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A Structural Analysis of Vacancy Referrals with Imperfect Monitoring and Sickness Absence

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Abstract

In many OECD countries unemployment insurance agencies send out job vacancy referrals (VRs) to unemployment benefit recipients. Refusals to apply for VRs are sanctioned with temporary benefit reductions. In this paper we study the impact of VRs and sanctions on unemployed workers' job search behavior, accounting for the possibility that workers may report sick to avoid sanctions. We develop a structural job search model that incorporates VRs, sanctions and sick reporting. We estimate our model using German administrative data from social security records that are linked to caseworker records on VRs, sick reporting and sanctions. Based on the estimated model we study a range of counterfactual policy scenarios. We find that increasing sanction enforcement reduces reservation wages, thereby leading to a higher job finding rate. Increasing the VR rate, in contrast, leads to higher reservation wages by raising the option value of search, but nevertheless elevates the job finding rate by increasing the job offer frequency. According to our estimates 9.2% of sick reports among unemployed workers are induced by VRs. We find substantial heterogeneity in the effects of eliminating VR induced sick reporting on job search outcomes. Effects are modest for around 75% of the population. For the remaining 25% of unemployed workers shutting down VR induced sick reporting reduces the mean unemployment duration by one week and a day.

Keywords: unemployment, vacancy referrals, wage, unemployment insurance, monitoring, moral hazard, structural estimation, counterfactual policy evaluation

JEL classification: J64, J65, C51, C54

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1 Introduction

Unemployment insurance (UI) systems in OECD countries typically imply specific job search requirements for the receipt of unemployment benefits and offer some form of job search assistance. Unemployed job seekers who do not comply with the job search requirements usually risk receiving a sanction. While the common goal of these eligibility rules and activation strategies is to reduce moral hazard and to increase the reemployment rate among UI benefit recipients, there exist large differences across countries in the institutions implemented to reach these goals (Immervoll and Knotz 2018 and Knotz 2018). These differences include variation in the strictness and the enforcement rate of sanctions, in the criteria for job offers a job seeker has to accept, and in the use of job vacancy referrals (VRs) to support and monitor the unemployed workers' job search effort. Given the differences in the institutional setup across countries and the interdependencies of the different policy measures, it is difficult to use cross-country comparisons or reduced-form analyses to learn something about the relative effectiveness of counterfactual policy designs.

This paper develops and estimates a structural job search model that incorporates vacancy referrals and punitive sanctions, two main features of many UI systems. UI agencies usually punish refusals to apply for referred job vacancies or to accept corresponding job offers by reducing unemployment insurance payments for a fixed time span. VRs complement individual job search effort of UI benefit recipients and the threat-effect of sanctions ensures that unemployed job-seekers cannot be too selective about applying for referred job vacancies. In the model, we additionally allow for the possibility to report sick after the receipt of a VR. In many UI systems the requirement to apply for a VR ceases in case of sickness. For a UI recipient this creates an incentive to call in sick strategically in response to receiving a VR that he deems unattractive. Our model further takes into account that job search effort is not perfectly observable and that the enforcement of sanctions is typically not structured by binding rules, but is - at least to some extent - subject to the discretion of caseworkers at the UI agency. As a direct consequence, the possibility of strategic sick reporting and the presence of imperfect sanction enforcement may hamper the effectiveness of VRs and sanctions in counteracting moral hazard. In evaluating policy changes related to VRs and sanctions it is thus important to take into account both these aspects.

We estimate our model using administrative data from social security records and from the public employment service in Germany. Our data covers the time period from 2000 to 2002. In particular, we use detailed information on unemployment and employment durations, benefit receipt, the arrival of vacancy referrals, imposed sanctions, sickness absence during unemployment and daily wages during employment. Additionally, the data feature a broad range of socioeconomic characteristics including education, family status and health restrictions. We use our model to simulate a range of counterfactual policy changes related to changing the VR arrival rate and the sanction enforcement rate. Our model is also suited to simulate changes in sanction duration (i.e. for how many time periods a sanction lasts) and sanction severeness (i.e. by how much UI benefits are reduced in case of a sanction). The results of these simulation exercises are helpful for understanding how effective different policy designs for sanctions and VRs are in reducing moral hazard and for evaluating their impact on accepted wages and unemployment durations.

We find that increasing sanction enforcement reduces moral hazard, i.e., incentivizes unemployed workers to reduce their reservation wages. By this mechanism increasing sanction enforcement considerably increases job finding rates. According to our estimates the status sanction enforcement rate is at a 13% rate, i.e. far below full enforcement. Moving from the status quo to full sanction enforcement reduces the average unemployment duration by three weeks.

In contrast, increasing the VR rate leads to more moral hazard, i.e., leads unemployed workers to raise their reservation wages. By this mechanism increasing the VR rate leads to a decrease in the job finding rate in months when a VR was received. Nevertheless, a higher VR rate leads to higher job finding rates, as the higher frequency at which VRs arrive mechanically leads to a higher job finding rate, even at increased reservation wages. Overall increasing the VR rate by a factor of 1.25 reduces the average unemployment duration by 1.1 months.

We further use our estimated model to study the consequences of VR induced sick reporting. We find that VR induced sick reporting accounts for a substantial share of overall sick reporting. According to our estimates, 9.2% of all observed sick reports are induced by VRs.[1] To study the consequences of VR induced sick reporting for job search outcomes we consider a hypothetical scenario in which we eliminate VR induced sick reporting. Looking at averages across the whole worker population we find modest effects of shutting down VR induced sick reporting on job search outcomes. There is however substantial heterogeneity in the propensity to call in sick after receiving a VR. For the 25% of workers with the highest propensity of VR induced sick reporting we find that eliminating VR induced sick reporting would reduce the mean unemployment duration by one week and a day.

Our study contributes to the literature that uses structural models to evaluate active labor market policies (see e.g. Lise, Seitz, and Smith 2015, Launov and Wälde 2016, Gautier et al. 2018 and Wunsch 2013). Fougère, Pradel, and Roger (2009) estimate a partial equilibrium job search

[1] This finding is consistent with the empirical results by van den Berg, Hofmann, and Uhlendorff (2014).

model to study the effect of job contacts through the public employment service (PES) on job seekers' search effort. Their results suggest that an increase in the support through the PES has a negative impact on private search and that it reduces the time spent in unemployment. van den Berg and van der Klaauw (2018) estimate a job search model with formal and informal search to analyze the impact of monitoring on the use of the different search channels and employment outcomes. Their findings indicate that monitoring leads to a substitution of informal search – which cannot be observed by the PES – by perfectly observable formal search. Cockx et al. (2018) study effects of a system of monitoring and sanctions on search effort in a non-stationary environment with imperfect monitoring. Their finding indicate that the intensity and the precision of the monitoring scheme is crucial for the effectiveness of the policy. Our paper is the first that provides a structural analysis of the interplay of vacancy referrals and sanctions. Moreover, we are the first who structurally investigate the role of strategic sick reporting in a monitoring system.

There exist a number of reduced-form analyses on job search monitoring and sanctions (see e.g. Lalive, van Ours, and Zweimüller 2005, van den Berg and van der Klaauw (2006), van den Berg, van der Klaauw, and van Ours 2004, Boone, Sadrieh, and Ours 2009 and Micklewright and Nagy 2010). These studies usually find positive effects of monitoring and imposed sanctions on reemployment rates. Some studies additionally indicate that these positive effects on employment probabilities go along with negative effects on initial wages (van den Berg and Vikström 2014 and Arni, Lalive, and van Ours 2013). There also exists some reduced-form evidence on the effects of VRs. van den Berg, Hofmann and Uhlendorff (2018) use the same data set as in this paper. Based on multi-spell duration models they show that the receipt of a VR increases the transition rate to employment and that these jobs go along with lower wages. They additionally find a positive impact of receiving a VR on the probability of reporting sick. In line with these results, Bollens and Cockx (2017) provide evidence that receiving a VR increases the transition rate to employment based on a sample of unemployed job seekers in Belgium. The reduced-form results reported in these studies cannot be used to study effects of alternative policy designs. The present paper provides a structural model which can be applied for counterfactual policy analysis.

The remainder of the paper is organized as follows: Section 2 describes the institutional background, i.e. the rules and institutions related to UI benefits, VRs and sanctions that German UI recipients face during our observation period. Section 3 describes the data. Section 4 develops the structural model. Section 5 derives the likelihood function and describes how we estimate our model. Section 6 presents estimation results. Section 7 presents the evaluation of counterfactual policies and section 9 concludes.

2 Institutional Background

In the following, we describe the institutional setting of the different policies relevant for our analysis. The description refers to our observation periods from 2000 to 2002.

2.1 UI Benefits

Unemployed who have worked at least twelve months within the last three years are eligible for UI benefits. The potential benefit duration depends on the age and the time spent in employment. It ranges from 6 months for individuals below the age 45 who have worked between 12 and 16 months in the last seven years to 32 months for unemployed job seekers who are older than 57 and have been employed for at least 64 months. The replacement rate corresponds to 67% for unemployed with at least one child and to 60% for individuals without children. After the expiration of the UI benefits unemployed are entitled to means-tested unemployment assistance with replacement ratios of 57% and 53%, respectively (Konle-Seidl, Eichhorst, and Grienberger-Zingerle, 2010).

2.2 Vacancy Referrals and Sanctions

With a vacancy referral, a caseworker asks an unemployed to apply for a specific job vacancy. A VR usually contains information about the occupation, the working hours and the starting date of the job, but not about the wage. The time lag between a VR and end of the hiring process depends on the sector and the occupation of the job vacancy. Qualitative evidence based on interviews with caseworkers indicates that this time lag is shorter for low skilled jobs than for high skilled positions, and that it usually does not exceed 2 weeks. Not applying to a referred job vacancy as well as not accepting a corresponding job offer can lead to a sanction. One condition for a sanction is that the job is "suitable". This implies during our observation period between 2000 and 2002 that the job has to be within 2.5 hours of commuting distance and that – within the first 3 months after the start of the unemployment spell – the wage is above 80% of the previous wage. This wage threshold drops to 70% within months 4 and 6, and after 6 months of unemployment all jobs with a wage above the UI benefit level and within the 2.5 hours of commuting distance are defined to be suitable.

Not applying to a job after receiving a corresponding VR or refusing to accept a suitable job offer is one of the main reasons for being sanctioned. In this case the unemployment benefit payments are cut completely for a period of 12 weeks. One strategy to prevent a job offer and the risk of being sanctioned might be to intentionally misbehave in the job interview. While it is more difficult to detect such behavior, it is still possible for the caseworker to impose a sanction in this case. In practice, this depends on the type of contact between the caseworker and the firm posting the job vacancy. Other reasons for "long" sanctions of 12 weeks are refusing to participate in or dropping out of active labor market policy measures. If an UI benefit recipient is not showing up at a scheduled meeting, this might lead to a short sanction of 2 weeks. All types of short and long sanctions imply a benefit cut by 100%.[2]

After the imposition of a sanction, the unemployed job seeker is supposed to go on with his job search effort and to comply with the obligations for UI benefit recipients. If the unemployed does not follow the job search requirements, he or she risks an additional sanction. If the accumulated duration of sanctions within one unemployment spell is above 24 weeks, the unemployed loses all claims for UI benefits. Qualitative evidence based on caseworker interviews suggest that the monitoring of unemployed workers' job search effort and the use of VRs do not change after a sanction. Sanctioned unemployed can apply for welfare benefits. These benefits are means-tested – i.e. they depend on the household income and savings – and not related to the previous wage.

Non-compliance with job search requirements is not always detected. First, during our observation period, between 400 and 1000 unemployed workers were allocated to one caseworker. This very high caseload implies that caseworkers cannot monitor the job search effort of all unemployed very closely. Second, even with an intense monitoring not every infringement can be fully observed. For example, detecting non-compliance after the receipt of a VR depends on the relationship between the caseworker and the human resources department of the employer offering the vacancy. Besides that, the caseworkers have some discretion whether or not to impose a sanction (Müller and Oschmiansky, 2006). After the detection of an violation of the job search requirements, the unemployed has the opportunity to explain and justify his behavior. At this stage, the caseworker has some degree of freedom to decide whether or not this justification is sufficient. If the caseworker evaluates the justification as insufficient, the benefits management department takes over and – in case of no objection – sends out a letter to the unemployed worker to inform him about the sanction. After that, the unemployed worker has the option to file an objection against the sanction.

[2]Another reason for a long sanction are voluntary job quits. In this case, individuals do not receive any benefits in the first 12 weeks of their unemployment spell. In this paper we exclude individuals from our analysis who are facing this type of sanctions.

2.3 Sick Leave

Following the guidelines for UI benefit recipients, unemployed job seekers have to hand in a sick note from a medical doctor to the PES if they are sick. While being sick, the unemployed continues receiving UI benefits and the UI entitlement duration continues to decline.[3] This implies that there are no direct financial incentives to report sick during UI benefit receipt. However, during sickness absence, the unemployed does not have to comply with the job search requirements and therefore does not risk a sanction if he or she does not send out an application after the receipt of a VR. This implies that an unemployed has an incentive to report sick in case of real sickness and in case of a VR which refers to a job which is unattractive for the unemployed. There is no direct way for the PES to evaluate the sick note. Only after the sickness, the unemployed can be sent to the medical service of the PES. At this service, the doctors evaluate the general work-related health status. Moreover, the unemployed can freely chose their doctor and can change the physicians at any time. This allows them to search for a doctor who is cooperative and willing to hand out a sick note, and it is not possible for the PES to verify the sick note.

3 Data

Our analysis is based on administrative records from the German PES (Bundesagentur für Arbeit). The data contain daily information about employment and unemployment spells, participation in ALMPs, earnings and UI benefits. Moreover, we have information about basic sociodemographic characteristics including education, family status and health restrictions. As common for this type of data, we do not have information about self-employment, inactivity, and civil servants (Dundler, 2006).

Our sample consists of men entering unemployment in the year 2000 and who have been employed for at least 12 months before the entry into unemployment. We focus on West Germany because in our observation period East and West German labor markets were substantially different. For example, public employment programs played an much more important role in the East German labor market. We select unemployed workers who are between 25 and 57 years old. The first age restriction is motivated by the educational system and the second one by the retirement schemes in Germany. In 2003, several labor market reforms have been introduced. Therefore, we

[3]If an unemployed is sick with the same diagnosis for more than 6 weeks, the unemployed enters sickness benefits. This benefit scheme requires a specific medical certificate. This certificate can be verified by a doctor of the medical service of the health insurance. In this paper, we focus on short-term sickness.

right-censor our observation at December 31, 2002. Our final estimation sample consists of 69,788 individuals.

In our data we observe arrivals of VRs, imposed sanctions and periods of sickness absence. The main outcome variables are transitions from unemployment to work and accepted wages upon exit to employment. We have no information about working hours. Therefore, our wages correspond to daily gross wages.[4] A transition from unemployment to employment is defined as a transition to regular jobs without receiving any benefits from the PES at the same time. Our model will be estimated in discrete time, and we discretize our duration data in monthly observations. Unemployment duration corresponds to the duration of benefit receipt. The institutional rules with respect to VRs and sanctions are the same for UI and UA benefits. Therefore, we do not distinguish between periods of these two types of benefits. Unemployment spells with transitions into inactivity, subsidized jobs or ALMP programs with training measure benefits (Unterhaltsgeld, UHG) are right-censored.

While we know the month in which an individual receives a VR, we have no information about the occupation or the sector of the firm with the open vacancy. We observe the intended length and the starting dates of sanctions. In our analysis we focus on long sanctions, and we exclude unemployment spells with a sanction due to voluntary job quits. For these types of sanctions, the sanction is imposed directly at the beginning of an unemployment spell. Besides that, we do not know the reason for long sanctions imposed at some point after the start of the unemployment spell. However, the majority of the observed sanctions are related to VRs. Following official statistics of the German PES, sanctions related to VRs were about 4 times as common as sanctions due to refusing or dropping out of a training measure (Bundesagentur für Arbeit, 2004). We define a sickness absence if in our data a sickness spell lasts at least 13 days. Given that the application period usually does not exceed two weeks, this ensures that individuals who are sick following our definition can effectively avoid an application to an assigned VR.

It is important to note that we do not observe whether a sickness absence occurs due to a VR. Moreover, we do not know whether a job found after receiving a VR is the one which the unemployed has been referred to.

[4]The wage information is right-censored at the social security contribution ceiling. This aspect should be of limited relevance for our analysis, since almost all observed post-unemployment wages are below this threshold.In 2002, the cap was at 4500 Euro per month in West Germany. Only 2.1% of our sample took up a job that paid more than 4000 Euro per month.

4 Model

In this section we present a structural job search model that includes VRs, sanctions and accounts for VR induced sick reporting. Our structural model builds on the standard sequential random search framework (see, e.g., Mortensen, 1986). We extend this framework by allowing for two kinds of job offers, regular job offers as well as job offers obtained through VRs (VR offers). If an unemployed worker turns down a VR offer he is at risk of receiving a sanction, i.e., a benefit reduction for several time periods. To avoid a sanction an unemployed worker can try to obtain a sick note and, if successful, is released of the duty to apply for the referred vacancy. Our model moreover includes terminal sanctions and reflects that unemployed workers can renew their benefit eligibility if they find a job and stay employed sufficiently long. The model extends the stylized framework that van den Berg, Hofmann, and Uhlendorff (2014) use to interpret their reduced form results.

We consider a population of unemployed workers who are risk neutral and discount the future at discount rate β. The model is set in discrete time. At the beginning of a time period an unemployed worker collects unemployment benefits, $b > 0$, unless he is currently sanctioned, in which case he receives no benefits.

Sickness In any given time period an unemployed worker falls sick with probability p_{sick}. If sick, he cannot accept job offers (neither regular nor VR offers). Furthermore, we assume that in case of sickness unemployed workers receive a sick note with probability one and thus never receive a sanction. If he falls sick the unemployed worker thus always moves on to the next period of unemployment, without responding to job offers and without receiving sanctions.

Choices and state variables Unemployed workers in our model choose whether to accept or reject the regular job offers and VR offers they receive. In case of a VR they furthermore decides whether to try to obtain a sick note. The decision rule of a given unemployed worker in our model is contingent on two state variables, the number of remaining periods of an ongoing sanction, s (where $s = 0$ for non-sanctioned workers), and the number of recorded past sanctions, P.

Regular Job Offers Regular job offers arrive at exogenous rate λ_J. A regular job offer is characterized by a random draw from the wage offer distribution F_J. Upon offer arrival the unemployed worker decides whether to accept or reject the offer. If he accepts, he becomes employed at the offered wage, starting in the next time period. If he rejects, he remains unemployed. Formally, the expected value of receiving a regular job offer is

$$A_J(s,P) = \int \max\Big\{ E(w,P),\ U(\max\{s-1,0\},P) \Big\}\, dF_J(w)\,,$$

where $U(s,P)$ denotes the value of being unemployed in state (s,P) and $E(w,P)$ is the value of starting a job at wage w and given past sanctions P.

Vacancy Referrals and Sanctions VRs arrive at exogenous rate λ_V. A VR is characterized by a wage draw from the offer distribution F_V. We assume that the unemployed worker learns the wage offer attached to a referred vacancy immediately when he receives the VR. After observing the wage offer he decides whether to try to get a sick note to avoid a sanction or not. If he tries to get a sick note, he is successful in obtaining one with probability p_{doc}. In this case the obligation to apply for the referred vacancy ceases and the unemployed worker continues his job search without being at risk of receiving a sanction. For the unemployed worker the expected value of receiving a VR equals

$$A_V(s,P) = \int \max\Big\{ B_V(w),\ p_{doc}\, U(\max\{s-1,0\},P) + (1-p_{doc})\, B_V(w) \Big\}\, dF_V(w)\,, \qquad (1)$$

where $B_V(w)$ is the value of applying for a VR with attached wage w.[5]

If an unemployed worker applies for a VR, there is a positive probability that the employer rejects him such that he does not receive a job offer. In this case the unemployed worker remains unemployed and is not sanctioned. We denote the probability that a job offer is received upon applying for a VR by ψ (i.e. the probability of being rejected by the employer is $1-\psi$). In case the unemployed worker fails to hand in a sick note, it is always optimal for him to apply for the referred vacancy and learn whether he is offered the job.[6] If he indeed receives a job offer he may accept and start the job at the offered wage or reject, in which case he is at risk of receiving a sanction. This risk is realized with probability p_{sanc}, where $p_{sanc} < 1$ reflects the possibility that the responsible caseworker may use his substantial discretionary leeway in deciding if a sanction is imposed or not. If the unemployed worker receives a sanction, no benefits are payed out to him for the next K time periods. In terms of the state variables this means that s is increased by K. Furthermore state variable P is increased by 1, bringing the unemployed worker one step closer to a terminal sanction. Formally, the value of applying for a referred vacancy with attached wage

[5] For better readability we suppress that $B_V(w)$ also depends on s and P.

[6] If substantial marginal costs of applying for a VR are introduced into the model, it may become optimal for the worker to refuse to apply and thereby risk a sanction before learning if he is offered to fill the vacancy. We assume that the marginal cost of applying for a vacancy is sufficiently small so that it is always favorable to apply and learn the employer's decision first.

offer w equals

$$B_V(w) = \psi \, \max\Big\{ E(w,P)\,,\, p_{sanc}\, U(K, P+1) \\ + (1-p_{sanc})\, U(\max\{s-1,0\}, P) \Big\} + (1-\psi)\, U(\max\{s-1,0\})\,. \qquad (2)$$

Terminal Sanctions Whenever an unemployed worker receives a sanction it may happen that his accumulated number of sanctions exceeds the terminal sanction threshold, $P \geq \overline{P}$. When this happens, a terminal sanction is imposed. The unemployed worker then loses benefit eligibility and continues his job search without collecting benefits or receiving VRs. The value function of a terminally sanctioned unemployed worker is

$$\Phi = \beta\Big((1-p_{sick})\lambda_J \int \max\{E(w,\overline{P}),\, \Phi\} dF_J(w) + \big(1-\lambda_J(1-p_{sick})\big)\Phi \Big).$$

Value of Unemployment The expected discounted lifetime utility of an unemployed worker in state (s, P) is given by the Bellman equation

$$U(s,P) = \quad b\,\mathbf{1}_{\{s=0\}} + \beta(1-p_{sick})\Big(\lambda_J A_J(s,P) + \lambda_V A_V(s,P) \\ + (1-\lambda_J-\lambda_V) U(\max\{s-1,0\}, P) \Big) + \beta p_{sick} U(\max\{s-1,0\}, P) \qquad (3)$$

if $P < \overline{P}$. Implicit in $A_J(s, P)$ and $A_V(s, P)$ are the optimal decisions the unemployed worker makes about accepting job offers that he receives on the labor market or through VRs as well as his optimal decisions about strategically calling in sick after receiving a VR. If $P \geq \overline{P}$ the unemployed worker is terminally sanctioned and the value of unemployment equals $U(s, P) = \Phi$.

Value of Employment The expected discounted lifetime utility of an employed worker depends on the per period wage and an exogenous job destruction rate δ. If a job is destroyed and the worker returns to unemployment it makes an important difference whether he gets a fresh start with his past sanctions P reset to 0 or whether P persists at the pre-employment level. Having P persist at the pre-employment level would imply that benefit eligibility once lost cannot be regained, thus overstating not only the likelihood of receiving a terminal sanction, but also the resulting utility loss. However if P is reset to 0 after any period of employment (however short), the threat of receiving a terminal sanction is strongly understated relative to the real institutional setting. We stick as close to the real setup as possible by assuming that when a job is destroyed P is reset to 0, only if the worker has been employed for more than $\overline{\tau}$ time periods. The value of employment thus becomes dependent on employment duration. We define τ as number of employment periods necessary to establish a new claim to unemployment benefits, i.e. after τ periods in employment P is set to 0. The value of being employed at wage w, given P and τ thus is

$$\tilde{E}(w,P,\tau) = \begin{cases} w + \beta(\delta U(0,P) + (1-\delta)E(w,P,\tau-1)) & \text{if } \tau > 0\,, \\ w + \beta(\delta U(0,0) + (1-\delta)E(w,0,0)) & \text{if } \tau = 0\,. \end{cases}$$

The value of becoming employed at wage w and given past sanctions P then equals

$$E(w,P) = \begin{cases} \tilde{E}(w,0,0) & \text{if } P = 0\,, \\ \tilde{E}(w,P,\overline{\tau}) & \text{if } P > 0\,. \end{cases}$$

Law of motion of the state variables In a given period the decisions of the unemployed worker depend on two state variables. The first state variable, denoted by s, counts the remaining time periods of an ongoing sanction. If $s > 0$, the unemployed worker does not receive unemployment benefits for the next s time periods. Upon arrival of a new sanction s is increased by K, i.e. the unemployed worker is sanctioned by a benefit reduction for the subsequent K time periods. The other state variable P counts the number of sanctions received in the past. If an unemployed worker's accumulated past sanctions cross a threshold value $\overline{P}$, a terminal sanction is imposed on him, i.e. he completely loses benefit eligibility.

Reservation wages It is straightforward to show that the value of employment is strictly increasing in w. It follows that the unemployed worker adopts a reservation wage strategy when deciding whether to accept or reject job offers. The worker's strategy is completely characterized by reservation wages for regular job offers $\overline{w}_J(s,P)$ and for job offers obtained through VRs $\overline{w}_V(s,P)$ for each combination of state variables $s \in \{0,...,K\}$ and $P \in \{0,...,\overline{P}\}$ and a reservation wage $\overline{w}_\Phi$ that characterizes decision-making of terminally sanctioned individuals.

5 Estimation

We estimate the model by maximum likelihood (ML), fitting the joint distribution of the observable data. Recall that we observe unbalanced panel data on employment status, the occurrence of VRs, reported sicknesses and imposed sanctions. Denote the vector of relevant observables for individual i in time period t by

$$Z_{it} = (e_{it+1}, e_{it},\ vr_{it},\ sick_{it},\ sanc_{it}, s_{it}, P_{it}),$$

where e_{it} is an indicator for employment status (1 for employed, 0 for unemployed). Data on the state variables s_{it} and P_{it} are derived from the individual specific history of past $sanc_{it}$ realizations. In time periods when an individual accepts a job, Z_{it} additionally includes the accepted wage, w_{it}^{acc}.[7]

Wage Offer Distributions For the estimation we impose a parametric form on the wage offer distributions, i.e., we require that F_J and F_V are specified up to a finite dimensional unknown parameterization. In principle any parametric distribution can, but the model is identified only if the wage offer distributions satisfy the Flinn and Heckman (1982) recoverability condition. For the structural estimation we specify F_J and F_V to be log-normal, with locaction and scale parameters μ_J, σ_J and μ_V, σ_V, respectively.

Measurement Error We allow for measurement error in accepted wages to reduce the sensitivity of our estimates to the lowest sampled accepted wage. Allowing for measurement error furthermore prevents the likelihood function from falling to zero, whenever the wage of a sampled individual is smaller than the reservation wage implied by our model. As we use administrative data for our estimation the wages we observe are not prone to the usual reporting errors that are to be expected in survey data. However to obtain monthly wages, we scale up daily payments by a constant, which introduces measurement error. We assume the measurement error enters log-wages additively as is standard in the literature on empirical search models (cf. Wolpin 1987), i.e. $ln(\tilde{w}^{acc}) = ln(w^{acc}) + \epsilon$, where ϵ is normally distributed with mean zero and variance σ_ϵ^2. The measurement error variance σ_ϵ^2 is treated as unknown parameter, i.e. estimated along with the structural model parameters.

Likelihood function For the ML estimation we fix the discount factor at $\beta = 0.997$. Note that we observe the exact unemployment benefits that an individual receives and thus we do not need to estimate b.[8] All remaining parameters are estimated. The complete vector of unknown parameters is

$$\theta = \big(\mu_J,\, \sigma_J,\, \mu_V,\, \sigma_V,\, \lambda_J,\, \lambda_V, \psi,\, p_{sick},\, p_{doc},\, p_{sanc},\, \delta,\, \sigma_\epsilon\big).$$

Given our data for individuals $i = 1, ..., N$, where each individual is observed for a sequence of time periods $t = 1, ..., T_i$ the likelihood function equals

$$\mathcal{L} = \prod_{i=1}^{N} \prod_{t=1}^{T_i} h_{it}\big(Z_{it} | \, \theta\big)$$

[7] To be more formally precise we could include an additional element $w_{it}^{acc} \cdot \mathbf{1}(e_{it+1} > e_{it})$ in Z_{it}.

[8] How we make use of the benefit data is described in more detail below in the section on observed heterogeneity.

For a derivation of the likelihood contributions $h_{it}\big(Z_{it}|\,\theta\big)$ see appendix A.4.

Heterogeneity We introduce heterogeneity by allowing a subset of the structural parameters to vary across individuals. To account for observed heterogeneity we assume the relationship between observables in our data X_i and structural parameters can be captured by standard parametric functional forms. We specify two separate functional forms depending on the structural parameter's range of admissible values. For μ_J and μ_V, which take only positive values, we specify the dependence on X_i by

$$\mu_J = \exp\left(\zeta_1' X_i\right), \quad \mu_V = \exp\left(\zeta_2' X_i\right).$$

For λ_J, λ_V, ψ, and δ, which take values in $[0, 1]$, we specify dependence on X_i by

$$\lambda_J = \big(1 + \exp(-\zeta_3' X_i)\big)^{-1}, \qquad \lambda_V = \big(1 + \exp(-\zeta_4' X_i)\big)^{-1},$$
$$\psi = \big(1 + \exp(-\zeta_5' X_i)\big)^{-1}, \qquad \delta = \big(1 + \exp(-\zeta_6' X_i)\big)^{-1}.$$

For the estimation we include in X_i age, dummy variables indicating health restrictions and completion of apprenticeship training as well as a constant. For computational tractability we discretize age into 10 year bins, spanning the range from 28 to 58 years. For variables that vary over time we focus on measurements in the first sampled time period to ensure parameter stability within individual. As we observe the exact amount of benefits each sampled individual receives, we can furthermore account for heterogeneity in benefits. In particular we allow the benefit level b in our structural model to be individual specific and set it equal to the monthly benefits received in the first sample period. We discretize benefits into bins of width 250 spanning the range between 500 and 1500 Euros.

We account for unobserved heterogeneity by introducing a latent factor ν that takes values in a discrete set $\{v_1, ..., v_M\}$. The probability that ν takes realization v_m is denoted by π_m. We impose a normalization on ν_M such that $\mathbb{E}[\nu] = 0$. The latent factor ν is assumed to enter a subset of the structural parameters, namely in p_{doc} and p_{sanc}, with different factor loadings, thereby introducing additional heterogeneity that is unrelated to X_i. Formally we specify

$$p_{doc} = \big(1 + \exp(-X_i' \zeta_8 - \gamma_{doc}\nu)\big)^{-1}, \tag{4}$$

$$p_{sanc} = \big(1 + \exp(-X_i' \zeta_9 - \gamma_{sanc}\nu)\big)^{-1}. \tag{5}$$

The advantage of using a one-factor specification relative to the unrestricted finite mixture model by Heckman and Singer (1984) is a reduction in the number of unknown parameters and a substantial reduction in computation time, as the one-factor specification requires computing a one-dimensional rather than a multidimensional integral. As the factor loadings γ_{doc} and γ_{sanc} may take arbitrary values, the one-factor specification is not restricting the impact of unobserved heterogeneity to be similar across parameters. However it imposes a relationship between variance and covariance of the structural parameters within the population.[9]

The likelihood function for the model specification with observed and unobserved heterogeneity accounts for the dependence of structural model parameters on X_i and ν. To account for unobserved heterogeneity each individual's likelihood contribution is averaged over unobserved types. The likelihood function then equals

$$\mathcal{L} = \prod_{i=1}^{N} \left(\sum_{m=1}^{M} \pi_m \prod_{t=1}^{T_i} h_{it}\big(Z_{it} | \, \theta(v_m, X_i)\big) \right), \tag{6}$$

where the dependence of the structural parameters θ on X_i and ν is governed by the parameters $\zeta_1, \zeta_2, ..., \zeta_9$ and γ_{doc} and γ_{sanc} respectively. We subsume these parameters into vectors ζ and γ and denote by π the vector containing the probabilities $\pi_1, ..., \pi_M$. Maximum likelihood estimation for the specification with observed and unobserved heterogeneity is performed by maximizing $\mathcal{L}$ over ζ, γ, π, σ_J, σ_V and σ_e.

Identification In order to provide intuition how each of the structural model parameters is identified, we present equations that link the parameters of our model to empirical moments of the observed data. By showing that a set of empirical moments uniquely maps into model parameter values, we demonstrate that the structural model is identified in the formal econometric sense (see e.g. French and Taber 2011). Moreover we hope that pointing to links between the observed data and the model parameters provides intuition about which variation in the data identifies the structural parameters. We make use of the identification result by Flinn and Heckman (1982), which can be applied to our setting to obtain identification of reservation wages and wage offer distributions. According to their argument the lowest sampled wage accepted by an unemployed worker in state (s, P) after receiving / not receiving a VR identifies the reservation wages $\overline{w}_V(s, P)$ and $\overline{w}_J(s, P)$, respectively. Given identification of the reservation wages, the wage offer distributions F_J and F_V are identified from the respective distribution of accepted wages if F_J and F_V

[9] For example two parameters that both vary in the population conditional on X_i are necessarily (positively or negatively) correlated. See van den Berg (2001) for a discussion of the one-factor specification of unobserved heterogeneity in the context of the multi-spell mixed proportional hazard model.

are recoverable.[10] The remaining structural parameters are identified from transitions between unemployment and employment together with joint observations of VRs, sanctions and sickness absences. We denote by vr_t, $sanc_t$ and $sick_t$ variables that indicate arrivals of VRs, sanctions and sickness absences, respectively, in period t. Conditional on the state (s_t, P_t) our model implies the following relationships between data moments and structural parameters.

$$P\big(e_{t+1} = 0 | e_t = 1\big) = \delta$$

$$P\big(vr_t = 1 | e_t = 0\big) = \lambda_V$$

$$P\big(sick_t = 0, vr_t = 0, sanc_t = 0, e_{t+1} = 0 | e_t = 0\big) = (1 - p_{sick})\big(1 - \lambda_J(1 - F_J(\overline{w}_J)) - \lambda_V\big)$$

$$P\big(sick_t = 1, vr_t = 0, sanc_t = 0, e_{t+1} = 0 | e_t = 0\big) = p_{sick}(1 - \lambda_V)$$

$$P\big(sick_t = 1, vr_t = 1, sanc_t = 0, e_{t+1} = 0 | e_t = 0\big) = \lambda_V\big(p_{sick} + (1 - p_{sick})F_V(\overline{w}_J)p_{doc}\big)$$

$$P\big(sick_t = 0, vr_t = 1, sanc_t = 1, e_{t+1} = 0 | e_t = 0\big) = (1 - p_{sick})\lambda_V(1 - p_{doc})\psi F_V(\overline{w}_V)p_{sanc}$$

$$\begin{aligned} P\big(sick_t = 0, vr_t = 1, sanc_t = 0, e_{t+1} = 0 | e_t = 0\big) &= (1 - p_{sick})\lambda_V\big(\psi F_V(\overline{w}_V)(1 - p_{doc}) \\ &\quad \cdot (1 - p_{sanc}) + (1 - \psi)(1 - p_{doc}F_V(\overline{w}_J))\big) \end{aligned}$$

It is straightforward to show that under this system of equations the left hand side empirical moments uniquely determine the right hand side structural model parameters. For estimation we use a slightly richer model specification that additionally accounts for parameter heterogeneity and measurement error in observed wages. We estimate the model by maximum likelihood, i.e. we fit the whole joint distribution of the observed variables. The above empirical moments coincide with a subset of the likelihood contributions that show up in the likelihood function.

6 Estimation Results

This section presents our parameter estimates. We provide estimates for a basic empirical specification that does not account for parameter heterogeneity and a full specification that does include both observed and unobserved parameter heterogeneity.[11] Table 1 presents parameter estimates

[10] For estimation we will restrict F_J, F_V to be log-normal. The log-normal distribution is recoverable (see Flinn and Heckman 1982).

[11] More precisely, the basic specification accounts for heterogeneity in unemployment benefit levels, but does not include heterogeneity in any of the structural model parameters. The full specification accounts for both, parameter heterogeneity and heterogeneity in unemployment benefits.

for the basic specification without heterogeneity, Table 2 presents estimates for the full specification. For ease of interpretation of our parameter estimates for the full specification, Tables C.1 and C.2 provide the implied mean structural parameter values and the implied parameter point estimates for individuals of median age (38 years) and for each combination of X_i and ν.

A first thing that is notable from the parameter estimates is that across specifications the mean of the VR wage offer distribution is lower than that of the wage offer distribution of regular job offers, indicating that job offers obtained through VRs are on average less attractive than regular job offers. The small estimate of the measurement error variance, σ_ϵ across both specifications suggests that measurement error in wages plays a limited role.

Another regularity across specifications is that the offer rate for regular job offers is generally lower than the VR arrival rate ($\lambda_J < \lambda_V$). Note however that the two arrival rates λ_J, λ_V have different interpretations. Regular job offers, that arrive at rate λ_J, if accepted result in a job that can be taken up immediately. VRs arrive at rate λ_V, but VR-recipients may still be rejected by the prospective employer (at rate $\psi < 1$) and hence the rate at which VRs effectively yield job offers is lower than λ_V.

In the full specification the impact of X_i, i.e., of age, health restrictions and apprenticeship training is significantly different from zero for all model parameters, indicating that it is relevant to account for observed heterogeneity. For all parameters that additionally include the unobserved factor ν, the estimated impact of the latent factor is statistically significant and sizable, implying that unobserved heterogeneity contributes significantly to the variation in p_{doc} and p_{sanc} across the sampled population. As observed and unobserved heterogeneity thus seem to play an important role, we focus on the full empirical specification that includes parameter heterogeneity in the further analysis.

Model Fit To assess how well our estimated model fits the observed data in Table 3 we contrast data moments with the corresponding predicted values from the estimated model. Our model generally fits the data well, although it somewhat understates the job finding rate.

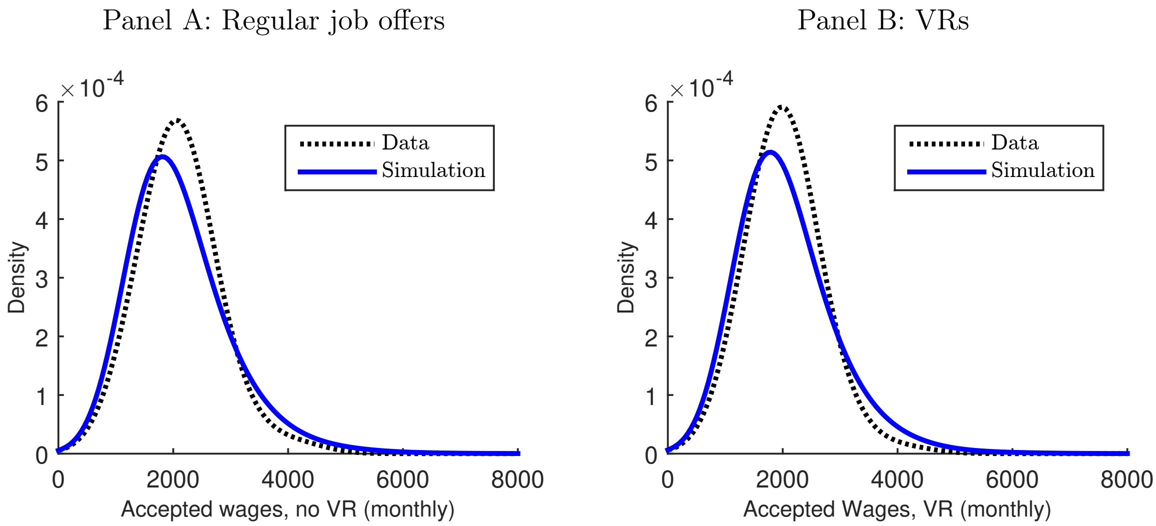
As further evidence on the model fit Figure 1 presents kernel estimates of the densities of observed and simulated accepted wages for regular job offers and VRs respectively, showing that our model provides a good fit for the distributions of accepted wages.

Table 1: Parameter estimates, basic specification.

Parameter	Estimate	SE
m_J	1870	2.68
m_V	1835	2.22
s_J	744	3.44
s_V	859	3.02
λ_J	0.03	0.05×10^{-3}
λ_V	0.11	0.16×10^{-3}
p_{sick}	0.02	0.07×10^{-3}
p_{doc}	0.05	1.27×10^{-3}
p_{sanc}	0.17	0.35×10^{-3}
ψ	0.16	0.20×10^{-3}
δ	0.07	0.23×10^{-3}
σ_ϵ	0.12	0.03×10^{-3}

Note: Standard errors are computed using the outer product of the score.

Figure 1: Model fit, accepted wages



Notes: Monthly accepted wages in Euro plotted separately for jobs taken up in a month in which no VR was received (panel A)/ a VR was received (panel B). All curves are smoothed using a normal kernel and a bandwidth of 250 (Euros).

Table 2: Parameter Estimates, Full Specification

Parameter	Estimate	SE	Parameter	Estimate	SE
m_J :			m_V :		
Intercept	7.381	1.3×10^{-5}	Intercept	7.431	4.1×10^{-5}
Age (divided by 10)	0.038	1.4×10^{-6}	Age (divided by 10)	0.018	2.7×10^{-6}
Apprenticeship	0.099	4.3×10^{-7}	Apprenticeship	0.091	5.8×10^{-7}
Health restrictions	-0.089	1.1×10^{-6}	Health restrictions	-0.122	1.5×10^{-6}
s_J :	707	1.7	s_V :	670	2.1
σ_ϵ :	0.197	1.5×10^{-5}			
λ_J :			λ_V :		
Intercept	-3.173	3.9×10^{-6}	Intercept	-1.359	7.4×10^{-6}
Age (divided by 10)	-0.035	7.4×10^{-7}	Age (divided by 10)	-0.185	1.9×10^{-6}
Apprenticeship	0.053	4.3×10^{-6}	Apprenticeship	0.351	3.2×10^{-6}
Health restrictions	-0.065	4.7×10^{-6}	Health restrictions	-0.167	4.8×10^{-6}
p_{sick} :			ψ :		
Intercept	-4.980	1.6×10^{-5}	Intercept	-1.482	5.5×10^{-6}
Age (divided by 10)	0.224	3.1×10^{-6}	Age (divided by 10)	-0.030	1.4×10^{-5}
Apprenticeship	0.063	7.0×10^{-6}	Apprenticeship	0.095	2.7×10^{-6}
Health restrictions	0.358	8.9×10^{-6}	Health restrictions	-0.455	1.2×10^{-5}
δ :					
Intercept	-2.585	2.9×10^{-6}			
Age	-0.001	7.6×10^{-7}			
Apprenticeship	-0.064	3.0×10^{-6}			
Health restrictions	0.058	3.0×10^{-6}			
p_{sanc} :			p_{doc} :		
Intercept	-1.867	6.0×10^{-6}	Intercept	-3.914	3.0×10^{-5}
Age (divided by 10)	-0.038	1.2×10^{-6}	Age (divided by 10)	0.047	1.0×10^{-5}
Apprenticeship	-0.026	4.2×10^{-6}	Apprenticeship	-0.817	2.3×10^{-5}
Health restrictions	-0.193	7.5×10^{-6}	Health restrictions	0.154	5.0×10^{-5}
γ_{sanc}	0.636	3.3×10^{-6}	γ_{doc}	1.561	2.2×10^{-5}
ν :			π :		
v_1	2.523		π_1	0.156	
v_2	-0.984	1.3×10^{-6}	π_2	0.421	2.6×10^{-4}
v_3	0.047	5.1×10^{-6}	π_3	0.423	1.5×10^{-4}

Note: Standard errors are computed using the outer product of the score.

Table 3: Model fit

	Data	Simulation
All unemploymed		
VR	13.04%	12.10%
Sickness absence ($\geq$ 2 weeks)	1.98%	2.37%
Job finding rate	4.94%	4.23%
Avg. accepted wage	2102	2084
VR received		
Sickness absence ($\geq$ 2 weeks)	3.30%	3.77%
Job finding rate	14.70%	11.86%
Sanction	0.35%	0.27%

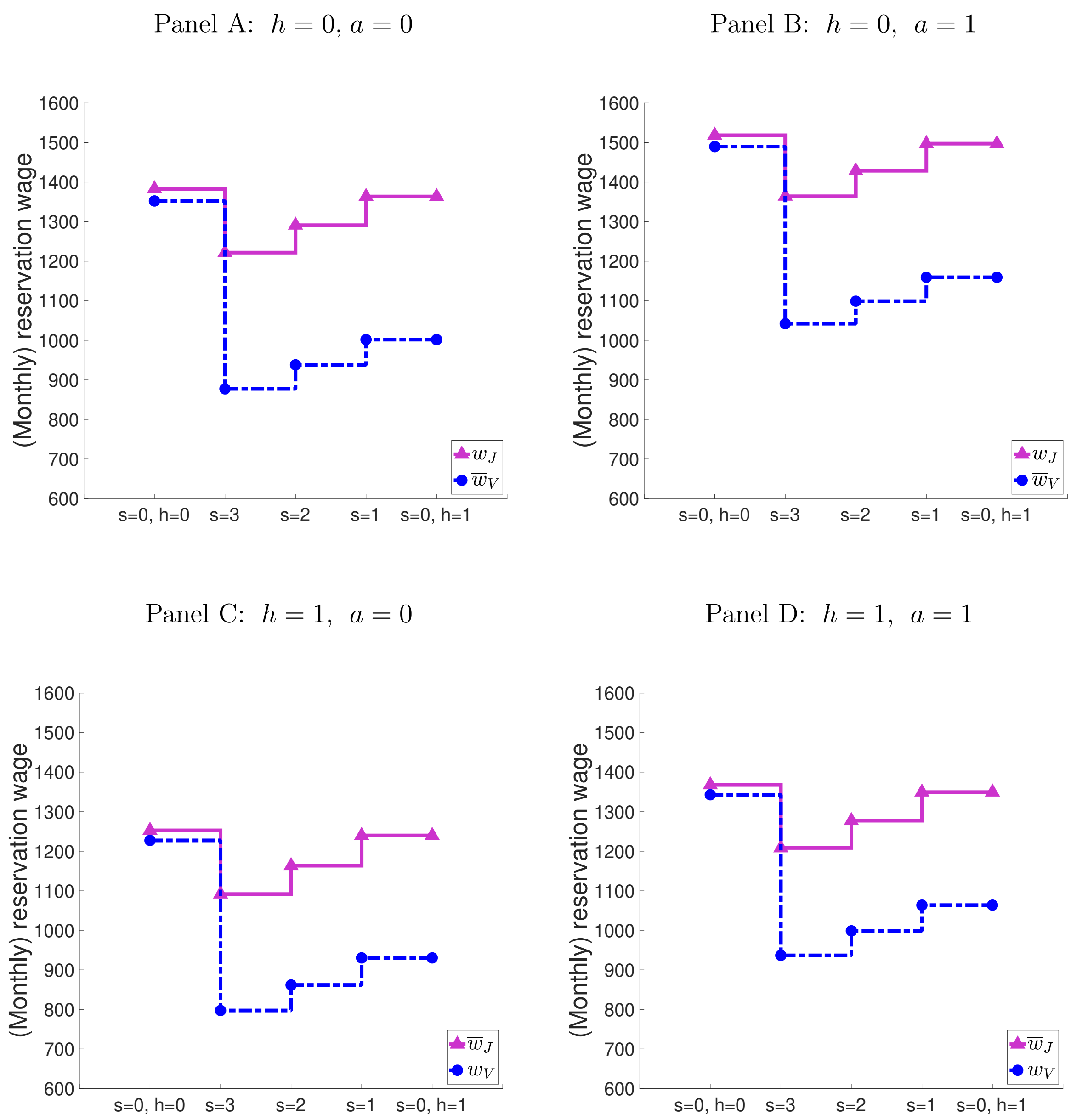
Notes: Data moments are computed from a sample of 79,617 workers observed from 2000 to 2002. The sample restrictions described in 2.3 apply. Model moments are computed from simulations draws for 40,000 workers. We simulate histories of 108 time periods (months) for each worker.

Implied Reservation Wages As a key implication the estimated model yields reservation wages for each agent type. Reservation wages in our model are dependent on the number of remaining sanction periods s and number of past sanctions P that an unemployed worker received. Figure 2 displays reservation wages for regular job offers and job offers obtained through VRs as function of (s, P). Note that any currently sanctioned unemployed worker trivially has received a sanction in the past (the sanction, which is still ongoing), and hence $P = 1$ if $s > 0$.[12]

Figure 2 shows that for unemployed workers who have never been sanctioned ($s = 0$, $P = 0$) the reservation wage for regular job offers, $\overline{w}_J$, is only slightly higher than the reservation wage for VR offers, $\overline{w}_V$. In contrast for unemployed workers who have previously been sanctioned there is a persisting and large positive gap between $\overline{w}_J$ and $\overline{w}_V$. Facing the risk of receiving a terminal sanction upon rejecting a VR makes these individuals accept much lower wage offers for VR offers than for regular job offers.

[12] Recall that in the institutional setting that we study, the second sanction already is a terminal sanction, so that $P \in \{0, 1\}$.

Figure 2: Implied reservation wages, h: health restrictions, a: apprenticeship



Notes: Reservation wages by (s, ps) plotted separately for jobs taken up in a month with/ without a VR. Plotted are reservation wages for agents with median benefit level (1000 Euro) and of median age (38) and for the modal unobserved type, $\nu = 0.047$. Each of the plots corresponds to a different observable type in terms of health restrictions (h) and apprenticeship training a.

7 Policy Simulations

In this section we use the estimated structural model to study how counterfactual policy changes impact job search outcomes and sick reporting. In particular we simulate two types of policy changes: Changes in sanction enforcement and changes in the VR rate. Increasing sanction enforcement corresponds to instructing caseworkers to use their discretionary leeway less and impose sanctions on unemployed workers who do not apply for VRs or reject resulting job offers more frequently. Changes in sanction enforcement are simulated by varying p_{sanc}. Increasing the vacancy referral rate corresponds to ordering caseworkers to send out VRs more frequently. Note that our model abstracts from the impact that a large scale roll out of VRs may have on firms' vacancy posting behavior and on the wage offer distribution. Our model abstracts from such equilibrium effects. Nevertheless we view our model as informative about the impact VRs and sanctions have on the job search behavior of the marginal unemployed worker.

For each counterfactual policy change we examine effects on job finding rates, average unemployment duration and post-unemployment wages and the rate at which unemployed workers receive sanctions.

Varying Sanction Enforcement We consider two extreme policy scenarios, in which we abandon sanctions altogether ($p_{sanc} = 0$) and move to perfect sanction enforcement with zero discretion for caseworkers ($p_{sanc} = 1$) as well as two intermediate scenarios in which sanction enforcement is doubled and tripled.[13]

Table 4 displays results on the impact of changing sanction enforcement on job search outcomes. The results presented in Table 4 show that increasing sanction enforcement leads to an increase in the overall job finding rate and correspondingly reduces average unemployment duration. Quantitatively, tripling the sanction enforcement rate p_{sanc} leads to a reduction in average unemployment duration by 0.16 months (around 5 days). Moving to full enforcement ($p_{sanc} = 1$), would reduce the average unemployment duration by 0.7 months (around 3 weeks). We find that accepted wages respond only slightly to changes in sanction enforcement. Moving to full enforcement, leads to a small decrease by 1.4% (30 Euro) in the mean accepted wage.

To shed light on the underlying mechanism we examine how reservation wages respond to

[13]Recall that sanction enforcement at baseline on average is on average at 13%. Yet, for a fraction of the population doubling and tripling p_{sanc} yields values greater than 1. For these individuals we fix counterfactual sanction enforcement at 1 (full enforcement).

Table 4: Changing sanction enforcement, simulation results

$\tilde{p}_{sanc}$	0	p_{sanc}	$2p_{sanc}$	$3p_{sanc}$	1
All unemployed					
Job finding rate	4.19%	4.23%	4.25%	4.28%	4.42%
Avg. accepted wage	2093	2084	2082	2079	2054
Avg. unemp. duration (months)	20.72	20.61	20.56	20.45	19.90
VR received					
Job finding rate	11.65%	11.86%	12.12%	12.26%%	13.28%
Sanction	0%	0.27%	0.49%	0.66%	1.24%

changes in sanction enforcement. Figure 3 displays the magnitude by which unemployed workers of the modal type in the considered population (in terms of observed and unobserved heterogeneity, X_i and ν) adjust their reservation wages when sanction enforcement is tripled. Figure 3 shows that tripling sanction enforcement leads to a minimal reduction in reservation wages for regular wage offers ($\overline{w}_J$) and a strong reduction in reservation wages for offers obtained through VRs ($\overline{w}_V$). Intuitively, an increased risk of receiving a sanction upon rejecting a VR, leads unemployed workers to be willing to accept a wider range of VR offers. By this mechanism job finding rates after VR reception increase and the distribution of accepted wages receives more mass at its lower end, leading to a reduction in average accepted wages in response to increases in sanction enforcement. The drop in $\overline{w}_V$ in response to tripling sanction enforcement is more pronounced for job searchers who have received a sanction in the past ($P = 1$) and who thus would receive a terminal sanction if they were to be sanctioned again.

Varying the VR Rate Next, we consider policy changes in the VR rate. In particular we consider counterfactual experiments in which the VR rate is increased and decreased by 25% and 50% of its status quo value.

Table 5 displays the simulation results, showing that in the considered experiments increasing the VR rate elevates the overall job finding rate, but decreases the job finding rate in months when a VR was received. Quantitatively, increasing the VR rate by a factor of 1.25 leads to a reduction in average unemployment duration by 1.1 months. Furthermore, the overall job finding rate increases by 0.29, while the job finding rate for months when a VR was received falls by 0.14 percentage points, as the VR rate is increased by a factor of 1.25.

It may perhaps seem surprising that VRs elevate overall job finding while reducing job finding

Figure 3: Increasing sanction enforcement, reservation wages

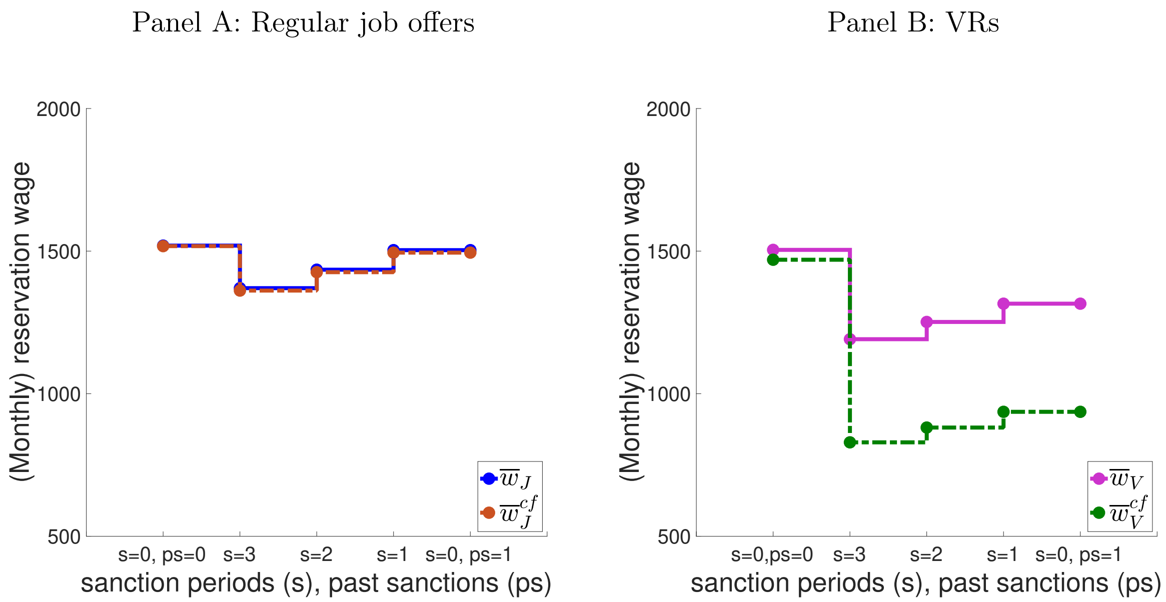
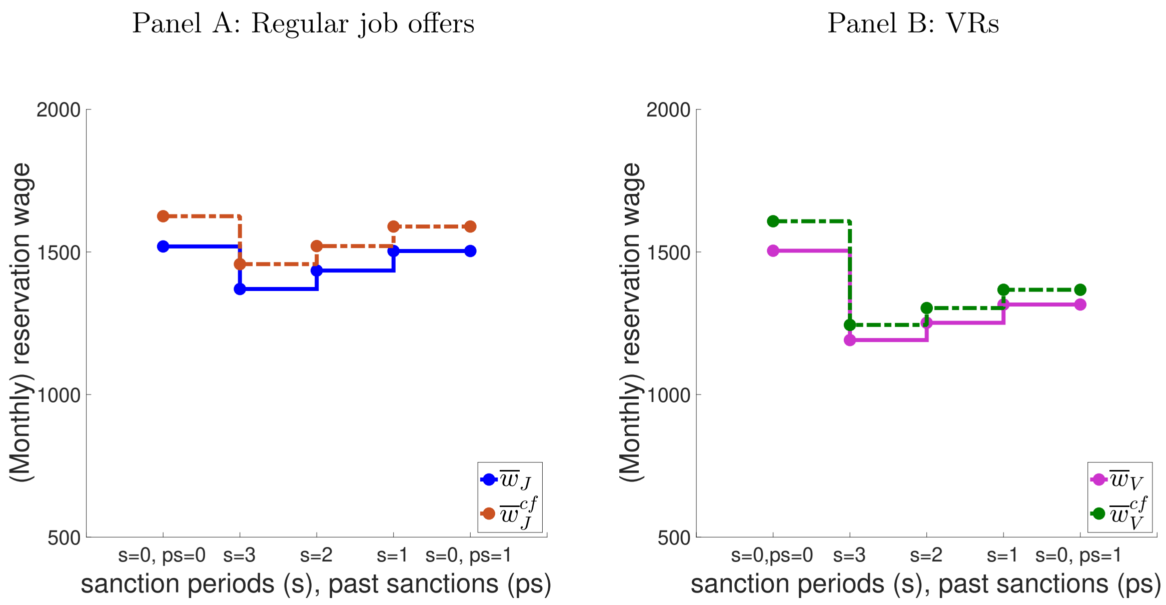


Table 5: Changing the VR rate, simulation results

$\tilde{p}_{vr}$	$0.5p_{vr}$	$0.75p_{vr}$	p_{vr}	$1.25p_{vr}$	$1.5p_{vr}$
All unemployed					
VR	6.06%	9.09%	12.09%	15.05%	18.04%
Job finding rate	3.64%	3.94%	4.23%	4.52%	4.81%
Avg. accepted wage	2072	2081	2084	2092	2106
Avg. unemp. duration (months)	23.19	21.84	20.61	19.50	18.50
VR received					
Job finding rate	12.46%	12.15%	11.86%	11.72%	11.55%
Sanction	0.23%	0.26%	0.27%	0.30%	0.31%

in months when a VR is received. The reason is that VRs have two counteracting effects on job search behavior. On the one hand as the VR rate is increased the risk of receiving a sanction in the future increases. This decreases the option value of search and thus pushes towards lower reservation wages. On the other hand higher VR rates increase the amount of job offers that unemployed workers can expect to sample in the future. This increases the option value of search and as a consequence pushes towards higher reservation wages. To examine which of these two opposing forces dominates, we examine the impact of increasing the VR rate on reservation wages.

Figure 4: Sending more VRs, reservation wages



Looking at the whole population we find that in the considered parameter range increasing the VR rate generally pushes towards higher reservation wages, both for regular job offers and for job offers obtained through VRs, and for all considered agent types. As the VR rate is increased unemployed workers thus become generally more selective about the range of job offers they are willing to accept, i.e., moral hazard increases when the VR rate is raised.

Figure 4 displays reservation wages for the modal type in the population. The figure shows that reservation wages rise as the VR rate is increased, meaning that the force pushing towards a higher option value of search, because more job offers are sampled, dominates.

The fact that increasing the VR rate leads to higher reservation wages explains the declining job finding rates in months when a VR as λ_V is increased: unemployed job searchers reject resulting job offers more often as they can expect to sample more job offers in the future, i.e., moral hazard increases. At the same time, despite higher moral hazard, the overall job finding rate increases, when λ_V is increased. This is because of the mechanical effect that ceteris paribus more VRs (and more resulting job offers) lead to more transitions into employment. This mechanical effect overrides the decline in the rate at which job offers that are accepted.

8 VR Induced Sick Reporting

In this section we examine to what extent unemployed job searchers call in sick to circumvent VRs and by how much this affects job search outcomes. Our model allows to decompose the observed sickness absence rate into a baseline sick rate and a VR induced sick rate. Conditional on agent type (i.e. conditional on X_i and ν) the overall probability to report sick for a particular individual in a given period equals

$$\begin{aligned} P(\text{ sick report } \mid X_i, \nu\,) &= p_{sick} + P(\text{ VR induced sick report } \mid X_i, \nu\,) \\ &= p_{sick} + (1 - p_{sick})\lambda_V\, p_{doc}\, F_V(\overline{w}_J) \end{aligned} \tag{7}$$

where all right hand side parameter values are implicitly conditioned on X_i and ν.

Looking at the overall unemployed population we find that VR induced sick reporting accounts for a substantial share of overall sick reporting. In particular

$$\begin{aligned} &\frac{P(\text{ VR induced sick report})}{P(\text{ sick report })} \\ &= \frac{\sum_{m=1}^{M}\sum_{x\in\mathbf{X}}\pi_m P(X_i = x) P(\text{ VR induced sick report } \mid X_i, \nu_i = v_m\,)}{\sum_{m=1}^{M}\sum_{x\in\mathbf{X}}\pi_m P(X_i = x) P(\text{ sick report } \mid X_i, \nu_i = v_m\,)} \\ &= \quad 9.2\%, \end{aligned} \tag{8}$$

i.e., according to our estimated model 9.2% of all observed sick reports among unemployed individuals occur because individuals try to circumvent a VR. This number corresponds closely to the empirical finding of van den Berg, Hofmann, and Uhlendorff (2014), who find that 9% of all sick reports are VR induced.

VR induced sick reporting hence accounts for a substantial share of overall sick reporting. In order to quantify to what extent VR induced sick reporting affects job search behavior we simulate a counterfactual scenario in which only individuals who are actually sick can obtain a sick note, i.e., in which VR induced sick reporting is completely shut down ($p_{doc} = 0$). While this counterfactual change does not immediately relate to a real world policy measure, this scenario can be interpreted as medical doctors becoming perfect in screening out individuals who ask for a sick note but in fact are not sick.

Table 6 displays sick reporting rates and job search outcomes for the counterfactual scenario in which VR induced sick reporting is shut down. Shutting down VR induced sick reporting reduces overall sick reporting by 9.2%, consistent with our above calculation based on (6). This overall effect is entirely driven by reduced sick reporting in months when a VR is received. Sick reporting in these months drops by 45% (from 3.77% to 2.06%), when VR induced sick reporting is eliminated.

Table 6: Eliminating VR induced sick reporting

$\tilde{p}_{doc}$	p_{doc}	0
All unemployed		
Sickness absence ($\geq$ 2 weeks)	2.37%	2.17%
Job finding rate	4.23%	4.25%
Avg. accepted wage	2084	2086
Avg. unemp. duration (months)	20.61	20.51
VR received		
Sickness absence	3.77%	2.06%
Job finding rate	11.86%	12.02%
Sanction	0.27%	0.35%

Despite the sizable effects on sick reporting we find, that shutting down VR induced sick reporting has only modest effects on job search outcomes averaged across the whole population. In periods when a VR is received we find a very modest increase in the job finding rate which translates into a slight reduction in average unemployment duration by 0.1 months (3 days). The mechanism here is that unemployed workers who circumvented VRs by handing in a doctor's note, are willing to accept some of these VR offers when the option of strategically calling in sick is removed.

Albeit average effects of eliminating VR induced sick reporting on job search outcomes are small, the magnitude of these effects strongly varies across individuals in the heterogeneous population and is sizable for some subgroups. To illustrate this we repeat our analysis, focusing only on unemployed workers above the 75th percentile of the distribution of VR induced sick reporting, $P($ VR induced sick report $\mid X_i, \nu\,)$.

Counterfactual outcomes for this subpopulation are displayed in Table 7. The presented results show that VR induced sick reporting constitutes 27% of overall sick reporting within this subpopulation. Moreover we find that VR induced sick reporting does have a sizable impact on job search outcomes. In particular, eliminating VR induced sick reporting leads to a 0.26 months (1 week and a day) reduction in average unemployment duration. What is more, as job searchers lose the possibility of circumventing VRs by reporting sick, the number of individuals who receive a sanction increases by a factor of 1.7 (but remains below 1%).

In table C.3 we present further results, for unemployed workers above the 90th percentile of the distribution of VR induced sick reporting. For this subgroup we find that eliminating VR induced sick reporting reduces average unemployment duration by 2 weeks, while the sanction rate increases by a factor of 2.1.

Table 7: Eliminating VR induced sick reporting, top 25%

$\tilde{p}_{doc}$	p_{doc}	0
All unemployed		
Sickness absence ($\geq$ 2 weeks)	3.23%	2.36%
Job finding rate	3.93%	3.99%
Avg. unemp. duration (months)	21.85	21.59
Avg. accepted wage	2061	2063
VR received		
Sickness absence	9.99%	2.25%
Job finding rate	11.28%	11.64%
Sanction	0.44%	0.75%

9 Conclusion

In this paper we study VRs and punitive sanctions, accounting for the possibility that workers may strategically report sick to avoid sanctions. We develop and estimate a structural job search model in which unemployed workers are forward looking and adjust their search behavior to receiving VRs or sanctions. Upon receiving a low wage VR, unemployed workers may rationally seek to get a sick note from their doctor to circumvent receiving a sanction.

We study a range of counterfactual policy changes. We find that increasing sanction enforcement leads to substantially reduced reservation wages for job offers obtained through VRs. By this mechanism, increasing sanction enforcement raises job finding rates. In contrast, increasing the VR rate, leads to higher reservation wages. Sending more VRs increases the amount of job offers that unemployed workers expect to sample in the future, thereby increasing the option value of search. This mechanism dominates the effect that higher VR rates also increase the risk of receiving sanctions in the future, which pushes towards lower reservation wages. Nevertheless, a higher VR rate leads to higher job finding rates, as the higher frequency at which VRs arrive mechanically leads to higher job take-up, even at increased reservation wages.

We find that VR induced sick reporting accounts for a substantial share of overall sick reporting. According to our estimated model, 9.2% of all observed sick reports are induced by VRs. Looking at averages across the population of unemployed workers we find modest effects of shutting down VR induced sick reporting on job search outcomes. However, there is substantial heterogeneity in the population. For the 25% and 10% of workers with the highest propensity of VR induced sick reporting we find that eliminating VR induced sick reporting would reduce the mean unemployment duration by one week and a day, and 2 weeks, respectively.

An interesting extension would be to study VRs and sanctions . It can be conjectured that some of the policies we study may have effects on wage setting and vacancy posting behavior. Moreover, increasing the VR rate may crowd other workers who applied for the referred vacancies. We view studying the equilibrium effects of VRs and sanctions in a search and matching framework as an interesting extension that is left for future work.

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A Derivations

A.1 Value of Employment

For the value of employment, $\tilde{E}(w,P,\tau)$, we have

$$\begin{aligned}\tilde{E}(w,0,0) &= w+\beta\big((1-\delta)E(w,0,0)+\delta U(0,0)\big) && (9)\\ &= \frac{w+\beta\delta U(0,0)}{1-\beta(1-\delta)}, && (10)\end{aligned}$$

for $P=0$ and $\tau=0$, and

$$\begin{aligned}\tilde{E}(w,P,\tau) &= w\sum_{l=0}^{\tau-1}\beta^l(1-\delta)^l+\beta\delta U(0,P)\sum_{l=0}^{\tau-1}\beta^l(1-\delta)^l+\beta^\tau(1-\delta)^\tau\tilde{E}(w,0,0)\\ &= w\frac{1-\beta^\tau(1-\delta)^\tau}{1-\beta(1-\delta)}+\beta\delta U(0,P)\frac{1-\beta^\tau(1-\delta)^\tau}{1-\beta(1-\delta)}+\beta^\tau(1-\delta)^\tau\tilde{E}(w,0,0)\\ &= \frac{w}{1-\beta(1-\delta)}+\beta\delta U(0,P)\frac{1-\beta^\tau(1-\delta)^\tau}{1-\beta(1-\delta)}+\beta^\tau(1-\delta)^\tau\frac{\beta\delta U(0,0)}{1-\beta(1-\delta)}\end{aligned} \tag{11}$$

for $P>0$. Reservation wages equalize the value of accepting and rejecting job offers. For regular job offers we thus have

$$E\big(\overline{w}_J(s,P),P\big)=U(\max\{s-1,0\},P), \tag{12}$$

for each (s,P) such that $P<\overline{P}$. Using (20) together with (10) yields

$$U(0,0)=\frac{\overline{w}_J(0,0)}{1-\beta} \tag{13}$$

(11), (20) and (13) together imply

$$U(0,P)=\frac{(1-\beta)\overline{w}_J(0,P)+\beta^{\tau+1}\delta(1-\delta)^\tau\overline{w}_J(0,0)}{(1-\beta)\big(1-\beta+\beta^{\tau+1}\delta(1-\delta)^\tau\big)}. \tag{14}$$

Inserting (13) and (14) back into (10) and (11) respectively, yields

$$\tilde{E}(w,0,0)=\frac{w}{1-\beta(1-\delta)}+\frac{\beta\delta\overline{w}_J(0,0)}{(1-\beta)(1-\beta(1-\delta))}. \tag{15}$$

A.2 Terminal Sanctions, Value Function

Terminally sanctioned unemployed workers search for a job while receiving reduced benefits, b_{low} and do not receive VRs. The value of being terminally sanctioned hence is given by

$$\Phi = b_{\text{low}} + \beta\Big(\lambda_J \int \max\{E(w,\overline{P}),\, \Phi\} dF_J(w) + (1-\lambda_J)\Phi\Big). \tag{16}$$

Rearranging and inserting (11) into (16) yields

$$(1-\beta)\Phi = b_{\text{low}} + \beta\,\lambda_J \int_{\overline{w}_\Phi}^{+\infty} \frac{w-\overline{w}_\Phi}{1-\beta(1-\delta)} dF_J(w). \tag{17}$$

Using that $\Phi = U(0,\overline{P}) = E(\overline{w}_\Phi,\overline{P})$ together with (11) yields

$$(1-\beta+\beta^\tau(1-\delta)^\tau)\Phi = \overline{w}_\Phi + \beta^{\tau+1}(1-\delta)^\tau\delta\, U(0,0) \tag{18}$$

Inserting Φ from equation (18) into (17) yields the reservation wage equation for terminally sanctioned unemployed workers

$$\frac{(1-\beta)\overline{w}_\Phi + \beta^{\tau+1}(1-\delta)^\tau\delta\,\overline{w}_J(0,0)}{1-\beta+\beta^\tau(1-\delta)^\tau} = b_{\text{low}} + \beta\,\lambda_J \int_{\overline{w}_\Phi}^{+\infty} \frac{w-\overline{w}_\Phi}{1-\beta(1-\delta)} dF_J(w). \tag{19}$$

Note that the reservation wage for regular job offers of unemployed workers with no past sanctions, $\overline{w}_J(0,0)$, enters this equation. The reservation wage of terminally sanctioned unemployed workers, $\overline{w}_\Phi$, thus cannot be solved for in isolation, but we need to solve equation (19) jointly with the rest of the model.

A.3 Derivation of the System of Reservation Wage Equations

Reservation wages equalize the value of accepting a job offer with the value of continuing to search for a job. For each combination of (s,P), we thus have

$$E\big(\overline{w}_J(s,P)\big) = U(\max\{s-1,0\},P), \tag{20}$$

and moreover for the reservation wages after receipt of a VR

$$E(\overline{w}_V(s,P)) = \begin{cases} (1-p_{sanc})U(\max\{s-1,0\},P) + p_{sanc}U(\overline{s},P+1), & \text{if } P < \overline{P}-1 \\ \\ (1-p_{sanc})U(\max\{s-1,0\}) + p_{sanc}\Phi, & \text{if } P = \overline{P}-1 \end{cases} \tag{21}$$

$$= \begin{cases} (1-p_{sanc})E\big(\overline{w}_J(s,P)\big) + p_{sanc}E\big(\overline{w}_J(\overline{s},P+1)\big), & \text{if } P < \overline{P}-1 \\ \\ (1-p_{sanc})E\big(\overline{w}_J(s,P)\big) + p_{sanc}E\big(\overline{w}_\Phi\big), & \text{if } P = \overline{P}-1. \end{cases} \tag{22}$$

For the value of unemployment, U, for $s > 0$, rearranging (3) yields

$$\begin{aligned} U(s,P) = \quad & \beta(1-p_{sick})\Bigg(\lambda_J \int\limits_{\overline{w}_J(s,P)}^{+\infty} \frac{w-\overline{w}_J(s,P)}{1-\beta(1-\delta)} dF_J(w) + \lambda_V A_V(s,P) \\ & +(1-\lambda_V)E(\overline{w}_J(s,P),P)\Bigg) + \beta p_{sick}E(\overline{w}_J(s,P),P). \end{aligned}$$

By inserting (20) into (1) and rearranging it follows that

$$A_V(s,P) = \int B_V(w)dF_V(w) + p_{doc}\int \max\{E(\overline{w}_J(s,P),P) - B_V(w),0\}dF_V(w). \tag{23}$$

Consider the first expression on the right hand side sum of (23). By inserting (2) and rearranging we get

$$\begin{aligned} \int B_V(w)dF_V(w) \quad &= \quad \psi \int \max\big\{E(w,P)\,,\, E(\overline{w}_V(s,P),P)\big\}dF_V(w) \\ & \quad\quad +(1-\psi)\; E(\overline{w}_J(s,P),P) \\ &= \quad \psi \int\limits_{\overline{w}_V(s,P)}^{+\infty} \frac{w-\overline{w}_V(s,P)}{1-\beta(1-\delta)} dF_V(w) + \psi E(\overline{w}_V(s,P),P) \\ & \quad\quad +(1-\psi)\; E(\overline{w}_J(s,P),P) \end{aligned}$$

Now consider the second term on the right hand side sum of (23). From (20) and (2) it follows that $B_V(w) \geq E(\overline{w}_J(s,P),P)$ if and only if $w \geq \overline{w}_J(s,P)$. The second term in equation (23) thus yields

$$
\begin{aligned}
& p_{doc} \int \max\{E(\overline{w}_J(s,P),P) - B_V(w), 0\} dF_V(w) \\
& = p_{doc} \int_0^{\overline{w}_J(s,P)} E(\overline{w}_J(s,P),P) - B_V(w) dF_V(w) \\
& = p_{doc}\, \psi \Bigg(F_V(\overline{w}_J(s,P)) \big(E(\overline{w}_J(s,P),P) - E(\overline{w}_V(s,P),P) \big) \\
& \quad - \int_{\overline{w}_V(s,P)}^{\overline{w}_J(s,P)} \frac{w - \overline{w}_V(s,P)}{1-\beta(1-\delta)} dF_V(w) \Bigg) \\
& = p_{doc}\, \psi \Bigg(F_V(\overline{w}_J(s,P)) \frac{\overline{w}_J(s,P) - \overline{w}_V(s,P)}{1-\beta(1-\delta)} - \int_{\overline{w}_V(s,P)}^{\overline{w}_J(s,P)} \frac{w - \overline{w}_V(s,P)}{1-\beta(1-\delta)} dF_V(w) \Bigg)
\end{aligned}
$$

After inserting (20), (2) and rearranging we have (for $s > 0$)

$$
\begin{aligned}
& E(\overline{w}_J(s+1,P),P) = \\
& \beta(1-p_{sick}) \Bigg[\lambda_J \int_{\overline{w}_J(s,P)}^{+\infty} \frac{w - \overline{w}_J(s,P)}{1-\beta(1-\delta)} dF_J(w) + \lambda_V \psi \int_{\overline{w}_V(s,P)}^{+\infty} \frac{w - \overline{w}_V(s,P)}{1-\beta(1-\delta)} dF_V(w) \\
& + p_{doc} \Bigg(F_V(\overline{w}_J(s,P)) \frac{\overline{w}_J(s,P) - \overline{w}_V(s,P)}{1-\beta(1-\delta)} - \int_{\overline{w}_V(s,P)}^{\overline{w}_J(s,P)} \frac{w - \overline{w}_V(s,P)}{1-\beta(1-\delta)} dF_V(w) \Bigg) \\
& - \psi \lambda_V \frac{\overline{w}_J(s,P) - \overline{w}_V(s,P)}{1-\beta(1-\delta)} \Bigg] + \beta E(\overline{w}_J(s,P),P). \qquad (24)
\end{aligned}
$$

Note from (3) that it holds that

$$U(0,P) = U(1,P) + b.$$

Together with (20) and (11) we thus have

$$\overline{w}_J(0,P) = \overline{w}_J(1,P) + (1-\beta(1-\delta))b. \qquad (25)$$

We use equation (24) (for $s = 1,...,K$ and $P = 1,...,\overline{P}-1$) equation (25), equation (22) (for $s = 0,...,K$ and $P = 1,...,\overline{P}-1$) and equation (18) to solve for the reservation wages $\overline{w}_J(s,P)$,

$\overline{w}_V(s,P)$ for (for $s=0,...,K$ and $P=1,...,\overline{P}-1$) and $\overline{w}_\Phi$. Taken togehter we thus have a system of $2\times K\times(\overline{P}-1)+1$ reservation wage equations that we solve for the same number of reservation wages.

A.4 Likelihood Contributions

In the following the individual subscript i is omitted for notational convenience. For transitions from unemployment to unemployment the likelihood contribution $h_t^{uu} = h_t(e_t = 0,\, vr_t,\, sick_t,\, sanc_t, e_{t-1} = 0|\, \theta)$ is given by

$$h_t^{uu} = \begin{cases} (1-p_{sick})\big(1-\lambda_J\big[1-F_J(\overline{w}_J(s,P))\big]-\lambda_V\big) & \text{if } (vr_t = 0,\, sick_t = 0, s_t = s, P_t = P) \\ p_{sick}(1-\lambda_V) & \text{if } (vr_t = 0,\, sick_t = 1) \\ \lambda_V\big[p_{sick} + (1-p_{sick})p_{doc}F_V(\overline{w}_J(s,P))\big] & \text{if } (vr_t = 1,\, sick_t = 1, s_t = s, P_t = P) \\ \lambda_V(1-p_{sick})\big[F_V(\overline{w}_V(s,P))(1-p_{doc})\psi(1-p_{sanc}) + [1-p_{doc}F_V(\overline{w}_J(s,P))](1-\psi)\big] & \text{if } (vr_t = 1,\, sick_t = 0,\, sanc_t = 0,\, s_t = s, P_t = P) \\ p_{vr}(1-p_{sick})F_V(\overline{w}_V(s,P))(1-p_{doc})\psi p_{sanc} & \text{if } (vr_t = 1,\, sick_t = 0,\, sanc_t = 1, s_t = s, P_t = P)\,. \end{cases}$$

For transitions from unemployment to employment $h_t^{ue} = h_t(e_t = 1,\, vr_t,\, e_{t-1} = 0|\, \theta)$ we have

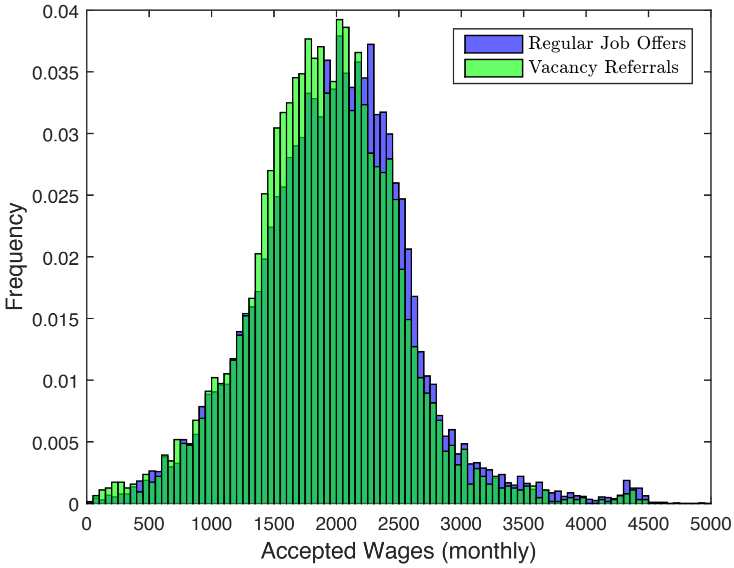
$$h_t^{ue} = \begin{cases} (1-p_{sick})\lambda_J \int f_J(w)\, \mathbf{1}\{w \geq \overline{w}_J(s,P)\}\, \frac{1}{\sigma_\epsilon}\, \phi\big(\frac{w-\tilde{w}^{acc}}{\sigma_\epsilon}\big) dw & \text{if } (vr_t = 0, \tilde{w}_t^{acc}, s_t = s, P_t = P) \\ (1-p_{sick})\lambda_V \psi \int f_V(w)\, \mathbf{1}\{w \geq \overline{w}_V(s,P)\}\; (1-p_{doc})^{\mathbf{1}\{w \leq \overline{w}_J(s,P)\}}\; \frac{1}{\sigma_\epsilon}\, \phi\big(\frac{w-\tilde{w}^{acc}}{\sigma_\epsilon}\big) dw & \text{if } (vr_t = 1, \tilde{w}_t^{acc}, s_t = s, P_t = P) \end{cases}$$

and finally for transitions from employment to unemployment $h_t^{eu} = h_t(e_t = 0,\, e_{t-1} = 1|\, \theta)$ and transitions from employment to employment $h_t^{ee} = h_t(e_t = 1,\, e_{t-1} = 1|\, \theta)$ we have

$$h_t^{eu} = 1 - h_t^{ee} = \delta\,.$$

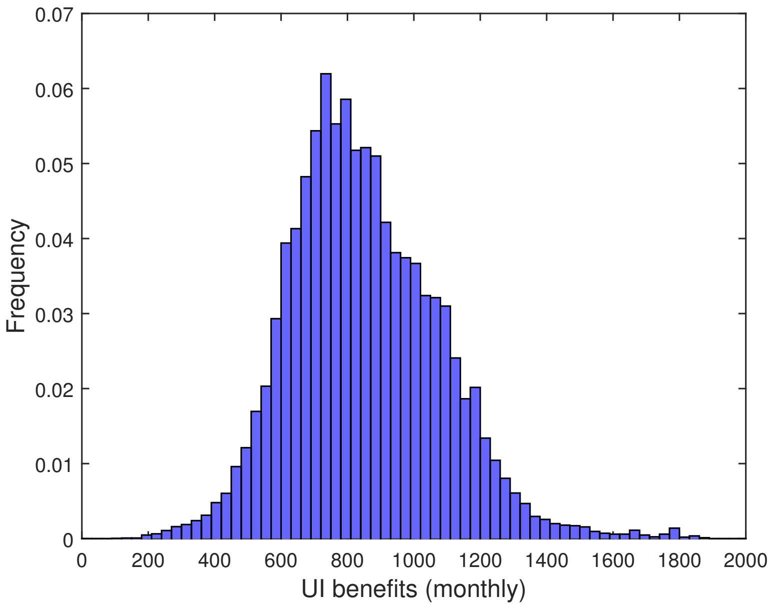
B Figures

Figure B.1: Empirical distribution of accepted wages



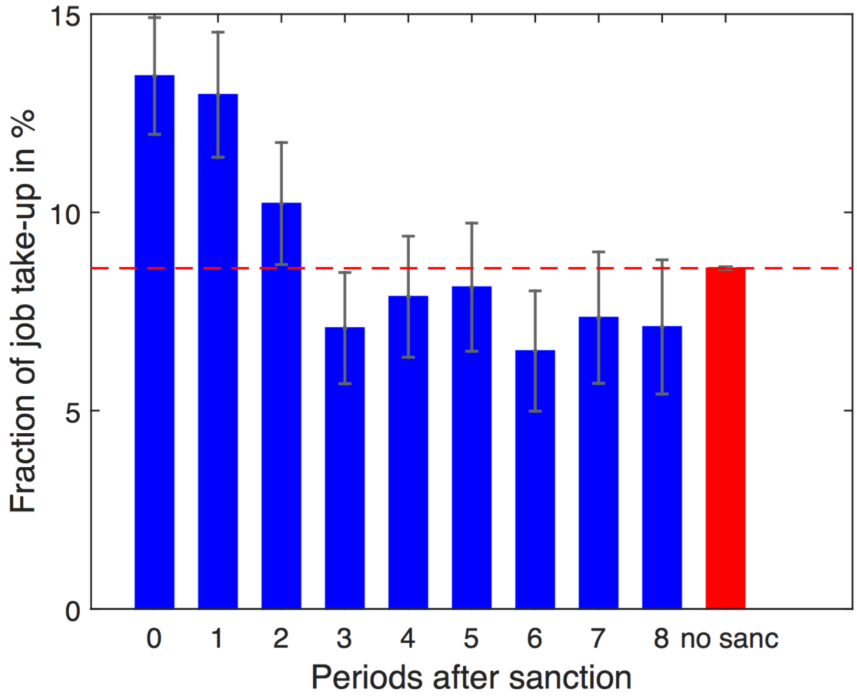
Notes: Monthly wages in Euro. Plotted separately for jobs found in months in which a VR was received and months in which no VR was received. Based on a sample of 69,788 workers observed from 2000 to 2002. The sample restrictions described in 3 apply.

Figure B.2: Empirical distribution of UI benefits



Notes: Monthly UI benefits in Euro. Plotted separately for jobs found in months in which a VR was received and months in which no VR was received. Based on a sample of 69,788 workers observed from 2000 to 2002. The sample restrictions described in 3 apply.

Figure B.3: Job take-up after sanctions



Notes: Month $t = 0$ refers to the first month after a sanction is imposed. Displayed are job take-up rates t months after a sanction is imposed and for non-sanctioned unemployed workers, together with 95% confidence intervals.

C Tables

Table C.1: Average structural parameters

Parameter	Population avg.
m_J	1889
m_V	1796
λ_J	0.04
λ_V	0.12
p_{sick}	0.02
p_{doc}	0.07
p_{sanc}	0.13
ψ	0.15
δ	0.07

Notes: The table displays estimates of the structural model parameters averaged over the empirical distribution of observables, X_i, and the estimated distribution of the unobserved factor, ν.

Table C.2: Implied structural parameters

ν	apprenticeship health restricted	0 0	0 1	1 0	1 1
	m_J	1854	1696	2046	1872
	m_V	1809	1601	1980	1753
	λ_J	0.035	0.033	0.037	0.035
	λ_V	0.113	0.097	0.153	0.133
	p_{sick}	0.016	0.023	0.017	0.024
	ψ	0.169	0.114	0.182	0.124
	δ	0.070	0.074	0.066	0.069
$\nu = 2.523$	p_{doc}	0.459	0.498	0.273	0.305
	p_{sanc}	0.400	0.355	0.394	0.349
$\nu = -0.984$	p_{doc}	0.004	0.005	0.002	0.002
	p_{sanc}	0.067	0.056	0.065	0.054
$\nu = 0.047$	p_{doc}	0.020	0.023	0.009	0.010
	p_{sanc}	0.121	0.102	0.118	0.100

Note: The table displays estimates of the structural model parameters for all combinations of observables, X_i, and the unobserved factor, ν, fixing individual age at its median value (age 38).

Table C.3: Eliminating VR induced sick reporting, top 10%

$\tilde{p}_{doc}$	p_{doc}	0
All unemployed		
Sickness absence ($\geq$ 2 weeks)	3.58%	2.36%
Job finding rate	3.70%	3.80%
Avg. unemp. duration (months)	23.05	22.56
Avg. accepted wage	1994	1989
VR received		
Sickness absence	13.95%	2.29%
Job finding rate	10.23%	10.78%
Sanction	0.37%	0.79%