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Employer Screening and Optimal Unemployment Insurance

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Abstract

This paper studies how firms' screening behavior and multiple applications per job affect the optimal design of unemployment policies. We provide a model of job search and firms' recruitment process that incorporates important features of the hiring process. In our model, firms have limited information about the productivity of each applicant and make selective interview decisions among applicants, which leads to employer screening. We estimate the model using German administrative employment records and information on job search behavior, vacancies and applications. The model matches important features of the hiring process, e.g. the observed decline in search effort, job finding rates and interview rates with increased unemployment duration. We find that allowing for employer screening is quantitatively important for the optimal design of unemployment insurance. Benefits should be paid for a longer period of time and be more generous in the beginning, but more restrictive afterwards, compared to the case where we treat the hiring and interview decisions of firms as exogenous. This is because more generous benefits lead to lower search externalities among job seekers and because benefits change the composition of the unemployment pool which alleviates screening for the long-term unemployed.

Keywords: Unemployment, Optimal Unemployment Insurance, Employer Screening
JEL codes: H20, J64, J65, J71

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1 Introduction

Most governments provide substantial levels of insurance against unemployment. Commonly, unemployment insurance systems pay benefits for a finite period of time and individuals move to more restrictive assistance schemes after benefits have expired. These features, especially the length for which benefits should be paid, are controversial. While benefits typically expire after six months in the US, they are often paid for years in European countries. At the same time, several European countries have experienced policy reforms that substantially lowered the benefits for the long-term unemployed.¹

An important consideration for policy is the empirical observation that job finding rates deteriorate with the length of the unemployment spell. The role of employers' screening behavior for this decline has received particularly much attention in recent years. In a field experiment, [Kroft, Lange, and Notowidigdo \(2013\)](#) document that the probability of being invited for an interview falls by almost 50% during the first six months of unemployment in the US and find that these results can best be explained as screening behavior, which refers to the notion that firms infer low productivity of a worker from a long unemployment spell.²

Optimal unemployment insurance schemes have often been analyzed as a partial equilibrium trade-off between providing insurance and distorting the search effort of workers (e.g. [Chetty \(2006\)](#), [Shimer and Werning \(2008\)](#)). However, when screening is taken into account, unemployment insurance policy does not only change the search effort of workers, but firms' interview and hiring decisions also adjust in equilibrium. The goal of this paper is to assess the role and importance of the equilibrium effects that result from screening. We build a quantitative model of the job search and recruitment process and use the model to analyze optimal unemployment insurance schedules.

The key feature of our model is that firms receive multiple applications from workers and only observe unemployment duration and a noisy signal about productivity. Firms rank workers by their expected productivity and workers with a long unemployment spell are less likely to be considered for interviews. Workers decide on their search effort and savings. Hiring and interview decisions are endogenous and depend on how many applicants a firm has and on the relative shares of high and low productivity workers. As a result, unemployment insurance policies do not only change the search effort of workers, but in equilibrium the hiring decision of firms adjust as well, if the composition of the pool of applications that firms receive changes.

We estimate the model using German administrative data on job finding rates and survey data on search effort, vacancies, applications and savings. In particular, we use a comprehensive

¹During the labor market reforms between 2000 and 2005, Germany reduced the benefit level for the long-term unemployed from 50-60% of the pre-unemployment wage to a fixed payment, which is 404 euros for singles in 2016, not including additional rent support. In Sweden, the unemployed get 80% of their pre-unemployment wage forever, but the payment is capped. In 2001, the government introduced duration-dependent caps, with a lower cap for the long-term unemployed (see [Kolsrud et al. \(2017\)](#) for details). In 2010, Denmark reduced the potential benefit duration from 4 to 2 years (afterwards, individuals may still receive welfare benefits).

²[Oberholzer-Gee \(2008\)](#), [Eriksson and Rooth \(2014\)](#) and [Farber, Silverman, and Von Wachter \(2017\)](#) use similar audit designs to investigate the role of CVs, callbacks and unemployment duration.

survey of establishments (the German Job Vacancy Survey) which contains information about the recruitment process. Vacancies on average receive 15 applications. When there is just one applicant for a vacancy, the probability that the applicant is interviewed is close to one. However, this probability drops to about 55% when there are 5 applicants, which is the median number of applications, and to 35% at the mean number of applications of 15. The Job Vacancy Survey also provides direct survey evidence that firms take workers' unemployment duration into account. About 45% of the establishments that consider unemployment applicants state that they are not willing to consider individuals with durations higher than 12 months. Our estimated model can match the empirical features of the job search and hiring process, namely the decline in job finding rates, the applications-per-vacancy ratio, the decline in interview rates and the decline in the job search effort of agents. We then use the estimated model to analyze the optimal unemployment insurance system and investigate the role of the equilibrium effects.

Our policy analysis is concerned with three features of an unemployment insurance system: the initial benefit level (first level), the length for which individuals are allowed to receive this level (potential benefit duration), and a second level for the long-term unemployed (second level). Benefit levels are always replacement rates in terms of the past wage. We find that the optimal schedule pays 73% for 42 months and drops close to zero afterwards. If we restrict the model to allow only for one application per vacancy, which shuts down the information friction, the optimal schedule pays 63% for 20 months and 27% afterwards. Thus, our first main result is that introducing employer screening matters substantially for optimal policy, relative to the case without screening.

We then use the model to assess how important the equilibrium channels of changing unemployment insurance benefits are relative to partial equilibrium effects. The equilibrium effects refer to changes in the probability of being hired conditional on applying to a firm. Our model features three channels through which unemployment policy can affect hiring probabilities. First, the information contained in unemployment duration depends on how different the shares of low and high types at that duration are. When changes to the unemployment insurance system increase the relative share of applications at high durations that come from high types, firms will take this into account and interview individuals with high durations more often. Second, unemployment insurance policy affects the overall applications-to-vacancy ratio. When there are more applications per vacancy, the long-term unemployed have worse job prospects because it becomes more likely that the firm has at least one applicant with a higher expected productivity. Third, unemployment insurance policy affects the composition of the pool of applicants, holding the overall ratio of applications per vacancy and firms' beliefs about productivity constant. For example, if policy reduces the search effort of individuals with low durations, this will increase the job prospects of individuals with high durations. In addition to these equilibrium adjustments, the partial equilibrium trade-off is between providing insurance and distorting the search effort of workers. Introducing employer screening, relative to a case with full information, interacts with this trade-off even in the absence of equilibrium effects. Moral hazard is represented by the

responsiveness of workers to benefits and as workers anticipate their lower job chances in the future due to screening, or actually experience them after becoming long-term unemployed, their responsiveness to benefits changes.

To isolate the role of equilibrium effects, we analyze the case where hiring probabilities decline with duration as under the current German benefit schedule, but are assumed to be invariant to policy. This corresponds to the partial equilibrium effects of employer screening, where falling hiring probabilities change workers' search incentives, but these hiring probabilities itself are treated as exogenous. Calculating the optimal schedule yields 64% for 26 months and 21% afterwards. Also allowing hiring rates to adjust, which was our previous experiment, leads to 73% for 42 months and almost 0 afterwards. Under the current schedule, the hiring probability declines from 0.3 to 0.15 after 12 months. Under the optimal schedule, this decline is more gradual and hiring rates decline to about 0.22 after 12 months. Our second main result is therefore that the equilibrium effects - the adjustment of hiring rates - turn out to be fairly important, especially for the length of the first step and the level of the second step.

In addition, our results indicate that even when allowing for employer screening, the second benefit level for the long-term unemployed is relatively low. In general, with duration dependence - which refers to declining job-prospects over the spell -, it is theoretically open if benefits for the long-term unemployed are higher or lower than for the short-term unemployed, primarily because duration dependence decreases the moral hazard cost of providing benefits for the long-term unemployed. This is due to the fact that as the overall job finding rates of the long-term unemployed decrease, they become less responsive to benefits. Therefore, it could be the case that introducing employer screening, relative to the case without screening, makes it optimal to provide high levels of insurance for the long-term unemployed. Quantitatively, in the case of fixed hiring rates, we find that this effect mainly increases the length for which workers can receive the first level, but has a smaller effect on the levels. Taking the adjustments of hiring rates into account, the optimal level for the long-term unemployed is even lower than in the case without screening. These results suggest that while employer screening increases the length for which benefits should be paid, it does not necessarily provide a reason for giving high benefits to job-seekers with very long durations.

Related Literature. Our paper contributes to the literature on optimal unemployment insurance by providing a model of the hiring process that can be used to quantify the impact of employers' screening behavior on optimal benefit schedules. Many papers in the literature focus on partial equilibrium models and distortions in search effort, where unemployment insurance is a trade-off between moral hazard and consumption smoothing, e.g. [Baily \(1978\)](#), [Gruber \(1997\)](#), [Chetty \(2006\)](#), [Chetty \(2008\)](#). The optimal schedule is often argued to be declining with duration or flat, as in [Hopenhayn and Nicolini \(1997\)](#) and [Shimer and Werning \(2008\)](#), respectively. Related to our approach, [Lentz \(2009\)](#) estimates a search model with savings to analyze optimal unemployment insurance levels. In [Schmieder and Von Wachter \(2016\)](#) the authors extend the

standard optimal unemployment insurance setting to a case where not only benefit levels but also the benefit duration is optimally chosen by the planner. The policies we look at are comparable to their setting. Most related to our paper, [Lehr \(2016\)](#) and [Kolsrud et al. \(2017\)](#) theoretically show that allowing for firms' screening behavior changes the optimality conditions for benefit levels by introducing an externality term, so that the standard Baily-Chetty formula does not hold. The contribution of our paper is that we build a quantitative model that can match the relevant empirical features of the recruitment process and use the model to assess the role of the equilibrium effects relating to employer screening. Our results suggest that these equilibrium effects are quantitatively important and should be taken into account when designing unemployment policies.

There is relatively little other work on the implications of duration dependence for optimal policy. [Shimer and Werning \(2006\)](#) investigate optimal unemployment insurance in a setting with exogenously falling wages or job arrival rates. [Pavoni \(2009\)](#) focuses on human capital depreciation. These papers analyze duration dependence in models where duration dependence is exogenous and invariant to unemployment insurance policy while screening, on the other hand, is endogenous to the benefit system. As a result, screening has different policy implications than other forms of duration dependence since we find that the equilibrium adjustments of the hiring rates are quite important.

Our paper is also related to the literature on duration dependence and recruitment behavior. [Lockwood \(1991\)](#) was an early paper in this literature. In his setting, firms test the unemployed before hiring and a high unemployment duration can be a bad signal. The idea of ranking applicants by unemployment duration was first explored by [Blanchard and Diamond \(1994\)](#), who assume that firms with multiple applications always hire the applicant with the shortest unemployment duration. Recently, the results from the audit studies have led to a growing amount of work that explores the broader implications of firm screening and incomplete information about applicants. [Jarosch and Pilossoph \(2016\)](#) investigate the quantitative link between the decline in callback rates and duration dependence and emphasize that statistical discrimination may not always lead to lower job-finding rates. [Doppelt \(2016\)](#) models the role of information contained in the history of unemployment spells, thereby stressing the life-cycle dimension. [Fernández-Blanco and Preugschat \(2015\)](#) consider a directed search model with endogenous wages, in which firms rank applicants by unemployment duration. There are two important features of our model relative to these papers. First, in our setting, firms rank multiple applicants according to unemployment duration and a signal, whereas previous models of ranking assume that firms only use duration. As a result, policy - in our case, unemployment insurance - can change how informative duration is relative to the signal. When policy makes the selection of types by duration weaker, firms rank applicants less by unemployment duration and more by the signal. Second, we integrate search effort and savings, which are crucial for the analysis of optimal unemployment insurance.

There have been recent studies that emphasize the role of equilibrium effects and market externalities, e.g. [Michaillat \(2012\)](#), [Landais, Michaillat, and Saez \(2016a\)](#) and [Landais, Michaillat, and](#)

Saez (2016b), Marinescu (2017) and Lalive, Landais, and Zweimüller (2015). These papers argue that search externalities among job seekers might be important for job outcomes which in turn has implications for the design of unemployment insurance benefits. Our concept of multiple applications generates search externalities among job seekers and the higher the applications-per-vacancy ratio the more important are search externalities. Hagedorn et al. (2015) argue that unemployment benefit extensions can have externalities on labor demand and decrease the incentive to create vacancies. Our model also allows for vacancy creation to close the model and to account for this effect.

The rest of the paper is organized as follows. In Section 2, we focus on the data and some descriptive facts. Section 3 presents the model and policy problem. Section 4 describes the estimation and discusses estimation results and model fit. In Section 5, we discuss welfare and the corresponding policy results. In Section 6, we discuss some extensions of our model and conclude in Section 7.

2 Data & Descriptive Facts

This section presents the data we use and empirical facts about job search behavior and the hiring process.

2.1 Data

In this paper we consider the case of Germany. In Germany most unemployed receive unemployment benefits for up to 12 months of unemployment and are eligible for unemployment assistance if they stay unemployed for longer than 12 months. Older individuals are eligible for longer unemployment insurance payments, but we restrict to individuals that receive 12 months of benefits. Unemployed individuals receive benefits that amount to 60% or 67% of their past wage, depending on their marital status. After individuals run out of unemployment insurance (UI) they receive means-tested unemployment assistance benefits (UA) which are on average around 40% of the past wage for the average unemployed. Unemployment benefits are financed by social security contributions of workers and firms.³

The German setting allows us to base the design and estimation of our model on several datasets that contain information on job-finding rates, search effort and vacancies. First, we use the German social insurance data (IEB) which provides us with information on the characteristics of the unemployed; in particular the length of their unemployment spell and their wage history. The data contains all individuals that were ever unemployed or regularly employed through an

³The German unemployment insurance system compares relatively well to unemployment insurance schemes in other developed countries, like the US or many other European countries. However, the US system has somewhat less generous potential benefit durations and replacement rates than Germany and no unemployment assistance system. For further details on the institutions in Germany we refer the reader to appendix B.

employment relationship that is subject to social insurance. We have access to a 2% random sample of the population and restrict ourselves to unemployment spells starting in the years from 2000 until 2011. Second, we use the IZA Evaluation dataset (IZA ED) which is a representative survey performed among UI entrants between June 2007 and May 2008. The data is a panel where participants were interviewed up to four times after their unemployment spell has realized. The first interview took place close to the beginning of unemployment. Additional interviews took place six, twelve and thirty-six months after the start of the UI spell, respectively. Participants are asked about their individual search effort, e.g. the number of applications or number of search channels, and they are asked to report their reservation wage. Third, we use the IAB Job Vacancy Survey (JVS) which is a representative survey conducted among firms on open vacancies and hiring decisions made by firms. The survey contains information on whether unemployed applicants were hired and how many applicants firms invite to an interview. Fourth, we use the Bundesbank Panel on Household Finances (PHF), which contains information on savings, liquid assets and debt levels. In the data individuals are also asked to report whether they are unemployed or employed.

Table 1 summarizes some of the main characteristics of the data sources. The average monthly re-employment wage after unemployment for job seekers is 1,606 euros. The re-employment wage is defined as the average monthly earnings an individual receives in the year after the UI spell has ended. Table 1 also reports some observable characteristics of unemployed job seekers. In the IZA ED data, individuals use roughly four to five search channels, where most people in the sample look for job advertisements, ask friends or relatives for jobs or use online search. Many individuals are also offered help from the local employment agencies. Table 1 shows that agents send out 13 applications on average at the beginning of the UI spell. From the PHF dataset we extract some information regarding assets, in particular liquid assets, of the unemployed. In Table 1 we show different quantiles from the net liquid asset distribution of the unemployed in the sample. We see that asset holdings are indeed very heterogeneous where nearly half of the individuals barely have any assets.⁴ In contrary, 10% of individuals have more than 40,000 euros in liquid assets. Net assets, which also include real estates, are on average larger. Finally, the JVS shows that firms receive on average 15 applications and that it takes around two months to fill an open vacancy.⁵

2.2 Descriptive Facts

Standard job search models assume that job finding rates are only determined by agents' search effort, potentially with declining job prospects in the form of duration dependence or heterogeneity in job finding rates.⁶ However, whether agents find jobs to exit unemployment also requires a firm to actually hire the job seeker. This drives a wedge between the search effort of an agent and the job finding rate of an agent. In addition, firms' hiring probabilities are potentially dependent

⁴Net liquid assets are defined as the difference between liquid assets and short-term debt, like credit card debt.

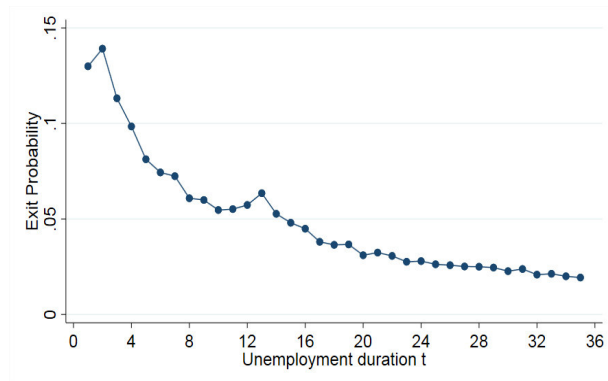
⁵This time is defined as the difference between the acceptance of a job offer by an applicant to the release of the job advertisement.

⁶See e.g. Chetty (2008), Lentz (2009), Hopenhayn and Nicolini (1997).

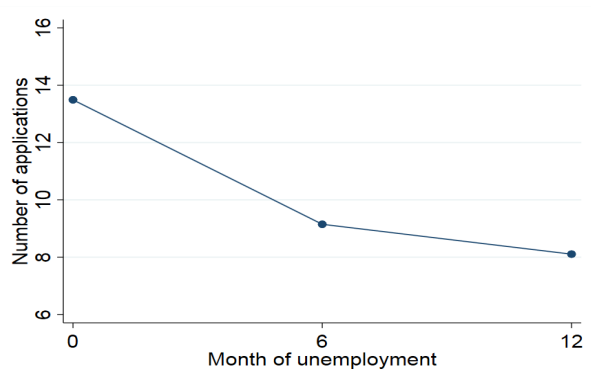
TABLE 1: Descriptive statistics

Variables	N	mean	s.d.
<i>Panel A: Employment Register</i>			
Re-employment wage (euros)	55,420	1,606.17	(1,059.95)
Unemployment duration (months)	59,793	12.57	(12.71)
Female	59,793	0.446	(0.497)
Age	59,793	30.80	(9.12)
Married	59,793	0.325	(0.468)
Children	59,793	0.302	(0.459)
College	56,727	0.096	(0.294)
Apprenticeship	56,727	0.751	(0.432)
<i>Panel B: IZA Evaluation Dataset</i>			
Number of applications Month 1	6,815	13.49	(14.95)
Number of applications Month 6	377	9.15	(10.09)
Number of applications Month 12	1,710	8.11	(9.78)
Search channels Month 1	6,898	4.78	(1.78)
<i>Panel C: Panel on Household Finances (Quantiles)</i>			
Net liquid assets (euros, p10)	295	-1,003	-
Net liquid assets (euros, p25)	295	0	-
Net liquid assets (euros, p50)	295	247	-
Net liquid assets (euros, p75)	295	4,885	-
Net liquid assets (euros, p90)	295	40,497	-
Net assets (euros, including home, p50)	295	894	-
<i>Panel D: Job Vacancy Survey</i>			
Number of applicants	62,904	14,79	(36.96)
Time vacancy is open (days)	76,240	56.88	(67.08)

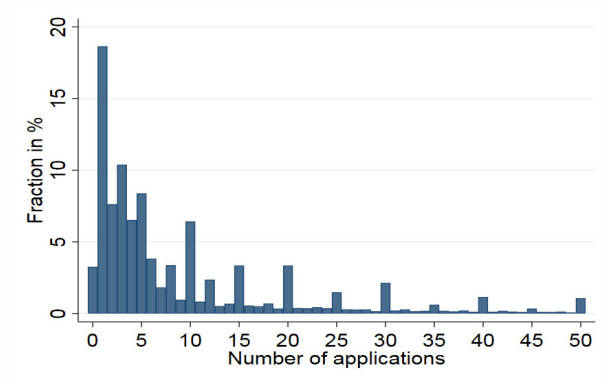
Notes: This table shows descriptive statistics from our different data sources. Panel A shows descriptive statistics from the administrative employment registers of individuals who experience their first unemployment spell at the time the spell starts. Panel B summarizes search effort measures from the IZA evaluation dataset. Panel C uses the Bundesbank Panel on Household Finances for information on assets. In Panel D statistics on vacancies are shown, coming from the IAB Job Vacancy Survey. N denotes the number of observations behind each statistic, and s.d. the standard deviation.



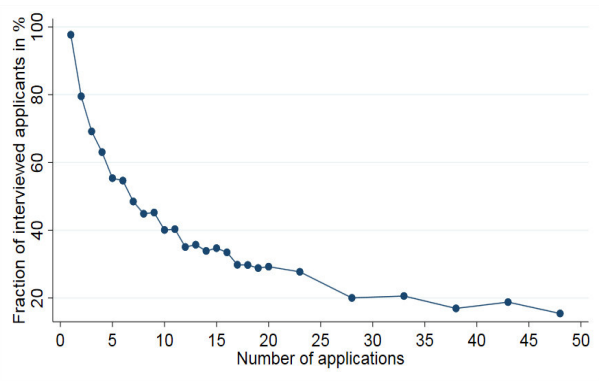
(a) Job finding rate



(b) Search effort



(c) Distribution of applications



(d) Share of interviewed applicants

FIGURE 1: Descriptive Facts

Notes: Panel (a): This figure shows the job finding probability (hazard rate) of individuals on the y-axis as a function of the unemployment duration on the x-axis. Source: SIAB. Panel (b): This panel shows the mean number of applications unemployed agents send out in the first month of unemployment, the sixth month of unemployment and after one year of unemployment. Source: IZA ED. Panel (c): This figure illustrates the distribution of applications across vacancies. The y-axis denotes the fraction of vacancies that receive a certain number of applications. Source: JVS. Panel (d): This panel shows the fraction of interviewed applicants as a function of the number of applications received. Source: JVS.

on the policy context. Hence, in the following we provide some evidence on job seekers search effort as well as on firms screening and interview decisions. Based on this evidence we build a job search model that incorporates all of the discussed features and makes distinct predictions along the evidence that we provide.

Job finding rates. The job finding rate of unemployed job seekers in Germany is shown in Figure 1 panel (a). In the first months of unemployment, exit rates out of unemployment are above 10%. However, job finding rates decrease throughout the spell and are only 5% after one year and 2.5% after two years of unemployment.⁷ Hence, the chance to find a job becomes smaller and smaller the longer someone is unemployed. There are two explanations for this decline in the hazard rate out of unemployment: (a) selection/heterogeneity, or (b) (true) duration dependence. Heterogeneity can enter in the form of productivity differences of job seekers. Duration dependence describes declining job prospects for individuals given their type. Most likely, both, selection and duration dependence, contribute to falling hazard rates.

Search effort. Since we are interested in dynamic UI policies it is important how individuals' search effort throughout their unemployment spell reacts, because search effort responses are a main determinant of the moral hazard costs associated with unemployment insurance. Figure 1 panel (b) illustrates the number of applications that agents write per month as a function of their unemployment duration. At the beginning of the spell they send out more than 13 applications per month, after six months around nine applications are sent out and after twelve months only eight applications are sent out on average. Hence, the average search effort seems to decrease over the spell.⁸ The graphs look very similar when restricting the sample to individuals who are unemployed for 12 months and tracking their search effort over time (see appendix C for details). Note, we have ignored other measures of search effort for now, e.g. the number of search channels or time used for job search. Our choice is motivated by the fact that our model explicitly allows agents to send out applications.⁹

Multiple applications per vacancy. A very important factor that determines job search outcomes is how many other applicants are searching for a similar job. Hence, depending on the number of applications per vacancy the job finding rate might be higher or lower for a given search effort. The importance of these *crowding out effects* depend on the number of competitors of an applicant for a job. Intuitively, if there are many applicants per vacancy some job searchers will get no offer for the job and need to continue their search. Figure 1 panel (c) plots the histogram of the number of applications an open vacancy receives. The average number of applications is around 15, with a median of 5 applications per vacancy. This panel suggests that firms have con-

⁷The small spike at 12 months is due to the benefit exhaustion which leads more people to exit unemployment. See DellaVigna et al. (2017) for a detailed exploration of the benefit exhaustion spike.

⁸Declining search effort over the UI spell was also documented for the US by Krueger and Mueller (2011).

⁹Lichter (2016) also uses the number of applications as a search measure and discusses this choice in more detail.

siderable levy to pick the best applicant and that the *outside option* of a firm is to screen or hire alternative applicants.

Employer screening. Employer screening by vacancies takes usually place by restricting first to a subset of applicants that get invited to an interview. In panel (d) of Figure 1 we show that the share of applicants that receive an interview invitation depend on the number of applications a vacancy receives. One can see that the more applications there are, the less likely it is to get invited to an interview. The interview shares are around 50% for vacancies with 5 applications, i.e. at the median, and only 30% for vacancies with 15 applications, i.e. at the mean. In the job vacancy survey, employers are also asked whether they consider unemployed applicants depending on the unemployment duration of the applicant. Conditional on considering unemployed applicants at all only 75% of firms consider applicants with more than a few months of unemployment duration and only 60% of firms consider applicants with more than twelve months of unemployment duration. Hence, only 60% of firms that are in principle willing to consider unemployed applicants are willing to accept long-term unemployed. Figure A2 in appendix C illustrates this graphically. Complementary to our survey evidence, the importance of employer screening for true duration dependence was also studied by Kroft, Lange, and Notowidigdo (2013) in an experimental audit study. They find that the callback rate (interview invitation) of an application that was sent out to open vacancies strongly depends on the unemployment duration presented in the CV of the applicant. In fact, the probability to receive a callback from an employer declines by roughly 50% over the unemployment spell. Note that declining callback rates can in principle also be generated by models of human capital depreciation. However, Kroft, Lange, and Notowidigdo (2013) demonstrate that the decline of the callback rate is much weaker when the unemployment-to-vacancy ratio is high. This finding is hard to rationalize with human capital depreciation, since human capital would depreciate independently of labor market conditions. Employer screening, on the other hand, predicts that unemployment duration is less informative about productivity under adverse labor market conditions, since then individuals with high productivity also stay unemployed longer. This is in line with the evidence provided by Kroft, Lange, and Notowidigdo (2013).¹⁰

3 Model

We extend a standard search model with risk aversion, endogenous search effort and savings, that has been used to study optimal UI, by incorporating firms' hiring decision to account for the empirical patterns described in the previous section. The key feature of our model is that workers are heterogeneous in productivity and firms have to select candidates from a pool of multiple applications. Since productivity is only observed by workers, firms base hiring decisions on the

¹⁰In addition, note that they find that the callback rate declines strongly within the first six months of unemployment and is essentially flat afterwards. If the decline in callback rates would mostly be about human capital depreciation, one would expect a more gradual decline that also affects the long-term unemployed.

expected productivity of each worker, taking unemployment duration and a noisy signal about worker quality into account.

3.1 Workers

Time is discrete and each period corresponds to a month. We follow the literature on optimal unemployment insurance by assuming that workers are born unemployed (Chetty (2006), Shimer and Werning (2008)) and that there is no job destruction, so that finding a job is an absorbing state. Workers live for T periods and in every period of the model, a unit mass of newly unemployed workers is born. Workers who have been unemployed for t periods get UI benefits that depend on t :

$$b_t = \begin{cases} b_1 & \text{if } t \leq D \\ b_2 & \text{if } t > D \end{cases}$$

Thus, workers can get an initial level b_1 for up to D months and a level of b_2 afterwards.¹¹ Workers differ in their productivity π_j and each generation of workers contains a share α_j of type $j = 1, \dots, J$. In addition, each type has an exogenous initial level of assets, denoted as $k_{0,j}$.

Employed workers only decide on the optimal level of consumption and savings and the corresponding value function and budget constraint for duration $t < T$ are:

$$\begin{aligned} V^e(k, t) &= \max_{k_{t+1} \geq 0} \left\{ u(c_t) + \beta V^e(k_{t+1}, t + 1) \right\} \\ c_t &= Rk_t + (1 - \tau)w - k_{t+1} \end{aligned}$$

k_t and k_{t+1} are the asset levels in each period. Workers are risk-averse and discount the future at rate β and the interest rate is given by R . There are no separations and employment is an absorbing state.¹² In addition, note that all workers face a no-borrowing constraint ($k_{t+1} \geq 0$).¹³

Unemployed workers decide on both consumption and savings and their search intensity. Searching with intensity s has a cost $\psi(s)$, but leads to a match probability $p(s) = s$, which can be interpreted as sending an application to a firm.¹⁴ Importantly, the probability of exiting unemployment - the hazard rate - contains both the probability of meeting a firm and of actually being

¹¹Note that in practice, the amount of unemployment benefits is often tied to the pre-unemployment wage. Because our model abstracts from wage heterogeneity the pre-unemployment wage is conceptually indistinguishable from the post-unemployment wage.

¹²Allowing for separations is in principle possible but would complicate the model by generating an endogenous initial asset distribution. Hence, for simplicity we assume that jobs last forever.

¹³The no-borrowing assumption is standard in the literature, see e.g. Chetty (2006), and creates an insurance motive for the government in the first place. Without borrowing constraints, individuals would just take a loan and there would be no need for the government to provide insurance to the unemployed.

¹⁴For simplicity, we focus on the case where workers may send out a single application, as is also done in Fernández-Blanco and Preugschat (2015) or Villena-Roldan (2012). The implications of multiple applications per worker are discussed in Section 6.

hired by the firm:

$$h_{j,t} = s_{j,t} \cdot g_j(t) \quad (1)$$

$g_j(t)$ is the expected hiring probability and is determined in equilibrium, as will be discussed in the next sections.¹⁵ Jobs start in the next period. The survival rate in unemployment, i.e. the probability of still being unemployed after t periods, is then defined as

$$S_{j,t} = \prod_{t'=0}^{t-1} (1 - h_{j,t'})$$

Taken together, the value function for unemployed workers is given by:

$$V^u(k, t) = \max_{s, k_{t+1} \geq 0} \left\{ u(c_t) - \psi(s) + \beta h_{j,t}(s) V^e(k_{t+1}, t+1) + \beta (1 - h_{j,t}(s)) V^u(k_{t+1}, t+1) \right\}$$

The budget constraint is $c_t = Rk_t + b_t - k_{t+1}$. Note that changes to the benefit system influence the value of unemployment relative to employment and therefore affect workers' search decisions.

In each period of the model, there is a pool of unemployed workers that consists of the new generation and workers from previous generations that did not find a job in previous periods. While further details will be discussed in the equilibrium section, it is useful to note that the number of workers of type j and duration t that are matched with firms in each period is given by:

$$a_{j,t} = \alpha_j \cdot S_{j,t} \cdot s_{j,t} \quad (2)$$

Here, α_j is the unconditional type share, $S_{j,t}$ is the survival rate until duration t and $s_{j,t}$ is the search effort at that duration. Aggregating over types and duration, this leads to a mass of matched workers that will be considered by firms, which we will refer to as the pool of applications.

3.2 Firms

When workers are matched with a firm, the match-specific productivity $q \in \{0, 1\}$ is drawn and the probability that it takes the value 1 is given by worker productivity π_j . Thus, high-productivity workers have a high chance of being productive in any match. We refer to the case of $q = 1$ as the worker being qualified for a vacancy.¹⁶ Firms produce an output y when employing

¹⁵Note that we use the term *hiring probability* for the probability of being hired conditional on being matched (as also e.g. [Lehr \(2016\)](#)), while similar terms are also often used in the literature to describe to number of new hires by firms over total employment.

¹⁶This is similar to the set-up of [Fernández-Blanco and Preugschat \(2015\)](#), who also assume that workers differ in their probability of being qualified for vacancies. In a similar spirit, [Jarosch and Pilossoph \(2016\)](#) assume that both workers and firms differ in their (deterministic) productivity and production only takes place when worker productivity is higher than firm productivity.

a qualified worker and zero otherwise. Thus, note that conditional on being qualified, workers produce the same output.¹⁷

Workers are matched to firms according to an urn-ball matching technology, where each matched worker randomly arrives at a firm. From the point of view of the firm, the number of applications it receives follows a Poisson distribution with parameter $\mu = \frac{a}{v}$, where a is the mass of matched workers and v is the mass of vacancies. For each candidate, firms do not observe if they are qualified, but only their unemployment duration and a noisy signal about the type of the worker. The signals sent by type j are drawn from a normal distribution, where we normalize the mean to j and estimate the variance σ to match the data. Thus, high types on average send better signals. Firms can interview applicants and thereby perfectly reveal their productivity. We restrict firms to pay the exogenous wage.¹⁸ Firms rank applicants by their expected productivity and sequentially interview applicants until one applicant turns out to be qualified.¹⁹ The other applicants are not hired. Since the firm always has to pay the wage, it will never hire an unqualified worker. A key feature of this framework is that firms rank applicants not only based on unemployment duration, but also take the signal into account.²⁰ Note that ranking is justified as long as there is a positive screening cost.²¹

Thus, a firm first computes the expected type probabilities of each applicant. Firms know the composition of the overall pool of applications, i.e. the mass of applications $a_{j,t}$ sent by agents of type j and duration t . Firms also know the distributions of the signals. Conditional on the realized signal ϕ and unemployment duration t , the probability of an applicant being type j follows from Bayes' rule:

$$P(j|\phi, t) = \frac{f_j(\phi) \cdot a_{j,t}}{\sum_k f_k(\phi) \cdot a_{k,t}} \quad (3)$$

This probability corresponds to the share of applications of type j in the overall pool of applications from agents with duration j , weighted by the density of the signal. Since the mass of applications is given by $a_{j,t} = \alpha_j S_{j,t} s_{j,t}$, a high duration of unemployment is a negative signal

¹⁷Allowing the output to differ between low and high types would in principle be feasible in our framework and an interesting extension because it would allow to investigate the trade-off between providing information about the quality of applicants for firms and veiling information to protect unproductive types from statistical discrimination. In our setup, the planner would like to eliminate statistical discrimination because it reduces the job prospects of the long-term unemployed. In contrast, when productivity differs the planner also has an incentive to *provide* information to firms to maximize production. Note, however, that in the current framework, reducing screening can also have an adverse effect on firms if it is achieved by increasing the search effort of low types and increasing the effort of high types, which would reduce vacancy creation.

¹⁸The implications of endogenous wages are discussed in Section 6. Assuming a fixed wage is broadly in line with evidence about constant reservation wages over the spell and a moderate decline in re-employment wages by duration.

¹⁹An alternative approach that would give similar outcomes is to assume that firms choose which share of applicants they screen, while discarding the others. This second approach to recruitment selection is used e.g. in Villena-Roldan (2012) or Wolthoff (2017).

²⁰In other ranking models in the literature (Blanchard and Diamond (1994), Fernández-Blanco and Preugschat (2015)), the ranking is only based on duration.

²¹In the main part of the analysis, we focus on the case of a screening cost $C \rightarrow 0$

about productivity when a large share of applicants with duration t has a low productivity. Note that this does not only depend on the relative survival rates, but also on the relative search effort. For example, if there are many more low types than high types, but low types do not search. Firms will take this into account and infer that the applicant must be a high type. Finally, note that in the limit case $\sigma \rightarrow 0$, the signal perfectly reveals workers' type and there is no reason to take the duration into account. Conversely, when $\sigma \rightarrow \infty$, the signal contains no information and firms only rank applicants based on duration. For intermediate cases with $\sigma \in (0, \infty)$, firms weigh the information contained in both components and their relative importance is endogenous. When the benefit system keeps productive types in the pool longer, duration can become less informative about productivity and the ranking order depends more strongly on the signal.

To arrive at the expected hiring rate, we first define the expected profit based on the conditional type probabilities:

$$\Pi(\phi, t) = \sum_j P(j|\phi, t) \pi_j y - w \quad (4)$$

It is useful to first focus on the case of an applicant i with fixed (ϕ, t, j) , with j being the type, who is matched with a vacancy that has just one randomly drawn other applicant \tilde{i} with characteristics $(\tilde{\phi}, \tilde{t}, \tilde{j})$. Applicant \tilde{i} is interviewed before applicant i whenever $\Pi(\tilde{\phi}, \tilde{t}) \geq \Pi(\phi, t)$ and hired if also being qualified for the job, which happens with probability $\pi_{\tilde{j}}$. We define $p(\phi, t)$ as the probability that given ϕ and t , agent i is *not* interviewed, because the firm interviews and hires worker \tilde{i} before, integrating over $(\tilde{\phi}, \tilde{t}, \tilde{j})$:

$$p(t, \phi) = \sum_{\tilde{j}=1}^J \frac{a_{\tilde{j}}}{a} \cdot \pi_{\tilde{j}} \cdot P(\Pi(\tilde{\phi}, \tilde{t}) \geq \Pi(\phi, t) \mid \tilde{j}, t, \phi) \quad (5)$$

$\frac{a_{\tilde{j}}}{a}$ is the probability of drawing type \tilde{j} from the pool of all applications, with a being the total number of applications and $a_{\tilde{j}}$ the number of applications sent by type \tilde{j} . This is multiplied with the probability that type \tilde{j} is hired according to the intuition described above.²² The probability $p(\phi, t)$ describes how likely it is to not be invited for the interview when there is one other applicant. In general, the number of other applicants follows a Poisson distribution, where the mean μ is the mean number of applications per vacancy. In addition, the signal ϕ that the agent sends is stochastic. Integrating over both the number of other applicants and the signal, we get the following expression for the expected hiring rate:²³

$$g_j(t) = \pi_j \int_{\phi} \exp(-p(\phi, t) \cdot \mu) dF_j(\phi) \quad (6)$$

²²In appendix A, we describe how the probability that the competitor sends a better signal is computed.

²³This expression follows from the fact that the number of other applicants for a vacancy is Poisson distributed. The Poisson probability density function is $f(k) = \exp(-\mu) \frac{\mu^k}{k!}$. The probability that agent (j, t) with signal ϕ is the best applicant is $\sum_{a=0}^{\infty} (1 - p(t, \phi))^a f(a)$, since given a other applicants $(1 - p(\cdot))^a$ is the probability that none of them is hired first. This can be simplified to the expression used for $g_j(t)$.

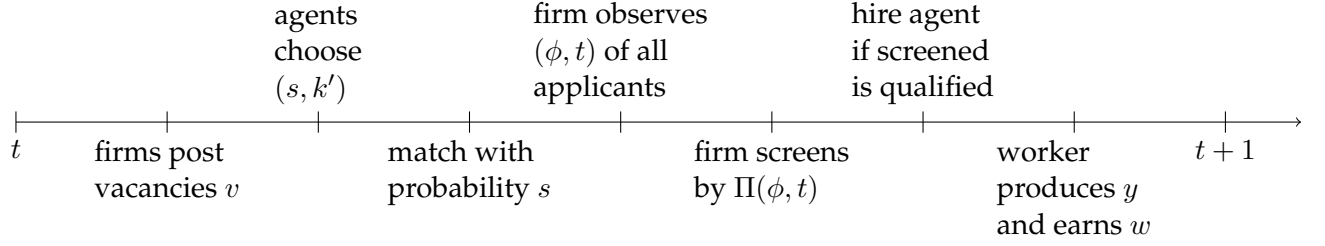


FIGURE 2: Timing of the model

The expected hiring rate of worker i consist of the integral, which is the probability that no other applicant is screened and hired before, and the probability π_j that the worker is qualified for the job. The integral can be interpreted as a *callback curve*: it represents the probability of being contacted and screened by an employer. Thus, it is the model analogue to recent audit studies which measure the decline in the callback rate (e.g. Kroft, Lange, and Notowidigdo (2013)). Callback rates map into hiring rates by pre-multiplying the probability of being qualified for the vacancy. Note that there are two components that lead to a decline in the callback curve with duration. First, for a given agent with a high duration, $p(\phi, t)$ tends to be high, which means that the firm is likely to first interview and potentially hire one other randomly drawn applicant. This depends on how informative duration is about types and on the composition of the pool of applications - if the short-term unemployed search a lot, it is more likely that a random other applicant has a short duration and is potentially considered first. Second, this effect is scaled by the mean number of applications per vacancy, which is given by μ . In the limit case of no competition ($\mu = 0$), the hiring rate is flat and equal to π_j . In the case of a large applications-per-vacancy ratio μ the competition for jobs is large and callback rates are lower.

The mass of vacancies is pinned down by a free-entry condition. As in Lise and Robin (2016), firms can pay $c(v)$ to advertise v vacancies. Vacancies last for one period. The value of an additional vacancy is the net output multiplied by the probability of receiving at least one qualified application.²⁴

$$J^v = \frac{y - w}{1 - \beta} \left(1 - \exp \left(- \frac{\sum \pi_j a_j}{v} \right) \right)$$

In equilibrium, the marginal vacancy costs are equal to the expected value of an additional vacancy:²⁵

$$c'(v) = J^v$$

Conceptually, free entry ensures that firms punish redistribution towards workers by exiting. Hence, vacancies might negatively or positively react to changes in unemployment policies. In our framework, different benefit schemes can reduce firm profits by either reducing overall search

²⁴Note that we assume that vacancies survive forever and that after the vacancy is filled it stays filled forever. This is a helpful approximation especially when T is large enough.

²⁵Depending on the functional form of $c'(v)$ vacancy creation rents accrue to firms if vacancy costs are not constant. However, it is not obvious how to interpret these rents and we ignore them throughout the rest of the paper.

effort or by reducing the applications of high types relative to low types, because each case makes it less likely that vacancies receive at least one qualified candidate. As a result, firms would reduce the amount of vacancies being posted. Later, when we discuss optimal policy, these incentives for vacancies must be taken into account. In Figure 2 we summarize the timing of our model graphically.

3.3 Equilibrium

The equilibrium of the model consists of

- Policy functions for search effort s_{j,t,k_t} and savings $k_{t+1} = g_u(k_t, t, j)$ for the unemployed and $k_{t+1} = g_e(k_t)$ for the employed, for each type j , duration t
- Survival functions $S_{j,t}$
- Expected hiring rates $g_{j,t}$
- A mass of vacancies v

such that the policy functions of workers solve the problems described by the value functions for the employed and unemployed, and such that the expected hiring rates are optimal according to equation (6) given the implied survival rates.²⁶

3.4 Optimal Policy

The governments' set of policy instruments $P = (b_1, b_2, D, \tau)$ consists of the benefits b_1 that are paid from period $t = 1$ until period $t = D$. D denotes the last month until benefits b_1 are received and represents the potential benefit duration. From period $t = D + 1$ until period T agents receive benefits b_2 . This defines the policy schedule b_t , where $b_t = b_1$ if $t \leq D$ and $b_t = b_2$ if $t > D$. The proportional income tax τ is collected from the employed to finance the expenditures. The tax has also the interpretation of an actuarial fair insurance premium here. We restrict the analysis to this class of schedules because it facilitates numerical optimization over the policy space. In addition, these schedules are fairly close to the policy instruments that are used in practice.²⁷

The objective of the planner is to maximize the value of a newly born generation of unemployed. We assume that every unemployed individual has the same welfare weight when born, which amounts to a standard utilitarian welfare criterion as in [Chetty \(2006\)](#):

$$W(P) = \int_j V_j^u(P) \alpha_j dj \quad (7)$$

²⁶While uniqueness of the equilibrium cannot be proved analytically, we checked for the possibility of multiple equilibria, especially around the estimated parameter values, and always converge to the same equilibrium.

²⁷See Section 5 for a discussion of the shape of more flexible classes of schedules.

However, the government can only maximize the welfare of agents subject to the following budget constraint, that balances expected revenue and expenditure from a cohort:

$$G(P) = \int_j \left(\underbrace{\sum_{t=0}^T R^{-t}(1 - S_{j,t})w\tau}_{\text{expected revenue}} - \underbrace{\sum_{t=0}^T R^{-t}S_{j,t}b_t}_{\text{exp. expenditure}} \right) \alpha_j dj \quad (8)$$

Note that revenues and expenditures are weighted by the survival rates, because individuals receive only benefits if they are still unemployed in period t and only pay taxes ($w\tau$) if they work in period t . The budget constraint implies that expected revenue generated with the employment tax must equal expected expenditures. As in [Kolsrud et al. \(2017\)](#) we assume that the budget must be balanced within a certain generation and therefore benefits and revenues are discounted by the interest rate.²⁸

Discussion. In this framework, the screening mechanism matters for optimal policy through various channels. First, there is the classical trade-off between providing insurance to risk-averse individuals and distorting their search incentives (see e.g. [Chetty \(2006\)](#)). Insurance is valued because agents are credit constrained and cannot borrow. Hence, agents deplete their assets throughout the unemployment spell until they become hand-to-mouth consumers. Depending on the initial asset position, agents move closer to becoming hand-to-mouth if they stay unemployed for longer. The key measure of moral hazard is the elasticity of search effort with respect to UI benefits. Note that introducing screening changes the extent of moral hazard: forward-looking individuals will anticipate that they will have lower job prospects if they become long-term unemployed and search more intensively in the beginning, which can reduce their responsiveness to benefits.

Second, the presence of screening gives rise to equilibrium effects: the UI system changes not only search decisions, but also the expected probabilities of being hired. On the one hand, this is due to the fact that UI policy changes the selection of types over the unemployment spell. For example, consider the case of raising benefits at each duration. This will lead high types to stay in the unemployment pool longer and this makes being unemployed for a certain time less informative about productivity, as the relative survival rates change. This channel is also theoretically discussed in [Kolsrud et al. \(2017\)](#) and [Lehr \(2016\)](#). On the other hand, in our framework, the size and composition of the pool of applications that firms get matters for the determination of hiring rates. If policy changes search effort, this impacts the applications-per-vacancy ratio and a higher mean number of applications reduces the job chances of the long-term unemployed. In addition, if the short-term unemployed search a lot, this reduces hiring rates for the long-term unemployed. In a similar spirit, if low types search a lot, this decreases job chances of the high types who are

²⁸Alternatively, one could remove the discounting and collect taxes from the steady state distribution of employed and pay benefits to the steady state distribution of unemployed. We prefer our specification because then the tax τ has the interpretation of an actuarial fair insurance premium assuming that agents do not know their type ex-ante or that insurance pricing by type is not feasible.

unemployed for the while. Furthermore, vacancies adjust in equilibrium and optimal policy must take into account that different benefit schemes might lead to a different vacancy posting behavior because the value of a vacancy might be affected, through a change in the composition of applicants or their search effort. Finally, since agents are heterogeneous, a utilitarian planner potentially redistributes between them.

Combining these channels, the shape of the optimal schedule is theoretically open. Without duration dependence or heterogeneity, moral hazard considerations typically lead to lower benefits for the long-term unemployed than for the short-term unemployed (see e.g. [Hopenhayn and Nicolini \(1997\)](#)). However, benefits for the long-term unemployed could also be higher because the unemployed run down their assets during the spell or because duration dependence reduces the moral hazard costs of providing benefits for the long-term unemployed. In addition, the equilibrium effects have to be taken into account and it is not clear if introducing screening matters mostly because of its influence on workers' search incentives or because of the equilibrium effects. These questions are addressed in our quantitative analysis in Section 5.

4 Estimation

So far we have described the data and some empirical facts followed by a discussion of the model and the mechanisms. In this section we will connect both by connecting our model to the data. We will first present the estimation setup and will then discuss the estimation results.

4.1 Setup

Specification. To estimate the model that we formulated in Section 3, we impose the following functional forms on the instantaneous utility function and the search cost function:

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

$$\psi(s) = \frac{s^{1+\frac{1}{\lambda}}}{1+\frac{1}{\lambda}}$$

where λ denotes the elasticity of search effort with respect to the value of employment. The functional form is a common assumption and used in [DellaVigna et al. \(2017\)](#) or [Lentz \(2009\)](#). The instantaneous utility function is a standard CRRA utility function where γ is the risk aversion parameter and at the same time the inverse of the intertemporal elasticity of substitution.²⁹

In our model agents are heterogeneous in two dimensions: (a) their probability of being qualified and (b) their initial assets. In our baseline version of the model we allow for two different

²⁹Alternatively, one could think about a CARA utility specification. The constant relative risk aversion choice is motivated by the possibility of wealth effects, which implies different attitudes toward gambles with respect to wealth, i.e. individuals who have less savings will search more. [Shimer and Werning \(2008\)](#) compare the implications of CARA and CRRA to optimal UI and find only minor differences, because wealth effects are quantitatively very small in a search model like ours.

productivity types π and three different initial asset types k_0 , which in total leaves us with $J = 6$ types.³⁰ Signals are drawn from normal distributions with mean 0 for the low type and mean 1 for the high type.³¹ We set initial assets for the unemployed to be uniformly distributed with 0, 500 and 3,000 euros. These values are set in order to match roughly the liquid assets of unemployed individuals in the PHF dataset. Every qualified type generates a profit $y > w$ for the firm in case he is qualified. y can be normalized because only the wedge between the vacancy cost and the $y - w$ gap is relevant for the determination of the vacancies. High types differ in their idiosyncratic match productivity. High types are qualified in π_H cases, while low types are qualified in π_L cases only. Unqualified applicants are always rejected. Hence, firms have an incentive to screen types with respect to their productivity in order to gain a higher expected profit. Since we do not aim to make any statements about production one can see these profits as a normalization. The wage agents receive during employment is fixed and we set $w = 1,606$ euros, which matches the mean re-employment wage in our sample of unemployed. The estimation is based on the current schedule, so that benefits b_t are set to a replacement rate of 63.5% within the first year and social assistance is equal to 40% after one year.³² These numbers capture closely benefits paid to unemployed in our sample period. The vacancy posting costs are quadratic in the number of vacancies and we calibrate ex-ante the marginal cost of a vacancy to be equal to $\kappa = 100$. The functional form for the vacancy posting costs we use is $c(v) = \kappa v^{1+\rho}$, where we set $\rho = 1$ to obtain quadratic vacancy costs. The time horizon in our model is $T = 96$, which amounts to eight years. By choosing this relatively large time horizon we avoid that agents' search behavior is influenced by *end-of-life* effects.³³

Estimation. Some additional parameters are set prior to estimation to standard values from the literature. We set the monthly time discount parameter equal to $\beta = 0.995$, which leaves us with an annual discount factor of roughly 5%. Risk aversion is equal to $\gamma = 2$ as in [Chetty \(2008\)](#) and [Kolsrud et al. \(2017\)](#). The interest rate is set to $R = \frac{1}{\beta}$ as in [Chetty \(2008\)](#), [Lentz \(2009\)](#), or [Shimer and Werning \(2008\)](#). This leaves us with the following parameters to be estimated:

$$\theta = \{\lambda, \pi_H, \pi_L, \alpha_L, \sigma\} \tag{9}$$

Thus the parameter vector contains the search effort elasticity λ , the productivity probability of the productive type π_H , the productivity probability of the unproductive type π_L , the unconditional type probability α_L and the variance of the signal σ .

³⁰Allowing for more types in both dimensions is easily possible but does not add any conceptual insights. Productivity and initial assets are uncorrelated, however, this can also easily be relaxed but has only negligible quantitative impacts.

³¹This is a pure normalization because we estimate the standard deviation of the normal distribution.

³²UA is means-tested and a fixed amount. Hence we choose a value for the replacement rate that roughly amounts to the replacement rate that a typical UA recipient would receive.

³³Mechanically, in $T = 96$ agents stop to search because it only provides disutility to them. This *end-of-life* effect also influences search effort in the periods before. However, in our specification these effects become small very quickly and do not influence search in a quantitatively important manner in the first years of unemployment.

In order to estimate the parameter vector θ , we apply a classical minimum distance (CMD) estimator as it is also applied by [DellaVigna et al. \(2017\)](#):

$$\min_{\theta} (m(\theta) - \hat{m})'W(m(\theta) - \hat{m}) \quad (10)$$

where $m(\theta)$ is the vector of model-implied moments, \hat{m} is the vector of empirical moments, and W is the weighting matrix which we set to be equal to the identity matrix. The theoretical moments are simulated from the model and the reduced form moments are estimated as described in Section 2.2. The CMD criterion essentially chooses parameters in such a way, that the distance between the model-implied moments and the observed empirical moments becomes smallest.³⁴ For the estimation of the parameters we use a genetic algorithm, which is a global optimization routine.³⁵ Standard errors are then given by the diagonal elements of $(H'WH)^{-1}(H'W\Lambda WH)(H'WH)^{-1}/N$, where W is the weighting matrix, H is the Jacobian of the objective function evaluated at the estimated parameter values and Λ is a matrix with the inverse of the empirical moment variances on the diagonal.

Moments. First, our moment vector includes the hazard moments from the first 24 months. Next, we include the average change in the search effort in month six and twelve relative to the first survey interview conditional on staying unemployed for one year. We also include the unconditional change in the search effort in month six and twelve relative to the first survey interview. Then we add the average number of acceptable applications that a vacancy receives as can be seen in Figure 1.³⁶ Finally, we add six multiple spell moments where we use the mean unemployment duration in spell two conditional on unemployment duration in spell one. Note that we mimic the multiple spell sample in our model by simulating two unemployment spells for workers with the same type and the identical level of initial assets. This preserves the intuition of the length of the first unemployment spell being informative about the second spell of a certain type, while avoiding to explicitly model job destruction and keeping our framework more in line with standard UI frameworks.³⁷ Figure A4 shows this non-parametrically. The Figure shows that the longer an individual's UI duration is in the first spell the longer is the UI duration in the second spell. As discussed in [Alvarez, Borovicková, and Shimer \(2016\)](#), the idea is that the stronger the correlation between the unemployment durations in the two spells, the more important heterogeneity must be. The relatively small slope of the curve suggests that duration dependence might be important and that heterogeneity is not the sole driver of the declining hazard. This leaves us with a total amount of 35 moments to match. Minimizing (1) with respect to θ gives us the estimated parameter vector.

³⁴Note that in the estimation we use percent deviations instead of levels to give all moments the same weight.

³⁵Global optimization routines are helpful for possibly non-differentiable problems and problems with local minima.

³⁶To be very precise, we truncate the moment at 250 applications. However, only a handful of firms report that many acceptable applications.

³⁷Empirically, we extent our sample to the period from 1983 until 2011 such that we have a sufficiently large sample of individuals with two unemployment spells.

TABLE 2: Estimation results

Parameter	Estimate	s.e.
λ	2.539	(0.001)
π_L	0.213	(0.000)
π_H	0.576	(0.001)
α_L	0.648	(0.001)
σ	6.850	(0.003)

Notes: This table summarizes the estimation results of our parameters. Column two shows the estimated parameters and column three the respective standard error.

Identification. The parameters are jointly identified if any parameter vector θ has distinct predictions for the behavior of agents. Intuitively, changing a certain parameter needs to have different implications for the moment vector $m(\theta)$ than changing another parameter. In our model, the level and slope of the hazard curve are closely aligned with the idiosyncratic productivity parameters π_j and the unconditional distribution of high types α_L . The search effort over the unemployment duration and especially the change in the search effort is informative about the search cost elasticity λ . The multiple spell moments deliver additional information on the unobserved heterogeneity in the model. The higher the slope of the curve of the mean durations, the more heterogeneity in job finding rates there should be. The intuition here is that the observation of two spells allows in principle to estimate a fixed-effect for individuals. If the correlation between UI duration in spell one is strongly correlated with UI duration in spell two, this hints towards sizeable heterogeneity (Alvarez, Borovicková, and Shimer (2016)), and vice versa. This information is particularly helpful to estimate σ since the variance of the signal determines the importance of duration dependence in the model.

4.2 Estimation Results

In Table 2 we show the estimated parameters and the respective standard errors. We estimate the search cost elasticity λ to be 2.5, which is a relatively large elasticity of search effort with respect to the value of employment. This implies that agents will react relatively strong to benefit changes because a large responsiveness in search effort translates into large responses to benefit changes. The productivity probabilities and unconditional type probability suggest that the majority of individuals are of the low type ($\alpha_L = 0.685$), and that low types fulfill the requirements of the firm in roughly 20% of all matches, while high types fulfill the requirements of the firm in 58% of all matches. The heterogeneity in the productivity will translate into a heterogeneity in hiring rates as shown in panel (b) of Figure 3. We estimate the variance of the signal to be equal to $\sigma = 6.85$ which implies that the productivity is relatively noisy. In other words, signals are relatively informative and firms have a relatively strong incentive to screen applicants according

to their unemployment duration because more high types are alive when an agent with a short duration is screened. To get a feeling for the importance of the signal versus the importance of the duration consider the case where only the duration is taken into account. Then the probability that an applicant with a shorter duration is interviewed is one. In our estimated model, the probability that a candidate with an unemployment duration of six months is screened versus a candidate who is unemployed for five months is between 0.31-0.38, depending on the agent type combination. Alternatively, the probability that a candidate with twelve months is screened relative to an applicant with eleven months of UI duration is between 0.28-0.35, depending on the type. If duration would be uninformative, the probabilities would be equal to 0.5. In panel (a) and (b) of Figure 3 we illustrate the screening and hiring behavior of firms that the model implies. Panel (a) shows the average decline in the callback rate of an application relative to period one. Our model suggests that the probability to get screened by a firm, i.e. the probability of a callback, declines throughout the unemployment spell and is only around 70% after one year and goes towards 60% after two years of unemployment. Note that callback rates for both types are very similar due to the large magnitude of σ . Hence, our model suggests only a small heterogeneity in the callback rate. This screening behavior translates directly into hiring rates since the hiring probability equals the callback probability times the productivity of the type, as shown in panel (b). For both types, hiring rates decline because the screening probability declines. However, the hiring probability per application of a high type is around 50% in the beginning because he is more qualified for firms than the low type. The low type has a hiring rate of 20% in the beginning which also declines the longer he is unemployed. Hence, we find considerable heterogeneity in productivity as well as important duration dependence in the hiring rate. The estimated heterogeneity and duration dependence in hiring rates then maps into job finding rates of agents. The job finding rate is the product of the hiring rate and the probability to send out an application, namely the search effort of the individual. The dashed line in Figure 4 shows the model-implied job finding rate of our model.

Model Fit. How well does our model fit the targeted data moments and how well does our model describe non-targeted empirical patterns? In terms of targeted moments the fit is extremely good. Figure 4 shows the fit of the hazard rate where the solid line is the data hazard and the dashed line the model-implied hazard. We are able to fit the hazard curve in basically every month except the time around the benefit exhaustion.³⁸ Table 3 shows the additional targeted data moments and the model implied moments. We can fit the unconditional and conditional changes in the search effort very well and also the second spell moments by capturing a positive slope. Finally, we slightly over-predict the mean number of applications a firm receives. Indeed, the data moment is equal to 4.3 while the model implied mean number of applications is 5.8.

These are two important pieces of evidence that we did not directly included in our estima-

³⁸Here, other factors might be important, e.g. that people exit registered unemployment because they are not eligible for social assistance. Because we do not model these features we disregard the spike at benefit exhaustion. See DellaVigna et al. (2017) for an exploration with present-biased and reference-dependent agents.

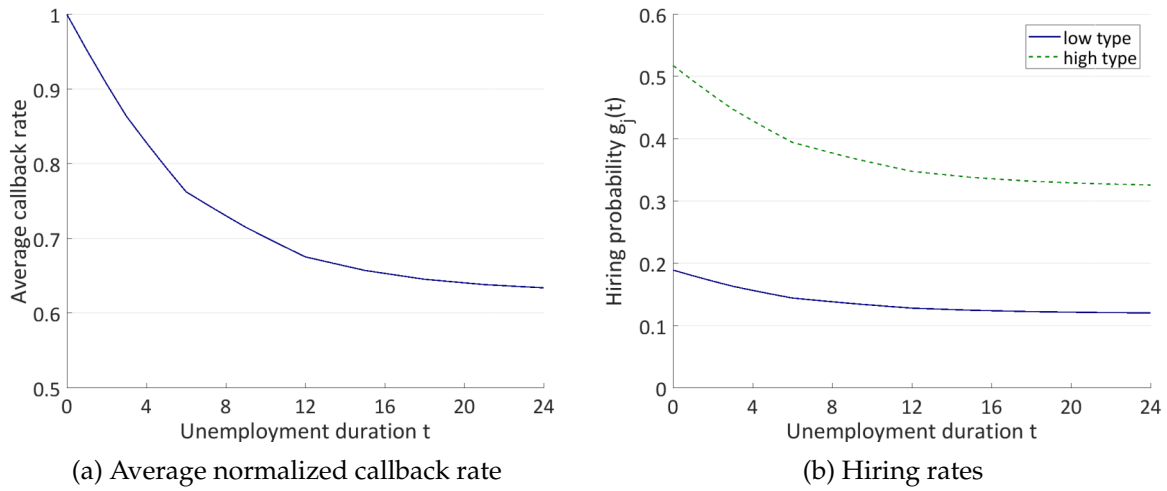


FIGURE 3: Model-implied callback and hiring rates

Notes: The left panel shows the model-implied average callback rate of an application normalized to one in period $t = 1$. The right panel shows the type-specific hiring rates for unemployed that the model generates. The solid line corresponds to the low type and the dashed line to the high type.

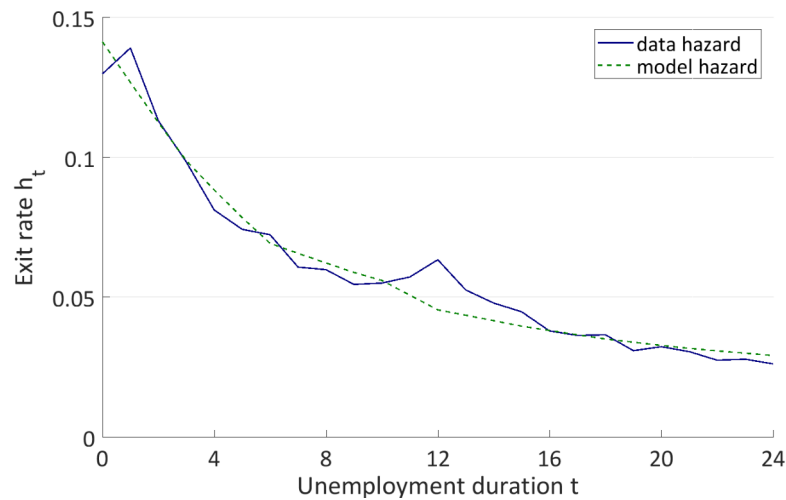


FIGURE 4: Model fit: Hazard rates

Notes: This figure illustrates the model fit of the job finding rate. The solid line corresponds to the data hazard and the dashed line corresponds to the model-implied job finding rate.

TABLE 3: Data moments versus model moments (excluding hazard)

Moment	Data	Model
Unconditional change in search effort $t = 6$	0.710	0.763
Unconditional change in search effort $t = 12$	0.601	0.618
Conditional change in search effort $t = 6$	0.740	0.751
Conditional change in search effort $t = 12$	0.730	0.599
Mean duration second spell bin [1,4]	0.118	0.108
Mean duration second spell bin [5,8]	0.129	0.116
Mean duration second spell bin [9,12]	0.139	0.123
Mean duration second spell bin [13,16]	0.136	0.132
Mean duration second spell bin [17,20]	0.138	0.140
Mean duration second spell bin [21,24]	0.134	0.148
Mean acceptable applications	4.302	5.760

Notes: This table shows the fitted moments from our model. In the second column one can see the data moments and in the third column the model-implied moments. The 24 hazard moments are excluded from the table and can be seen in Figure 4. The second spell moments are divided by 100.

tion: (a) callback rates and (b) duration elasticities with respect to potential benefit durations. Kroft, Lange, and Notowidigdo (2013) find in an experimental audit study that the callback rate from an application declines by about 40 percentage points after one year. In addition, the JVS data suggest that 40 percentage points of firms are not willing to consider unemployed applicants with an unemployment duration of one year or more as shown in Figure A2. Our model indeed implies a very similar pattern in terms of callback probabilities. As discussed above our estimated model predicts a very similar average decline in callback rates. This makes us confident that the magnitude of the estimated screening channel in our model is plausible, since it compares well to the empirical findings on firm-induced duration dependence.

In Schmieder, von Wachter, and Bender (2012) the authors exploit quasi-experimental variation in age cutoffs of potential benefit durations in Germany. If one loses his job above a specific age cutoff the maximal potential benefit duration increases from 12 to 18 months. In their paper they implement a regression discontinuity design and find that additional six months of benefits increase the mean non-employment duration by 0.78 months. In our model, we can perform this simulation and we find that a benefit extension of six months implies an increase in the mean duration by 0.81 months. This is extremely close to the causal estimate from the data and makes us confident that our estimate of the search elasticity λ is reasonable. It ensures that the model-implied responsiveness to benefits is realistic. Since we are finally interested in optimal unemployment insurance we want to have plausible behavioral patterns with respect to benefit payments.

Robustness. Our model is estimated using a genetic algorithm routine. The advantage of this approach is a solution that can better handle non-differentiable objective functions and is bet-

ter suited to find the global solution in a problem with possibly many local minima. However, the drawback is that it is a stochastic optimizer and possibly delivers different estimates in each estimation. Therefore we were running a bunch of estimations with different bounds on the parameter spaces and different initial population spaces. The estimates were always very similar to the reported ones above. We have chosen to report the set of parameters that attained the smallest value of the criterion function. We also tried to use different moments for the estimation including 12 or 35 hazard moments, dropping search moments, dropping multiple spell moments and different definitions of the mean number of applications. In all cases, the estimates were close to the reported ones. We also have tried different functional forms and specifications of the predetermined parameters. There the estimated parameters naturally differ by more, however the qualitative features and conceptual predictions stay the same. Note that two particular specifications are important for the results: (a) the risk aversion parameter γ and (b) the curvature of the vacancy cost ρ , which we assume to be quadratic. The higher the risk aversion γ the larger demand for insurance and the higher optimal UI benefits. Second, the larger the curvature of the vacancy cost function the less responsive are vacancies in equilibrium. This can then determine the sign and magnitude of the applications-per-vacancy channel which translates into either increasing or decreasing hiring rates. For our baseline specification we have used parameters that are either in line with previous literature as discussed above or deliver the best fit to our data moments.

So far, we did not allow for observables like gender, education and other observables from our model. One might suspect that job finding rates differ for these groups and that there is sorting along the unemployment spell on observables which might affect our findings. Therefore, we have computed observable-adjusted hazard rates which were extremely similar to the average hazard rate that we report. We tried restricting the sample to men and different time periods. Again, the hazard rates, the search behavior of agents and other data moments were very similar. It might be that less educated individuals or older individuals survive longer in unemployment and that this creates heterogeneity that our model wrongly attributes to heterogeneity in unobservables. We have therefore created samples for observable education, age and gender cells and compared job finding rates. Besides minor differences in the level there was basically no difference in the decline in the hazard. This is a consequence of only little sorting along the unemployment spell in terms of observables. In Figure A5 and A6 in appendix C we have plotted the mean education of the unemployed sample along the unemployment duration and the fraction of female along the unemployment duration. We see that the curves are pretty flat and that there is not much sorting in terms of observables. This makes us confident that ignoring observables in our model is a good approximation in our setting and allows us to work with a more parsimonious model.³⁹

³⁹To save space, we do not report figures and tables on the discussed robustness checks. All of the robustness checks and alternative specifications are available on request from the authors.

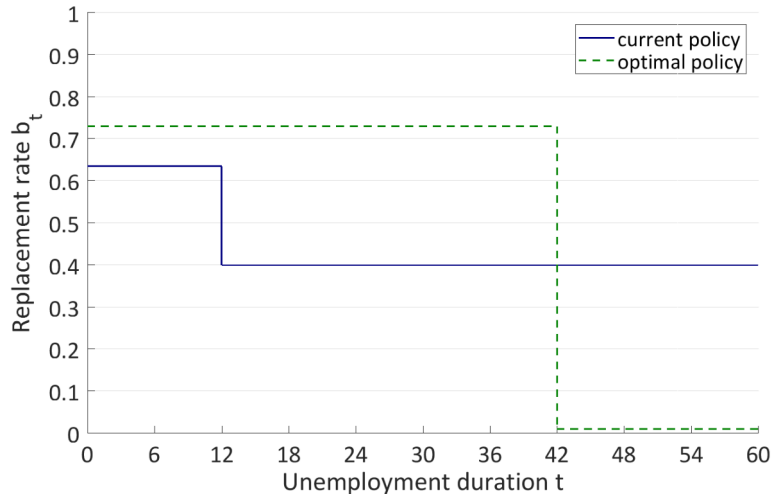


FIGURE 5: Optimal UI versus current UI

Notes: In this graph we compare the current UI policy in Germany (solid line) to the optimal policy suggested by the estimated model (dashed line). The x-axis shows the unemployment duration in months and the y-axis the replacement rate of benefits in terms of the past wage.

5 Welfare Analysis

In this section we use the estimated model for welfare analysis by solving for the optimal policy problem discussed in Section 3. Afterwards we compare the optimal policy to different counterfactual policy simulations, followed by a discussion of more flexible UI schedules.

5.1 Optimal Policy Results

To solve the optimal policy problem outlined in Section 3, we solve the model on a grid for the policy parameters b_1 and b_2 and for each potential benefit duration D , using 1 percentage point steps for the benefit levels. The tax is automatically calculated via the budget constraint. This gives us the global optimum of the welfare problem. The dashed line in Figure 5 shows the optimal policy schedule implied by our model. To have a meaningful benchmark we compare the optimal schedule to the current UI schedule in Germany as shown in the solid line in Figure 5. The current policy pays benefits for one year and offers social assistance thereafter. We find that the optimal policy should pay 73% of the wage in the first 42 months and a 1% replacement rate afterwards.⁴⁰ As one can see the optimal schedule differs substantially from actual policies. Our main finding is that benefits should be (a) higher in the first years, (b) paid for around three and a half years and (c) be very low afterwards. The resulting optimal schedule is a combination of incentivizing agents to search enough, providing insurance to budget constraint agents and to

⁴⁰We solve for the optimal policy on a discrete grid and can therefore evaluate the welfare for each policy. We find that the optimal policy is unique because no other policy schedule leads to the same welfare.

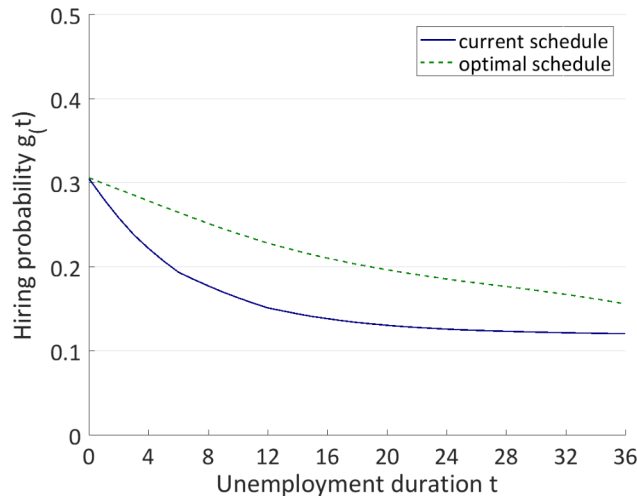
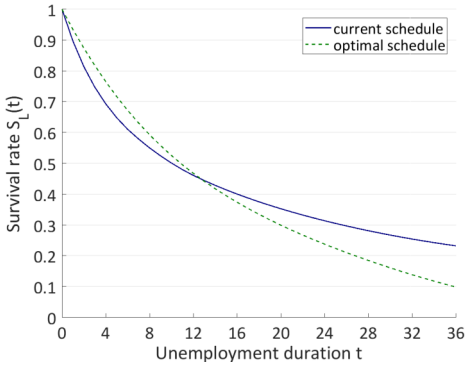


FIGURE 6: Optimal UI versus current UI

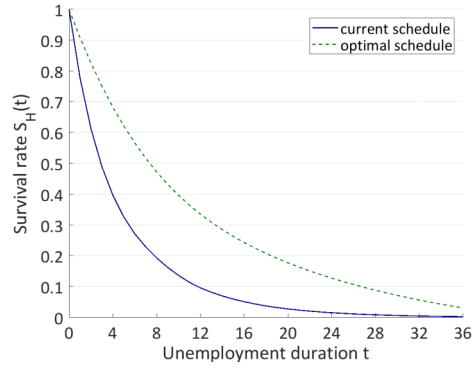
Notes: In this graph we compare the current UI policy in Germany (solid line) to the optimal policy suggested by the estimated model (dashed line). The x-axis shows the unemployment duration in months and the y-axis the replacement rate of benefits in terms of the past wage.

account for firms hiring, screening and vacancy responses.

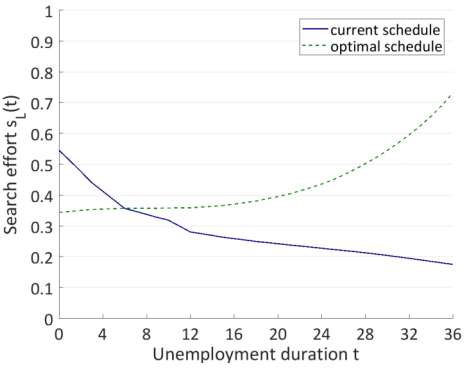
To build intuition for the relevance of equilibrium effects for the optimal policy result in Figure 5 consider the average hiring rate of unemployed in Figure 6. Figure 6 plots the average hiring rate of unemployed job seekers as a function of the unemployment duration. The solid line shows the hiring probability under the current policy, i.e. at the estimated level. In contrast, the dashed line shows that the hiring probability is less declining with unemployment duration under the optimal policy. Hence, the planner reduces the importance of screening by duration and shifts the hiring probability of agents upwards. A higher hiring probability suggests that firms are more willing to hire the long-term unemployed. Panel (a) and (b) of Figure 7 illustrates why this happens when the optimal policy is implemented. Panel (a) and (b) show the survival probability of the unproductive and productive type, respectively. Note that in the long term, under the current schedule some unproductive types stay unemployed for very long, while under the optimal policy after four years almost all unproductive types are working. In both panels the solid line shows the survival probability at the estimated level and the dashed line under the optimal policy. One can see that the optimal policy considerably alters the dynamic composition of the unemployment pool. As panel (a) and (b) suggest, at any point of the unemployment duration the relative composition changes towards the productive type, i.e. at any point there are relatively more good types unemployed compared to the current setting. This in turn implies that firms are more likely to consider long-term unemployed because the pool of applicants is of a better quality under the optimal policy. The changed composition of unemployed is a result of the change in search incentives for the two types as illustrated in panel (c) and (d) of Figure 7. Again, the dashed



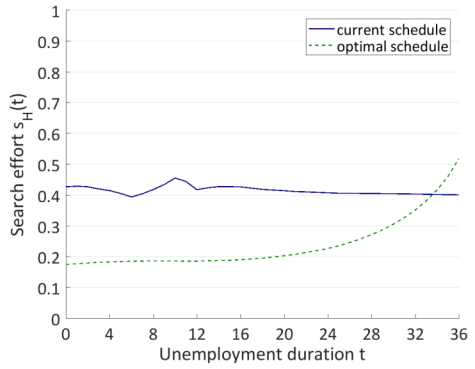
(a) Survival of unproductive type



(b) Survival of productive type



(c) Search effort of unproductive type



(d) Search effort of productive type

FIGURE 7: Counterfactual model simulations

Notes: The above panels show counterfactual model simulations of the search effort of unemployed and the survival probability in unemployment. Panel (a) shows the survival in unemployment of the unproductive type under the current policy (solid line) and the optimal policy ((dashed line) as a function of the unemployment duration in months on the x-axis. Panel (b) shows the same for the productive type. Panel (c) shows the search effort of the unproductive type under the current policy (solid line) and the optimal policy (dashed line) as a function of the unemployment duration in months on the x-axis. Panel (d) shows the same for the productive type.

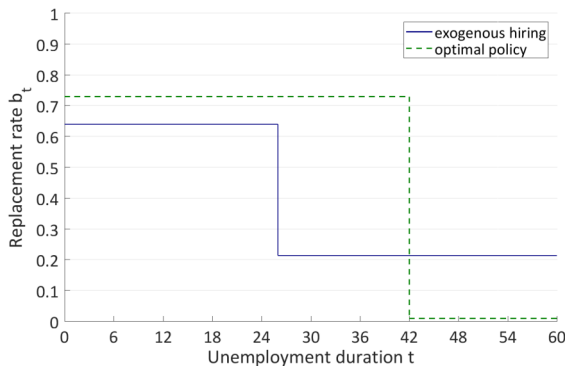
line shows the search effort under the optimal policy and we compare it to the setting with the current policy. Under the optimal policy the unproductive type is incentivized to search more while the productive types searches less on average. Hence, the composition of unemployed will move towards the productive types because now relatively more unproductive types exit early in their spell. Hence, the planner considerably alters search behavior of agents and hence the hiring and screening behavior of firms. However, Figure 5 does not allow to distinguish how important these endogenous firm responses are in terms of changing the optimal policy, relative to a setting without endogenous firm responses where only search incentives and insurance motives are at work. We will discuss the relevance of this firm adjustments and how they shape optimal policy in equilibrium in the next subsection.

How large is the welfare gain of moving from the current policy to the optimal policy for the unemployed? In other words, how much cash-on-hand would we need to pay an unemployed individual under the current regime such that he is as well off as with the optimal policy? When we implement this experiment we find that the gain of moving to the optimal policy amounts to a lump-sum payment of nearly 5,500 euros to an unemployed at the beginning of his spell. This is a fairly large amount and moving to the optimal policy implies a large welfare gain in our model.

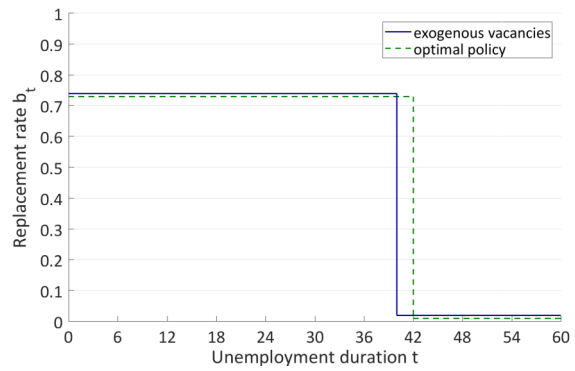
5.2 Discussion

To show the quantitative importance of firm responses for the baseline result presented in the last subsection, we perform various counterfactual simulations to decompose the importance of firm responses for the optimal policy design problem.

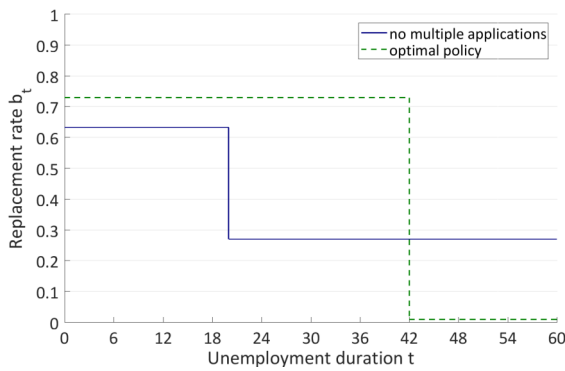
Exogenous hiring rates. In the baseline model hiring rates for job seekers are endogenous to UI policies. As we have illustrated in Section 3 higher benefits can lead to higher hiring rates through the adjustment of firm beliefs about the pool of applicants and through changes in the applications-per-vacancy ratio. If we fix hiring rates for job seekers at the level of the estimated model under the actual policy in place and then re-solve the planner problem we can decompose the component of the optimal UI policy that can be attributed to the endogenous firm responses, namely hiring rates and vacancy creation. In panel (a) figure 8 we compare the optimal UI policy in the baseline model (dashed line) with the optimal policy when hiring rates are exogenously set at the level of the estimated model (solid line). We find that the schedules substantially differ and that UI with exogenous hiring is less generous and paid for a shorter amount of time. Benefits after two years are however higher with exogenous hiring rates, which is because with exogenous hiring more agents survive longer in unemployment and the insurance motive becomes stronger. To be more precise, endogenous hiring rates allow the planner to lift up these hiring rates by providing different incentives for job seekers and firms. By implementing the optimal schedule the planner increases the value of search and therefore reduces long-term unemployment. However, this is an equilibrium effect, because more search effort of job seekers increases the value of a vacancy and the expected profit of hiring. These equilibrium adjustments are absent in partial



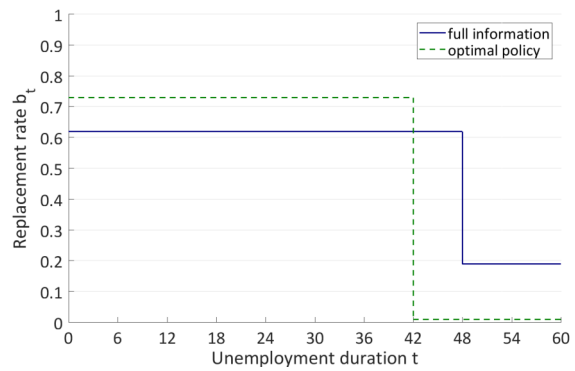
(a) Exogenous hiring rates



(b) Exogenous vacancies



(c) No multiple applications



(d) Full information

FIGURE 8: Counterfactual policy results

Notes: This figure compares the optimal policy of our baseline model (dashed line in both panels) with different counterfactuals. Panel (a) compares to a setting where hiring rates are policy invariant at the level of the estimated model (solid line in panel (a)). Panel (b) to a setting where the mass of vacancies is policy invariant at the level of the estimated model (solid line in panel (b)). Panel (c) to a setting without multiple applications and without screening (solid line in panel (c)). Panel (d) to a setting where firms observe agents' productivity, i.e. $\sigma = 0$ and signals are informative (solid line in panel (d)). In all panels, the x-axis shows the unemployment duration in months and the y-axis the replacement rate of benefits in terms of the past wage.

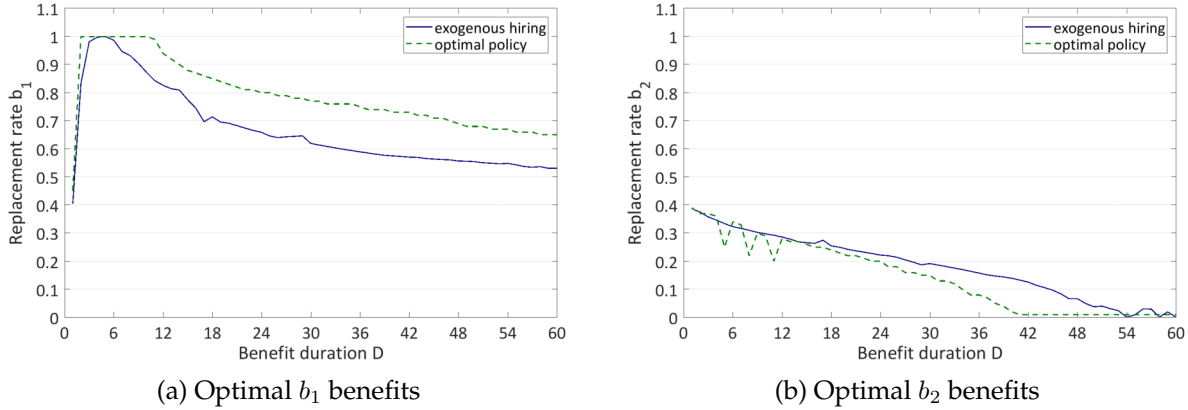


FIGURE 9: Non-linear optimal UI

Notes: Panel (a) illustrates benefits b_1 for the baseline case (dashed line) and the case with exogenous hiring rates (solid line) as a function of the potential benefit duration D on the x-axis. The y-axis denotes the optimal benefit level for b_1 . Panel (b) shows the same two cases for optimal benefits b_2 as a function of the benefit duration D .

equilibrium models. What panel (a) shows is that a large part of the benefit extension compared to the actually implemented schedules is driven by endogenous firm responses. The reason for this finding is that even small changes of hiring rates can create large changes in search effort and survival rates. This shows that incorporating endogenous hiring decisions is quantitatively very important for welfare conclusions in terms of optimal UI policies, because it changes the optimal benefit level and benefit duration in a non-negligible manner.

Exogenous mass of vacancies. The above finding in panel (a) of Figure 8 is a mix between vacancy responses and hiring rate responses of firms. Therefore, in panel (b) of figure 8 we exogenously fix the amount of vacancies in the economy at the level of the estimated model and allow hiring rates to be endogenous. This experiment allows us to decompose the importance of the hiring response, i.e. the applications-per-vacancy channel and the firm beliefs, holding fixed the number of open positions. We find that the vacancy channel is quantitatively very small and optimal benefits are similar to our baseline policy where vacancies are allowed to adjust in equilibrium. Hence, the longer potential duration and the generosity of benefits is mainly driven by the endogeneity of hiring rates, not vacancies.

No multiple applications. This naturally leads to the question how optimal UI would look like in our model if there was only one application per vacancy, i.e. there are infinitely many vacancies and no crowding-out among applicants. This limiting case where vacancy costs κ are equal to zero is an important benchmark for our model, because it shuts down the employer screening channel. This implies that every applicant gets screened and hired in case he is qualified. The difference to the exogenous hiring case is that the callback rate is flat and that there is no duration dependence

in the model. The single applications per vacancy limit is equivalent to a standard partial equilibrium search model with heterogeneity in job arrival rates. Figure 8 panel (c) illustrates the optimal policy in this setting compared to our screening model with multiple applications per vacancies. The solid line shows how optimal UI should look like in the absence of employer screening. Interestingly, the optimal schedule is close to the actually implemented schedule. The only difference is that benefits are paid a few months longer and that b_2 is somewhat smaller. The optimal schedule is similar to the case with exogenous hiring, however D is smaller when there are no multiple applications. This is because if agents do not need to compete with other applicants their job finding rates are higher and the demand for insurance is lower.

Full information of vacancies. One additional interesting comparison on the importance of screening is the full information case where there are multiple applications but firms perfectly observe agents' types and productivity. In this case hiring rates become flat and true duration dependence disappears, but the applications-per-vacancy ratio is endogenous and not equal to one. The solid line in Figure 8 in panel (d) shows how optimal UI looks like if there is full information about the productivity of applicants. Because this implies lower job finding rates of bad types the demand for insurance, even in the long term increases. Hence, optimal UI is paid for longer (48 months) and b_2 is at a higher level.

Fully dynamic UI schedules. So far we have restricted to optimal UI schedules with four policy parameters. This is for two reasons: (a) our optimal schedules mimic current policies and (b) solving the government problem with more flexible parametrizations is numerically not feasible. However, we can illustrate fully flexible optimal UI policies with a distinct b_t for each unemployment duration t by calculating the optimal b_1 and b_2 level for each potential duration D . This gives some indication about the shape of a more flexible schedule. In Figure 9 panel (a) the dashed line shows how the optimal b_1 level in the baseline is set as a function of the potential duration D on the x-axis. In panel (b) the dashed line shows how the optimal b_2 level is set as a function of the potential benefit duration D . Panel (a) suggests that optimal benefits should follow a hump-shaped pattern and that UI benefits should be increasing in the first months of unemployment and be decreasing thereafter. To see this, note that if only paid for 1 month, the optimal level of b_1 is only about 0.4. If paid for two months, however, this level is higher, which can only be the case if the optimal schedule is increasing at first.

The solid lines in the two figures allow us to compare the optimal shape to the setting with exogenous hiring rates at the level of the estimated model. One can see that under screening b_1 is increasing faster and stays at a high level for longer than in the setting without screening.⁴¹ Hence, fully dynamic optimal UI schedules under screening should follow a more pronounced hump-shape and be more generous and paid for a longer time than in a setting with exogenous

⁴¹Note that we restrict to policies with $b_t \leq 1$ because benefit levels above the wage are not of practical interest. However, this restriction leads to numerical fluctuations in panel (b) as one can see with the spikes in the optimal b_2 level at durations where b_1 hits the upper bound. The spikes disappear if the upper bound is set to a higher level.

hiring rates, which is perfectly in line with our more restrictive policy results in the baseline case with four policy parameters.

Alternative Parametrizations. In appendix D Figures A7, A8, A9 and A10 we show some additional alternative parametrizations of the model to check how important various parameters and assumptions are for the optimal policy outcomes. Naturally, the risk aversion of agents matters for the generosity of benefits. The more risk averse agents are the longer the potential benefit duration and vice versa. As DellaVigna et al. (2017) suggests agents seem to have large discount factors or behave as if they are present biased. Therefore, as an alternative we use $\beta = 0.95$ which amounts to an annual discount factor of 0.54. If agents discount the future at the higher rate, benefits are higher early on but lower later in the spell, which is exactly what one would expect if agents value the present more relative to the future. The elasticity of the vacancy creation channel seems to be not very important for optimal UI schedules as we show in appendix D. Finally, if we assume that all agents start without assets to the unemployment spell, then optimal UI policy hardly changes compared to the optimal schedule.

6 Extensions

In this final section we will discuss three extensions of our model and how they would alter our findings: multiple applications of the unemployed, screening costs of the firm and endogenous wages.

Multiple applications per worker. While we focused on the case of each worker sending out at most one application, it is also possible to consider the general case where workers can send out more applications. The main advantage of this extension is that it allows the model to replicate the observed facts about the number of applications individuals send (see Figure 1) more directly.

Following Kaas (2010) and Shimer (2004), a convenient way to include multiple applications is to allow workers to search with continuous search intensity s and stochastically send out a number of applications that follows a Poisson distribution with mean s . In this case, the hazard rate is the expected probability of at least one application resulting in an offer, $h_j(t) = 1 - \exp(-g_j(t)s)$, and $g_j(t)$ has the interpretation of being the endogenous *success probability* of each application, while s is the expected number of applications sent.⁴² Introducing multiple applications in this way does not change the rest of the model.

We experimented with this version of the model and the results are qualitatively similar. A main difference is that multiple applications, in principle, introduce another coordination friction, since agents get multiple offers and can accept only one. As a result, some vacancies make of-

⁴²A worker who sends a applications gets at least one offer with probability $1 - (1 - g_j(t))^a$ and the expression results from taking the expectation over a , which follows a Poisson distribution with mean s . It is interesting to note that this setting provides a micro-foundation for using $1 - \exp(-\lambda s)$ as a functional form for the arrival rate, which is commonly used in partial equilibrium models.

fers that are rejected. This gives rise to the question if these firms should be allowed to contact other applicants, if their first offer gets rejected. Otherwise, the coordination friction reduces firm profits and therefore the number of vacancies. There are different approaches to this issue in the literature. Some recent paper allow for *recalls*, i.e. the possibility to contact other applicants (see e.g. Kircher (2009)), while others do not (Kaas (2010), Gautier, Moraga-González, and Wolthoff (2016), Albrecht, Gautier, and Vroman (2006)). Without recall, it can be desirable to make workers search less, since this makes the additional coordination friction less severe and increases entry. For simplicity, and since we do not want to focus on this additional coordination friction, we restrict ourselves to the case of one application per worker, as is also done in Fernández-Blanco and Preugschat (2015) or Villena-Roldan (2012).

Screening costs. Another possible extension is to make screening costly for firms, rather than assuming that screening costs are tiny. In our setting, firms would still screen all applicants for most realistic values of the screening cost (since the lower bound of the expected profit is $\pi_L y$, which is the expected profit of the low type).⁴³ While one could argue that the screening costs are included in the vacancy posting costs, an interesting feature of introducing screening costs is that it would make the vacancy cost partially endogenous: when unemployment duration or signals are not informative, firms on average have to screen more applicants before finding a qualified one and would have less incentives to create vacancies. From a policy perspective, screening costs may provide a rationale for trying to make duration informative, since this would make hiring easier for firms. In the current version of the model, the potential welfare gains from a decrease in screening already have to be weighted against the potential decline in the number of vacancies. Screening costs would amplify the latter effect.

Endogenous wages. A further extension would be to depart from the assumption of a fixed wage. Our main motivation for this assumption is that it is a reasonable approximation of the empirical evidence, which is discussed below, and that introducing endogenous wages in our framework likely makes the analysis much less tractable. In standard matching models with just one applicant per vacancy, wages are often assumed to be determined by Nash bargaining. However, this is more problematic when there are multiple applicants per vacancy, since firms would have to simultaneously bargain with each of the applicants. With wage posting, on the other hand, characterizing the equilibrium becomes challenging, especially in our context of endogenous search effort and savings, both of which are important for the analysis of optimal UI.⁴⁴

From an empirical point of view, there is increasing evidence to support the assumption of a fixed wage, conditional on worker characteristics. For example, Krueger and Mueller (2016) find that reservation wages stay remarkably constant over the unemployment spells. Hall and Mueller (2015) show that individuals often accept the first job offer they get. Their evidence also suggests

⁴³See Jarosch and Pilossoph (2016) for a discussion of how to calibrate a parameter for screening costs.

⁴⁴Fernández-Blanco and Preugschat (2015) consider the case of wage posting with directed search, but assume that workers do not know their type and that there is no effort or savings choice.

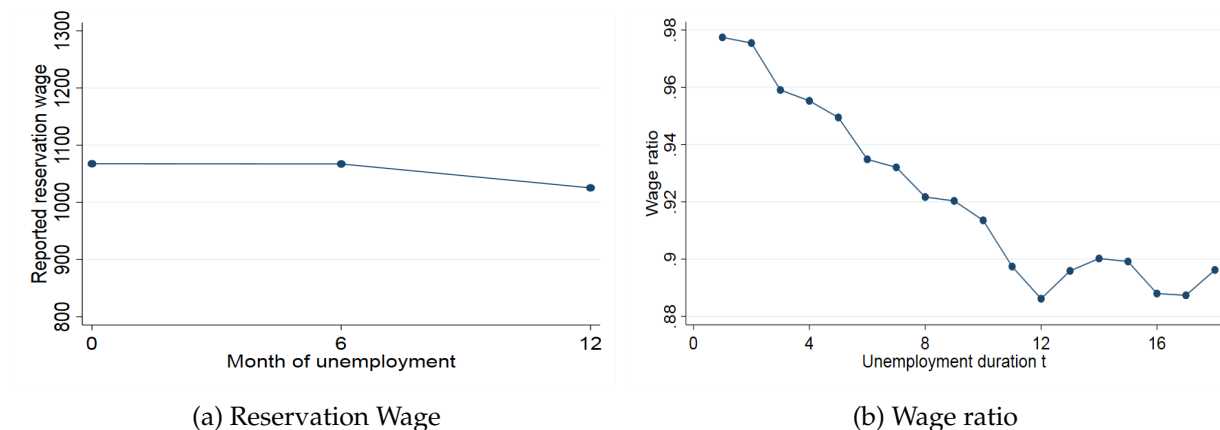


FIGURE 10: Reservation wages and realized wages by unemployment duration

Notes: The left panel shows the mean reported reservation wage (from the IZA ED) of individuals who have been unemployed for zero, six or twelve months. The right panel shows the (realized) ratio of the wage before and after unemployment (based on SIAB data) by unemployment duration.

that relatively few individuals have the opportunity to bargain about their wages, but rather face the option to accept fixed offers. Our datasets support these findings for reservation wages as can be seen in Figure 10 panel (a). There one can see that self-reported reservation wages are essentially flat throughout the unemployment spell. In addition, in the JVS data employers report whether the hiring process included some form of wage bargaining with the applicant and only 34% of firms report that this was the case. Looking at realized wages, Figure 10 shows that the average ratio between the post- and pre-unemployment wage drops fairly moderately from 98% to 90% after one year, even without controlling for selection on observables throughout the spell.⁴⁵

7 Conclusion

This paper has analyzed a dynamic search model where firms can choose from a pool of applicants and have incomplete information about their quality. Firms rank applicants by their expected productivity, which makes it less likely that the long-term unemployed are invited for interviews in the presence of other applicants. The model is estimated to match several important features of the data regarding job-finding rates, search effort and vacancies.

Our welfare analysis suggests that equilibrium effects in the form of endogenous hiring and interview decisions are quantitatively very important for the optimal design of unemployment benefits. We find that allowing for these equilibrium effects leads to benefit schemes that are more generous in the first place, benefits are paid for a longer time, but benefits are very low at longer unemployment durations. More generally, our results demonstrate that modeling the details of the hiring process can have quantitatively sizable implications for optimal UI policy and that this

⁴⁵See also [Schmieder, von Wachter, and Bender \(2016\)](#) for a more detailed analysis of the wage effects throughout the unemployment spell.

requires integrating features into search and matching models that have often been abstracted from - most importantly, the possibility of multiple applications per vacancy.

An interesting aspect that we have not made explicit so far is that long-term unemployment is not such a bad signal in recessions when the applications-per-vacancy ratio is high. If there are many unemployed applicants per open vacancy then screening matters more and benefits can be more generous and paid for a longer time. Hence, our findings can rationalize benefit extensions as those implemented through the Great Recession in the US. Another important question for future research is to find additional quasi-experimental evidence on the importance of competition for jobs among many applicants and employer screening. Reduced-form evidence on how hiring decisions respond to unemployment policies would nicely complement our more structural approach. Alternatively, one could think of non-standard policy instruments, for example hiring subsidies for firms that are used in some countries.⁴⁶ Such an instrument could help to mitigate screening by giving firms incentives to screen unemployed with a long unemployment duration.

⁴⁶In 2014, the German government announced to spend 150 million euros on wage subsidies for the long-term unemployed.

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Appendix

Appendix A: Numerical Solution of Model

In this section, we outline the algorithm used to solve for the equilibrium of the model.

General approach. We start by guessing a matrix of hiring rates $g_j(t)$. Given these values and the functional forms described in Section 4, we can solve the agent problem backwards. In each period, the optimal level of search intensity has a closed-form solution:

$$s_{j,t} = A(\beta g_j(t)(V_j^e(t) - V_j^u(t)))^\lambda$$

To obtain policy functions for savings, we use the method of endogenous grid points (Carroll (2006)). In period T , agents will consume their remaining assets. For each previous period, we can rearrange the Euler equations so that k_t is expressed as a function of k_{t+1} and k_{t+2} . Since we know the policy function for period $t + 1$ and can replace k_{t+2} by a function of k_{t+1} , this results in an equation that just contains k_t and k_{t+1} . We use a grid of 50 points for k_{t+1} and can compute the corresponding k_t . To obtain the full policy function, we interpolate linearly between the grid points (Judd (1998)).

Given the solution to the agent problem, the update of the firm problem consists of two steps. First, we have to update the hiring probabilities $g_j(t)$ via the equation described in the model section (and, in more detail, below). Second, we need to update v using the free-entry condition. The equilibrium is computed by iterating these steps until convergence.

Computing the hiring rates. Recall the following two expressions needed for the hiring rates:

$$p(t, \phi) = \sum_{k=1}^J \frac{a_k}{a} \cdot \pi_k \cdot P(\Pi(\tilde{\phi}, \tilde{t}) \geq \Pi(\phi, t) | k)$$

$$g_j(t) = \pi_j \int_{\phi} \exp(-p(\phi, t) \cdot \mu) dF_j(\phi)$$

We compute these expressions as follows:

- $P(\cdot | k)$ is the probability that a random draw of type j from the pool is better than a given applicant. This is the following probability:

$$\int_{\tilde{\phi}} \left(\sum_{\tilde{t}=1}^T \mathbb{1}(\Pi(\tilde{\phi}, \tilde{t}) \geq \Pi(\phi, t)) \frac{S_{j,\tilde{t}} s_{j,\tilde{t}} \alpha_j}{\sum_t S_{j,t} s_{j,t} \alpha_j} f_j(\tilde{\phi}) \right) d\tilde{\phi}$$

We evaluate the integral using Gauss-Legendre quadrature.

- Given these probabilities, we calculate $g_j(t)$ using Gauss-Hermite quadrature with 5 nodes.

Appendix B: Institutional Details

We create two samples of unemployment spells. One from 2000 until 2011 as specified in Section 2.1 and a sample from 1983 until 2010. The second is necessary to create a sample of unemployed individuals that receive two or more unemployment spells in their work history, because in the estimation part we use some moments from a multiple spell sample to identify the heterogeneity parameters. In the following we describe the sample creation for the 1983 sample, because the 2010 sample is just a simple subsample of the former. To account for changing rules and laws over the sample period that determine UI eligibility we use an eligibility simulator and drop all individuals that are not eligible for 12 months of UI. The simulator includes age cutoffs (older individuals receive benefits for longer), employment history regulations and drops individuals that might be subject to carry-forward rules that come into play for individuals with multiple unemployment spells. Shorter durations are applied to individuals with unstable working histories; longer durations to older workers. In order to obtain a proper sample of unemployment spells it is necessary to implement the main features of the German unemployment insurance system. To do so, we restrict ourselves to unemployment spells starting from January 1st, 1983 until the end of the last day of 2011. Since our data ends in 2014 we only consider unemployment spells that we observe for at least three years. We choose 1983 as the beginning, since we need to observe the employment history of individuals four years prior to their unemployment spell in order to determine UI eligibility. In Germany, the duration of UI reciprocity depends on the employment history in the last four years from January 1st 1983 until June 30th 1987, the last three years from July 1st 1987 until January 31st 2006 and the last two years from from February 1st 2006 until December 31st 2011. The number of years that are considered for the employment history is legally called base period (*Rahmenfristen*). In our analysis, we will only consider individuals that are eligible for 12 months of unemployment benefits when they lose their job. The general rule is determined by an abeyance ratio (*Anwartschaftsverhältnis*). The abeyance rule says that the months worked in the base period divided by 3 (from 1.1.1983 until 30.6.1987) or 2 (from 1.7.1987 until 31.12.2011) determines the maximal UI eligibility (abstracting from age cutoffs). Table A1 summarizes the mapping from the months worked in the base period into the months of UI eligibility for the period from 1983 until 2011. (See Hunt (1995); Schmieder, von Wachter, and Bender (2010) for similar tables.) For individuals with a certain age, special rules apply that extend the potential UI duration to more than 12 months. For these individuals the base period is seven years. These individuals are not in our sample and the table does not show the potential durations for these individuals⁴⁷. The table entries with ages in brackets show when individuals become eligible for longer durations due to their age. All individuals that are below the age cutoff receive 12 months of benefits. We drop all unemployment spells from our sample to which certain age restrictions apply.

For the estimation, we use some moments that use information from the second unemployment spell of individuals. However, for individuals that experience their second unemployment spell complex carry-forward rules apply if the second spell is not more than four years after the

⁴⁷I.e. the table ignores working histories of more than 48 months.

beginning of the first spell. To avoid modelling these rules we restrict second spells to be at least four years after the beginning of the first spell. Second, we restrict unemployment spells to individuals aged between 20 and 55. For individuals older than 55 the German social security system offers several early retirement schemes. For individuals below the age of 20, there is often the opportunity to go back to some form of school. We then drop third and fourth unemployment spells from the data, even though only a handful individuals are eligible for UI three or more times. Further, we exclude any ambiguous spells from the sample. These are in particular the following cases that can arise: (a) individuals that receive UI and UA at the same time for more than 30 days and (b) individuals that are employed and receive UI at the same time for more than 14 days.⁴⁸ If we observe two consecutive unemployment spells within 14 days we pool them together and count them as one spell. With all these restrictions we arrive at a final estimation sample of 179,696 individuals, where 18,432 individuals experience an additional second spells. In our sample from 2000 onwards we have 59,793 first unemployment spells.

An unemployment spell is defined as the transition from employment to UI within 30 days. Individuals that register more than 30 days after their last job has ended are dropped to avoid voluntary quitters that have a waiting period of 3 months and to avoid to wrongly measure unemployment spells due to individuals that do not take-up UI within a month. Employment consists of either socially insured employment, apprenticeships, minor employment, or other forms of registered employment. We define unemployment duration as the time between the start of UI reciprocity until next employment starts (similar as in [Card, Chetty, and Weber \(2007\)](#) and [Schmieder, von Wachter, and Bender \(2012\)](#)), though we also count moves to apprenticeship, or minor employment relationships as re-employment. We also cap unemployment durations at 36 months. This is necessary, because in the data there are many spells with long tails and some individuals that never return to work or have an additional entry. The re-employment wage is defined as the wage the individual earns at the first employed position after unemployment.

⁴⁸It is not entirely clear where these cases come from, however there are only a few of them.

Appendix C: Additional Figures & Tables

TABLE A1: Potential unemployment benefit durations

Months worked in base period	1.1.83 - 31.12.84 (4 years)	1.1.85 - 31.12.85 (4 years)	1.1.86 - 30.6.87 (4 years)	1.7.87 - 31.3.97 (3 years)	1.4.97 - 31.12.04 (3 years)	1.1.05 - 31.1.06 (3 years)	1.2.06 - 31.7.08 (2 years)	1.8.08 - 31.12.11 (2 years)
12	4	4	4	6	6	6	6	6
16	4	4	4	8	8	8	8	8
18	6	6	6	8	8	8	8	8
20	6	6	6	10	10	10	10	10
24	8	8	8	12	12	12	12	12
28	8	8	8	14(\geq 42)	14(\geq 45)	12	12	12
30	10	10	10	14(\geq 42)	14(\geq 45)	15(\geq 55)	15(\geq 55)	15(\geq 50)
32	10	10	10	16(\geq 42)	16(\geq 45)	15(\geq 55)	15(\geq 55)	15(\geq 50)
36	12	12	12	18(\geq 42)	18(\geq 45)	18(\geq 55)	18(\geq 55)	18(\geq 50)
40	12	12	12	20(\geq 44)	20(\geq 47)	18(\geq 55)	18(\geq 55)	18(\geq 50)
42	12	14(\geq 49)	14(\geq 44)	20(\geq 44)	20(\geq 47)	18(\geq 55)	18(\geq 55)	18(\geq 50)
44	12	14(\geq 49)	14(\geq 44)	22(\geq 44)	22(\geq 47)	18(\geq 55)	18(\geq 55)	18(\geq 50)
48	12	16(\geq 49)	16(\geq 44)	24(\geq 49)	24(\geq 52)	18(\geq 55)	18(\geq 55)	24(\geq 50)

Notes: This table is based on [Hunt \(1995\)](#); [Schmieder, von Wachter, and Bender \(2010\)](#) and own calculations. For individuals with a certain age, special rules apply that extend the potential UI duration to more than 12 months. For these individuals the base period is seven years. These individuals are not in our sample and the table does not show the potential durations for these individuals. The table entries with ages in brackets show, if individuals become eligible for longer durations due to their age (for working histories of less than 48 months). All individuals that are below the age cutoff receive 12 months of benefits.

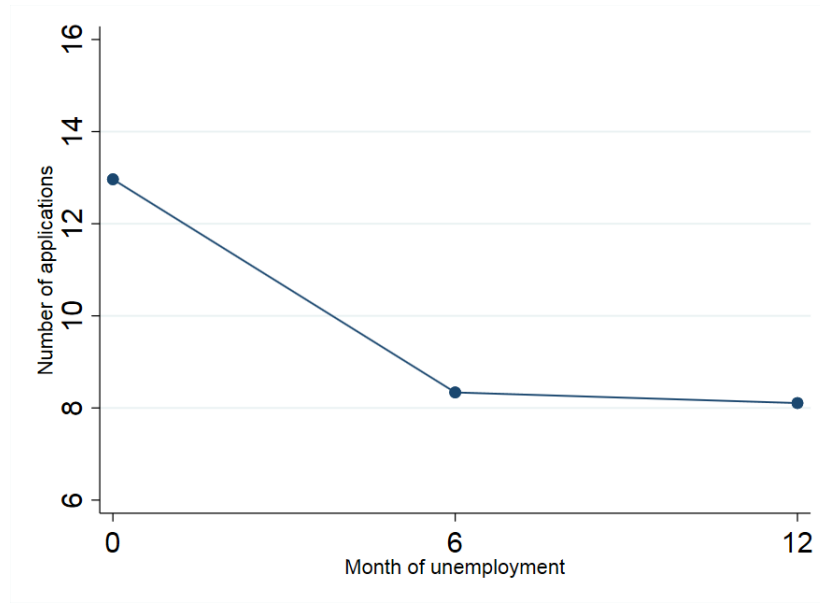


FIGURE A1: Conditional Search Effort

Notes: The figure shows the average search effort conditional on staying unemployed for at least one year. Search effort is measured on the y-axis in terms of the number of applications. Source: IZA ED.

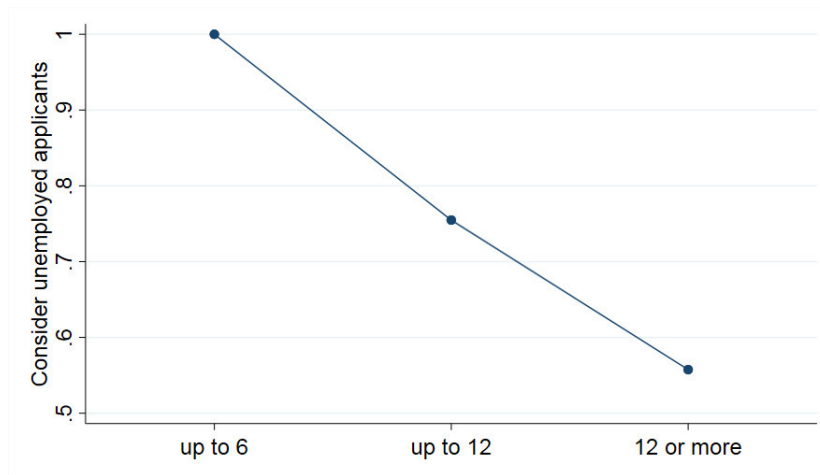


FIGURE A2: Consider unemployed applicants

Notes: This graph shows the response to whether vacancies consider unemployed applicants as a function of the unemployment duration in months. The answers in the figure are conditional on reviewing unemployed applicants at all. The x-axis shows the categories in the survey question (consider applicants with up to 6 months of UI duration, up to 12 months of UI duration or longer than 12 months of UI). The y-axis plots the fraction of firms that still consider certain applicants. Source: JVS.



FIGURE A3: Labor market tightness

Notes: This figure plots the labor market tightness for Germany from 2000 until 2014. Labor market tightness is defined as the ratio of open vacancies over the number of registered unemployed. The horizontal line denotes the average labor market tightness over the period. This figure shows that there are fewer vacancies than unemployed and that even when each vacancy is filled there remain some job seekers, which provides additional evidence that crowding-out factors and multiple applications among job seekers might be of importance. Source: Insitute for Employment Research (IAB).

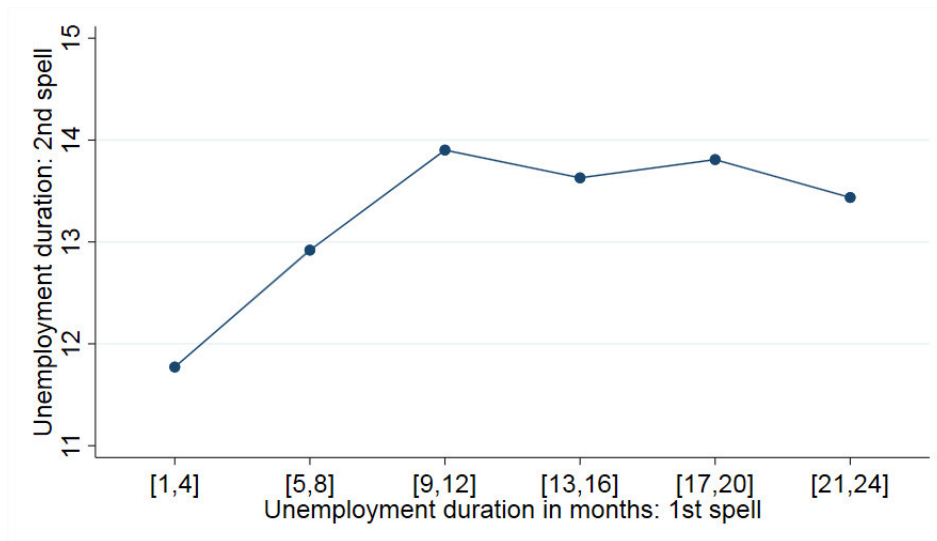


FIGURE A4: Mean duration in second unemployment spell

Notes: The x-axis of this figure puts the unemployment duration of the first UI spell into 4-month bins and shows the mean duration in the second spell on the y-axis. The sample of spells is extended to the period from 1983 until 2011. Source: SIAB.

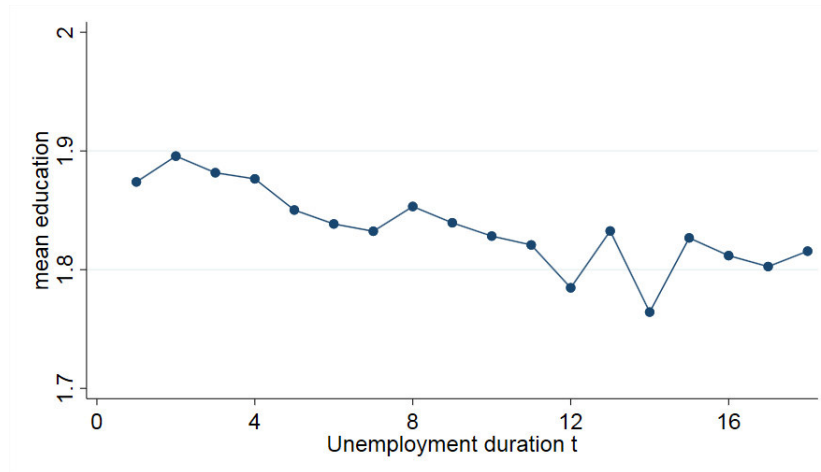


FIGURE A5: Mean education over UI spell

Notes: In this graph we plot the mean education of unemployed as a function of the UI duration. The education variable is defined as follows: 0 no school degree. 1 school degree. 2 apprenticeship. 3 college. Source: SIAB.

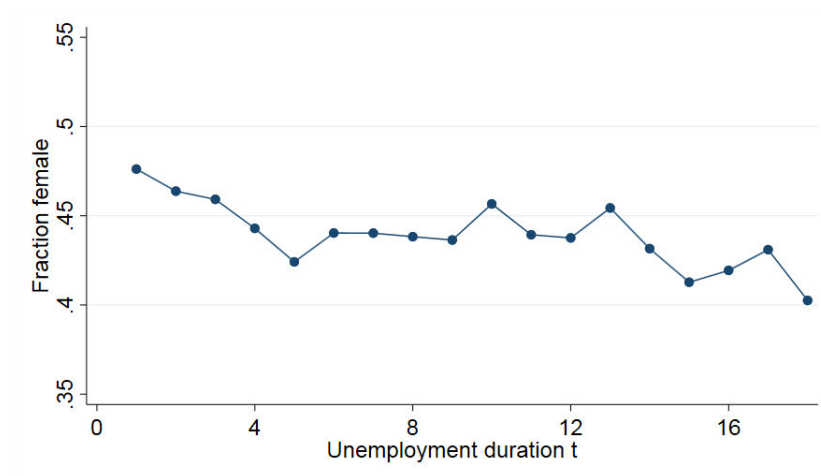
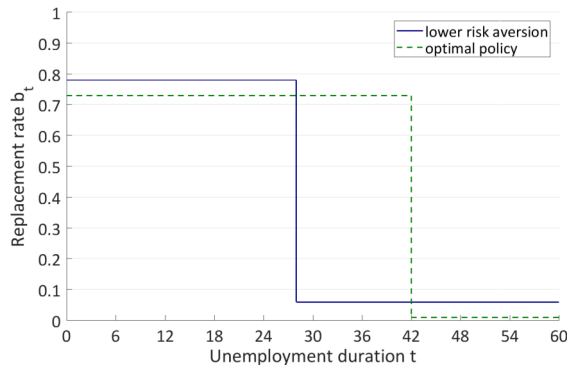


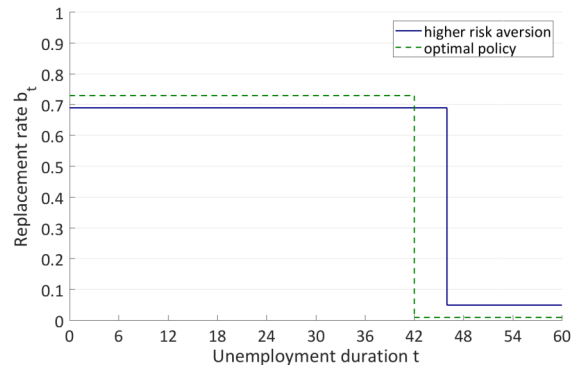
FIGURE A6: Fraction female over UI spell

Notes: In this graph we plot the fraction of female unemployed as a function of the UI duration. Source: SIAB.

Appendix D: Alternative Parametrizations



(a) Lower risk aversion



(b) Higher risk aversion

FIGURE A7: Different risk aversion

Notes: This figure compares the optimal policy of our baseline model (dashed line in both panels) with a setting where agents are either less risk averse with $\gamma = 1.8$ (solid line, panel (a)) or more risk averse with $\gamma = 2.2$ (solid line, panel (b)).

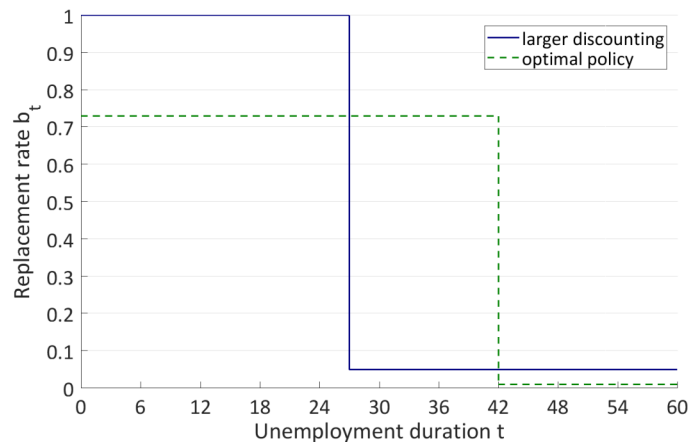


FIGURE A8: Higher discounting

Notes: This figure compares the optimal policy of our baseline model (dashed line) with a setting where agents have a larger monthly discounting factor, i.e. $\beta = 0.95$. The optimal policy under this assumption is illustrated with the solid line.

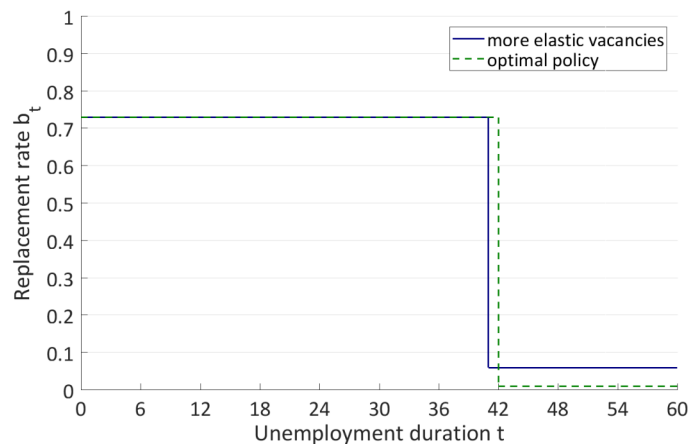


FIGURE A9: Higher elasticity of vacancy creation

Notes: This figure compares the optimal policy of our baseline model (dashed line) with a setting where $\rho = 0.5$, i.e. the vacancy creation is more elastic and vacancy costs are closer to linear. The optimal policy can be seen in the solid line.

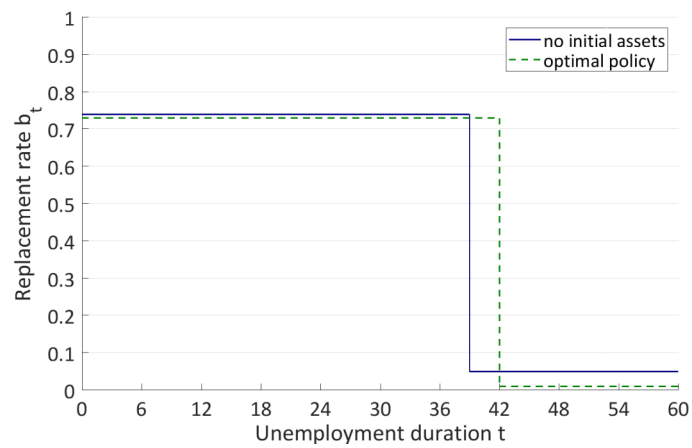


FIGURE A10: No initial assets

Notes: This figure compares the optimal policy of our baseline model (dashed line) with a setting where no agent has initial assets (solid line).