglu and Shimer, 2000; Schmieder et al., 2016, and Nekoei and Weber, 2017). However, the method I propose to isolate the relative effects from a wage decomposition is novel. This method is not particular to my setting and can be applied in other work that aims to quantify how cash transfers such as UI affect the quality margin of job search.

Next, I investigate what my estimates imply along two dimensions. First, my empirical results suggest that higher UI benefits lower the labor costs of firms with high unemployment risk by increasing the likelihood that workers would remain in the firm rather than making a job-to-job transition.[5] I estimate the effects of higher benefits on workers' survival probability in a firm and show that these estimates can inform

[4] I use wage earnings and four metrics of firm quality to measure the effects of higher benefits on job outcomes. I consider value-added per worker, firms' wage premium (AKM), firms' average layoff rates, and a poach rank index of firms based on Sorkin (2018). I set all these measures to zero when a worker is not registered with an employer. Thus, the estimates of higher benefits on average job quality capture the negative employment effect together with any positive compensating effects on job quality, such as higher selectivity or an improvement in firm performance.

[5] UI benefits can affect firm costs through other mechanisms that I do not consider here. Higher benefits could, for instance, increase equilibrium wages, thereby reducing profits for filled positions, see Hagedorn et al. (2018)

the wage compensation a firm must offer to retain a worker facing a risk of job loss. Using values for the marginal rate of substitution from the literature, I provide a simple back-of-the-envelope calculation. To increase the share of workers remaining in the firm by one percent, the firms in my sample need to increase workers' current wages by, on average, 1.6 percent. The level of unemployment insurance directly lowers this premium by offering workers economic protection against jobloss risk.

Second, the estimated mobility and earnings effects of higher UI benefits have implications for the net cost of providing UI. As more workers become unemployed while the taxable wage earnings of employed workers remain fairly stable, the net cost of providing benefits increases. This fiscal externality constitutes an additional cost to taxpayers, which the individual worker does not internalize. I quantify this fiscal effect using individual data on benefits received and taxes paid together with the regression kink design. Observing individual tax payments is a clear advantage in my study, as I can directly capture the net impact of UI on government tax revenue.[6] I find that for each dollar increase in benefits, the government needs pay an additional 50 cents because of the behavioral responses. Most of the behavioral effect comes from the increased unemployment inflow, which accounts for nearly 80 percent of the effect. The remaining 20 percent captures an increase in the duration of unemployment. In line with the evidence on workers' wage earnings, there is no significant effect on government tax revenue. Overall, my findings highlight the importance of including UI's effect on the inflow of workers into unemployment in the empirical literature on optimal UI. Disregarding this effect can lead to an underestimation of the full cost of a more generous UI.

Related Literature: This paper contributes to an extensive labor and public finance literature that studies the tradeoff between incentives and insurance in determining optimal UI. A vast empirical literature investigates how UI affects the search behavior and job outcomes for unemployed workers (see, e.g., Card et al., 2007; Schmieder and Von Wachter, 2016, and Kolsrud et al., 2018). My results add to this literature by documenting that distortions to search are not limited to unemployed workers' behavior but also affect how workers at risk of job loss search on the job.

Only a few empirical studies investigate how UI benefits affect search behavior for employed workers (see, e.g., Burgess and Low, 1998; Light and Omori, 2004, Britto, 2016 and Gutierrez, 2016). Most of these studies use a control function approach to account for potential endogeneity, and none of these studies investigate the effect on job outcomes. The closest related study is by Britto (2016), who use a regression kink design to identify the effects of UI benefits on employment duration for Brazilian workers. I add to the findings in this paper by documenting how UI jointly affects job outcomes and job mobility and how the effects vary with unemployment risk. The effect I estimate for the employment-to-unemployment probability is also consistent with the evidence in Jäger et al. (2019). They find that an Austrian reform that changed potential UI duration from one to four years triggered an increase in separations (largely into non-employment) of 11 percentage points over a five-year horizon.

The distinction between the effect on transition rates and job outcomes is inspired by Nekoei and Weber (2017) and the work of Acemoglu and Shimer (2000, 1999). They argue that higher UI benefits can

[6] The estimated fiscal externality captures the direct effect on government costs and revenue from changes in individual tax payments and the uptake of UI. My estimate will not capture potential tax effects stemming from changes in firm behavior.

improve efficiency because it allows workers to search longer while unemployed to obtain jobs with higher productivity. Nekoei and Weber (2017) document that these selectivity effects can lead to a positive UI wage effect in a partial equilibrium setting. I extend their framework to one where workers search on the job to avoid future job loss. Moreover, my findings on the effects on average firm productivity directly inform the tradeoff highlighted by Acemoglu and Shimer (2000).

My results indicate that workers act on information layoff risk. This finding is in line with a growing literature that analyzes workers' pre-layoff behavior. These include Hendren (2017), Landais et al. (2021), Cederlöf et al. (2021). Hendren (2017) find that workers' beliefs about layoff risk affect their savings decisions and spousal labor supply. Cederlöf et al. (2021) find that workers with advance layoff notification have shorter non-employment durations and experience better subsequent job matches. I contribute by documenting that UI distorts pre-layoff search and leads to a higher inflow of workers to unemployment.

Finally, my paper speaks to a literature in finance that investigates the link between firm-level unemployment risk and firms' labor costs. Brown and Matsa (2016) document that more risky firms receive fewer job applications, and Baghai et al. (2021) document that talented workers leave distressed firms at a higher rate. Using a UI reform in Brazil, Doornik et al. (2021) show that tighter requirements for UI benefits induced a movement of workers towards firms with higher unemployment risk. I contribute to this literature by documenting that UI increases the survival rate of workers in high-risk firms. Moreover, I use this empirical evidence to provide a rough calculation of how sensitive this survival rate is to a firm's wage compensation.

Road map: The remainder of this paper is structured as follows. Section 2 develops a conceptual framework where workers at risk search on the job for new employment. Section 3 describes the Norwegian institutional context and the data sources I use. Section 4 describes my empirical strategy, and in Section 5, I present my main empirical findings. In Section 6, I investigate the implications of my empirical results for the fiscal externalities of UI and firms' labor costs and quantify the selectivity effects of higher benefits. Section 7 contains a brief conclusion.

2 Conceptual Framework

In this section, I present a stylized model of on-the-job search that motivates and guides the empirical analysis. Jobs differ along two dimensions; wages and job security. The heterogeneity in job security allows UI to play a pivotal role in workers' on-the-job search behavior. Higher UI benefits lower the value of job-security relative to wages and increase worker selectivity when searching for new jobs. This slows down reallocation and incentivizes workers to target jobs with higher wages. I assume here that the distribution of job offers is exogenously given. The assumption on the dimension of firm heterogeneity is drawn from Jarosch (2021), but rather than considering jobs with different productivity, I consider jobs with different wages. For simplicity, I abstract away from human capital accumulation and assume that workers' earnings potential is independent of employment status and tenure. Search is directed in this model. This allows for a tractable decomposition of the wage effects of higher benefits, similar to that of Nekoei and Weber (2017). However, the qualitative results do not rest on the directed search assumption. The same effects would be present in a random search framework where worker selectivity would be expressed through reservation wages (see Gutierrez, 2016 and Appendix section B).

From this framework, I derive two main predictions that I use in the main empirical analysis. First, higher benefits lower the job-finding rate for workers subject to job-destruction risk. Second, under a benefit profile where benefits are a function of wages subject to a maximum benefit threshold, the job-finding rate is a kinked function of wages, kinked upward at the maximum benefit threshold for workers with a positive job-destruction risk and continuous for workers with no job-destruction risk. These changes in behavior affect the optimal level of UI benefits. Higher benefits lower the job-finding rate and increase the share of workers who makes am employment to unemployment transition, which generates additional fiscal externalities. I conclude this section by introducing on-the-job search into a standard framework for studying optimal benefits.

While my results are based on a partial equilibrium model, the matching process are consistent with a general equilibrium framework. In a setting where matching is endogeneously determined by firms' vacancy posting and the number of workers applying for each vacant position, there would be longer queues for more attractive jobs. Firms that post higher wages would then find workers more more quickly, but pays a higher cost for the position (see e.g Moen, 1997 and Acemoglu and Shimer, 2000). In my setting, this is captured by a job-finding rate that falls with the target job quality the workers aim for.

2.1 Setup

A unit mass of initially identical employed workers search on the job among a set of posted vacancies. I denote a job type by a vector $\upsilon = (w, \delta)$, where $w \in [\underline{w}, \bar{w}]$ denotes the wages the firm post, and $\delta \in (0,1)$ denotes a the exogenous job-destruction probability. All jobs are initially safe, $\delta_0 = 0$, but becomes insecure with a probability p in which the job-destruction rate is δ. After this risk is realized, workers make their search decision. At this point, workers know that their current job has a probability of destruction δ and that their job-finding rate λ depends on their target job quality $\hat{V} = V(\hat{w}, \delta_0)$. As in Nekeoi and Weber (2017), this mechanism is captured by a matching function E that is decreasing in the value of their targeted job $\hat{V}$, and increasing in search effort s. There are three different outcomes for the employed workers; with probability $\delta(1-\lambda)$ the worker becomes unemployed, with probability $(1-\delta)(1-\lambda)$, the worker remains in her current position, and with probability λ the worker reallocates to a new position. All three outcomes are affected by workers' efforts and job selectivity. Thus, unemployment risk in this framework is the product of a given job-destruction rate and an endogenously determined job-finding rate. Employed workers pay taxes τ and receive $w-\tau$ in net wages, while unemployed workers recieve benefits b. All workers live hand-to-mouth. With these assumptions, the value function of an employed worker in a job with wages w and job-loss risk δ, can be characterized as:

$$V(w,\delta) = \max_{\substack{\hat{V},s \\ \lambda=E(\hat{V},s)}} u(w-\tau)+\beta[\delta(1-\lambda)V_u(c_b)+(1-\delta)(1-\lambda)V(w,\delta)+\lambda\hat{V}]-\psi(s) \tag{1}$$

where $u(.)$ is the flow utility of consumption, ψ the disutility of search and $\beta \in (0,1)$ the discount factor. [7] The value function of an unemployed worker is:

$$V_u(c_b) = \max_{\hat{V},s} u(c_b)+\beta[\lambda\hat{V}+(1-\lambda)V_u(c_b)]-\psi(s) \tag{3}$$

The associated first order conditions of equation (1) are:

$$\begin{aligned} \frac{\partial V(w,\delta)}{\partial \hat{V}}:\quad & \lambda'_{\hat{V}}[V(\hat{w},\delta_0)-\delta V_u(c_b)-(1-\delta)V(w,\delta)]+ \quad \lambda &= 0 \\ \frac{\partial V(w,\delta)}{\partial s}:\quad & \lambda'_s[V(\hat{w},\delta_0)-\delta V_u(c_b)-(1-\delta)V(w,\delta)]- \quad \psi'(s) &= 0 \end{aligned} \tag{4}$$

where $\{V(\hat{w},\delta_0)-\delta V(b)-(1-\delta)V(w,\delta)\}$ is the surplus of the new match and λ' and ψ' denotes the partial derivative.

2.2 The Effects of UI Benefits on Workers' Search-behavior

The first-order conditions (4) highlight the tradeoff workers face in this framework. Workers trade off the potential gains of higher quality jobs and lower search costs against the cost of a lower job-finding rate. The magnitude of this cost is governed by workers' job-destruction risk and the level of benefits they receive if ending up unemployed. Higher benefits increase the option value of workers' current position relative to other jobs if workers are subject to risk. As all jobs are initially safe, higher benefits increase the value of the current risky position more than any targeted position.

It follows that higher benefits lead to lower job-finding rates as the cost of being more selective or exerting lower efforts falls. As the job-finding rate decreases in the value of workers' target, selectivity increases in

[7] The value function for a worker in a safe position is given by:

$$V(w,0) = \max_{\substack{\hat{w}\varepsilon W \\ \lambda=E(\hat{w})}} u(w-\tau)+\beta[(1-\lambda)V_0(w)+\lambda V(\hat{w})]-c \tag{2}$$

where, $V_0(w)$ is given by $V_0(w) = (1-p)V(w,0)+pV(w,\delta)$

benefits for a given search effort. This is summarized in the following proposition (see appendix for proof).

Proposition 1. *If the job-finding rate $\lambda(V(\hat{w};b),s)$ is decreasing in target job quality and workers face a positive probability of job-destruction, the job-finding rate is decreasing in benefits. For a given search effort, target job quality is increasing in benefits.*

$$\lambda = \lambda(V(\hat{w};b),s) \qquad \text{where } \frac{d\lambda(V(\hat{w};b),s)}{db} \leq 0$$

$$\hat{V} = V(\hat{w};b) \qquad \text{where } \frac{dV(\hat{w};s)}{db} \geq 0$$

Note that there will be no effect on the job-finding rate or selectivity if workers face no risk $\delta = 0$.[8] Using these results, it is possible to make a prediction of how the job-finding rate should behave when benefits are a kinked function of workers' wages at a maximum benefit threshold. In the appendix, I show that under a benefit profile with a maximum benefit threshold, the job-finding rate is a kinked function of job quality for workers with a positive job-destruction risk and a smooth function for workers with no risk $\delta = 0$. This follows as the value of the target job-quality is strictly increasing in current job quality $V(w,\delta)$, which is kinked at the benefit threshold.

Proposition 2. *Under a benefit profile where benefits are a function of wages $b(w)$ subject to a maximum benefit threshold at $w = w_k$, the job-finding rate λ is a kinked function of wages, kinked upward at the maximum benefit threshold for workers with a positive job-destruction risk and smooth for workers with no job-destruction risk.*

$$\hat{V} = V(\hat{w};V(w,b(w))) \qquad \text{where } \frac{\partial \hat{V}|w \leq w_k}{\partial w} > \frac{\partial \hat{V}|w > w_k}{\partial w}$$

$$\lambda = \lambda(V(\hat{w};V(w,b(w)))) \qquad \text{where } \frac{\partial \lambda|w \leq w_k}{\partial w} \leq \frac{\partial \lambda|w > w_k}{\partial w}$$

These two results depend on the assumption that higher benefits increase the value of a current risky job relative to other jobs. If workers could target jobs with higher layoff risk and higher wages, higher benefits could increase workers' job-finding rate. Moreover, the framework ignores the potential interaction between benefits and other institutional features such as employment protection. Higher benefits could induce high-tenured workers, better protected from layoff, to search for higher-paying but more risky positions. In such a setting, higher benefits would increase the probability that a worker makes a job-to-job transition. This mechanism seems, however, to be at odds with my empirical findings (see Section 5).

2.3 On-the-job Search and Fiscal Externalities

Higher benefits distort workers' on-the-job search, which has implications for the level of optimal benefits. As workers become more selective or lower their efforts, their job-finding rate falls and the share of workers

[8] In this framework, I assume that workers target overall quality υ rather than each component (w,δ) separatly. This means that I abstract away from how benefits affect the value of wages to relative to job-security when workers search for a new job.

who transitions from employment to unemployment increase. At the same time, workers who do find a new job potentially might find a better position because they have been more selective in their search. The net effect of these forces affects the behavioral costs of a marginal increase in benefits. This behavioral cost is known as the fiscal externality, as it captures the additional cost to the insurer from the changes in behavior, which is not taken into account by the individual worker. This fiscal externality needs to be balanced against the insurance value of higher benefits. Below I show how the standard formula for optimal benefits is affected by introducing on-the-job search, building on the framework from (Hendren et al., 2021). Here I allow for heterogeneity in job-destruction rates and job-finding probabilities based on worker type.

Optimal Benefits with Heterogeneity

Workers are employed at firms with different job-destruction rates δ_j and their job-finding rate depends both on their target wage $\hat{w}_i$, and their type i. Each worker is risk averse and has utility $u(c_i)$ over final consumption which is strictly increasing and weakly concave. Suppose that each employed worker could buy an insurance contract at the cost of $p(b)$ today that provides benefits b in the event of unemployment next period.[9] Workers' consumption under insurance contract b is given by $c_i = w_i - p(b)$ and let $V_i(w;b)$ denote the net value for an individual of type i, that buys insurance b at the cost of $p(b)$:

$$V_i(w;b) = \max_{\hat{w}\varepsilon W,b} \quad u(w_i - p(b)) \quad + \beta \left\{ \delta_j (1 - \lambda_i(\hat{w}(b)) V_u(c_b) + (1-\delta_j)(1-\lambda_i(\hat{w}(b)) V_i(w) + \lambda_i(\hat{w}(b)) V(\hat{w}_i) \right\}$$

The workers' targeted wages are denoted $\hat{w}_i$, and $\lambda(\hat{w}_i)$ is the associated job-finding rate. $V_u(c_b)$ denotes the value function of an unemployd worker. Finally, denote the net cost for the insurer of insuring individual i, by $C_i(b) = \pi_i(b)b - p(b)$, equal to the probability of unemployment times the insurance payout net of the price of the insurance contract. Here $\pi_i(b) = \delta_j(1 - \lambda_i(\hat{w}(b))$ denotes the risk of unemployment. As workers choose their insurance covarage, the optimal level of insurance must satisfy the associated first order condition such that the marginal benefit of one unit extra of coverage next period equals the marginal cost:

$$\frac{dV_i(w;b)}{db} = 0 \qquad \Longleftrightarrow u'(w_i - p(b))p'(b) \quad = \quad \pi_i(b)\beta V_u'(c_b)$$

I denote the expected marginal utility of consumption in the state of unemployment by $E_i(c_u) \equiv \pi_i(b)\beta V_u'(c_b)$ and the marginal utility in the period of employment as $u'(c_e) \equiv u'(w_i - p(b))$. The marginal rate of substitution (MRS), that describes how much consumption workers are willing to give up when employed to increase their consumption when unemployed, is given by:

[9] If the worker choose optimal benefit levels each period only covering one period ahead, we can disregard the continuation value of higher benefits across all states.

$$MRS = \frac{p'(b)}{\pi_i(b)} = \frac{E_i(c_u)}{u'(c_e)} \tag{5}$$

Giving the same weight to all individuals, the total welfare effect of a marginal increase in benefits across all types is given by:

$$\frac{dE(W_i)/db}{E(\pi_i)} = \underbrace{E\left\{\frac{\pi_i}{E(\pi_i)}\frac{E_i(c_u)-u'(c_e)}{u'(c_e)}\right\}}_{\text{WTP for insurance}} - \underbrace{E\left\{\frac{\pi_i}{E(\pi_i)}(\varepsilon_{\pi_i,b})\right\}}_{\text{Cost for insurer}}$$

Here the first term denotes the average premium individuals are willing to pay for insurance, weighted by the likelihood of unemployment. The second term is the total cost for the insurer also weighted by the likelihood of unemployment. The willingness to pay is governed by the gap in marginal utilities across states, while the total cost to the insurer depends on how higher benefits affect the net cost for the government through behavioral changes. These behavioral changes captures the fiscal externalities of higher benefits. Assuming that $E(W_i(b))$ is concave in b, there is an optimal level of benefits. Optimal benefits are the same as in the standard Baily-Chetty formula (Baily 1978, Chetty 2006) and equates the average willingness to pay for one dollar extra in insurance to the increase in cost from the behavioral responses that dollar generates. In the next subsection, I unpack the components that govern this net cost under the assumption of a balanced budget and linear income taxes.

Fiscal Externalities

Effect on Tax Revenue

Higher benefits affect tax revenue both through their effect on employment and through their effect on workers wages. Total tax income depends not only on the number of employed workers but also on the share of workers who reallocate to a higher-paid position. The next period's expected gross wage income can then be written as a weighted sum of reallocating and remaining workers wage income:

$$E(w) \equiv \int w_i(e_i(b)-\lambda_i(b)) + \hat{w}_i(b)\lambda_i(b)$$

Taking the derivative of $E(w)$ w.r.t. b we see that the effect of higher benefits on the gross wage income depends on two counteracting forces:

$$\frac{dE(w)}{db} = \int \underbrace{\left\{\lambda_i \frac{d\hat{w}_i}{db}\right\}}_{\text{Quality effect}} + \underbrace{\left\{\frac{d\lambda_i}{db}(1-\delta_j)[\hat{w}_i - w_i] + \frac{d\lambda}{db}\delta(\hat{w}-0)\right\}}_{\text{Transition effect}} \tag{6}$$

On the one hand, higher benefits affect wages for workers who obtain a new match (quality effect) if they aim for higher quality jobs. On the other hand, the probability of obtaining a new position falls as benefits increase and workers become more selective or induce less effort (transition effect). The transition effect can further be decomposed into the foregone reallocation gains among the share of remaining workers (first term) and the foregone reallocation gains for workers who become unemployed. The net effect depends on the relative strength of these two forces and how much the workers change their selectivity relative to efforts when benefits increase.

Effect on Total Benefits

Total benefits depend on both the probability that the worker becomes unemployed (E-U) and the probability that an unemployed worker transitions back into employment (U-E). In my framework both these transition probabilities are affected by the benefit level through workers' job-finding probability $\lambda_i(b)$. The E-U probability is given by $(1-e_i(b))$ and I denote the U-E probability by $D(b)$.[10] Then the total cost of benefits is given by $B = b(1-e(b))D(b)$ and total tax income is given by $T = \tau E(w)$.The government budget simplifies to:

$$b(1-e(b))D(b) = \tau E(w) \tag{7}$$

Equation (7) implicitly defines the tax rate τ as a function of benefits b, where the necessary percentage change in the tax rate from a one unit change in benefits is given by:

$$\frac{d\tau}{db}\frac{b}{\tau} = 1 + \underbrace{\varepsilon_{EU,b}}_{\text{E-U effect}} + \underbrace{\varepsilon_{D,b}}_{\text{"Duration" effect}} - \underbrace{\varepsilon_{E(w),b}}_{\text{Wage effect}}$$

The total cost equals the mechanical cost plus the fiscal externality which consist of three terms. First, higher benefits affect the probability that a worker transitions from employment to unemployment, $\varepsilon_{EU,b}$, it potentially affects the probability that an unemployed worker transitions back to employment, $\varepsilon_{D,b}$, and it can affect the government tax income because it affects employment and can change the average wage earnings of the workers if they respond by being more selective, $\varepsilon_{E(w),b}$. In section 6.1, I estimate the total effect on benefits and taxes paid in my sample, and decompose the effects into the three terms in the above equation. In section 6.2, I quantify the selectivity effects of higher benefits using the structure in the framwork I have developed in this section.

3 Context and Data

3.1 The Norwegian UI schedule

The Norwegian UI schedule has a benefit replacement rate (ratio of benefits to pre-earnings) of 62.4 percent of workers' eligible pre-earnings subject to a maximum benefit amount. Workers with pre-earnings above the maximum benefit threshold receive no additional benefits for earnings above this threshold. The threshold

[10] In my discrete time setting, with a unit mass of initially employed workers there will be no U-E transitions in the next period. However, I relax this assumption here, and assume that workers who enters unemployment within period can transition back to employment. This requires a slight rewrite of the value function for unemployed workers:

$$V_u(c_b) = \max_{\hat{V},s}(1-\lambda_u)u(b) + \lambda_u V(\hat{w},\hat{\delta}) + \beta(1-\lambda_u)[\lambda_u(V(\hat{w},\hat{\delta}) - (1-\lambda_u)V_u(c_b))] - \psi(s)$$

where $D(b) \equiv \lambda_u$. When I estimate the fiscal externalities in the empirical section, $D(b)$ corresponds to the average duration workers spend unemployed.

is adjusted annually based on inflation and reported in basic amounts.[11] The earnings threshold is at six basic amounts, or approximately 60 000 USD, and maximum benefits constitute 62.4 percent of this amount, approximately 37 500 USD. This maximum benefit amount substantially reduces the average replacement rate for workers with earnings above the threshold. While a worker earning 70 000 USD receives the same benefit amount as a worker earning 60 000 USD, benefits will only replace about 55 percent of the high earner's income. This kink is salient. Workers can quickly check what benefit amount they will receive in the event of unemployment by calculating it directly or using online calculators.[12]

Compared to UI systems in other countries, the Norwegian schedule is fairly generous. Most countries have replacement rates between 50 percent and 65 percent with a cap at a maximum benefit amount Schmieder and Von Wachter (2016). The potential duration of benefits in Norway extends longer than in most other countries, which typically compensate workers up to six months after they lose their job. In Norway, UI benefits are paid up to 24 months for workers with pre-earnings above two base amounts ($\approx$200 000 NOK) and up to 12 months for those with pre-earnings less than two base amounts. UI benefits are financed from general tax revenue, and there are no employer contributions.

Eligible pre-earnings include wage earnings and taxable benefits such as sickness benefits, work assessment allowance, and parental benefits. If average earnings the three years before the spell exceed the earnings the calendar year before the spell, average earnings are used. Eligible pre-earnings are registered and updated at the Norwegian Labour and Welfare Administration (NAV). Workers under the age of 67 who suffer a reduction in working hours of more than 50 percent and with pre-earnings of more than 1.5 base amounts ($\approx$ 150 000 NOK) are eligible for the insurance. In addition, workers need to register as job-seekers in the Norwegian Labour and Welfare Administration (NAV).

Two other important Norwegian social insurance schemes have a maximum benefit amount capped at pre-earnings of six basic amounts. Norwegian Disability Insurance (DI) consists of a basic benefit amount and supplementary benefits increasing in pre-earnings, capped at six basic amounts. Workers seeking DI need to use written medical evidence on their inability to engage in substantial gainful activity (SGA) and go through an application process to receive benefits (see Dahl et al., 2014 for details).[13] Employees who cannot work because of illness or injury are entitled to sickness benefits covered in part by the employer and in part by the government. Wages are fully covered up to six basic amounts, and workers are not entitled to benefits exceeding this amount.

The kink in DI and sickness benefits is problematic in my setting as I cannot distinguish between the effect of these transfers relative to the UI benefits. To isolate the effect of UI, I use public sector workers as a placebo sample. These workers have a low risk of involuntary unemployment but above-average DI and sickness benefits uptake. Appendix Figure A.2 displays the average uptake of DI and sickness benefits in

[11] One basic amount in 2021 was 106 399 NOK or $\approx$ 10 600 USD.

[12] There are additional benefits for workers with dependents. An additional 17 NOK or $\approx$ 1.7 USD is given a day for each child, independent of workers' pre-earnings. For a worker with two dependents, this amounts to an extra 800 USD annually and constitutes about 2 percent of the maximum benefits amount. The additional benefits provided for individuals with children do not alter the kink point but mean that there is individual heterogeneity in the level of benefits which affects the estimated marginal effects. A worker with two dependents, has a benefit replacement rate at the kink of approximately 0.63, compared to 0.624. In practice, this difference will not alter the results significantly.

[13] The SGA is used to determine eligibility for different types of social security benefits. There is a strong incentive to earn income above the threshold. The threshold for SGA is one basic amount.

each industry sorted by the industry level unemployment risk. [14] There are no signs of a clear relationship between unemployment risk and uptake of these benefits. Public sector workers, defined as employed either in public administration or the health sector, have low unemployment risk but relatively high uptake of DI and sickness benefits.

3.2 Data

Data Sources

My analysis uses several data sources from Norway linked through unique identifiers for each individual and each firm. Each data set on individuals covers the universe of the adult population in Norway. These data sources are combined in two main steps.

In the first step, I construct a dataset with relevant worker information and their registered employer. I start with information from third-party registered tax records from Statistics Norway (SSB). These records give annual information on individuals' income and wealth components including wage earnings, UI benefits and other transfer benefits for the years 2000-2018. The tax registry information also gives information about the annual UI-benefits workers recieve and the total taxes each individual pays which I use for the analysis of fiscal externalities. I combine these records with SSB's Register of Employers and Employees. In this register, I can track all employer-employee relationships over time together with information on the employee's occupation, wages paid, job start, and termination dates for 2000-2019. I complement this with data on workers' exact registered UI eligible pre-earnings from NAV, including wage earnings and taxable benefits. Together with the policy rule, this gives me a precise measure of all workers' potential UI-benefits. Finally, I also attach information from other longitudinal administrative registers provided by SSB. These registers cover information such as gender, age, marital status, residential municipality, and education.

In the second step, I add detailed information on firm characteristics and corporate bankruptcies from the Brønnøysund Register Centre (BRREG) and the Norwegian Courts Administration (NCA). The former is a Norwegian government agency responsible for the management of many public registers and governmental systems for digital information exchange. These registers contain information on firms' income statement and balance sheets, the number of employees, location, and detailed information on corporate bankruptcies for the set of firms petitioned for bankruptcy. The data from the Norwegian Courts Administration covers all bankruptcies petitioned in the period from 2004-2018 and contains information on the exact date the petition was received by the Court, the outcome of the case, and the exact decision date.

Sample Construction

My sample consist of employed workers of working age (18-62) over the period 2008-2014. During this period, there were no important revisions to the Norwegian UI scheme.[15] I exclude the period 2015-2018 as there was a change in the administration and enforcement of data reporting standards in 2015, which

[14] Data on industry-level sickness benefits are taken from NAV: https://www.nav.no/no/nav-og-samfunn/statistikk/sykefravar-statistikk

[15] Over the period 2004-2007, taxable benefits included in eligible pre-earnings were revised, and the criteria for when a worker was counted as unemployed changed.

created a break in some employment relationships between 2014 and 2015.[16] To identify workers' future unemployment risk, I use a predictive model based on firm characteristics (see section 3.4) where firms' average layoff rates enter as a key predictor. To limit noise in the layoff rate estimate, I restrict the sample to workers in firms with at least 50 workers. Including smaller firms increases the variance of firms' layoff rates over time and results in poorer unemployment predictions.[17] Finally, I use on workers in the private sector for my main estimation and use workers in the public sector as a placebo group. Public sector workers comprise of workers in public administration and defence and workers in the health sector.[18]

Variable Definitions

I define a worker as employed in a given year if the worker is registered with a wage in the firm and does not receive any unemployment insurance that year. From the Register of Employers and Employees, I observe total annual wage payments for each worker-firm contract each year from 2000 to 2014. I adjust wage payments by the number of days a worker has been with the firm over a given calendar year and use this as the primary measure of wages. I observe the total wage earnings from all working relationships in a given year from the tax-registry data. I also report the results using total wage earnings. For the employed workers, I compute the annual survival probability, job-to-job probability, and employment-to-unemployment probability. A transition is defined as a job-to-job transition for a worker if the worker is registered as employed in year t and $t-1$, but is registered at different firms. For an individual worker, the transition is represented by an indicator variable ($\hat{h}_{it}$):

$$\begin{aligned}\hat{h}_{it} &= 1 \quad \text{if firm } j \text{ at time } t \mid \text{firm } i \text{ at time } t-1 \\ &= 0 \quad \text{otherwise.}\end{aligned}$$

Here firm i denotes a worker's employer at year t, and firm j denotes a different firm. If the worker receives any unemployment insurance at year t, the transition is not classified as a job-to-job transition but instead an employment-to-unemployment transition. I classify workers as non-employed if they are registered with wage earnings less than one basic amount, equal to the threshold for substantial gainful activity in Norway.[19] Similarly, the worker is defined as surviving if he or she was employed in a firm i in year $t-1$ and remains in the same firm in year t. The average value of these variables for a given bin of pre-earnings gives the expected probability conditional on the worker's pre-earnings.

To estimate the effects of higher benefits on reallocation outcomes, I use information on workers' total wage earnings from the tax-registry data and workers' annual wages adjusted for the number of working days at the job. I also compute four measures that capture different components of firm quality. First, I compute the value added per worker in the set of firms with registered balance sheet information. Value-added is

[16] After 2015, a larger set of small short-term contracts are included in the dataset and the registration is done on a monthly basis.
[17] The main results with no restriction on firm size aligns well with the population estimates with the restricted sample
[18] NACE industry codes 84, 86 and 88
[19] Unemployment insurance is also granted to workers that are temporarily laid off. These workers will also be counted as unemployed by my definition.

computed as sales net of intermediates. Second, I estimate the firm wage premium using the framework of Abowd et al. (1999) (AKM). This measure captures firm-level wages controlling for the composition of employee characteristics. I obtain this measure by regressing the log of wages on employer, employee, and year-fixed effects, using the employer-fixed effects as the measure of firm wage premia. [20] Third, I measure the job-loss risk as the firm average layoff rate adjusted by the average job-to-job separations from that firm. This measure draws on the conceptual framework I present in section 2 to identify the exogenous job destruction risk in a firm. [21] The firm level job-destruction risk is identified under the assumption that there are no systematic within-firm differences in job-destruction rates among workers.

Finally, I estimate a poach-rank index of the firms in my sample following the approach of Sorkin (2018). This method estimates workers' preferences for different firms using the net inflow of workers across different employers. The approach is closely related to the ranking of firms by workers' revealed choices. The ranking is s obtained through value-function iteration, where each firm is first given a rank based on the net inflow of workers from other firms. In the next iteration, the ranks are updated based on the estimated rank of the sending firm. This procedure continues until a fixed point is reached, where the ranking of all firms does not change after further iterations. This ranking picks up not only firm wages but potentially also job security and amenities that workers may value.

3.3 Worker Characteristics at the Maximum Benefit Threshold

Workers close to the maximum benefit threshold are fairly representative compared to the overall population of workers in my sample. Table 1 displays summary statistics for variables on demographics, earnings and transition rates for the full sample of workers (Panel A), and for workers with pre-earnings less than one basic amount (≈10 000 USD) on either side of the threshold (Panel B). Relative to the full sample, workers close to the threshold are slightly older, more educated, higher tenured and more experienced. Their average wage income and pre-earnings are slightly higher than for the full sample. The major difference between workers close to the threshold and the full sample of workers, is that workers at the threshold has a higher probability of surviving in the firm, lower probability of making a job-to-job transistion and a lower probability of making a E-U transition. Thus, these workers appear to be in more stable matches than the rest of the population. This fact is consistent with search models with job-ladders comprising of both wage income and job-loss risk, where workers at the lower rungs have lower earnings and lower job-security, see Jarosch (2021).

[20] I remove firms with fewer than five movers to reduce labor mobility bias

[21] I use the setup from my conceptual framework where the probability of unemployment (u) is given as the product of the exogenous job-destruction rate (δ) and the probability of not receiving another job-offer $(1-\lambda)$. In my framework $u = \delta(1-\lambda)$ such that $\delta = u/(1-\lambda)$.

Table 1: **Descriptive Statistics: Workers at the Maximum Benefit Treshold**

	A. Full sample		**B. Workers close to threshold (5G-7G)**	
	Mean	Std. Dev.	Mean	Std. Dev.
Demographics				
Age	38.78	[12.79]	43.11	[10.53]
Female	0.48	[0.50]	0.46	[0.47]
Foreignborn	0.13	[0.34]	0.11	[0.31]
< High school	0.25	[0.43]	0.20	[0.40]
High school	0.75	[0.45]	0.80	[0.48]
Any college	0.41	[0.49]	0.46	[0.50]
Tenure (years)	5.49	[6.53]	7.13	[7.09]
Wage income				
Wage income (1000 NOK)	491.75	[401.73]	494.59	[111.38]
Pre-earnings (Basic amounts)	5.87	[5.32]	5.91	[0.56]
Transition probabilities				
Pr(Survival)	0.68	[0.47]	0.79	[0.41]
Pr(Job-to-Job)	0.24	[0.42]	0.17	[0.38]
Pr(E-U)	0.09	[0.28]	0.04	[0.20]
Observations	6,978,055		3,244,976	
Workers	2,076,781		984,843	

Notes: This table reports descriptive statistics for the sample of employees in firms with more than 50 employees over the period 2008-2014. The full sample includes employees across the full earnings distribution, while the sample of workers close to the threshold includes all workers with eligible pre-earnings within one basic amount of the maximum benefit threshold at six basic amounts. Wage income is the total annual wage income from the tax-register data. Pre-earnings is the registered pre-earnings from the Norwegian Labour and Welfare Administration (NAV) used to estimate what benefits workers are eligible for. Pre-earnings are measured in basic amounts (G) where 1 G $\approx$10 000 USD. The survival rate measures the probability for an employed worker at year $t-1$ to remain in that firm in year t. The probability of a job-to-job transition measures the share of workers employed in year $t-1$ that transition to a new job in in year t without any intermediate spell of unemployment. The probability of an employment-to-unemployment transition (E-U) measures the probability of a worker employed in year $t-1$ to transitioning to unemployment in year t. Nominal values are deflated to 2014 using the average wage growth (basic amounts). The average exchange rate in 2022 is about NOK/USD = 9.

3.4 Heterogeneity in Unemployment Risk

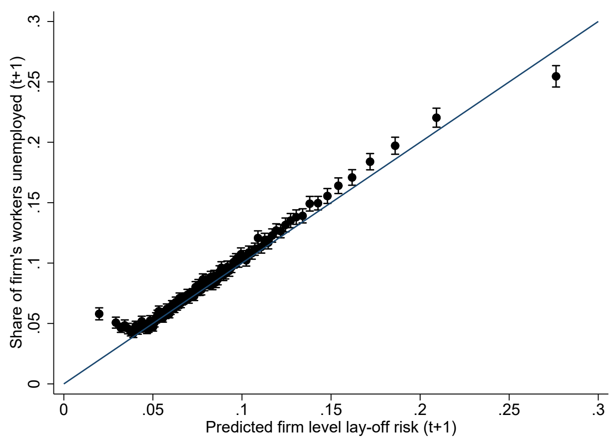
The conceptual framework in Section 2 predicts that an employed worker's response to more generous UI depends on their perceived job-destruction risk. Workers with high levels of job security are unlikely to change their search behavior in response to the thresholds in the UI schedule, as future unemployment poses no threat. To capture how responses vary with job-destruction risk, I build a predictive model of job-loss risk using firm-level information.

Predictive Model of Unemployment Risk

I use variation in firms' average layoff rates to capture differences in unemployment risk over time and across firms. My measure of risk $\pi_{j,t+1}$ is the probability that a worker transitions to unemployment from one calendar year to the next. Following Landais et al. (2021), I use information available for the worker in year t to predict job-loss risk in $t+1$. As a baseline, I estimate a linear regression model using firm average layoff rates, employment growth, and an indicator for bankruptcy petitions in year t as main predictors. The model is estimated on the baseline sample of firms with more than 50 employees from 2005 to 2014. In the predictive model, I do not include individual observable risk factors, such as education, tenure, age, and occupation. These factors may be important in explaining unemployment risk. However, they represent uninsurable risk factors that only partly can be mitigated by moving to a different firm. By focusing on firm-level characteristics, I aim to capture firm-level risk factors that a worker can mitigate by making a job-to-job transition.

To assess the predictive power of the baseline model, I plot the share of a firm's workers that makes an E-U transition in $t+1$ for 50 different bins of the predicted layoff risk in Figure 1. The baseline model provides a good prediction on average. The firms' realized layoff risk is very close to the predicted risk for the majority of the sample in each bin, except for firms at the bottom and top of the distribution.[22] Appendix Table A.4 displays the average realized risk for different percentiles of predicted risk and the overall mean and R^2 from the model. Overall, the prediction model accounts for 16 percent of the total variation. The variation in realized layoffs is considerably higher than the variation in predicted risk, suggesting significant heterogeneity within each firm. However, the model matches the average risk in the deciles of the distribution well.

Figure 1: **Layoffs and Predicted Unemployment Risk**



Notes: The figure displays the share of a firm's workforce that makes an employment-to-unemployment transition in year t+1 on the vertical axis for 50 different equally sized bins of predicted firm-level layoff risk sorted along the horizontal axis. The prediction is based on firm-specific predictors. These include the firm's leave-one-out average layoff rate at year t , the firm's number of employees at year t in logs, an indicator for a bankruptcy petition, employment growth, and an indicator of negative sales growth for the firm. The estimation is based on a full sample of employed workers of working age (18-62) over the period 2005-2014 in firms with more than 50 employees.

The predictive model captures permanent differences in unemployment risk across firms but also differences over time within a given firm. Variation in unemployment risk over time for a given firm constitutes a considerable share of the overall variance in unemployment risk. At the firm level, 58 percent of the total

[22] The predictive model of layoff risk is based on a sample of all workers and are not limited to workers at the earnings threshold. In Appendix Figure A.13 , I include a plot of predicted layoff risk using only workers within one basic amount from the earnings threshold. The average layoff risk is close to 5 percent for this sample.

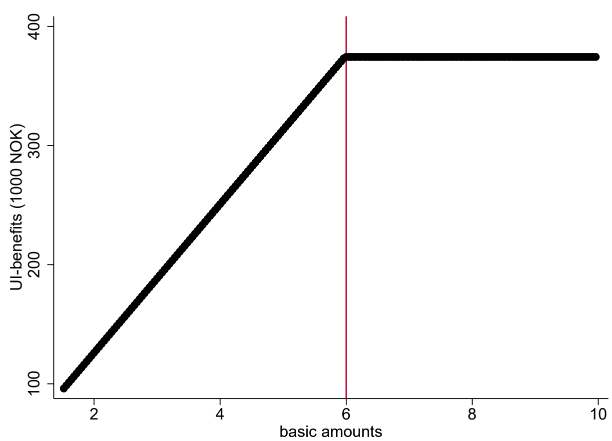
variation in unemployment risk can be attributed to within-firm variation.[23] A potential implication of the time variation in unemployment risk is that workers might seek to mitigate changes in unemployment risk by moving firms. In the next section, I outline the empirical strategy for identifying whether higher UI benefits affects workers' mobility decision when they face the risk of future job loss.

4 Empirical Strategy

4.1 Empirical Design

To estimate the effect of increased benefits on the job-to-job transition probability, job quality, and expected wages, I exploit the kink in the Norwegian UI schedule. The UI replacement rate (ratio of benefits to base earnings) is constant up to a maximum benefit amount and exhibits a kink at this maximum benefit amount (see section 3.1). The policy rule is illustrated in Figure 2, which plots UI benefits as a function of workers' pre-earnings. The schedule displays a sharp kink at pre-earnings of six basic amounts, and features a zero marginal replacement rate for earnings above the threshold. This implies that the average replacement rate falls with pre-earnings above the income threshold. Thus, workers above the threshold have lower relative insurance than workers below the threshold.

Figure 2: **Norwegian UI schedule: Illustration of Policy Rule**



Notes: The figure illustrates how UI benefits evolve with workers' pre-earnings in the Norwegian UI schedule. UI benefits increase with workers' pre-earnings (measured in basic amounts) up to a maximum benefit that is granted for earnings above six basic amounts. Workers' pre-earnings are measured in basic amounts that are annually adjusted for inflation. One basic amount in 2021 was 106 399 NOK ≈10 600 USD

In my design, I consider a sample workers employed at year $t-1$ and evaluate the effect of higher benefits on outcomes in year t and $t+1$ for that worker. I pool all workers registered as employed over the period 2008-2014 in my main regressions and estimate the outcomes for these workers one and two years ahead. This gives me a total of about 3,4 million worker-year observations less than one basic amount on

[23]Let $\delta_{j,t}$ denote the share of workers in a firm j that makes an E-U transistion from year $t-1$ to t. We can decompose the variance of $\delta_{j,t}$ using a fixed effects regression. $\delta_{j,t} = d'\theta + \varepsilon_{j,t}$ is a linear regression model of firm-level unemployment risk, where $d'\theta$ is a vector of firm fixed effects and $\varepsilon_{j,t}$ is the residual term. The total variance of $\delta_{j,t}$ can be decomposed as follows: $Var(\delta_{j,t}) = Var(d'\theta) + Var(\varepsilon_{j,t})$, where $Cov(\varepsilon_{j,t}, d'\theta) = 0$ by construction.

either side of the earnings threshold of the UI schedule.

To estimate the marginal effect of UI benefits, I follow Card et al. (2015b) and use a regression kink design (RK). This design has been implemented in several papers that evaluate the effect of UI-replacement rates (see, e.g. Kolsrud et al. 2018; Landais et al. 2021). Formally, consider the following model:

$$Y = y(b, w_b, u),$$

where Y is the outcome variable of interest (i.e, the job-to-job transition probability), w_b is base earnings and u is unobserved heterogeneity. I am interested in estimating the marginal effect of benefits on the outcome variable Y, $\alpha_k = \partial Y/\partial b$. The design exploits that benefits b is a continuous function kinked at $w_b = w_k$. Identification relies on two fundamental assumptions. First, the direct marginal effect of the assignment variable (w_b) on the outcome (i.e, job-finding rate) is smooth for an interval around the kink. This smoothness assumption ensures that the change in the outcome variable is not driven by a discontinuous effect of the assignment variable itself. Second, any heterogeneity affecting the outcome variable u should evolve smoothly with the assignment variable at the kink. Under these assumptions, the marginal effect of benefits α_k can be identified as:

$$\alpha_k = \frac{lim_{w_b \to w_k^+} \frac{\partial E(Y|w_b)}{\partial w_b} - lim_{w_b \to w_k^-} \frac{\partial E(Y|w_b)}{\partial w_b}}{lim_{w_b \to w_k^+} \frac{\partial b}{\partial w_b} - lim_{w_b \to w_k^-} \frac{\partial b}{\partial w_b}} \equiv \frac{\gamma_k}{v_k}$$

I apply a sharp RK-design and estimate α_k as $\hat{\alpha}_k = -\hat{\gamma}_k/v_k$. Here, $\hat{\gamma}_k$ is the estimated change in slope of the relationship between Y and w_b at w_k from below the kink to above the kink, and v_k is the deterministic change in slope for the benefit replacement rate around the kink. In the baseline results, I estimate γ_k using a polynomial model of the following form:

$$E(Y|w_b) = \beta_0 + \sum_{\rho=1}^{2} \beta_\rho (w_b - w_k)^\rho + \gamma_\rho (w_b - w_k)^\rho * 1[w_k \geq w_b] \quad (8)$$

Here, γ_1 measures the slope change in the outcome variable around the threshold. The model is estimated for $[w_b - w_k| < h]$ where h is the bandwidth size. In my main results, I report the estimated kink-cofficient $\hat{\gamma}_1$, together with the implied elasticities $\varepsilon_{y_k,b} = -\frac{\gamma_1}{\bar{y_k}}$, which gives the percentage change in the outcome variable for a one-percentage increase in benefits at the margin. [24]

The baseline model includes a quadratic term in order to avoid misspesification due to an underlying non-linear relationship between the outcome and the assignment variable around the threshold. For the baseline results, I choose a bandwith of one basic amount for all variables, to make the sample used for inference comparable across different outcomes.[25] As a robustness, I also report the main outcomes using

[24] The benefit replacement rate has a slope of zero above the kink and 0.624 below the kink, thus $v_k = -0.624$. This means that the implied semi-elasticity is obtained as $\varepsilon_{y_k,r} = \frac{\gamma_1}{-0.624} \frac{1}{\bar{y_k}}$ where $\bar{y_k}$ is the mean of the outcome variable at the kink. Similarly, the elasticity w.r.t benefits is given by $\varepsilon_{y_k,b} = \frac{\gamma_1}{-0.624} \frac{r_{max}}{\bar{y_k}} = \frac{\gamma_1}{-0.624} \frac{0.624}{\bar{y_k}} = \frac{-\gamma_1}{\bar{y_k}}$. To see this, note that total benefits at the kink per unit of wages is given by $b_{max} = r$, and the change in benefits at the threshold (from above to below the kink) is given by $\Delta b = 0 - 0.624$. Benefits in Norway are taxed progressively, but at the margin the tax rate remains constant at 0.33. Thus, taxes do not change the estimated elasticity: $\varepsilon_{y_k,b} = \frac{\gamma_1}{-(0.624-\tau)} \frac{0.624-\tau}{\bar{y_k}} = \frac{-\gamma_1}{\bar{y_k}}$.

[25] The optimal mean-squared-error (MSE) bandwith from Calonico et al. (2014) for the probability of a job-to-job transition is

the mean-squared-error (MSE) optimal bandwidth from Calonico et al. (2014). To ensure that my effects are not biased by choosing a too large bandwidth, I use Calonico et al. (2014)'s bias correction method which corrects for assymptotic bias by using higher-order local polynomials to estimate the derivatives in the bias term. I implement this method by estimating a local linear estimator using a quadratic approximation to adjust for assymptotic bias.

4.2 Validity

Manipulation and Smoothness of Observables

A key threat to the validity of my design is that workers adjust their pre-earnings based on the kink in the UI schedule. This would lead to non-random sorting of workers across the threshold and bias my results. I start by testing for manipulation of pre-earnings around the maximum benefit threshold. Manipulation could arise either through wage-setting based on the different UI replacement rates or through the selection of workers into jobs.[26] Figure 3a displays the probability density function of pre-earnings and reports a test for the continuity of the assignment variable following McCrary (2008) for the full estimation sample. Reassuringly, there is no evidence of bunching around the threshold, which rules out any clear manipulation of the assignment variable around the kink in benefits. This is true both for the full sample and for the sample of workers in firms in the upper part of the risk distribution. Appendix Figure A.3 displays the probability density function of pre-earnings for workers in firms inside the upper predicted risk quartile.

Consistent with the tests for manipulation, the observable characteristics of workers in my sample appear to evolve smoothly across the threshold. Figure 3b displays a binned scatter plot of a composite index of worker characteristics, including age, education, gender, and whether a worker is foreign-born. To compute the composite index, I use each characteristic to jointly predict the probability of a job-to-job transition in a fully flexible regression. The index evolves nonlinearly with the assignment variable, but there is no significant kink in the relationship. Appendix Figure A.4 displays a binned scatter plot of workers' age, the proportion of females, the proportion of foreign-born workers, and the proportion of workers with a college degree as a function of their pre-earnings. For one of the individual variables, the probability of having a college degree, there is visual sign of a downward kink, about 30 000 NOK above the earnings threshold for UI benefits. To ensure selection effects do not drive my results, I also report my main findings controlling for the set of worker characteristics, firm-fixed effects, and industry-fixed effects. The main results remain near unchanged if I include these controls, which supports the assumption of smoothness of unobservable heterogeneity affecting the outcome variable (see Appendix Table A.6).

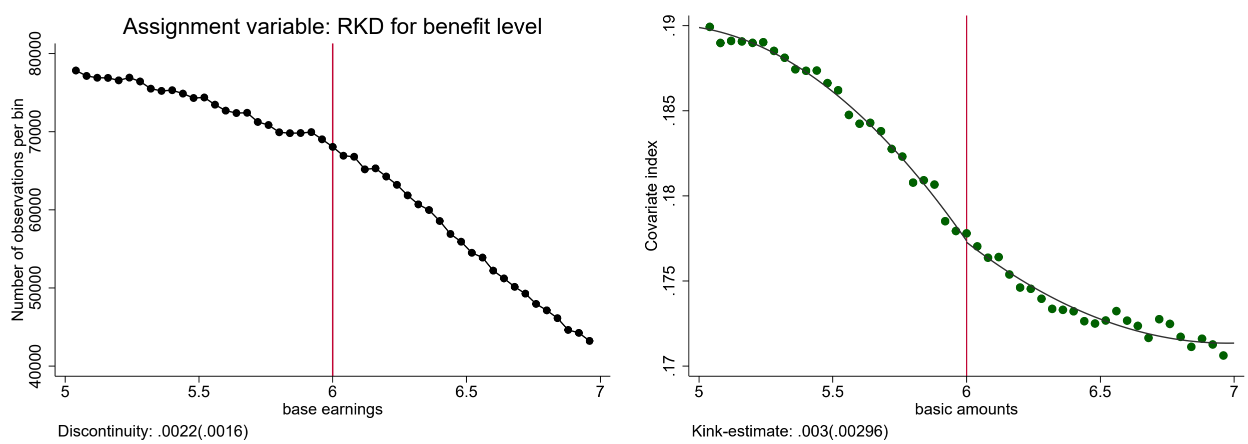
1.08 basic amounts while the optimal bandwith for the probability of an E-U transition is 1.2, both using a second degree polynomial estimation.

[26] Workers with relatively lower UI coverage have incentives to leave risky firms at a higher rate. Over time this process could lead to a non-random selection of worker types across the threshold. If, for instance, only high-mobility workers are able to respond to the UI incentives and leave the firm at a higher rate above the kink, there would be a tendency of bunching of the remaining low-mobility workers above the kink.

Figure 3: **Validity: Test for Manipulation and Smoothness of Observables**

(a) Test for Manipulation: P.D.F of Pre-Earnings

(b) Smoothness of Distribution of Observable Characteristics



Notes: Figure 3a plots the distribution of the assignment variable (pre-earnings) around the earnings threshold to assess the smoothness of the distribution and observable characteristics. The figure also displays a McCrary test of the discontinuity of the probability density function of pre-earnings. I report the difference in density at the threshold together with the standard errors. The test rejects the presence of a discontinuity at the threshold. Figure 3b displays the smoothness of a covariate index to test for kinks in the observable characteristics of workers across the threshold. The index is a linear combination of a vector of worker characteristics that correlate with the outcome. The index is created by regressing the indicator for job-to-job transition on a full set of age dummies, education dummies, gender and whether the worker is foreignborn. The lines displays a quadratic slope around the threshold together with the kink-estimate using the specification in equation 8.

Confounding Policies and Non-linearities

The presence of kinks in DI and sickness benefits at the same earnings threshold as the kink in UI benefits are a cause for concern in my setting (see Section 3.1). The regression kink design alone cannot distinguish the effect of these confounding policies from the effect of UI benefits. To disentangle these effects, I use the population of public sector workers as a placebo group. This group has low unemployment risk but a relatively high probability of receiving DI or Sickness benefits compared to other sectors.[27] If my results are driven by the confounding policies, we should see a clear kink in outcome variables for the placebo group as these workers arguably are exposed to the same incentives to apply for DI and Sickness benefits as for private sector workers. Appendix Figure A.5 displays the how the probability of making a job-to-job transition evolves over the earnings distribution for public sector workers. The change in slope around the earnings threshold for this group is negligable, and I reject the presence of a kink in this sample at any conventional confidence levels. Similarly, for the workers in the lower predicted unemployment risk quintile there are no signs of any kink in the outcome variables (see Panel C in Table 2). These results suggest that the effect of the confounding policies is not driving my main results.

To formalize this intuition, I apply a difference-in-kink design building on the insights from the difference-in-discontinuity designs from the RDD literature (see Grembi et al. (2016) and Spenkuch and Toniatti (2018)). The RK-estimator identifies the causal effect of all benefits at the threshold under the smoothness assumptions in section 4.1. The difference-in-kink design estimates the difference in kink for the treat-

[27]Public sector workers are defined as workers employed at firms with sector code for Public Administration or Health base on NACE classification of industries. The health sector in Norway consist mainly of workers employed at government financed entities.

ment group relative to the placebo group. The design isolates the effect from higher UI benefits as long as the treatment effects of the confounding policies are constant across the two groups and there is no treatment effect of UI benefits on the placebo groups. This difference-in-kink design has been implemented in other papers, see e.g., Landais (2015) and Gamba, Jakobsson and Svensson (2022). My contribution is to formalize the identifying assumptions behind the approach. In the Appendix section C, I provide precise identification assumptions for this approach and provide further supporting evidence of these assumptions. The difference-in-kink estimator can be implemented as:

$$\begin{aligned} E(Y|w_b) &= \beta_0^c + \beta_1^c(w_b - w_k) + \gamma_1^c(w_b - w_k) * 1[w_k \geq w_b] + x'\theta^c \\ &+ T_i[\beta_0^\tau + \beta_1^\tau(w_b - w_k) + \gamma_1^\tau(w_b - w_k) * 1[w_k \geq w_b] + x'\theta^\tau] \end{aligned} \tag{9}$$

where T_i is an indicator for being in the treatment group, w_b is pre-earnings, w_k is where UI benefits are kinked and $x'\theta = \beta_2(w_b - w_k)^2 + \gamma_2(w_b - w_k)^2 * 1[w_k \geq w_b]$ is the vector of polynomial controls. The coefficient γ_1^τ measures the difference in kink between the two groups. In my main results, I report this coefficient together with the estimated kink coefficient from the RK design.

Comparing effects against a placebo group also addresses another common threat to identification in the RK design. Nonlinearities in the relationship between the assignment variable and the outcome variable unrelated to the kink in the UI schedule may falesy be attributed as kinks in the outcome variable (Kolsrud et al. 2018). To address this concern, I estimate the kink in the outcome variables for the public sector workers and the group of workers in the lower quintile of predicted unemployment risk. [28]

5 Main Empirical Findings

5.1 Mobility and Employment Responses

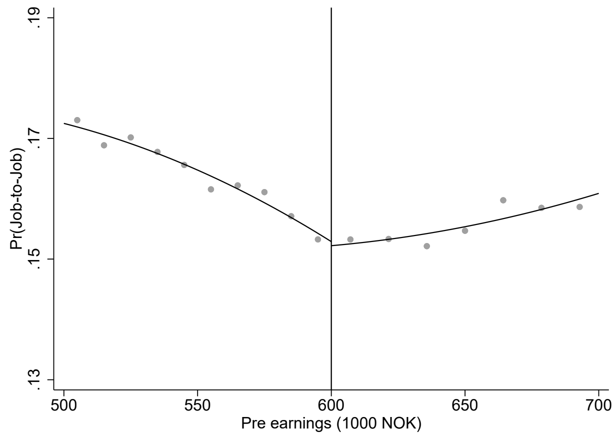
Job Mobility

Figure 4 provide visual evidence of the change in slope for workers' probability of making a job-to-job transition around the kink in the benefit replacement rate. The figure displays a binned scatter plot of the outcome variable as a function of workers' pre-earnings together with the slope from a local polynomial regression below and above the earnings threshold. Figure 4 displays a clear upward kink in the job-to-job probability at the earnings threshold, suggesting that workers with relatively less insurance to a larger extent directly reallocate to new firms. In contrast, there are little signs of any change in slope for the placebo sample of public sector workers displayed in Appendix Figure A.5.

Table 2, Column 1 displays the estimated effect on workers' likelihood of making a job-to-job transition from one year to the next, using the main empirical specification from Equation (8). In line with the visual evidence, there is a significant effect on job-to-job transitions for private sector workers. The implied elasticity of the job-to-job probability is -0.18. This elasticity is large and in the same order of magnitude as

[28] To assess whether public sector workers constitute a valid control group in my setting, I test if the public and private sector workers have different trends in the outcome variable above the earnings-threshold where all benefits are constant. For most variables, there are no significant differences between the trend in the outcome for the two groups. Second, I test whether there are any systematic differences in the uptake of DI and sickness pay between private and public sector workers using the difference-in-kink design. I find no evidence of any differential treatment effects for these two policies. See Appendix Section C.0.2 and C.

Figure 4: **Graphical evidence at threshold: Probability of a Job-to-Job Transition**



Notes: The figure displays the probability of making a job-to-job transition in year t conditional on being employed in period $t-1$, for different bins of workers' UI-eligable pre-earnings measured in basic amounts (1 base amount $\approx 100'$ NOK in 2019). The bin size is selected using an integrated-mean-squared-error optimal polynomial regression selector from Cattaneo et al. 2019**.** The lines displays the slope from a local polynomial regression below and above the kink. The figure is based on a full sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees.

estimates of the elasticity of unemployment duration to benefits ranging between 0.6-0.9 for the US (Card et al. (2015a)) in the post-recession period and 1.5-1.8 in the Swedish context (Kolsrud et al. 2018). As the effect for the placebo-group is close to zero, the estimated difference-in-kink nearly identical to the main effect.

These findings align well with the qualitative predictions from the conceptual framework developed in Section 2. Higher benefits lower the probability that a worker makes a job-to-job transition, and the job-finding probability is kinked upward at the earnings threshold. The estimated kink in the job-finding probability also matches quantitatively well with a calibrated version of the model in Section 2 (see Appendix Section A). The model is calibrated by targeting the level and slope change in the job-finding probability on the left-hand side of the earnings threshold. The job-destruction risk is set to the average layoff rate in the baseline sample, and I use CRRA utility with a coefficient of risk-aversion of 2. The model produces a kink that is very close to what I estimate in the data. The estimated kink from Table 2 (Column 2, Panel A) is 0.032 percentage points, while the model produces an upward kink of 0.016 percentage points.

However, the model cannot account for the upward sloping job-finding probability on the right-hand side of the earnings threshold in Figure 4. This upward slope, together with the upward slope for the public sector workers in Appendix Figure A.5, suggests that there might be important worker heterogeneity in the data that is not accounted for in the model. Workers with higher earnings are likely to be of higher ability and more attractive to new employers. This would create a positive association between wage payments and the job-finding probability. A natural extension of the framework is to allow for a positive association between workers' pre-earnings and the job-finding probability to capture such a mechanism. [29] Importantly though, the visual evidence suggest that this positive association between pre-earnings and the job-finding

[29] An alternative mechanism that could account for this is fixed costs of searching on the job. If search costs are fixed, then the relative potential gain of search will increase when workers' earnings increase.

probability evolves smoothly around the cut-off. As long as worker heterogeneity evolves smoothly, it would not affect the estimated kink in the job-finding probability in the data or in a model.

Table 2: **RK Estimates: Mobility and Employment Responses**

	Pr(J-J)	Pr(Survival)	Pr(E-U)	Pr(E-U$_{t+1}$)	Employment$_{t+1}$
	(1)	(2)	(3)	(4)	(5)
A: *Private sector*					
γ_k	0.032	-0.029	-0.003	-0.007	0.016
	(0.0069)	(0.0143)	(0.0027)	(0.004)	(0.0044)
Elasticity ($\varepsilon_{y_k,b}$)	-0.18	0.04	0.16	0.20	-0.02
	(0.041)	(0.010)	(0.135)	(0.118)	(0.005)
γ_k^τ (Difference vs placebo)	0.039	-0.033	-0.009	-0.011	-0.006
	(0.015)	(0.016)	(0.004)	(0.006)	(0.0088)
Number of observations:	2 431 822	2 431 822	2 431 822	2 056 271	2 056 271
B: *Placebo (Public sector)*					
γ_k	-0.007	0.005	0.003	0.004	0.017
	(0.0137)	(0.0139)	(0.0026)	(0.0040)	(0.0080)
Number of observations:	813 154	813 154	813 154	640 327	640 327
C: *Placebo (Lower risk quintile)*					
γ_k	0.009	-0.001	-0.005	-0.010	0.010
	(0.0120)	0.0128	(0.0033)	(0.0054)	(0.0082)
Number of observations:	655 006	655 006	655 006	521 853	521 853

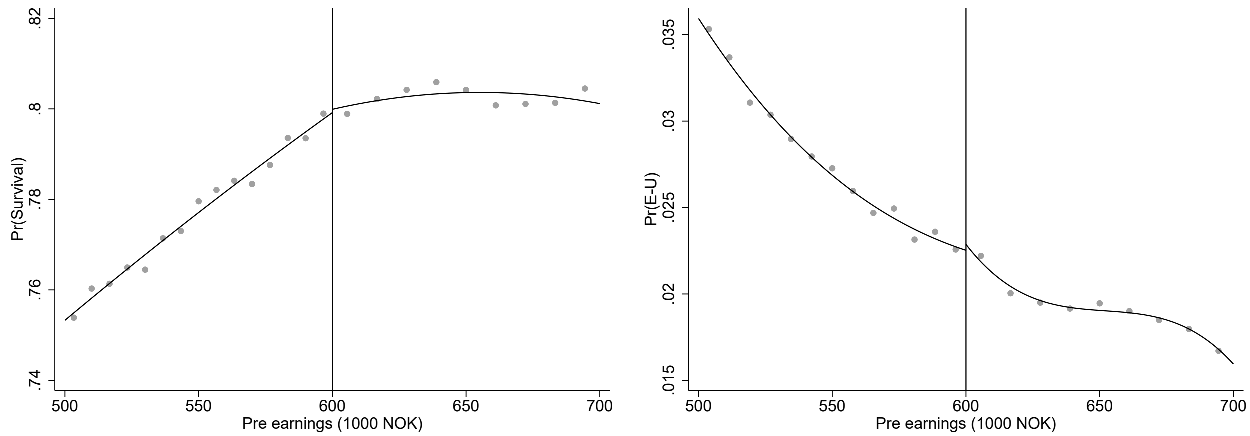
Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the estimated slope change γ_1 from Equation (8) and γ_1^τ from Equation (9) at the treshold in the benefit replacement rate for the the annual probability of a job-to-job transition in Column 1, the probability of survival in Column 2, and the probability of an employment-to-unemployment transition in Column 3. Column 4 reports the effect for the probability of a E-U$_{t+1}$ where workers employed at year $t-1$ transitions to unemployment in year $t+1$. Column 5 report the effect on the probability of remaining employed at year $t+1$ conditional on being employed at year $t-1$. Employment is measured as having wage earnings above the SGA-threshold ($\approx$ 1 basic amount). Workers pre-earnings are measured in year $t-1$. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees. Panel A reports the estimates for the sample of private sector workers employed at year $t-1$. Panel B reports the estimates for public sector workers. Panel C reports the estimates for workers in the lowest quintile of unemployment risk (see Section 3 for predictive model). The implied elasiticity $\varepsilon_{y_k,b} = -\frac{\gamma_1}{\bar{y}_k}$ gives the percentage change in the outcome variable for a one percent change in benefits..

The results in Table 2 are robust to using optimal bandwidths, including a full set of non-parametrical worker and industry controls and to using a linear estimator with the bias-correction methods of Calonico et al. (2014), see Table A.5 and Table A.6. The results change very little by including worker and industry controls, which indicates that worker heterogeneity that affect the outcome variables evolves smoothly around the kink.

Figure 5: **Graphical evidence at threshold: Survival Probability and E-U Transitions**

(a) Probability of Remaining in the Firm one additional year (b) Probability of an Employment-to-Unemployment Transition



Notes: Subfigure 5 displays the probability of remaining in the firm in year t conditional on being in the firm in period $t-1$, for different bins of workers' UI-eligable pre-earnings measured in basic amounts (1 base amount $\approx 100'$ NOK in 2019). The lines displays the slope from a local polynomial regression below and above the kink. Subfigure 5 displays the probability of making a E-U transition for workers employed in a firm in year $t-1$, for different bins of workers' UI-eligable pre-earnings measured in basic amounts (1 base amount $\approx 100'$ NOK in 2019). The lines displays the slope from a local polynomial regression below and above the kink. The bin size is selected using an integrated-mean-squared-error optimal polynomial regression selector from Cattaneo et al. 2019. The figures are based on a full sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees.

Survival Probability and Employment-to-Unemployment Transitions

Figure 5 shows signs of a downward change in slope for the survival probability. This suggests that workers with relatively less insurance, to a lesser extent, remain in their existing firm. For the placebo sample of public sector workers displayed in Appendix Figure A.5, there are little signs of any change in slope. Table 2, Column 2, displays the estimated effect on workers' survival probability. There is a significant effect on survival with an implied elasticity of the survival probability with respect to benefits of 0.04.

There is also evidence of a positive effect on the probability that the workers make an employment-to-unemployment (E-U) transition. Figure 5 displays a binned scatter plot of the E-U probability as a function of workers' pre-earnings. There is a visible small downward kink in the relationship. Table 2 displays the estimated effect on the probability of making an E-U transition looking at both a transition to unemployment in year t and a transition in year $t+1$. The estimated elasticity is sizeable, ranging between 0.16 and 0.20 between the two years. However, the standard errors of this effect are quite large, and the effects are not significant. The noise in the estimate is likely affected by the non-linear slope of the variable around the threshold. Using a linear estimator and a smaller (optimally selected) bandwidth, I find larger and more significant effects using the bias-correction and robust standard errors of Calonico et al. (2014), see Table A.6. The estimated elasticity from this specification is around 0.40 and significant (p<0.025). The difference-in-kink estimate is also larger and significant.

Finally, I look at whether higher benefits affect the probability of employment in year $t+1$, where employment is defined more broadly, as having wage earnings above the SGA-threshold. Consistent with the effects on the E-U transitions, there is a small negative effect on employment in year $t+1$. Even though the estimated elasticities are fairly small, they are economically significant. The estimated elasticity of 0.02 corresponds to a reduced form effect of approximately 1.5 percentage points lower probability of employment next period.[30] The estimated effects for the full set of private sector workers likely masks substantial heterogeneity in the effects based on workers' perceived unemployment risk. In the next section, I investigate to what extent the overall effects are driven by workers with high predicted unemployment risk.

5.2 Risk Heterogeneity

Figure 6 plots the estimated elasticity of the job-to-job probability with respect to benefits for five different quintiles of predicted layoff risk. There is no effect for workers in firms with low predicted layoff rates (first two quintiles), but a strong and significant effect for workers at the third and fourth quintiles. Surprisingly, there is no clear effect for workers in the upper risk quintile. In Appendix Figure A.12 and A.11, I divide the sample into workers above median risk and below median risk. The figures display the survival rate and probability of making a job-to-job transition as a function of these workers' pre-earnings near the earnings threshold. Consistent with the estimated elasticities, there is a clear slope change in the survival rate for the high-risk workers but no change for low-risk workers and similar for the slope in job-to-job transitions. Overall, this evidence suggests that higher benefits lower the mobility rates for workers in firms with high layoff rates, consistent with the theory in Section 2.

Next, I investigate to what extent these lower rates of mobility affect the next periods' employment for workers at risk. Figure 7 plots the estimated elasticity of the employment with respect to benefits, for five different quintiles of predicted layoff risk. The estimated effect increases with firm-layoff risk. There is no effect for workers at the lowest risk-quintile but a significant negative effect for workers at the third and fourth quintile. For the upper risk-quintile, there is no clear effect of higher benefits on employment. This mirrors the estimated effect on job-to-job transitions in the upper risk quintile.

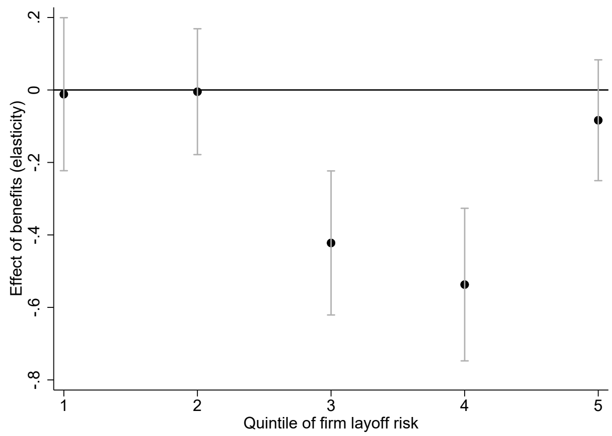
One potential explanation for the lack of response among these workers is that they, to a larger extent, face a sectorial or macro-level risk that they cannot escape by moving to a new firm. Another potential explanation is that the lack of response is driven by sorting of specific type of workers into firms with high layoff risk. To assess whether this sorting affect my results, I construct an alternative measure of predicted layoff risk. I residulize all my my predictors for observable worker characteristics and industry-fixed effects. Appendix Figure A.14 shows that the results remains largely unchanged when accounting these characteristcs. The lack of an effect in the upper risk quintile could still reflect some narrow sectorial or occupational level risk that is not captured by the control.A full investigation of this explanation would, however, require a risk measure that isolated the idiosyncratic firm-level risk and is beyond the scope of this paper. [31]

[30] There is also a significant estimated effect for employment using the placebo sample of public sector workers. Thus, I cannot rule out that the estimated effects for employment are not driven by other benefits.

[31] In Appendix Figure A.15 and A.16, I investigate how responses vary with individual characteristics. I find that older, higher educated, and female workers respond the most. Workers with high predicted unemployment risk based on their individual characteristics respond slightly more. Interestingly workers with higher levels of liquid assets, measured by their bank deposits, respond less. This suggest that precautionary job mobility is a substitute to savings in buffering income risk.

Figure 6: **Estimated Mobility Response to Higher Benefits by Quintiles of Predicted Unemployment Risk**

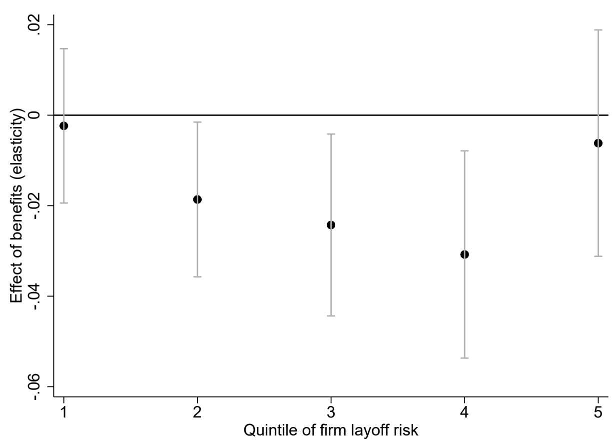
Probability of job-to-job transition



Notes: This figure displays the estimated elasiticity of job-to-job transitions with respect to benefits ($\varepsilon_{y_k,b} = -\frac{\gamma_1}{\bar{y_k}}$ where, γ_1 is defined in Equation (8)) for different quintiles of predicted unemployment risk. The outcome variable is the probability of making a job-to-job transition in year t conditional on being employed in period $t-1$. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees. The spikes represent 95 percent confidence intervals.

Figure 7: **Estimated Employment Response to Higher Benefits by Quintiles of of Predicted Unemployment Risk**

Employment$_{t+1}$



Notes: This figure displays the estimated elasiticity of employment$_{t+1}$ with respect to benefits ($\varepsilon_{y_k,b} = -\frac{\gamma_1}{\bar{y_k}}$ where, γ_1 is defined in Equation (8)) for different quintiles of predicted unemployment risk. The outcome variable is probability of remaining employed (5) at year $t+1$ conditional on being employed at year $t-1$. Employment is measured as having wage earnings above the SGA-threshold ($\approx$ 1 basic amount).The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees. The spikes represent 95 percent confidence intervals.

5.3 Effects on Wage Earnings and Measures of Average Job Quality

As outlined in Section 2.3 there are two opposing forces affecting the net effect on wage earnings and other measures of job-quality. On the one hand, higher benefits leads to lower mobility and a higher likelihood of future unemployment. On the other hand, higher benefits might induce workers to become more selective when searching for a new position. In that case, workers who do find a new job would tend to find a better job. This latter effect could potentially compensate compensate for the negative employment effect documented in the previous section.

Unconditional Effects

To see how higher UI benefits affects the overall quality of worker reallocation, I estimate the effect of benefits on different measures of job quality. I set all measure of job quality to zero if the worker is not registered as employed, where employment is defined as not being registered with wage earnings above the threshold for substantial gainfull activity. Thus, the estimation identifies the unconditional effects on job quality taking the negative employment effects into account.

I begin by looking at the overall effect on workers' wage earnings, measured as the level of earnings one year ahead. Column 1 in Table 3 displays the estimated effect on workers' total wage earnings in year $t+1$ as reported in the tax-registry data. There is a small, but significant, negative effect on workers wage earnings for private sector workers. However, the effects are close to zero using the difference-in-kink estimator, suggesting that other confounding policies could drive the effect.

Clearly, the quality of a job is not fully captured by the wages it pays. To investigate the effects of higher benefits on a broader measure of job quality, I use a poach-rank index for firms developed by Sorkin (2018). This measure ranks firms based on the relative net inflow of workers. The key idea behind this approach is that firms that workers value highly would tend to poach workers from other firms. Top-ranked firms would poach workers from other high-ranked firms, whereas low-ranked firms would poach few workers from other firms.[32] Column 2 displays the estimated effect on rank of the firm the worker is employed at, allowing the rank to be zero if the workers is not employed. In contrast to wage earnings, I find no signs of an effect on average firm ranking. The estimated effect is very close to zero with fairly low standard errors.

One key aspect of job quality is layoff risk. Column 3 displays the estimated effect on firm level layoff risk measured as the share of workers within a firm that makes an E-U transition. Interestingly, there are no significant effects on this measure of layoff risk. This suggests that workers to do not systematically target higher risk firms on average wjhen benefits increase. This could reflect that worker do not have sufficient information about employee risk to target this aspect of job-quality. Alternatively, it might be that there is little variation in job-loss risk among hiring firms.

Finally, I look at whether higher benefits incetivizes workers to move to more productive firms with a

[32] I obtain a ranking of firms through a fixed-point iteration. In the first iteration, each firm is given a rank based on the net inflow of workers over the sample period. In the second iteration, I weight the inflow of workers by the rank of the "sending" firms. I continue this procedure until a fixed point is reached where the distribution of ranks remains unchanged. Note that this procedure will only give a consistent ranking for firms in a strongly connected set, meaning that each firm needs to at least receive and send a worker to another firm in the set. As my sample draws on workers in firms with at least 50 employees, there is less of a concern that this ranking is inconsistent due to few firm linkages.

higher wage premium. Column 4 reports the estimates for value-added per worker in the firms in which the worker is employed and Column 5 reports the firm wage premium obtained by an AKM regression. I allow these measures to be zero for workers who are not employed. For both these measures there are signs of a small negative effect.

In total, higher benefits do not seem to improve the average job quality for the workers in my sample. This is not surprising given that higher benefits seem to increase the inflow of workers into unemployment and nonemployment as documented in Section 5.1 The unconditional effects of benefits on job quality are the combination of these negative transition effects and any potential offsetting positive selectivity effect. In the next section, I investigate whether the observed worker movements across firms are consistent with workers becoming more selective when benefits increase.

Table 3: **RK Estimates: Wage earnings, layoff risk and firm "quality"**

	Wage earnings$_{t+1}$ (1000 NOK)	Firm rank (Sorkin 2018)	Firm layoff risk	VA per worker (1000 NOK)	Firm wage premium (AKM)
	(1)	(2)	(3)	(4)	(5)
A: *Private sector*					
γ_k	14.26	-0.0017	-0.014	62.00	0.223
	(3.035)	(0.0083)	(0.0117)	(64.642)	(0.0578)
Elasticity ($\varepsilon_{y_k,b}$)	-0.05	0.01	0.02	-0.09	-0.03
	(0.010)	(0.027)	(0.029)	(0.090)	(0.007)
γ_k^τ (Difference vs placebo)	4.89	-0.013	-0.001	163.72	0.012
	(5.988)	(0.0163)	(0.003)	(114.617)	(0.118)
Number of observations:	2 094 356	2 094 356	2 094 356	2 094 356	2 094 356

Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the estimated slope change, γ_1, from Equation (8) and γ_1^τ from Equation (9) at the treshold in the benefit replacement rate for workers wage earnings$_{t+1}$ in Column 1, firm layoff risk$_{t+1}$ in Column 2 and firm rank$_{t+1}$ measured using the poach rank developed by Sorkin 2018 in Column 3, value added per worker in Column 4 and firm-fixed wage effects from an AKM decomposition in Column 5. All, outcomes have the entry zero if the worker is without employment the given year. Workers' pre-earnings are measured in year $t-1$. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees. The implied elasiticity $\varepsilon_{y_k,b} = -\frac{\gamma_1}{\bar{y}_k}$ gives the percentage change in the outcome variable for a one percent change in benefits. The firm wage premium is obtained by running the following regression on workers' log wages, controlling for age, education and gender: $w_{i,t} = \alpha_i + \psi_{J(i,t)} + \varepsilon_{i,t}$, where $\psi_{J(i,t)}$ is the measure of firm wage premium.

Movement to Higher Quality Jobs?

As documented in Section 5.1, higher benefits lower the probability that a worker moves directly to a new firm. I now investigate to what extent the reduction in mobility reflects that workers become more reluctant to move to lower-quality firms. This would be consistent with workers becoming more selective when benefits increase.[33] I investigate this by decomposing the moving response using job-destination characteristics for workers.

Let $Q_{i,t}$ denote a continuous-valued measure of job quality for worker i in period t. An upward job-move

[33] If, on the other hand, the reduction in mobility is mainly driven by a change in search effort, higher benefits should have little effect on the direction of worker movement.

is a move to a higher Q and a downward move is a move to a lower Q. The probability of making a job-to-job transition can be decomposed as follows:

$$\underset{\{\text{Tot. probability of J-J}\}}{\mathbb{P}(\lambda_{i,t}=1)} = \underset{\{\text{Prob. moving upwards}\}}{\mathbb{P}(\lambda_{i,t}=1 \quad \cap \quad Q_{i,t} \geq Q_{i,t-1})} + \underset{\{\text{Prob. moving downwards}\}}{\mathbb{P}(\lambda_{i,t}=1 \quad \cap \quad Q_{i,t} < Q_{i,t-1})} \tag{10}$$

I consider three main measures of job quality. Individual wages from the matched employer-employee dataset, the firm rank measured by the poach-rank index, and the firm's layoff risk, measured by the share of workers within a firm that makes an E-U transition. For each of these measures, I separately estimate the effect of benefits on each of the components in Equation (10) using the regression kink design introduced in Section 4.1.

Panel A in Table 4 displays the decomposition using workers' annualized wages as a measure of job quality. Nearly 70 percent of the reduction in worker mobility (Column 1) can be attributed to a reduction in moves to jobs that pay lower wages. A reduction in upward moves explains only 30 percent. This asymmetry is also true for firm layoff risk. More than 60 percent of the reduction in mobility is explained by a reduction in moves to firms with higher layoff risk (Panel B). Looking at the firm rank, measured using the poach rank developed by Sorkin (2018), there is little difference between upward and downward moves.

Table 4: **Decomposition of Job Mobility Response by Job-destination Characteristics**

	Total probability of J-J $\mathbb{P}(\lambda_{i,t}=1)$ (1)	Prob. moving upwards $\mathbb{P}(\lambda_{i,t}=1 \cap Q_{i,t} \geq Q_{i,t-1})$ (2)	Prob. moving downwards $\mathbb{P}(\lambda_{i,t}=1 \cap Q_{i,t} < Q_{i,t-1})$ (3)
A. Wages (annualized)=Q			
$\varepsilon_{y_k,b}$	-0.16	-0.05	-0.11
	(0.043)	(0.026)	(0.034)
Percent of total effect	100 %	31 %	69 %
B. Firm layoff risk=Q	-0.16	-0.10	-0.06
	(0.043)	(0.031)	(0.029)
	100 %	63 %	37 %
C. Firm rank (Sorkin 2018)=Q	-0.16	-0.07	-0.09
	(0.043)	(0.027)	(0.032)
	100 %	44 %	56 %
Number of observations:	2 094 356	2 094 356	2 094 356

Standard errors (in parentheses) are clustered at the individual level.

Note: Column 1 reports the elasiticity $\varepsilon_{y_k,b} = \frac{\gamma_1}{\bar{y_k}}$ where γ_1 is the estimate from Equation (8) at the treshold in the benefit replacement rate for the probability that a worker makes a job-to-job transition from year $t-1$ to year t. I decompose this effect into a reduction in the probability of moving to a job with higher quality (Column 2) and a reduction in the probability of moving to a job with lower quality (Column 3). Panel A reports the elasticities using annualized wages as a metric of job quality. Panel B reports the elasticities using firm layoff rates as a metric of job quality. Panel C uses the firm relative rank (Sorkin 2018) as a metric of job quality. The estimation is based on a sample of employed workers of working age (18-62) over the period 2008-2013 in private sector firms with more than 50 employees, employed at year $t-1$.

Overall, the reduction in job mobility caused by higher benefits appears to reflect that workers become more reluctant to move to lower-paying or more insecure firms. These estimates offer strong support for the importance of selectivity effects of higher benefits. If the reduction in job-mobility was driven by a reduction in workers' search effort, one would expect a symmetric response. In Section 6.2, I quantify how important these selectivity effects are in counteracting the negative transition effects documented above.

6 Implications: Fiscal Externalities, Selectivity and Firm's Labor Costs

In this section, I investigate three important implications of my findings. My results suggest that the distortions to search for employed workers at risk can generate additional fiscal costs that are passed on to the taxpayers. In Section 6.1 I estimate the associated fiscal externalities using data on benefits received and taxes paid for workers in my sample. In Section 6.2, I quantify the selectivity effects of higher benefits in a simple decomposition excersise. In Section 6.3, I show how my empirical estimates can be used to quantify how UI affects the labor costs of firms at with high unemployment risk.

6.1 Fiscal externalities

My findings in the previous section suggest that higher benefits may lead to significant negative fiscal externalities due to how they distort workers' search behavior. In this section, I quantify these externalities by looking at how higher benefits affect the total benefit received and taxes paid for my sample of workers. The tax-registry data contain information on the annual amount of UI benefits each worker has received and information on the total annual amount of taxes each worker has paid.[34] Since a worker in Norway can receive benefits for up to two years, I look at the total amount of benefits received over a two-year window and do the same for taxes paid. To ensure that UI benefits drive the effects I find, I report the estimated effect from the difference-in-kink estimator and the implied elasticity.

Column 1 displays the total effect on benefits received over a two-year window. Higher benefits increase the amount paid per worker, with an estimated elasticity of 0.5. Note that this effect only captures the behavioral effect, as the mechanical effect (one dollar of benefits costs one dollar) is differenced out. This behavioral effect partly reflects a higher inflow of workers into unemployment but can also reflect that workers that do become unemployed remain unemployed longer (duration effect). Column 2 displays the estimated effect on the probability that the worker makes an E-U transition by looking at the probability that a worker is registered as unemployed in one of the two subsequent years. The estimated elasticity is close to 0.4, suggesting that the main effect is mostly driven by the transition effect and not through the duration. A few other studies also find similar significant and sizable effects from UI on the inflow of workers to unemployment. Jäger et al. (2019) find that an increase in potential benefits duration in Austria from one to four years increased separations by 10 p.p, and Lalive et al. (2011) argues that this change in policy affected the steady state unemployment rate.

I do not have data on the spell length of unemployment and cannot directly estimate the duration effect. However, in Column 3, I report the implied duration effect.[35] This implied duration effect is small and

[34] The tax information is obtained by taking the difference between a worker's disposable income before and after taxes.

[35] Let the total benefits a worker receives B_i be a function of annual benefits paid b, the probability that a worker becomes

contributes to a lower share of the total effect than the effect on the E-U probability. It is in the lower range of duration effects found elsewhere in the literature. Studies using variation in benefit levels, typically find a duration response ranging from 0.1 to 2, with a median of 0.53 (see Schmieder and Von Wachter, 2016 for a survey). Finally, column 4 displays the total effect on taxes paid over a two-year window. The estimated total effect is small and not significant, which is surprising given the large effect on the E-U rate. Part of the reason why there is no negative effect on tax income can be that unemployed workers pay taxes on their benefits. However, it might also reflect important offsetting selectivity effects which I will investigate in the Section 6.2.

The estimated effect on benefits received and taxes paid suggests a net additional fiscal cost of higher benefits of around 0.5, mostly driven by the effect on the E-U probability. Thus, a one percent increase in benefits requires a 1.5 percent increase in government revenue for the budget to be balanced. To put this in context, we can compare this cost to the estimates of workers' marginal willingness to pay for higher insurance. As a benchmark, consider the estimated values reported in Landais and Spinnewijn 2021. Their estimates are derived using Swedish data from a similar period, and they estimate a willingness to pay in the range of 1.1 to 2.1. Thus, the net fiscal cost I document, lies well within this range of values, suggesting that the willingness to pay for insurance is close to the fiscal cost I estimate.

The estimated fiscal externality is based on benefits received and taxes paid by the workers in my sample but does not account for any potential effect of higher benefits on the profits of firms. In Section 6.3 I show that the estimated effect on workers' survival probability implies that UI lowers the labor costs of firms with high unemployment risk.

Table 5: **Difference-in-Kink Estimates: Fiscal externalities**

	Benefits per worker (1000 NOK)	Pr(E-U)	Unemployment duration (Implied)	Taxes per worker (1000 NOK)
	(1)	(2)	(3)	(4)
γ_1^τ	-2.49	-0.016		-6.35
	(0.938)	(0.006)		(4.323)
$\varepsilon_{y_k,b}$	0.54	0.43	0.11	0.02
	(0.203)	(0.152)		(0.016)
Number of observations:	2 598 902	2 598 902		2 598 902

Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the difference in kink estimator γ_1^τ from Equation (9) at the treshold in the benefit replacement rate. Column 1 shows the estimated effect for total benefits received in year t and $t+1$. Column 2 shows the estimated effect for the probability that the worker transitions to unemployment in year t or year $t+1$ and Column 3 shows the estimated effect for total taxes paid for each worker over the years t and $t+1$.The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees, employed at year $t-1$. The implied elasiticity $\varepsilon_{y_k,b} = \frac{\gamma_1^\tau}{\bar{y}_k}$ gives the percentage change in the outcome variable for a one percent change in benefits.

unemployed $\pi_i(b)$, and the duration the worker is unemployed $D_i(b)$. The total percentage change in benefits paid for a one percent increase in benefits can be written as $\varepsilon_{B_i.b} = \varepsilon_{\pi_i.b} + \varepsilon_{D_i.b} + 1$. The term 1, reflects the mechanical cost which is differenced out with my estimator. The duration effect can then be written as the total behavior effect net of the effect on transitions into unemployment: $\varepsilon_{D_i.b} = \varepsilon_{\hat{B_i}.b} - \varepsilon_{\pi_i.b}$

6.2 Quantifying the Selectivity Effects from Higher Benefits

The theory model in Section 2 predicts that higher benefits improve job quality among the set of workers that do make a job-to-job transition. However, estimating this conditional effect directly from data would most likely give a biased estimate of the effect. There are two main reasons for this. First, workers who make a job-to-job transition are likely to differ systematically from workers who remain. Only looking at the sub-section of workers who do make a transition would not give a representative estimate. Second, the likelihood of making a job-to-job transition is an outcome that depends on the benefits workers receive. If the mechanisms I present in Section 2 are correct, workers who do not increase their target in response to higher benefits are those who are most likely to make a transition. Thus, conditioning on a transition could bias the result.

In order to quantify the selectivity effect, I use the model structure presented in Section 2. I show that the selectivity effects can be identified in my setting under two key assumptions. First, I assume that wages remain constant if the worker remains in the same firm. Second, I assume that the firm-level job-destruction rate is the same for all workers in a firm. The decomposition relies on the discrete-time directed search framework from Section 2. I will use wages as the main metric of job quality in the following decomposition, but I will look at different metrics of job-quality when I quantify the effects. In Appendix section B, I show how the decomposition applies to a random search framework and can be used in the context of unemployed workers job search.

Decomposition

Workers are employed at firms with different job-destruction rates δ_j and earn w_i in ther current job. The probability of transitioning to a new job, $\lambda_i(b)$, depends both on their target wage $\hat{w}_i$, and their type i. The likelihood of transitioning to unemployment is given by $\delta_j(1-\lambda_i)$ and the likelihood of remaining in a firm, $(1-\delta_j)(1-\lambda_i)$. Next period's expected wages for an individual i can then be written as:

$$w^e_{i,t+1}(b) \quad = \quad \underset{\{\text{Unemployment}\}}{\delta_j(1-\lambda_i(b)) * 0} \quad + \quad \underset{\{\text{Remaining}\}}{(1-\delta_j)(1-\lambda_i(b))w_{i,t}} \quad + \quad \underset{\{\text{Reallocating}\}}{\lambda_i(b)\hat{w}_{i,t}(b)}.$$

We can rewrite this equation by separating it into two different terms:

$$w^e_{i,t+1}(b) \quad = \quad \underset{\{\text{Wages without search}\}}{(1-\delta_j)w_{i,t}} \quad + \quad \underset{\{\text{Contribution from search}\}}{\lambda_i(b)[\hat{w}_{i,t}(b) - w_{i,t}(1-\delta_j)]}.$$

The first term reflects the wages the worker would have if the worker did not search on the job. If workers wages remain constant, then the worker would receive $w_{i,t}$ next period if the job is not exogenously destroyed. In expectation, the worker would receive $(1-\delta_j)w_{i,t}$ in wage earnings if he remained in his current firm. The second term reflects the contribution of search for next periods expected wages. With probability $\lambda_i(b)$ the worker can transition to a new firm and obtain wages $\hat{w}_{i,t}(b)$ which represent a gain relative to the wages the worker would earn without on-the-job search. Moving the first term to the left-hand side of the equation, we have the following identity:

$$
\begin{array}{ccccc}
w^e_{i,t+1}(b) & - & (1-\delta_j)w_{i,t} & = & \lambda_i(b)[\hat{w}_{i,t}(b) - w_{i,t}(1-\delta_j)] \\
 & & & & \{\text{Contribution from search}\}
\end{array}
$$

The left-hand side measures a worker's next periods expected wages relative to the counterfactual expected wage, measured as the workers' current wage discounted by the job-destruction risk. By rewriting this identity in logs and taking the derivative with respect to benefits and summing over all workers, the total effect can be decomposed into two terms:

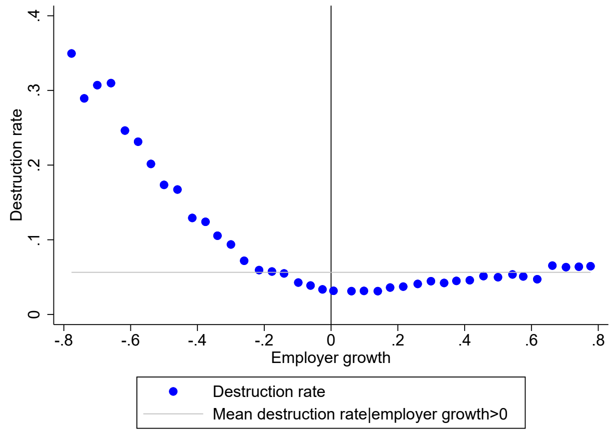
$$
\begin{array}{ccccc}
E(\varepsilon_{\Delta w^e_{i,t+1}}) & = & E(\varepsilon_{\lambda_i(b)}) & + & E(\varepsilon_{\Delta \hat{w}_{i,t}}) \\
\{\text{Total effect (scaled)}\} & & \{\text{Transition}\} & & \{\text{Selectivity}\}
\end{array}
$$

The left-hand side measures the percentage change in the expected wage growth relative to the counterfactual, where a worker's current wage is discounted by the probability that the job is destroyed. This effect can be identified in data with a proxy for the exogenous job-destruction rate. The first term on the right-hand side is the elasticity of the job-to-job transition with respect to benefits that I identified in Section 5.1. The last term is the elasticity of workers' target wages with respect to benefits. This can be identified as a residual from the identity above. If workers respond to higher benefits by increasing their selectivity, this residual will be positive. If workers mobility responses only are driven by search effort, there should be no residual effect.

Implementation

The job-to-job transition $\lambda_i(b)$ rate, and workers' current and next period wages ($w_{i,t}$ and $w_{i,t+1}$) are directly observable in the data. However, the job-destruction rate is not directly observable. As a proxy for this destruction rate, I use that the probability of unemployment (u) is the product of the exogenous job-destruction rate (δ) and the probability of not receiving a job-offer $(1-\lambda)$, such that $\delta = u/(1-\lambda)$. As long as workers within a firm face the same exogenous job-destruction risk, I can compute this measure as the share of workers in a firm who transitions to unemployment over the share of workers in that firm who does not make a job-to-job transition. Figure 8 plots my proxy of job-destruction risk as a binned scatter plot of firms' net employment growth over the sample period. The proxied destruction rate is low and constant for firms with positive employment growth but high for firms with a significant net employment decline.

Figure 8: **Proxy for Destruction Rate and Firm Employment Growth**



Notes: The figure displays the estimated firm-level proxy for job-destruction rate masures as $u_j/(1-\lambda_j)$, where u_j is the average share of workers in a firm j that transitions to unemployment and λ_j is the average share of workers in a firm j who makes a job-to-job transition within a year. Employer growth measures the net growth in the number of workers in a firm from one year to the next. The bins displays the average destruction rates for different bins of employer gorwth and the line displays the mean destruction rate.

Table 6 displays the estimated elasticities together with the implied selectivity residual. For each outcome variable, the value is set to zero if the worker is not registered with any employment in the next year. Panel A displays the effect on workers' discounted wage earnings growth. There is a positive total effect on wage earnings growth with an estimated elasticity of 0.37. Without any selectivity effect, the total effect would have been equal to the negative transition effect, which is the elasticity of the job-finding probability with respect to benefits equal to -0.18. Thus, these estimates imply a positive selectivity that more than compensates for this negative transition effect. Panel B shows the decomposition using the poach rank index as a measure of job quality. The estimated total effect is close to zero, again indicating an important compensating selectivity effect. Panel D and C show the decomposition using value added per worker and the firm wage premium as outcome variables. The total effects on these variables are slightly negative indicating that higher benefits lower productivity on average. However, these effects would have been more adverse if there was no compensating effect. Overall, this evidence does not suggest that the mobility responses I document in Section 5 are driven by workers reducing search effort alone. On the contrary, the decomposition suggests that increased selectivity is an important mechanism that attenuates the negative transition effects I document.

Table 6: **Decomposition of Quality Effects**

	Total effect $E(\varepsilon_{\Delta w^e_{i,t+1},b})$	Transition effect $E(\varepsilon_{\lambda_i,b})$	Selectivity "residual" $E(\varepsilon_{\Delta\hat{w}_{i,t},b})$
A: Wage earnings	0.37	-0.18	0.54
	(0.14)	(0.044)	
B: Firm rank (Sorkin 2018)	0.08	-0.18	0.26
	(0.051)	(0.044)	
C: VA per worker	-0.15	-0.18	0.02
	(0.314)	(0.044)	
D: Firm wage premium	-0.08	-0.18	0.10
	(0.03)	(0.044)	
Number of observations	2 015 465	2 015 465	2 015 465

Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the the implied elasiticity $\varepsilon_{y_k,b} = \frac{\gamma_1^\tau}{\bar{y}_k}$ using the difference in kink estimator γ_1^τ from Equation (9) at the treshold in the benefit replacement rate. The total effect correspond to the effect on $y^e_{i,t+1}(b) - (1-\delta_j)y_{i,t}$, where y is some metric of job quality. The transition effect corresponds to the elasticity of the probability that a worker makes a job-to-job transition and the selectivity residual is the total effect net of the transition effect. Wage earnings are measured directly from the tax-registry data. Firm rank is measured using the poach rank developed by Sorkin 2018. Value added per worker is measured as sales minus intermediates. The wage premium is measured as firm-fixed wage effects from an AKM decomposition. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees, employed in year $t-1$.

6.3 Unemployment Risk and Firms' Costs of Retaining a Worker

The estimated effect of benefits on workers' survival probability suggests that higher UI benefits lower the labor cost of firms with high unemployment risk. In this section I show how these effects can be translated into a measure of the wage compensation a firm must pay in order to retain a larger share of its workforce.

Consider a one-period change in a worker's current wages, Δw, and a one-dollar reduction in the next period's potential benefits, Δb, that leaves the worker's job-value unchanged. Intuitively, the marginal utility of higher wages when employed must be equal to the discounted marginal utility loss of a one-unit reduction in benefits for the worker to have the same job value. Using the value function of an employed worker at risk Equation (1) from Section 2, the necessary offsetting wage change is given by:

$$\Delta w = \frac{\pi\beta u'(c_u)}{u'(c_e)}\Delta b. \tag{11}$$

Here β denotes the discount factor, π denotes the unemployment risk and ${}^{\beta u'(c_u)}/_{u'(c_e)}$ is the marginal rate of substitution across states. Using this equation, we can express the change in benefits in terms of current wage compensation, $db = dw/\pi MRS$, where $MRS = \beta u'(c_u)/u'(c_e)$. With this identity, we can translate the estimated elasticity of the survival probability with respect to benefits into a measure of the wage compensation a firm must pay in order to increase the survival rate in the firm by one percent:

$$\frac{dw}{ds}\frac{s}{w} = \frac{r\pi MRS}{\varepsilon_{s,b}} \tag{12}$$

Here, I have used the relationship between a change in benefits and wages, $db = dw/\pi MRS$, and that benefits, $b = rw$, where r is the benefit replacement rate. The elasticity of the survival probability with

Table 7: **Implied Wage Compensation across Quintiles of Risk**

	Risk Quintile				
	(1)	(2)	(3)	(4)	(5)
A. Elasticity of survial w.r.t benefits	-0.013	-0.016	0.075	0.093	0.033
	(0.017)	(0.018)	(0.018)	(0.022)	(0.031)
B. Predicted unemployment risk	0.04	0.06	0.07	0.08	0.12
C. Wage compensation to offset benefit change (MRS=1.5)	0.06	0.09	0.10	0.11	0.17
D. Wage compensation to offset benefit change (MRS=2.1)	0.08	0.12	0.14	0.16	0.24
E. Wage compensation (percent) to increase the survival probability by one percent (MRS=1.5)	.	.	0.87	0.81	3.4
Number of observations:	512 935	587 901	544 284	456 899	405 813

Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the elaisticity $\varepsilon_{y_k,b} = \frac{\gamma_1}{\bar{y}_k}$ where γ_1 is the estimate from Equation (8) at the threshold in the benefit replacement rate for the probability that a worker survives one additional year in the firm. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees, employed at year $t-1$. The predicted unemployment risk is based on the predictive model of unemployment risk from Section 3 for the sample of workers of one basic amount on either side of the threshold. The wage compensation needed to offset a percentage change in benefits is given by: $dw = db\pi MRS$, where $MRS = \beta u'(c_u)/u'(c_e)$. Panel C reports this wage compensation for a marginal rate of substitution across states of 1.5, and Panel D reports this wage compensation for a marginal rate of substitution of 2.5. These values are taken from Landais and Spinnewijn 2021. Panel E reports the necessary percentage change in wages to increase the probability that a worker remains in a firm for one additional year by one percent. This change is obtained by using Equation (12) with two estimates of the marginal rate of substitution from the literature.

respect to benefits is denoted by $\varepsilon_{s,b}$. The left-hand side of the above equation expresses the percentage wage increase needed to increase the annual survival rate of the workers in the firm by one percent.

Panel A Table 7 displays the estimated elasticity of survival with respect to benefits for five different quintiles of predicted firm layoff risk, and Panel B displays the average predicted layoff risk for each quintile based on the predictive model in Section 3. I calculate the wage compensation needed to offset a marginal benefit change using the predicted risk and a marginal rate of substitution across states of 1.5 and 2.1, as reported in Landais and Spinnewijn (2021). The calculations are reported in Panel C and D in Table 7. Naturally, this wage compensation increases with layoff risk, but it also depends on how workers value consumption across states. According to these calculations, firms in the three upper risk quintiles need to increase current wages by between 0.17 and 0.24 dollars to offset a dollar change in benefits. Panel E reports the wage compensation needed to increase the survival rate in the firm by 1 percent based on Equation (12) and an MRS of 1.5. For the firms in the three upper quintiles, wages need to be increased by on average 1.6 percent to increase the annual survival probability by one percent.

Higher UI benefits lower this wage compensation and can allow firms to retain a larger share of its workforce.[36] Moreover, these calculations also highlight that UI is an efficient policy to reduce layoff risk. First, UI benefits is targeted because it is only provided to laid-off workers. Second, the marginal value of

[36] As documented by Baghai et al. 2021, financially distressed firms can experience a large outflow of talented workers, which tends to worsen the situation for the firm. Agrawal and Matsa (2013) find that higher UI benefits increase corporate leverage for labor-intensive and financially constrained firms using changes in state unemployment insurance laws in the US. They argue that this effect is driven by lower demand for wage compensation among workers that are better insured against layoff risk.

consumption when unemployed is typically higher than when employed. Because of this, a dollar received when unemployed is worth more to the worker than a dollar received in wages when employed.

7 Conclusion

Economists and policymakers have long been concerned over the potential negative reallocation effects of UI. However, there is little empirical evidence on UI's overall impact on reallocation in the labor market (Giupponi et al. 2022). While the empirical literature has focused on the behavior of unemployed workers, UI can also affect how employed workers' search for new jobs.

In this paper, I provide novel empirical evidence on the importance of UI benefits for employed workers' job mobility and job outcomes. Using a sharp kink in the Norwegian UI schedule, I find that higher benefits lower workers' mobility substantially. This effect is driven by workers in firms with a high layoff risk and leads to more employment-to-unemployment transitions. I show that my findings are consistent with a model where higher benefits increase workers' selectivity when searching for a new job. In this framework, higher selectivity lower job-finding rates and improves the quality of jobs for workers who find new employment. A calibrated version of this framework can reproduce the qualitative and quantitative effects of higher benefits on job-to-job transitions.

The estimated effect on different measures of job quality and firm productivity also implies that workers do not only change their search effort in response to higher benefits. They also become more selective when searching for a new position. Despite the adverse employment effects I document, there is little sign of any drop in workers' wage earnings or other measures of average job quality. Decomposing the effect on wages and job quality, I find that selectivity attenuates the negative employment effect to a large extent. However, the unconditional effect on wage earnings and firm productivity, which is not significantly different from zero, suggests that the efficiency gains from higher benefits could be limited. The distortions to on-the-job search seem to generate additional fiscal costs. I find that a one percent increase in benefits requires a 1.5 percent increase in government revenue to keep the budget balanced. Most of the behavioral effect is driven by the increased inflow into unemployment, while only a small part can be attributed to longer unemployment durations. These estimates are based on benefits received and taxes paid by the workers in my sample but do not account for how higher benefits affect the profits of firms. However, my estimates suggest that higher UI benefits can lower the labor costs of firms with high unemployment risk by increasing their propensity to retain workers. Overall, the reduced form evidence presented in this paper points to important distortions to reallocation from higher UI benefits affecting both firms and workers. However, a better understanding of how higher benefits affect allocative efficiency requires further research. One promising avenue would be to combine the reduced form evidence in this paper with a structural labor market model that also incorporates firms' hiring decisions to quantify the full effects on reallocation and efficiency.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

Acemoglu, D. and Shimer, R. (1999). Efficient unemployment insurance. *Journal of political Economy*, 107(5):893–928.

Acemoglu, D. and Shimer, R. (2000). Productivity gains from unemployment insurance. *European economic review*, 44(7):1195–1224.

Agrawal, A. K. and Matsa, D. A. (2013). Labor unemployment risk and corporate financing decisions. *Journal of Financial Economics*, 108(2):449–470.

Baghai, R. P., Silva, R. C., Thell, V., and Vig, V. (2021). Talent in distressed firms: Investigating the labor costs of financial distress. *The Journal of Finance*, 76(6):2907–2961.

Baily, M. N. (1978). Some aspects of optimal unemployment insurance. *Journal of Public Economics*, 10(3):379–402.

Britto, D. (2016). Unemployment insurance and the duration of employment: Theory and evidence from a regression kink design. *Available at SSRN 2648166*.

Brown, J. and Matsa, D. A. (2016). Boarding a sinking ship? an investigation of job applications to distressed firms. *The Journal of Finance*, 71(2):507–550.

Burgess, P. L. and Low, S. A. (1992). Preunemployment job search and advance job loss notice. *Journal of Labor Economics*, 10(3):258–287.

Burgess, P. L. and Low, S. A. (1998). How do unemployment insurance and recall expectations affect on-the-job search among workers who receive advance notice of layoff? *ILR Review*, 51(2):241–252.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, 82(6):2295–2326.

Card, D., Chetty, R., and Weber, A. (2007). Cash-on-hand and competing models of intertemporal behavior: New evidence from the labor market. *The Quarterly journal of economics*, 122(4):1511–1560.

Card, D., Johnston, A., Leung, P., Mas, A., and Pei, Z. (2015a). The effect of unemployment benefits on the duration of unemployment insurance receipt: New evidence from a regression kink design in missouri, 2003-2013. *The American Economic Review*, 105(5):126–130.

Card, D., Lee, D. S., Pei, Z., and Weber, A. (2015b). Inference on causal effects in a generalized regression kink design. *Econometrica*, 83(6):2453–2483.

Cederlöf, J., Fredriksson, P., Nekoei, A., and Seim, D. (2021). Mandatory advance notice of layoff: Evidence and efficiency considerations.

Chetty, R. (2006). A general formula for the optimal level of social insurance. *Journal of Public Economics*, 90(10):1879–1901.

Chetty, R. (2009). Sufficient statistics for welfare analysis: A bridge between structural and reduced-form methods. *Annual Review of Economics*, 1:451–487.

Dahl, G. B., Kostøl, A. R., and Mogstad, M. (2014). Family welfare cultures. *The Quarterly Journal of Economics*, 129(4):1711–1752.

Doornik, B. F. N. V., Fazio, D., Schoenherr, D., and Skrastins, J. (2021). Unemployment insurance as a subsidy to risky firms. *Available at SSRN 3466314*.

Giupponi, G., Landais, C., and Lapeyre, A. (2022). Should we insure workers or jobs during recessions? *Journal of Economic Perspectives*, 36(2):29–54.

Grembi, V., Nannicini, T., and Troiano, U. (2016). Do fiscal rules matter? *American Economic Journal: Applied Economics*, pages 1–30.

Gutierrez, I. A. (2016). Job insecurity, unemployment insurance and on-the-job search. evidence from older american workers. *Labour Economics*, 41:228–245.

Hagedorn, M., Karahan, F., Manovskii, I., and Mitman, K. (2018). Unemployment benefits and unemployment in the great recession: the role of macro effects.

Hendren, N. (2017). Knowledge of future job loss and implications for unemployment insurance. *American Economic Review*, 107(7):1778–1823.

Hendren, N., Landais, C., and Spinnewijn, J. (2021). Choice in insurance markets: A pigouvian approach to social insurance design. *Annual Review of Economics*, 13:457–486.

Jäger, S., Schoefer, B., and Zweimüller, J. (2019). Marginal jobs and job surplus: a test of the efficiency of separations. Technical report, National Bureau of Economic Research.

Jarosch, G. (2021). Searching for job security and the consequences of job loss. Technical report, National Bureau of Economic Research.

Kolsrud, J., Landais, C., Nilsson, P., and Spinnewijn, J. (2018). The optimal timing of unemployment benefits: Theory and evidence from sweden. *American Economic Review*, 108(4-5):985–1033.

Lalive, R., van Ours, J. C., and Zweimüller, J. (2011). Equilibrium unemployment and the duration of unemployment benefits. *Journal of Population Economics*, 24(4):1385–1409.

Landais, C., Nekoei, A., Nilsson, P., Seim, D., and Spinnewijn, J. (2021). Risk-based selection in unemployment insurance: Evidence and implications. *American Economic Review*, 111(4):1315–55.

Landais, C. and Spinnewijn, J. (2021). The value of unemployment insurance. *The Review of Economic Studies*, 88(6):3041–3085.

Light, A. and Omori, Y. (2004). Unemployment insurance and job quits. *Journal of Labor Economics*, 22(1):159–188.

Lise, J. (2013). On-the-job search and precautionary savings. *Review of economic studies*, 80(3):1086–1113.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142:698–714.

Moen, E. R. (1997). Competitive search equilibrium. *Journal of political Economy*, 105(2):385–411.

Nekoei, A. and Weber, A. (2017). Does extending unemployment benefits improve job quality? *American Economic Review*, 107(2):527–61.

Schmieder, J. F. and Von Wachter, T. (2016). The effects of unemployment insurance benefits: New evidence and interpretation. *Annual Review of Economics*, 8:547–581.

Schmieder, J. F., von Wachter, T., and Bender, S. (2016). The effect of unemployment benefits and nonemployment durations on wages. *American Economic Review*, 106(3):739–77.

Simmons, M. (2022). Pre-layoff search. *Working paper*.

Sorkin, I. (2018). Ranking firms using revealed preference. *The quarterly journal of economics*, 133(3):1331–1393.

Spenkuch, J. L. and Toniatti, D. (2018). Political advertising and election results. *The Quarterly Journal of Economics*, 133(4):1981–2036.

A Predicted Effect on Mobility from Model Calibration

To evaluate whether the estimated mobility response from the regression kink design aligns with my model framework, I do a simple calibration of the framework presented in section 2. After calibrating the model to my data, I evaluate the predicted kink in the job-finding probability from my model to the estimated kink reported in 2.

Setup

For simplicity, I assume that all workers search with equal intensity and only differ in terms of their initial wages. Time is discrete and runs annually. Workers seek to maximize:

$$V(w,\delta) = \max_{\substack{\hat{V} \\ \lambda=E(\hat{V})}} u(w(1-\tau)) + \beta[\delta(1-\lambda)V_u(c_b) + (1-\delta)(1-\lambda)V(w,\delta) + \lambda\hat{V}] \tag{13}$$

$$V_u(c_b) = \max_{\hat{V}} u(b(1-\tau)) + \beta[\lambda\hat{V} - (1-\lambda)V_u(c_b)] \tag{14}$$

Search costs are normalized to zero for both employed and unemployed workers. Within-period consumption preferences are given by:

$$u(c) = \frac{(c^{1-\gamma}-1)}{1-\gamma}$$

I assume that the annual job-finding probability follows a logistic form:

$$\lambda(\hat{V}) = \frac{1}{(1+e^{\alpha_0+\alpha_1\hat{V}})}$$

Here, α_0, is a constant, and α_1 determines how fast the job-finding probability falls with the target job quality. I separate how efficient employed and unemployed workers are in their job search by scaling the job finding probability for unemployed workers by 0.4. Here, I use the results from Kroft, Lange, and Notowidigdo 2013. They show that the likelihood of receiving a callback for an interview significantly decreases when a worker enters unemployment,

Identification and Calibration

The model can be solved with information on seven different parameters $(b,\tau,\beta,\gamma,\alpha_0,\alpha_1,\delta)$. I set five of these parameters externally and solve for the parameters that govern the job-finding probability through indirect inference.

Externally Calibrated Parameters

Benefits, b and taxes τ are set according to the institutional setup where net benefits are given by $b = max[rw(1-\tau),\bar{b}]$. I set the linear tax rate τ to 0.33 equal to the tax rate at the earnings threshold, and benefits are given by the policy rule where $r = 0.624$. I assume a discount factor $\beta = 0.95$ and fix the coefficient of relative risk aversion $\gamma = 2$. The coefficient of relative risk aversion is the same as used by Lise (2013). Together these two parameters (β, γ) determine the marginal rate of substitution between unemployment and employment (see equation 5). With CRRA-utility and linear taxes, this is given as

$$MRS = \beta \left(\frac{rw(1-\tau)}{w(1-\tau)} \right)^{-\gamma} = \beta (r)^{-\gamma}$$

The implied MRS from these externally set parameters matches well with what is found in the literature. Landais and Spinnewijn (2021) reports an MRS ranging from 1.6-2.1 based on estimates of the marginal propensity to consume across states and Swedish workers' choice of UI coverage. In comparison, my set of parameters gives an MRS of 1.7 when accounting for the estimated savings responses across states in the literature. [37] To get a measure of the job-destruction probability, δ, I use the average firm layoff risk from Table A.4 which gives me an annual job-destruction probability of 0.08.

Internally Calibrated Parameters

The two parameters that govern the job-finding rate are identified by targeting the level of the job-finding probability at 5 basic amounts and the slope of the job-finding probability from 5 basic amounts to 6 basic amounts for private sector workers. This corresponds to the level and slope before the earnings threshold in Figure (4). The change in slope prior to the kink informs how workers in the model change their target $\hat{V}$ as wages and benefits increase, and identifies α_1.The parameter α_0 is identified from the job-finding probability at 5G. Since I only use information about the job-finding probability prior to the earnings threshold, I let the model freely predict the kink in the probability of a job-to-job transition induced by the kink in benefits. I compute α_1 and α_0 by minimizing the squared distance between the target moments and the data moments.

Table A.1: **Calibrated Parameters**

Externally Calibrated Parameters

Parameter	Value	Source
Discount factor β	0.95	
CRRA γ	2	Lise (2013)
Replacement rate r	0.62	Policy Rule
Tax rate τ	0.33	Average tax rate at earnings threshold
Job Destruction δ	0.08	Average layoff rate (Table A.4)

Internally Calibrated Parameters

$\lambda(\hat{V})$: *Indirect Inference*

Parameter	Value	Target	Model	Model
Job finding prob: α_0	-12.03	0.175	0.171	Level Pr(Job-to-Job) 5G
Job finding prob: α_1	0.8	-0.015	-0.025	Slope Pr(Job-to-Job) 5G-6G

Note: Wages are measured in basic amounts where one basic amount ≈ 10,000 USD.

[37] Hendren (2017) reports a consumption drop prior to job loss of 9 percent adjusted for the perceived probability of job loss workers report. Without adjusting for savings, I get an implied MRS of 2.4.

Model vs. Data

The model matches the targeted moments fairly well. The level of the job-finding rate is exactly on target, but the slope prior to the earnings threshold is steeper in the model than in the data. The most likely reason for this is that the model lacks a mechanism that can create a positive association between workers' earnings and their job-finding probability. The job-finding probability over the earnings threshold is upward sloping in the data and upward sloping for the public sector workers that are arguably unaffected by the policy rule (see Figure 4). This upward slope could be driven by worker heterogeneity in data. Workers with higher earnings might be more productive and more likely to find a new job because of their productivity. Alternatively, workers might face fixed search costs independent of their wages. If search costs are fixed, then the gain of search relative to the search cost is higher as you move up on the income distribution and targets better positions. Neither of these mechanisms is captured in my model framework. This explains why the model produces a steeper negative slope between the job-finding probability and workers' earnings in the data. There is no positive compensating effect on the job-finding probability in the model, while this seems to be the case in data.

Figure A.1 compares the kink in the job-finding probability I find in the data with the predicted job-finding probability from my model. The left panel of Figure A.1 displays the binned scatter plot of the job-to-job probability around the earnings threshold also displayed in section 5. The right panel of Figure A.1 displays the predicted job-finding probability for the same window around the earnings threshold. The model prediction reproduces the kink in the job-finding rate well, and the estimated kink is surprisingly similar. While I estimate an upward kink in the job-finding rate in section 5 of 0.032, the estimated kink in the predicted job-finding rate is 0.016. However, as discussed above, the job-finding rate above the kink is weakly decreasing in the model but increasing in data. The slopes from the model prediction are tilted clockwise relative to the slopes in the data. This feature can be captured by adding either a fixed search cost or an additional term to the job-finding rate in the model that captures the potential heterogeneity among workers in the data. However, importantly, this potential sorting would not affect the kink estimates as long as the worker characteristics evolves smoothly with wages over the threshold.

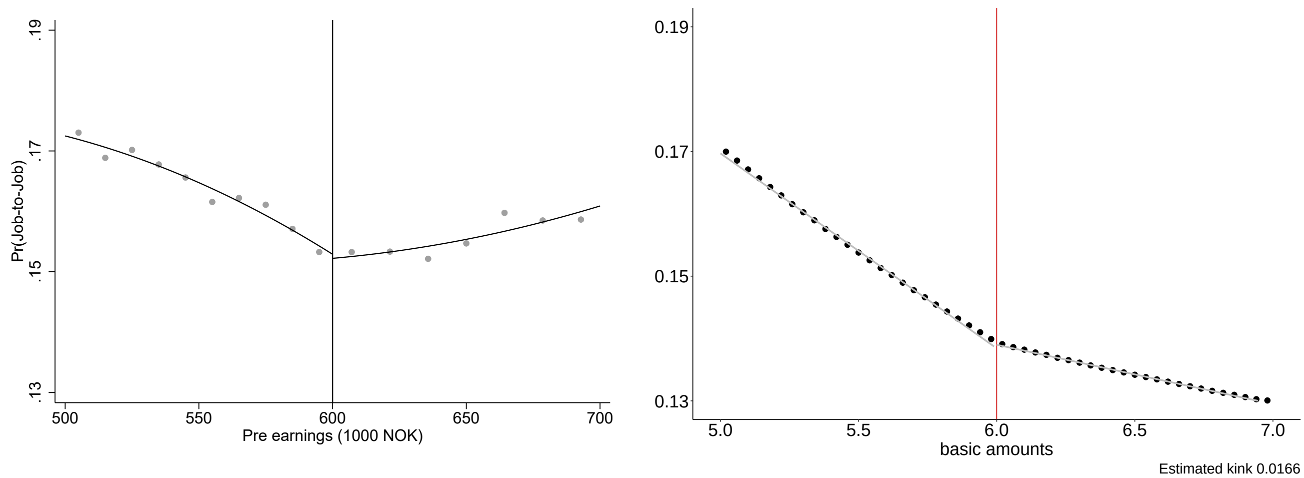
B Identifying Selectivity Effects in a Random Search Framework

In section 6.2, I showed how one could identify selectivity effects of higher benefits. This derivation was based on a directed search framework where workers could target a specific wage. In this section, I show how the decomposition can be applied in a random search framework. I consider two different applications. First, I show how the decomposition from section 6.2 can be written in terms of random search. Second, I show how the decomposition can be used in applications where higher benefits affects unemployed workers' search for new matches in an environment where wage offer depends on the length workers spend unemployed (i.e there is duration dependence).

Consider the setup in section 6.2. Workers are employed at firms with different job-destruction rates δ_j and earn w_i in their current job. In a random search framework, new jobs for individual i offer a wage w_i^* and are drawn from a distribution with a cumulative distribution function $F(w_i^*)$. A worker accepts the

Figure A.1: **Kink in Probability of Job-to-Job transition: Data vs Model**

(a) *Data*: Estimated kink: 0.032 (b) *Model*: Estimated kink: 0.027



Notes: Subfigure A.1 displays the probability of making a job-to-job transition in year t conditional on being employed in period $t-1$, for different bins of workers UI-eligable earnings measured in basic amounts (1 base amount $\approx 100'$ NOK in 2019) The bin size is 0.04 base amounts or ≈ 4000 NOK. The lines displays the slope from a local polynomial regression below and above the kink. Subfigure is based on a full sample of employed workers in working age (18-62) over the period 2008-2014 in private sector firms with more than 50 employees. The kink-estimate is he estimated slope change, γ_1, from equation 8. Subfigure A.1 displays the predicted kink from the calibrated model. The kink-estimate from the model is obtained by taking the slope-change within a bandwith of 0.1 basic amount

job offer if the wage draw w_i^*,exceeds her reservation wage $w_i^r(b)$. Workers' reservation wages depend on benefits as they are the solution to the workers' optimization problem. The probability of transitioning to a new job, $\lambda_{i,t}(b)$ is given by the likelihood of drawing a wage offer higher than the reservation wage: $\lambda_{i,t}(b) \equiv 1-F(w_{i,t}^r)$. Denote the expected wage given an acceptable offer by $\hat{w}_i \equiv \frac{\int_{w_i^r}^{\infty} w_i^* dF(w_i^*)}{1-F(w_i^r)} = E(w_i^*|w_i^* \geq w_i^r)$. By this reformulation, we can perform the exact same decomposition as in section 6.2. The only difference is that the job finding probability, $\lambda_i(b)$, is given by $1-F(w_i^r)$ and that, $\hat{w}_i$, now denotes the expected wage given an acceptable offer, $E(w_i^*|w_i^* \geq w_i^r)$, rather than the target wage.

Now, I illustrate how the decomposition can be used in an application where higher benefits affect unemployed workers' search for new matches. Suppose that wages dependens on unemployment duration, such that workers potential job offers changes over the spell of unemployment. The expected wage for an unemloyed worker i in month t of the unemployment spell is given by:

$$w_{i,t}^e(b) \quad = \quad \underset{\{\text{Unemployment}\}}{F(w_{i,t}^r)*0} \quad + \quad \underset{\{\text{Transitions to new job}\}}{(1-F(w_{i,t}^r))*E(w_{i,t}^*|w_{i,t}^* \geq w_{i,t}^r)}$$

Here, $w_{i,t}^r$, denotes the worker i's reservation wage in month t after unemployment, $F(w_{i,t}^*)$ is the cummulative distribution of wage offers for that individual that month, such that $F(w_{i,t}^r)$ is the probability that a worker draws a wage offer below the reservation wage and do not transition to new employment. Denote $\lambda_{i,t}(b) \equiv 1-F(w_{i,t}^r(b))$ and $\hat{w}_{i,t} \equiv \frac{\int_{w_{i,t}^r(b)}^{\infty} w_{i,t}^* dF(w_{i,t}^*)}{1-F(w_{i,t}^r(b))} = E(w_{i,t}^*|w_{i,t}^* \geq w_{i,t}^r(b))$. Then we have:

$$w_{i,t}^e(b) \quad = \quad \lambda_{i,t}(b)*\hat{w}_{i,t}$$

By taking logs, the derivative w.r.t to benefits and summing over all workers we get:

$$E_t(\ \varepsilon_{w^e_{i,t},b}) \quad = E_t(\varepsilon_{\lambda_{i,t},b}) \quad + E_t(\varepsilon_{\hat{w}_{i,t}})$$

Here, the left-hand side measures the effect of higher benefits on expected wage income for workers in month t. The first term on the right-hand side measures the elasticity of the job-finding probability with respect to benefits, and the last term measures the elasticity of wages given reemployment with respect to benefits. Even if the researcher has identified some exogenous variation in benefits, this latter term is only observable for workers who transition out of unemployment. As these workers might differ systematically from workers who remains unemployed, a direct estimate of this effect would be biased. However, the term can be identified as a residual:

$$E_t(\varepsilon_{\hat{w}_{i,t}}) = E_t(\ \varepsilon_{w^e_{i,t},b}) \quad - \quad E_t(\varepsilon_{\lambda_{i,t},b})$$

For each month t after unemployment, this residual gives an unbiased estimate of the selectivity effects of higher benefits. By tracking this term over the months after the start of the unemployment spell, one can directly infer how workers' selectivity change over the duration of unemployment.

C Difference in Kink Design

C.0.1 Identification in the difference in kink design

The Norwegian institutional setup consists of three different treatments, all kinked at the same benefit threshold at 6 basic amounts. Define $B_i(w_b)$ as the unemployment benefits, where $B_i(w_b)$ is a continuous function kinked at $w_b = w_k$. Similarly, define $O_i(w_b)$ as the other benefits; also, a continuous function kinked at $w_b = w_k$. Both variables consist of a constant replacement rate, denoted by a lower case letter r, up to the maximum benefit threshold. The relationship between these benefits and pre-earnings can be described as follows:

$$b \equiv \frac{\partial B_i}{\partial w_b} = \begin{array}{ll} b_r & \text{if } w_b \leq w_k \\ 0 & \text{otherwise} \end{array}$$

$$o \equiv \frac{\partial O_i}{\partial w_b} = \begin{array}{ll} o_r & \text{if } w_b \leq w_k \\ 0 & \text{otherwise} \end{array}$$

Define $y(b,o) = \frac{\partial Y}{\partial w_b}$ as the potential slope between the outcome variable and pre-earnings, where $b = (b_r, 0)$ and $o = (o_r, 0)$. The observed slope can be written in terms of potential outcomes:

$$y = 1[b=b_r]1[o=o_r]y(b_r,o_r) + 1[b=b_r]1[o=0]y(b_r,0) + 1[b=0]1[o=o_r]y(0,o_r) + 1[b=0]1[o=0]y(0,0)$$

The estimator for the change in slope of the outcome variable, $\hat{\gamma}_k$, would identify the effect of the change in UI-benefits if this was the only policy kinked at this threshold. In my setting, however, this is not true because of the confounding treatment from other benefits. Since both treatments are kinked at the same threshold, we can only estimate the effect of the combined treatment using the RK design:

$$y = [y(b_r, o_r) * 1[w_k \geq w_b] + y(0,0) * 1[w_k < w_b]$$

I borrow notation from Grembi et al. (2016) and define $Z^- = lim_{w_b \to w_k^-} \frac{\partial E(Y|w_b)}{\partial w_b}$ and$Z^+ = lim_{w_b \to w_k^-} \frac{\partial E(Y|w_b)}{\partial w_b}$, where Z^- denotes the slope between the outcome variable and pre-earnings just below the kink and Z^+ denotes the slope change just above the kink. Under the smoothness assumptions in Card et al. (2015b), the regression kink estimator would identify the kink in the outcome$\hat{\gamma}_k = Z^- - Z^+ = y^- - y^+$ driven by the policy changes. First, the direct marginal effect of the assignment variable (w_b) on the outcome (i.e. job-finding rate) is smooth for an interval around the kink. This smoothness assumption ensures that the change in the outcome variable is not driven by a discontinuous effect of the assignment variable itself. Second, any heterogeneity affecting the outcome variable u should evolve smoothly with the assignment variable at the kink. However, even if all unobserved heterogeneity evolves smoothly with the assignment variable at the cut-off, the estimated kink in outcome would not identify the treatment effect of UI benefits:

$$\begin{aligned}
\hat{\gamma}_k \equiv y^- - y^+ &= y(b_r, o_r)^- - y^+(0,0) \\
& \quad [y(b_r, o_r)^- - y(0, o_r)^-] + [y(0, o_r)^- - y^+(0,0)] \\
& \quad \text{Under smoothness assumption:} \\
&= [y(b_r, o_r)^- - y(0, o_r)^-] + [y(0, o_r)^+ - y^+(0,0)] \\
&= E[(y(b_r, o_r) - y(0, o_r)|w_b = w_k] + \\
& \quad E[y(0, o_r) - y(0,0)|w_b = w_k]
\end{aligned}$$

The first term on the right-hand side captures the true causal effects of the change in the replacement rate at the cut off, holding other benefits fixed. The second term captures the bias from the confounding policy. That is, the effect of the change in the replacement rate of other benefits at the cut off, keeping unemployment benefits fixed. I now show how this can be solved by exploiting the difference in kinks between a treatment group and a placebo group. Define treatment T as an indicator taking the value one if an individual is in the treatment group and zero if an individual is in the placebo group and let y_τ be the potential slope between the outcome variable and pre-earnings for the treatment group and y_c be the potential slope for the placebo group. The difference-in-kink estimator can be written as:

$$\hat{\gamma}_{DD} \equiv (y_\tau^- - y_\tau^+) - (y_c^- - y_c^+)$$

Under the following assumptions, the estimator returns the true causal effect of the change in the UI-benefit replacement rate at the cut-off:

Assumption 1: All potential slopes between the outcome variable and the assignment variable $E[y(b_r, o_r, u)|w_b = w_k, T = 1]$ and $E[y(b_r, o_r, u)|w_b = w_k, T = 0]$ are continuous at the threshold ($w_b = w_k$).

Assumption 2: There is no treatment effect from the main policy b_r on the placebo group: $y_c(b_r, o_r) = y_c(0, o_r)$

Assumption 3: The effect of the confounding policy is the constant across the treatment and control group: $[y_c^+(0,0) - y_c(0, o_r)^-] = [y_\tau^+(0,0) - y_\tau(0, o_r)^-]$ Under assumptions 1-3, $\hat{\gamma}_{DD}$ identifies the causal effects on higher benefits on the outcome variable:

$$
\begin{aligned}
\hat{\gamma}_{DD} \equiv (y_\tau^- - y_\tau^+) \quad -(y_c^- - y_c^+) &= [y_\tau(b_r, o_r)^- - y_\tau^+(0,0)] - [y_c(b_r, o_r)^- - y_c^+(0,0)] \\
&\qquad \text{No treatment effect of } b_r \text{on control group:} \\
&= [y_\tau(b_r, o_r)^- - y_\tau^+(0,0)] - [y_c(0, o_r)^- - y_c^+(0,0)] \\
&\qquad \text{Constant effect of confounding policy:} \\
&= [y(b_r, o_r)^- - y^+(0,0)] - [y(0, o_r)^- - y^+(0,0)] \\
&\qquad y(b_r, o_r)^- - y(0, o_r)^+ \\
&\qquad \text{Under smoothness assumption:} \\
&= [y(b_r, o_r) - y(0, o_r)]
\end{aligned}
$$

C.0.2 Tests of underlying assumption

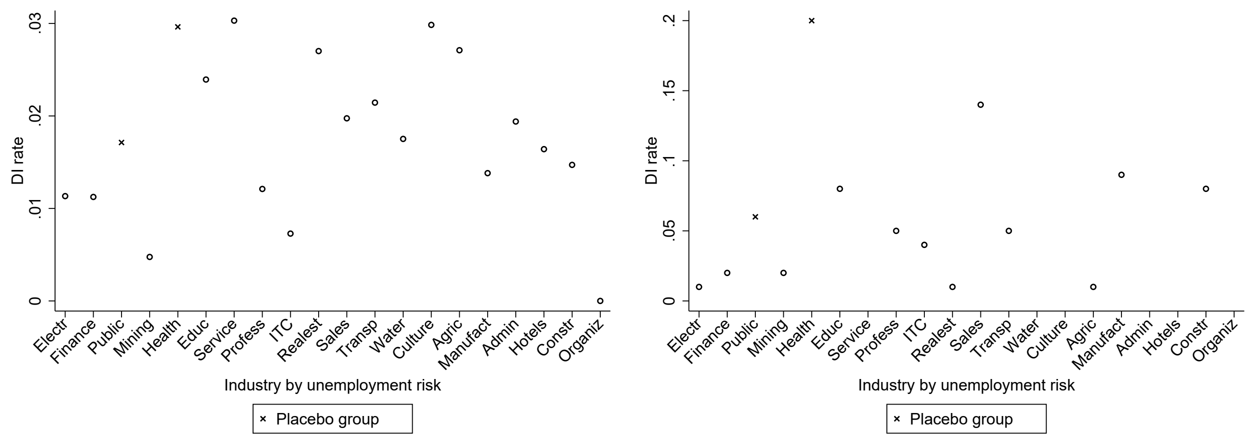
The first assumption would hold under the normal assumption of the regression kink design. I provide evidence in support of this smoothness assumption in section 4.2. Figure 4 (b) and the estimated kink for the placebo group in Table 2 documents that there is no evidence of a treatment effect from the main policy b_r for the placebo group. The third assumption cannot be tested directly as both UI benefits and other benefits are kinked at the same threshold. However, I can test whether, in the absence of treatment, the treatment and control groups are on differential trends. To this end, I estimate the following regression equation for workers with earnings in an interval (one basic amount) above the earnings threshold.

$$
\begin{aligned}
E(Y|w_b) &= \beta_0^c + \beta_1^c w_b + x'\theta^c \\
&+ T_i \times [\beta_0^\tau + \beta_1^\tau w_b + x'\theta^\tau]
\end{aligned}
\tag{15}
$$

Here T_i is an indicator for being in the treatment group, w_b is pre-earnings and $x'\theta = \beta_2(w_b - w_k)^2$ is the polynomial controls. The coefficient β_1^τ measures the difference in slope between the two groups. In Table A.2 , below, I display the estimated difference in slope for the main set of outcome variables. For most variables, there are no significant differences between the trend in the outcome for the two groups. There is a small and significant difference for the probability that a worker makes an employment-to-unemployment transition in year $t+1$, and a significant difference in workers' survival probability but no significant differences for the other variables. Taken together, this provides support for the assumption that the placebo group of workers serves as a good counterfactual in my setting.

Figure A.2: **Uptake of DI and Sickness benefits by Industry**

(a) DI-rate by Industry (b) Sickness benefits by Industry



Notes: Figure A.2 a displays the industry level share of workers on Disability Insurance in 2014 where industries are sorted by the share of workers that transitions to unemployment. Figure A.2 b displays the industry level share of workers on Sickness benefits in 2014 based on data from NAV, sorted by the share of workers that transitions to unemployment. To identify the industry of unemployed workers and workers on DI, I use the industry classification of their last job prior to benefits. The shares are calculated as the total number of DI and UI in an industry over the average number of workers in each industry for the average over the sample period, 2008-2014.

Table A.2: **Difference in Kink: Test of parallel trends in absence of treatment**

	Pr(Survival)	Pr(Job-to-Job)	Pr (E-U)	Pr (E-U$_{t+1}$)	Employment$_{t+1}$
	(1)	(2)	(3)	(4)	(4)
β_1^{τ}	0.031	-0.014	-0.006	-0.0138	-0.0039
	(0.0111)	(0.0103)	(0.0035)	(0.0051)	(0.01053)
Number of observations:	1 398 296	1 398 296	1 398 296	1 398 296	1 398 296

Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the estimated difference in slope ,β_1^{τ}, from equation 15 for workers above the treshold in the benefit replacement rate. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees.

C.0.3 Uptake of DI and Sickness Benefits

Figure A.2 displays the average uptake of DI and sickness benefits in each industry sorted by the industry level unemployment risk. There are no signs of a clear relationship between unemployment risk and the uptake of these benefits. Table A.3 tests whether there are systematic differences in the uptake of other benefits between the public and private sector workers around the threshold. There are no significant differences in the uptake of these benefits between the placebo and treatment groups. This suggests that the difference-in-kink estimator is able to control for the potential confounding treatments of other benefits.

Table A.3: **Difference-in-Kink: DI and Other Benefits**

	Pr(DI)	Pr(Other benefits)
	(1)	(3)
γ_1^τ	0.002	-0.005
	(0.0028)	(0.0078)
$\varepsilon_{y_k,b}$	-0.28	0.07
	(0.411)	(0.116)
Number of observations:	3 244 976	3 244 976

Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the difference in kink estimator γ_1^τ from equation 9at the treshold in the benefit replacement rate for (1) the probability that a worker receives disability benefits, year t and (2) the probability that a worker receives other benefits (excluding UI) in year t. I identify other benefits using total government transfers net of DI and UI. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in private sector firms with more than 50 employees, employed at year $t-1$. The implied elaisticity $\varepsilon_{y_k,b} = \frac{\gamma_1^\tau}{\bar{y_k}}$ gives the percentage change in the outcome variable for a one percent change in benefits.

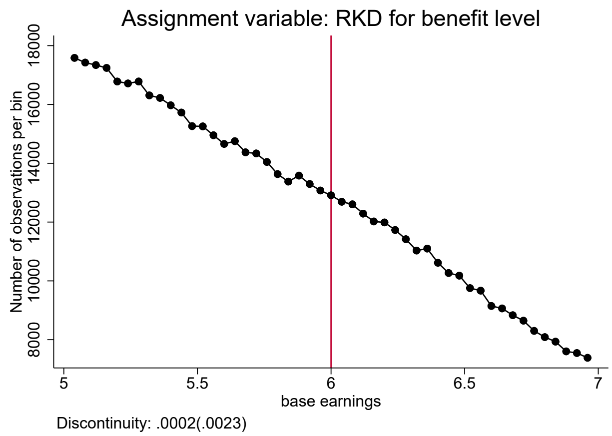
D Validity and Robustness

Table A.4: **Model Fit: Key statistics**

	A. Probability of E-U transition		**B. Predicted Unemployment Risk**	
	Mean	Std. Dev.	Mean	Std. Dev.
Full sample	0.08	0.268	0.07	0.0387
Distribution of risk				
p10	0.04	0.187	0.04	0.0004
p25	0.06	0.232	0.05	0.0002
p50	0.07	0.255	0.07	0.0002
p75	0.09	0.293	0.09	0.0004
p90	0.13	0.331	0.12	0.0013
p95	0.15	0.357	0.15	0.0031
R^2		0.16		
Observations		14,125,891		

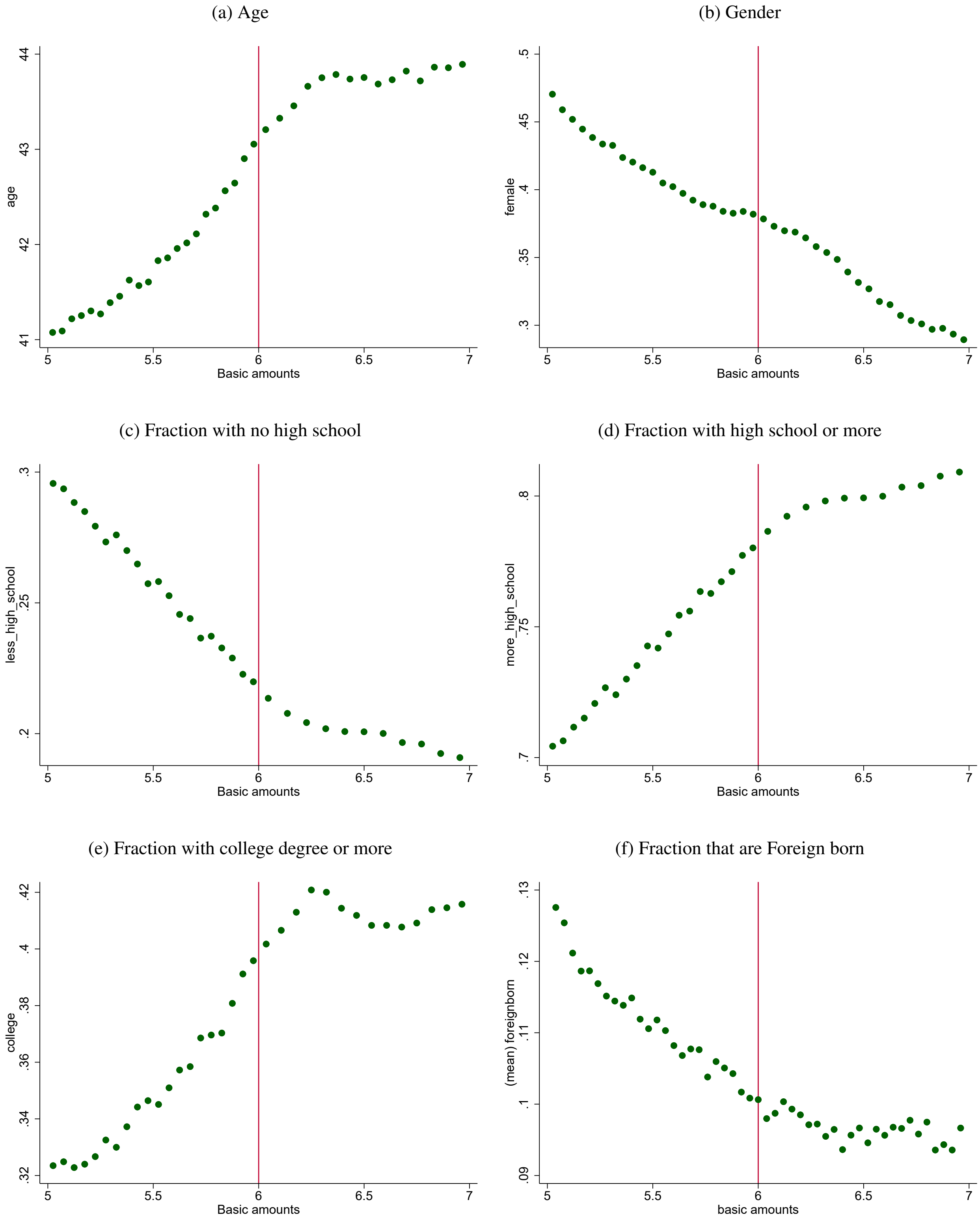
Notes: The table displays the average probability of an employment-to-unemployment transition in year $t+1$ for different percentiles of predicted unemployment based on firm-specific variables. These include the firm's leave-one-out average layoff rate at year t , the firm's number of employees at year t in logs, an indicator for a bankruptcy petition, employment growth, and an indicator of negative sales growth for the firm. The estimation is based on a full sample of employed workers of working age (18-62) over the period 2005-2014 in firms with more than 50 employees. The estimation is based on a full sample of employed workers in working age (18-62) over the period 2005-2014 in firms with more than 50 employees.

Figure A.3: **Test for Manipulation: P.D.F of Pre-Earnings upper risk quartile**



Notes: This figure plots the distribution of the assignment variable around the earnings-threshold for workers in firms that are at the upper risk quartile. The figure also displays a McCrary test of the discontinuity of the probability density function of pre-earnings. I report the difference in density at the threshold together with the standard errors. The test rejects the presence of a discontinuity at the threshold.

Figure A.4: **Robustness of Design: Smoothness of Covariates**

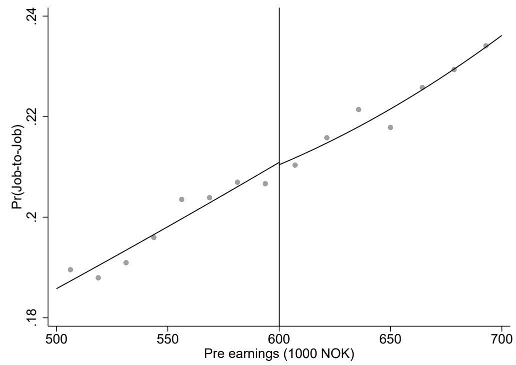


Notes: The figures displays worker characteristics for different bins of workers UI-eligable earnings measured in basic amounts (1 base amount $\approx 100'$ NOK in 2019). The bin size is selected using an integrated-mean-squared-error optimal polynomial regression selector from (Cattaneo et al. 2019)**.** The figure is based on a full sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees.

Figure A.5: **Graphical evidence at threshold: Placebo of Public Sector Workers**

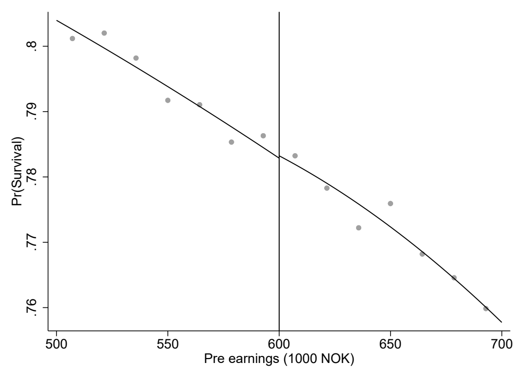
Panel I: Probability of job-to-job transition

(a) Placebo (public sector)



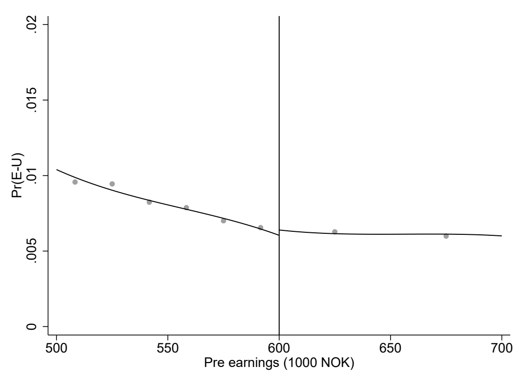
Panel II: Probability of remaining in the firm one additional year

(b) Placebo (public sector)



Panel II: Probability of remaining in the firm one additional year

(c) Placebo (public sector)



Notes: Figure A.5 displays the probability of making a job-to-job transition in year t conditional on being employed in period $t-1$, for different bins of workers UI-eligable pre-earnings measured in basic amounts (1 base amount $\approx 100'$ NOK in 2019). Figure A.5 displays the probability of remaining in the firm in year t conditional on being in the firm in period $t-1$ and Figure A.5 displays the probability of making a E-U transition for workers employed in a firm in year $t-1$ for different bins of workers UI-eligable pre-earnings. The bin size is selected using an integrated-mean-squared-error optimal polynomial regression selector from (Cattaneo et al. 2019)**.** The lines displays the slope from a local polynomial regression below and above the kink. The figures use a "placebo" sample of public sector workers including workers in the health sector based their firms registered industry nace-code.

Table A.5: **Robustness: Optimal Bandwith and Controls for Covariates**

	Robustness main specification		
	Quadratic estimator, see equation 8		
	Baseline	Optimal Bandwith	+ Covariate control
	(1)	(2)	(3)
Panel A:	$y_{i,t}$:Probability of Job-to-Job Transistion		
γ_1	0.0316	0.0320	0.0270
	(0.0071)	(0.0072)	(0.0074)
Bandwith (basic amounts)	1	1.08	1.08
N:	2 431 822	2 523 549	2 523 549
Panel B:	$y_{i,t}$:Probability of Surviving in the Firm		
γ_1	-0.029	-0.035	-0.026
	(0.0143)	(0.0076)	(0.0074)
Bandwith (basic amounts)	1	1.12	1.12
N:	2 431 822	2 605 927	2 605 927
Panel C:	$y_{i,t}$:Probability of (E-U) transition		
γ_1	-0.003	-0.000	-0.0031
	(0.0027)	(0.0020)	(0.0021)
Bandwith (basic amounts)	1	1.29	1.29
N:	2 431 822	2 933 783	2 933 783

Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the estimated slope change, γ_1, from equation 8. Column 1 is without controls and use a bandwith of 1 basic amount (1 basic amount $\approx$ 10000 USD). Column 2 reports γ_1, from equation (8) using the mean-squared-error (MSE) optimal bandwith selection from Calonico et al. (2014). Column 3 reports γ_1, from Equation (8) using optimal bandwith and flexible controls for covariates. Standard errors are clustered on individuals in the baseline specification, and clustered at the firm-level in the other specifications. Panel A reports estimates for the probability that a worker employed in year $t-1$ makes a job-to-job transition in year t. Panel B reports estimates for the probability that a worker employed in year $t-1$ is employed at the same firm in year t. Panel C reports estimates for the probability that a worker employed in year $t-1$ is non-employed in year t, where non-employment is defined as having wage income below the SGA-threshold. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees.

Table A.6: **Robustness: Local Linear Estimator with Bias Correction**

	Pr(Survival)	Pr(J-J)	Pr(E-U)	Pr(E-U$_{t+1}$)	Employment$_{t+1}$
	(1)	(2)	(3)	(4)	(5)
Panel A.	*Local linear estimator with optimal bandwith*				
	Conventional estimates				
γ_k	-0.029	0.034	-0.007	-0.009	0.016
	(0.0143)	(0.0100)	(0.0041)	(0.0068)	(0.0067)
Bandwidth (basic amounts)	0.338	0.401	0.346	0.320	0.337
N	1 026 552	866 571	887 973	798 746	744 283
Panel B.	*Local linear estimator with optimal bandwith*				
	Quadratic bias correction				
γ_k	-0.016	0.033	-0.012	-0.017	0.023
	(0.0201)	(0.0160)	(0.0051)	(0.0081)	(0.0084)
Bandwidth (basic amounts)	0.790	0.735	0.954	0.761	0.869
N	1 831 084	1 813 442	2 329 074	1 891 640	1 841 178

Standard errors (in parentheses) are clustered at the individual level.

Note: This table reports the estimated slope change, γ_1, from Equation (8). Column 1 displays the estimated effect for the probability of remaining in the firm in year t. Column 2 displays the estimated effect on the probability of a job-to-job transition from year $t-1$to year t. Column 3 displays the estimated effect on the probability of making a E-U transition from year $t-1$ to t. Column 4 displays the estimated effect on the probability of an E-U transition from year $t-1$ to $t+1$. Column 5 displays the estimated effect on and the probability of being employed in year $t+1$. Employment is measured as having wage income above the SGA threshold. Panel A reports the conventional linear kink estimates with MSE optimal bandwidths with conventional standard errors clustered at the firm level. Panel B reports the linear estimator with optimal bandwidth selection and quadratic bias correction with robust standard errors clustered at the firm level using the method of Calonico et al. (2014). The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees.

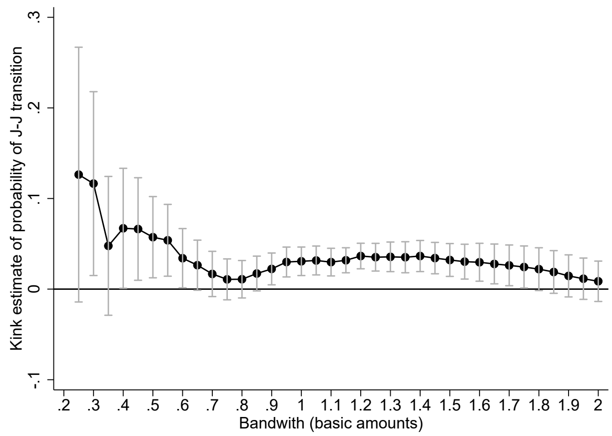
Table A.7: **Robustness Fiscal externalities: Local Linear Estimator with Bias Correction**

	Benefits per worker	Pr(E-U)	Unemployment duration	Taxes per worker
	(1000 NOK)		(Implied)	(1000 NOK)
	(1)	(2)	(3)	(4)
γ_1	-3.10	-0.018		-0.058
	(1.144)	(0.009)		(3.951)
$\varepsilon_{y_k,b}$	0.70	0.51	0.11	0.000
	(0.261)	(0.243)		(0.014)
Bandwidth (basic amounts)	1.199	1.078		0.933
Number of observations:	2 413 165	2 198 999		1 965 043

Standard errors (in parentheses) are clustered at the individual level.

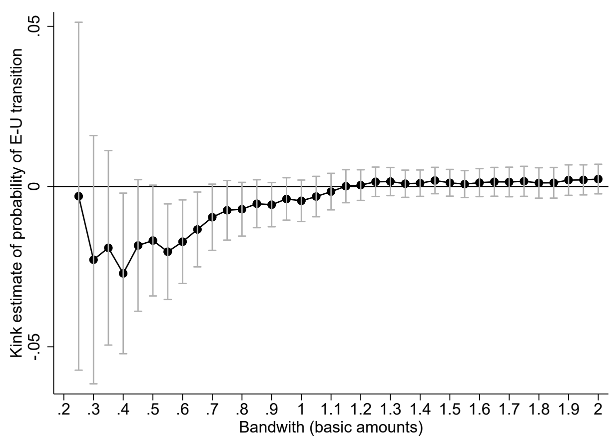
Note: This table reports the estimated slope change, γ_1, at the treshold in the benefit replacement rate. Column 1 displays the estimated effect on total benefits received in year t and $t+1$. Column 2 displays the estimated effect on the probability that the worker transitions to unemployment in year t or year $t+1$. Column 3 displays the estimated effect on the total taxes paid for each worker over the years t and $t+1$.The implied elasiticity $\varepsilon_{y_k,b} = \frac{\gamma_1}{\bar{y}_k}$ gives the percentage change in the outcome variable for a one percent change in benefits. The estimated slope change uses a linear estimator with optimal bandwidth selection and quadratic bias correction with robust standard errors clustered at the firm level using the method of Calonico et al. (2014). The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees.

Figure A.6: **Bandwith sensitivity: Pr(Job-to-Job)**



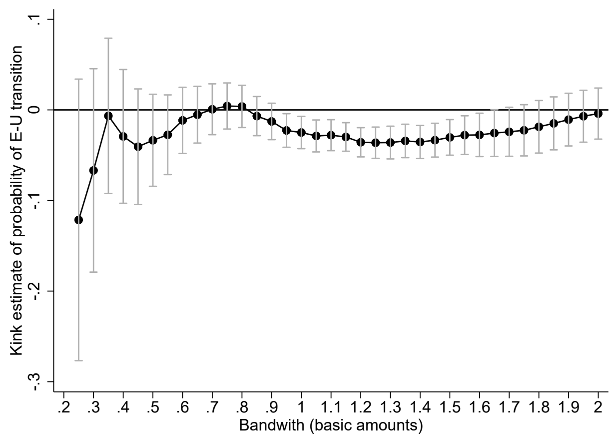
Notes: The figure plots the estimated slope change, γ_1, from Equation (8) for the annual probability of a job-to-job transition for different bandwiths ranging from 0.2 basic amounts to 2 basic amounts. 1 basic amount $\approx$ 10 000 USD.

Figure A.7: **Bandwith sensitivity: Pr(E-U)**



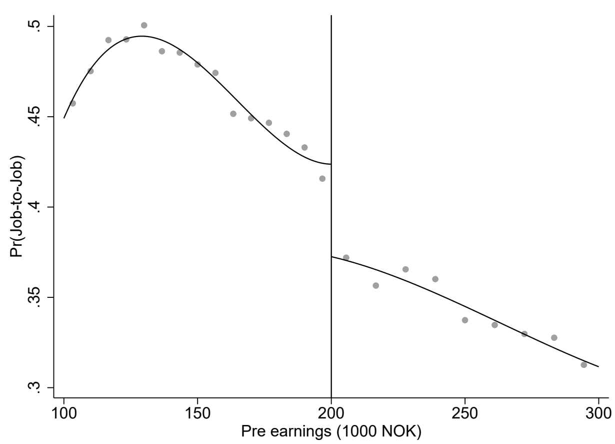
Notes: The figure plots the estimated slope change, γ_1, from Equation (8) for the annual probability of a employment-to-unemployment transition for different bandwiths ranging from 0.2 basic amounts to 2 basic amounts. 1 basic amount $\approx$ 10 000 USD.

Figure A.8: **Bandwith sensitivity: Pr(Survival)**



Notes: The figure plots the estimated slope change, γ_1, from Equation (8) for the annual probability of a employment-to-unemployment transition for different bandwiths ranging from 0.2 basic amounts to 2 basic amounts. 1 basic amount $\approx$ 10 000 USD.

Figure A.9: **Probability of Job-to-Job transition at benefit duration threshold**



Notes: The figure plots the probability of a job-to-job transition at the benefit duration threshold. Potential duration increases from 52 to 104 weeks for workers with earnings of more than 2 basic amounts $\approx$ 20000 USD. The bin size is selected using an integrated-mean-squared-error optimal polynomial regression selector from Cattaneo et al. (2019**).**

Figure A.10: **Full Distribution**

(a) Pr(Job-to-Job) (b) Density: Pre-Earnings

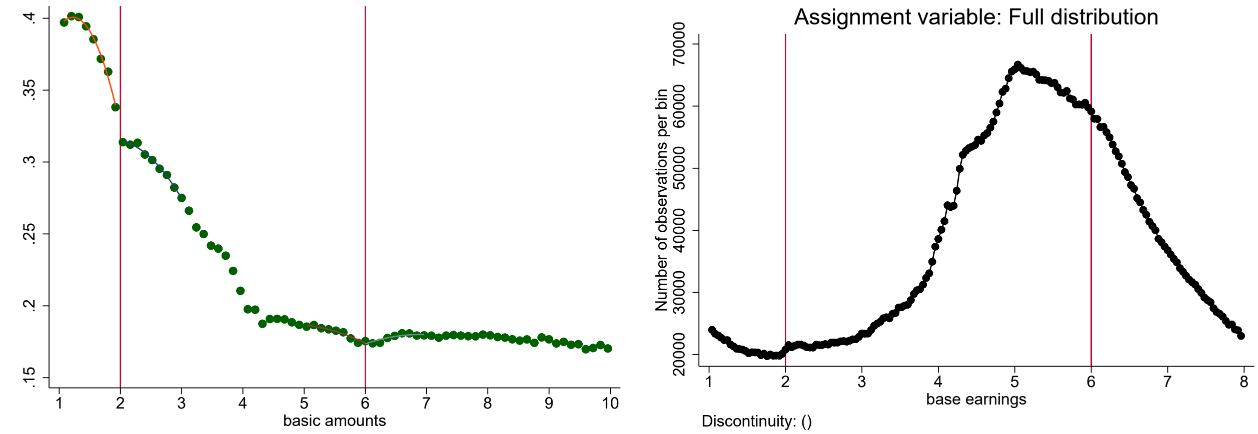
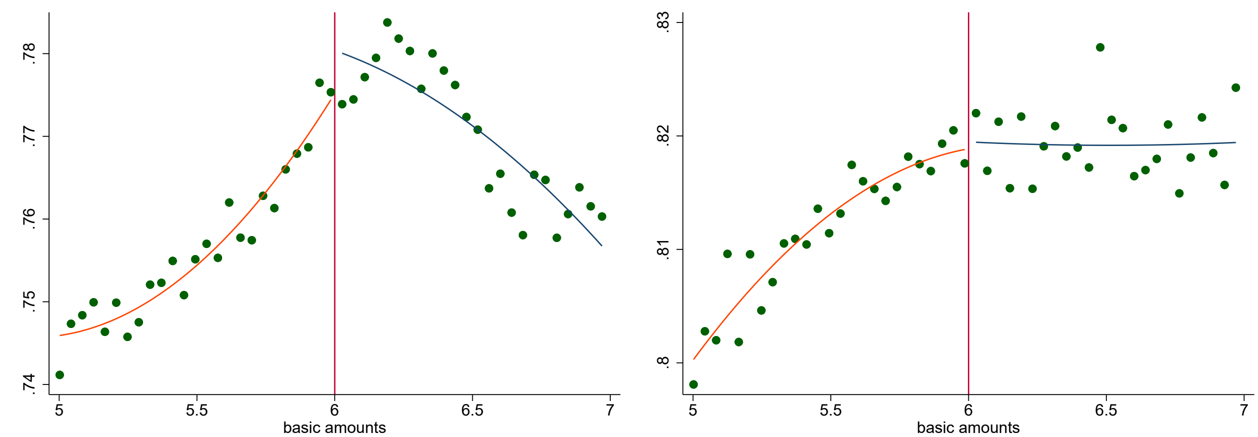


Figure A.11: **Graphical evidence at threshold: Survival probability by layoff risk**

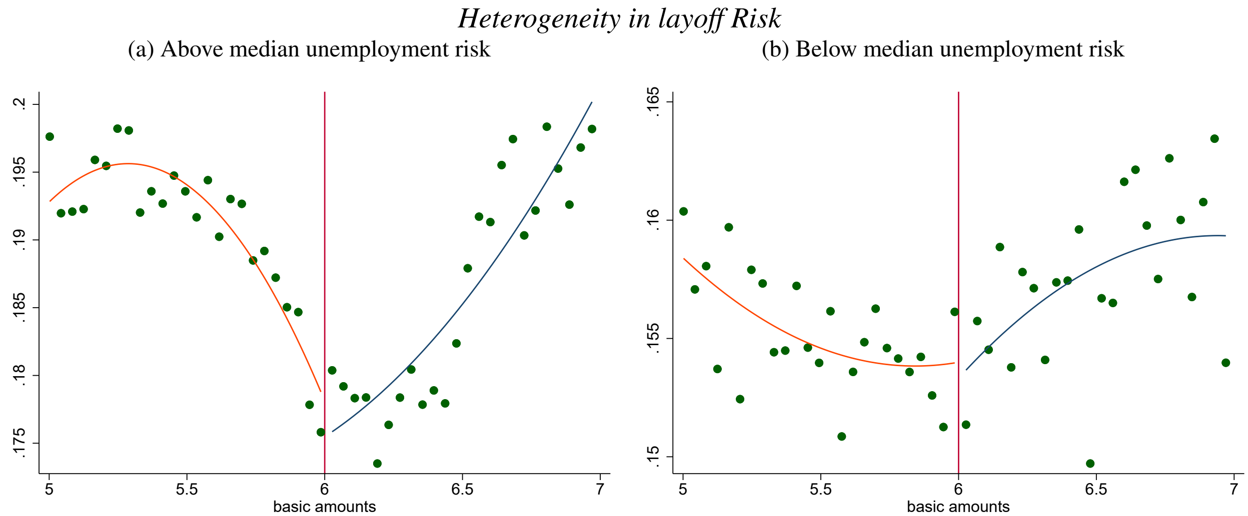
Heterogeneity in layoff Risk

(a) Above median risk (b) Below median risk



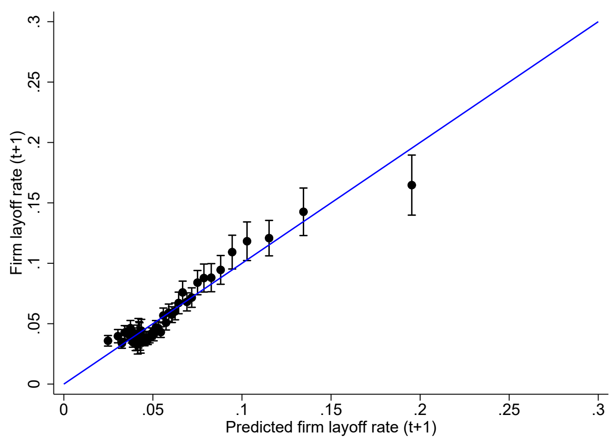
Notes: The figure displays the probability of being in the bankrupt petitioned firm in year t conditional on being in the firm in period $t-1$, for different bins of workers' UI-eligable earnings measured in basic amounts (1 base amount $\approx 100'$ NOK in 2019) The bin size is 0.04 basic amounts or ≈ 4000 NOK. The lines displays the slope from a linear regression below and above the kink.

Figure A.12: **Graphical evidence at threshold: Probability of job-to-job transition by layoff risk**



Notes: The figure displays the probability of making a job-to-job transition in year t conditional on being employed in period $t-1$, for different bins of workers UI-eligable earnings measured in basic amounts (1 base amount $\approx 100'$ NOK in 2019) The bin size is 0.04 base amounts or ≈ 4000 NOK. The lines displays the slope from a linear regression below and above the kink.

Figure A.13: **Predicted and realized unemployment risk: Workers at the Threshold**



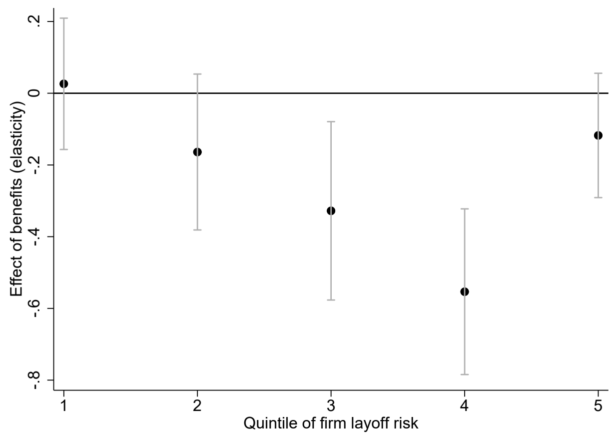
Notes: The figure displays the share of a firms workers that makes an employment to unemployment transition in year $t+1$ for 50 different equally sized bins of predicted firm level layoff risk based on firm-specific variables. This includesfirm leave-one-out average layoff rate at year t, firm number of employees at year t in logs, an indicator for bankruptcy petition, employment growth and an indicator of a negative sales growth for the firm. The estimation is based on the sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees with earnings of one basic amount on either side of the earningsthreshold

E Derivations and proofs

Benefits and search behavior

Proof. If the job-finding rate $\lambda(V(\hat{w};b),s)$ is decreasing in target job-quality and workers face a positive probability of job-destruction, the job-finding rate is decreasing in benefits. For a given search inten-

Figure A.14: **Estimated Mobility Response to Higher Benefits by Quintiles of Predicted Unemployment Risk**



Notes: This figure displays the estimated elasiticity of job-to-job transitions with respect to benefits ($\varepsilon_{y_k,b} = -\frac{\gamma_1}{\bar{y_k}}$ where, γ_1 is defined in Equation (8)) for different quintiles of predicted unemployment risk. The predicted unemployment risk is based on predictors rezidualized for observable worker characteristics (age, education, gender and foreign bord) and industry fixed effects The outcome variable is the probability of making a job-to-job transition in year t conditional on being employed in period $t-1$. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees. The spikes represent 95 percent confidence intervals.

sity/effort, target job-quality is increasing in benefits. $\square$

Rewrite equation (1):

$$V(w,\delta) = u(c) + \beta\left\{\delta V(b(w)) + (1-\delta)V(w,\delta)\right\} + \max_{\hat{V},s} \lambda\beta\left\{\hat{V} - \delta V(b) - (1-\delta)V(w,\delta)\right)\} - \psi(s)$$

Consider a worker with potential benefits b that search for $\hat{V}_1$ with intensity s_1 and another worker with potential benefits $b' > b$ searching for $\hat{V}_2$ with intensity s_2 Higher benefits affects the value of both the current and the targeted position. Maximization implies that:

$$\lambda(\hat{V}_2,s_2)\left\{\hat{V}_2(w,b') - \delta V(b') - (1-\delta)V(w,b') - \psi(s_2)\right\} \geq \lambda(\hat{V}_1,s_1)\left\{\hat{V}_1(w,b') - \delta V(b') - (1-\delta)V(w,b') - \psi(s_1)\right\}$$

$$\lambda(\hat{V}_2,s_2)\left\{\hat{V}_2(w,b) - \delta V(b) - (1-\delta)V(w,b) - \psi(s_2)\right\} \leq \lambda(\hat{V}_1,s_1)\left\{\hat{V}_1(w,b) - \delta V(b) - (1-\delta)V(w,b) - \psi(s_1)\right\}$$

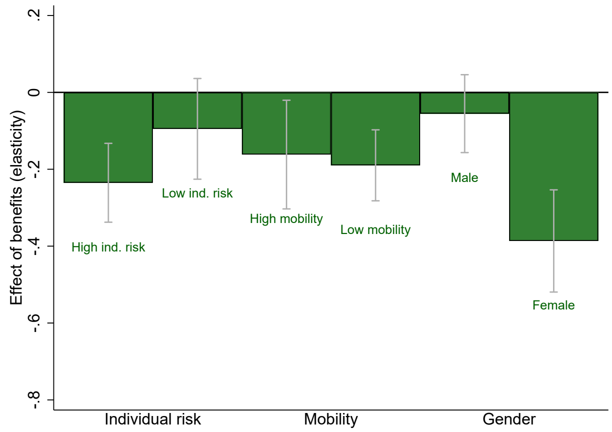
Combining the inequalites and subtracting, we get:

$$\begin{gathered}\lambda(\hat{V}_2,s_2)\left\{[\hat{V}_2(w,b') - \hat{V}_2(w,b)] - \delta[V(b') - V(b)] - (1-\delta)[V(w,b') - V(w,b)]\right\} \\ \geq \\ \lambda(\hat{V}_1,s_1)\left\{[\hat{V}_1(w,b') - \hat{V}_1(w,b)] - \delta[V(b') - V(b)] - (1-\delta)[V(w,b') - V(w,b)]\right\}\end{gathered} \tag{16}$$

Using the envelope condition and equation (3) we have that:

$$\frac{\partial V(b)}{\partial b} = \frac{u'(b)}{1-\beta(1-\lambda)} > 0 \qquad \text{for} \qquad u'(b) > 0$$

Figure A.15: **Estimated Mobility Response to Higher Benefits by Worker Types**



Notes: This figure displays the estimated elasiticity of job-to-job transitions with respect to benefits ($\varepsilon_{y_k,b} = -\frac{\gamma_1}{y_k}$ where, γ_1 is defined in Equation (8)) for worker type. Estimates are displayed for workers with above/below median predicted unemployment risk (based on individual characteristics), above/below median predicted mobility (based on individual characteristics) and gender. The outcome variable is the probability of making a job-to-job transition in year t conditional on being employed in period $t-1$. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees. The spikes represent 95 percent confidence intervals.

$$\frac{\partial V(w,b)}{\partial b} = \frac{\beta\delta V'(b)}{1-\beta(1-\lambda)(1-\delta)} > 0 \qquad \text{for} \qquad u'(b) > 0$$

The direct impact of higher benefits on the targeted job, keeping the target wage constant is given by:

$$\frac{\partial \hat{V}(w,0)}{\partial b} = p\frac{\beta\delta V'(b)}{1-\beta(1-\lambda)(1-\delta)}$$

Note that since all jobs are initially safe and has the same probability of becoming risky, $\frac{\partial \hat{V}_2(w)}{\partial b} = \frac{\partial \hat{V}_1(w)}{\partial b}$. For a marginal change in benefits, we can rewrite the term:

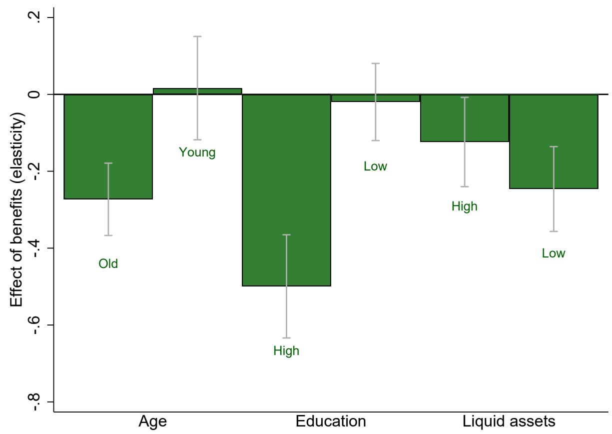
$$[\hat{V}(w,b') - \hat{V}_2(w,b)] - \delta[V(b') - V(b)] - (1-\delta)[V(w,b') - V(w,b)] \quad = \quad \frac{\partial \hat{V}(w)}{\partial b} - \delta\frac{\partial V(b)}{\partial b} - (1-\delta)\frac{\partial V(w,b)}{\partial b}$$

Finally, I show that the term $\frac{\partial \hat{V}}{\partial b} - \delta\frac{\partial V(b)}{\partial b} - (1-\delta)\frac{\partial V(w,b)}{\partial b}$ is negative:

$$\begin{gathered}\frac{\partial \hat{V}}{\partial b} - \delta\frac{\partial V(b)}{\partial b} - (1-\delta)\frac{\partial V(w,b)}{\partial b} \\ = \\ \delta V'(b)[\frac{p\beta}{1-\beta(1-\lambda)(1-\delta)} - \frac{(1-\delta)\beta}{1-\beta(1-\lambda)(1-\delta)} - 1] \\ = \\ \delta V'(b)[\frac{p\beta}{1-\beta(1-\lambda)(1-\delta)} - \frac{(1-\delta)\beta}{1-\beta(1-\lambda)(1-\delta)} - 1] \quad < \quad 0 \\ \text{if} \\ \beta(1-\lambda(1-\delta)) < 1\end{gathered}$$

It follows that $\lambda(\hat{V}_1, s_1) \geq \lambda(\hat{V}_2, s_2)$ as $V(b') > V(b)$ and $V(w,b') > V(w,b)$. As λ is decreasing in the value of the target quality $\hat{V}_2 \geq \hat{V}_1$ for a given search intensity $s_1 = s_2 = s$. Similarly, as λ is increasing in

Figure A.16: **Estimated Mobility Response to Higher Benefits by Worker Types**



Notes: This figure displays the estimated elasiticity of job-to-job transitions with respect to benefits ($\varepsilon_{y_k,b} = -\frac{\gamma_1}{\bar{y}_k}$ where, γ_1 is defined in Equation (8)) for worker type. Estimates are displayed for workers with above/below median age, above/below median years of education, and liquid assets based on bank deposits. The outcome variable is the probability of making a job-to-job transition in year t conditional on being employed in period $t-1$. The estimation is based on a sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees. The spikes represent 95 percent confidence intervals.

search intensity, $s_1 > s_2$for a given quality.

Proof. Under a benefit profile where benefits is a function of wages $b(w)$ subject to a maximum benefit threshold, the job-finding rate is a kinked function of wages, kinked upward at the maximum benefit threshold for workers with a positive job-destruction risk and continues for workers with no job-destruction risk. The kinked benefit profile means that the value of a worker's current position, V, is a kink function of wages w. If workers' target job quality $\hat{V}$ is a strictly increasing function of the value of their current job V, $\hat{V}$ must also be a discontinues function of wages. As the job-finding rate is assumed to be decreasing in $\hat{V}$, the job-finding rate will be discontinues. I begin by showing that V is a kinked function of wages: □

$$V = \max_{\hat{V},s} \quad u(c) + \beta[\delta(1-\lambda)V(b(w)) + (1-\delta)(1-\lambda)V + \lambda\hat{V}] - \psi(s)$$

$$\lambda = E(\hat{V},s) \qquad\qquad \text{s.t } b = \begin{matrix} b_r & \text{if } w \leq w_k \\ 0 & \text{if } w > w_k \end{matrix}$$

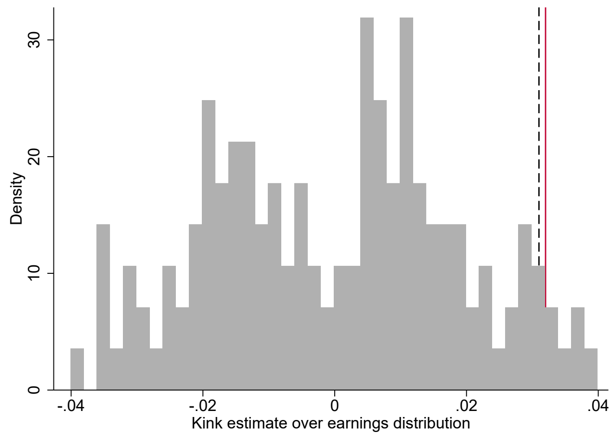
Using the envelope condition and equation (3) we have that:

$$\frac{dV(b)}{dw} = \frac{u(b')\frac{\partial b}{\partial w}}{1-\beta} > 0 \qquad \text{for} \qquad u'(b) > 0, \beta < 1$$

The derivative of benefits with respect to wages is kinked at $w = w_k$ which means that $\frac{\partial b}{\partial w} = 0$ for $w > w_k$ and:

$$\frac{\partial(V|w \leq w_k)}{\partial w} > \frac{\partial(V|w > w_k)}{\partial w} \qquad \text{if } \delta > 0\text{as}$$

Figure A.17: **Placebo test: Kink estimates over the earnings distribution**



Notes: This figure displays the distribution of the estimated slope change of job-to-job transitions at different earnings thresholds (γ_1 is defined in Equation (8)) over the income distribution. The estimates is obtained by using placebo thresholds at 10 000 NOK intervals. The red line displays the estimated effect at the kink. The dashed line displays the 95th percentile of the distribution. The estimation is based on the sample of employed workers in working age (18-62) over the period 2008-2014 in firms with more than 50 employees with earnings of one basic amount on either side of the earningsthreshold

$$\frac{u'(c)\frac{\partial c}{\partial w}+\beta\delta(1-\lambda)\frac{\partial V(b)}{\partial b}\frac{\partial b}{\partial w}}{1-\beta(1-\delta)(1-\lambda)} > \frac{u'(c)\frac{\partial c}{\partial w}}{1-\beta(1-\delta)(1-\lambda)} \qquad \text{if } \delta > 0$$

$$\frac{\partial(V|w \leq w_k)}{\partial w} = \frac{\partial(V|w > w_k)}{\partial w} \qquad \text{if } \delta = 0$$

I then show that $\hat{V}$ is a strictly increasing function of V. The first order condition in equation 4 defines $\hat{V}$ as an implicit function of V. I write this as $\hat{V}(V)$.Differentiating 4 w.r.t V gives:

$$\frac{\partial \hat{V}}{\partial V}[\lambda''_{\hat{V}}[\hat{V}-\delta V(b)-(1-\delta)V]+2\lambda'_{\hat{V}}] = (1-\delta)$$

Similarly, if we let $V(\hat{\theta})$ be an implicit function of b, differentiating 4 w.r.t b gives:

$$\frac{\partial \hat{V}}{\partial b}[\lambda''_{\hat{V}}[\hat{V}-\delta V(b)-(1-\delta)V]+2\lambda'_{\hat{V}}] = \frac{\delta u'(b)}{1-\beta}$$

We know that $\hat{V}$is increasing in benefits, thus the term $\lambda''_{\hat{V}}[V(\hat{\theta})-\delta V(b)-(1-\delta)V(\theta)]+2\lambda'_{\hat{V}} \geq 0$. Then:

$$\frac{\partial \hat{V}}{\partial V} = (1-\delta)/[\lambda''_{\hat{V}}[\hat{V}-\delta V(b)-(1-\delta)V]+2\lambda'_{\hat{V}}] \geq 0$$

It follows that $\hat{V}$ is an increasing function of w, kinked at $w = w_k$ where $\frac{\partial \hat{V}|w \leq w_k}{\partial w} > \frac{\partial \hat{V}|w > w_k}{\partial w}$ and $\frac{\partial \lambda|w \leq w_k}{\partial w} \leq \frac{\partial \hat{V}|w > w_k}{\partial w}$