Employer Screening, Unemployment Stigma and Optimal Unemployment Insurance[*]

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Abstract

This paper studies how statistical discrimination against the long-term unemployed affects the optimal design of unemployment insurance. In our model, firms choose from a pool of applicants and have incomplete information about their productivity. They observe a noisy signal and unemployment duration and rank applicants according to their expected productivity. The probability of being hired declines with duration due to declining beliefs about productivity and competition by other job-seekers. We estimate the model using German administrative employment records and information on job search behavior, vacancies and applications. The model matches the observed decline in search effort and job finding rates and the implied decline of callback rates is in line with recent evidence from audit studies. Optimal policy takes into account that unemployment benefits can affect hiring probabilities by making unemployment duration more or less informative and by changing the applications-per-vacancy ratio due to search effort or vacancy responses. In theory, optimal benefits for the long-term unemployed can be higher or lower than for the short-term unemployed and the equilibrium elasticity of unemployment duration to benefits can be larger or smaller than the standard micro elasticity. Our quantitative findings suggest that benefit levels should increase in the first year and then decline and be more generous than in current systems.

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

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1 Introduction

Most governments provide substantial levels of insurance against unemployment. In the US, the total expected expenditures on unemployment insurance (UI) benefits for the fiscal year 2016 are \$32.5 billion.[1] The program gives rise to important policy questions. How generous should the system be? Should benefits expire after six months, as in the US, or be paid for years, as in some European countries? These issues are especially relevant since various European governments, e.g. Denmark, Germany or Sweden, recently moved closer to the US system by considerably cutting benefits for the long-term unemployed.[2]

At the same time, growing evidence suggests that firm behavior plays an important role in shaping labor market outcomes. Vacancies are often reported to get more than 10 applications on average. Firms have to select suitable candidates out of this pool, while having limited information about their quality.[3] Recent evidence suggests that unemployment duration contains some information that is useful for firms. The probability of being invited to an interview falls by almost 50% during the first six months of unemployment (Kroft, Lange, and Notowidigdo (2013)). These features of the hiring process have potentially important implications for policy. First, if long unemployment spells make it hard to find employment, unemployment can be riskier than suggested by standard models. Second, firm behavior during the hiring process depends on the number and quality of applicants, which is influenced by policy.

In this paper, we incorporate these features of the hiring process into a job search model and analyze their consequences for optimal unemployment policy. In our model, firms face a pool of applicants and have incomplete information about their suitability for the job. They observe only a noisy signal and unemployment duration and can reveal if the worker is productive by interviewing them. Firms proceed by sequentially screening applicants according to their expected profitability and hire the first candidate that turns out suitable. If applicants with high durations are more likely to be less productive types, firms respond by being less likely to screen these workers. Thus, the probability of being hired declines with duration. Importantly, this effect relies on the presence of other applicants since then firms may prefer to screen these. In particular, the applications-per-vacancy ratio determines how important screening is and how strong the competition or crowd out for a job among applicants. Firm decisions feed back into the search intensity decisions of workers. The relative informativeness of duration and the signal is determined by the equilibrium degree of sorting by duration.

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[1]Source: Unemployment Insurance Outlook (US Department of Labor).

[2]In 2010, Denmark reduced the potential benefit duration from 4 to 2 years (afterwards, individuals may still receive welfare benefits). During 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. (2016) for details).

[3]Wolthoff (2016) reports on average 14 applicants for vacancies covered in the EOPP data for the US and 59 applicants per online job ad in the 2011 CareerBuilder data. In the German Job Vacancy Survey, firms report an average of 15 applicants.

We estimate the model based on several data sets. We use German social insurance data supplemented with survey evidence about firms' hiring and workers' search behavior.[4] The estimated model matches the data quite well and can explain the falling patterns of search effort and the job finding rate. In addition, the implied decline in the callback rate is fairly similar to the results from audit studies. The decline in the job-finding rate is the product of both duration dependence and heterogeneity. Agents differ in their probability of being suitable for a vacancy, but each additional period of unemployed makes it less likely to be considered for a job. Theoretically, search effort may both increase or decrease due to duration dependence, since it decreases both the returns to search and the value of being unemployed. If the first effect dominates, an individuals' search effort declines with duration as observed in the data (Krueger and Mueller (2011) documents this effect for the US).

Our estimates suggest that firm behavior has important implications for policy. First, it affects how workers react to benefits. If hiring probabilities decline with duration, workers have a strong incentive to search in the beginning of their spell and may become less responsive to benefits. In addition, workers with a high realized duration may also be less responsive if their remaining chances of finding a job are relatively small. Second, the hiring process gives rise to equilibrium effects. The degree of unemployment stigma itself is endogenous to policy. When benefits are high and both productive and unproductive types stay unemployed longer, the quality in the pool is better and firms react by being less reluctant to consider applications from the long-term unemployed. Thus, when benefits are high, unemployment duration can contain less information and hiring probabilities for the long-term unemployed may be higher. If hiring probabilities increase or decrease also depends on the crowding out channel and firms' vacancy response. If policy makes it harder for firms to find workers, they can respond by posting less vacancies. In addition, job-seekers can crowd each other out and search effort by the short-term unemployed may reduce the job-finding rates of the long-term unemployed. These externalities drive a wedge between the *equilibrium elasticity* of unemployment duration to benefits and the standard micro elasticity and the equilibrium elasticity can be higher or lower, depending on which effects dominate. In particular, if benefits are higher reduced search effort lowers the applications-per-vacancy ratio and mitigates competition for jobs. However, at the same time the return to a vacancy gets smaller and fewer firms post vacancies, increasing the applications-per-vacancy ratio. Depending on which effect dominates affects if hiring rates are higher or lower with more generous benefits. We find that the first effect dominates the latter and that crowding out is weaker under higher benefits. Reduced crowding out then maps directly into the screening behavior of firms where callback rates, i.e. screening probabilities, decline less if firms receive less applications. This suggests that the stigma of being unemployed for longer becomes weaker.

Our policy analysis is concerned with both the overall level and the timing of benefits. The

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[4]We use German rather than US data because the Job Vacancy Survey is more detailed than comparable US datasets and since the administrative data permits to consider a sample of multiple unemployment spells per individual, giving more information on the relative importance of duration dependence and heterogeneity (see e.g. Alvarez, Borovicková, and Shimer (2016)).

estimated model suggests that the optimal schedule increases at first and benefits start to decline after a year. Especially for the long-term unemployed the optimal benefit levels are higher than the benefits currently provided in many countries. Optimal benefits follow a hump-shaped pattern and start at about 70% of the pre-unemployment wage in the first six months, rise to nearly 80% thereafter and fall to about 60% after 3 years. Under a benchmark case with infinite labor demand, the decline in benefits is much more strong and benefits decline to 30% after three years. The equilibrium elasticity of the survival rate turns out to be slightly higher than the micro elasticity for low durations and higher for high durations.

This paper contributes to the literature on optimal unemployment insurance by analyzing optimal policy in a model of firms' recruitment behavior that can be matched to the available evidence. In particular, we show that the presence of screening and crowding out alters the standard optimal UI trade-off and that optimal UI could be higher or lower depending on the importance of search adjustments and vacancy adjustments. Many papers in the literature entirely abstract from firm decisions and focus on partial equilibrium models that emphasize the trade-off between consumption smoothing and moral hazard (Baily (1978), Gruber (1997)). The optimal schedule is often argued to be declining or flat (e.g. Shavell and Weiss (1979), Hopenhayn and Nicolini (1997), Werning (2002), Shimer and Werning (2008)). Related to our approach, Lentz (2009) estimates a search model with savings to analyze optimal UI levels. While many of these papers assume that the environment is stationary, a recent body of evidence emphasizes the importance of negative duration dependence, referring to declining job prospects of an individual with each additional period of unemployment. Stigma effects or human capital depreciation are prominent explanations for this effect (see Kroft, Lange, and Notowidigdo (2013) for a discussion). Schmieder, von Wachter, and Bender (2016) find evidence for a negative causal impact of unemployment duration on re-employment wages. Nekoei and Weber (2016) find a small positive effect and argue that potential gains in match quality have to be weighted against the impact of negative duration dependence. Kolsrud et al. (2016) find that the responsiveness to benefits is lower for the long-term unemployed than for the short-term unemployed and emphasize the role of duration dependence and heterogeneity. Several field experiments send fictitious CVs that differ in unemployment duration and show that the probability to be invited to an interview declines with duration (e.g. Kroft, Lange, and Notowidigdo (2013), Eriksson and Rooth (2014) or Oberholzer-Gee (2008)). There is relatively little work that analyzes the implications of duration dependence for optimal policy. Kolsrud et al. (2016) conclude that UI benefits should rather be increasing than decreasing with the length of the spell. Shimer and Werning (2006) investigate optimal UI in a setting with (exogenously) falling wages or arrival rates. Pavoni (2009) focuses on human capital depreciation. These papers analyze UI in a partial equilibrium setting where duration dependence is exogenous. Relative to models with exogenous duration dependence, modeling firm behavior allows to analyze how duration dependence changes with policy, which is also important even if one focuses only on the interaction between UI and agent behavior. Lehr (2016) derives sufficient statistics that allow for firms' hiring responses.

There have been recent studies that emphasize the role of equilibrium effects and market externalities. Michaillat (2012) argues that job rationing, rather than matching frictions, may explain unemployment in recessions and emphasizes competition between job seekers. Landais, Michaillat, and Saez (2016a) and Landais, Michaillat, and Saez (2016b) analyze optimal UI in a DMP model with risk aversion and search effort and argue that benefits can have the additional role of bringing market tightness closer to its optimal level. In their model higher benefits can alleviate a *rat race* for jobs. In the empirical literature, Lalive, Landais, and Zweimüller (2015) show that UI programs can have important spillover effects on non-affected job-seekers. As a result, the equilibrium elasticity of benefits may be smaller than the micro elasticity, since the reduction of search effort by some individuals increases the job-finding rate of others. Our concept of crowding out through the applications-per-vacancy ratio is loosely related to these equilibrium effects and market externalities. Hagedorn et al. (2015) argue that UI extensions can have externalities on labor demand and decrease the incentive to create vacancies. Marinescu (2016) uses data from an online job board and argues that benefit extensions decrease the degree of competition for jobs. Our model features related crowd out externalities, which also drive a wedge between the micro and the equilibrium elasticity.

Our paper is also related to the macro literature on unemployment stigma, 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 signal low performance on previous tests. In Gonzalez and Shi (2010) they argue instead that learning about own job finding rates creates duration dependence. The idea of ranking applicants by unemployment duration was first explored by Blanchard and Diamond (1994), who assume that firms always hire the applicant with the shortest unemployment duration. They use an urn-ball meeting technology, which leads to multiple applications for each firm. Urn-ball matching is also used in e.g. Shimer (2005), who studies coordination frictions in the assignment of job seekers to firms. 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. Doppelt (2016) considers a model in which periods of unemployment influence the information contained in the resume of workers and focuses on the consequences over the life-cycle. 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. Fernández-Blanco and Preugschat (2015) provide a directed search model in which ranking by duration arises as the equilibrium outcome. Our model combines elements of screening and ranking: firms compare applicants based on both a signal and duration, rather than just unemployment duration, and the informativeness of duration is endogenous. This reflects the evidence from Kroft, Lange, and Notowidigdo (2013), who show that callback rates decline less in weak labor markets, suggesting that changes in the informativeness of duration are important. At the same time, our model also allows for the presence of other applicants, which is likely to be a driver of discrimination.

The rest of the paper is organized as follows. In section 2, we present the model and discuss the mechanisms. Sections 3 and 4 focus on data, institutional background and descriptive statistics. Section 5 describes the estimation and discusses estimation results and model fit. In section 6, we discuss the optimal insurance problem of the government and the corresponding results. In sections 7 and 8, we discuss extensions of our model and conclude.

2 Theory

We will start out by describing our model framework followed by a discussion of the mechanisms the model generates. The motivation of the model is to extend a standard job search model with risk aversion, endogenous search effort and savings (as in Lentz (2009)), which has been used to study optimal UI, by incorporating firms' hiring decisions and a notion of statistical discrimination, as in the models of Kroft, Lange, and Notowidigdo (2013), Jarosch and Pilossoph (2016) or Fernández-Blanco and Preugschat (2015). One feature is our model is that firms can choose between potentially many applicants, while observing unemployment duration and a noisy signal, and workers can crowd each other out. Since applicants are heterogeneous in their productivity firms try to screen applicants in order to hire the applicant with the highest expected productivity.

2.1 Model

Framework. The model is set in discrete time and a period corresponds to a month. In every period, a unit mass of unemployed workers is born and lives for T periods. Workers are heterogeneous in their ability and there is a mass α_j of each of the J types. Unemployed workers get UI benefits b_t, which depend on their unemployment duration t, and pay a proportional tax τ on re-employment wages.

The events that occur in each period are summarized in figure 1. Unemployed agents decide on search effort and savings. Searching with intensity $s \in [0,1]$ leads to a probability s of sending an application to a random vacancy.[5] Matching occurs according to an urn-ball matching technology and vacancies can receive more than one application. Firms do not observe if the worker is suitable for the vacancy, but only unemployment duration and a noisy signal about the type of workers. The signal represents all other information contained in the application or the CV. Firms have access to a screening technology that reveals if a given worker is suitable.[6] Given a pool of applicants, they screen the candidates with the highest expected productivity first.[7] As a result, a (j,t) worker who sends out an application is hired with probability $g_j(t)$, which both

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[5]For 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 7.

[6]This could for example be an interview or assessment center.

[7]This follows the literature on ranking. An 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 (2016).

depends on the distribution of his signal and his unemployment duration. The hazard of exiting unemployment after t periods contains both the matching and the probability of being hired:

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

Thus, the hazard rate depends on both the search intensity of the agent and on firm decisions and these are jointly determined in equilibrium.[8]

Problem of the worker. Workers are risk-averse and endowed with an initial asset level of $k_{0,j}$. They discount the future at a rate $\beta \in (0,1)$ and can save by investing in a risk-free bond that yields interest rate R and face a no-borrowing constraint. The presence of a borrowing constraint is important for the insurance role of unemployment benefits and is in line with empirical evidence about limited capacity of self-insurance (see e.g. Chetty (2008)). Jobs pay an exogenous wage level w and last until T.[9] Employed workers only decide on their optimal level of consumption and the corresponding value function for $t < T$ is:

$$V^e(k,t) = \max_{k'} \left\{ u(c_t) + \beta V^e(k',t') \right\}$$

k and k' denote the asset levels of the current and the next period and c_t is the consumption level, which satisfies the usual budget constraint ($c_t = Rk + (1-\tau)w - k'$).

Unemployed agents decide on both consumption and search intensity. Searching with intensity s has cost $\psi(s)$, but leads to a match probability s. The value function of unemployed workers is given by:

$$V^u(k,t) = \max_{s,k'} \left\{ u(c_t) - \psi(s) \quad + \quad \beta h_{j,t}(s) V^e(k',t') \right.$$
$$\left. + \quad \beta(1 - h_{j,t}(s)) V^u(k',t') \right\}$$

The budget constraint of unemployed agents is $c_t = Rk + b_t - k'$. In steady state, the mass of unemployed type j workers with duration t is given by the survival rate $S_{j,t}$.[10] (j,t)-workers submit on average $s_{j,t}$ applications, so that the total number of applications from each (j,t) group is

$$a_{j,t} = S_{j,t} \cdot s_{j,t} \cdot \alpha_j \tag{2}$$

The mass of applications sent by agents of type j and the aggregate number of applications result from summing over all durations ($a_j = \sum_t a_{j,t}$) and over both durations and types ($a = \sum_j \sum_t a_{j,t}$).

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[8]The framework nests partial equilibrium models that are commonly used to analyze optimal UI (e.g. Chetty (2008), Lentz (2009)) by assuming that the hiring probability is exogenous.

[9]The implications of endogenous wages are discussed in section 7. 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 and also the approach used e.g. by Lentz (2009) or Hall (2005).

[10]The survival rate is the probability of still being unemployed after t periods: $S_{j,t} = \prod_{t'=0}^{t-1} (1 - h_{j,t'})$.
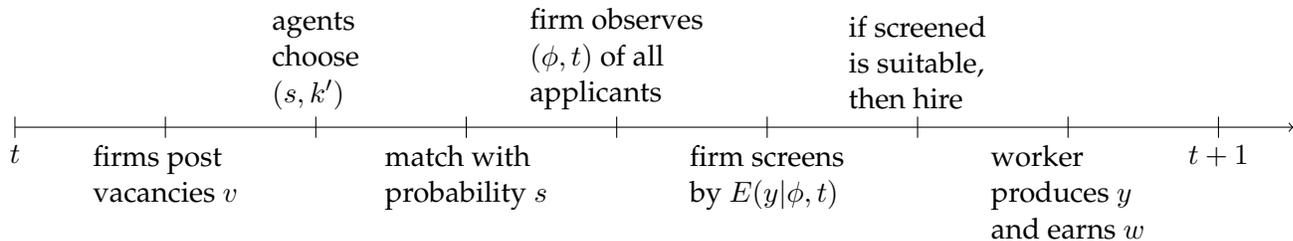
FIGURE 1: Timing of the model

Matching and production. We use an urn-ball matching technology, where each worker may throw a ball (application) at a random urn (vacancy). The number of applications that a firm receives follows a Poisson distribution with parameter $\mu = \frac{a}{v}$, where v is the number of vacancies. We will often refer to μ as the applications-per-vacancy ratio. The applications-per-vacancy ratio governs the strength of crowding out of applicants. Workers differ in their probability π_j of being suitable for a vacancy and produce output $y > w$ if suitable and 0 otherwise. Suitability can be interpreted in terms of different job requirements across vacancies. Some agents are more likely to fulfill the requirements than others.[11]

Firm screening. Firms do not observe if a worker is suitable for the job, but only unemployment duration and a noisy signal, which is drawn from a density f_j. We assume that better types on average send better signals.[12] Firms have access to a screening technology and first screen the applicant with the highest expected productivity.[13] An important feature of our setting is that firms do not rank applicants only according to unemployment duration, but take both the duration and the signal into account. The weight of each component is endogenous and depends on the distribution of worker types and search effort by unemployment duration. The probability that the type of an applicant is j follows from Bayes' rule:

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

An applicant (ϕ,t) is more likely to be a high type if they either send a good signal or if overall many applications with duration t come from high types.[14] Recall that the mass of applications is

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[11]We follow Fernández-Blanco and Preugschat (2015) in using this concept of suitability. The setting of Jarosch and Pilossoph (2016) is comparable: workers and firms differ in their productivity (x and y) and production only takes place when $x \geq y$. A difference is that suitability does not imply that high types are productive whenever low types are.

[12]In practice, we assume that signals are drawn from $N(Y_j, \sigma)$ distributions, normalize the means Y_j and estimate σ to match the data.

[13]This can be motivated by a tiny screening cost (e.g. the cost of an interview), since otherwise firms are indifferent between all screening orderings.

[14]This is most intuitive in the case with a high and a low type, where the formula simplies to $P(H|\phi,t) = \frac{1}{1+\frac{f_L(\phi)a_{L,t}}{f_H(\phi)a_{H,t}}}$. The probability of meeting a high type is determined by the ratio of the densities and the ratio of the

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given by $a_{j,t} = S_{j,t} s_{j,t} \alpha_j$. The share of applications coming from agents (j,t) will be high if either many agents of type j are unemployed until t $(S_{j,t})$, search effort for (j,t) is high $(s_{j,t})$ or if the overall population share of type j is high (α_j).

In the limit case $\sigma \to 0$, the signal perfectly reveals workers' type and suitability and there is no reason to take the duration into account. Conversely, when $\sigma \to \infty$, the signal contains no information and firms only discriminate based on duration. For intermediate cases with $\sigma \in (0, \infty)$, firms weigh the information contained in both components and there is an important equilibrium relationship between the search behavior of agents and the decline of expected productivity and hiring rates with unemployment duration.

The expected profit follows from the conditional type probabilities:

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

To derive the hiring probabilities, focus first on the competition between a worker (j, t) with a fixed signal ϕ, and a single other applicant, who is randomly drawn from the pool of all applications. The competitor is of type k, has duration $\tilde{t}$ and sends a signal $\tilde{\phi}$. The firm observes (t, ϕ) and $(\tilde{t}, \tilde{\phi})$ and screens the applicant with the highest expected profitability (according to equation 4). If this applicant is suitable, the firm hires him. If not, the firm screens the other candidate. Since $(\tilde{\phi}, \tilde{t}, k)$ is random, we get a probability that the other applicant is hired rather than worker (j, t):

$$p(t, \phi) = \sum_{k=1}^{J} \frac{a_k}{a} \cdot \pi_k \cdot P\big(\Pi(\tilde{\phi}, \tilde{t}) \geq \Pi(\phi, t) \mid k \big) \tag{5}$$

a_k/a is the probability of drawing type k from the mass of all applications. The third factor is the probability that the expected profit of the competitor is higher.[15] To calculate the actual hiring probability, we need to take into account that the signal ϕ and the number of other applicants at the firm are stochastic. Taking the expectation over these dimensions leads to the following expression:[16]

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

The integral can be interpreted as a *callback curve*: it represents the probability of being contacted and screened by an employer. Thus, the model can be related 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 suitable for the vacancy. Overall, the hiring probability is determined by the probability that (ϕ, t) is a relatively good signal,

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number of applications.

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

[16] This expression follows from the fact that the number of other applicants for a vacancy is Poisson distributed. The Poisson pdf 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 to the expression used for $g_j(t)$.

compared to a random other applicant, and the mean number of other applicants (μ), which can potentially be screened first. 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.

Entry. 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. The value of an additional vacancy is the net output multiplied by the probability of receiving at least one suitable application:

$$J^v = (y - w)\Big(1 - \exp\big(-\frac{\sum \pi_j a_j}{v}\big)\Big)$$

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

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

Conceptually, free entry ensures that firm profit are always zero and do not have to be taken into account by the social planner. If policy makes it harder for firms to find suitable candidates, they will respond by posting less vacancies.

Equilibrium. The equilibrium of the model is a set of policy functions for search intensities and savings, a set of hiring rates $g_j(t)$ and a mass of vacancies v that solve the problems described above. More details about the equilibrium and its computation are discussed in appendix A.

2.2 Discussion

In this section, we briefly illustrate the main mechanisms of our model and discuss the equilibrium dynamics.

Employer screening and competition for jobs. Firms have the opportunity to choose from a pool of applications and screen applicants according to their expected productivity. Workers' job finding rates decline the longer they are unemployed, as it becomes more likely that another applicant is screened first. This can be interpreted as unemployment stigma: individuals with a high duration are less likely to be considered for vacancies they are qualified for, simply because firms believe other applicants to be more likely to be qualified. Firms always screen workers when there are no other applicants.

Search intensity choice. Importantly, the decline in hiring rates interacts with agents' search decisions. When hiring rates are flat, agents have a strong incentive to increase their search intensity the longer they are unemployed, since they deplete their assets and come closer to benefit expiration. If hiring rates fall, workers anticipate that their employment prospects will decline

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if they stay unemployed for long and have an incentive to increase their search intensity in the beginning. As agents remain unemployed, two countervailing forces affect their search intensity decision.[17] First, duration dependence creates an incentive to search *more*. Intuitively, if the wedge between the value of employment and unemployment is very large, agents respond to lower job prospects by increasing their search intensity. Second, there is also an incentive to search *less*, since the returns to search fall. Thus, depending on the calibration, the model can explain the observed decline in search effort over the unemployment spell.[18]

Duration dependence vs heterogeneity. The model includes both heterogeneity and duration dependence as mechanisms for the observed decline in the average hazard rate.[19] Heterogeneity enters through the suitability probability π_j. In the absence of the screening mechanism, the average hazard can still fall since the long-term unemployed will mostly be those agents who have a persistently lower probability of being suitable for vacancies. The degree of duration dependence is captured by the parameter σ. If signals are perfectly informative ($\sigma = 0$), there will be no duration dependence and the larger σ, the bigger the decline of hiring rates and the job finding rate.

The role of unemployment insurance. The classic trade-off of optimal UI is that providing benefits helps risk-averse individuals to smooth consumption, especially when facing a borrowing constraint, but distorts their search decision (see e.g. Chetty (2006)). The screening mechanism interacts with this trade-off: as individuals face a strong incentive to exit unemployment quickly, they can become less responsive to benefits. In addition, if the long-term unemployed have worse job prospects (since their applications get screened less often), their responsiveness to benefits is also less strong.[20] The role for consumption smoothing is illustrated by figure 2, which shows the model-implied evolution of assets over the spell. Workers run down their assets in the first months of the spell and start to increase their savings the closer they come to benefit expiration (after which benefits are assumed to fall to a lower level). The figure illustrates that benefits are more valuable for workers with high unemployment durations, since they are most likely to have depleted their assets. This could give rise to an increasing schedule that pays higher benefits for the long-term unemployed.

Importantly, the screening mechanism also gives rise to equilibrium effects. High levels of unemployment insurance can decrease the stigma effect of being long-term unemployed, since then

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[17]Formally, this can be seen by examining the FOC for search intensity, which follows directly from the value function of unemployment: $\psi'(s) = \beta g_j(t) \big(V^e(k', t') - V^u(k', t') \big)$. The search decision equates the marginal cost of search to the marginal expected utility gain in the next period, which results from a higher probability of being employed.

[18]For the US, this decline has been documented by Krueger and Mueller (2011). In section 4, we show that our findings for a German sample of job seekers are similar. This could be interpreted as *rational de-motivation*: individuals may decrease their search intensity as it becomes harder to find a job.

[19]Duration dependence refers to *within-individual* declines in the hazard rate over the unemployed spell. The declining average hazard can also be explained by persistent heterogeneity: there could be multiple types who each have a constant within-individual hazard.

[20]Empirically, Kolsrud et al. (2016) find that the short-term unemployed react stronger to benefits than the long-term unemployed and attribute this to either duration dependence or heterogeneity. The screening mechanism is one possible way to rationalize such a finding.
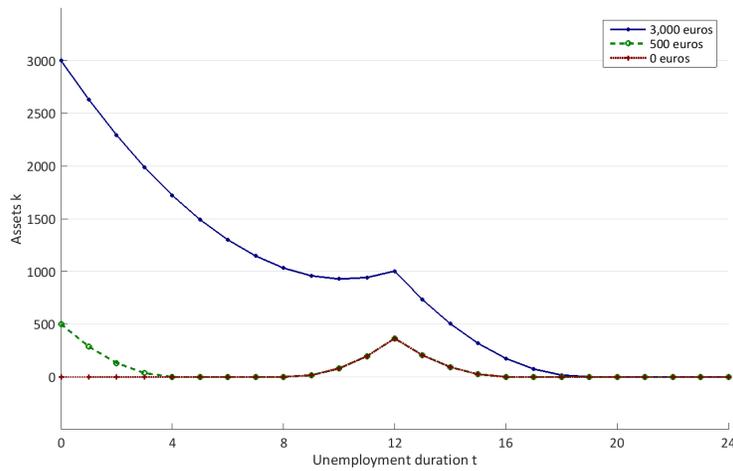
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FIGURE 2: Illustration of savings behavior of unemployed

Notes: This figure shows how agents use their assets over the unemployment spell. The three lines correspond to different initial assets k_0. The graphs are drawn for the specification of the estimated model.
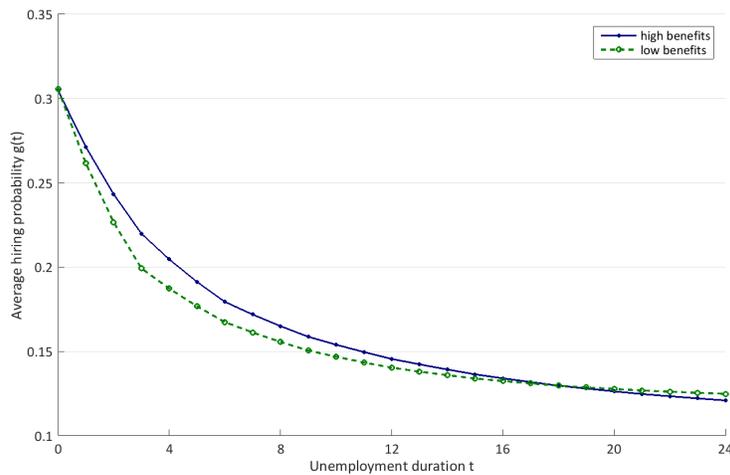

FIGURE 3: Illustration of hiring rates with high and low benefits

Notes: This figure shows how average hiring rates differ between a setting with flat benefits at 60% of the wage versus flat benefits at 40% of the wage. The graphs are drawn for the specification of the estimated model.

the more productive types are also unemployed longer. This decreases the risk agents face: due to search frictions, some unlucky individuals are long-term unemployed and suffer from lower hiring rates. On the other hand, generous UI benefits may also decrease market tightness if it becomes less profitable for firms to post vacancies. If this effect is strong, increasing UI leads to more screening by duration, since there are more applicants per vacancy. Figure 3 illustrates the reaction of hiring probabilities to a benefit increase in the estimated model. In this figure we compare two settings: one where benefits $b_t = 0.4w$ for all t (low benefits) relative to a setting where $b_t = 0.6w$ for all t (high benefits). This amounts to replacement rates of 40% and 60%, respectively. Under high benefits agents search less which lowers the applications-per-vacancy ratio. At the same time, the expected revenue from posting a vacancy declines and less vacancies exist in equilibrium, increasing the applications-per-vacancy ratio. In our setting, the first effect dominates and crowding out between applicants gets weaker. Higher benefits therefore increase hiring rates for the first 18 months and decrease them afterwards. The decline after 18 months is driven by the fact that low types are *de-motivated* to search and only good types still have an incentive to search. For most individuals however, the probability to get hired is higher when benefits are more generous. In section 6, we discuss the implications of this mechanism for optimal UI in more detail.

3   Institutions & Data

After having discussed the theory and the mechanisms of our model, we now move to a description of the German unemployment insurance system and the data we use.

3.1   Unemployment Insurance in Germany

The 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. We will restrict ourselves to the sample period of 2000 until 2014. In Germany, the potential benefit duration depends on the employment history in the years before the UI spell begins.[21] In our analysis we will only consider individuals that are eligible for 12 months of unemployment benefits when they lose their job. We make this choice because the majority of individuals is eligible for 12 months of unemployment benefits.[22] With this restrictions we can create a consistent sample of unemployment spells that is subject to very similar institutional regulations. This allows us to avoid modelling heterogeneity coming from different potential benefit

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[21]Three years from 2000 until January 2005 and thereafter only two years.

[22]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.

durations. More details can be found in appendix B.

Individuals that become unemployed are required to register at their local employment agency as unemployed in order to receive any benefits. Take-up of UI is relatively high in Germany and replacement rates for singles are 60% of average earnings from the year before the unemployment spell has started and 67% for married unemployed, respectively. In addition, the employment agencies in Germany assist job seekers in their job search. For example, the agencies help with applications and provide information about vacancies. After a worker runs out of UI benefits and in case of continued unemployment he moves into unemployment assistance, i.e. social welfare. Unemployment assistance (UA) is means-tested and was subject to large reforms, especially in the early 2000s (Hartz reforms). We ignore UA as much as possible in our analysis and assume in our model that individuals receive social welfare benefits after UI has expired. This allows us to capture unemployment benefit exhaustion in our model, while avoiding to model regulations like asset testing.

3.2 Data

We use administrative employment records from Germany which are provided by the federal employment agency in Germany. The data source are the integrated employment histories (IEB) that the public social security providers collect.[23] Employers are required to report any employment contract to the social security providers. Unemployment spells are directly reported by the employment agency. We have access to a 2% random sample of all individuals that have at least one registered employment (and unemployment) spell from 1975 until 2014 (SIAB). Individuals can be followed via a unique identifier over the lifetime. The key variables included in the dataset are day-to-day information on employment and unemployment spells, daily wages during employment, unemployment benefits and several demographic variables, such as age, gender and education. In addition, we can match the individual employment records to firms via the establishment history panel (BHP) that is also provided by the employment agency. This dataset contains occupational information, size and age of the establishment, median wages within the firm and whether unemployed individuals return to their previous employer.

From this data we create a sample of unemployment spells starting in 2000 until the end of 2011 for those who are eligible for 12 months of benefits. Spells that start in 2012 and later are not considered in order to ensure that we observe every UI spell for at least three years. We also drop individuals that experience a recall to their previous employer. We define an unemployment spell as the transition from employment to registered unemployment within 30 days and drop all individuals that register more than 30 days after their prior job has ended. We also drop individuals with ambiguous entries, e.g. individuals who receive UI and are currently employed; and we exclude individuals that receive social welfare benefits on top of unemployment benefits. Further, only individuals between 20 and 55 are considered in order to avoid old-age regulations

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[23]This accounts for roughly 80% of all employment contracts. Students, self-employed and public employees are not observed in the data (Schmieder, von Wachter, and Bender (2012)).

and early retirement schemes. Unemployment duration is counted as the time between the start of receiving UI benefits and the start of the next registered employment spell. We also truncate unemployment spells at 36 months as in Schmieder, von Wachter, and Bender (2012). This avoids giving large weights to individuals that never return to work or leave the labor market.

We complement the employment records by three additional data sources. 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 begin 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. Next, 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 firms perceive applications from job seekers. Finally, 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. Unfortunately, it is not possible to match the survey datasets to the administrative records. However, by using information from all of them we are able to observe a variety of empirical regularities that we will discuss in the next section.

4 Reduced Form Results

In this section we will first show some basic descriptive statistics of our data. After that, we will show reduced form evidence on the decline of job finding rates, search behavior of agents over the spell and firms' hiring behavior.

4.1 Descriptive Statistics

Our sample of individuals that enter unemployment between 2000 and 2011 has the following characteristics: Around 44% of unemployed are female, the average entry age is 31, and roughly 30% are married or have children. We define observables at the point when the first spell starts. In total, we observe 59,793 unemployment spells and 11,473 second spells. The fraction of college-educated unemployed is lower than in the overall population. However, this is not surprising in light of the fact that highly educated individuals face a much lower unemployment risk. The average monthly re-employment wage after unemployment 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. 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

TABLE 1: Descriptive statistics

Variables	N	mean	s.d.
Panel A: Employment Register			
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)
Panel B: IZA Evaluation Dataset			
Number of applications Wave 1	6,815	13.49	(14.95)
Number of applications Interim Wave	377	9.15	(10.09)
Number of applications Wave 2	1,710	8.11	(9.78)
Search channels Wave 1	6,898	4.78	(1.78)
Panel C: Panel on Household Finances (Quantiles)			
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	-
Panel D: Job Vacancy Survey			
Number of applicants	62,904	14,79	(36.96)
Number of acceptable applicants	83,431	4,36	(14.63)
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.
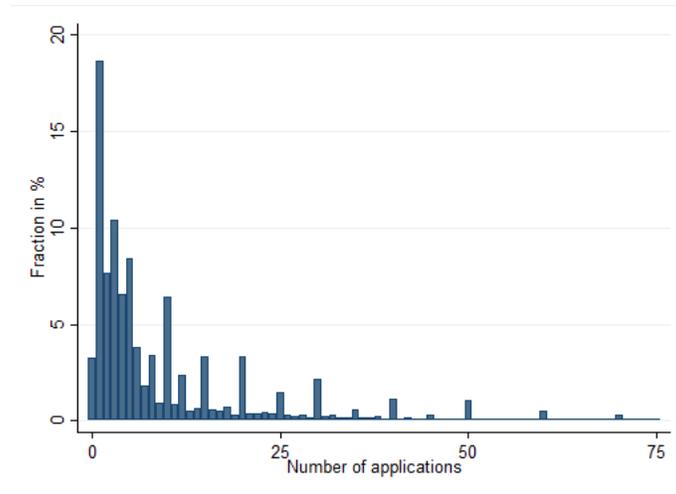
FIGURE 4: Distribution of applications

Notes: The figure shows the distribution of applications that open vacancies receive. Source: JVS.

1 shows that agents send out 13 applications on average at the beginning of the UI spell. This number decreases with the length 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 plot 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.[24] 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.[25] Table 1 summarizes these results.

4.2 Competition for Jobs: Crowding Out

Standard partial equilibrium search models assume that finding rates are only determined by agents' search effort. In our model firms potentially receive many applications from different job seekers and the search effort plus the hiring decision of the firms defines job finding rates. In addition, the number of vacancies and the number of unemployed that exist in equilibrium might not match. This drives a wedge between the job search effort and the job finding rate by allowing for hiring and vacancy decisions of firms. The importance of crowding out effects depend on the number of competitors of an applicant for a job. Intuitively, if there are many unemployed applicants but less open vacancies some job searchers may not find a job regardless of their search intensity. The average labor market tightness in Germany is around 0.25 in the period from 2000

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

[25]The time is defined as the difference between the acceptance of a job offer by an applicant to the release of the job advertisement.
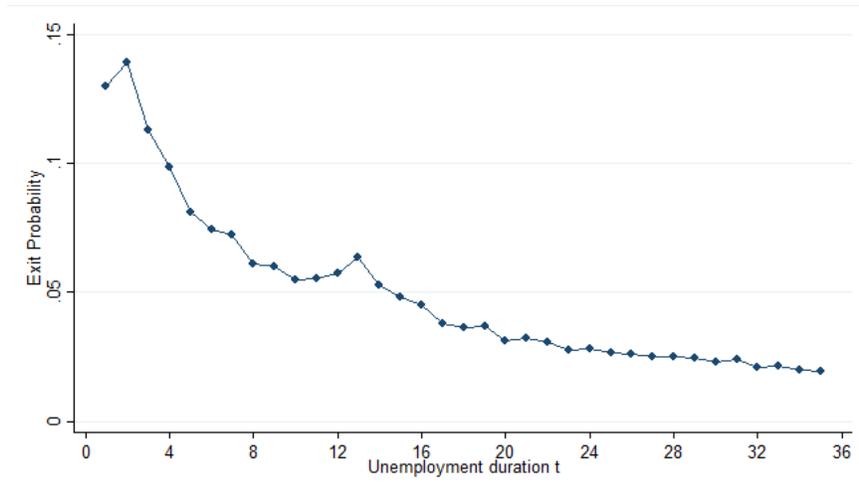
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FIGURE 5: Exit rate out of unemployment

Notes: This figure plots the exit rate out of unemployment. The sample consists of all unemployment spells starting from 2000 until 2011 and only considers individuals who are eligible for 12 months of benefits. Source: SIAB.

until 2014.[26] Therefore there are about four unemployed job seekers per vacancy. This can lead to substantial crowding out effects because even if every open vacancy is filled with an unemployed there remain three other unemployed job seekers. Second, the larger the number of applications firms receive the larger the potential crowd out between applicants might be. Figure 4 plots the distribution of applications per vacancy. The mean number of applications is around 15, though the median is only five due to long tails of the distribution. This figure suggests that firms have indeed a choice to pick the best applicant and that the *outside option* of a firm is to screen or hire alternative applicants. In the JVS data firms are also asked to report the number of *acceptable* applications among all applications. We interpret this number as the number of applications that are potentially considered for screening by the firm. Here the mean is around 4.5 applications.[27] In any case, an applicant must compete with many other applicants for a job. A consequence might be that individuals get screened out and that the firm hires an alternative candidate that looks more suitable to the firm. Our model tries to capture these empirical patterns by matching moments from the applications distributions of firms to the data.

4.3 Job Finding Rates & Search Effort

Job finding rates. The job finding rate of unemployed job seekers in Germany is shown in figure 5. 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%

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[26]See figure A1 in the appendix for the time series graph of the labor market tightness.

[27]Later on, we will focus on this number because our agents are only allowed to send out one application and this allows us to balance the applications-per-vacancy ratio more appropriately.
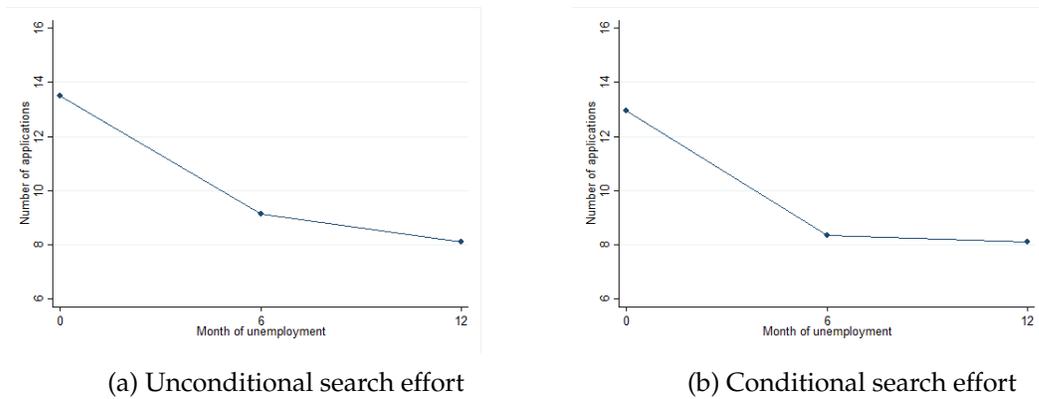
(a) Unconditional search effort   (b) Conditional search effort

FIGURE 6: Search effort: Applications

Notes: The left panel shows the average search effort in number of applications per month on the y-axis. In the right panel, the search effort is plotted conditional on staying unemployed for at least one year. Source: IZA ED.
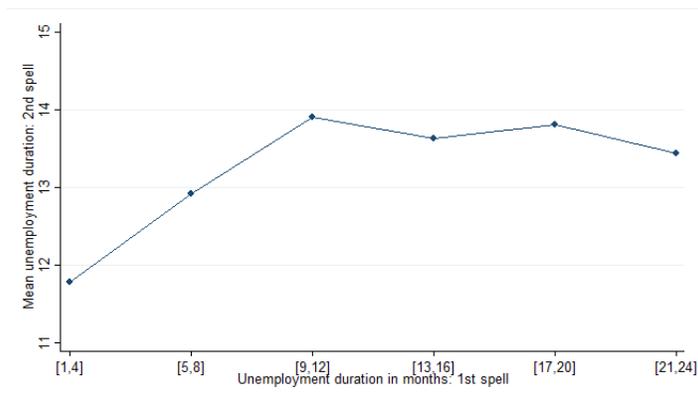

FIGURE 7: Mean duration in second unemployment spell

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.

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after two years of unemployment.[28] Hence, the chance to find a job becomes smaller and smaller the longer someone is unemployed. As we have discussed in section 2 there are two explanations for this decline in the hazard rate out of unemployment: (a) selection/heterogeneity, or (b) (true) duration dependence. Our model features heterogeneity in the suitability of job seekers which creates a margin of selection over the UI spell. In addition, the presence of employer screening creates true duration dependence in job finding rates. Hence, in equilibrium selection and duration dependence will both contribute to falling hazard rates. The importance of employer screening for true duration dependence was studied by Kroft, Lange, and Notowidigdo (2013) in an experimental audit study. They find that the callback rate 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. They argue that this decline in callback rates can best be rationalized by an employer screening model. In the job vacancy survey, employers are asked whether they consider unemployed applicants depending on the unemployment duration of the applicant.[29] Conditional on considering unemployed applicants at all, figure A2 shows that 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. These two pieces of evidence hint towards considerable firm responses in terms of the unemployment duration of an applicant. and the possibility that a long unemployment spell is a bad signal about the quality of an applicant.

Search effort. Since our model allows for endogenous search effort it is important how agents search throughout their unemployment spell, because search effort responses are a main determinant of the moral hazard costs associated with unemployment insurance. This is important because in the presence of screening the search effort could react in two ways: (a) agents want to compensate the lower hiring rates by increasing their search effort, or (b) agents get *rationally de-motivated* to search in the presence of very low hiring rates. The latter argument basically says that a unit of search effort does not increase the likelihood to find a job sufficiently enough in order to cover the marginal search costs. It is a quantitative question which effect is stronger. Figure 6 illustrates search effort for two settings. The left figure shows the average (unconditional) number of applications unemployed job seekers send out. 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. However, this decline could also be driven by selection effects where individuals that search less survive longer in UI. Therefore, we plot in the right panel the mean number of applications for those who stay unemployed for at least twelve months. We see

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[28]The small spike at 12 months is due to the benefit exhaustion which leads more people to exit unemployment.

[29]In figure A2 we only consider employers that are willing to screen unemployed applicants at all.

the exact same pattern there. Hence, conditional on staying unemployed long, search effort is also declining the longer an individual is unemployed. This hints towards a decline in the search effort even within individuals.[30] 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.[31]

Multiple unemployment spells. What can we learn about the relative importance of heterogeneity and true duration dependence from the data? As, e.g. Alvarez, Borovicková, and Shimer (2016) point out, it is possible to make statements about duration dependence versus heterogeneity from a sample of individuals with multiple unemployment spells. The idea here is that the stronger the correlation between the unemployment durations in the two spells, the more important heterogeneity must be. If there is no heterogeneity, the correlation between the unemployment duration in spell one versus spell two should be zero. Figure 7 tries to show this non-parametrically.[32] In this graph we bin up individuals in four month bins of the unemployment duration in the first spell. On the y-axis we plot the mean unemployment duration in the second spell between the bins. We see that there is a weak positive correlation between unemployment durations. When being unemployed for less than four months in the first spell the average duration of unemployment in the second spell is 11.7 months, while it is more than 13 months for individuals who were unemployed for a year ore more in their first spell. This 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.

5 Estimation

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

5.1 Setup

Specification. To estimate the model that we formulated in section 2, we impose the following functional forms on the instantaneous utility function and the search cost function:

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

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

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

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

[32]To draw this curves, we extend our sample to the period from 1983 until 2011 such that we have a sufficiently large sample of individuals with two unemployment spells.

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. (2016) 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.[33]

In our model agents are heterogeneous in two dimensions: (a) their probability of being suitable and (b) their initial assets. In our baseline version of the model we allow for two different suitability types π and three different initial asset types k_0, which in total leaves us with $J = 6$ types.[34] 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 suitable type generates a profit $y = w + 100$ for the firm in case he is suitable. High types differ in their idiosyncratic match suitability. High types are suitable in π_H cases, while low types are suitable in π_L cases only. Unsuitable applicants are always rejected. Hence, firms have an incentive to screen types with respect to their suitability 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 normalizations. 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. 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. 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 set 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.

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. (2016). 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:

$$\theta = \{\lambda, \ \pi_H, \ \pi_L, \ \alpha_L, \ \sigma\} \tag{7}$$

Thus the parameter vector contains the search effort elasticity, the suitability probability of the productive type, the suitability probability of the unproductive type, the unconditional type probability and the variance of the signal.

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[33]Alternatively, 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.

[34]Allowing 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.

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. (2016):

$$\min_{\theta} \ (m(\theta) - \hat{m})' W (m(\theta) - \hat{m}) \tag{8}$$

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 4. 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.[35] For the estimation of the parameters we use a genetic algorithm, which is a global optimization routine.[36] 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 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 interview. Then we add the average number of acceptable applications that a vacancy receives as can be seen in figure 1.[37] Finally, we add six multiple spell moments where we use the mean unemployment duration in spell two conditional on unemployment duration in spell one.[38] This leaves us with a total amount of 35 moments to match. Minimizing (1) with respect to θ gives us the estimated parameter vector.

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 suitability 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

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[35]Note, that in the estimation we use percent deviation instead of levels to give all moments the same weight.

[36]Global optimization routines are helpful for possibly non-differentiable problems and problems with local maxima.

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

[38]We mimic the multiple spell sample by treating each spell as being generated by the model, while keeping the worker type constant. Introducing a positive job destruction rate would generate very similar results as long as the destruction rate is realistically small.

TABLE 2: Estimation results

Parameter	Estimate	s.e.
λ	2.539	(0.001)
π_H	0.213	(0.000)
π_L	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.
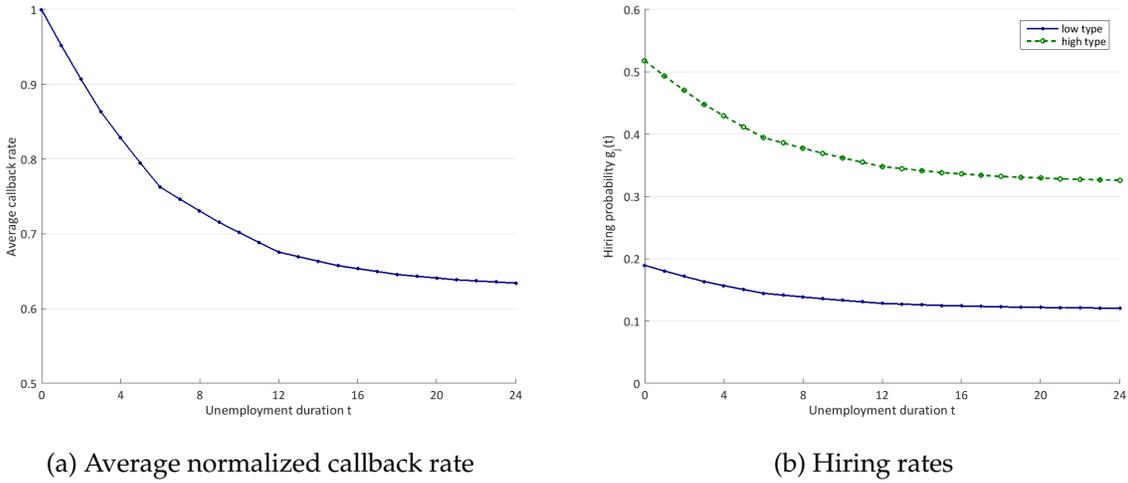

(a) Average normalized callback rate   (b) Hiring rates

FIGURE 8: 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.

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.

5.2 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
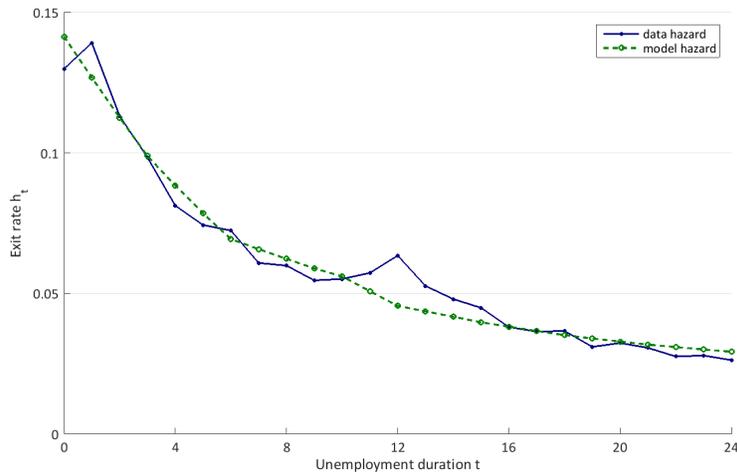
FIGURE 9: Model fit: Hazard rates

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.

changes. The suitability 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 suitability will translate into a heterogeneity in hiring rates as shown in panel (b) of figure 8. We estimate the variance of the signal to be equal to $\sigma = 6.85$ which implies that the suitability is relatively noisy. In other words, signals are not very informative and firms have a 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. In panel (a) and (b) of figure 8 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 suitability 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 suitable 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 suitability 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

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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 9 shows the model-implied job finding rate of our model. Finally, our model estimates also imply, as shown in figure 3, that crowding out is lower with higher benefits. Hence, our model predicts that the reduced search effort outweighs the vacancy adjustment in equilibrium and that there is lower competition for a job with higher benefits.

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 9 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.[39] Table A2 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.

Three are two important pieces of evidence that we did not directly included in our estimation: (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.

Kroft, Lange, and Notowidigdo (2013) also measure the responsiveness of the callback rate with respect to market tightness and find that the callback rate is less declining in labor markets with high unemployment rates. In our model, increasing the vacancy cost (which can be interpreted as making the market less tight) has two countervailing effects. First, it increases the length of spells and makes it more likely that applicants with high durations are productive types. As a result, firms can get more willing to screen agents with high durations and the decline in callback rates becomes less pronounced. Second, it can also increase the ratio of applications per vacancies, since there are less vacancies, which would lead to a more pronounced decline. Thus, our model can replicate the variation of callback rates with tightness if the first effect is stronger than the second. Importantly, the second effect depends on how strongly the ratio of applications per vacancies, rather than market tightness, changes. If the average number of applications a firm

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[39]Here, 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.

gets varies weakly with tightness, e.g. because there are less applications from employed individuals when tightness is low, the first effect is more likely to dominate. In our data, the number of applications per vacancy was relatively constant over time even though the unemployment rate in Germany dropped by half. For the US, Marinescu (2016) documents that almost half the job seekers in her data are employed. Thus, we do not focus on fitting these results from Kroft, Lange, and Notowidigdo (2013), as it would be require a more sophisticated modeling of the number of applications firms get over the business cycle.

In Schmieder, von Wachter, and Bender (2012) the authors exploit quasi-experimental variation in age cutoffs of potential benefit durations in Germany. If one looses 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 better suited to find the global solution in a problem with possibly many local maxima. 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 pre-determined 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 crowding out 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 A3 and A4 in the appendix 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.[40]

6   Welfare Analysis

In this section we will use the estimated model for welfare analysis. We start by presenting the government problem which we then solve for the optimal unemployment policy. Afterwards we will discuss the resulting schedule and compare it to different benchmarks.

6.1   Government Problem

The governments' set of policy instruments $P = (b, \tau)$ consists of the benefit vector b where benefits b_t are paid to unemployed agents in period t and the proportional income tax τ that is collected from the employed to finance the expenditures. The tax has also the interpretation of an actuarial fair insurance premium here. 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):

$$W(P) = \int_j V_j^u(P) \alpha_j dj \tag{9}$$

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

However, the government can only maximize the welfare of agents subject to the following budget constraint:

$$G(P) = \int_j \Big(\underbrace{\sum_{t=0}^{T} R^{-t}(1 - S_{j,t})w\tau}_{\text{expected revenue}} - \underbrace{\sum_{t=0}^{T} R^{-t}S_{j,t}b_t}_{\text{exp. expenditure}} \Big)\alpha_j dj \tag{10}$$

Note that revenues and expenditures are survival weighted because individuals receive only benefits if they are still unemployed in period t and only pay taxes if they work in period t. The budget constraint implies that expected revenue generated with the employment tax must equal expected expenditures. We assume that the budget must be balanced within a certain generation and therefore benefits and revenues are discounted by the interest rate.[41] In principle, one can solve for the fully dynamic optimal policy contract. However, this is numerically and analytically infeasible and therefore we restrict to multi-step UI policies. In particular, we solve the optimal policy problem by solving for optimal six-month schedules for the first three years, an additional benefit level after three years until T, plus the employment tax. This leaves us with a policy space in eight dimensions. This is flexible enough to capture most of the patterns that a fully flexible schedule would generate and is numerically feasible. We solve the planner problem using a gradient-based numerical search method.

6.2 Optimal Unemployment Insurance

The standard trade-off the government faces is on the one hand to insure the agent against his unemployment earnings shock, i.e. to allow the agent to smooth consumption. In our model, the consumption smoothing component creates an interesting dynamic trade-off. Agents start out with some assets but deplete them over the unemployment spell. Therefore, their demand for liquidity is larger after they have spent some time in unemployment because they are closer to the borrowing constraint. This alone implies that benefits should increase with the length of the unemployment spell. On the other hand, the government needs to take into account moral hazard in search effort that comes with paying benefits to the unemployed agent. The higher benefits, the less agents will search. Since the government cannot enforce agents to search the optimal contract will incentivize agents to do so by paying less benefits. Because agents are forward-looking, the moral hazard costs usually increase the longer an individual is unemployed which gives a strong motive to declining benefits (Hopenhayn and Nicolini (1997)). In the presence of heterogeneity and duration dependence the standard trade-off is quickly altered and the level and the timing of unemployment benefits is a quantitative exercise. In cases, where duration dependence is strong enough one might actually find increasing optimal unemployment schedules as in Kolsrud et al. (2016). In their model they derive dynamic sufficient statistics formulas that characterize the local optimality of unemployment benefits. The sufficient statistics capture the optimal policy as a trade-off between consumption smoothing gains, i.e. the wedge between marginal utility in

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[41] Alternatively, 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.
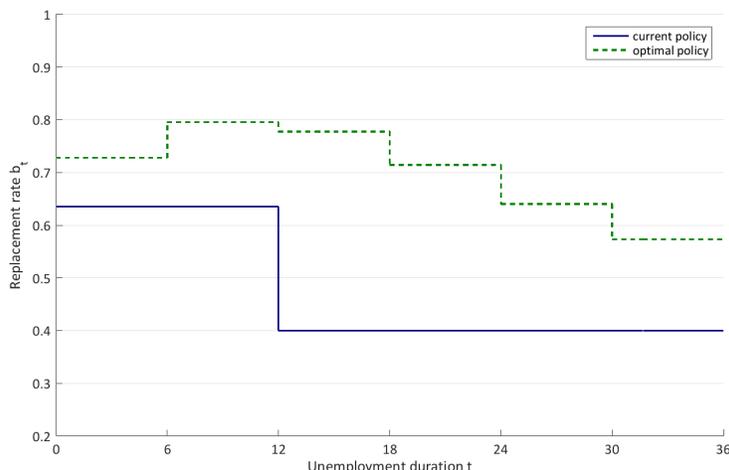
FIGURE 10: Optimal UI versus current UI

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). Our policy space consists of six-month step schedules where we solve for one optimal benefit level for each six month period. After three years we allow for one additional benefit level that runs until T. In addition we solve for the budget balancing tax τ.

employment minus marginal utility in unemployment scaled by the risk aversion, versus moral hazard in the survival rate of being unemployed. The equality of consumption smoothing and moral hazard implies the optimality of the UI policy (Chetty (2006)). In the end, it is theoretically open if benefits should increase or decrease throughout the spell and at which levels unemployed should be insured.

Unique to our setting is the presence of firms that screen unemployed agents from a pool of applicants. Hence, the firm decision is endogenous and not invariant to UI policies. Practically, the firm receives a certain number of applications and must decide which applicants to screen and which applicant to hire. In our model, it will screen the applicants sequentially by the likelihood of being the most productive type, i.e. the one with the best (ϕ, t) combination. The government must internalize (a) the responses of firms in their screening and hiring behavior and (b) how strong crowding out is. Due to the free entry condition in our model, firm profits are in expectation always zero and we do not need to add the value of a vacancy to the government problem. The firm decisions solely enter the government trade-off through the hiring rates $g_j(t)$.

The dashed line in figure 10 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 10. The current policy pays benefits for one year and offers social assistance thereafter. We find that the optimal policy is hump-shaped starting at a replacement rate of 73% in the first six months, followed by a replacement rate of 80% in the next six months. From then on benefits start to decline and reach a level of 60% at the end of the third year. After three years benefits are very low and only 15% until period T (not in

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the figure). As one can see the optimal schedule differs quite a lot from actual policies. Our main finding is that benefits should be (a) higher in the first years, (b) paid for around three years and (c) be very low after three years. The increasing section of the schedule might seem counter-intuitive at first. The reason for the high levels and increasing slope is twofold: First, the presence of screening and competition for jobs might give a motive to policy to reduce crowding out by reducing *wasteful* search effort. Stringent UI policies have a downside and upside when firms enter the trade-off. On the one hand they reduce moral hazard, but on the other hand they increase crowding out and strengthen the importance of screening. Lower competition leads to higher hiring rates and a smaller decline of the callback curve which improves the welfare of the unemployed. Second, policy must not incentivize agents through a declining schedule because the threat of being screened out by the firm suffices for a high search effort of the unemployed. Agents anticipate that there is crowding out and they also anticipate that the probability of a callback is low when they have reached a high unemployment duration. Therefore they start to search right at the beginning and moral hazard is low. This allows the government to pay generous benefits for individuals with short and medium unemployment durations. This is consistent with the finding of Kolsrud et al. (2016) who argue that the optimal time profile of UI should be increasing because duration dependence mitigates moral hazard.

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.

6.3 Discussion

To understand how our problem differs from the standard partial equilibrium trade-off and how important crowding out and screening are we decompose the behavioral responses of agents into a search response and a hiring response. Thereafter we will look at a setting where firms do not matter for job finding rates.

Micro versus equilibrium elasticities. Recall equation (1) where the job finding rate is defined as the product of the search effort times the hiring probability. In a partial equilibrium setting the hiring probability $g_j(t)$ is an exogenous object and the search effort $s_{j,t}$ is the only endogenous determinant of the job finding rate and hence the survival rate $S_{j,t}$.[42] In our model $g_j(t)$ is also endogenous and not invariant to policy. In particular, the hiring probability is the product of the individual specific suitability times the screening probability. The probability to get screened de-

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[42]Our model is therefore non-nested by the sufficient statistics formulas of Chetty (2006) or Kolsrud et al. (2016). Compared to the sufficient statistics formulas, our model wouldlead to an additional term that measures the hiring response.
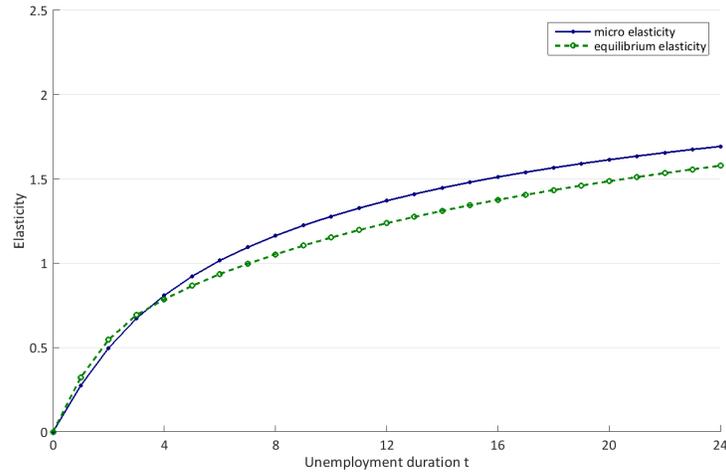
FIGURE 11: Micro and equilibrium elasticity of the survival rate

Notes: This figure illustrates the micro and equilibrium elasticity of the average survival rate at a flat UI schedule of $b_t = 0.6w \; \forall \; t$. There is one micro elasticity and one equilibrium elasticity for every duration. The solid line corresponds to the micro elasticity with fixed hiring rates and the dashed line to the equilibrium equilibrium elasticity where hiring rates are endogenous.
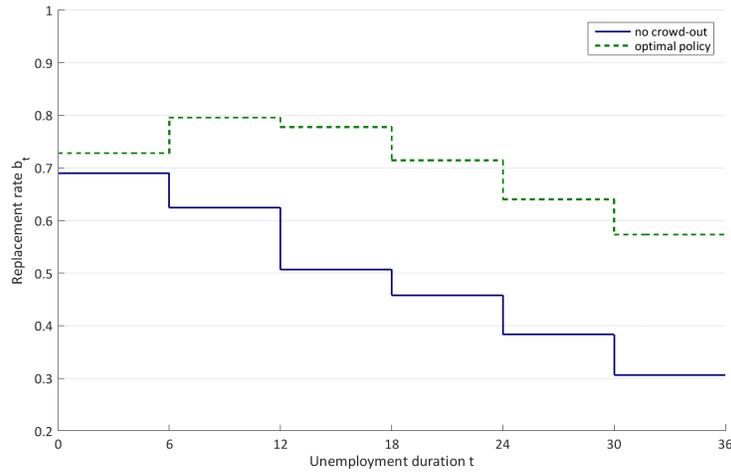

FIGURE 12: Optimal UI without crowding out

Notes: This graph compares the optimal policy schedule suggested by the model (dashed line) compared to the optimal policy without crowd out and without screening (solid line), i.e. a setting with infinite labor demand. Our policy space consists of six-month step schedules where we solve for one optimal benefit level for each six month period. After three years we allow for one additional benefit level that runs until T. In addition we solve for the budget balancing tax τ.

pends on the competition for the job. The more applicants a firm receives the larger crowding out and screening. The hiring probabilities therefore adjust in equilibrium when unemployment benefits are changed. The main determinant of how generous benefits can be is illustrated in the responsiveness of the survival rate with respect to benefits b. The larger the unemployment duration response the larger moral hazard and the fewer benefits can be paid in the optimum. Let us decompose the survival response to benefit changes into the component that comes from adjusted search effort while holding fixed hiring rates; and the equilibrium response of the survival. For an illustration we use a setting with flat benefits $b_t = 0.6w \; \forall \; t$. At this point we marginally increase unemployment benefits and look at the following elasticities:

$$\varepsilon^m = \left. \frac{\partial S_t}{\partial b} \frac{b}{S_t} \right|_{g_j(t)=g_j^*(t) \; \forall \; j,t} \tag{11}$$

$$\varepsilon^e = \frac{\partial S_t}{\partial b} \frac{b}{S_t} \tag{12}$$

where ε^m is the micro elasticity of the average survival rate with respect to a marginal benefit change conditional on fixed hiring rates $g_j^*(t)$. The equilibrium elasticity ε^e then includes all equilibrium adjustments of hiring rates and entry decisions.[43] In figure 11 we plot these elasticities. The solid line represents the micro elasticity and the dashed line the equilibrium elasticity. How can we interpret this figure? If we fix hiring rates, then a 1 percentage points increase in benefits increases the survival to be still unemployed after one year by 1.4 percentage points (solid line). In equilibrium, however, the survival rate of still being unemployed after one year only increases by 1.2 percentage points (dashed line). The firm responses drive a wedge between the micro elasticity and the equilibrium elasticity. Depending on the sign of the wedge benefits can be higher or lower. We see that in the first months the macro elasticity is slightly larger but is smaller from month four onwards. This tells us that the search response of the unemployed at every point t gets mitigated by a countervailing equilibrium response. This is due to the fact that the crowding out becomes weaker and that screening gets mitigated as we have seen in section 2. This response relaxes the planner problem and benefits can be higher than with exogenous hiring rates. As a remark, if the vacancy margin would dominate the search margin and competition would increase with higher benefits, then the equilibrium elasticity would be larger than the micro elasticity and benefits would be lower.

No crowding out case. This naturally leads to the question how optimal UI would look like in our model if there is infinite labor demand. This limiting case where vacancy costs κ are equal to zero is an important benchmark for our model. When $\kappa = 0$ then there are infinitely many vacancies and there is no competition or crowding out for jobs. This also implies that every applicant gets screened and hired in case he is suitable. The no crowding out limit is equivalent to a standard partial equilibrium search model with heterogeneity in arrival rates. Figure 12 illustrates

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[43]Note the local nature of these objects. The elasticities are always defined relative to the point of evaluation.

the optimal policy in this setting compared to our screening model with crowding out. Now, benefits start at a replacement rate of 70% and are strongly decreasing throughout the spell and reach 30% by the end of the third year. This declining optimal schedule nicely compares to the standard timing results of Hopenhayn and Nicolini (1997). Hence, the presence of screening considerably alters the optimal UI path and makes it flatter and more generous for a longer time.

Full information case. One additional interesting comparison on the importance of screening is the full information case where there is crowding out of applications but firms perfectly observe agents' types and suitability. In this case hiring rates become flat and true duration dependence disappears. Our model predicts that under full information hiring rates are much lower than in the benchmark model. This is because crowding out gets larger because the short-term unemployed must also compete with the long-term unemployed now. This is due to the fact that under full information all applications are considered by the firm which increases crowding out for applications with low durations. This basically leads to lower exit rates in equilibrium and optimal benefits are lower than in the no crowding out limit and also lower than in the screening model. The benefit path is similar to the no crowding out case with steeply declining benefits.

6.4 Alternative Policy Instrument: Hiring Subsidy

Our framework also gives rise to another interesting policy question. While it may be possible to reduce unemployment stigma by increasing benefits, a different approach could be to introduce hiring subsidies for the long-term unemployment. Policies of this kind are common in many countries. Katz (1996) gives an overview about the US experience with this policy instrument. Besides that, e.g. Australia, Austria, Germany and France currently have similar policies.[44]

Our screening model provides a rationale for why these policies might increase welfare, since introducing a hiring subsidy could reverse the order in which firms screen applicants. Suppose firms get a subsidy H whenever they hire a long-term unemployed worker, but have to pay C for each candidate they screen. If H is sufficiently high, firms would first screen long-term unemployed applicants. If the applicant turns out to be suitable, he would be hired. If not, the firm would be stuck with cost C and proceed by screening the next applicant. An interesting feature of this setting is that the hiring subsidy would not lead to inefficient hiring (since only suitable candidates are hired), but only give firms an incentive to *consider* the application of long-term unemployed workers, instead of beginning by screening candidates with low duration. On the one hand, this would lead to wasteful screening expenditures, since firms would now screen candidates that are less likely to be suitable. On the other hand, a wage subsidy would decrease the risk agents face and possibly be welfare-improving.

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

7 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 wage bargaining.

7.1 Multiple Applications

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 6) 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, $h_j(t) = 1 - \exp\left(-g_j(t)s\right)$, 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.[45] 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, the offers of some vacancies are rejected. This reduces firm profits and the number of vacancies that are posted and gives rise to the question if firms should be able to contact other applicants if their offer gets rejected. There are different approaches to this issue in the literature. Some recent paper allow for *recall*, 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 report the results for the case of one application per worker, as is also done in Fernández-Blanco and Preugschat (2015) or Villena-Roldan (2012).

7.2 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

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[45] A 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.
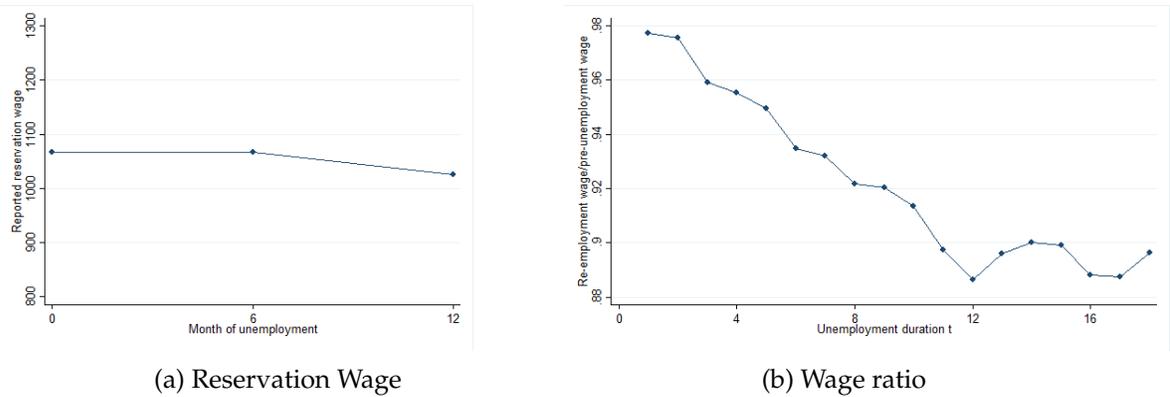
(a) Reservation Wage   (b) Wage ratio

FIGURE 13: 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.

expected profit of the low type).[46] 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 suitable 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 unemployment stigma already have to be weighted against the potential decline in the number of vacancies. Screening costs would amplify the latter effect.

7.3 Wage bargaining

A final extension is to depart from the assumption of a fixed wage and e.g. introduce wage bargaining. Since firms have a screening technology and can reveal the type of applicants before hiring them, there is complete information before the hiring decision is made and one could use Nash bargaining, which is commonly used in the literature. We use a fixed wage mainly for simplicity and to focus on the screening margin.

Under Nash bargaining, wages would also depend on UI policy, since an increase in benefits would raise workers' outside option and they would demand higher wages. Wages would also be asset-dependent, as wealthy workers would have a better outside option. In turn, firms would find it less profitable to post vacancies. This would generate an interesting interaction with the screening margin: in our model, increasing UI can reduce the stigma effect of unemployment, but it can also *increase* discrimination by duration if it leads to a lower tightness and more competition for jobs. Once wage bargaining is introduced, the latter effect is amplified and increasing benefits

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

is more likely to lead to increased competition. Thus, it would be even less clear if one can raise hiring rates for the long-term unemployed by increasing benefits (and reducing stigma) or by lowering benefits (and reducing competition).

From an empirical point of view, there is some evidence that supports the assumption of a rather rigid wage. For example, Krueger and Mueller (2016) find for the US that reservation wages stay remarkably constant over the unemployment spell and Hall and Mueller (2015) show that individuals often accept the first job offer they get. Their evidence also suggests 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 13 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 35% of firms report that this was the case. On the other hand, there is also some evidence that unemployment duration has a (negative) causal impact on the re-employment wage (e.g. Schmieder, von Wachter, and Bender (2016)). Relatedly, the right panel in figure 13 shows the ratio of the last wage before and the first wage after unemployment, based on our sample from the social insurance records. The observed (within-individual) drop over time is modest. The ratio decreases from about 0.99 for individuals who exit after a month to about 0.9 for those who exit after a year. This decline in wages could be either due to worse bargaining outcomes of the long-term unemployed or through human capital depreciation. Overall, the evidence suggests that a fixed wage can be a reasonable approximation. At the same time, there are some interesting implications of introducing endogenous wages.

8 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. The model can explain several important features of the data and gives rise to a declining callback rate with unemployment duration, which has been documented in recent field experiments.

Based on the estimated model, the welfare analysis suggests that optimal policy deviates substantially from a benchmark case without screening. We find that benefits should be more generous, especially after the first year of unemployment. Introducing screening changes the trade-off between consumption smoothing and moral hazard and gives rise to equilibrium effects. When benefits are high and the productive types stay unemployed longer, duration is less informative about worker type. Higher benefits also affect the hiring process through changes in the applications-per-vacancy ratio, which can result from adjusted search effort and vacancy responses. If screening is important then alternative policy instruments like hiring subsidies could be useful instruments to avoid statistical discrimination of long-term unemployed job seekers.

An important aspect that is missing from our analysis is the variation in hiring rates over the business cycle. In principle, in recessions crowding out is likely to be larger and policy could turn

out to be more generous in recessions. Alternatively, long-term unemployment is not seen as such a bad signal in recessions and benefits might be lower. Another important question for future research is to find additional quasi-experimental evidence on the importance of competition for jobs among applicants and employer screening. Reduced-form evidence on how hiring decisions respond to unemployment policies would nicely complement our more structural approach.

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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 5, we can solve the agent problem backwards. In each period, the optimal level of search intensity has a closed-form solution:

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

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:

$$
\begin{aligned}
p(t, \phi) &= \sum_{k=1}^{J} \frac{a_k}{a} \cdot \pi_k \cdot P\big(\Pi(\tilde{\phi}, \tilde{t}) \geq \Pi(\phi, t)|k\big) \\
g_j(t) &= \pi_j \int_\phi \exp\big(-p(\phi, t) \cdot \mu\big) dF_j(\phi)
\end{aligned}
$$

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:

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

  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

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 recipiency 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 individuals[47]. 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 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 ambigous 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

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

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

TABLE A1: Potential unemplyoment 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	$14(\geq42)$	$14(\geq45)$	12	12	12
30	10	10	10	$14(\geq42)$	$14(\geq45)$	$15(\geq55)$	$15(\geq55)$	$15(\geq50)$
32	10	10	10	$16(\geq42)$	$16(\geq45)$	$15(\geq55)$	$15(\geq55)$	$15(\geq50)$
36	12	12	12	$18(\geq42)$	$18(\geq45)$	$18(\geq55)$	$18(\geq55)$	$18(\geq50)$
40	12	12	12	$20(\geq44)$	$20(\geq47)$	$18(\geq55)$	$18(\geq55)$	$18(\geq50)$
42	12	$14(\geq49)$	$14(\geq44)$	$20(\geq44)$	$20(\geq47)$	$18(\geq55)$	$18(\geq55)$	$18(\geq50)$
44	12	$14(\geq49)$	$14(\geq44)$	$22(\geq44)$	$22(\geq47)$	$18(\geq55)$	$18(\geq55)$	$18(\geq50)$
48	12	$16(\geq49)$	$16(\geq44)$	$24(\geq49)$	$24(\geq52)$	$18(\geq55)$	$18(\geq55)$	$24(\geq50)$

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.

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 recipiency 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.

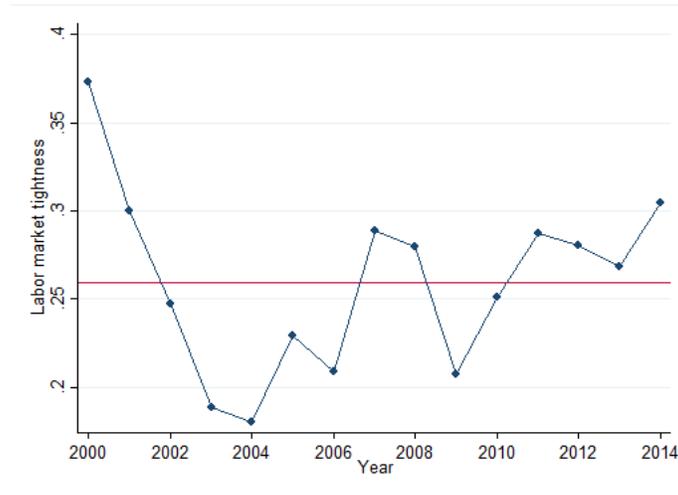**Appendix C: Additional Figures & Tables**

FIGURE A1: 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. Source: Insitute for Employment Research (IAB).
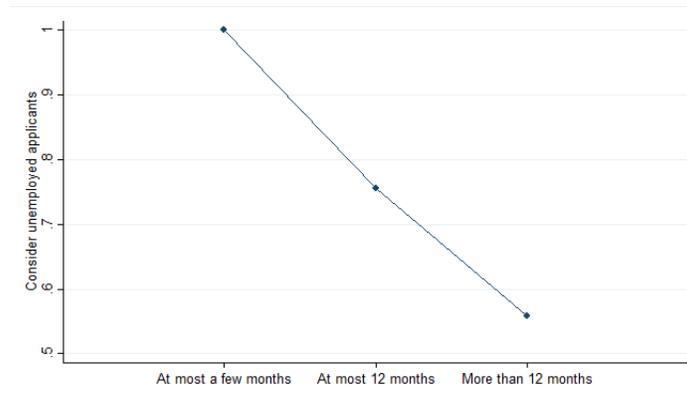

FIGURE A2: Consider unemployed applicants

Notes: This graph shows the response to whether vacancies consider unemployed applicants as a function of the unemployment duration. The answers in the figure are conditional on reviewing unemployed applicants at all. The x-axis shows the categories in the survey question. The y-axis plots the fraction of firms that still consider certain applicants. Source: JVS.
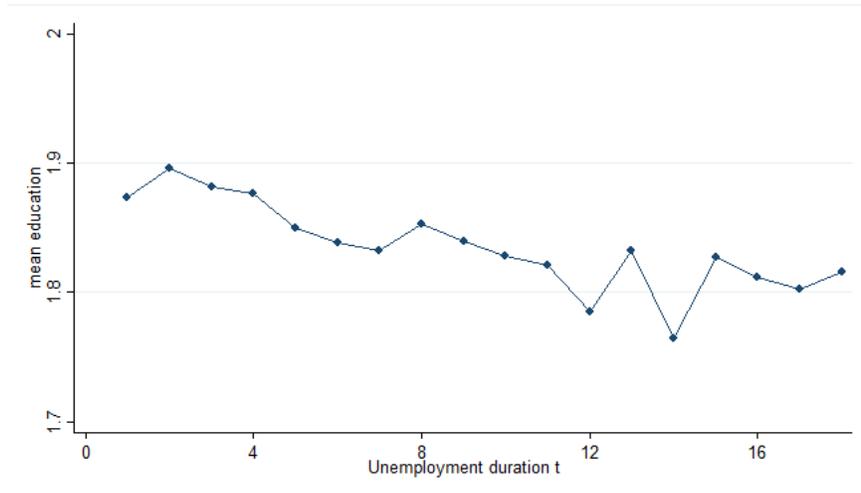
FIGURE A3: Mean education over UI spell

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.
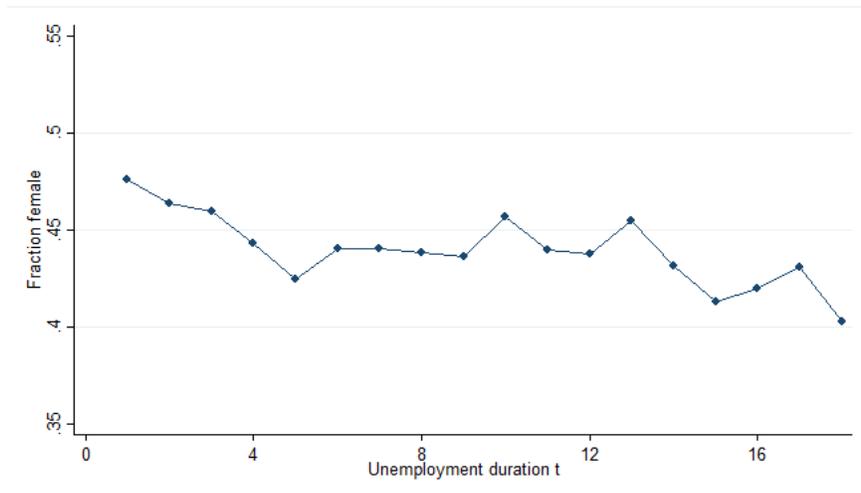

FIGURE A4: Fraction female over UI spell

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

TABLE A2: 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 9. The second spell moments are divided by 100.