Policy Evaluation Under Biased Job Search

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November 3, 2017

Abstract

In this (preliminary) work I apply the dynamic job search model of DellaVigna *et al.* (2017) to hazard rates out of unemployment on the Danish labor market. In contrast to standard job search theory, which struggles to adequately predict hazard rates, the job search model is enriched with cognitive biases known from behavioural economic theory. While included biases have shown improvements before, I extend the model further with an altered version of Spinnewijns' (2015) overconfidence in job search. This partial equilibrium framework is then used to evaluate a number of hypothetical reforms of the UI system. Further, I present suggestive evidence that, given the estimated structural model, a policy change from the current one-step system to a multi-step policy could have overall beneficial effects.

Keywords: job search, cognitive biases, structural estimation, policy evaluation

WORK-IN-PROGRESS

1 Introduction

In academia and public alike, the scheme of the unemployment insurance (UI) is an actively debated topic. The Danish system, which is characterized by relatively generous replacement rates, has been subject to several reforms over the last decades with the aim to speed up the exit into employment. These reforms mainly focused on cutting the length of benefit entitlement once individuals become unemployed and before the transition into social security with significantly lower transfers.

Generally, the exit rates into employment are characterized by strong hazards right after the beginning of the unemployment spell that quickly decline, just to rise again in anticipation of the exhaustion of the unemployment insurance benefits. After this transition into social security/welfare transfers, the hazard rates shrink again to eventually settle at a somewhat constant level. While the evaluation of hypothetical policy changes often relies on structural models, it is striking that the standard model of job search theory is often not able to sufficiently replicate the patterns present in the hazard rates or it relies on an unrealistic degree of unobserved heterogeneity, at least in the Danish context. Thus, policy evaluation that employs the standard job search theory needs to be viewed with caution. To overcome the problems of bad data fit, research in labor economics recently showed increased interest in the theories of behavioral economics, first established with the seminal prospect theory of Kahneman and Tversky (1979). Especially cognitive biases, which are well documented through a number of studies and that influence and alter decision making, like reference dependence, present bias and overconfidence, can possibly explain features of the hazard rates that the standard model cannot fit. Thus, a combination of job search theory with concepts of behavioral economics promises a more realistic modelling of job search efforts.

In this work I am building on the job search model by DellaVigna *et al.* (2017) who included reference dependence and present bias in their estimations. These extensions have shown to fit the patterns of the unemployment hazard rates on the Hungarian labor market better than the standard formulation of job search theory, but still drift apart at times. Further, I am invoking the concept of overconfidence in the subjective job offer arrival rate, introduced by Spinnewijn (2015) in another model of job search. The novel part of my estimations is not only the combination of both approaches, but I additionally alter the definition and formulation of the overconfidence to the assumption of a bias that vanishes over time, i.e. the unemployed job seekers adjust to the true probability of finding employment over the course of the unemployment spell, which approximates learning. I estimate the structural parameters of the model with a minimum-distance approach that minimizes the weighted distance between parametric moments and the empirical hazard rates out of unemployment.

The project aims to answer the question if features of behavioral economics can also explain the hazard rates out of unemployment on the Danish labor market as well as if the novel definition of overconfidence can increase the data fit in comparison a reference-dependent job search model. Further, the work tries to shed light on the effects of possible policy changes and the opportunities of exploiting the behavioral components of the unemployed agents decision making. The work therefore contributes to the literature on behavioral labor economics as well as the research on job search and optimal unemployment insurance design.

2 Related Literature

In recent years behavioral economics spread into the field of labor economics and found varying applications in the job search literature. While this work uses a structurally estimated model, it is to note that some other contributions included concepts of cognitive biases, focusing for example on the influence of backward-looking reference points on reservation wages (Koenig *et al.*, 2016), non-search behavior (Damgaard, 2017), labor supply in general (Camerer *et al.* (1997), Goette *et al.* (2004)) and with a focus on reactions to wage changes (Doerrenberg *et al.*, 2016) as well wage rigidity induced by loss aversion in search and matching (Eliaz and Spiegler, 2013). Concerning present bias, DellaVigna and Paserman (2005) explore the influence of impatience induced by hyperbolic-discounting on search intensity and reservation wages.

More related to this work, several studies have examined possible applications of reference dependence, present bias and biased beliefs in structural models of job search. The first notable applications can be found in Paserman (2008) who quantitatively estimates the degree of the present bias in a job search model and predicts effects of altered UI benefit policies on US data. The study estimates the present bias parameter β below 1, in line with the hyperbolic discounting assumption. The impact of a policy change that induces higher search-effort, and thus works against the present bias, is highly dependent on the underlying structure of the model and policy intervention. There are however interventions that may increase search effort and social welfare whilst decreasing the duration of the unemployment spell.

Building up on the assumption of biased beliefs, Spinnewijn (2015) examines the influence of overconfidence in job search. The study finds empirically that unemployed job seekers strongly overestimate their probability to find a job and calibrates a model with tax-financed benefits. This model adds overconfidence to characterize optimal unemployment insurance policies when beliefs about the job offer probability are biased. In Spinnewijns, setting an overconfident individual prefers a lower benefit, leading to a lower tax as the job seeker expects to stay unemployed shorter than the actual realized duration. If in addition to the overconfidence the externality induced by differences between actual and perceived returns to search is small, then the optimal unemployment insurance policy is characterized by increasing benefits and taxes for people who remain in unemployment for a long time

Finally, DellaVigna *et al.* (2017) present a study involving a job search model with endogenous savings that adds reference dependent utility and hyperbolic discounting. In contrast to most current research (see f.e. Köszegi and Rabin (2007)) they use a backwards looking reference point that accounts for the differences between the current benefit level and the prior wage income. The model is estimated on Hungarian unemployment data with the interesting characteristic of a change from a single-tier to a two-tier benefit system in 2005 and shows distinct differences in the behavior of the unemployed job seekers in both regimes. The results indicate a significant degree of present bias as well as reference dependence and the authors hypothesize that a decreasing multi-step benefit system might be desirable if the unemployed are reference dependent.

3 Theoretical Framework

The main model of this thesis builds on the before-mentioned discrete time job search intensity model of DellaVigna *et al.* (2017). Their work is the first job search model adding reference dependence to yield more realistic predictions of search effort choices by unemployed individuals and it builds on the frameworks developed by Card *et al.* (2007) and Lentz and Tranæs (2005), allowing for endogenous saving decisions. In this work I abstract from saving decisions, as on the one hand the computational intensity increases enormously and my prior work to this paper has shown little importance for savings decisions in this context, possibly due to the overall generous UI system (Fluchtmann, 2016). This section introduces the theoretical framework and all its extensions used. It is straightforward to disable some of these extensions in the estimations by setting certain model specific parameters to 0 or 1, respectively.

In each of the periods an unemployed job seeker needs to choose the utility maximizing job search effort $s_t \in [0, 1]$ which mirrors the probability of receiving a job offer in the upcoming period, i.e. the job offer arrival rate. Naturally the wage w_t of a job offer is drawn from the cumulative wage offer distribution $F(w)$. The search effort results in costs each period represented by the twice continuously differentiable cost function $c(s_t)$ with $c'(s_t) > 0$, $c''(s_t) < 0$, $c(0) = 0$ and $c'(0) = 0$.

During the unemployment spell the agent receives transfers b_t in each of the periods, which are consumed instantaneously. The unemployment insurance benefits b_1 are granted for the first T periods. After this, the eligibility of UI benefits is exhausted and the agent enters the welfare system receiving the significantly lower social security transfers that are characterized by $b_2 = \psi b_1$, where ψ represents the fraction of b_1 that the job seeker receives after transitioning.

The agent faces a reference-dependent gain-loss utility in the fashion of Köszegi and Rabin (2006) that she derives from the transfers b_t or the wage w_t. The individual compares her consumption decision to her prior wage level for the first N periods after the unemployment spell, governed by the reference point r_t. Note that the gain-loss utility also affects the periods after an individual changes from unemployment benefits to social security as well as the utility in employment. The reference-dependent utility function is given as:

$$u(c_t \mid r_t) = \begin{cases} v(c_t) + \eta[v(c_t) - v(r_t)] & if \quad c_t \geq r_t \\ v(c_t) + \eta\lambda[v(c_t) - v(r_t)] & if \quad c_t < r_t \end{cases} \tag{1}$$

where η is the weight on gain-loss utility, fixed at 1 as in most reference-dependence literature, and λ is the parameter specifying the loss-aversion, assumed to be larger than 1. While being unemployed the reference point r_t is always higher than or equal to the current benefit level and therefore the individual experiences a loss and weights the difference with $\eta\lambda$.[1]

Contrary to the current research (Köszegi and Rabin, 2007), that assumes forward-looking reference points, the reference point is modelled as a backward-looking weighted average of the current income and the preceding N periods. Following this it is defined as:

$$r_t = \frac{1}{N+1} \sum_{k=t-N}^{t} y_k \tag{2}$$

It is a strong assumption that the unemployed job seeker compares her current consumption to her average past income, it is however necessary to make the model computable. Other variations, for example a forward looking reference point or one that considers actual consumption rather than income when allowing for endogenous savings, increase the computational requirements enormously.

To allow for inconsistency in the discounting between different periods an additional discount factor $\beta \in (0, 1]$ between the current period and the future is added. This builds up on the theory of hyperbolic discounting by Laibson (1997) and O'Donoghue and Rabin (1999). I assume that the agent behaves naive according to her time preference, i.e. she assumes that she will only be faced by δ-discounting in the future and thus thinks she will

[1]Note that if I set η to 0 I arrive back at a basic model without gain-loss utility.

follow a time consistent consumption and search effort path while being faced with the additional discount factor β only in the current period. Reaching the next period however, she is again faced with the additional β and thus deviates from her initial plans that just involved δ-discounting.

Finally, I allow the agent to be biased in her belief about her employment prospects and thus I manipulate the agents beliefs about the job offer arrival rate, i.e. the probability of obtaining a job offer given the exerted search effort. These biased beliefs are inspired by Spinnewijn (2015). I however use a functional form that approaches the actual probability of obtaining a job offer over time, approximating learning about the true arrival rate[2]. I formulate the bias in the perceived job offer arrival rate as an exponential decay:

$$\varphi_t(s_t) = s_t \cdot (\pi e^{-\xi t} + 1), \quad \xi \geq 0 \tag{3}$$

where s_t is the actual job offer arrival rate, π is the baseline bias at the beginning of the unemployment spell and ξ models the speed of the adaption to the true arrival rate. For $\pi = 0$, I end up with the prior model without any bias in the beliefs and $\xi = 0$ yields a constant bias as in Spinnewijn (2015). For $\xi > 0$ it is obvious that the bias vanishes over time and the perceived job offer arrival rate $\varphi_t(s_t)$ approaches s_t.

While the individual is unemployed and seeks for a job, her utility is given by:

$$V_t^{U,n} = \max_{s_t} u(y_t|r_t) - c(s_t) + \beta\delta \left[\varphi_t(s_t) \int_{\phi_{t+1}}^{\infty} V_{t+1|t+1}^E(w) - V_{t+1}^U \, dF(w) + V_{t+1}^U\right] \tag{4}$$

where $V_{t+1|t+1}^E$ is the value of being employed in period $t+1$ conditional on finding a job starting in period $t+1$ and V_{t+1}^U is the future value of being unemployed under exponential discounting. In every period she draws a wage offer from $F(w)$ with an arrival rate equal to her search effort s_t.[3] Obviously, the job seeker only accepts wage offers that exceed her reservation wage ϕ_{t+1}, otherwise she finds employment under this offer less attractive than to search and wait for another offer in the next period while staying unemployed. The value function under employment is:

$$V_{t+1|t+1}^E(w_{t+1}) = u(w_{t+1}|r_{t+1}) + \delta V_{t+2|t+1}^E = \frac{v(w_{t+1})}{1-\delta} + \eta \sum_{i=1}^{N} \delta^i [v(w_{t+1}) - v(r_{t+i|t+1})] \tag{5}$$

where w_{t+1} is the realized wage in period $t+1$ after accepting an offer in period t. The

[2]The agent knows that her perceived job offer arrival rate will be lower in the future if she does not find a job. While proper Bayesian updating is not feasible in the context of this model this gives a slight approximation of the learning effect of rejected applications that an agent would anticipate.

[3]She expects this arrival rate to be $\varphi_t(s_t)$.

reservation wage ϕ_{t+1} is the single wage offer that satisfies:

$$\phi_{t+1} = \left\{ w \mid V^E_{t+1}(w) = V^U_{t+1} \right\} \tag{6}$$

The interior optimality condition[4] is then found by taking the first order derivative of (4) with respect to s_t. This implies:

$$c'(s^*_t) = \beta\delta(\pi e^{-\xi t} + 1) \left[\int_{\phi_{t+1}}^{\infty} V^E_{t+1|t+1}(w) - V^U_{t+1} \, dF(w) \right] \tag{7}$$

The hazard rate h_t in period t depends on the true job offer arrival rate, namely the search effort s_t, as well as on the acceptance rate given the reservation wage ϕ_{t+1} and is therefore given as:

$$h_t = s_t(1 - F(\phi_{t+1})) \tag{8}$$

Further, the expected re-employment wage in every period t is given as:

$$E[ln\ w|w \geq \phi_t] = \frac{\int_{\phi_t}^{\infty} ln\ w \ dF(w)}{(1 - F(\phi_t))} \tag{9}$$

Exactly N periods after the benefits drop, i.e. at $T + N$, the search effort becomes stationary as there are no income related shocks anymore. The model is then solved from the point of steady state after the benefit drop in T for every preceding period by backwards induction/dynamic programming.

4 Institutional Setting and Data

4.1 The Danish Unemployment Insurance System

The Danish unemployment insurance system is based on a voluntary scheme. Individuals who decide to join the insurance system have the right to receive unemployment benefits under special requirements once they become unemployed and register as unemployed at the Public Employment Service. To become insured one needs to be registered at one of several unemployment insurance funds which involves a monthly fee. The unemployed must be a member of an unemployment insurance fund for a minimum amount of one year and have worked at least 1,924 hours in the preceding three years to eligible to receive the benefit payments. This roughly represents one year of full-time work and to regain access to the benefits after their exhaustion an unemployed individual needs to fulfill this criteria again.

[4] I additionally check for solutions at the boundaries of s_t in the model computations.

The unemployment insurance benefit amounts to up to 90% of the prior income, but is capped at 836 DKK per day for 5 days a week as per 2016, which represents 4,180 DKK per week for recently employed[5]. Even though the unemployment insurance funds are private associations, the benefits are mostly financed by the Danish state. Therefore the amount and the duration of the benefits is subject to parliamentary legislation and the duration of the benefits as well as the requirements to receive it were subject to several reforms over the last decades. Most recently and in the wake of the European economic and financial crisis the maximum unemployment insurance benefit entitlement was cut from four to two years, which was gradually introduced from 2008 to 2011.[6] After exhausting the right to receive benefits, i.e. after staying unemployed longer than the unemployment insurance entitlement, the unemployed enter the welfare system and receive the lower welfare/social security benefits *kontanthjælp* which amount to roughly 80% of the unemployment insurance benefit for recipients with children and on the other hand to 60% for recipients without children. To receive the benefits, individuals however need to deplete their savings first and comply with rules regarding total household wealth.

The initial aim of significantly reducing the unemployment rate, subject to stark rises since 2008, through the unemployment insurance reform was not fulfilled and the reform itself was subject to strong opposition of the Danish trade unions who feared an erosion of the income security in Denmark (Madsen, 2013). To respond to these factors the government implemented "acute-measures" that delayed the benefit exhaustion for long-term unemployed who would lose their right to benefits in late 2012 by another six months. The acute-measures moved the final implementation of the 2 year unemployment insurance benefit period to people who became unemployed since the beginning of 2011.

4.2 Data

The data used in this thesis mainly comes from the DREAM database of the Danish Ministry of Employment, which contains information on weekly transfers for the whole Danish population. Data is available from mid 1991 and the latest version accessible to me ran until July 2017. The received transfers are distinguished by type and thus make it possible to calculate the unemployment duration in weeks for every person registered in Denmark as well as the transition into social security, transitions out of the labor force and several other states. Information on employment and wages comes from the BFL register of Statistics

[5]In 2008 this was 703 DKK per day for former employed as well as 766 DKK per day in 2011

[6]Individuals entering the system in 2008 were the last ones receiving benefits for four years and the duration was cut step-by-step until individuals entering the system in 2011 were the first ones subject to two years of benefit entitlement.

Denmark which contains detailed information on received income and time spent working since 2008.

The empirical basis for the structural estimation of this paper are two cohorts of insured unemployed individuals who entered the system with a full availability of benefits around the unemployment insurance reform and who held a regular job prior to this for at least 4 continuous weeks. That is on the one hand the 2008 cohort which was the last cohort to receive benefits for 4 years as well as the 2011 cohort which was the first group of recipients that were faced with only 2 years of benefits after the reform of the unemployment insurance system. To allow for out-of-sample consistency checks I am using the cohort of individuals that entered the system in the second half of 2010. This group was directly affected by the extension of the benefit period, but did not expect this while entering unemployment in the first place.

Due to the availability of special pension schemes and other labor market programmes I exclude individuals older than 49 years at any point during their unemployment spell and further exclude individuals that start unemployment with an age younger than 25 years. I allow for up to four weeks in self-support, without benefits or income from employment, before exit into employment and the job must held for four continuous weeks at least. Spells that end with leaving the labor force or transitioning into self-support longer than four weeks are censored. Due to the fact that interruptions in the unemployment spell occur rather frequently, I allow the individuals to temporary leave the unemployment category for up to three weeks and still regard the spell as uninterrupted.

Table 1 shows the basic descriptive statistics for both cohorts that are used in the structural estimation. It is evident that both cohorts are differ significantly, yet the differences are generally small and negligible with a few exceptions such as gender. Further robustness checks will therefore control for the observational differences when estimating the hazard rates in addition to the procedure of the following section[7].

4.3 Empirical Hazard Rates

The structural model of this paper is estimated on the empirical hazard rates out of unemployment and the corresponding re-employment wages. I use a simple linear probability model to estimate the hazard rates for pre- and post-reform separately for each period after entering the spell, following DellaVigna *et al.* (2017):

$$h(t_i^* = t | t_i^* \geq t) = h_{0,t} + h_{1,t} d_{2008,i} + \epsilon_{it} \tag{10}$$

[7] Work-in-progress.

where $h_{0,t}$ is the baseline hazard for the 2011 cohort and $h_{0,t} + h_{1,t}$ marks the hazard in the 2008 regime. Figure 1 plots the results of the estimation for the hazard rates. The data clearly shows interesting dynamics around the point of benefit exhaustion in both regimes.

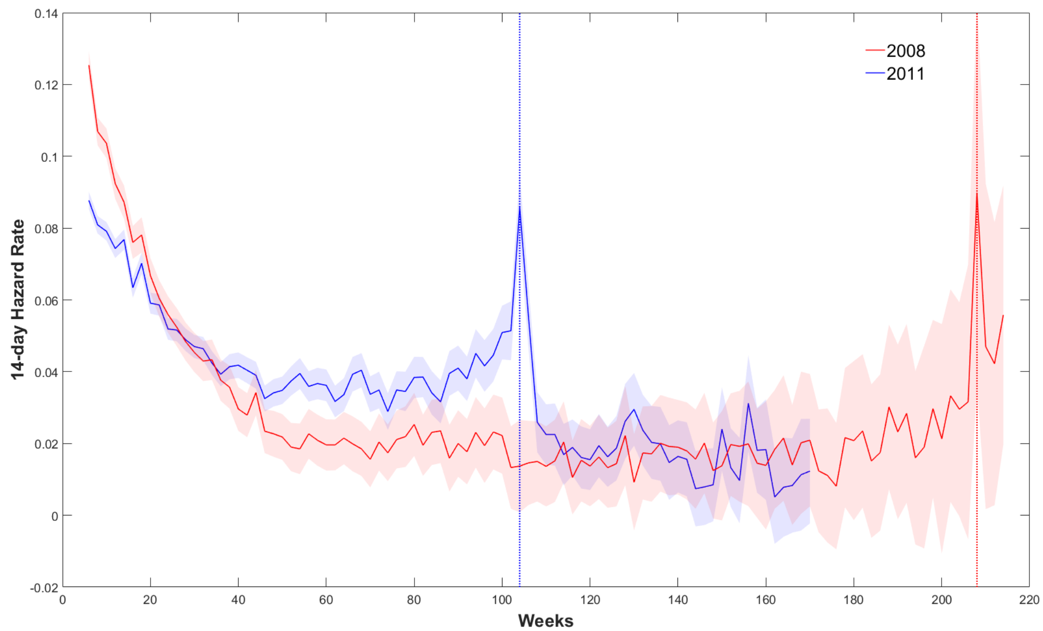

Figure 1: 14-day hazard rates from unemployment into employment for three different benefit regimes in Denmark with 95% confidence bands, vertical lines indicate benefit exhaustion.

Looking at the 2008 data, the hazard rates are dropping sharply right after the beginning of the unemployment spell and just begin to increase in anticipation of the transition to social security with a peak at week 208. The sample size after this peak is not big enough to observe more of the dynamics and estimate a possible reference point adaption after this. In the 2011 cohort the benefit exhaustion occurs much earlier and one observes a lager amount of individuals entering social security in this cohort. Interestingly, there are differences in the hazard rates right after the unemployment spell start. While the hazard still decreases strongly after entering unemployment it does so much slower than in the pre-reform regime and it also stays on a higher level afterwards. Nevertheless, I observe that both cohorts show stable search efforts from the same time around week 45. As expected the hazard rates show a strong spike at the point of benefit exhaustion and decline sharply afterwards, falling roughly to the same level as the 2008 cohort.

The average re-employment wages in figure 2 are a relatively noisy measure with a high variance, especially after the 2 year mark. One can however make out some slight trends as shown in the depicted figure. For both regimes the re-employment wages are mostly

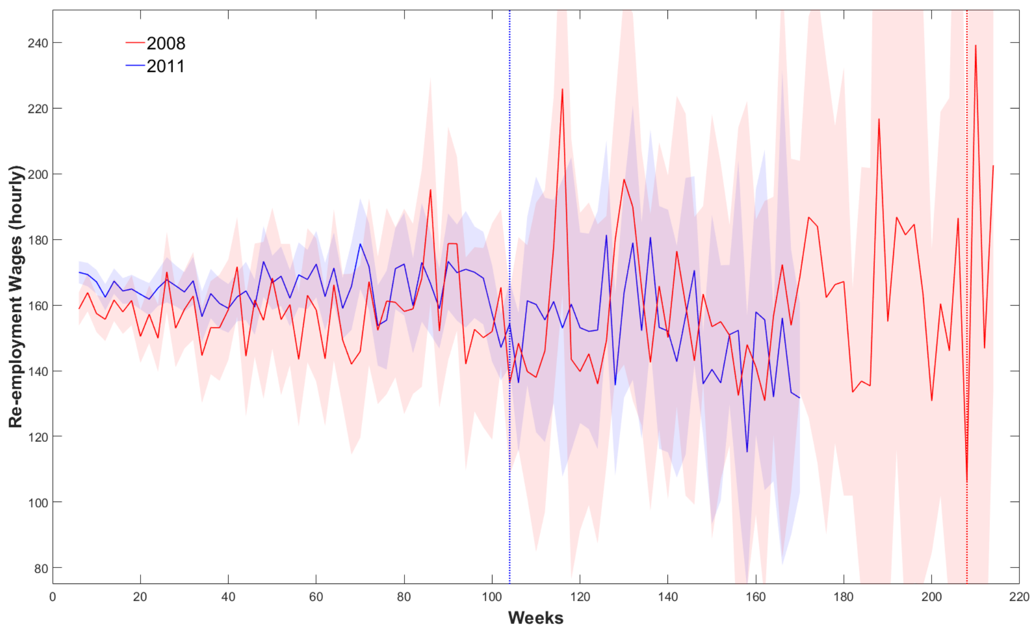

Figure 2: 14-day re-employment wages for two different benefit regimes in Denmark with 95% confidence bands, vertical lines indicate benefit exhaustion.

stationary right from the unemployment spell start. The 2011 data shows a level change after the benefit exhaustion and seems to be decreasing somewhat afterwards, though the confidence bands are wide. For the 2008 cohort one cannot make out such a trend as there is clear lack of data availability after the benefit exhaustion. The wages are stable over the full spell, even though the second half shows a high volatility in the data. One carefully can conclude that there seems to be very slight effect of the benefit exhaustion, lowering the re-employment wages while they are relatively stationary at other times.

5 Estimation

5.1 Functional Form Specifications

To solve the model and to estimate the parameters of interest I need to establish some further assumptions. Following DellaVigna *et al.* (2017) I define the search cost function, that depends on the effort input, in power form such that $c(s_t) = \frac{ks_t^{1+\gamma}}{1+\gamma}$. This way γ represents the inverse search effort elasticity with respect to the individuals net valuation of employment. Further, I also specify the utility as a simple log function, $v(b) = ln(b)$ which brings concavity. I fix the exponential two-week discount factor at $\delta = 0.995$. This is done as δ is not separately identifiable from other estimated parameters like the search costs k and features of the benefit structure, i.e. ψ. It is therefore common practice to fix it at prespecified values (Paserman, 2008). The wage offer distribution is assumed to be a time invariant log-normal distribution and independent of the search effort s_t, thus it depends only on the distributional mean μ_w and standard deviation σ_w and can be recovered from the distribution of accepted re-employment wages that are observed in the data (Flinn and Heckman, 1982).

In some of the estimations I assume unobserved heterogeneity in the search costs which leads to two types of agents with population shares p_l for the lower cost type k_l as well as $1 - p_l$ for the higher cost type k_h.

The bi-weekly pre-unemployment wage is set to the rounded median of the individuals who became unemployed and claimed benefits, that is 14,400 DKK for 2011 and 14,200 DKK for 2008. The median claimed unemployment insurance benefit is 7,660 DKK in 2011 and 7,030 DKK in 2008, both corresponding to the maximum available benefit level in the respective years.

5.2 Minimum-Distance Estimation

To estimate the parameters of interest I use a minimum distance approach, as described in Cameron and Trivedi (2005). Minimum-distance estimation is a mathematical technique that allows to estimate model parameters in settings were a maximum likelihood method is not practicable due to problems in obtaining the likelihood functions or difficulties in their evaluation. The method replaces the likelihood function with the distance between empirical and parametric moments and minimizes this objective function. The parametric moments are the hazard rates for every period obtained from the model, which was descried in section 3, while the empirical moments are the empirical hazard rates out of unemployment obtained in section 4. The vector of model parameters is then estimated by:

$$\hat{\theta} = \arg\min_{\theta} \, (h(\theta) - \hat{h})' W (h(\theta) - \hat{h}) \tag{11}$$

where $\hat{\theta}$ is the minimum-distance estimate of the underlying parameters of the model, i.e. λ, the magnitude of the loss aversion, N, the adjustment speed of the reference point, β, the hyperbolic-discounting parameter, π and ξ, the parameters defining the bias in the beliefs about the subjective job finding probability, k and γ, specifying the search costs and their curvature, ψ, the share of the benefits that is payed out as welfare transfers as well as the mean and standard deviation of the wage offer distribution $F(w)$. The hazard moments generated by these parameters are $h(\theta)$ and the empirical hazard rates found in the underlying data are $\hat{h}$. The estimator is weighted by a weighting matrix W, a diagonal matrix with the inverted variance of each moment. Given this, the minimum-distance estimator (11) achieves normality with variance

$$V(\hat{\theta}) = (\hat{G}'W\hat{G})^{-1} \cdot (\hat{G}'W \cdot Var(\hat{h}) \cdot W\hat{G}) \cdot (\hat{G}'W\hat{G})^{-1} \tag{12}$$

where $G = \frac{\partial h(\theta)}{\partial \theta'} |_{\hat{\theta}}$ (Cameron and Trivedi, 2005).

In the estimation of the parameters I supply 376 bi-weekly moments from the empirical data[8]. To find the minimum of the objective function (11) I use the *MultiStart* class of the *Global Optimization Toolbox* in *MATLAB*, as conventional solvers tend to find local solutions and computation times turn out to be extremely large. The *MultiStart* class runs *fmincon*[9] routines from a range of different starting values and obtains the global solution to the problem as the minimum of all local optima. Additionally, it offers parallel computing options that run the estimations with different starting values on multiple processor cores, effectively separating sub-tasks of the computations to more processor cores in order to decrease overall running time.

I start the estimation with a scattered grid of 200 starting points. Additionally, I restrict the bounds for other parameters to a wide, yet economically reasonable interval. I am aware that under the highly non-linear structure of the minimization problem I can never guarantee to find the true global minimum, but I am confident that the number of starting points leads to satisfactory outcomes, especially as the best solutions all tend to converge to roughly the same values.

5.3 Identification

Due to the chosen estimation strategy all parameters are identified jointly in the minimum-distance process. Just like in DellaVigna *et al.* (2017) and Paserman (2008) it is however possible to roughly classify the central sources of identification of the parameters. The inverse of the search cost elasticity towards utility gains of becoming employed, i.e. the search cost curvature γ, is identified by the sharpness of the hazard rate reactions towards changes in the income, such as the initial unemployment spell or the transition into social security at week 104. When looking at a standard model, turning off the behavioral extensions, one can clearly observe that the heterogeneity in the search costs enables shrinking search efforts after the benefit exhaustion compared to the model without heterogeneity. Thus the search

[8]83 hazard moments and 83 re-employment wages from 2011 as well as 105 hazard moments and 105 re-employment wages from 2008

[9]Minimizer for constrained nonlinear multivariable functions.

costs k_i are identified by the non-linearities in the path of the hazard rates as well as by the overall level of the hazard rates. Further, the loss aversion parameter λ is identified by the magnitude of the spike around the income shocks as well as the dynamics leading up to it. The length of this effect, i.e. the time until the search effort becomes constant after the transition into social security identifies the adjustment speed of the reference point N. As argued in Paserman (2008), the short-run discounting parameter β is identified by the relative difference between search efforts and the distribution of accepted re-employment wages. The parameter has no effect on the wages which are a future payoff (and thus independent of β), yet it directly influences the search decisions which lead to costs in the present. Lastly, the overconfidence parameters π and ξ are identified by relative differences between the initial search efforts to the later level, especially around the income shocks.

6 Results

The outcome of the estimation for the full model (1), that is the model that includes all biases introduced in section 3, is shown in table 2 as well as figures 3 and 4. The model exhibits a relatively strong data fit over both benefit regimes. Right from the unemployment start the simulated hazard rates are extremely close to the empirical moments and the distinct difference between the 2008 and 2011 cohorts is captured well. Up until the point of benefit exhaustion one can observe a continued strong fit for the simulation of the 2011 cohort, though the strong spike at this point is not completely captured. One of the reasons for the extreme hazards here could potentially be some sort of exploitation of the unemployment insurance system by delaying starting times for newly found jobs and therefore subsidized leisure until the benefits are exhausted. Boone and Van Ours (2009) find some evidence for this on Slovenian data.

After the benefit exhaustion, the empirical hazards fall a bit faster than the simulated ones, but the model catches up quickly with a continued strong fit to the data. For the 2008 cohort one can observe a continually close fit to the dynamics of the empirical data, while the same problems of capturing the spike at benefit exhaustion are obvious. Looking at the parameter estimates one can observe relatively tight confidence bands around the coefficients which hints at a proper identification of the model, with an exception of the hyperbolic discount parameter β. This leads to the conclusion, that under this model present bias does not seem to play a role. Further, the loss aversion parameter λ falls almost exactly onto the usual estimates from prior experimental studies (Tversky and Kahneman (1991), Tversky and Kahneman (1992)). The perceived job offer arrival rate is roughly 32% higher than the actual one at the beginning of the unemployment spell and falls to about 10% after two as

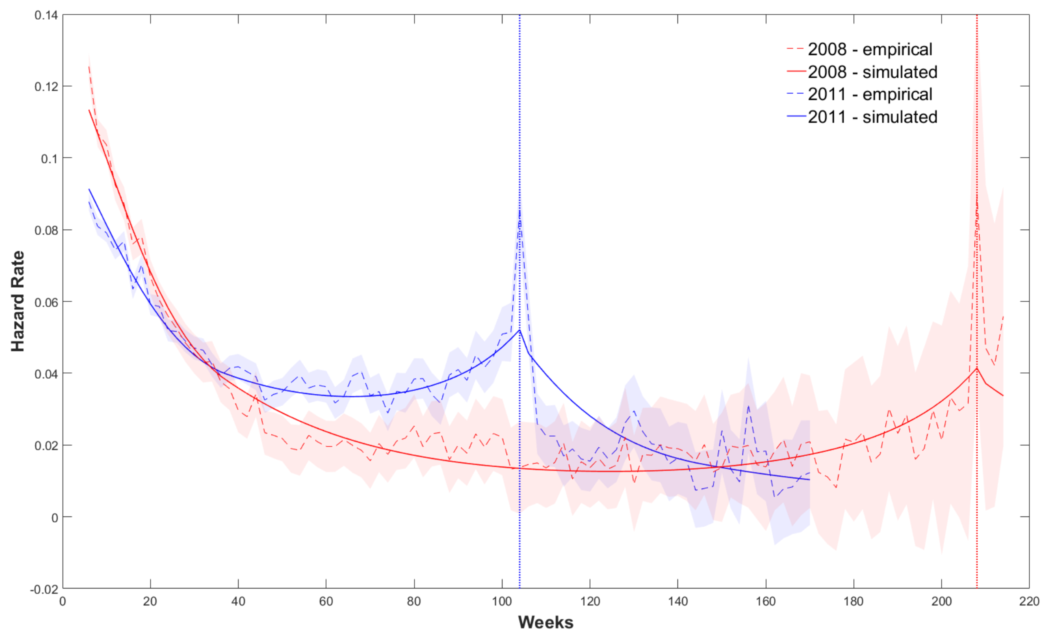

Figure 3: Empirical and estimated hazard rates for two benefit regimes.

well 3% after four years, hinting at some degree of overconfidence in job search that gradually adjusts.

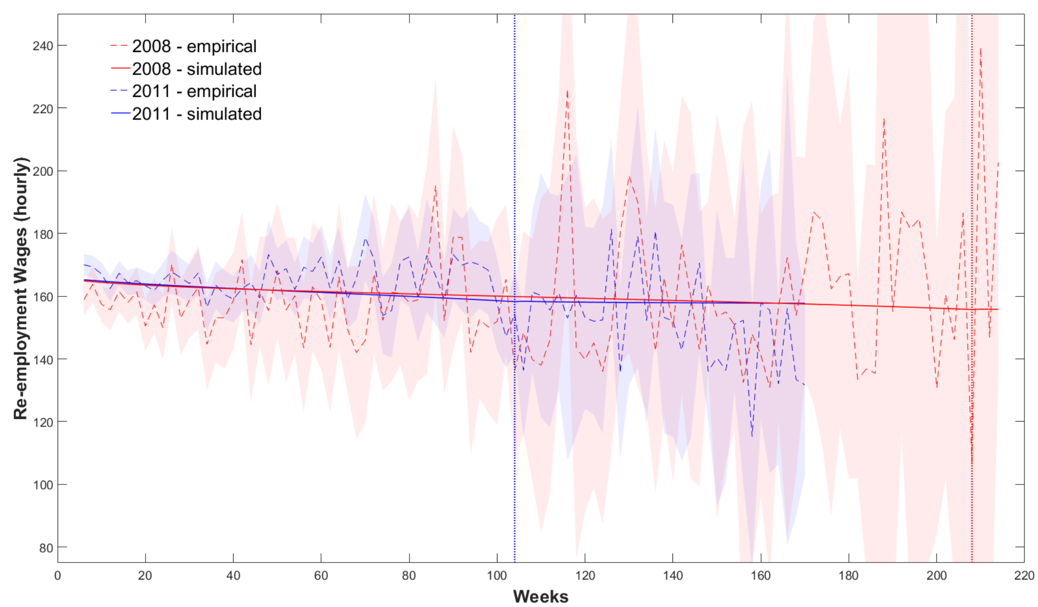

Figure 4: Empirical and estimated re-employment wages for two benefit regimes.

As the re-employment wages are somewhat volatile, but fluctuate mostly around a constant level, one does not observe much variation in the simulated moments. The modeled re-employment wages are nevertheless able to capture the level of the data quite well and there is also a (very) slight decrease in the 2011 cohort after benefit exhaustion. As the simulated moments generally fall within the confidence bands of the empirical data I conclude that the simulation here works well enough.

The outcomes for the reference dependence specification (2) can be found in figures 5 and 6. It becomes obvious that this model has a harder time fitting the data and over- or undershoots the empirical hazards at several points quite severely. One also has to note that the estimate for the loss aversion parameter λ is quite high in comparison to usual literature estimates. Due to the very low estimate of the standard deviation of the wage offer distribution, the re-employment wages are essentially flat. The standard model (3) with unobserved heterogeneity, which can be found in figures 7 and 8, requires a very low search cost estimate for the low type to fit the initial decline in the hazard rates. This leads to the situation that almost all low types have left the unemployment insurance system after two years for the 2011 cohort and the hazards become essentially flat over the social security spell, clearly diverging from the empirical data. Just as in the cases before, the re-employment wages are also virtually flat, induced by a very low estimate of the wage offer standard deviation.

At last I estimate the reference dependence model (4) with unobserved heterogeneity of two types. The outcomes are shown in figures 9 and 10. The model shows a strikingly good fit on the 2011 cohort and even matches the benefit exhaustion spike almost perfectly. The fit on the 2008 data becomes a bit worse relative to the full model, but performs better than the basic reference dependence specification (2), yet it somewhat undershoots the hazards from weeks 70 to 170 as well as at the point of benefit exhaustion here. The goodness of fit measure (GOF) increases by roughly 17% in comparison with the full model and it also estimates the reference dependence parameter λ at a similar magnitude. When looking closer at the estimates, two issues appear with this model estimation. First, the welfare fraction of the original benefits ψ falls to an unreasonably low level of around 22%, which induces the stark increase in the hazards prior to benefit exhaustion as well as the strong drop afterwards. This level corresponds to roughly 1685 DKK of bi-weekly welfare transfers over the rest of the unemployment spell while the average bi-weekly welfare transfer at the same time in Denmark amounted to about 3665 DKK[10]. Further, following DellaVigna *et al.* (2017) who also find strong model performances under unobserved heterogeneity, I have a look at the dynamic selection throughout the UI spell. I regress the individual

[10] See Statistikbanken, DST.dk

unemployment duration on observable characteristics[11] and predict the expected duration in unemployment for every individual. When plotting these values over time together with the corresponding expected duration of the model simulations in figure 11, it becomes apparent that the reference dependent model with two cost types needs an unreasonably high degree of heterogeneity and type-shifts to fit the dynamics of the data. These strong type shifts are clearly induced by the wide differences in search-costs for the low- and high type. While the data does not exhibit a constant expected duration over time, the path is relatively flat and the full model without type-shifts falls reasonably close. I conclude that the good fit of model (4) is thus somewhat suspicious as the needed degree of heterogeneity is enormous relative to the data, even though only a part of the selection is observed. I therefore continue to employ the full model (1) which shows a good data fit and a much closer expected duration relative to the data.

7 Robustness and Consistency

WORK-IN-PROGRESS

8 Policy Evaluation

8.1 Hypothetical Policies

Following Paserman (2008), I can use the earlier estimated models to evaluate hypothetical changes in the unemployment insurance system as the search effort was linked to the hazard rates out of unemployment. This becomes especially interesting when considering the reference dependence and a hypothetical multi-step unemployment insurance system under which the actual paid out benefits drop more often than just after 104 weeks when the unemployed job seeker enters social security. I can analyze the job seekers welfare, the government expenditure, the expected unemployment duration as well as the share of individuals entering the social security system induced by different policies and thus I am able to give simple policy recommendations based on the results. As Paserman points out, one needs to be aware that the presented model is not a general equilibrium model. The models lacks the government side that finances the unemployment insurance transfers through taxes as well as the firms that hire the workers. Policy analysis on partial equlibria, just like in the case of this paper, therefore needs to be viewed with caution.

[11] The unemployment duration is estimated on gender, age, age squared, kid, married, ethnicity, region of residence, living in city, education, pre-unemployment wage, prior occupation and generates a reliable R^2 of 0.05

There are four policies of interest that I am evaluating, two of which are standard in the policy evaluation literature on UI systems. The first one simply cuts the benefit level b_1 over the whole range of unemployment insurance entitlement by a certain amount so that the unemployed job seekers receive less benefits in every period. Similar policies that involve cuts or increases of the benefit level have been studied widely (Carling *et al.* (2001), Eugster (2015), Lalive *et al.* (2006)) and generally point to positive effects of benefit cuts on the unemployment duration, i.e. a lower (higher) benefit level decreases (increases) the unemployment duration. Second I evaluate a reduction of the unemployment insurance entitlement length, i.e. a cut of the duration the benefits b_1 are paid to the unemployed job seeker before she transitions into social security. The shortening and extension of benefit entitlement was also subject to prior examination (Van Ours and Vodopivec (2006), Card and Levine (2000)) and the evidence leads to roughly same conclusions as benefit cuts.

Third, I evaluate a relatively new idea of re-designing the unemployment insurance system. Just like DellaVigna *et al.* (2017) propose, consider an unemployment insurance system that pays benefits $\bar{b}$ for T_1 periods until the unemployed individuals transition to benefits $\underline{b}$ from period T_1 until T. From T onward the individuals who are still unemployed are subject to social security transfers b_2, just as in the status-quo. Assume now that a hypothetical change from a one-step to a two-step system (*front-loading*) would occur in the unemployment insurance in a way such that the total amount of benefits payed for an unemployed job seeker over T periods is exactly the same as in the current setting. This would change the system from $\bar{b} = \underline{b} = b_1$ (the initial case) to $\bar{b} > b_1 > \underline{b} > b_2$, which needs to satisfy the following identity:

$$\bar{b}T_1 + \underline{b}(T - T_1) = b_1 T \tag{13}$$

The new step after T_1 here could possibly exploit the reference dependence of the job seekers to induce higher search efforts around the new benefit drop due to the same dynamics present in the empirical data when transitioning into social security. The conclusion will however highly depend on the magnitude of loss aversion λ as well as the length until the reference point adapts. I further evaluate a three-tier system under which the unemployed job seeker receives $\bar{b}$ for T_1 periods until her benefits decrease to the initial level b_1 for T_2 periods. After this she again drops to the third benefit tier with $\underline{b}$ before entering the social security system at T. I still assume the same condition as in equation (13), which in this case updates to $\bar{b}T_1 + b_1 T_2 + \underline{b}(T - T_1 - T_2) = b_1 T$.

At last I consider a re-employment bonus that is paid out as a lump-sum transfer if employment has been found during the first year of unemployment. This makes obtaining a job more attractive relative to continued unemployment and following the theoretical model this increases search effort. The reference dependent utility might also have effects here, as the bonus is evaluated as a gain during employment until reference point adaption. The literature on re-employment bonuses is not conclusive as experimental evidence has shown positive effects on re-employment speed (Woodbury and Spiegelman (1987), Anderson (1992), Decker and L'Leary (1995)) as well as null-effects in more recent settings (Van der Klaauw and Van Ours, 2013).

8.2 Evaluation

For the analysis I use the model estimations that generated the best fit to the empirical data while showing a reasonably close expected duration relative to the observed data, i.e. the full model (1) with all added extension. The present bias in the formulation of the theoretical model induces dynamic inconsistency and thus a definition of the job seekers welfare is hard to choose as plans, actions and expectations differ over the time paths. I follow Paserman (2008) here who evaluates the utility of the long-run selves of the job seekers, just like in O'Donoghue and Rabin (2001). Paserman evaluates the modelled decision paths of the present biased agent using normal exponential discounting. As Paserman points out this welfare measure somewhat represents a not-unemployed voter deciding about possible changes of the UI system. Fortunately, the benchmark estimation does not indicate any present bias and thus circumvents this problem as the long run utility here corresponds to the utility of the hyperbolic discounter.

Further, I evaluate the expected duration in unemployment under all policy regimes. The average expected duration is defined as the integral under the estimated survival curve and in the discrete case here it is calculated as:

$$\hat{\mu} = \int_0^\infty \hat{S}(t)dt = \sum_{i=1}^{m}(t_{(i)} - t_{(i-1)})\hat{S}(t_{(i)}) \tag{14}$$

I calculate the expected government expenditure by multiplying the respective point estimate of the survival rate with the monetary transfer for every period and sum it afterwards. Lastly, the share of individuals entering the social security system is simply the point estimate of the survival curve right after the benefit exhaustion. I present a number hypothetical policy changes as introduced in the preceding section.

The outcomes of changing the benefit level can be seen in figures 12 and 13. One easily observes that a cut of the status-quo benefit level leads to a shorter expected duration in unemployment and this measure is decreasing with the level of the benefit cut, in line with prior literature evidence. The increased speed of exit into employment is due to higher hazards, induced by a lower value of unemployment. On the other hand, the effect of loss aversion weakens around the transition into welfare benefits as the difference between benefits and welfare transfers shrinks. Further, reductions of the government expenditure as well as the share of the people that would exhaust their right to UI benefits can be observed. While these effects of a benefit cut are positive, it has consequences on the long-run utility of the individuals. As one would expect, a decrease of the benefit level lowers the utility even though employment is found faster.

Similar effects can be found when looking at the outcomes of a change of the entitlement length of UI benefits as shown in figures 14 and 15. A shorter entitlement length shifts the benefit exhaustion spike to the left and raises the hazards in anticipation of this point. While the effects on government expenditure and expected duration in unemployment are weaker than under a change of the benefit level, there is a strong effect on the share of individuals exhausting their benefits. Interestingly, even-though a shortening of the entitlement length means that the point of benefit exhaustion approaches faster, the amount of people reaching this point decreases. The reactions on the long-utility are a bit flatter around the status-quo, but show similar dynamics than under a benefit change.

Next I turn to the front-loaded UI system, which is a change from a one-tier to a two-tier benefit path with $T_1 = 52$ weeks. Figures 16 and 17 display the effect of this policy change. The new drop in the benefits after one year induces an additional spike in the hazards with higher rates around this point. A reduction in the difference between prior wages at the unemployment spell start and the welfare transfers at benefit exhaustion dampens the hazards at these points. It is striking that long-run utility is increasing with the level of the first tier of the benefits, while the expected duration as well as amount of people entering social security is decreasing. This increase in the first tier benefits is almost expenditure-neutral on the government side, decreasing the spending by a maximum of roughly 3% when lifting the first benefit tier by 12%. Higher levels of increases eventually lead to increases in the government spending overall. Under a cautious assumption that the structural model under partial equilibrium represents the actual data generating process well enough, a change to a front-loaded benefit structure might therefore lead to desirable changes on all considered measures. The effects are nevertheless relatively weak in comparison with a standard cut in the overall benefits. A three tier system with $T_1 = T_2 = 35$ weeks shows comparable effects as evident in figures 18 and 19. Here two additional and weaker spikes are observed. Interestingly, the government expenditure shrinks in comparison with the benchmark case over the full considered interval of first tier front-loading.

At last I examine the effects of the introduction of a re-employment bonus. The outcomes of this can be found in figures 20 and 21. The hazard paths are raised over the period the bonus is payed and drop sharply once it is not available anymore. Interestingly, the difference between benchmark hazards and the ones under the bonus increases strongly the closer one comes to the end of the first year, a possible implication of the reference dependence and the higher gains once employment is found. When looking at the policy outcomes, one can observe somewhat strong effects even under relatively small bonus payments that quickly flatten out. The government expenditure first decreases, but quickly increases to levels higher than under the benchmark policy with higher bonuses. The strong effects even under low levels of the bonus are induced by relatively low estimated search cost curvature γ and thus a high elasticity with respect to the individuals net valuation of employment. There is nevertheless a region, reaching to roughly 1.5 times the benefit level, under which reduction in expenditure and duration as well as long-run utility increases are observed.

9 Conclusion

In this work I combined approaches that added cognitive biases to models of job search, which were then estimated with a minimum-distance approach. By doing so I was able to achieve a strong and increased fit to the empirical hazard rates on the Danish labor market in comparison with standard models and without relying on unreasonably high levels of unobserved heterogeneity. Especially the combination of reference dependence and decaying overconfidence in job search led to strong results, while a present bias in the form of hyperbolic discounting does not seem to play role. The estimate of the reference dependence parameter λ is surprisingly close to prior findings in experimental settings.

Following the estimations, I used the job search model to evaluate hypothetical changes of the Danish UI system. As expected, reductions in the benefit level or the entitlement length lead to increased re-employment speed as well as decreasing government expenditure, but also lower long-run utility of the job-seekers. As the reference-dependence in the utility of the individuals might have positive implications for the *structure* of the UI system, I also tested the effects of introducing multiple tiers in the UI benefits while holding the total amount of available transfers fixed. It turns out that this front-loading to a two- or three-tier system not only reduces government expenditure and unemployment duration, but also increases the long-run utility of the individuals, a situation that appears Pareto-improving. The same effects can be observed under an introduction of a low-level re-employment bonus.

While I found some interesting effects of the policy changes, the results of this exercise need to be viewed with some caution, due to its nature as a partial equilibrium model. Further, the welfare criterion on the individual side only concerns individuals voting for changes in the system *before* actually entering it. An unemployed job-seeker might as well feel very different about the introduction of a multiple-step benefit system, especially once she has been unemployed for a longer period of time facing the then lower tiers. Further work should therefore shed more light on the welfare criteria as well as on a possible general equilibrium setting of this model, even though the reference dependence would increase the computational complexity in this case enormously.

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Appendix A. Tables

Table 1: Descriptive statistics for both benefit regimes, standard deviations in parentheses.

UI benefit regime	**2008**	**2011**	**T-stat**
Number of Spells	29,255	35,822	
Female	0.41 (0.49)	0.45 (0.50)	-10.53
Age Start	37.15 (6.95)	37.29 (7.03)	-2.43
Child <18y	0.50 (0.50)	0.51 (0.49)	-2.40
Married/cohabiting	0.49 (0.50)	0.50 (0.50)	-2.94
Living in city	0.26 (0.44)	0.27 (0.44)	-2.43
Compulsory education	0.11 (0.32)	0.07 (0.26)	18.22
Secondary education	0.60 (0.49)	0.61 (0.49)	-2.90
Academic education	0.22 (0.41)	0.26 (0.49)	-11.77
Pre-unemployment wage (DKK/h)	192.23 (85.25)	194.07 (77.25)	-2.78

Table 2: Estimates of the different structural model specifications, standard errors in parentheses.

	Full	**Ref. Dep**	**Standard** 2-type	**Ref. Dep.** 2-type
	(1)	(2)	(3)	(4)
Utility parameters				
Discount factor β	1.00	1.00	-	0.970
	(0.003)	(0.015)		(0.009)
Loss aversion λ	2.038	10.448	-	2.337
	(0.167)	(1.891)		(0.083)
Adjustment speed in days N	269	476	-	311
	(14.500)	(1.676)		(5.879)
Belief parameters				
Baseline bias π	0.329	-	-	-
	(0.022)			
Decay ξ	0.022	-	-	-
	(0.001)			
Search cost parameters				
Curvature γ	0.034	0.208	0.136	0.145
	(0.003)	(0.043)	(0.020)	(0.016)
Costs k	153.642	226.158	-	-
	(17.315)	(21.574)		
Population share low type p_l	-	-	0.632	0.830
			(0.008)	(0.039)
Costs low type k_l	-	-	24.647	39.483
			(2.694)	(3.687)
Costs high type k_h	-	-	137.277	459.858
			(7.073)	(51.567)
Other parameters				
Wage offer mean (log)	9.219	9.397	9.384	9.359
	(0.095)	(0.008)	(0.005)	(0.008)
Wage offer std. deviation	0.536	0.195	0.106	0.161
	(0.082)	(0.034)	(0.013)	(0.014)
Welfare fraction ψ	0.740	0.800	0.713	0.216
	(0.007)	(0.006)	(0.023)	(0.039)
Model fit				
Used moments	376	376	376	376
Estimated parameters	10	8	7	10
GOF	720.9	1283.2	1284.5	594.8

Appendix B. Figures

Reference Dependence Model

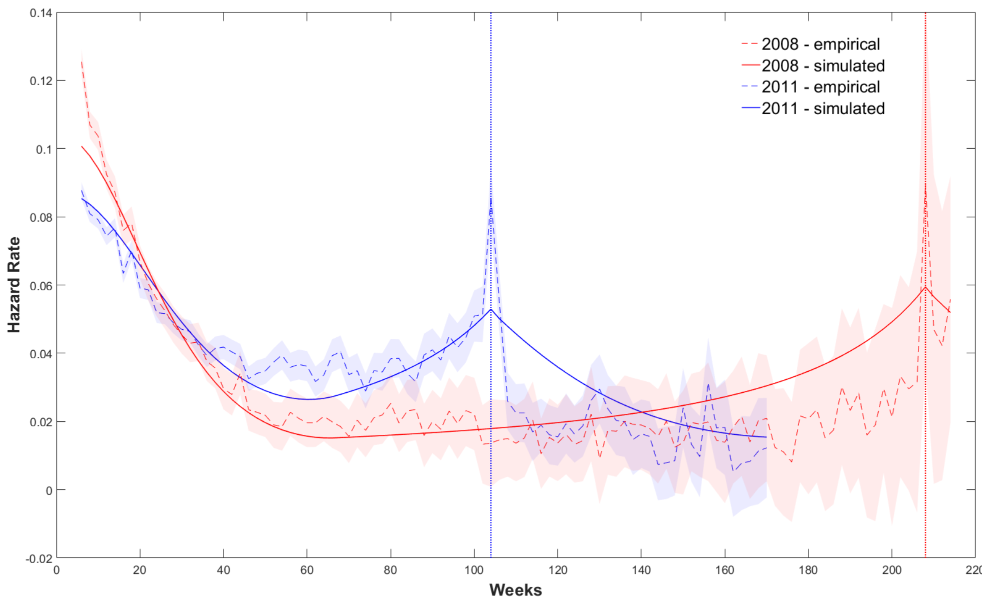

Figure 5: Empirical and estimated hazard rates for two benefit regimes.

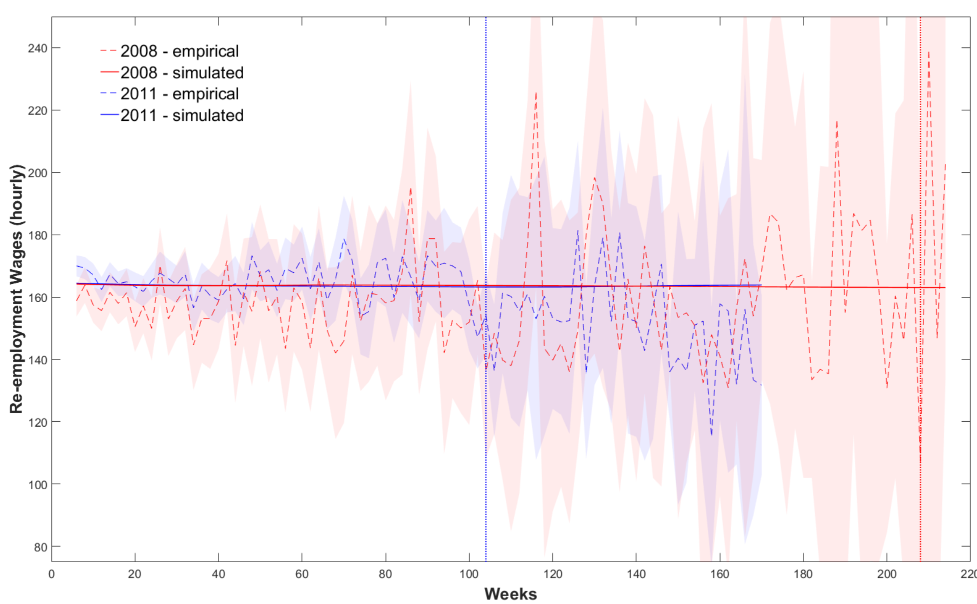

Figure 6: Empirical and estimated reemployment wages for two benefit regimes.

Standard Model

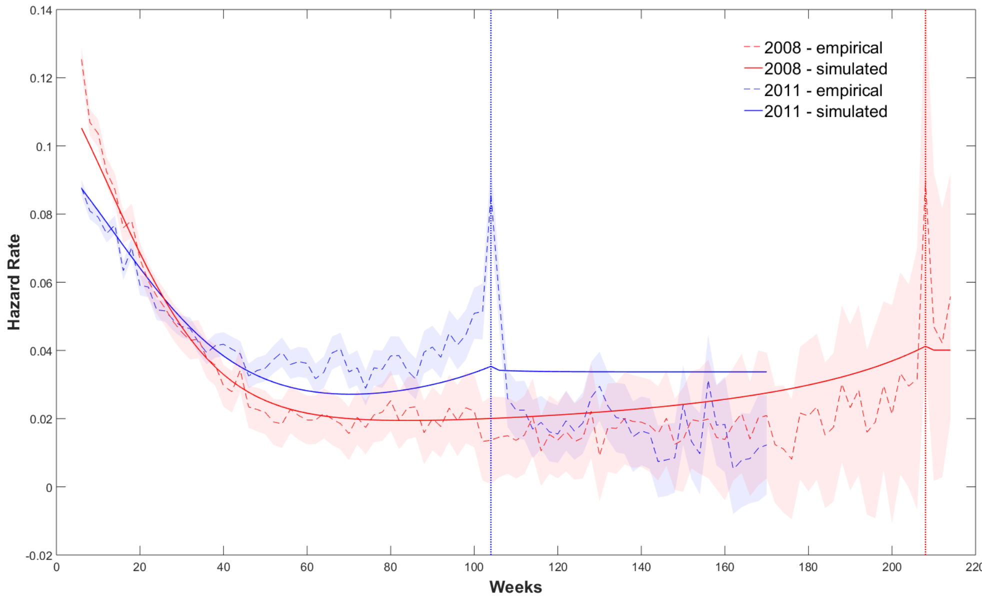

Figure 7: Empirical and estimated hazard rates for two benefit regimes.

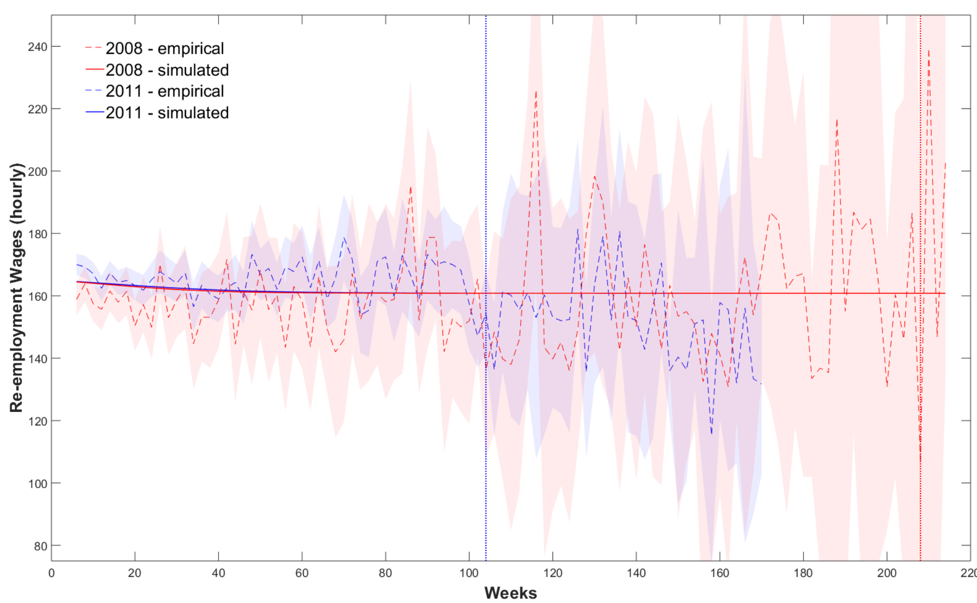

Figure 8: Empirical and estimated reemployment wages for two benefit regimes.

Reference Dependence Model with Unobserved Heterogeneity

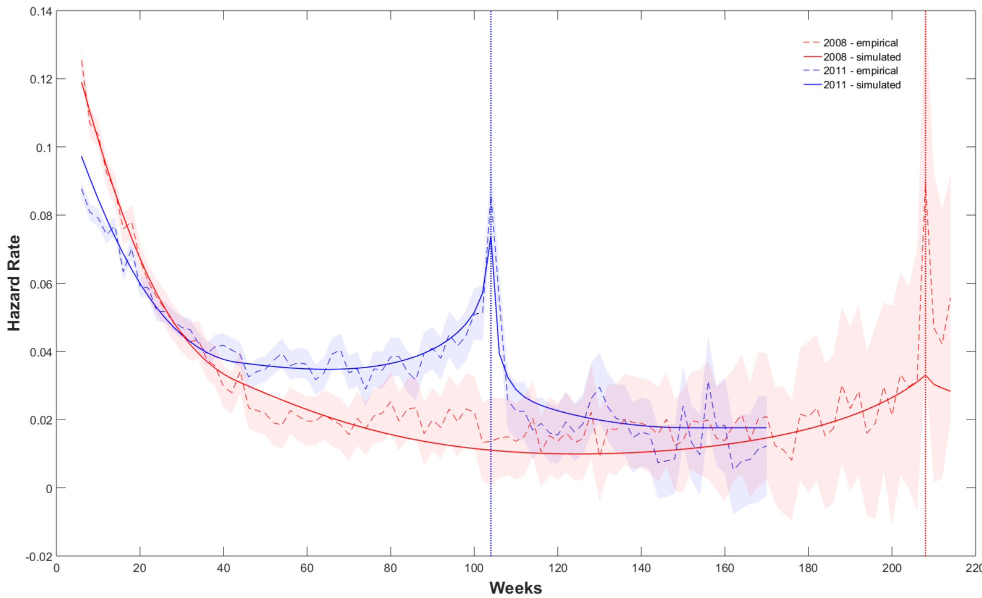

Figure 9: Empirical and estimated hazard rates for two benefit regimes.

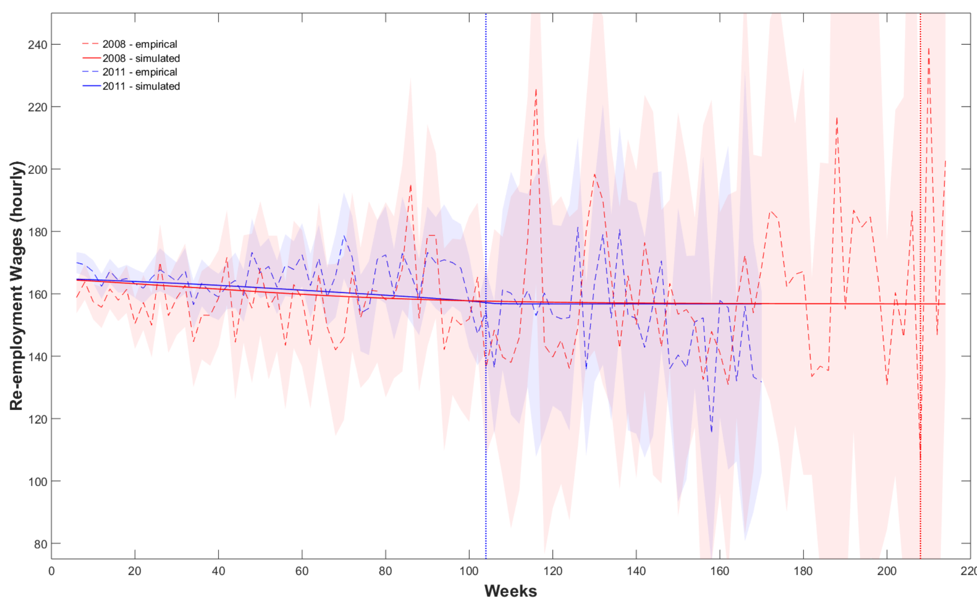

Figure 10: Empirical and estimated reemployment wages for two benefit regimes.

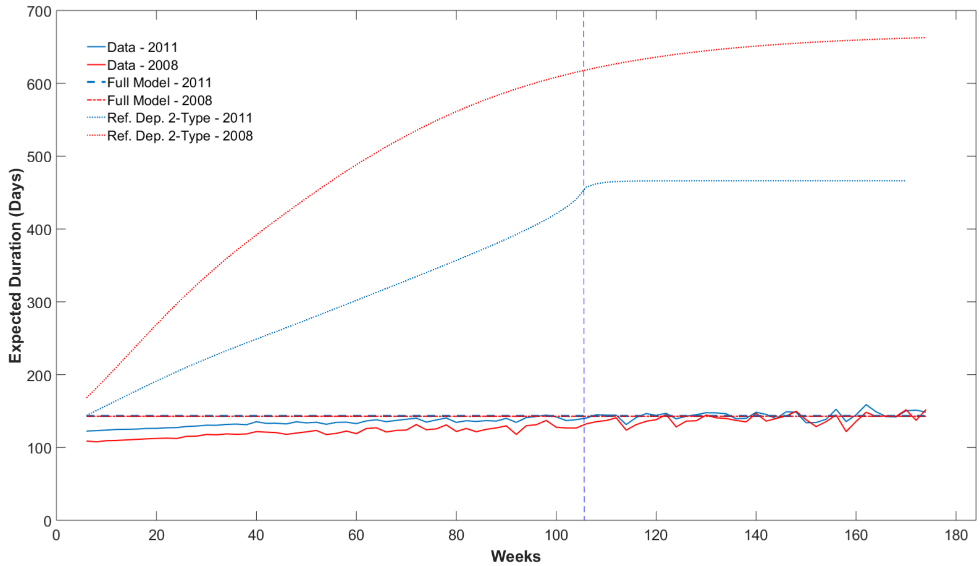

Figure 11: Predicted unemployment duration of individuals exiting at t, regression of unemployment duration on observable characteristics and model outcomes induced by type-shifts.

Policy Evaluation

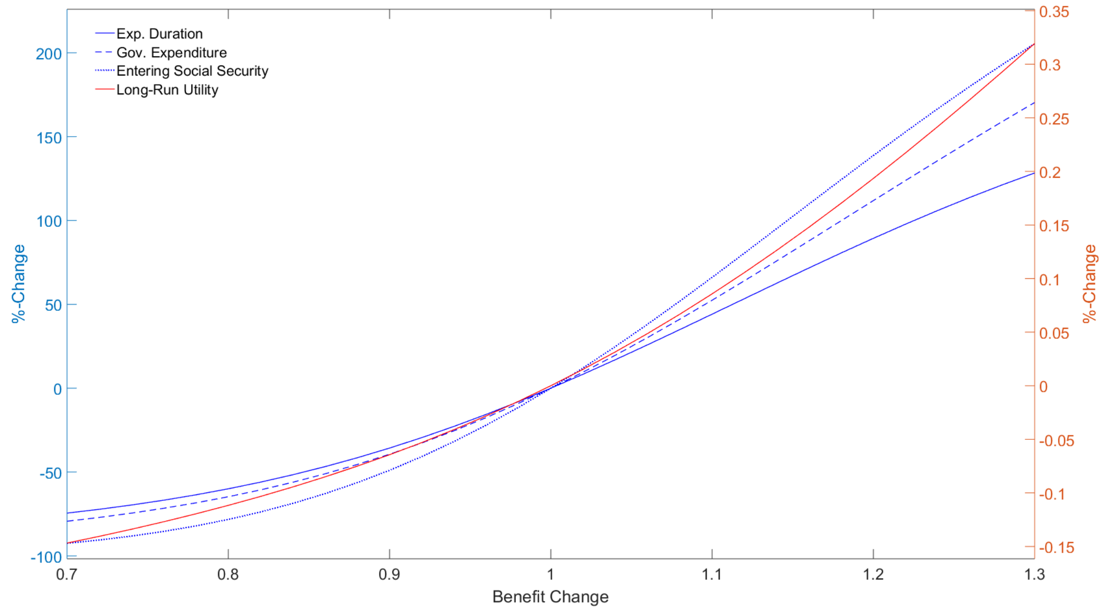

Figure 12: Outcomes of changes of the benefit level, fraction of original benefits on the x-axis.

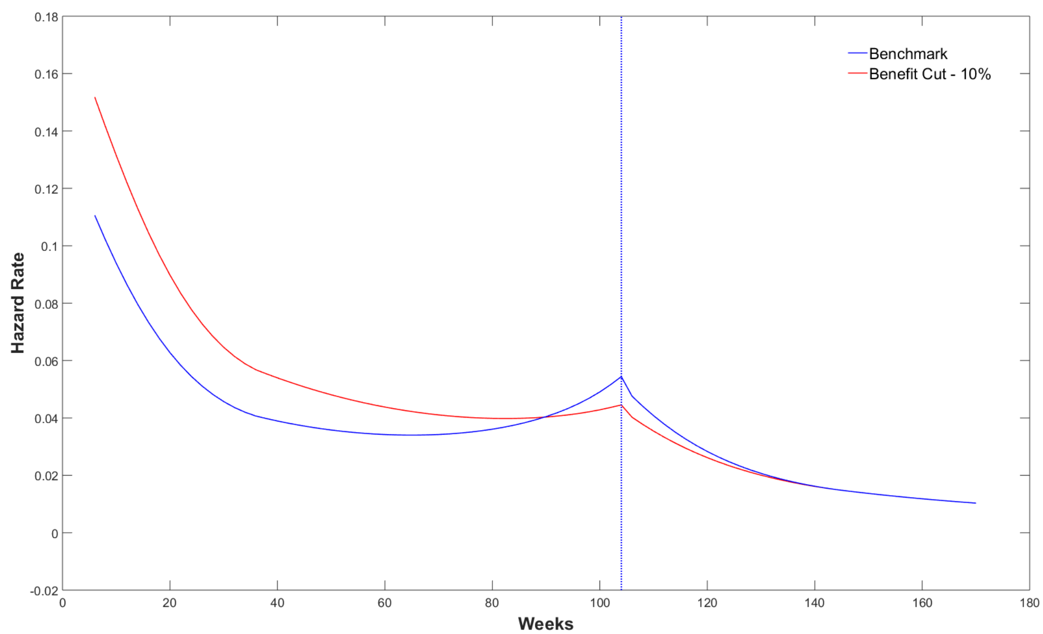

Figure 13: Hazards under changes of the benefit level.

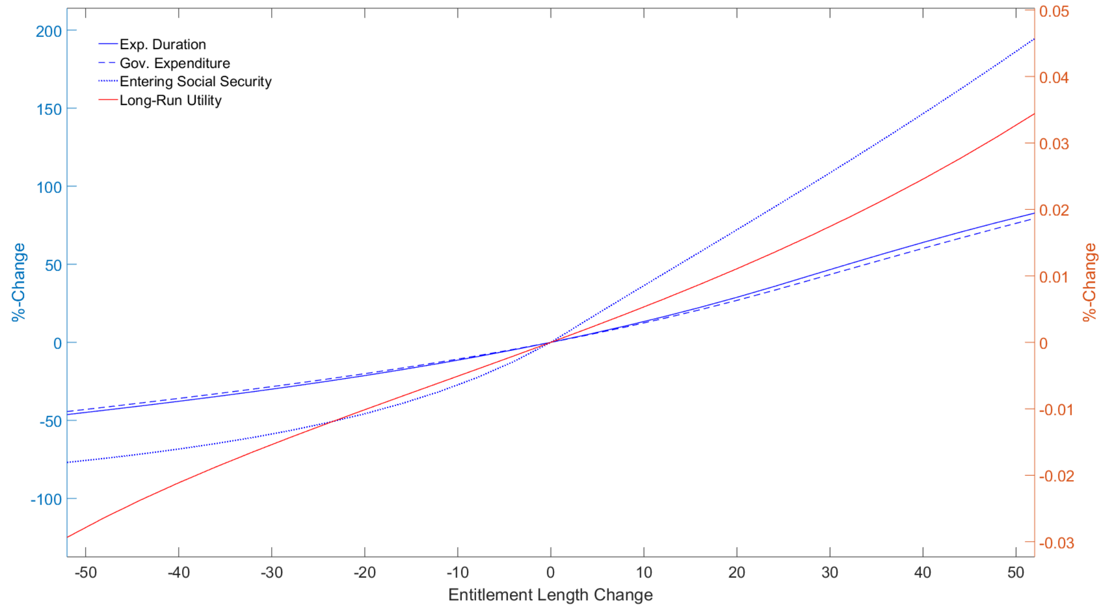

Figure 14: Outcomes of changes of the entitlement length, change in weeks on the x-axis.

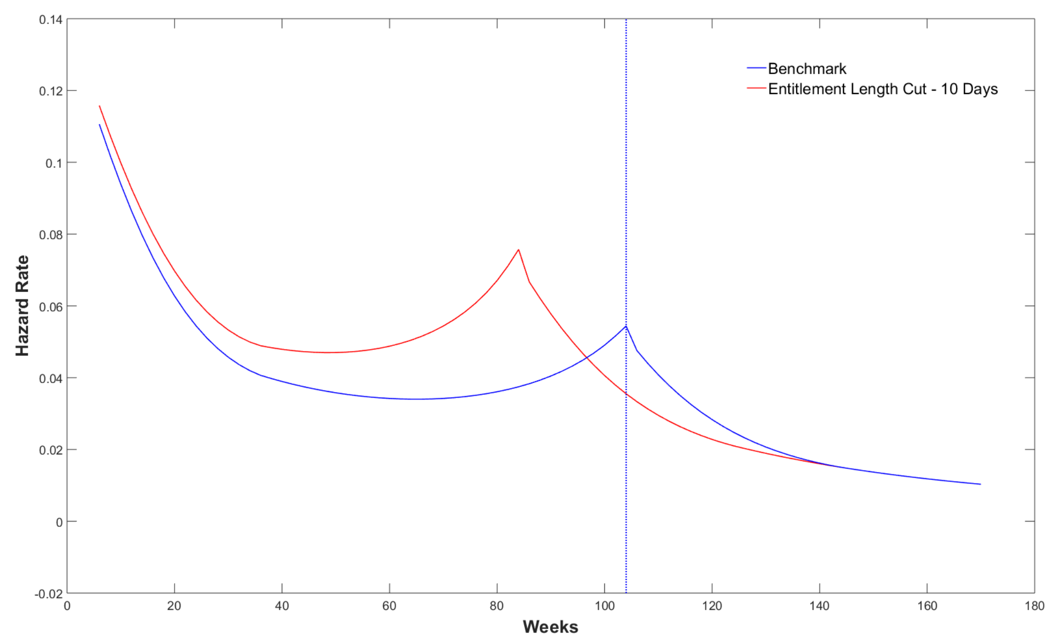

Figure 15: Hazards under changes of the entitlement length.

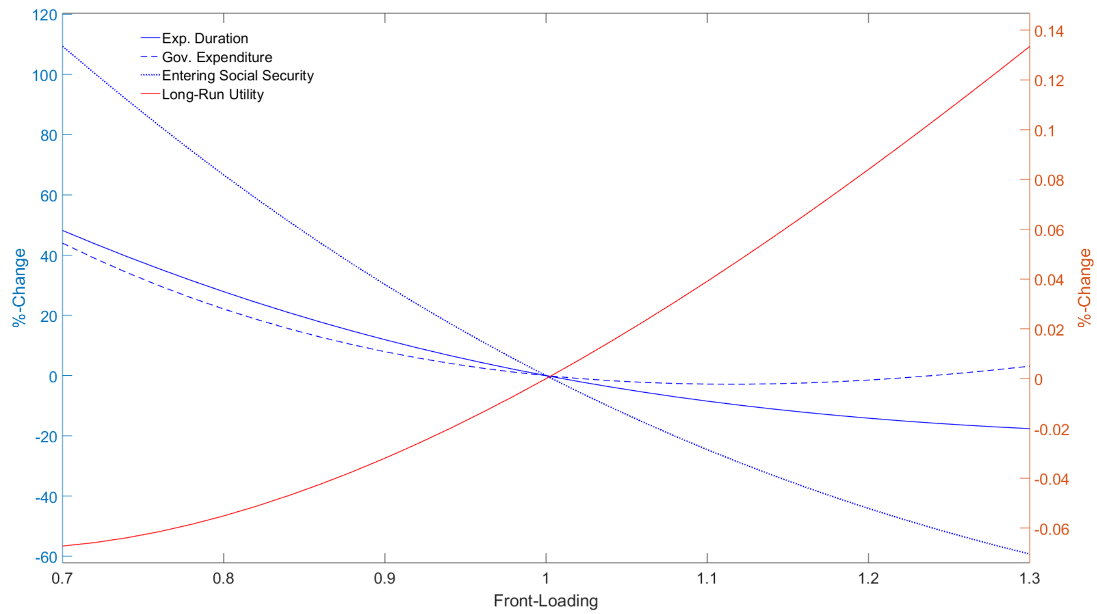

Figure 16: Outcomes of front-loading the benefit path with two tiers, first tier benefits as a fraction of original benefits on the x-axis.

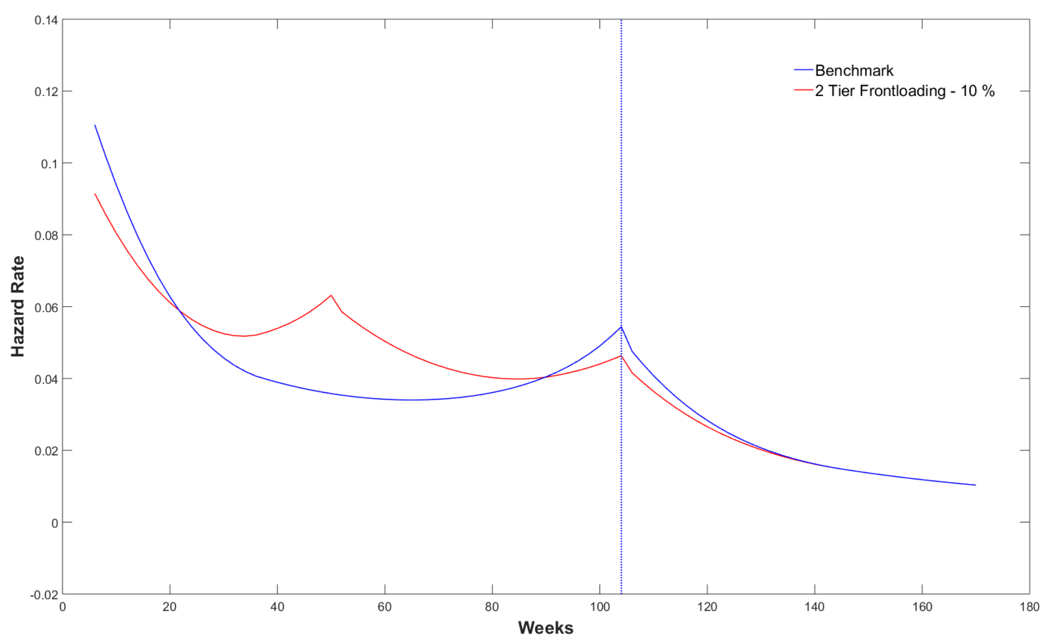

Figure 17: Hazards under front-loading the benefit path with two tiers.

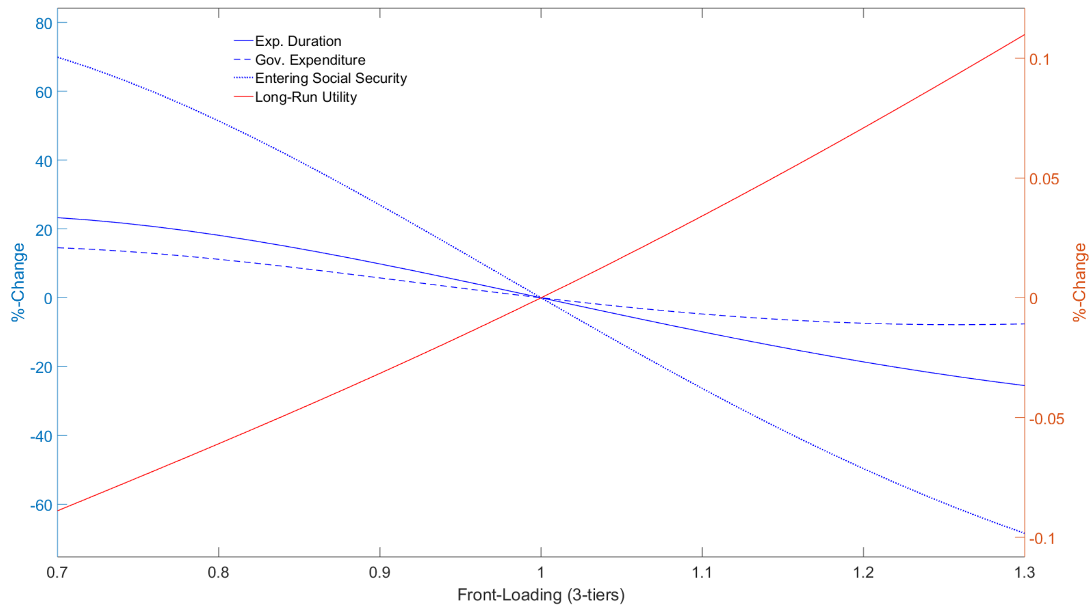

Figure 18: Outcomes of front-loading the benefit path with three tiers, first tier benefits as a fraction of original benefits on the x-axis.

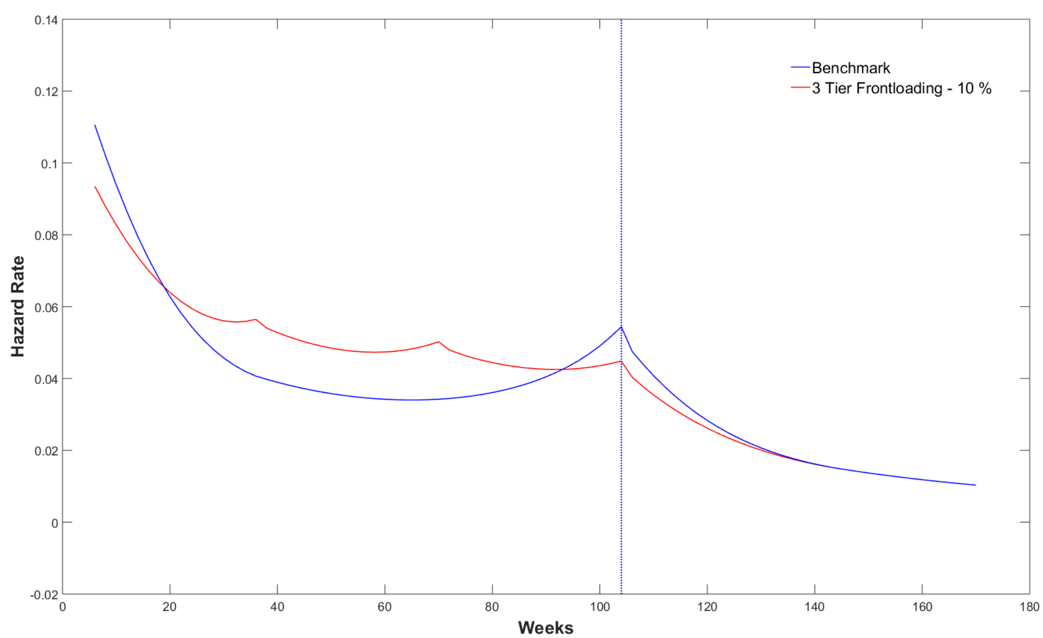

Figure 19: Hazards under front-loading the benefit path with three tiers.

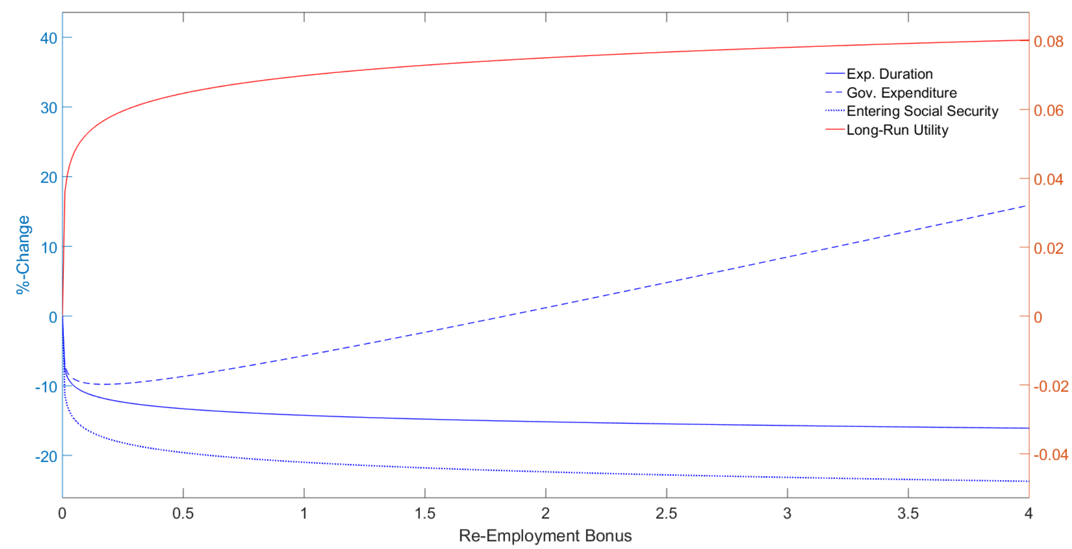

Figure 20: Outcomes of introducing a re-employment bonus over first year, bonus as a multiple of monthly benefits on the x-axis.

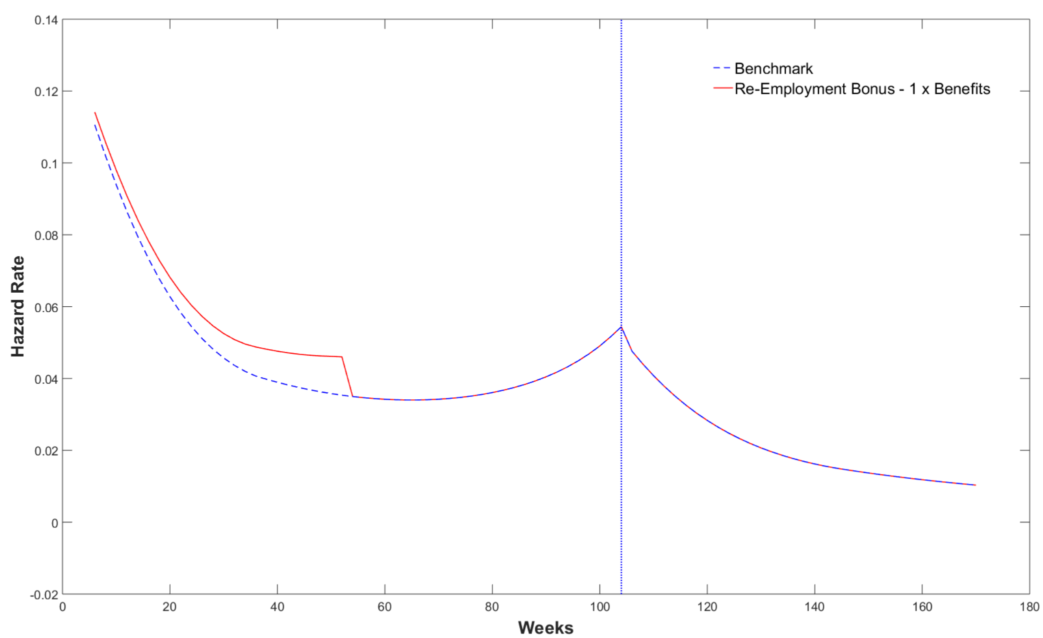

Figure 21: Hazards after introducing a re-employment bonus over first year.